

CT PLAQUE RADIOMICS IN CORONARY ARTERY DISEASE: A SYSTEMATIC REVIEW

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ABSTRACT

Background: Coronary computed tomography angiography (CCTA) is a popular non-invasive method for assessing coronary artery disease (CAD) however; conventional evaluation focuses primarily on luminal stenosis and may fail to capture plaque vulnerability or future disease progression. High-dimensional quantitative information can be extracted from CT images using radiomics and artificial intelligence (AI) approaches, thereby improving plaque characterization and cardiovascular risk prediction. **Objective:** The Objective is to thoroughly examine retrospective research by assessing the use of AI and radiomics in coronary CT imaging for cardiovascular risk assessment, plaque progression prediction, and susceptible plaque identification. **Materials and Methods:** This systematic review was conducted in accordance with PRISMA 2020 guidelines, carried out on retrospective original studies published between 2021 and 2026 searching electronic databases such as PubMed, Scopus, Web of Science, and Google Scholar. Studies that used radiomics and/or AI in coronary CT angiography or CT imaging for outcomes linked to plaque were included. Methodological variability led to a qualitative synthesis of the data. From a comprehensive literature search, 10 retrospective observational studies specifically applying radiomics to coronary plaque analysis using CCTA were included for detailed synthesis. Data on study design, population, imaging methodology, radiomics pipelines, and outcomes were extracted. Risk of bias was assessed using QUADAS-2, and radiomics methodological quality was evaluated using the Radiomics Quality Score (RQS). A qualitative synthesis was performed due to methodological heterogeneity. **Result:** Across the 10 included studies, CT plaque radiomics demonstrated consistent associations with vulnerable plaque characteristics, plaque progression, hemodynamically significant stenosis, and adverse cardiovascular outcomes, providing incremental value beyond conventional anatomical assessment. QUADAS-2 assessment revealed a moderate risk of bias, primarily related to retrospective study design, patient selection, and flow-and-timing domains, while the reference standard domain showed low risk of bias across studies. RQS evaluation indicated moderate methodological quality, with strengths in feature reduction and internal validation, but limitations related to external validation, clinical utility assessment, and open science practices. **Conclusion:** CT-based coronary plaque radiomics shows significant potential to enhance risk stratification and plaque characterization beyond traditional CCTA metrics. However, current evidence is limited by retrospective design, methodological heterogeneity, and moderate radiomics quality. Prospective, multicenter studies with standardized workflows, external validation, and evaluation of clinical impact are required before routine clinical implementation.

INTRODUCTION

Coronary artery disease (CAD) is still the biggest killer globally, and it's becoming increasingly clear that just looking at the diameter of a vessel isn't enough to save lives. We need a way to see what's actually happening inside the vessel wall. Right now, Coronary Computed Tomography Angiography (CCTA) is our best non-invasive tool for mapping out coronary anatomy and spotting blockages. But there's a catch: the way we usually read these scans is pretty old-school. It relies on a doctor's eyes or basic measurements of plaque volume, which simply can't capture the biological "red flags" that tell us if a plaque is actually dangerous or just sitting there.

This is exactly where radiomics changes the game. It moves us past visual guesswork by using math to extract thousands of hidden data points from CT images—features that the human eye has no way of seeing. Think of it as a "digital biopsy" that reveals the inner texture and spatial complexity of a plaque. We've seen landmark studies prove that these CCTA-derived features are much better at identifying high-risk plaques and predicting heart attacks than the standard clinical models we've used for years ^[1,2]. Researchers are now using radiomics to find patterns in both calcified and soft plaques that were previously invisible, which is a massive step forward in spotting vulnerable lesions ^[5,6]. It's even being used to track how atherosclerosis physically "evolves" over time in a patient, giving us a time-lapse view of the disease ^[2,1].

The clinical impact here isn't just theoretical. We're seeing radiomics models catch early disease in people who were labelled "low risk" and accurately point out the "culprit" lesion in a heart attack when standard CCTA was unclear ^[7,15]. There's even evidence that it can predict the functional significance of a blockage—similar to what we'd get from an invasive FFR test—without the patient ever needing a catheter ^[22].

