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Meta-analysis of the correlation between MRI radiomics and HER2 overexpression in breast cancer

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► ***Original article***

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Keywords: *MRI Radiomics correlates with HER2 overexpression in breast cancer and demonstrates high diagnostic accuracy, offering a novel approach for HER2 evaluation.*

ABSTRACT

Background: To evaluate the diagnostic efficacy of Magnetic resonance imaging (MRI) radiomics in predicting the overexpression of Human Epidermal Growth Factor Receptor 2(HER2) in breast cancer via meta-analysis, so as to investigate the correlation between MRI radiomics and HER2 overexpression in breast cancer. ***Materials and Methods:*** PubMed, Embase, and Web of Science were searched for studies on radiomics and HER2 overexpression in breast cancer (inception–September 2025). Two reviewers independently screened literature, extracted data, and assessed quality (RevMan 5.3). Pooled sensitivity (SEN), specificity (SPE), and AUC were calculated (Stata 17.0). Heterogeneity and bias were evaluated via subgroup/ sensitivity analyses and Deeks' test. ***Results:*** 13 studies (4,756 patients) were included. The training set showed pooled SEN 0.90(95%CI:0.81-0.95), SPE 0.82(95%CI:0.72-0.89), and AUC 0.92(95%CI:0.90-0.94). The validation set had SEN 0.74(95%CI:0.62-0.83), SPE 0.80(95%CI:0.70-0.87), and AUC 0.84(95%CI:0.80-0.87). Heterogeneity (I^2> 75%) stemmed from sample size and country differences (both P<0.05). Fagan's plot indicated radiomics increased HER2 overexpression post-test probability to 48%-56% (from 20% pre-test) and reduced negative results to 3%-8%. Sensitivity analysis confirmed robustness; no publication bias was detected (P>0.05). ***Conclusion:*** MRI Radiomics correlates with HER2 overexpression in breast cancer and demonstrates high diagnostic accuracy, offering a novel approach for HER2 evaluation.

INTRODUCTION

Breast cancer (BC) is one of the most common malignant tumors in women worldwide, with more than 2.3 million new cases worldwide in 2020, posing a serious threat to women 's health [1]. Human epidermal growth factor receptor 2 (HER2) is a key biomarker in the treatment of breast cancer, and its overexpression plays a key role in the development, treatment selection and prognosis evaluation of breast cancer [2]. HER2 is overexpressed in about 20 % of breast cancer. This type of breast cancer is highly invasive and has a high recurrence rate, but anti-HER2 targeted therapy (such as trastuzumab) can significantly improve prognosis [3, 4]. Therefore, accurate detection of HER2 expression is essential for individualized treatment of breast cancer. Traditional HER2 detection methods include immunohistochemistry (IHC) and fluorescence in situ hybridization (FISH), but there are limitations such as invasiveness, time-consuming and high cost [5]. As an emerging quantitative analysis technology, radiomics can extract quantitative features from medical images in a high-throughput way for in-depth analysis of tumor biological characteristics [6]. There are differences in radiomics features under different imaging modes: CT focuses on anatomical structure information, ultrasound is greatly affected by resolution and operator, while MRI can more accurately reflect the internal heterogeneity of tumors by virtue of its advantages of high soft tissue resolution, multi-parameter imaging and no radiation, and provide more abundant information for accurate diagnosis and molecular typing of breast cancer [7]. Although studies have explored the relationship between MRI radiomics and HER2 status, there is a lack of systematic reviews specifically focusing on the relationship between MRI radiomics and HER2 overexpression in breast cancer [8]. Therefore, the aim of this study is to systematically evaluate the correlation between MRI radiomics features and HER2 overexpression in breast cancer by Meta-analysis, and to provide more reliable evidence for the clinical application of MRI radiomics in the evaluation of HER2 status in breast cancer.

MATERIALS AND METHODS

Literature search strategy

PubMed, Embase, and Web of Science databases were searched to collect studies on the correlation between radiomics and HER2 overexpression in breast cancer. The search time was from the establishment of the database to September

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2025.The search formula was constructed by combining subject words and free words, and was adjusted according to the characteristics of the database. Taking Pubmed as an example, the specific search strategy is shown in table 1.

Table 1. Search strategies in the Pubmed database.

