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Artificial Intelligence-Enabled Coronary CT Angiography for Plaque Quantification: A Systematic Review and Meta-Analysis

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Abstract

Background

Artificial intelligence-enabled coronary CT angiography (AI-CCTA) enables automated plaque quantification; however, its correlation with invasive imaging remains uncertain.

Objectives

To evaluate the correlation between AI-CCTA-derived plaque metrics and intracoronary imaging modalities.

Methods

A systematic review and meta-analysis of studies comparing AI-CCTA with IVUS, OCT, or NIRS-IVUS was performed. Correlation coefficients were pooled using a random-effects model after Fisher z transformation. Heterogeneity and publication bias were assessed. Subgroup analysis was performed for IVUS-based studies.

Results

Six studies (n = 2,598) were included. AI-CCTA demonstrated a strong correlation with reference imaging (r = 0.91, 95% CI: 0.87–0.94). Heterogeneity was substantial (I^2 = 94.6%, Q test p < 0.001). Sensitivity analysis excluding the largest study demonstrated a persistent strong correlation with reduced heterogeneity. In IVUS-only studies (n = 4), correlation remained high (r = 0.93, 95% CI: 0.89–0.95) with persistent heterogeneity. Funnel plot asymmetry was observed, though interpretation was limited by the small number of studies.

Conclusions

AI-CCTA demonstrates strong correlation with invasive imaging for plaque quantification, though substantial heterogeneity across studies limits direct comparison and highlights the need for standardized validation frameworks before widespread clinical implementation.

INTRODUCTION

Coronary computed tomography angiography (CCTA) has become an established non-invasive modality for evaluation of coronary artery disease, enabling assessment of both luminal stenosis and atherosclerotic plaque burden.[9] Beyond stenosis assessment, plaque characterisation has emerged as a critical determinant of cardiovascular risk and clinical decision-making.[10]

However, conventional plaque quantification remains limited by interobserver variability and time-intensive manual analysis. Recent advances in artificial intelligence (AI) and deep learning have enabled automated plaque segmentation and quantification from CCTA datasets.[2–5] These tools may improve the reproducibility and efficiency of coronary plaque assessment while reducing dependence on time-intensive manual analysis.

Several studies have validated AI-based CCTA plaque quantification against invasive imaging modalities such as intravascular ultrasound (IVUS), optical coherence tomography (OCT), and near-infrared spectroscopy (NIRS).[2–5] While individual studies demonstrate strong correlation, variability in methodology and patient populations necessitates systematic evaluation.

We performed a systematic review and meta-analysis to evaluate the correlation between AI-enabled CCTA plaque quantification and invasive intracoronary imaging modalities.

METHODS

Study Design and Reporting Standards

This systematic review and meta-analysis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines.[1] The study protocol was developed a priori to define the research question, inclusion criteria, and statistical approach.

Search Strategy

A comprehensive literature search was performed using PubMed, Embase, and the Cochrane Library from database inception through March 2026. The search strategy incorporated a combination of keywords and controlled vocabulary terms related to artificial intelligence, coronary computed tomography angiography (CCTA), plaque quantification, and intracoronary imaging modalities.

Representative search terms included:

- “artificial intelligence” OR “deep learning” OR “machine learning”
  AND
- “coronary CT angiography” OR “CCTA” OR “CTA”
  AND
- “plaque” OR “atheroma” OR “coronary stenosis”
  AND
- “intravascular ultrasound” OR “IVUS” OR “optical coherence tomography” OR “OCT” OR “intravascular imaging”

In addition to database searches, manual screening of reference lists and relevant articles was performed to identify additional studies.

Study Selection

A total of 312 records were identified, including 308 from database searches and 4 from additional sources. After removal of 72 duplicate records, 240 unique studies remained for title and abstract screening. Of these, 192 were excluded based on irrelevance to the study objectives. The remaining 48 studies underwent full-text assessment for eligibility.