But here is the reality check: despite the hype, getting this into clinics is hard because the current research is a bit of a mess. Most studies are retrospective, and there is zero consistency in how images are taken or how the plaques are "mapped out" by software ^[13,1]. This lack of a standard "playbook" means a model that works in one lab might fail in the next. Plus, very few researchers are sharing their code or data, which makes it nearly impossible to double-check these results ^[22,16]. We realized that before this technology can actually help patients, we need to stop and look at the evidence objectively. That's why we did this review. Following PRISMA 2020 guidelines and using strict tools like the Radiomics Quality Score (RQS) and QUADAS-2, we've analyzed the field to find the gaps and figure out how to make coronary radiomics a reality ^[2-5].

MATERIALS AND METHODS

Study Design and Reporting criteria: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting criteria are followed in this systematic review of randomized and non-randomized studies.

Method of Search: As part of the systematic review, we searched a number of databases in January 2026, including Google Scholar, PUBMED, EMBASE, and Web of Science. Below is a complete description of the methodical search procedure, including the specific search phrases. The last day of the search was January 10, 2026. In order to find other pertinent papers, we also looked through the grey literature.

Inclusion criteria

Our review specifically looked at adult patients who had undergone coronary CT imaging. We kept our scope broad regarding the types of scans used, including not only standard coronary CT angiography (CCTA) but also non-contrast cardiac CT and low-dose CT protocols. The "index test" we focused on was the application of CT-based radiomics; we included research where radiomics was used as a standalone tool as well as studies that paired it with machine learning or deep learning models. To ensure we were looking at primary evidence, we limited our selection to original observational research, which allowed us to pull data from a variety of retrospective, longitudinal, and multicenter study designs. The outcomes of interest were the detection and characterization of coronary plaques, assessment of plaque vulnerability and progression, evaluation of coronary calcification or stenosis, and prediction of cardiovascular events. Reference standards included expert interpretation of CCTA images, follow-up imaging findings, clinical outcomes, or histopathological validation where available. Finally, only full-text articles published in English were considered eligible for inclusion. These characteristics were consistently observed across all included studies that justify their inclusion in the final analysis.

Exclusion criteria

We had to be quite strict with our selection to ensure the focus remained entirely on radiomics. Any research that stuck to basic CT measurements without exploring radiomic features was filtered out. We also set aside studies using other imaging types, like MRI or invasive IVUS, unless they were being compared directly alongside CT-based radiomics. To ensure the quality of our data, we did not consider non-original articles, including editorials, letters, and conference abstracts that lacked a full-text report. Since our goal was to evaluate clinical potential in humans, all preclinical work involving animal models or phantoms was removed from the selection. We also omitted studies that failed to define clear plaque-related outcomes or lacked

proper validation for their models. Finally, to prevent data overlap and ensure the integrity of our synthesis, we excluded any duplicate articles or studies that utilized overlapping patient cohorts.

Data extraction: Data were independently extracted from all included studies using a standardized extraction form, capturing study design, population characteristics, imaging modality, radiomics methodology, outcomes, and validation strategies.

Quality Assessment: Methodological quality and risk of bias were assessed using the QUADAS-2 tool, evaluating patient selection, index test, reference standard, and flow and timing domains. In addition, the Radiomics Quality Score (RQS) was applied to assess radiomics-specific methodological rigor, including image acquisition, feature extraction, model development, validation, and clinical utility. Discrepancies were resolved by consensus, ensuring a robust and transparent quality assessment process.

RESULTS

The study selection process was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. PRISMA is an evidence-based guideline that ensures transparent and standardized reporting of study identification, screening, eligibility, and inclusion in systematic reviews. The literature search, as previously described, resulted in 4410 studies. After removing 160 duplicates, 4250 remained for screening. Following this screening, 4199 records were excluded. Record for full-text articles were 51 and are assessed for eligibility. Out of 51, 29 were excluded due to narrative reviews or meta-analysis (n=3) and different methodologies (n=26). Consequently, 22 studies were included in qualitative synthesis. Ultimately, 10 studies met all inclusion criteria and were included in final analysis.