Steps	
#1	(MRI[Title/Abstract]) OR (Magnetic resonance imaging [Title/Abstract])
#2	Radiomics [Title/Abstract]
#3	((Breast Cancer [Title/Abstract]) OR (Breast Neoplasms [Title/Abstract])) OR (Breast Tumor[Title/Abstract])
#4	(((HER2 Overexpression [Title/Abstract]) OR (HER2 Over-expression [Title/Abstract])) OR (HER2 Overexpressing [Title/Abstract])) OR (HER2 positive [Title/Abstract])
#5	#1 AND #2 AND #3 AND#4

Literature inclusion and exclusion criteria

Inclusion criteria: (1) The study subjects were breast cancer patients confirmed by pathology;(2) HER2 expression has been detected in surgical specimens or tissues of breast cancer, and it is defined as HER2 over-expression in breast cancer. The methods used to detect HER2 expression must include immunohistochemistry (IHC) and in situ hybridization (ISH). fluorescence in situ hybridization (FISH) or silver in situ hybridization (SISH) should be used for in situ hybridization. There is also a clear IHC scoring method for HER2 overexpression and a clear in situ hybridization positive definition (HER2 overexpression is defined as IHC 3+ or IHC 2+ plus FISH positive or SISH positive) [9]; (3) Features were extracted by MRI radiomics methods and the relationship between them and the overexpression of HER2 in breast cancer could be analyzed; (4) The true positive, false positive, true negative and false negative data of the diagnostic test can be obtained, or can be calculated by the data in this paper; (5) The literature is published in English.

Exclusion criteria: (1) repeated publications; (2) reviews, case reports, conference abstracts, meta-analyses and other non-original studies; (3) articles whose full text could not be obtained or whose key data were missing and could not be obtained after contacting the authors; (4) literature with low research quality.

Literature screening and data extraction

Two researchers independently conducted literature screening and data extraction. First, the literature was screened by reading the title and abstract of the literature, and the literature that clearly did not meet the inclusion criteria was excluded. Then read the full text of the literature after the initial screening to determine the final inclusion of the literature. If there is a difference between the two researchers on the inclusion of the literature, it will be resolved by discussing or consulting a third researcher. Data extraction included: first author, year of publication, research country, research type, sample size, radiomics used (machine learning, deep learning, etc.), radiomics-related software, criteria for HER2 overexpression, sensitivity, specificity, AUC, and true positive (TP), false positive (FP), true negative (TN) and false negative (FN) data.

Literature quality evaluation

Two researchers used the quality assessment of diagnostic accuracy studies-2 (QUADAS-2) scale [10] to evaluate the quality of the included literature. The quality of the literature was evaluated independently. When the opinions were inconsistent, the independent researchers of the third party discussed and decided to evaluate the risk of bias and clinical applicability of the included literature.

Statistical analysis

Meta-analysis was performed using RevMan5.3 and Stata 17.0 software. RevMan5.3 software was used to evaluate the quality of the literature, and the quality assessment of diagnostic accuracy studies-2 (QUADAS-2) scale was used to evaluate the quality of the included literature. Stata 17.0 software is used for subsequent calculations. The pooled sensitivity (SEN), specificity (SPE), positive likelihood ratio (PLR), negative likelihood ratio (NLR) and diagnostic odds ratio (DOR) were calculated. The heterogeneity of the included studies was tested by constructing a forest plot of combined sensitivity and specificity. Cochran's Q method and heterogeneity index (I^2) were used to evaluate the heterogeneity of literature (test level a=0.05). If $I^2<50\%$ and $P>0.1$, the heterogeneity between studies was considered to be small, and Meta-analysis was performed directly. If $I^2\geq50\%$ or $P\leq0.1$, inter-study heterogeneity was considered to be large, and subgroup analysis was used to analyze the source of heterogeneity. If heterogeneity was significant ($I^2>80\%$), only descriptive analysis was performed. The total receiver operating characteristic (SROC) curve was drawn and the area under the curve (AUC) was calculated to evaluate the diagnostic efficacy of MRI radiomics for HER2 overexpression in breast cancer. The AUC score indicated that the level of discrimination ability was as follows: 0.5-0.7 was low discrimination ability, 0.7-0.9 was medium discrimination ability, and >0.9 was high discrimination ability. Subgroup analysis used Meta regression to explore the source of heterogeneity, and sensitivity analysis was used to evaluate the stability of the included literature. Deeks' funnel plot was drawn to evaluate publication bias, and P>0.05 indicated that there was no publication bias. The clinical practicability of ultrasound radiomics in predicting HER2 overexpression in breast cancer was evaluated by Fagan plot analysis.

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RESULTS

Results of literature search

After searching according to the search strategy, we retrieved a total of 31 articles, 8 duplicate articles were excluded, and 4 articles were excluded after reading the title and abstract, because they were reviews or irrelevant to our research. The remaining 19 articles were read in full text, and finally a total of 13 articles were included.

Basic characteristics of the included literature

In total, 13 articles were eligible for inclusion, with a total number of cases ranging from 88 to 752, including 4756 patients. One was prospective studies and 12 were retrospective studies. Two studies were conducted in the United States and South Korea, and 11 studies were conducted in China. All included studies used IHC+FISH/ISH/SIHS etc. to determine HER2 expression status, and the characteristics of all study literature are shown in table 2.

Table 2. Characteristics of each study literature.

