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Original Research

Nomogram Model Construction and Validation with Virtual Touch Tissue Imaging Quantification and Clinicopathological Features to Predict Recurrence in Breast Cancer

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Abstract

Background: This study aimed to develop a nomogram model integrating virtual touch tissue imaging quantification (VTIQ) with clinicopathological features to predict postoperative breast cancer recurrence, guide individualized treatment, and improve prognosis. **Methods**: This study retrospectively included 420 female patients who underwent radical mastectomy for breast cancer and received an elastography touch imaging quantification examination before surgery at our hospital (2017–2022). The patients were divided into training and validation sets at a ratio of 7:3. After a 3-year follow-up, both cohorts were stratified into recurrence and non-recurrence groups. Clinicopathologic characteristics and VTIQ parameters (shear wave velocity, SWV) were compared between the two groups. A nomogram for predicting postoperative recurrence in breast cancer was developed using multivariable logistic regression. The performance was evaluated using a receiver operating characteristic (ROC) analysis, calibration assessment, and decision curve analysis (DCA) to assess discrimination, calibration, and clinical usefulness. **Results**: The training set showed significantly higher SWV values in recurrent patients than in non-recurrent patients ($p < 0.05$). Logistic regression identified histological grade (odds ratio (OR): 3.36, 95% confidence interval (CI): 1.23–9.19), calcification (OR: 3.16, 95% CI: 1.15–8.68), estrogen receptor (ER)/progesterone receptor (PR) (OR: 2.74, 95% CI: 1.03–7.31), and SWV (OR: 3.71, 95% CI: 1.75–7.84) as independent predictive factors for postoperative recurrence of breast cancer ($p < 0.05$). The area under the ROC curve (AUROC) was 0.789 (95% CI: 0.729–0.850) for the training set and 0.728 (95% CI: 0.615–0.841) for the validation set. These findings indicate that the nomogram model demonstrates good discrimination for the postoperative recurrence of breast cancer. Calibration and DCA curves confirmed that the predicted probabilities of the model closely matched the actual pathological grading results, demonstrating the clinical utility of the model. **Conclusions**: The nomogram model integrating VTIQ parameters with clinicopathological features demonstrates good predictive value for postoperative recurrence of breast cancer. This model provides an important reference for identifying patients at high risk of recurrence before surgery and may improve patient prognosis.

Keywords: VTIQ; clinicopathological features; breast cancer; postoperative recurrence; nomogram

1. Introduction

Breast cancer remains a leading global malignancy in women, with persistently high incidence and mortality rates [1]. Although surgery is the mainstay of breast cancer treatment, postoperative recurrence remains a significant factor affecting patient prognosis, with approximately 20%–30% of patients experiencing local recurrence or distant metastasis within 5 years after surgery [2]. Current clinical practice mainly uses tumor size, nodal status, and histological grade to evaluate recurrence risk [3]. However, these conventional markers have important limitations. Their assessments are largely based on static morphological observations, which fail to dynamically reflect the biological behavior heterogeneity and micrometastatic potential of tumors. This can lead to overtreatment in some low-risk patients and undertreatment in high-risk patients [4,5]. Therefore, the search for novel and more effective predictive markers and methods has become an important direction in current breast cancer research.

Ultrasound has become a commonly used modality for clinical evaluation of breast cancer, due to its advantages of being non-invasive, convenient, and repeatable. Two-dimensional grayscale ultrasound can clearly display the morphology, size, boundaries, and internal echogenicity of breast cancer, aiding in the identification of cystic or solid components within masses [6]. Color Doppler ultrasound, on the other hand, reflects tumor angiogenesis by detecting blood flow signals within and around the tumor [7]. However, in predicting postoperative recurrence of breast cancer, both modalities still have limitations in terms of specificity and sensitivity, making it difficult to accurately identify patients at higher risk of recurrence [8,9]. Virtual touch tissue imaging quantification (VTIQ), as a novel ultrasound technique, is capable of non-invasively and real-time re-

flecting the stiffness characteristics of tumors by quantitatively measuring the shear wave velocity (SWV) [10]. It has currently become an important clinical tool for the evaluation of breast cancer [11]. Research shows the stiffness of tumor tissue is closely related to its invasiveness, proliferative capacity, and recurrence risk [10]. As the core parameter of VTIQ, SWV shows a significant positive correlation with histological grade and nuclear proliferationantigen-67 (Ki-67) index of breast cancer tissues, which are indicators of malignancy [12]. Moreover, its diagnostic performance is significantly superior to that of traditional ultrasound elastography scores [12]. Other studies have also shown that tumor stiffness is closely related to the extracellular matrix remodeling and stromal fibrosis, which are components of the pro-invasive microenvironment. Parameters of VTIQ (such as the maximum value of Young's modulus) can serve as potential biomarkers for predicting lymph node metastasis and chemosensitivity [13,14]. However, the existing studies have predominantly focused on the diagnostic value of VTIQ as a single modality, with a lack of research on the construction of multiparametric predictive models by integrating VTIQ with clinicopathological features.