Studies were included if they:

1. Evaluated artificial intelligence-enabled CCTA for coronary plaque quantification
2. Compared AI-derived measurements with a reference intracoronary imaging modality (IVUS, OCT, or NIRS-IVUS)
3. Reported quantitative correlation metrics (e.g., Pearson’s correlation coefficient)
4. Included human subjects

Studies incorporating externally validated intracoronary imaging reference cohorts were considered eligible if quantitative correlation metrics between AI-CCTA and invasive imaging were reported.

Studies were excluded if they:

- Were review articles, editorials, or case reports
- Did not include a comparator imaging modality
- Did not report quantitative correlation data
- Represented duplicate or overlapping cohorts

Following full-text review, 42 studies were excluded, and 6 studies were included in the final qualitative and quantitative synthesis.

Study selection was performed independently by two reviewers, with discrepancies resolved by consensus.

Data Extraction

Data were independently extracted by two reviewers using a standardized data collection form. Extracted variables included:

- Study characteristics (author, year, country, design)
- Sample size
- Type of AI model
- Imaging modality used for comparison
- Plaque quantification parameters (e.g., total plaque volume, plaque subtypes)
- Reported correlation coefficients between AI-CCTA and reference imaging

Where correlation values were not explicitly reported, they were derived from available data or extracted from figures when feasible.

Risk of Bias Assessment

Risk of bias and methodological quality were assessed using the QUADAS-2 (Quality Assessment of Diagnostic Accuracy Studies-2) tool, which is specifically designed for diagnostic accuracy and imaging validation studies. The following domains were evaluated:

• Patient selection

• Index test

• Reference standard

• Flow and timing

Each domain was assessed for risk of bias as low risk or some concerns in accordance with QUADAS-2 guidance.[11] Applicability concerns were additionally considered where relevant. Quality assessment was performed independently by two reviewers, with disagreements resolved by consensus. Detailed QUADAS-2 assessments are provided in Supplementary Table S2 and Supplementary Figures S3-S4.

Statistical Analysis

Correlation coefficients reported in individual studies were transformed using Fisher's z transformation to stabilize variance and normalize distribution. Pooled estimates were calculated using a random-effects model with restricted maximum likelihood (REML) estimation.

The pooled effect size was subsequently back-transformed to correlation coefficients (r) for interpretability.

Statistical heterogeneity was assessed using the I^2 statistic, with values greater than 75% indicating substantial heterogeneity, and Cochran's Q test, with a p-value <0.05 considered statistically significant. Between-study variance was quantified using τ^2.

Sensitivity analysis was performed using a leave-one-out approach to evaluate the influence of individual studies on the pooled estimate.

Subgroup analysis was conducted based on reference imaging modality, with a predefined subgroup of studies using intravascular ultrasound (IVUS).

Publication bias was assessed through visual inspection of funnel plots and Egger's regression test. Given the limited number of included studies, interpretation of publication bias was performed with caution.

All statistical analyses were performed using R software (R Foundation for Statistical Computing, Vienna, Austria), utilizing the metafor package.[12]

RESULTS

Study characteristics are summarized in Table 1.