Author	Year	Country	Research type	Radiomics Used	Radiomics-related software	Criteria for HER2 overexpression	Sample size	TP	FP	FN	TN	AUC	Accuracy
Zheng S (11)	2024	China	Retrospective study	Machine learning	ITK-SNAP software, R 4.1.2	IHC/ISH+FISH	407/174	107/44	92/33	21/20	187/77	0.809/0.737	0.722/0.697
Bitencourt AGV (12)	2020	USA	Retrospective study	Machine learning	ITK-SNAP software	IHC+FISH	311	277	6	2	26	Not mentioned	0.974
Guo X (13)	2023	China	Retrospective study	Deep learning	Python 3.7	IHC+ISH	329/61	214/31	25/5	24/13	66/12	0.868/0.763	0.851/0.705
Song X (14)	2024	China	Retrospective study	Machine learning	Unetsoftware, Python 3.6	IHC+FISH	374/160	55/18	28/13	8/3	283/126	0.93/0.92	Not mentioned
Sheng W (15)	2022	China	Retrospective study	Machine learning	3D Slicer, SAS 9.4, R 3.6.1	IHC+FISH	133/57	15/5	3/1	26/13	89/38	0.807/0.805	0.786/0.768
Jeong J (16)	2025	Korea	Prospective study	Machine learning	Python 3.8	IHC+SISH	233	15	24	2	192	0.79	0.87
Xu A (17)	2022	China	Retrospective study	Machine learning	PyRadiomics, R 3.6.1	V	128/86	37/24	14/18	5/4	72/40	0.927/0.826	0.851/0.744
Luo HJ (18)	2024	China	Retrospective study	Machine learning	PyRadiomics, R 4.1.0	IHC+FISH	250/152	66/22	91/29	7/9	86/92	0.777/0.765	0.608/0.750
Huang Y (19)	2023	China	Retrospective study	Deep learning	Python 3.7, Onekey AI platform	IHC+FISH	409/343	178/136	24/25	8/24	199/158	0.974/0896	0.919/0.856
Yue WY (20)	2023	China	Retrospective study	Machine learning	ITK-SNAP software, PyRadiomics	IHC+FISH	517	132	100	17	268	0.868	0.774
Shang Y (21)	2024	China	Retrospective study	Machine learning	ITK-SNAP software, R 4.3.2	IHC+FISH	305/77	78/17	80/20	28/10	119/30	0.746/0.718	0.646/0.610
Chen X (22)	2025	China	Retrospective study	Machine learning	Python v3.7.6	IHC+FISH	61/27	22/9	0/5	0/1	39/12	1.000/0.806	1.000/0.778
Huang Y (23)	2021	China	Retrospective study	Machine learning	PyRadiomics	IHC+FISH	162	69	29	12	52	0.840	0.790

Note: In the sample size, TP, FP, FN, TN columns, the first number is the training set, the second number is the validation set, and only one number represents that the study only sets up the training set.

Literature quality assessment

The QUADAS-2 scale was used to evaluate each included study, as shown in figure 1(A、B). Literature quality analysis suggested that the quality of the 13 literatures was high and the applicability was good.

Summary of sensitivity and specificity

It can be seen from the forest map that the I^2 values of the combined sensitivity of the training set and the validation set of the MRI radiomics prediction of HER2 overexpression in breast cancer were 94.79% and 78.97%, respectively, and the Q test was all P<0.01. The I^2 values of the combined specificity of the training set and the validation set were 96.37% and 82.85%, respectively, and the Q test was all P<0.01, suggesting that there was a large heterogeneity in the literature of MRI radiomics predicting HER2 overexpression (figure 2A, 2B). Specifically, the training set of radiomics to predict HER2 overexpression in breast cancer had a pooled sensitivity of 0.90 (95%CI:0.81-0.95), specificity of 0.82 (95%CI:0.72-0.89). The validation set had a pooled sensitivity of 0.74 (95%CI:0.62-0.83), specificity of 0.80 (95%CI:0.70-0.87). The AUC of the SROC curve in the training set was 0.92 (95%CI:0.90-0.94), and the validation set was 0.84 (95%CI:0.80-0.87), suggesting that radiomics has a high diagnostic value in predicting MRI HER2 overexpression in breast cancer (figure 3A, 3B).

Subgroup analysis

To explore the source of heterogeneity, a subgroup analysis was performed on factors such as study country, sample size, radiomics used, and validation set. The results showed that the heterogeneity of pooled sensitivity may come from research country. The pooled sensitivity of articles from other countries (South Korea and the United States) was significantly higher than that of articles from China, and the differences were statistically significant (P<0.05). The heterogeneity of pooled

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specificity may come from the sample size. The pooled sensitivity of literatures with sample size <200 cases was significantly higher than that of literatures with sample size ≥200 cases, and the difference was statistically significant (P<0.05). See table 3.

Sensitivity analysis

The analysis results after eliminating individual studies item by item showed that no individual study significantly affected the whole, indicating that the literature included in the meta-analysis had good stability and high reliability (table 4).

Table 3. Results of subgroup analysis.