This study aims to construct and validate a nomogram model combining VTIQ quantitative parameters (SWV) with clinicopathological features to predict postoperative recurrence of breast cancer. By integrating these parameters, we seek to provide a reference for accurately identifying patients at high risk of recurrence and metastasis, thereby optimizing treatment strategies and improving patient prognosis.

2. Materials and Methods

2.1 Study Design and Population

This study retrospectively included 420 female patients who underwent radical mastectomy for breast cancer and received elastography touch imaging quantification examination before surgery at our hospital (2017–2022). The patients were divided into the training set and the validation set in a ratio of 7:3. After 3-year follow-up, both cohorts were stratified into recurrence and non-recurrence groups by recurrence status. Inclusion criteria: the postoperative pathological examination confirmed the diagnosis of breast cancer [15]; 18 years $<$ age $<$ 70 years; primary breast cancer surgery and had not received any targeted therapy, immunotherapy, radiotherapy, or other treatments before surgery; breast VTIQ examination was completed preoperatively; clinical data and follow-up information were complete; all participants provided written informed consent prior to enrollment. Exclusion criteria: comorbid with malignant tumors; being in pregnancy or lactation; having other infectious diseases or malignant hematological disorders; male patients with breast cancer; comorbid with severe hepatic or renal dysfunction; patients with incomplete clinical data. Criteria for dropout: loss of access; refusal to follow up due to the occurrence of other diseases; non-breast cancer-related mortality. The study received Wuxi People's Hospital Affiliated to Nanjing Medical University's ethics approval (Ethics Approval Number: KY23040), and written informed consent was obtained from all patients. All procedures complied with institutional ethics guidelines and the Declaration of Helsinki.

In this study, nine independent variables are planned to be included. The total sample size is set at 5–10 times the number of independent variables. Based on clinical data from our hospital, the postoperative recurrence rate of breast cancer is approximately 18%. Considering a potential sample loss of 10%–20%, the required sample size was calculated using the formula: $N = a \times 10 \times (1 + 0.1)/b$, where a represents the number of independent variables, and b is the disease recurrence rate. Substituting the values: $N = 9 \times 5 \times (1 + 0.2)/0.18 = 300$. Therefore, a minimum sample size of 300 cases is required. Based on the actual case availability at our institution, the final sample size was determined to be 420 cases.

2.2 Baseline Data

Baseline data for 420 breast cancer patients were retrospectively collected from the hospital's electronic medical record system. The collected information encompassed age, body mass index (BMI), menopausal history, obstetric history, smoking history, drinking history and family history.

2.3 Clinical-Pathological Data

Clinical-pathological characteristics of 420 breast cancer patients were collected, including alcohol consumption history, preoperative tumor quadrant, tumor maximum diameter, location of the tumor, clinical stage, histological grade, tumor shape, doppler flow signals, marginal characteristics, calcification, vascular invasion, estrogen receptor (ER)/progesterone receptor (PR), human epidermal growth factor 2 (HER2), Ki-67, and SWV. The status of ER and PR was assessed using the Allred scoring system, with a score equal to or greater than 2 considered positive. HER2 status was considered negative if it was 0 or +1, and positive if it was +++. Cases with a score of ++ required further fluorescence *in situ* hybridization (FISH) testing. If gene amplification was detected by FISH, the result was considered positive; otherwise, it was considered negative. The Ki-67 index $\geq$14% was defined as high expression [16]. Patients were followed up for 3 years using outpatient review and telephone follow-up, with visits scheduled every 3 months. The early recurrence status of the patients was recorded, defined as local or regional recurrence occurring within 3 years after surgery. Follow-up was discontinued upon recurrence.

