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REVIEW ARTICLE

Breast MRI Radiomics in Predicting Response to Neoadjuvant Chemotherapy: A Systematic Review and Meta-Analysis

Lydia Purna Kuntjoro[1,2,*,†], Ignatius Riwanto[3], Hermina Sukmaningtyas[1], Yan Wisnu Prajoko[3], Suhartono[4], Lina Choridah[5], Endang Mahati[6], Clarissa Aulia Pravitha[7,†], Kevin Christian Tjandra[7], and Danendra Rakha Putra Respati[7]

[1]*Department of Radiology, Faculty of Medicine, Universitas Diponegoro, Semarang, Indonesia*
[2]*Doctoral Study Program of Medical and Health Science, Universitas Diponegoro, Semarang, Indonesia*
[3]*Department of Surgery, Faculty of Medicine, Universitas Diponegoro, Semarang, Indonesia*
[4]*Department of Environmental Health, Faculty of Public Health, Universitas Diponegoro, Semarang, Indonesia*
[5]*Department of Radiology, Faculty of Medicine, Public Health and Nursing, Universitas Gadjah Mada, Yogyakarta, Indonesia*
[6]*Department of Pharmacology and Therapeutics, Faculty of Medicine, Universitas Diponegoro, Semarang, Indonesia*
[7]*Faculty of Medicine, Universitas Diponegoro, Semarang, Indonesia*

([*]Corresponding author's e-mail: lydiakuntjoro@gmail.com)

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Abstract

Introduction: Breast magnetic resonance imaging (MRI) has become a well-established tool for evaluating response to neoadjuvant chemotherapy for breast cancer; however, the results are limited by natural subjectivity and possible human error. This study evaluated the diagnostic performance (sensitivity, specificity, accuracy, and AUC value) of pathological complete response to neoadjuvant chemotherapy using the MRI imaging approach for radiomic texture analysis **Materials and Methods:** This systematic review and meta-analysis was conducted according to PRISMA guidelines. Four databases were searched until March 2025 and eligible studies were extracted by three readers. The selected articles were divided into 3 groups: Radiomics, clinical models, and radiomics + clinical models. Those groups were compared on each sensitivity, specificity, accuracy, and AUC value using a random-effects model. QUADAS-2, I^2 statistic, Cochran's Q I 2 statistics, and Egger's regression test for publication bias, and meta-regression were used. **Results:** 11 studies were included in this analysis. The pooled sensitivity, specificity, accuracy, and area under the curve (AUC) across all models were 0.76 (95% CI: 0.69 - 0.82), 0.72 (95% CI: 0.63 - 0.78), 0.77 (95% CI: 0.70 - 0.83), and 0.76 (95% CI: 0.72 - 0.81), respectively. The combined Radiomics + Clinical model demonstrated the highest diagnostic performance with a sensitivity of 0.79 (95% CI: 0.65 - 0.89), specificity of 0.75 (95% CI: 0.69 - 0.81), accuracy of 0.83 (95% CI: 0.68 - 0.91), and AUC of 0.81 (95% CI: 0.74 - 0.87). **Conclusions:** Radiomic MRI can enhance the predictive performance of neoadjuvant chemotherapy for breast cancer.

Keywords: Breast cancer, Diagnostic test accuracy, Radiomics, Magnetic resonance imaging

Introduction

Breast cancer is one of the most commonly diagnosed and prevalent malignant diseases affecting women worldwide. According to the Global Cancer Observatory (GCO) 2022, approximately 2.3 million women are diagnosed with breast cancer, resulting in 670,000 deaths worldwide, making it the leading cause of cancer-related mortality among women [1]. The

[†]These authors contributed equally to this work

burden is particularly high in developing regions, where late diagnosis and limited access to care contribute to poor outcomes. This rising incidence underscores the urgent need for early detection and accurate prediction of treatment response to improve prognosis and optimize therapeutic strategies.

Neoadjuvant chemotherapy (NAC) has emerged as the standard of care for patients with locally advanced breast cancers. It offers several advantages, including reduction in tumor size, decreased risk of metastasis, and facilitation of breast-conserving surgery [2]. Pathological complete response (pCR), defined as the absence of residual invasive cancer following NAC, has been established as a strong surrogate marker of treatment efficacy and predictor of improved disease-free and overall survival [2,3]. However, the likelihood of achieving pCR varies across molecular subtypes - luminal A shows the lowest pCR rate, while luminal B, triple-negative, and HER2-positive tumors demonstrate higher rates of 8.3%, 23.2%, and 38.7%, respectively [4]. Despite the overall response rates ranging from 69% to 100%, approximately 30% of patients still experience suboptimal outcomes [5]. Therefore, identifying reliable and non-invasive predictors of NAC response remains a key clinical priority.

Magnetic resonance imaging (MRI) is a highly sensitive modality for evaluating breast cancer and monitoring treatment response [6]. It provides superior soft-tissue contrast and dynamic information, allowing accurate assessment of the tumor extent before and after therapy [7]. Dynamic contrast-enhanced MRI (DCE-MRI) has been shown to outperform mammography and ultrasound in predicting tumor response to NAC [8]. Nonetheless, conventional MRI interpretation is subject to human variability and potential observer bias [9], creating a need for more objective and reproducible evaluation methods.

Radiomics, an emerging field in quantitative medical imaging, addresses this challenge by extracting high-dimensional data from medical images to uncover patterns beyond visual perception [10]. Through mathematical algorithms, radiomics quantifies tumor heterogeneity by analyzing features related to intensity, shape, texture, and kinetics - collectively forming a radiomic signature [9,11]. These features can be derived from various imaging modalities, including MRI, computed tomography (CT), and positron emission tomography (PET) [10], and have shown promise in oncologic applications, such as diagnosis, prognosis, and treatment response prediction.

Recent studies have explored MRI-based radiomics to predict pCR in patients with breast cancer receiving NAC. Hajri *et al.* [12] reported a maximum area under the curve (AUC) of 0.72 (95% CI: 0.59 - 0.85) for pCR prediction using MRI radiomics, while Druker et al. achieved an AUC of 0.82 in patients with lymph node-positive disease [13]. Meta-analytical evidence indicates pooled AUC values ranging from 0.78 to 0.83, suggesting moderate diagnostic accuracy [14,15]. However, most existing research has focused primarily on imaging-derived features alone, with limited integration of clinical and pathological variables that may further enhance the predictive performance.

As summarized in **Table 1**, previous studies have highlighted the growing potential of MRI-based radiomics for predicting pathological complete response (pCR) following neoadjuvant chemotherapy (NAC) in breast cancer. Conventional MRI studies, such as those by Kwak *et al.* [16], have demonstrated moderate accuracy in evaluating post-treatment responses, while more advanced radiomics and machine learning approaches, such as those by Hajri *et al.* [12] and Drukker *et al.* [13], have achieved higher predictive performance with AUC values up to 0.82. Systematic reviews and meta-analyses have further supported the moderate-to-excellent diagnostic capability of MRI radiomics, with pooled AUCs ranging from 0.78 to 0.83 [14,15]. More recent investigations employing multimodal MRI sequences (DCE-MRI, DWI, T2-weighted, ADC maps) and integrated models combining radiomic, clinical, and molecular features have reported even higher predictive accuracies, reaching AUC values of 0.88 - 0.89 [16–19]. Despite these advancements, considerable heterogeneity remains across imaging protocols, feature-extraction techniques, and analytical frameworks. Importantly, only a limited number of studies have systematically explored the synergistic potential of integrating radiomic signatures with clinicopathological variables to improve individualized treatment stratification.

Integrating radiomic features with clinicopathological data could facilitate personalized therapeutic decision-making, enhance prognostic precision, and minimize unnecessary interventions.

Therefore, the present systematic review and meta-analysis aimed to comprehensively evaluate the diagnostic performance of MRI-based radiomics in predicting pCR after NAC in breast cancer, both as an independent imaging model and in combination with clinicopathological variables, by pooling sensitivity, specificity, accuracy, and AUC estimates from the existing literature.