Variables	n	Sensitivity	*P*	Specificity	*P*
Country					
China	11	0.87 [0.80 - 0.94]	0.03	0.81 [0.72 - 0.91]	0.43
Other Countries	2	0.98 [0.94 - 1.00]		0.86 [0.69 - 1.00]	
Sample Size					
≥200	10	0.91 [0.85 - 0.97]	0.62	0.78 [0.68 - 0.89]	0.03
<200	3	0.82 [0.60 - 1.00]		0.93 [0.84 - 1.00]	
Radiomics Used					
Machine learning	11	0.88 [0.81 - 0.96]	0.37	0.82 [0.72 - 0.91]	0.66
Deep learning	2	0.94 [0.84 - 1.00]		0.83 [0.62 - 1.00]	
Validation set					
Yes	9	0.87 [0.78 - 0.96]	0.07	0.84 [0.74 - 0.93]	0.68
No	4	0.94 [0.87 - 1.00]		0.79 [0.61 - 0.96]	

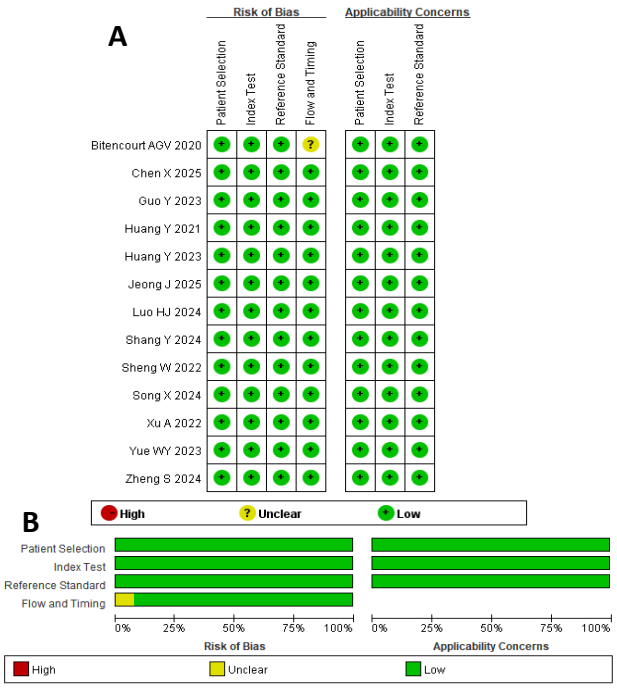

Figure 1. Results of quality assessment of the included literature (A. Summary chart of risk of bias; B. Risk of bias plot).

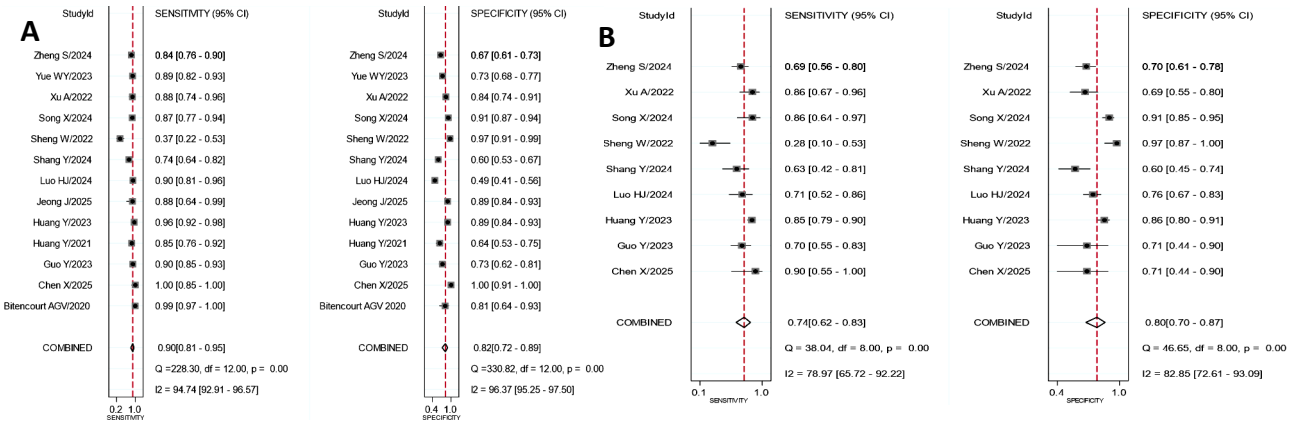

Figure 2. Forest plot of sensitivity and specificity of MRI radiomics for predicting HER2 overexpression in breast cancer (**A.** training set; **B.** Validation set). Note: Each "Study ID" corresponds to an included study, and the black dot to the right of it represents the point estimate of sensitivity/specificity in that study. The horizontal lines on either side of the dots represent the 95% confidence interval (95% CI) for this estimate. The diamond symbol corresponding to "COMBINED" at the bottom of the figure represents the pooled sensitivity/specificity of the 13 studies. The internal value of the diamond is the point estimate of the combined effect, and the left and right extension range of the diamond corresponds to the 95% CI of the combined effect. The red vertical dotted line in the figure is the reference line for the combined effect size, which can be used to visually compare the degree of deviation between the results of each study and the combined results.