2.4 Virtual Touch Tissue Imaging and Quantification Examination

A Siemens ACUSON OXANA2 ultrasound diagnostic system (Siemens AG, S/N 216293, Munich, Germany), equipped with a 9L4 linear array probe. During the examination, the examinee was positioned in a lateral or supine position with both arms abducted to fully expose the bilateral breasts and axillary regions. A systematic scanning was performed centered on the nipple. Patients held their breath during VTIQ examination. The transducer was carefully positioned on the skin surface without exerting extra pressure. The VTIQ mode was activated, and the largest cross-sectional area of the lesion was captured. Images were acquired three times, and the best-quality image (displayed in green) was selected for analysis. The same lesion was assessed three times by two experienced physicians, each with over 10 years of clinical experience. Three to four sampling points were obtained from the relatively harder and softer regions of the mass, respectively. The SWV was measured and recorded in m/s, with the maximum SWV value used as the quantitative parameter for assessment. During the examination, the physicians were blinded to the clinical information of the examinees. The inter-operator intraclass correlation coefficient (ICC) for SWV measurements was 0.945, indicating excellent agreement. All pathological diagnoses were confirmed by postoperative histopathological examination. The pathological examination results were determined through a joint consultation by two pathologists with over 10 years of experience in breast examination and pathology.

2.5 Statistical Analysis

Analyses were performed using SPSS 27.0 (IBM Corporation, Armonk, NY, USA) and R 4.3.0 (Lucent Technologies, Murray Hill, NJ, USA). All variables to be assessed were statistically described, and the presence of outliers and missing values was analyzed. Missing values were imputed using multiple imputation, and variables with missing data exceeding 20% were discarded. Continuous variables were converted into binary or multicategorical variables as needed. For normally distributed numerical variables with homogeneity of variance, data are presented as mean $\pm$ standard deviation (SD). For repeated-measures data, between-group comparisons were performed using one-way analysis of covariance (ANCOVA), while within-group comparisons were conducted using paired t-tests. Non-normally distributed continuous variables are expressed as median with interquartile range (IQR), and between-group differences were analyzed using the Wilcoxon rank-sum test. Categorical variables are presented as frequencies (n) and percentages (%), with between-group differences assessed using the chi-square (χ^2) test. Fisher's exact test was applied when the expected frequency in any cell was less than five. The factors with $p < 0.05$ from the single-factor analysis were included in the multivariate logistic regression analysis to determine the independent influencing factors for the recurrence of breast cancer after surgery, and the multicollinearity test was conducted. The nomogram model derived from multivariate analysis. Receiver operating characteristic (ROC) curves, calibration curves, and decision curve analysis (DCA) curves were used to evaluate the stability, consistency, and applicability of the nomogram model for predicting postoperative recurrence of breast cancer based on VTIQ combined with clinicopathological features. A p-value < 0.05 indicated significance.

3. Results

3.1 Baseline Data

This study analyzed 294 breast cancer patients in the training set, of whom 53 experienced postoperative recurrence and 241 did not. In the validation set, there were 126 breast cancer patients, with 23 experiencing postoperative recurrence and 103 remaining recurrence-free. No significant differences existed in age, BMI, menopausal history, obstetric history, smoking history, drinking history and family history between recurrence and non-recurrence groups across training and validation sets ($p > 0.05$), ensuring group comparability. See Table 1.

3.2 Clinicopathological Features

In the training set, the pathological images of patients in the recurrence group showed that the cancerous tissue exhibited glandular or cord-like structures, with nuclei that were deeply stained and showed evident pleomorphism and mitotic figures, and obvious proliferation of surrounding fibrous tissue (Fig. 1A). In contrast, the pathological results of patients in the non-recurrence group revealed that the atypical cells within the mass were arranged in irregular nests (Fig. 1B).

The recurrence group had a higher proportion of patients with tumor maximum diameter $\geq$5 cm, clinical stage III, histological grade III, irregular tumor shape, calcification, vascular invasion, ER/PR all negativity, and HER2 positivity ($p < 0.05$). See Table 2.

3.3 VTIQ Parameters

SWV measurements were significantly elevated in the recurrence versus non-recurrence group ($p < 0.05$). See Table 3 and Fig. 2. Fig. 2 shows the preoperative VTIQ quantitative images of patients with and without postoperative recurrence.

3.4 Multivariate Analysis of Postoperative Recurrence in Breast Cancer Patients

Logistic regression assessed postoperative recurrence using tumor maximum diameter, clinical stage, histological grade, tumor shape, calcification, vascular invasion, ER/PR, HER2, and SWV as predictors. The results showed that histological grade (odds ratio (OR): 3.36, 95% con-

Table 1. Comparison of baseline data between the two groups in both the training and validation sets.