Table 1 Comparison table with previous study.

Author	Design	n	Population	Modality/Imaging type	Aim of study	Key outcomes
Hajri *et al.* [12]	Cohort	235 patients	Women with non-metastatic, histologically confirmed invasive breast cancer	MRI + Machine Learning (Radiomics)	Evaluate ML-based biomarkers for predicting pCR and recurrence-free survival (RFS)	Radiomics-MRI model achieved AUC = 0.72 for pCR prediction
Drukker *et al.* [13]	Cohort	158 patients	Women with invasive lymph-node-positive breast cancer scheduled for NAC	DCE-MRI with Radiomics	Assess radiomics-based MRI for predicting NAC response before treatment	AUC = 0.82 for pCR prediction including LN features
Pesapane *et al.* [14]	Systematic Review and Meta-analysis	34 studies	Breast cancer patients undergoing NAC	MRI-based Radiomics	Summarize radiomics-MRI studies predicting pCR and pool diagnostic metrics	Pooled AUC = 0.78 (95% CI 0.74 - 0.81) for MRI-based radiomics
Zhang *et al.* [15]	Systematic Review and Meta-analysis	10 studies	Patients with triple-negative breast cancer (TNBC) undergoing NAC	MRI-based Radiomics	Evaluate MRI-radiomics accuracy for predicting pCR in TNBC	Pooled AUC = 0.83 (95% CI 0.79 - 0.86) indicating excellent discrimination
Kwak *et al.* [20]	Cohort	225 patients	Patients with invasive breast cancer who underwent breast MRI before and after NAC	Conventional MRI	Evaluate MRI performance in assessing treatment response and outcomes after NAC	MRI moderately predicted pathologic response (overall accuracy = 69%, sensitivity = 76%, PPV = 77%)
Eom *et al.* [21]	Prospective Cohort	1,062 patients	Patients with locally advanced breast cancer receiving NAC	DCE-MRI and contrast-enhanced MRI (CE-MRI)	Compare DW-MRI vs. CE-MRI in predicting tumor response in breast cancer.	CE-MRI has a higher specificity (89.3%) and sensitivity (65.3%) than DW-MRI
Liu *et al.* [22]	Retrospective Cohort	296 patients	Breast cancer patients undergoing NAC	Multimodal MRI Radiomics	Evaluate the predictive value of pre-treatment multiparametric	The clinical-imaging fusion model demonstrated optimal predictive performance, with

Author	Design	n	Population	Modality/Imaging type	Aim of study	Key outcomes
					MRI radiomics for pCR	AUC values of 0.813 (95 % CI: 0.742 - 0.884)
Yu *et al.* [23]	Retrospective Cohort	150 patients	HER2-positive breast cancer treated with NAC	MRI Radiomics combined with Clinical Data	Establish a model combining radiomic and clinicopathological factors	Combined model (radiomics + clinical) improved AUC from 0.86 to 0.98
Sun *et al.* [24]	Cohort	95 patients	Patients with invasive breast cancer undergoing NAC	DCE-MRI Radiomics using Deep Learning	Develop deep-learning-assisted radiomics to predict pCR	Deep-learning-radiomics model achieved highest AUC = 0.92 for pCR prediction
Zeng *et al.* [25]	Retrospective Cohort	142 patients	Patients with primary invasive breast cancer	DCE-MRI with Radiomics	Compare the value of radiomics and diameter% based on pre- and early-treatment dynamic enhanced MR (DCE-MRI)	AUC of delta radiomics model, pre-NAT, early-NAT, and the Diameter% radiomics models (0.87, 0.57, 0.78 and 0.83)

Materials and methods

Study design and eligibility criteria for study selection

This systematic review and meta-analysis were conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The study protocol was prospectively registered in the Open Science Framework (https://doi.org/10.17605/OSF.IO/SH2BY).

Studies were included if they met the following eligibility criteria: (1) articles on female post-NAC breast cancer; (2) underwent MRI before and after NAC; (3) used a validated radiomics methodology; (4) used MRI-Based Radiomics data; (5) reported sensitivity and specificity data; (5) were published in English; and (6) evaluated the diagnostic performance of radiomics-based MRI in predicting pCR to NAC. Case reports, reviews, editorials, conference abstracts, and studies with insufficient data were excluded. The present study was conducted in accordance with the PICO framework (**Table S1**).

Search strategy and study selection

Two independent evaluators (CAP and DRPR) conducted a computerized search and systematic examination of articles in PubMed, Scopus, ProQuest, and ScienceDirect databases. All articles published online until March 2025 were included in this study. The search terms included combinations of (breast and cancer) AND (magnetic and resonance and imaging) AND (pathology and complete and response) AND (radiomics) AND (neoadjuvant and chemotherapy) and related keywords.

Titles and abstracts of the results were assessed for eligibility. Following the elimination of duplicates, complete texts of the appropriate studies were acquired, and irrelevant findings were discarded. The outcomes of each search and analysis phase were compared and critically assessed by a third reader. Discrepancies were resolved by consensus using a third arbitrator (KCT).

Data extraction

Three independent authors (CAP, KCT and SS) collected information on the study characteristics,

patient demographics, MRI acquisition parameters, radiomics model development, and performance metrics including sensitivity, specificity, accuracy, and AUC. Data were extracted using a standardized form in Microsoft Excel.

Risk of bias assessment

The quality of the included studies was assessed based on the risk of bias and applicability concerns using the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool. Each domain was individually rated and an overall risk of bias judgment was assigned to each study. Two independent reviewers (KCT and DRPR) conducted the assessments, and disagreements were resolved through discussion or consultation with a third reviewer (KCT).

Statistical analysis

Statistical analysis was conducted using R with the "meta" and "metafor" packages. A random-effects model was used to calculate the pooled sensitivity, specificity, accuracy, and AUC, accounting for study heterogeneity, assessed using I^2 and Cochran's Q tests. The SROC curve illustrates the overall diagnostic performance. Publication bias was evaluated using funnel plots and Egger's test (Supplementary Data). Sensitivity analyses were performed to assess the robustness of the results, and statistical significance was set at $p < 0.05$.

Results and discussion

Eligible studies and quality assessment

After searching the four databases, 801 studies were identified and screened. After removing 654 duplicates, 147 articles were screened based on type, title, abstract, full-text availability, and relevance. Ultimately, 11 studies were included in this systematic review and meta-analysis (**Figure 1**), all of which had a low risk of bias (**Figure 2**).

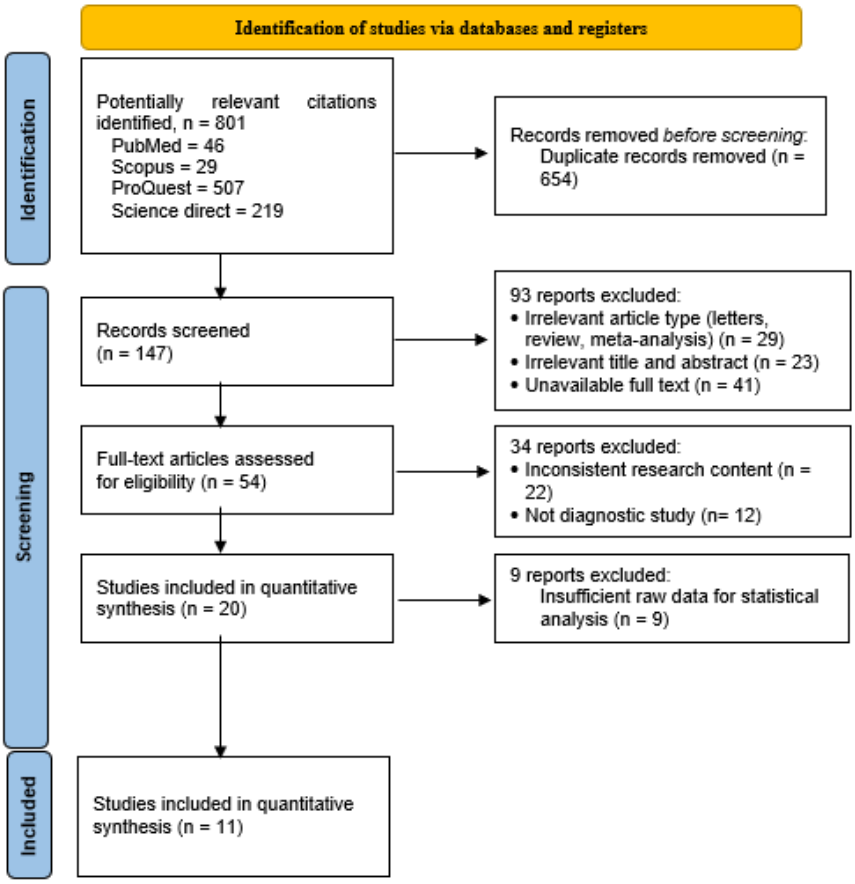

Figure 1 PRISMA 2020 flow diagram.