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Table 4. Sensitivity analysis.

Elimination study	Pooled sensitivity	I^2	Q	*P*	Pooled specificity	I^2	Q	*P*
Bitencourt AGV 2020	0.87(95%CI:0.79-0.92)	93.24%	162.68	<0.001	0.82(95%CI:0.71-0.90)	96.17%	286.89	<0.001
Chen X 2025	0.88(95%CI:0.79-0.94)	94.29%	192.68	<0.001	0.79(95%CI:0.70-0.87)	95.81%	262.83	<0.001
Guo Y 2023	0.90(95%CI:0.80-0.95)	95.15%	226.89	<0.001	0.83(95%CI:0.72-0.90)	96.82%	346.41	<0.001
Huang Y 2021	0.90(95%CI:0.81-0.95)	95.36%	237.00	<0.001	0.83(95%CI:0.73-0.90)	96.85%	348.73	<0.001
Huang Y 2023	0.89(95%CI:0.79-0.94)	94.68%	206.92	<0.001	0.81(95%CI:0.70-0.89)	96.32%	299.30	<0.001
Jeong J 2025	0.90(95%CI:0.80-0.95)	95.01%	220.35	<0.001	0.81(95%CI:0.70-0.89)	96.37%	302.69	<0.001
Luo HJ 2024	0.90(95%CI:0.80-0.95)	95.16%	227.39	<0.001	0.84(95%CI:0.75-0.90)	95.56%	247.78	<0.001
Shang Y 2024	0.90(95%CI:0.82-0.95)	94.87%	214.60	<0.001	0.83(95%CI:0.73-0.90)	96.30%	297.58	<0.001
Sheng W 2022	0.82(95%CI:0.86-0.95)	89.94%	109.34	<0.001	0.80(95%CI:0.70-0.88)	96.37%	303.19	<0.001
Song X 2024	0.90(95%CI:0.80-0.95)	95.09%	224.25	<0.001	0.81(95%CI:0.70-0.89)	96.08%	280.36	<0.001
Xu A 2022	0.90(95%CI:0.80-0.95)	95.24%	231.30	<0.001	0.82(95%CI:0.71-0.90)	96.67%	330.18	<0.001
Yue WY 2023	0.90(95%CI:0.80-0.95)	95.23%	230.83	<0.001	0.83(95%CI:0.72-0.90)	96.73%	336.02	<0.001
Zheng S 2024	0.90(95%CI:0.81-0.95)	95.27%	232.79	<0.001	0.83(95%CI:0.73-0.90)	96.55%	319.25	<0.001

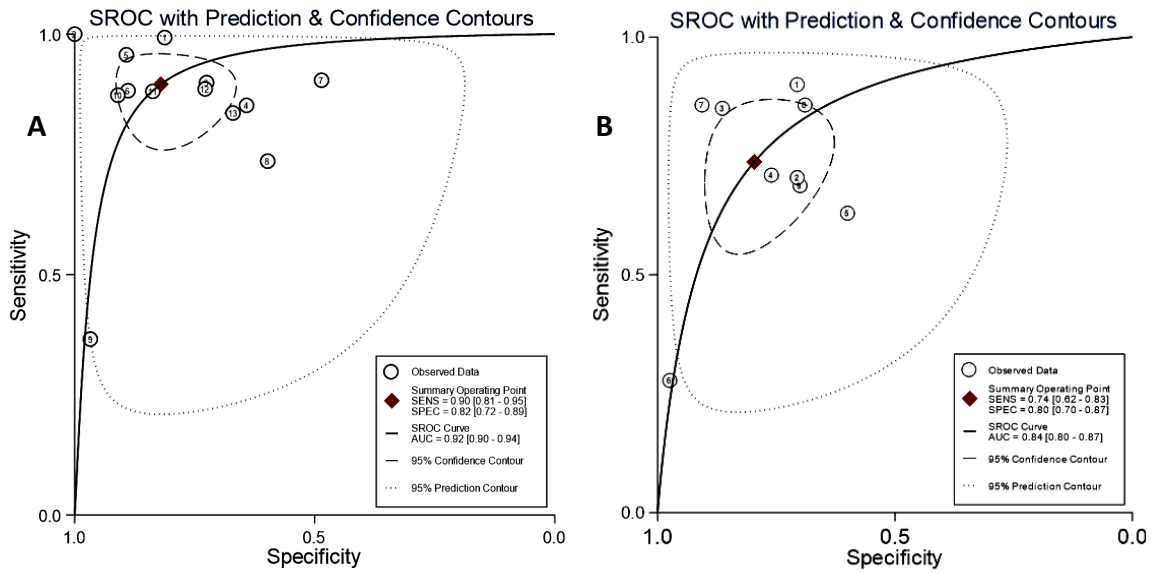

Figure 3. SROC curve of MRI radiomics in predicting HER2 overexpression in breast cancer (**A.** training set; **B.** Validation set). Note: The white circles marked with numbers in the figure correspond to the actual combination of sensitivity (vertical axis) and specificity (horizontal axis) observed in each included study. The numbers represent the numbers of different studies, which directly reflect the individual differences in diagnostic performance among the studies. The red diamonds in the figure are the comprehensive diagnostic efficacy points of all included studies, and the corresponding indicators are: combined sensitivity and combined specificity, representing the average diagnostic ability of MRI radiomics to identify HER2 overexpression. The black solid line in the figure is the summary ROC curve obtained by fitting. The closer the curve is to the upper left corner of the figure, the higher the diagnostic efficiency is. The area under the curve (AUC) is marked in the figure, and the AUC closer to 1 indicates that the technology has higher diagnostic accuracy.