Table 1
Characteristics of Included Studies

Study	Year	Country	Study Design	Sample Size	AI Model / Software	Comparator Modality	Plaque Quantification Parameters	Key Findings
Abdul Ihdayhid et al.	2024	USA	Retrospective	300	AI-QCPA (HeartFlow)	IVUS	Total plaque volume; calcified and non-calcified plaque	Strong correlation with IVUS for plaque quantification
Narula et al. (REVEALPLAQUE)	2024	Multicenter (USA/ Japan)	Multicenter observational	237	AI-QCPA (HeartFlow)	IVUS	Total plaque volume; plaque subtypes	Excellent correlation with IVUS (high ICC)
Nakanishi et al.	2026	Japan	Retrospective cohort	200	Deep learning-based model	IVUS	Total plaque burden; percent atheroma volume	Strong correlation with IVUS-derived plaque metrics
Guanyu Li et al.	2026	China	Retrospective	150	Convolutional neural network (CNN)	OCT	Plaque characteristics; stenosis severity	Strong correlation with OCT-derived plaque quantification
Omori et al.	2023	Japan	Retrospective	100	AI-based plaque analysis	NIRS-IVUS	Plaque composition; lipid-rich plaque	Significant correlation with invasive plaque characterization
Lin et al. 2022	2022	Multicenter (UK)	Multicenter validation study	1611	Machine learning-based model	External IVUS validation cohort	Plaque burden; segment involvement score	Large-scale multicenter validation demonstrating strong correlation with invasive plaque metrics

AI = artificial intelligence; CCTA = coronary computed tomography angiography; IVUS = intravascular ultrasound; AI-QCPA = artificial intelligence-based quantitative coronary plaque analysis; OCT = optical coherence tomography; NIRS = near-infrared spectroscopy; CNN = convolutional neural network.

A total of 6 studies comprising 2,598 patients were included. One included multicenter study utilized an externally validated IVUS reference cohort rather than direct paired intracoronary imaging acquisition but met predefined eligibility criteria through quantitative validation against invasive imaging metrics.[2–7] Included studies utilized AI-CCTA for automated plaque quantification and compared results with IVUS, OCT, or NIRS-IVUS reference standards.

AI-CCTA correlated strongly with invasive imaging modalities ($r = 0.91$, 95% CI: 0.87–0.94), although heterogeneity across studies was substantial ($I^2 = 94.6\%$; Q test $p < 0.001$).

Leave-one-out sensitivity analysis demonstrated that exclusion of Lin et al. 2022, the largest included study, resulted in only modest attenuation of the pooled effect estimate (pooled $r = 0.895$, 95% CI 0.867–0.918), while heterogeneity decreased from 94.6% to 74.3%. These results suggest that the association remained stable even though the Lin et al. cohort contributed a large share of the overall weight.

Subgroup analysis restricted to IVUS-based studies ($n = 4$) demonstrated that the pooled correlation remained high ($r = 0.93$, 95% CI: 0.89–0.95). Even so, heterogeneity remained high ($I^2 = 94.6\%$, $\tau^2 = 0.045$), suggesting that differences in the reference imaging modality alone cannot explain variability across studies.

Funnel plot analysis suggested asymmetry, with Egger's regression test demonstrating possible small-study effects ($p < 0.001$).

Included studies varied in design, sample size, and plaque quantification methodology, reflecting the heterogeneity of current AI-CCTA validation approaches. QUADAS-2 assessment demonstrated overall acceptable methodological quality across included studies, although most retrospective studies were judged to have some concerns in patient selection and index test domains. Only the prospective multicenter REVEALPLAQUE study was rated as low risk across all domains.

DISCUSSION

In this meta-analysis, AI-enabled coronary CT angiography (AI-CCTA) showed a strong correlation with invasive intracoronary imaging techniques for coronary plaque quantification. The pooled correlation coefficient of 0.91 indicates that AI-derived plaque measurements closely track invasive reference standards across multiple imaging platforms and study designs.[2–7] As plaque burden and plaque composition are increasingly recognised as important markers of cardiovascular risk beyond luminal stenosis alone, these findings further support the expanding role of AI-assisted CCTA in contemporary coronary imaging.[9,10]

The dominant finding of this analysis, however, was the magnitude of heterogeneity across studies. Even after restricting analysis to IVUS-based cohorts, heterogeneity remained essentially unchanged (I^2 = 94.6%), despite preservation of a strong pooled correlation (r = 0.93). This suggests that differences in comparator modality alone do not adequately explain the heterogeneity observed between studies. Instead, the current AI-CCTA literature remains methodologically heterogeneous at multiple levels.