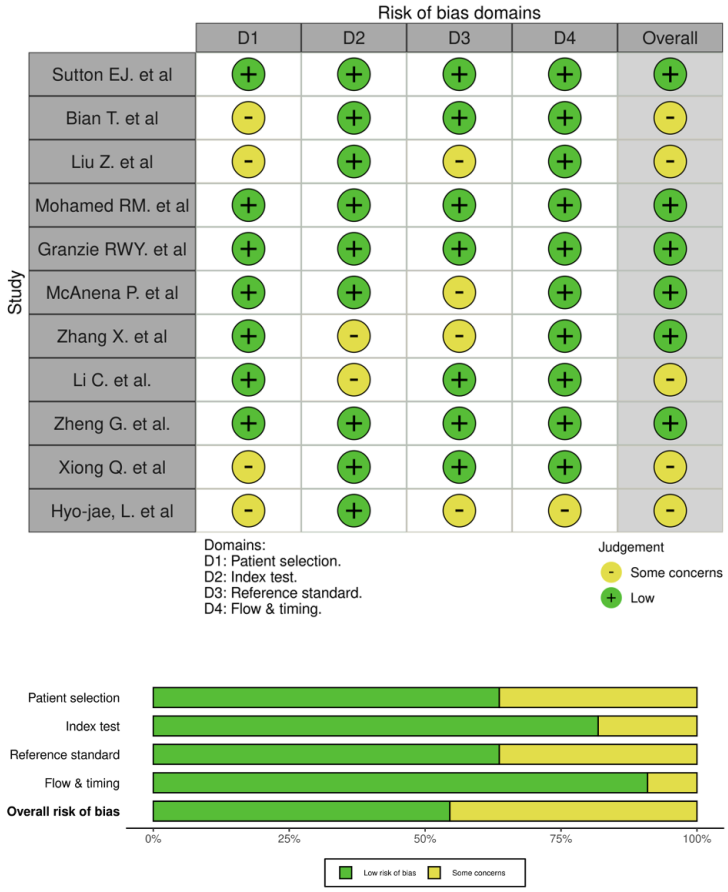

Figure 2 Risk of bias in diagnostic accuracy studies.

Eligible study characteristics

Eleven studies met the inclusion criteria, with sample sizes ranging from 50 to 350 patients, published between 2019 and 2024, and originating from various countries including the United States, China, and Europe. All the studies used different radiomic feature selection methods and machine learning models to predict pCR, primarily DCE-MRI, diffusion-weighted imaging (DWI), and T2-weighted imaging (T2WI). Variations in the preprocessing techniques and segmentation approaches may have contributed to the differences in the reported outcomes (**Table 2**).

Table 2 Characteristics of the included studies.

No	Authors	Year	Study design	Age	Sample size	MRI sequences	MRI magnet	ML
1	Liu *et al.* [16]	2019	Cohort	44.52 ± 11.49	80	DWI & T1WI & T2WI	1.5 T & 3.0 T	SVM
2	Bian *et al.* [5]	2020	Cohort	49.6 ± 10.2	45	T2WI, DWI, DCE, Combined	3.0T	LR
3	Xiong *et al.* [17]	2020	Cohort	49 (24 - 67.7)	62	T2WI, DCE, DWI	1.5 T & 3.0 T	LR
4	Granzie *et al.* [18]	2021	Cohort	52 (28 - 79)	168	DCE-T1WI, T2WI	1.5 T & 3.0 T	LR
5	Sutton *et al.* [19]	2020	Cohort	51.3 ± 11.8	56	DCE, T1W	1.5 & 3.0 T	RF
6	Li *et al.* [26]	2022	Cohort	48 (39 - 54.8)	86	T1+C, T2W1, DWI-ADC	NR	SVM + RF
7	McAnena *et al.* [27]	2022	Cohort	48.6 (7.9)	74	DCE	1.5T	LR + SVM
8	Zhang *et al.* [28]	2024	Cohort	50 (23 - 72)	197	DCE	1.5 T & 3.0 T	LR
9	Zheng *et al.*[29]	2024	Cohort	50.50 (25 - 85)	40	T1WI, DCE, T1+C	3.0 T	LR

No	Authors	Year	Study design	Age	Sample size	MRI sequences	MRI magnet	ML
10	Mohamed *et al.* [30]	2024	Cohort	49 (23 - 78)	163	DCE and DWI	3.0-T	LR
11	Hyo-jae *et al.* [31]	2024	Cohort	52.0 (45.5 - 57.5)	135	DCE, T1W	3.0 T	LR

NR: Not Reported; ML: Machine Learning; MRI: Magnetic Resonance Imaging; T1WI: T1-Weighted Imaging; T2WI: T2-Weighted Imaging; C: Contrast; DCE: Dynamic Contrast-Enhanced; ADC: Apparent Diffusion Coefficient; DWI: Diffusion-Weighted Imaging; LR: Logistic Regression; SVM: Supporting Vector Machine; RF: Random Forest.

Breast MRI radiomics sensitivity

Among the three subgroups reporting sensitivity outcomes (Radiomics, Clinical model, and Radiomics + Clinical model) (**Figure 3**), the overall effects and results across most subgroups were statistically significant. The overall pooled sensitivity across all studies was 0.76 (95% CI: 0.69 - 0.82). High heterogeneity was found among the subgroups (I^2 = 91%, p < 0.0001), indicating variable diagnostic performance across the MRI methods. The funnel plot showed asymmetry, suggesting publication bias or study differences, with studies with higher standard errors deviating from their sensitivity estimates (**Figure S1**). Additionally, the Egger test showed an intercept of −0.2613 (SE = 0.2938, p = 0.3914), indicating no significant publication bias (**Table S2**). The slope was significant (estimate = 5.0118, p = 0.00017), suggesting that smaller studies reported larger effect sizes, which likely reflects true heterogeneity rather than bias, as the non-significant intercept is key in assessing publication bias (**Figure S2**).