Evaluation of clinical practicality

Fagan plot showed that in the training set, the combined positive likelihood ratio was 5.00, and the combined negative likelihood ratio was 0.13. The pre-test probability of MRI radiomics predicting HER2 overexpression in breast cancer was 20 %, the post-test positive probability was 56 %, and the negative probability was 3 %, which increased by 36 % and decreased by 17 %, respectively. In the validation set, the combined positive likelihood ratio was 4.00, and the combined negative likelihood ratio was 0.33. The pre-test probability of MRI radiomics predicting HER2 overexpression in breast cancer was 20 %, the post-test positive probability was 48 %, and the negative probability was 8 %, which increased by 18 % and decreased by 12 %, respectively (figure 4A, 4B).

Bias of publication

The results of Deeks' test showed that there was no publication bias in the literature on the prediction of HER2 overexpression in breast cancer by MRI radiomics (training set: P=0.29; validation set P=0.33) (figures 5A, B), suggesting that the results of Meta-analysis were reliable.

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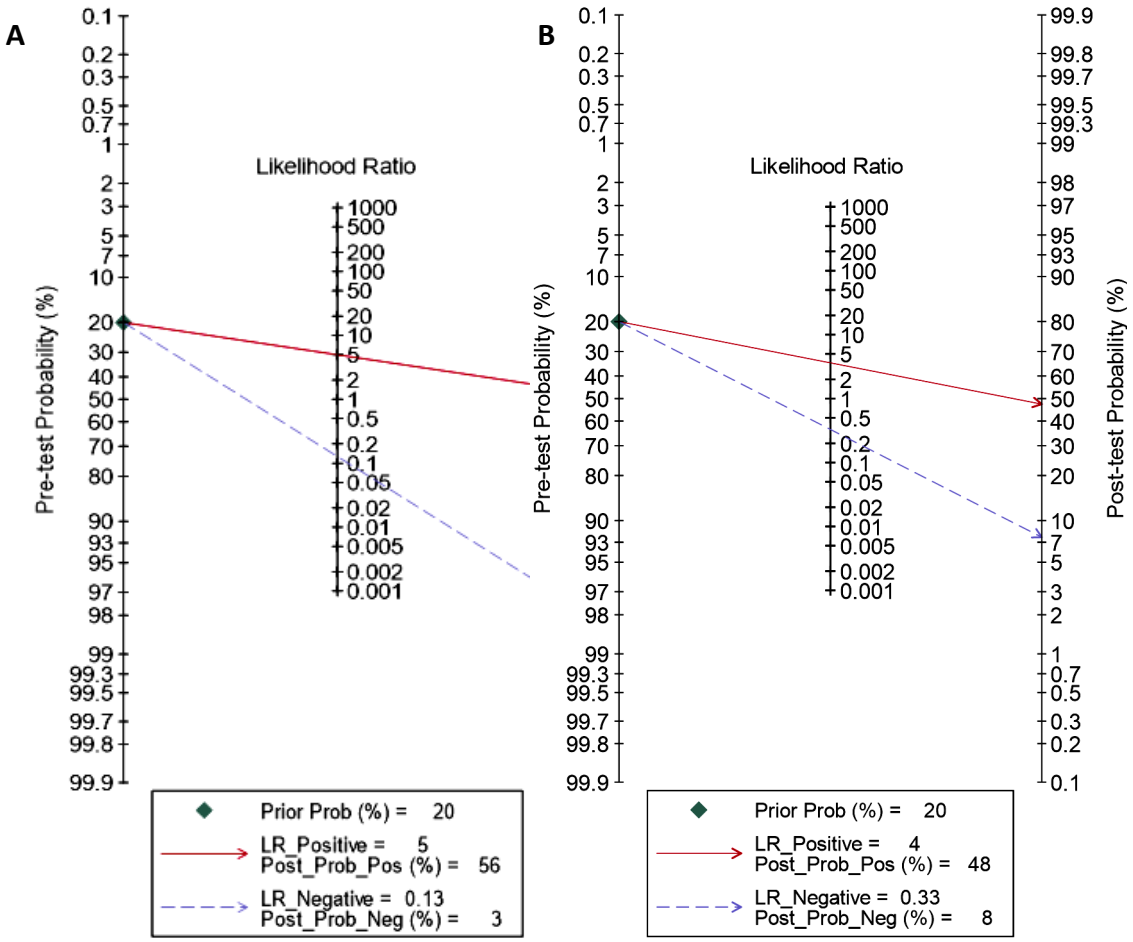