The included studies varied in their AI model designs, training datasets, imaging protocols, plaque definitions, and quantification methods. Some studies assessed total plaque volume, whereas others focused on plaque composition, stenosis severity, or adverse plaque phenotypes. The unit of analysis also varied considerably, with correlations reported at the patient, vessel, lesion, or plaque level. These inconsistencies likely contribute more to between-study variability than the invasive reference modality itself. Large multicenter validation cohorts such as REVEALPLAQUE and the international validation study by Lin et al. further emphasize how study size, population diversity, and external validation frameworks can influence pooled estimates.[3,7] Because only six studies met inclusion criteria, formal meta-regression was not performed, as such analyses would likely produce unstable and unreliable estimates.

Despite the degree of heterogeneity, the direction of effect remained remarkably consistent. No included study demonstrated weak or contradictory association between AI-CCTA and invasive imaging metrics, and leave-one-out sensitivity analysis showed minimal change in pooled effect size following sequential exclusion of individual studies. Several studies additionally reported high intraclass correlation coefficients, further supporting reproducibility between AI-CCTA and invasive imaging measurements.[2–7] This pattern suggests that the heterogeneity is more likely due to differences in the strength of the effect across studies, rather than disagreement in the overall association itself. Notably, when the large multicenter validation cohort reported by Lin et al. was excluded, heterogeneity decreased substantially while the pooled correlation remained strong (r = 0.895), suggesting that the association was not driven solely by this study despite its large contribution to the overall sample size.

The present findings are particularly relevant because they address one of the central questions surrounding AI-enabled plaque analysis: whether automated non-invasive quantification can approximate invasive imaging with sufficient consistency to become clinically actionable. The strong pooled correlation observed across IVUS-, OCT-, and NIRS-IVUS-based studies suggests that AI-CCTA is approaching that threshold, especially for global plaque burden assessment. At the same time, the persistence of substantial heterogeneity indicates that standardization remains incomplete. Current studies differ not only in technical implementation but also in what constitutes plaque quantification itself, making direct comparison challenging. The REVEALPLAQUE and Lin validation cohorts are especially important in this regard because they move beyond small single-center feasibility analyses and demonstrate reproducible performance across broader and more diverse patient populations.[3,7]

The observed funnel plot asymmetry and significant Egger's regression test should be interpreted cautiously. Statistical tests for publication bias are known to be unreliable in meta-analyses containing fewer than ten studies, and the significant result observed here may reflect methodological heterogeneity and small-study effects rather than true publication bias. The relatively recent emergence of AI-based plaque quantification likely further contributes to the limited number of currently available validation studies.

An additional limitation of the existing literature is that correlation alone does not establish agreement. High correlation may coexist with systematic overestimation or underestimation of plaque burden, particularly when different segmentation algorithms or plaque definitions are used. Although several included studies reported favorable intraclass correlation coefficients, standardized agreement analyses such as Bland-Altman assessment and limits-of-agreement reporting remain inconsistently applied across studies. Future validation work should therefore focus not only on maintaining strong correlation with invasive imaging, but also on demonstrating reproducible agreement across platforms, centers, and patient populations.

Ultimately, for AI-CCTA to move from a promising research tool to a clinically reliable alternative for invasive plaque characterisation, the field will need standardized validation frameworks more than small gains in correlation alone. The strongest studies included in this analysis already suggest that this transition is feasible. What remains unresolved is whether future multicenter validation studies can demonstrate sufficiently consistent agreement across imaging platforms and clinical settings to support routine implementation in coronary risk stratification and longitudinal plaque monitoring.