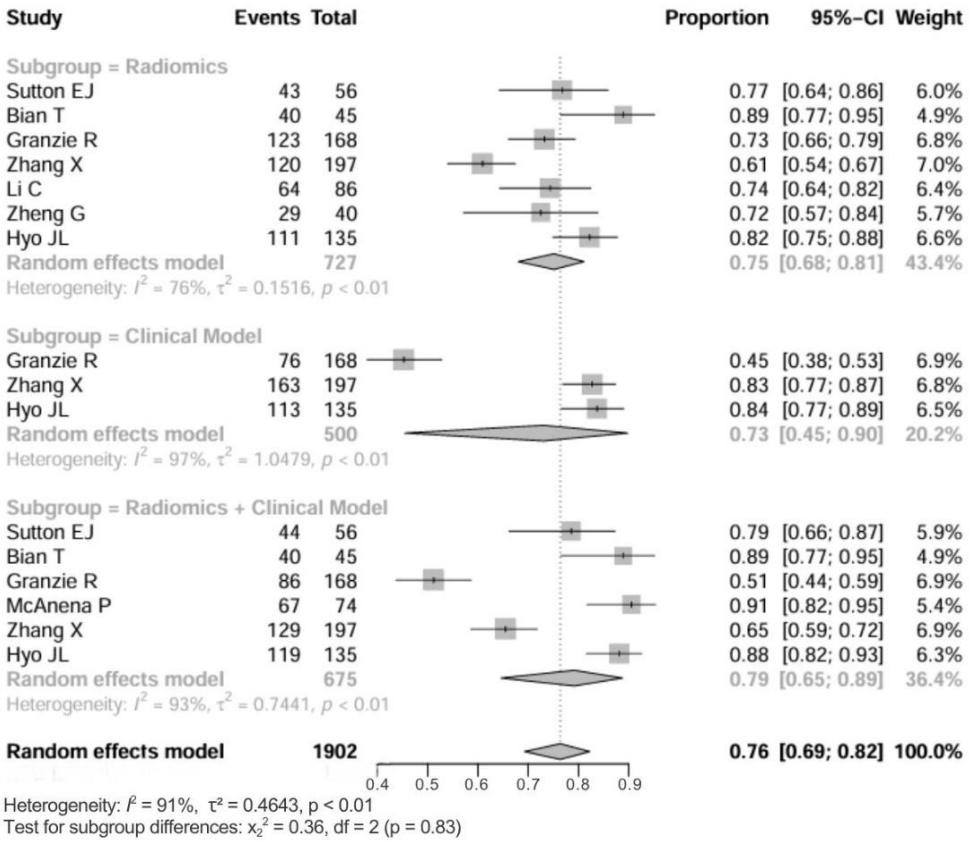

Figure 3 Forest plot of sensitivity comparison between radiomics, molecular subtype, and combined models in predicting pCR to NAC.

Breast MRI radiomics specificity

The overall pooled specificity across all studies was 0.72 (95% CI: 0.63 - 0.78). Substantial heterogeneity was observed among the subgroups (I^2 = 91%, $p < 0.0001$), indicating considerable variability in the diagnostic performance (**Figure 4**). The funnel plot demonstrated visible asymmetry, suggesting potential publication bias or methodological differences between studies (**Figure S3**). Egger's plot may indicate publication bias, in which smaller studies with more extreme or favorable specificity outcomes are selectively published or reported (**Figure S4**). However, the intercept of Egger's test was –0.4317 with a standard error of 0.3667 (p = 0.2618), indicating that the asymmetry was not statistically significant and thus provided no strong evidence of publication bias. The slope was statistically significant (estimate = 5.202, p = 0.00066), suggesting a strong relationship between study size and reported specificity (**Table S3**).

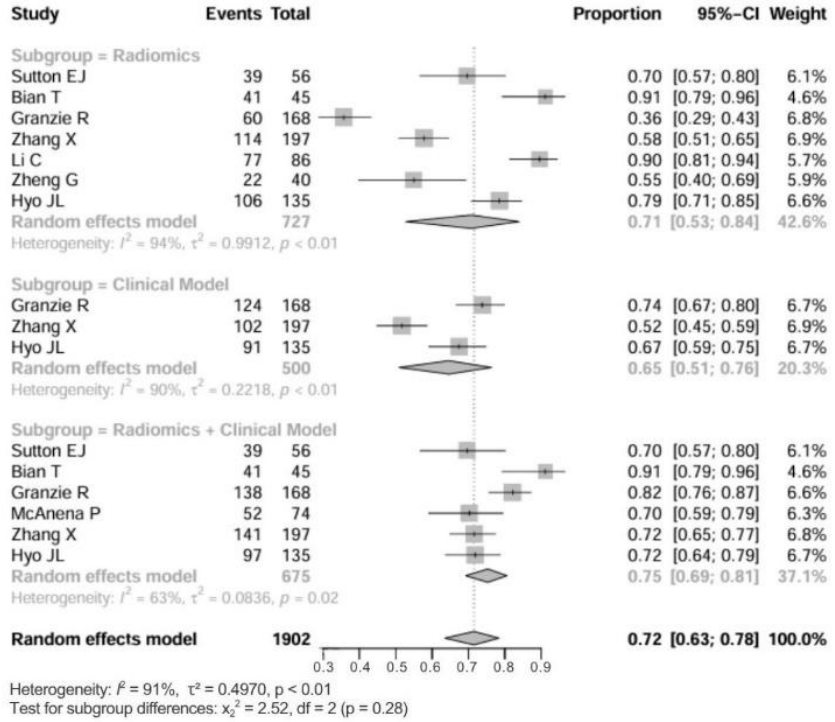

Figure 4 Forest plot of specificity comparison between radiomics, molecular subtype, and combined models in predicting pCR to NAC.

Breast MRI radiomics accuracy

The pooled accuracies for the radiomics subgroup were 0.76 [95% CI: 0.65 - 0.85], 0.73 [95% CI: 0.55 - 0.86] for the clinical model subgroup, and 0.83 [95% CI: 0.68 - 0.91] for the Radiomics + Clinical model subgroup. The overall pooled accuracy was 0.77 [95% confidence interval (CI): 0.70 - 0.83] (**Figure 5**). There was moderate to high heterogeneity in accuracy among the subgroups (I^2 = 84%, $p < 0.0001$), suggesting differences in diagnostic performance across MRI methods. Funnel plot asymmetry indicated potential publication bias or study variation, with smaller studies deviating from the expected patterns (**Figure S5**). Egger's plot is indicative of a small-study effect and may indicate the presence of publication bias, where smaller studies with more favorable or extreme accuracy estimates are more likely to be published (Figure S6). However, the Egger's test showed a non-significant intercept (0.1887, p = 0.4437), suggesting no publication bias. Although the slope was significant (estimate = 3.7321, p = 0.00042), it likely reflects true heterogeneity rather than systematic bias (**Table S4**).

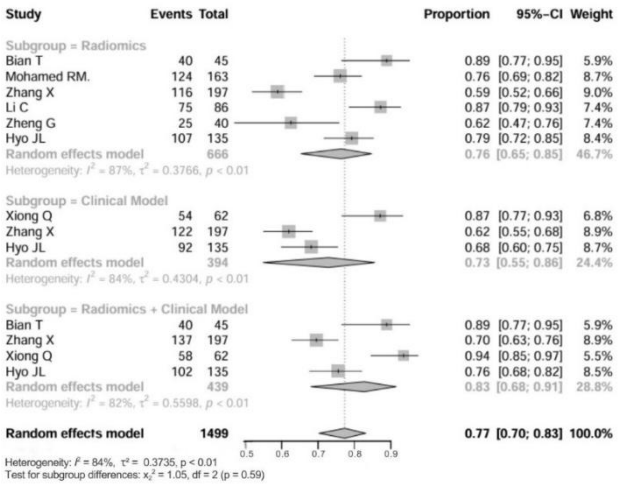

Figure 5 Forest plot of accuracy comparison between radiomics, molecular subtype, and combined models in predicting pCR to NAC.

Breast MRI radiomics AUC

Pooled AUCs were 0.76 [95% CI: 0.69 - 0.83] for Randomics, 0.71 [95% CI: 0.63 - 0.79] for the Clinical model, and 0.81 [95% CI: 0.74 - 0.87] for Radiomics + Clinical model. The overall pooled AUC was 0.76 [95% CI: 0.72 - 0.81] (**Figure 6**). High heterogeneity was observed (I^2 = 79%, p < 0.0001) with funnel plot asymmetry, suggesting possible publication bias or methodological differences (**Figure S7**). However, Egger's plot indicated that no substantial small-study effect or publication bias was visually evident (**Figure S8**). Egger's test also showed a non-significant intercept (0.0019, p = 0.993), indicating no publication bias. The significant slope (estimate = 4.3643, p < 0.0001) likely reflects true heterogeneity, rather than bias (**Table S5**).