Figure 4. Fagan diagram of radiomics prediction of HER2 overexpression in breast cancer (**A.** training set; **B.** Validation set). Note: Horizontal axis (Likelihood Ratio: represents the likelihood ratio of the MRI radiomics results, the value> 1 is LR_Positive, indicating that the probability of disease increases when the results are positive, and the value < 1 is LR_Negative, indicating that the probability of disease decreases when the results are negative. The left vertical axis (Pre-test Probability, %) represents the estimated probability (prior probability) of HER2 overexpression before the trial (when MRI radiomics results were not obtained). The right vertical axis (Post-test Probability, %) represents the updated probability (posterior probability) of HER2 overexpression after the trial (when the MRI radiomics results were obtained). The left and right vertical axis ranged from 0.1% to 99.9%, corresponding to the whole range of disease occurrence probability.

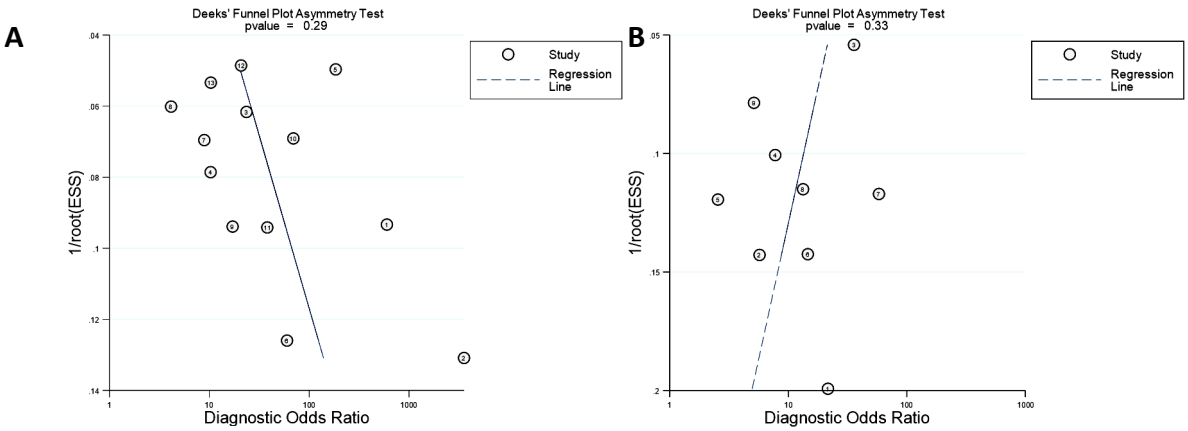

Figure 5. Funnel plot of Deek's test (**A.** training set; **B.** Validation set). Note: The horizontal axis (Diagnostic Odds Ratio) represents the diagnostic odds ratio (DOR) of each included study, which is an indicator to comprehensively reflect the sensitivity and specificity of diagnostic tests. The higher the value, the higher the diagnostic efficacy of MRI radiomics in that study. Vertical axis (1/root (ESS)): where "ESS" is the Effective Sample Size, which reflects the accuracy of sample statistics in diagnostic studies. The smaller the value of 1/root (ESS), the larger the sample size of the study and the higher the statistical accuracy. White circles (Study): Each numbered circle corresponds to an included study, whose position was determined by the DOR (horizontal axis) and 1/root (ESS)(vertical axis) of the study, and the number is the number of the study. The blue dotted Line (Regression Line) is the regression fitting line of Deeks' funnel plot, which is used to describe the overall distribution trend of the research points. The "symmetry" of the funnel plot should be determined by combining the distribution relationship between the line and the research points. "p value" is the P value of Deeks' funnel plot asymmetry test. In the publication bias test, if P > 0.05, it indicated that the funnel plot distribution was symmetrical and there was no significant publication bias.

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DISCUSSION

The concept of radiomics was first elaborated by Gillies *et al.*in 2010, and then further improved and developed through in-depth research by Lambin *et al.* [24, 25]. The core of radiomics is to extract a large number of image features from medical image images such as ultrasound, CT and MRI efficiently and quantify them, so as to further explore the characteristics of microscopic lesions; it can also find the details of the lesions that the human eye cannot distinguish through the computer, and extract the complete omics features from the smallest unit voxel, which makes the information hidden in the image fully excavated and utilized [26, 27]. In recent years, MRI radiomics research has made great progress in predicting the HER2 expression status of breast cancer. Zhou [28] *et al.* found that the evaluation of intratumoral and peritumoral radiomics using multi-parametric MRI can predict the HER2 expression level of breast cancer, and its AUC reached 0.795. Ramtohul [29] *et al.* showed that radiomics based on multi-parametric MRI could accurately predict the different expression of HER2 in breast cancer patients, and the AUC could reach 0.77 and 0.80, respectively. Thirteen studies, including 4756 breast cancer patients, were comprehensively evaluated in this meta-analysis, and the diagnostic performance of MRI radiomics for predicting HER2 overexpression was systematically and quantitatively synthesized for the first time. The results showed that the MRI-based radiomics model showed excellent discrimination ability in both the training and validation sets, confirming the significant correlation between MRI-based radiomics features and HER2 overexpression.