Indicators	Training set				Validation set			
	Recurrence group (n = 53)	Non-recurrence group (n = 241)	χ^2/t	p	Recurrence group (n = 23)	Non-recurrence group (n = 103)	χ^2/t	p
Age ($\bar{x} \pm s$, years)	56.93 ± 9.21	56.82 ± 9.34	0.079	0.937	56.23 ± 10.15	56.16 ± 10.73	0.026	0.979
BMI ($\bar{x} \pm s$, kg/m^2)	21.92 ± 2.12	22.00 ± 2.20	0.242	0.809	21.32 ± 2.36	21.83 ± 2.44	0.896	0.372
Menopausal history (n, %)			0.320	0.572			0.013	0.910
Yes	31 (58.49)	151 (62.66)			14 (60.87)	64 (62.14)		
No	22 (41.51)	90 (37.34)			9 (39.13)	39 (37.86)		
Obstetric history (n, %)			0.031	0.860			0.229	0.632
Yes	43 (81.13)	198 (82.16)			18 (78.26)	85 (82.52)		
No	10 (18.87)	43 (17.84)			5 (21.74)	18 (17.48)		
Smoking history (n, %)			0.111	0.740			0.126	0.723
Yes	2 (3.77)	7 (2.90)			1 (4.35)	3 (2.91)		
No	51 (96.23)	234 (97.10)			22 (95.65)	100 (97.09)		
Drinking history (n, %)			0.038	0.845			0.049	0.826
Yes	8 (15.09)	39 (16.18)			4 (17.39)	16 (15.53)		
No	45 (84.91)	202 (83.82)			19 (82.61)	87 (84.47)		
Family history (n, %)			0.062	0.803			0.064	0.801
Yes	11 (18.87)	42 (17.43)			5 (21.74)	20 (19.42)		
No	42 (81.13)	199 (82.57)			18 (78.26)	83 (80.58)		

BMI, body mass index.

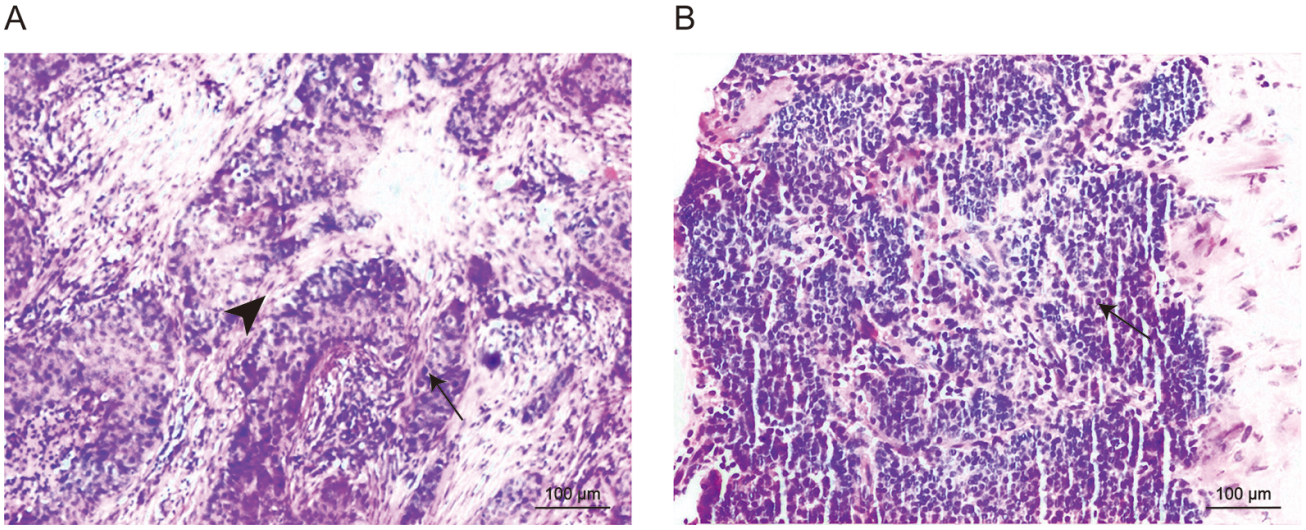

Fig. 1. Pathological examination results of the two groups of patients (100×). (A) The recurrence group shows cancerous tissue with glandular or cord-like structures, nuclei that are deeply stained and exhibit significant atypia, and obvious proliferation of surrounding fibrous tissue. (B) The non-recurrence group shows atypical cells within the mass arranged in irregular nests, with cellular atypia. Black long arrows indicate nuclei, and black short arrows indicate fibrous tissue proliferation (Scale bar: 100 μm).

fidence interval (CI): 1.23–9.19), calcification (OR: 3.16, 95% CI: 1.15–8.68), ER/PR (OR: 2.74, 95% CI: 1.03–7.31), and SWV (OR: 3.71, 95% CI: 1.75–7.84) were all independent influencing factors for predicting postoperative recurrence of breast cancer. In this study, the variance inflation factor (VIF) values were all less than 5, indicating the absence of multicollinearity. See Table 4.