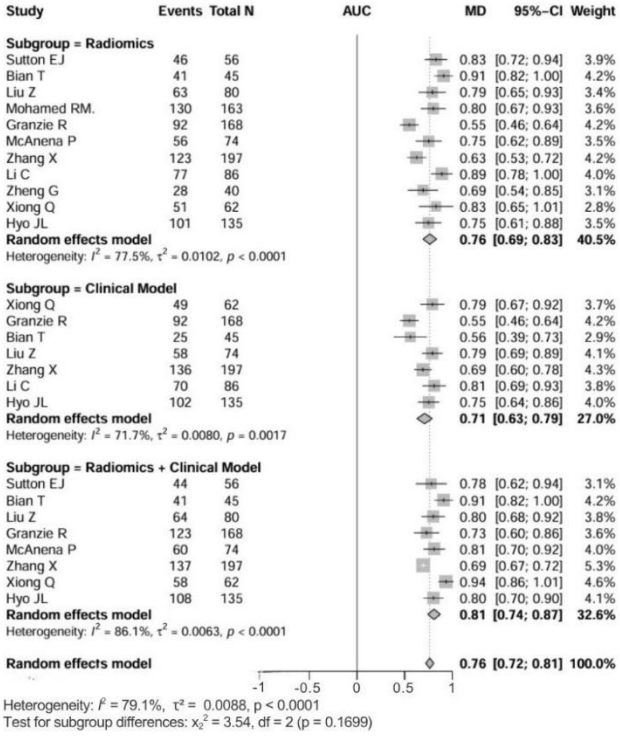

Figure 6 Forest plot of AUC comparison between radiomics, molecular subtype, and combined models for predicting pCR to NAC.

Summary receiver operating characteristic curve

The solid curves represent the fitted SROC curves for each subgroup, indicating an overall trend in the diagnostic performance. The Radiomics subgroup showed moderate diagnostic performance with balanced sensitivity and specificity. The Clinical model subgroup demonstrated a slightly more variable performance, with some studies clustering at lower sensitivity values. The Radiomics + Clinical model subgroup generally showed improved diagnostic accuracy, with studies clustering closer to the upper-left region of the plot, indicating a higher sensitivity and specificity (**Figure S9**). The diagonal dashed line represents the chance level (no-discrimination threshold) at which a test performs no better than random guessing does. Further studies from this perspective demonstrated stronger diagnostic capabilities. Overall, the curve suggests that integrating radiomics and clinical models may enhance the diagnostic accuracy of MRI in breast cancer.

Summary of findings

Neoadjuvant chemotherapy (NAC) is widely used in breast cancer treatment to improve surgical outcomes, enable breast conservation, and enhance the quality of life of patients with advanced-stage disease [32]. MRI is a key imaging modality that plays a critical role in evaluating complete response to NAC [33]. DCE-MRI combined with DWI-MRI enables the detection of response to NAC in breast cancer. However, both techniques have limitations; DCE-MRI requires precise interpretation of enhancement patterns, and DWI-MRI can be affected by image distortion and scanner quality. Radiomics has demonstrated substantial potential as a non-invasive imaging biomarker across various tumor types by enabling the extraction of high-dimensional quantitative features from routine medical images [34]. By incorporating a wide array of descriptors, such as shape, intensity, texture, gradient, wavelet transformations, and other advanced imaging markers, radiomics provides a rich dataset that enhances predictive modeling. Previous studies have suggested that combining DWI, DCE-MRI, and advancements in radiomics has significantly enhanced the detection, diagnosis, and monitoring of breast neoplasms [35].

The results of this meta-analysis underscore the growing potential of radiomics-based breast MRI as a tool for predicting pCR after NAC. The pooled sensitivity (0.76), specificity (0.72), accuracy (0.77), and AUC (0.76) across studies support radiomics as a valuable adjunct to traditional clinical models, which generally show lower performance than radiomics. This ability aids in recognizing subtle patterns in tumor characteristics that might not be visible without assistance, thus enhancing the precision of predictive models for treatment outcomes [36]. This objective and reproducible approach enhances the evaluation of tumor response to NAC, as demonstrated in a study in which specific radiomic features were identified as significant predictors of treatment response [27]. Several studies have also demonstrated that radiomic features have significant potential for detecting breast tumors and predicting treatment response, tumor molecular subtypes, and the presence of axillary lymph node metastases in patients with breast cancer [37–39].

Moreover, integrating radiomic features with clinical data further improved the predictive performance, achieving a pooled accuracy of up to 0.83 and an AUC of up to 0.81. This combination suggests that radiomics can capture subtle imaging biomarkers that, when complemented by clinical parameters, such as age, tumor stage, and molecular subtype, provide a more robust and personalized framework for treatment planning. In clinical practice, this approach may help identify patients most likely to achieve pCR, thus optimizing surgical decision making and offering opportunities for breast-conserving treatment strategies.

Nonetheless, it is crucial to comprehend the independent contribution of clinical models, as they remain essential indicators in clinical decision-making. In this study, a clinical model was constructed using basic patient information, including age, tumor stage, and molecular subtype, which demonstrated a lower AUC performance owing to its limited scope. Although it is easy to implement, it lacks the ability to fully capture the biological complexity of breast cancer, making it more prone to underfitting than image-based models. Consequently, clinical models often perform inconsistently across datasets, with varying patient distributions. In addition to molecular profiles, tumor stage is a critical factor in predicting response to NAC. Goorts et al. found that patients with lower T stages were more likely to achieve pCR, identifying clinical tumor staging as a key prognostic indicator [40]. Age has

emerged as a relevant factor. Crosbie et al. observed that patients in the pCR group tended to be younger than those who did not achieve pCR (53.3 vs. 57.5 years old) [41]. Although clinical data capture important tumor characteristics, they may represent only a limited portion of the tumor's complexity.

Table 3 Summary of findings.

Subgroup	Sensitivity (95% CI)	Specificity (95% CI)	Accuracy (95% CI)	AUC (95% CI)
Randomics	0.75 (0.68 - 0.81)	0.71 (0.53 - 0.84)	0.76 (0.65 - 0.85)	0.76 (0.69 - 0.83)
Clinical model	0.73 (0.45 - 0.90)	0.65 (0.51 - 0.76)	0.73 (0.55 - 0.86)	0.71 (0.63 - 0.79)
Radiomics + Clinical model	0.79 (0.65 - 0.89)	0.75 (0.69 - 0.81)	0.83 (0.68 - 0.91)	0.81 (0.74 - 0.87)
Overall Pooled	0.76 (0.69 - 0.82)	0.72 (0.63 - 0.78)	0.77 (0.70 - 0.83)	0.76 (0.72 - 0.81)

Clinical implication and explnation of mechanism

The findings of our meta-analysis suggest that MRI-based radiomics offers significant clinical value in the management of breast cancer via NAC. With a pooled sensitivity of 0.76 and specificity of 0.72, radiomics models show moderate to high promise in identifying patients who are likely to achieve pathological complete response (pCR). Importantly, the improved performance when combining radiomic features with clinicopathological variables (accuracy up to 0.83, AUC up to 0.81) suggests that such integrated approaches may serve as actionable tools in real-world settings. For example, patients predicted to respond well may be prioritized for breast-conserving surgery and less aggressive axillary management, whereas those predicted to respond poorly could be considered as alternative regimens early, sparing them from ineffective NAC and its associated toxicities. Furthermore, centers with advanced imaging workflows might implement dynamic "(delta-radiomics)" MRI after early NAC cycles to adapt treatment paths, aligning with evolving precision medicine [42–44].

Mechanistically, radiomics leverages imaging phenotypes as surrogates of underlying tumor biology. Key MRI sequences such as DCE-MRI quantify perfusion and microvascular permeability heterogeneity, DWI/ADC assesses cellular density and treatment-induced cell death, and texture/shape features capture intratumoral heterogeneity and stromal interactions. Studies have shown that higher baseline heterogeneity and its reduction during treatment correlate with the response, linking imaging features to angiogenic, hypoxic, and proliferative microenvironments [45]. For instance, multiparametric MRI radiomic fusion models achieved AUCs above 0.90 for tumour response prediction, when combining morphological, kinetic, and textural features [46]. These mechanistic links provide biological plausibility to radiomic prediction; radiomics is not simply statistical modelling, but may reflect the spatial-temporal evolution of tumor ecosystems under therapy.