The results of this study showed that MRI radiomics had a high comprehensive diagnostic efficacy in predicting HER2 overexpression in breast cancer. The high AUC value of the training set (0.92) proved the potential of model development, while the AUC of the validation set was 0.84, both of which were above the medium discrimination ability, suggesting that it had good generalization [30]. It is worth to note that the combined sensitivity (0.90) and specificity (0.82) of MRI radiomics in predicting HER2 overexpression in breast cancer were higher than those of ultrasound radiomics reported by Fu [31] *et al.* (0.76) and specificity (0.78). This is mainly due to the unique advantages of MRI imaging. Zhang [32] *et al.* showed that the excellent performance of MRI radiomics in predicting HER2 overexpression in breast cancer may be related to its ability to deeply explore the biological characteristics of tumors. Breast cancer cells with HER2 overexpression usually have specific biological characteristics, such as active cell proliferation and rich angiogenesis, which may show up as specific quantitative features such as texture and shape in medical imaging. Through high-throughput extraction of these features and analysis by machine learning algorithms, MRI radiomics can achieve accurate prediction of HER2 overexpression [33].

In this study, large heterogeneity (I^2>75%) was found in the process of meta-analysis, and subgroup analysis revealed two key sources of heterogeneity, namely, study country and sample size, suggesting that the size of study sample and the differences in study country may be important factors leading to heterogeneity, which is similar to the results of previous studies [34, 35]. On the one hand, studies with a small sample size (<200 cases) may have the risk of overfitting, leading to overestimation of reported specificity. On the other hand, studies in different countries may have differences in patient populations, HER2 detection methods, MRI imaging equipment, and other aspects, which may lead to the heterogeneity of study results [36]. Sensitivity analysis showed that the changes of pooled sensitivity and specificity did not significantly affect the overall results after excluding individual studies one by one, indicating that the literature included in the Meta-analysis had good stability and high credibility, which was consistent with the results of previous studies [37]. This result may be related to the higher quality of the included literature, which was rigorously evaluated using the QUADAS-2 scale in this study, ensuring that the risk of bias and clinical applicability of the literature were low. Sensitivity analysis also suggested that the results of a single study had little influence on the overall meta-analysis results, which further enhanced the reliability and robustness of this study [38]. In addition, the clinical utility of MRI radiomics in predicting HER2 overexpression in breast cancer was validated in the Fagan diagram analysis. When the pretest probability of HER2 overexpression was 20%, a positive radiomics result improved the post-test probability to 48%-56%, and a negative radiomics result reduced the post-test probability to 3%-8%. These results indicate that MRI radiomics has certain clinical utility in predicting HER2 overexpression in breast cancer and can provide valuable reference information for clinical decision-making [39].

Publication bias analysis showed that no significant bias was found by Deeks' funnel plot test, indicating that the results of the included studies were highly reliable. This result may be related to the strict criteria and procedures adopted in the literature retrieval and screening process of this study, which ensured the comprehensiveness and representativeness of the included literature. At the same time, the evaluation results of publication bias further enhanced the reliability and robustness of this study [40]. Although this study has achieved some results in predicting HER2 overexpression in breast cancer by MRI radiomics, there are still some limitations and challenges [39]. First of all, most of the included studies were from China, which reflected the

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activity of this field in China, but may lead to regional bias and limit the generalizability of the conclusions to different races and medical systems. Second, although the total sample size was substantial, the sample sizes of the studies varied widely (from 88 to 752), and most of the studies were retrospective in design, with an inherent risk of selection bias. Finally, the lack of unified standards on MRI scanning parameters, ROI delineation, feature extraction and model construction procedures in the included studies is an important reason for the observed heterogeneity, which also makes it uncertain to directly compare or combine model performance from different studies. In the future, by promoting technical standardization, conducting prospective multicenter studies, and deepening the exploration of association with biological mechanisms, MRI-based radiomics is expected to be transformed into a reliable auxiliary method for noninvasive and accurate evaluation of HER2 status in breast cancer in clinical practice [41].

In conclusion, the present study systematically evaluated the correlation between MRI radiomics and HER2 overexpression in breast cancer through meta-analysis. The results showed that there was a correlation between MRI radiomics and HER2 overexpression in breast cancer, and MRI radiomics had a high diagnostic efficacy in predicting HER2 overexpression in breast cancer. Despite the heterogeneity, both the sensitivity analysis and the publication bias assessment results indicated that the results of this study were stable and reliable. MRI radiomics is expected to serve as an auxiliary diagnostic tool, providing a new perspective for the precise assessment of HER2 overexpression in breast cancer.

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