3.5 Development of the Nomogram

Based on logistic regression findings, we developed a postoperative recurrence nomogram. The nomogram identified histological grade and ER/PR as the strongest predictors of postoperative breast cancer recurrence, followed by SWV and calcification. The total score ranges from 0 to 350 points, corresponding to predicted probabilities of postoperative breast cancer recurrence between 0.1 and 0.7. See Fig. 3.

Table 2. Comparison of clinical and pathological characteristics between the two groups in the training set (n, %).

Indicators	Recurrence group (n = 53)	Non-recurrence group (n = 241)	χ^2	p
Preoperative tumor quadrant			0.243	0.993
Outer upper	14 (26.41)	68 (28.22)		
Outer lower	7 (13.21)	32 (13.28)		
Inner upper	15 (28.30)	71 (29.46)		
Inner lower	13 (24.53)	55 (22.82)		
Central area	4 (7.55)	15 (6.22)		
Tumor maximum diameter			7.313	0.007
<5 cm	35 (66.04)	199 (82.57)		
≥5 cm	18 (33.96)	42 (17.43)		
Location of the tumor			0.968	0.325
Left	22 (41.51)	118 (48.96)		
Right	31 (58.49)	123 (51.04)		
Clinical stage			4.353	0.037
I–II	36 (67.92)	195 (80.91)		
III	17 (32.08)	46 (19.09)		
Histological grade			16.164	<0.001
I–II	25 (47.17)	181 (75.10)		
III	28 (52.83)	60 (24.90)		
Tumor shape			6.196	0.013
Regular	28 (52.83)	170 (70.54)		
Irregular	25 (47.17)	71 (29.46)		
Doppler flow signals			0.672	0.412
Rich blood flow	23 (43.40)	90 (37.34)		
Poor blood flow	30 (56.60)	151 (62.66)		
Marginal characteristics			0.041	0.840
Distinct	25 (47.17)	110 (45.64)		
Indistinct	28 (52.83)	131 (54.36)		
Calcification			17.266	<0.001
Yes	14 (26.42)	17 (7.05)		
No	39 (73.58)	224 (92.95)		
Vascular invasion			8.635	0.003
Yes	17 (32.08)	36 (14.94)		
No	36 (67.92)	205 (85.06)		
ER/PR			24.543	<0.001
All negative	35 (66.04)	72 (29.88)		
Positive in any one	18 (33.96)	169 (70.12)		
HER2			11.404	<0.001
Positive	31 (58.49)	81 (33.61)		
Negative	22 (41.51)	160 (66.39)		
Ki-67			1.714	0.190
High expression	37 (69.81)	145 (60.17)		
Low expression	16 (30.19)	96 (39.83)		

ER, estrogen receptor; PR, progesterone receptor; HER2, human epidermal growth factor 2; Ki-67, nuclear proliferationantigen-67.

Table 3. Comparison of VTIQ parameters between the two groups in the training set.

Indicators	Recurrence group (n = 53)	Non-recurrence group (n = 241)	t	p
SWV ($\bar{x} \pm$ s, m/s)	7.33 ± 2.60	4.06 ± 1.50	8.840	<0.001

VTIQ, virtual touch tissue imaging quantification; SWV, shear wave velocity.