From a translational perspective, the adoption of radiomics in clinical workflows requires certain prerequisites: standardized MRI acquisition protocols, robust segmentation pipelines, external model validation, and calibration for specific patient populations. The high heterogeneity ($I^2 > 80\%$) in the studies included in our meta-analysis signals the need for consensus regarding radiomics methodology before widespread deployment. Additionally, the potential for small-study effects, where smaller cohorts report inflated performance, should prompt cautious interpretation and preference for multicenter prospective validation studies. Nonetheless, with careful implementation, MRI radiomics models could become part of multidisciplinary tumor board discussions, supporting personalized treatment planning and real-time adjustments during NAC.

Strengths and limitations

Our meta-analysis offers several advantages over previous studies by providing a more focused and comprehensive evaluation of radiomic MRI for predicting pCR following NAC. Earlier meta-analyses explored a variety of MRI protocols, including DCE-

MRI, T2-weighted imaging, and DWI, to compare predictive strategies, such as conventional biomarkers and radiomic analyses, at different treatment stages before, during, or after NAC. One study specifically assessed the methodological quality of radiomics-based research on pCR prediction in neoadjuvant settings, whereas another recent meta-analysis employed MRI protocols to predict axillary lymph node metastasis (ALNM) and sentinel lymph node metastasis (SLNM). In contrast, our study uniquely centers on the use of radiomic MRI to predict pCR after NAC, thereby offering a more targeted approach. Our findings underscore the promising potential of radiomics-MRI improves the predictive accuracy, ultimately supporting the development of more personalized and effective treatment strategies for breast cancer management [47].

However, several limitations of this study should be considered before routine adoption. The meta-analysis revealed high heterogeneity across studies, likely stemming from differences in MRI protocols, radiomic feature selection, and machine learning algorithms. In addition, the potential publication bias suggested by funnel plot asymmetry raises concerns that favorable or extreme results may have been preferentially published, inflating estimates of diagnostic performance. Therefore, clinicians must be cautious when interpreting and applying these findings in the context of rigorous standardized protocols. Prospective multicenter validation trials with harmonized imaging and analysis pipelines are crucial for confirming these promising results.

Clinical implications

Ultimately, radiomics-enhanced breast MRI holds considerable potential for clinical application, offering noninvasive, objective, and reproducible support for NAC response prediction. When carefully integrated with clinical variables, radiomics may advance precision oncology by guiding more tailored and effective breast cancer treatment strategies, reducing overtreatment, and improving patient quality of life. As evidence accumulates and standards evolve, these imaging biomarkers may play a central role in future breast cancer management.

Conclusions

This systematic review and meta-analysis demonstrated that MRI-based radiomics exhibits promising diagnostic performance in predicting pathological complete response (pCR) to neoadjuvant chemotherapy (NAC) in patients with breast cancer. The pooled results showed a sensitivity of 0.76, specificity of 0.72, accuracy of 0.77, and AUC of 0.76, indicating that radiomics can effectively identify treatment responders with moderate-to-high precision. Compared with clinical models alone, radiomics consistently achieves superior diagnostic metrics across all parameters, underscoring its ability to capture subtle intratumoral heterogeneity and imaging biomarkers that are not discernible through conventional analysis.

Furthermore, integrating radiomic features with clinicopathologic variables further enhanced diagnostic accuracy (pooled accuracy 0.83; AUC 0.81), supporting the synergistic value of combining imaging-based biomarkers with clinical parameters, such as age, tumor stage, and molecular subtype. This integrated approach provides a more comprehensive and personalized framework for response prediction, potentially guiding tailored treatment strategies, and improving patient selection for breast-conserving surgery.

Despite these encouraging findings, the substantial heterogeneity observed across studies - stemming from differences in imaging protocols, feature extraction techniques, and modeling algorithms - highlights the need for methodological standardization and external validation in larger, multicenter cohorts. Future research should aim to establish robust and reproducible radiomics pipelines and integrate multi-omics and deep-learning approaches to further refine predictive performance and facilitate clinical translation.

In summary, radiomics-enhanced MRI represents a promising noninvasive biomarker for predicting the therapeutic response in breast cancer, offering the potential to improve individualized treatment planning and optimize clinical outcomes following neoadjuvant chemotherapy.

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Declaration of Generative AI in Scientific Writing

The authors acknowledge the assistance of generative AI tools for language refinement and grammatical editing only (e.g. Paperpal by Editage). No part of the content, data analysis, or interpretation was generated by AI. The authors remain fully responsible for the originality, accuracy, and conclusions presented in this manuscript.

CRediT Author Statement

Lydia Purna Kuntjoro: Conceptualization, Validation, Writing – original draft. **Ignatius Riwanto:** Conceptualization, Supervision, Writing – review and editing. **Hermina Sukmaningtyas:** Project administration, Writing – review and editing. **Yan Wisnu Prajoko:** Supervision, Validation. **Suhartono Suhartono:** Methodology, Resources. **Lina Choridah:** Conceptualization, Writing – review and editing. **Endang Mahati:** Methodology, Supervision. **Clarissa Aulia Pravitha:** Data curation, Investigation, Writing – original draft. **Kevin Christian Tjandra:** Formal analysis, Methodology, Data visualization. **Danendra Rakha Putra Respati:** Formal analysis, Software, Data visualization.

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Supplementary Materials

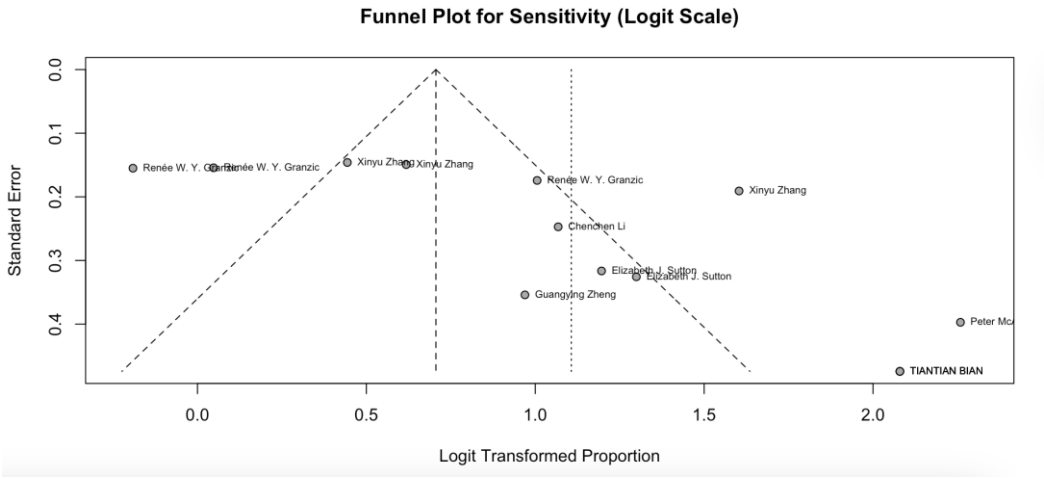

Figure S1 Funnel plot for sensitivity of each included study.