LIMITATIONS

This study has several methodological limitations that should be considered. First, the number of included studies was limited, which may reduce the statistical power of subgroup and publication bias analyses. Second, differences in AI model architectures and training datasets were not standardized across studies. Third, included studies varied in the unit of analysis, with some reporting patient-level, vessel-level, lesion-level, or plaque-level correlations, which may have contributed to between-study heterogeneity. Fourth, formal meta-regression analysis was not performed because the limited number of included studies would likely yield unstable estimates. Additionally, the review protocol was not prospectively registered in PROSPERO, which may limit transparency regarding predefined methodological decisions. Finally, most included studies were observational in design, which may introduce inherent bias.

CONCLUSIONS

AI-enabled coronary CT angiography showed a strong correlation with invasive intracoronary imaging modalities for plaque quantification, supporting its potential as a non-invasive approach to the assessment of coronary atherosclerotic burden. However, broader clinical implementation will require standardised validation frameworks and more consistent agreement across diverse imaging platforms and patient populations.

Declarations

FUNDING

No external funding was received for this study.

DISCLOSURES

The authors report no relevant conflicts of interest.

AI DISCLOSURE

Generative artificial intelligence tools (ChatGPT, OpenAI) were used for language editing, grammar refinement, and manuscript formatting assistance. All scientific content, study selection, data extraction, statistical analyses, interpretation of findings, and final manuscript decisions were performed and verified by the authors.

DATA AVAILABILITY

The data underlying this study are available from the corresponding author upon reasonable request.

AUTHOR CONTRIBUTIONS

Yasaswini Nimmagadda: Conceptualisation, Methodology, Data curation, Formal analysis, Writing – original draft, Visualisation.

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Figures

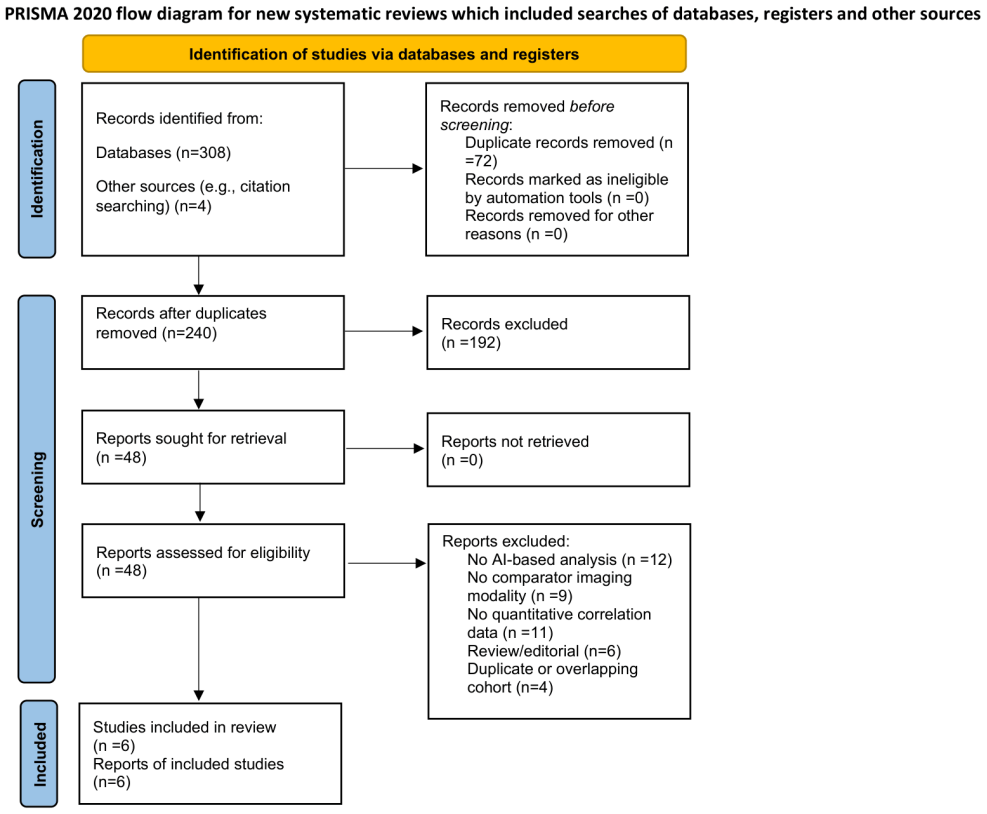


Figure 1

PRISMA 2020 flow diagram illustrating the study selection process for inclusion in the systematic review and meta-analysis, including database identification, screening, eligibility assessment, and final study inclusion.