Characteristics of the Included Studies: Among the 22 retrospective studies, 14 employed retrospective cross-sectional or cohort designs, six were retrospective longitudinal studies with follow-up outcomes, and two were retrospective multicenter analyses. From these, 10 key studies specifically addressing coronary plaque radiomics using coronary computed tomography angiography (CCTA) were identified for detailed synthesis. These studies evaluated radiomics features derived from coronary plaques or coronary artery

calcification to assess vulnerable plaque characteristics, plaque progression, ischemia, or prediction of adverse cardiovascular events.

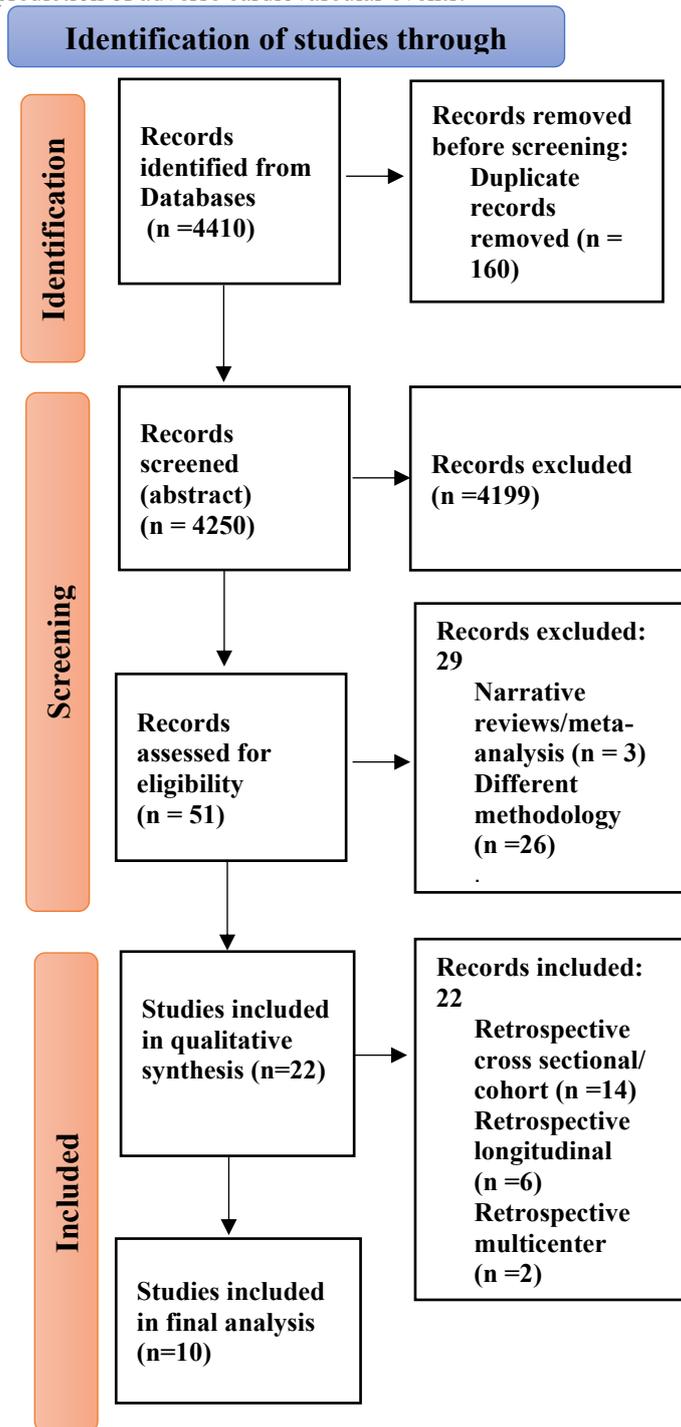


Table 1: Characteristics and Key Findings of the Included Studies on CT Plaque Radiomics in CAD.