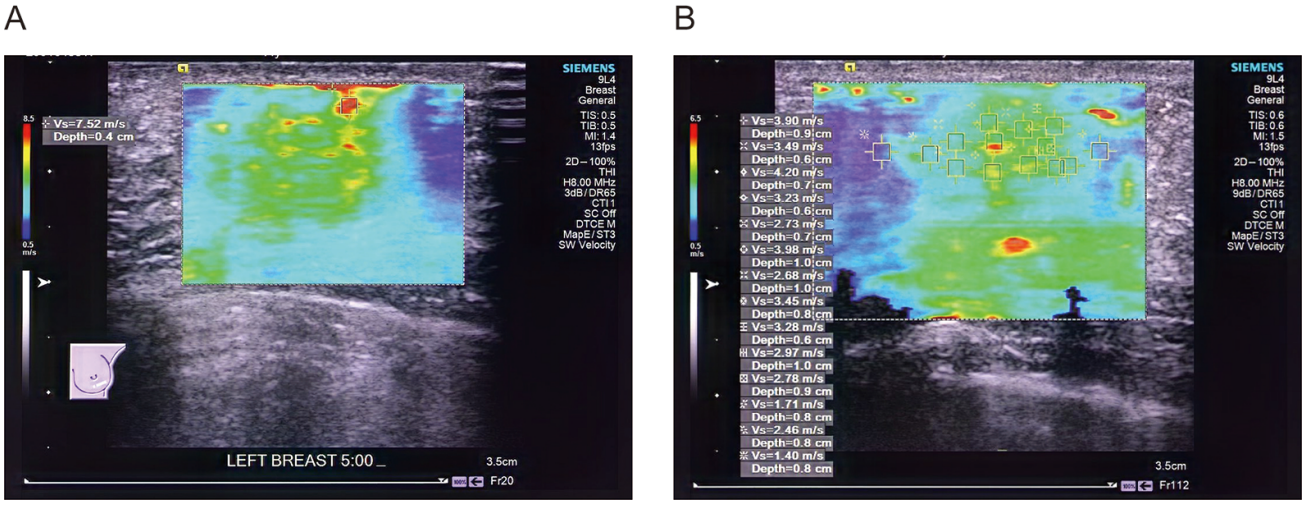

Fig. 2. Preoperative VTIQ quantitative images of patients with and without postoperative recurrence. (A) The preoperative VTIQ of patients in the recurrence group shows the SWV of the tumor at 7.52 m/s. (B) The preoperative VTIQ of patients in the non-recurrence group shows the SWV of the tumor at 3.90 m/s.

Table 4. Multivariate analysis of postoperative recurrence in breast cancer patients.

Variables	β	S.E	Z	p	OR (95% CI)	Tolerance	VIF
Tumor maximum diameter							
<5 cm					1.00 (Reference)		
≥5 cm	0.42	0.41	1.025	0.305	1.52 (0.68–3.41)	0.809	1.236
Clinical stage							
I–II					1.00 (Reference)		
III	–0.24	0.44	–0.551	0.582	0.78 (0.33–1.86)	0.596	1.679
Histological grade							
I–II					1.00 (Reference)		
III	1.21	0.51	2.358	0.018	3.36 (1.23–9.19)	0.405	2.469
Tumor shape							
Regular					1.00 (Reference)		
Irregular	–0.67	0.52	–1.284	0.199	0.51 (0.19–1.42)	0.343	2.918
Calcification							
No					1.00 (Reference)		
Yes	1.15	0.52	2.232	0.026	3.16 (1.15–8.68)	0.710	1.409
Vascular invasion							
No					1.00 (Reference)		
Yes	0.06	0.45	0.139	0.889	1.06 (0.44–2.57)	0.667	1.499
ER/PR							
Positive in any one					1.00 (Reference)		
All negative	1.01	0.50	2.019	0.044	2.74 (1.03–7.31)	0.410	2.437
HER2							
Negative					1.00 (Reference)		
Positive	–0.40	0.56	–0.722	0.471	0.67 (0.22–1.99)	0.287	3.486
SWV							
≤4.65 m/s					1.00 (Reference)		
>4.65 m/s	1.31	0.38	3.430	<0.001	3.71 (1.75–7.84)	0.783	1.277

S.E, standard error; VIF, variance inflation factor; OR, odds ratio; CI, confidence interval.

3.6 Validation of the Nomogram Model

The nomogram demonstrated good predictive accuracy with training set area under the curve (AUC) = 0.789 (95% CI: 0.729–0.850) and validation set AUC = 0.728 (95% CI: 0.615–0.841). See Fig. 4A,B. Calibration curves indicated strong agreement between nomogram-predicted