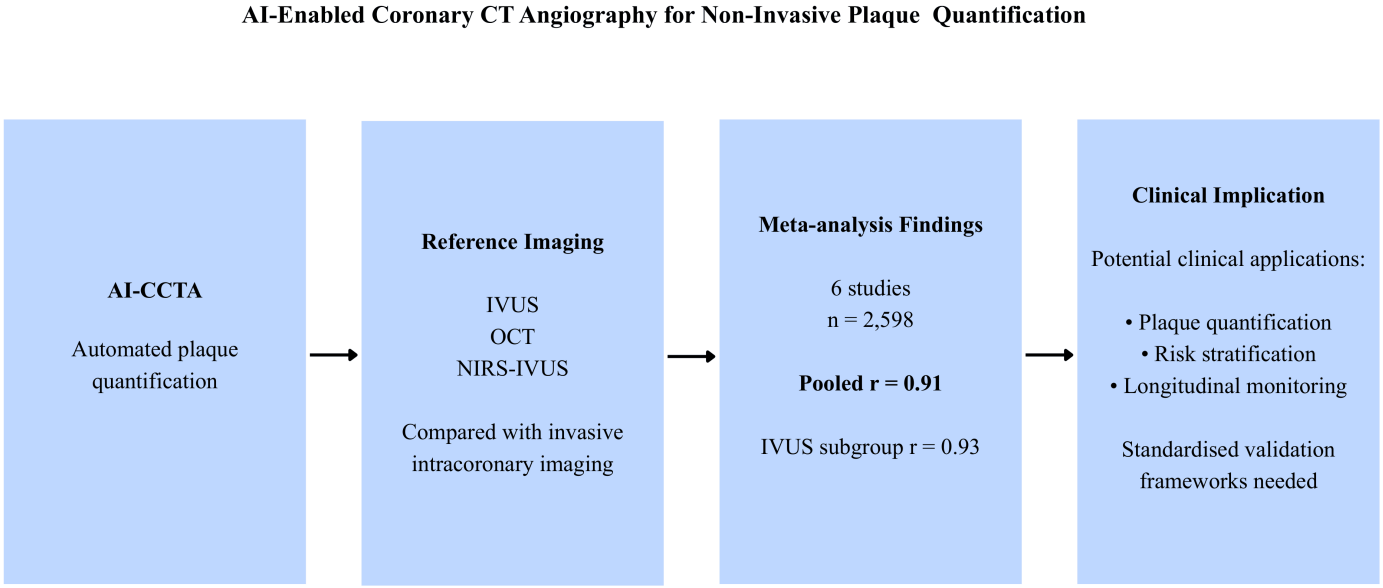


Figure 2

Central Illustration. AI-Enabled Coronary CT Angiography for Non-Invasive Plaque Quantification

Artificial intelligence-enabled coronary CT angiography (AI-CCTA) demonstrated a strong correlation with invasive intracoronary imaging modalities for plaque quantification across 6 studies involving 2,598 patients. Persistent heterogeneity across studies highlights the need for standardised validation frameworks before broader clinical implementation.