| Author/year | Title | Study design | Population/Dataset | Imaging modality | Radiomics | Aim |
|---------------------|---|----------------------|---|------------------|----------------------------|--|
| Chen Q et al., 2023 | A Coronary CT Angiography Radiomics Model to Identify Vulnerable Plaque and Predict Cardiovascular Events | Retrospective cohort | Patients undergoing CCTA with follow-up | CCTA | Radiomics + ML classifiers | Identification of vulnerable plaques and prediction of cardiovascular events |

| | | | | | | |
|---------------------------|--|---|---|-----------------|--------------------------------|---|
| Zhang R et al., 2025 | Combined Radiomics–Clinical Model for Early Plaque Detection | Retrospective Cohort | CCTA-negative individuals or low risk populations | CCTA | Radiomics + clinical variables | Early detection of coronary plaque development |
| Chen YC et al., 2024 | Coronary CTA-Based Vascular Radiomics Predicts Atherosclerosis Development Proximal to LAD Myocardial Bridging | Retrospective longitudinal | Patients with myocardial bridging | CCTA | Vascular/Plaque radiomics | Predict plaque development related to myocardial bridging |
| Li L et al., 2021 | Radiomic Features of Plaques to Identify Hemodynamically Significant Stenosis | Retrospective cohort | Patients with invasive FFR reference | CCTA | Plaque Radiomics | Identify functionally significant stenosis |
| Huang EP et al., 2023 | Lower Attenuation and Higher Kurtosis of Coronary Artery Calcification Associated With Vulnerable Plaque | Retrospective propensity-matched | Patients with coronary artery calcification | Non-contrast CT | CAC radiomics | Assess association between CAC radiomics and plaque vulnerability |
| Kolossváry M et al., 2021 | Contribution of Risk Factors to the Development of Coronary Atherosclerosis | Retrospective longitudinal | Patients with serial CCTA | CCTA | Plaque Radiomics | Assess risk-factor-driven plaque development |
| Kahmann J et al., 2024 | Combined Conventional Factors and Radiomics Signature of Coronary Plaque Texture | Retrospective cohort | Patients undergoing clinically indicated CCTA | CCTA | Plaque texture radiomics | Improve cardiac risk prediction |
| Zhang S et al., 2025 | Incremental Value of Coronary CTA-Based Radiomics in Identifying Culprit Lesions | Retrospective cohort | Patients with acute myocardial infarction | CCTA | Plaque radiomics | Identify culprit lesions beyond anatomic analysis |
| Feng C et al., 2023 | Predicting Coronary Plaque Progression with Radiomics | Retrospective longitudinal | Patients with serial CCTA | CCTA | Plaque Radiomics | Prediction of coronary plaque progression |
| Kolossváry M et al., 2025 | Coronary Plaque Radiomic Phenotypes Predict Fatal or Nonfatal Myocardial Infarction | Retrospective multicenter, longitudinal | SCOT-HEART trial participants | CCTA | Plaque radiomics phenotyping | Predict fatal and non-fatal myocardial infarction |

Quality Assessment and Risk of Bias Evaluation:

In this systematic review, study quality was evaluated using the Quality Assessment Scale (QAS), QUADAS-2, and the Radiomics Quality Score (RQS). QAS was used to assess overall methodological rigor and reporting quality,

QUADAS-2 evaluated the risk of bias and applicability of diagnostic accuracy studies, and RQS assessed the methodological robustness, reproducibility, and clinical relevance of radiomics-based studies.

Table 2: Quality Assessment and Risk of Bias Summary of the Included Studies.

| Study | Patient Selection (Risk Of Bias) | Index Test Imaging+ radiomics (Risk Of Bias) | Reference Standard (Risk Of Bias) | Flow and Timing (Risk Of Bias) | Applicability concerns |
|---------------------------|----------------------------------|--|-----------------------------------|--------------------------------|------------------------|
| Chen Q et al., 2023 | Moderate | Moderate | Low | Moderate | Low |
| Zhang R et al., 2025 | Moderate | Moderate | Low | Moderate | Low |
| Chen YC et al., 2024 | Moderate | Moderate | Low | Moderate | Low |
| Li L et al., 2021 | Moderate | Moderate | Low | Moderate | Low |
| Huang EP et al., 2023 | Moderate | Moderate | Low | Moderate | Low |
| Kolossváry M et al., 2021 | Moderate | Moderate | Low | Moderate | Low |
| Kahmann J et al., 2024 | Moderate | Moderate | Low | Moderate | Low |

| | | | | | |
|----------------------------|----------|----------|-----|----------|-----|
| Zhang S et al., 2025 | Moderate | Moderate | Low | Moderate | Low |
| Feng C et al., 2023 | Moderate | Moderate | Low | Moderate | Low |
| Kolossvary M et al., 2025 | Moderate | Moderate | Low | Moderate | Low |