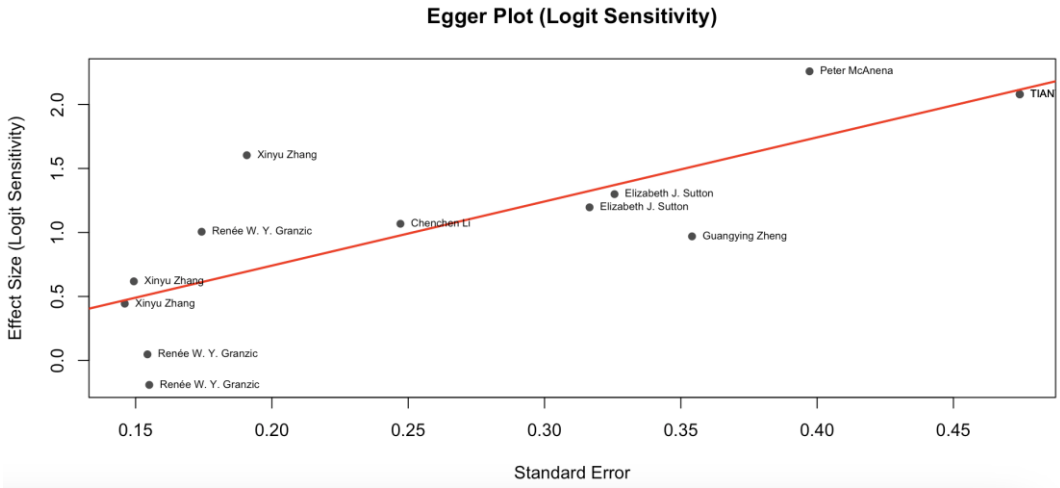

Figure S2 Egger's plot for sensitivity of each included study.

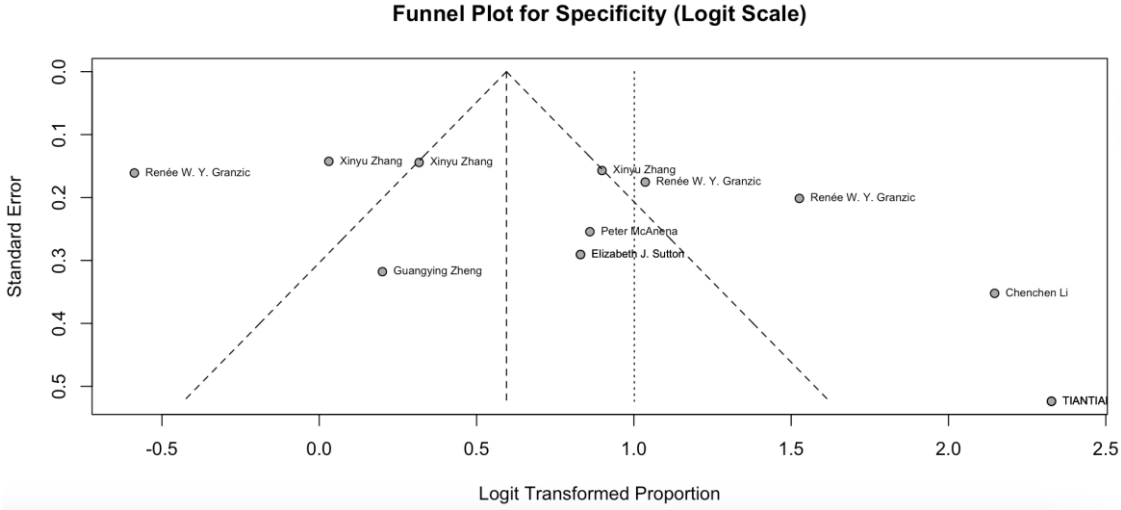

Figure S3 Funnel plot for specificity of each included study.

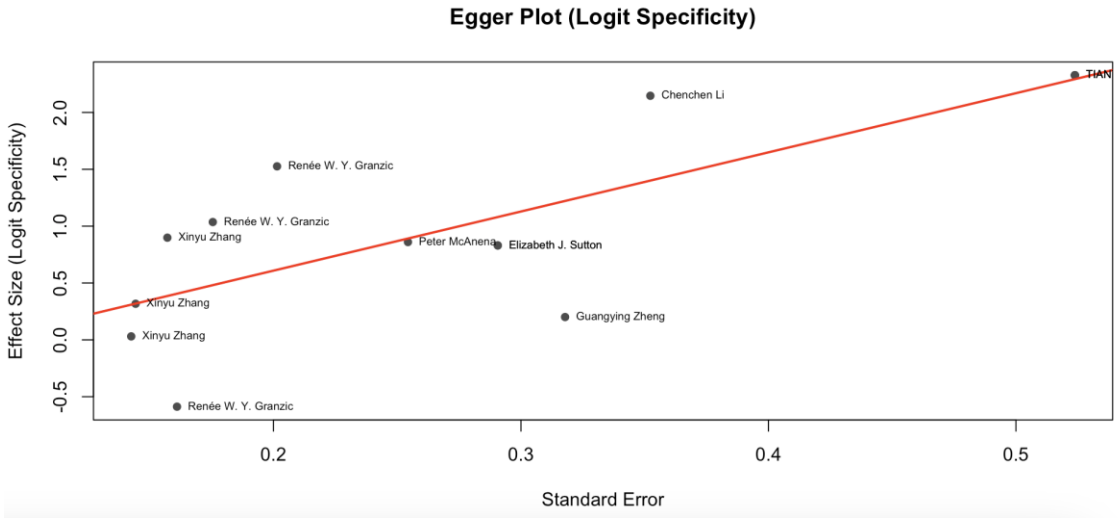

Figure S4 Egger's plot for specificity of each included study.

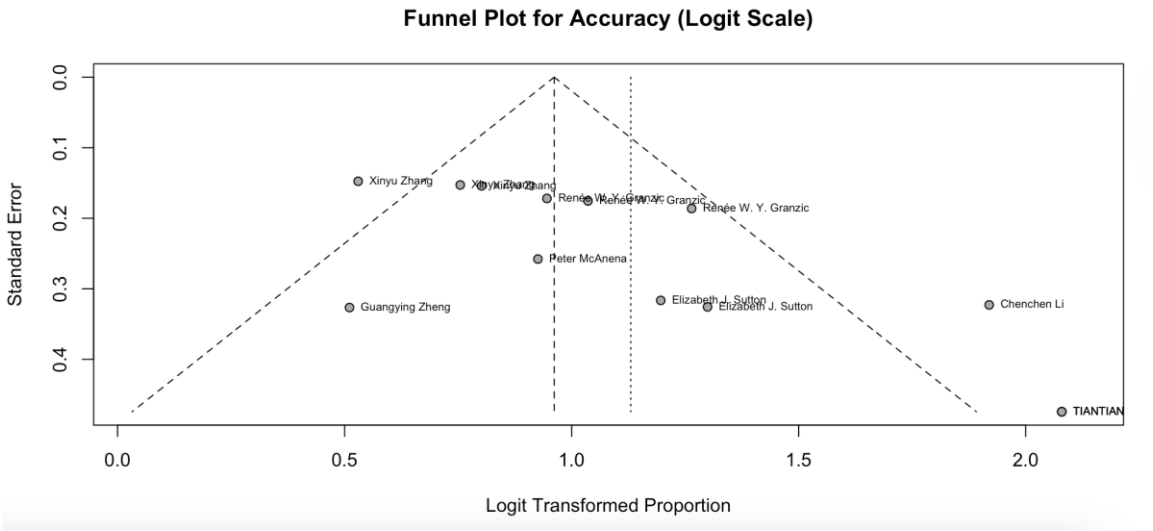

Figure S4 Funnel plot for accuracy of each included study.