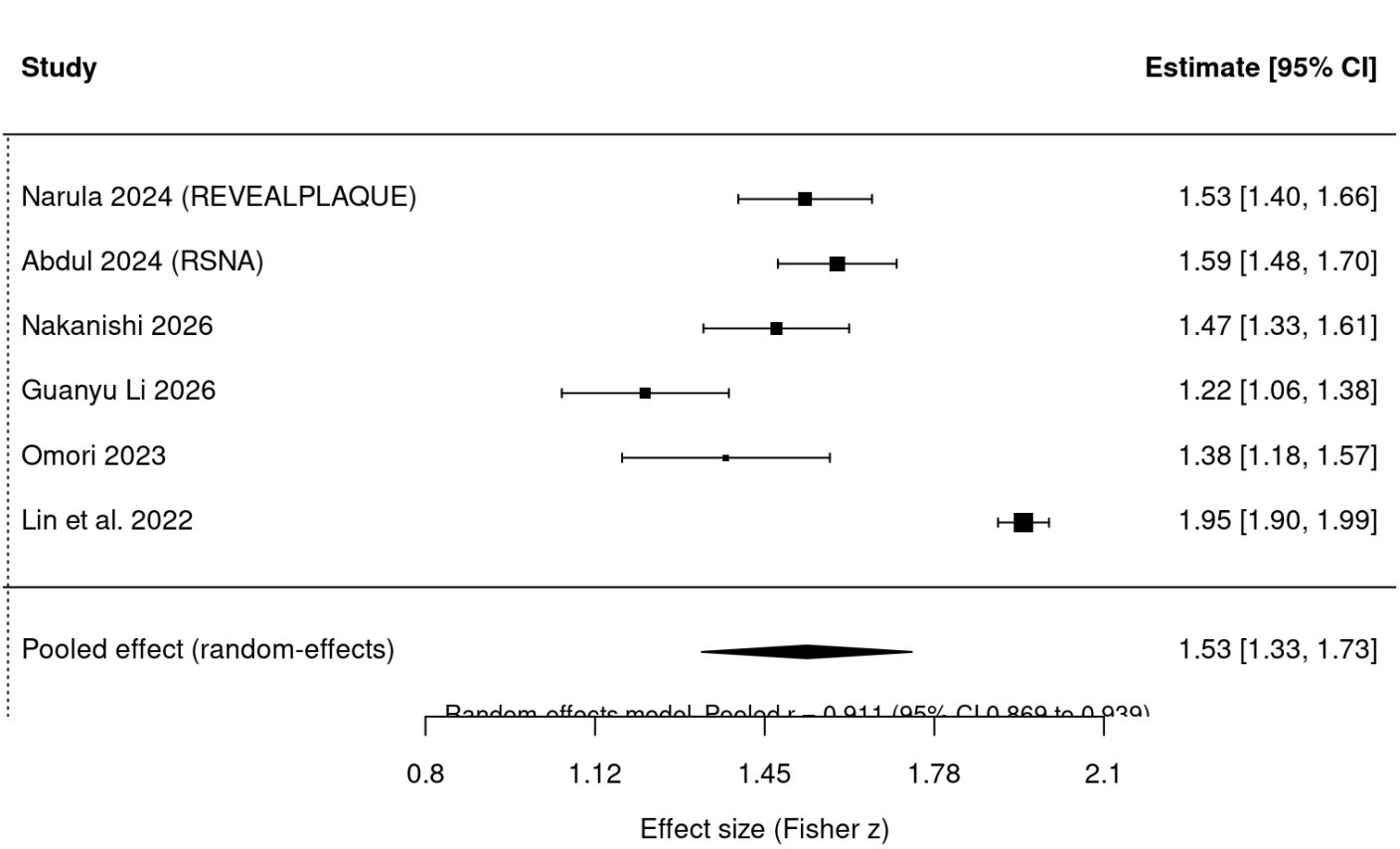


Figure 3

Forest plot demonstrating pooled correlation between AI-enabled coronary CT angiography and invasive intracoronary imaging modalities for plaque quantification using a random-effects model. The pooled analysis demonstrated a strong overall correlation between AI-CCTA and invasive plaque imaging reference standards.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryFileAICCTA.docx