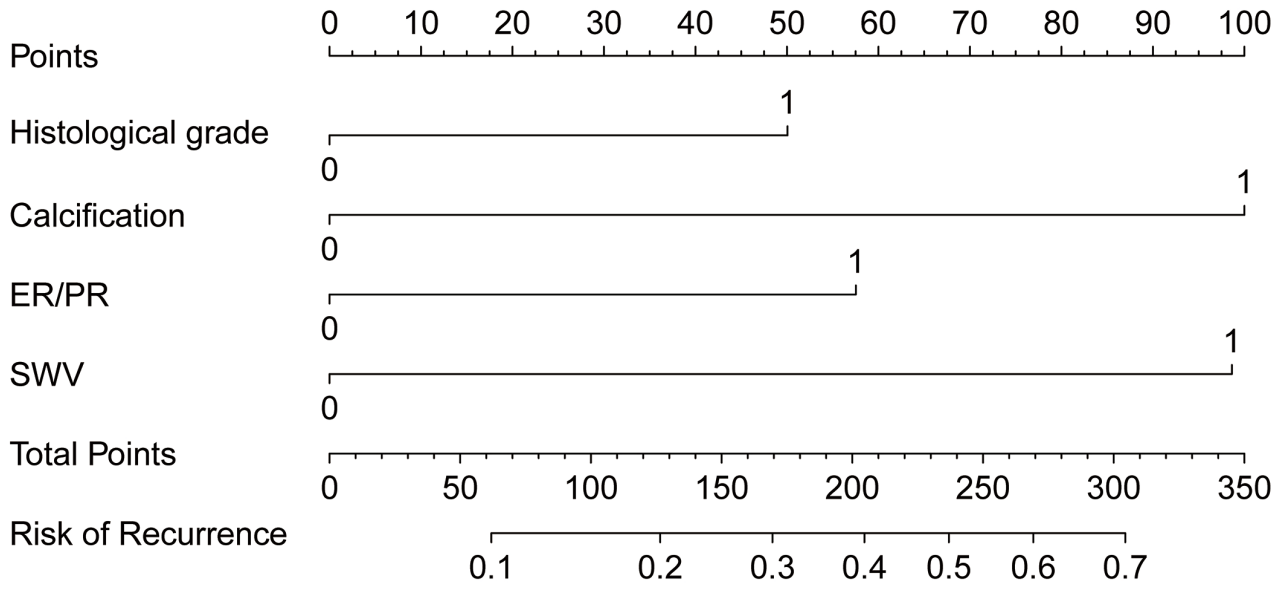

Fig. 3. Nomogram model for predicting postoperative recurrence in breast cancer.

and observed recurrence probabilities in both training and validation sets, with a slope of 1, indicating good model calibration. See Fig. 4C,D. The DCA showed that the decision curves for predicting postoperative recurrence of breast cancer by the nomogram model in between the training and validation sets were located in the upper right of the graph. When the probability threshold of the nomogram ranged from 1% to 60%, the model yielded high net clinical benefit in predicting lymph-node metastasis in both cohorts, indicating its potential clinical utility. See Fig. 4E,F.

4. Discussion

Breast cancer recurrence, characterized by its high incidence, unpredictability, and severe threat to quality of life, has emerged as a significant challenge in clinical oncology, imposing a substantial economic and psychological burden on patients and their families [17,18]. This research effectively developed and validated a nomogram incorporating VTIQ parameters (SWV) and essential clinicopathological characteristics to forecast the recurrence risk in breast cancer patients post-radical surgery. The study results confirmed that SWV values, as well as histological grade, calcification, and ER/PR status, are independent predictors of postoperative recurrence in breast cancer. The nomogram indicated robust predictive capability (AUC $>$0.72) and clinical applicability in both the training and validation sets, providing a new tool for individualized recurrence risk assessment.

In this study, we analyzed 294 breast cancer patients in the training set, among whom 53 experienced recurrence and 241 did not. In the validation set, there were 126 breast cancer patients, with 23 experiencing recurrence and 103 remaining recurrence-free. Between the training and validation sets, no statistically significant differences were observed between the recurrence and non-recurrence groups regarding age, BMI, menopausal history, obstetric history, smoking history, drinking history and family history ($p >$ 0.05). This indicates that the patients in the two groups within the training and validation sets were comparable in terms of SWV and clinicopathological features.

The influencing factors of postoperative recurrence in breast cancer are complex, with extratumoral factors including lifestyle behaviors, endocrine function, tumor grade, molecular subtypes, and histological grade [19,20]. In this study, univariate analysis showed that patients in the recurrence group had a higher proportion of tumor maximum diameter $>$5 cm, clinical stage III, histological grade III, irregular mass shape, calcification, vascular invasion, ER/PR negativity, and HER2 positivity compared to those in the non-recurrence group ($p < 0.05$). Logistic regression analysis identified histological grade (OR: 3.36, 95% CI: 1.23–9.19), calcification (OR: 3.16, 95% CI: 1.15–8.68), ER/PR (OR: 2.74, 95% CI: 1.03–7.31), and SWV (OR: 3.71, 95% CI: 1.75–7.84) as independent predictors of postoperative recurrence in breast cancer ($p < 0.05$). Histological grade reflects the degree of cellular atypia and proliferative capacity of tumor cells [21]. This study suggested that histological grade III is an independent predictor of postoperative recurrence in breast cancer, aligning with the findings reported by Groen *et al.* [22]. The analysis suggests that tumor cells with high histological grade typically exhibit stronger invasiveness and proliferative capacity. These cells are more likely to breach the basement membrane, invade surrounding tissues and blood vessels, thereby increasing the risk of recurrence. The presence of calcifications in breast cancer may indicate tumor aggressiveness [23]. This study demonstrated that calcification