Table 3: Radiomics Quality Score (RQS) assessment of methodological quality of included radiomics studies

| Study (Author / Year) | Image Protocol & Reporting | Segmentation & Reproducibility | Feature Reduction & Validation | Clinical Utility Analysis | Open Science | Overall RQS Level |
|----------------------------|----------------------------|--------------------------------|--------------------------------|---------------------------|--------------|-------------------|
| Chen Q et al., 2023 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Zhang R et al., 2025 | Partial | Partial | Adequate | Partial | Poor | Moderate |
| Chen YC et al., 2024 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Li L et al., 2021 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Huang EP et al., 2023 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Kolossvary M et al., 2021 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Kahmann J et al., 2024 | Partial | Partial | Adequate | Partial | Poor | Moderate |
| Zhang S et al., 2025 | Partial | Partial | Adequate | Partial | Poor | Moderate |
| Feng C et al., 2023 | Partial | Partial | Adequate | Poor | Poor | Moderate |
| Kolossvary M et al., 2025 | Partial | Partial | Adequate | Partial | Poor | Relatively High |

Risk of Bias Assessment (QUADAS-2): Risk of bias assessment using the QUADAS-2 tool demonstrated a predominantly moderate risk of bias across the included key studies. All studies showed moderate risk of bias in the patient selection domain, largely due to retrospective designs and non-consecutive patient inclusion. The index test domain, encompassing CT imaging and radiomics analysis, also demonstrated moderate risk of bias, reflecting retrospective feature selection and model optimization. In contrast, the reference standard domain was consistently rated as low risk of bias, as all studies employed established and clinically accepted standards such as invasive fractional flow reserve, validated CCTA plaque assessment, Agatston scoring, or adjudicated clinical cardiovascular outcomes. The flow and timing domain demonstrated a moderate risk of bias, attributable to variable follow-up durations and exclusion of incomplete datasets. Applicability concerns were low across all studies, indicating good alignment between study populations, index tests, and the objectives of this review.

Radiomics Methodological Quality (RQS): Assessment using the Radiomics Quality Score (RQS) revealed an overall moderate level of methodological quality across the key CT plaque radiomics studies. Most studies partially fulfilled criteria related to image acquisition reporting and segmentation reproducibility, while feature reduction and model development were adequately addressed using established statistical or machine-learning approaches. However, clinical utility analyses were infrequently performed, and external validation was rarely reported. Additionally, open science practices, including public sharing of data or

source code, were generally absent. Only one study demonstrated relatively higher radiomics methodological quality through the use of multicenter data and longitudinal outcome validation, although limitations related to clinical impact assessment remained.

Study designs included: This PRISMA-compliant systematic review included retrospective observational studies evaluating coronary CT plaque radiomics, with qualitative synthesis performed due to methodological heterogeneity.

Radiomics and AI Approaches: All included studies extracted quantitative radiomics features from coronary CT images. Seven studies used radiomics combined with machine learning classifiers, one multicenter study integrated deep learning and radiomics for automated plaque detection and stenosis grading and some studies combined radiomics with clinical variables to improve predictive performance.

Synthesis of Clinical Outcomes and Radiomic Applications: Four main categories can be used to classify the main results examined in the various studies:

Finding Vulnerable Coronary Plaques: Numerous investigations, including those verified against histology and those separating patients with acute coronary syndrome from those without symptoms, showed that radiomics characteristics generated from CCTA could separate susceptible plaques [18].

Forecasting the Development of New Plaques and Plaque Progression: Baseline radiomics characteristics were linked to future plaque progression and the formation of new atherosclerotic plaques, frequently surpassing

traditional plaque measures, according to retrospective longitudinal investigations [23].

Forecasting the Severity of Coronary Calcification and Stenosis: The role of quantitative imaging biomarkers was supported by radiomics from low-dose and standard CT imaging, which showed promise in predicting coronary artery calcification and stenosis severity [8].