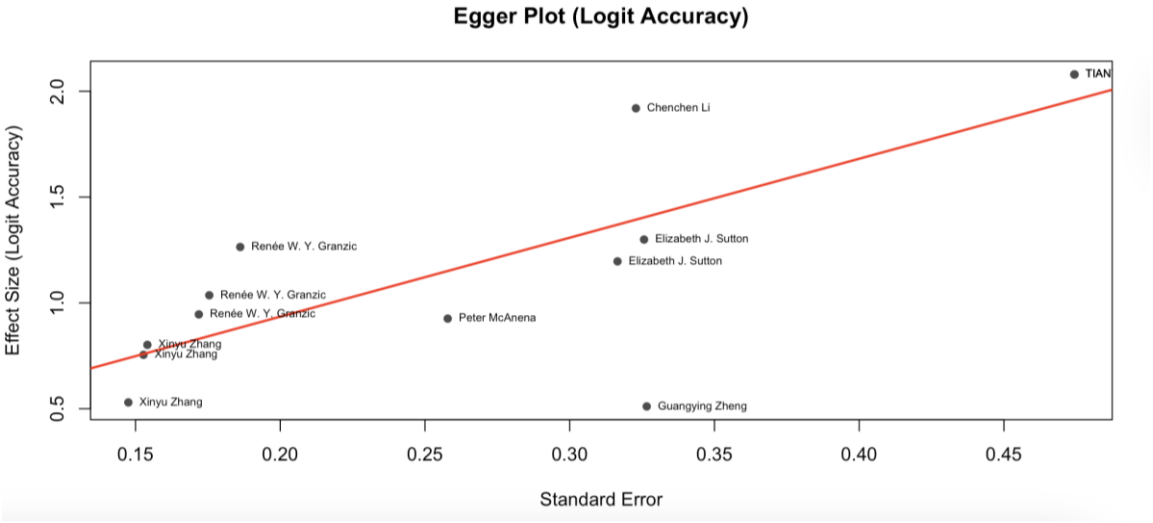

Figure S5 Egger's plot for accuracy of each included study.

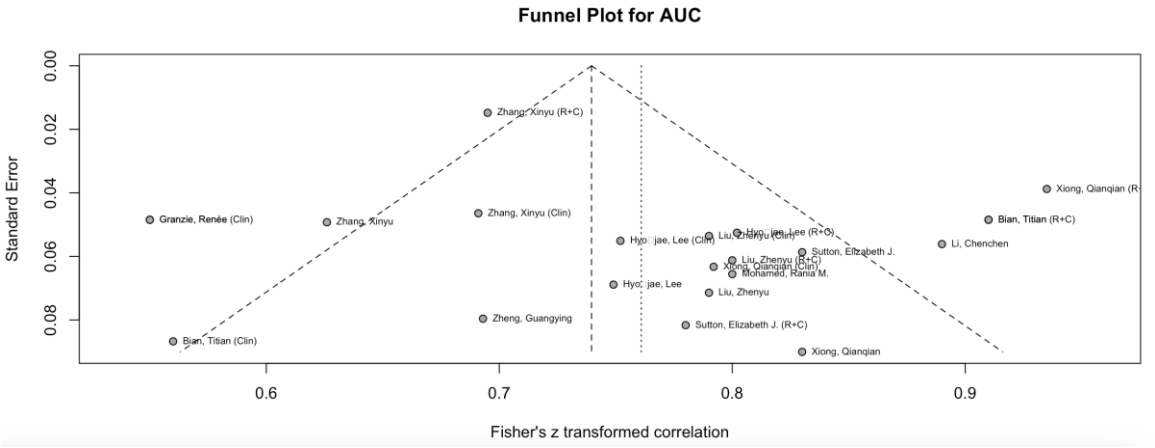

Figure S6 Funnel plot for AUC of each included study.

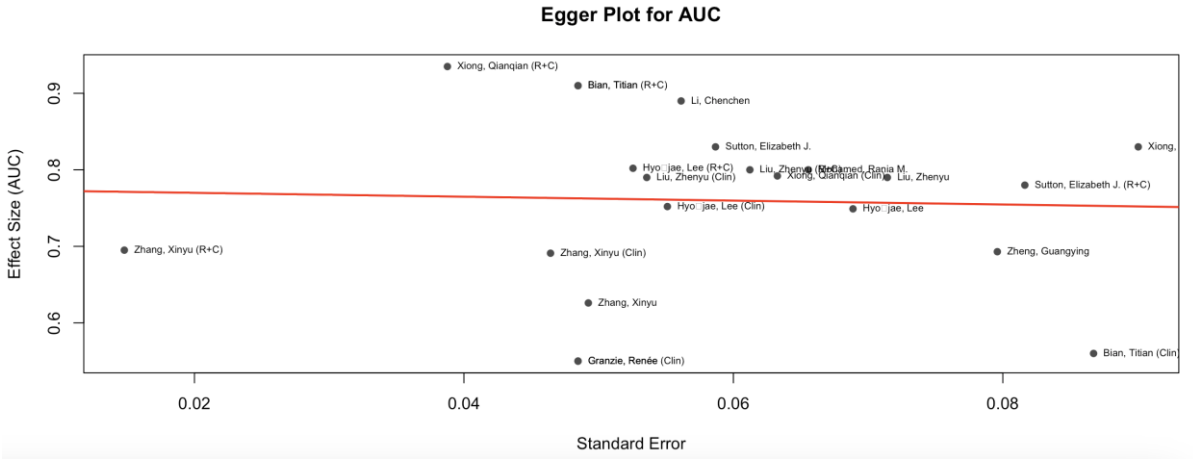

Figure S7 Egger's plot for AUC of each included study.

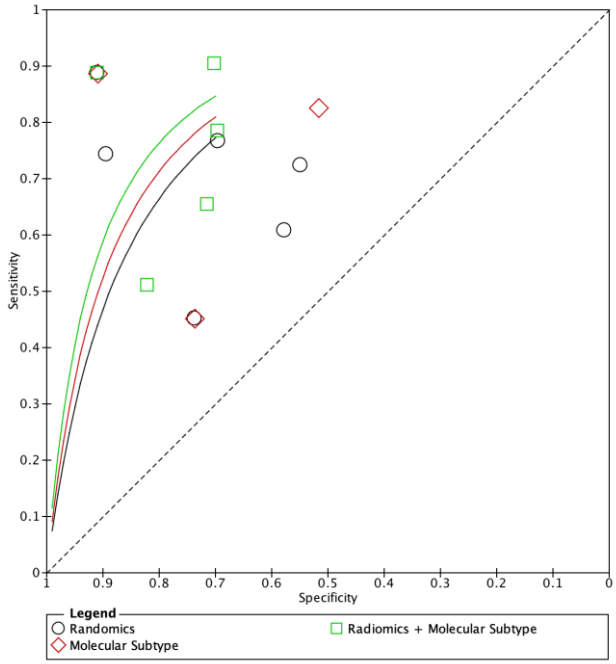

Figure S8 SROC curve for diagnostic performance of radiomic, clinical model, and combined models.

Table S1 PICO of this study.

Population	Any female patients over 18 who are diagnosed with breast cancer and are going through neoadjuvant chemotherapy or targeted therapies (NAC)
Intervention	Breast MRI-based radiomic used to predict pathological complete response (pCR)
Comparison	Non-radiomic prediction models (e.g., clinical data, conventional biomarkers) or no specific comparator.
Outcomes	radiomic analysis can forecast complete pathological response, shown by: (1) area under the curve (AUC), (2) sensitivity, (3) specificity, and (4) accuracy of pre-op MRI in predicting response (pCR) to neoadjuvant therapies

Table S2 Egger's regression analysis for comparing sensitivity studies on publication bias.

Parameter	Estimate	Std. Error	t value	*p*-value	Significance
Intercept (bias)	–0.2613	0.2938	–0.889	0.39135	Not significant
Slope (seTE)	5.0118	0.9345	5.363	0.00017	*** (Significant)

Table S3 Egger's's regression analysis for comparing specificity studies on publication bias.

Parameter	Estimate	Std. Error	t value	*p*-value	Significance
Intercept (bias)	–0.4317	0.3667	–1.177	0.26184	Not significant
Slope (seTE)	5.202	1.1413	4.558	0.00066	*** (Significant)

Table S4 Egger's's regression analysis for comparing accuracy studies on publication bias.

Parameter	Estimate	Std. Error	t value	*p*-value	Significance
Intercept (bias)	0.1887	0.2382	0.792	0.44366	Not significant
Slope (seTE)	3.7321	0.775	4.815	0.00042	*** (Significant)

Table S5 Egger's regression analysis for comparing AUC studies on publication bias.

Parameter	Estimate	Std. Error	t value	p-value	Significance
Intercept (bias)	0.0019	0.2154	0.009	0.993	Not significant
Slope (seTE)	4.3643	0.6652	6.561	2.69E-05	*** (Significant)