Automated Identification and Categorization of Plaques: Deep learning is used together with radiomics was able to automatically identify, categorize, and grade stenosis across various vendors and locations, according to a large multicenter retrospective study [9].

Overall Findings: Radiomics-based models consistently outperformed traditional visual or quantitative plaque evaluation in all included retrospective studies. Radiomics features showed strong potential for early identification of high-risk plaques, prediction of disease progression, and risk stratification in patients undergoing coronary CT imaging. However, heterogeneity in imaging protocols, feature extraction methods, AI models, and outcome definitions precluded quantitative meta-analysis.

Summary of Evidence: There are 10 included studies, all retrospective, predominantly uses CCTA. It is non-invasive prediction of plaque vulnerability and progression. There is no methodological heterogeneity as there are other studies as well. But there is lack of standardized radiomics pipe lines.

DISCUSSION

This systematic review synthesized evidence from ten key studies evaluating CT-based coronary plaque radiomics using coronary computed tomography angiography (CCTA) in patients with coronary artery disease, demonstrating the growing role of radiomics in advanced plaque characterization beyond conventional anatomical assessment [1,2]. Several studies consistently demonstrated that plaque-level radiomics features are significantly associated with vulnerable plaque characteristics and adverse cardiovascular outcomes, supporting the biological relevance of radiomics-derived texture and heterogeneity metrics [1,2]. Radiomics phenotyping of coronary plaques was shown to predict fatal and nonfatal myocardial infarction independent of traditional risk factors and standard plaque metrics, highlighting its potential prognostic value [2]. Longitudinal investigations further strengthened these findings by demonstrating associations between baseline plaque radiomics features and atherosclerosis development or plaque progression on follow-up imaging [6,2,1]. These results suggest that radiomics may capture dynamic plaque behaviour related to disease evolution rather than static anatomical descriptors alone [1,6]. Beyond plaque vulnerability and progression, several studies

reported incremental clinical value of plaque radiomics in functional assessment and lesion-specific evaluation [22,15]. Plaque radiomics features were shown to identify hemodynamically significant coronary stenosis when validated against invasive fractional flow reserve, indicating potential utility in functional risk stratification [22]. In acute myocardial infarction populations, radiomics-based models improved identification of culprit lesions compared with anatomical and hemodynamic analysis alone [6]. Early disease detection was another important application, as combined radiomics-clinical models enabled identification of coronary plaque development even in CCTA-negative or low-risk populations, suggesting a role for radiomics in subclinical disease detection [7]. These findings support the hypothesis that radiomics can detect subtle plaque changes not apparent on routine visual assessment [7,1]. Despite these promising results, all included studies employed retrospective designs, contributing to moderate risk of bias related to patient selection, retrospective feature optimization, and variable follow-up intervals [1,2]. External validation was limited across studies, raising concerns regarding reproducibility and generalizability across scanners, institutions, and populations [13,6]. Methodological heterogeneity was also evident, with substantial variability in plaque segmentation strategies, radiomics feature extraction, and machine-learning approaches, which limits direct comparison between studies and precludes quantitative meta-analysis [7,16]. Furthermore, formal assessment of clinical utility and impact on patient management was infrequently performed, representing a major barrier to clinical translation [15,22]. Overall, the evidence from these ten studies suggests that CT plaque radiomics is a promising imaging biomarker for enhanced risk stratification, plaque characterization, and prognostic assessment in coronary artery disease, while underscoring the need for prospective, multicenter validation and standardized radiomics workflows [1,2].

Strengths and Limitations: The strengths of this review include adherence to PRISMA guidelines, systematic quality assessment using QUADAS-2 and RQS, and focused synthesis of studies directly evaluating coronary plaque radiomics. Limitations include the predominance of retrospective evidence, exclusion of quantitative meta-analysis due to methodological heterogeneity, and reliance on reported study-level data.

Radiomics for Identification of Vulnerable Plaques: Vulnerable plaques might be successfully distinguished using radiomics features collected from coronary CT angiography (CCTA), according to several included studies. Significantly, one study strengthened biological plausibility by validating radiomics results against histopathological reference standards. Furthermore, propensity-matched analyses showed that radiomics of calcified plaques could differentiate between asymptomatic people

with a similar calcium burden and patients with acute coronary syndrome (ACS), indicating that radiomics captures microstructural information not visible on traditional imaging.

These results lend credence to the idea that radiomics allows for a more detailed description of plaque heterogeneity and composition, which are important factors influencing plaque instability. This could assist get around the drawbacks of conventional CCTA, which mainly concentrates on luminal stenosis rather than plaque biology [21].

Prediction of Plaque Progression and New Plaque Formation: This review's longitudinal retrospective research showed that baseline radiomics characteristics are linked to the establishment of new atherosclerotic lesions and future plaque progression. Radiomics-based models are better than traditional plaque characteristics like plaque volume or degree of stenosis in several investigations. This implies that radiomics could identify early subclinical alterations that precede obvious plaque development.

Early detection of patients at risk for plaque progression could allow for prompt preventative measures, potentially changing the course of the disease. This makes such predictive capability clinically useful [19].

Radiomics and AI for Risk Stratification: Beyond characterizing plaque, it has been demonstrated that radiomics paired with machine learning can help with cardiovascular risk stratification, including the prediction of cardiovascular events and the severity of stenosis. When compared to single-center models, a multicenter study that combined radiomics and deep learning showed strong performance across vendors and institutions, suggesting better generalizability. Predictive accuracy was further improved by integrating radiomics with clinical variables, supporting the usefulness of multimodal models that incorporate imaging biomarkers with conventional risk factors [24].

Clinical Implications: All things considered, the results point to the potential of coronary CT radiomics to enhance the identification of high-risk plaques, predict disease progression before evident stenosis develops, support tailored risk stratification; and expand the clinical utility of CCTA beyond anatomical assessment. Radiomics-based tools could be used as decision-support systems in regular CCTA processes if they are verified in prospective, multicenter trials [1].

Conclusion of Discussion: In summary, coronary CT plaque radiomics represents a promising tool for improving the characterization and risk stratification of coronary artery disease. Nevertheless, current evidence is limited by moderate risk of bias and methodological constraints, underscoring the need for well-designed prospective studies before routine clinical implementation can be recommended.

CONCLUSION

Following PRISMA 2020 guidelines, this systematic review identified, screened, and synthesized evidence from studies published since 2021 investigating CT-based radiomics for the assessment of coronary artery disease. The structured study selection process ensured transparent reporting and reproducibility, allowing for a comprehensive synthesis of evidence related to coronary plaque detection, characterization, vulnerability assessment, and cardiovascular outcome prediction. Qualitative synthesis of the included studies demonstrated that radiomics features extracted from coronary CT angiography, non-contrast cardiac CT, and low-dose CT consistently provided incremental diagnostic and prognostic value beyond conventional CT parameters. Radiomics-based models, particularly when combined with machine learning or deep learning techniques, showed improved performance in identifying high-risk plaque phenotypes and predicting adverse cardiovascular events. However, integration of PRISMA-based evidence synthesis with methodological quality assessment revealed important limitations. QUADAS-2 evaluation indicated that the majority of studies exhibited moderate to high risk of bias, primarily within the patient selection and index test domains, largely due to retrospective study designs, selective inclusion criteria, and absence of blinded model assessment. Applicability concerns were also identified, reflecting limited generalizability to broader clinical populations. Similarly, Radiomics Quality Score assessment demonstrated that most studies achieved low to moderate RQS values, with consistent deficiencies in protocol standardization, feature robustness analysis, test-retest evaluation, and external or prospective validation. These findings indicate that, despite promising performance metrics, methodological weaknesses reduce confidence in the clinical readiness of current radiomics models. In line with PRISMA recommendations, the combined interpretation of evidence synthesis and quality assessment underscores a clear gap between proof-of-concept research and clinical implementation. Future investigations should prioritize prospective, multicenter study designs, standardized imaging and radiomics pipelines, rigorous external validation, and comprehensive reporting aligned with PRISMA, QUADAS-2, and RQS frameworks. In conclusion, while CT-based coronary plaque radiomics represents a promising non-invasive tool for advancing precision cardiovascular imaging, its translation into routine clinical practice will depend on methodological rigor, standardization, and high-quality evidence generation guided by established systematic review and radiomics quality standards.

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