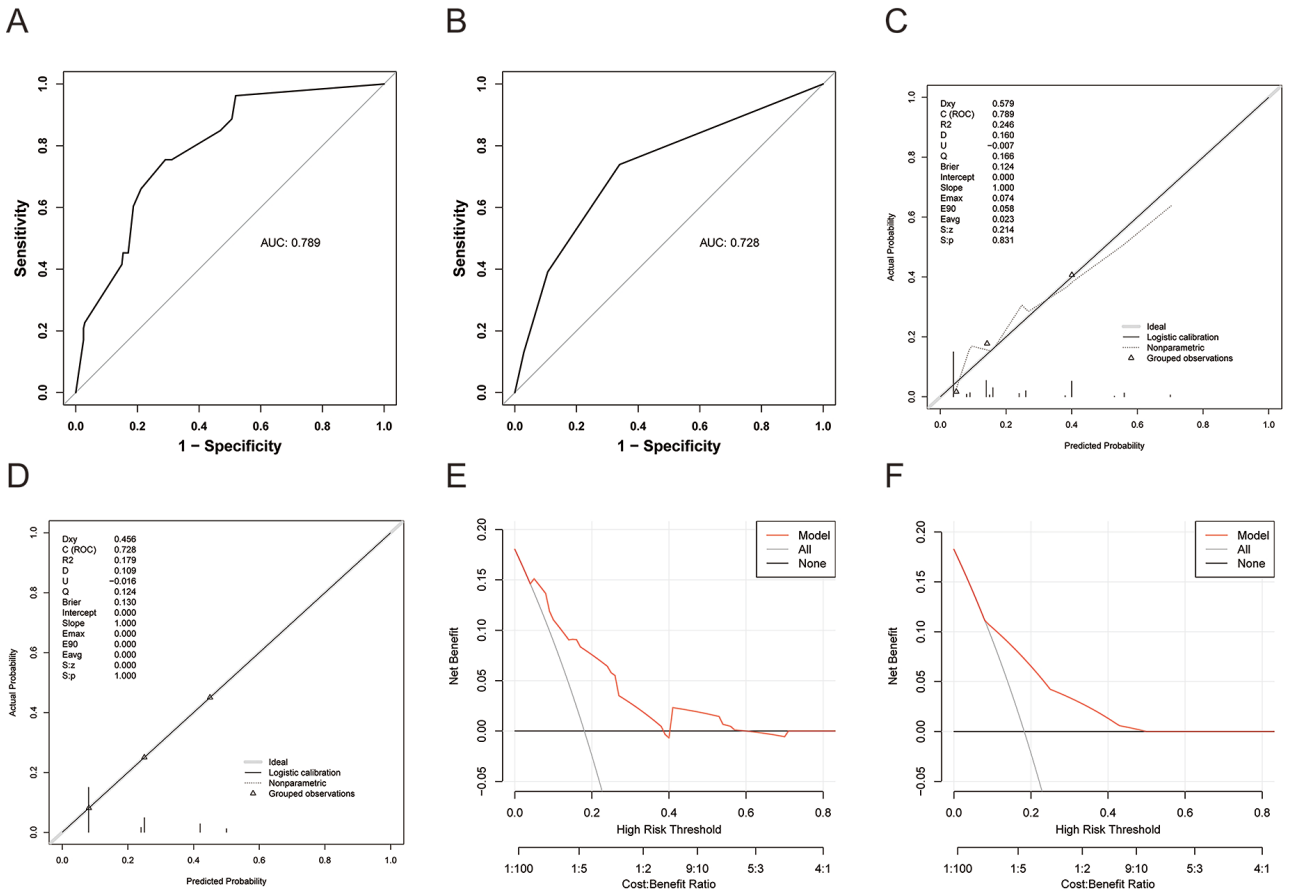

Fig. 4. Validation of nomogram model for predicting postoperative recurrence in breast cancer. (A) The receiver operating characteristic (ROC) curve for predicting postoperative recurrence of breast cancer in the training set using the nomogram model. (B) The ROC curve for predicting postoperative recurrence of breast cancer in the validation set using the nomogram model. (C) The calibration curve for predicting postoperative recurrence of breast cancer in the training set using the nomogram model. (D) The calibration curve for predicting postoperative recurrence of breast cancer in the validation set using the nomogram model. (E) The decision curve analysis (DCA) curve for predicting postoperative recurrence of breast cancer in the training set using the nomogram model. (F) The DCA curve for predicting postoperative recurrence of breast cancer in the validation set using the nomogram model.

is an independent predictor of postoperative recurrence in breast cancer, which is consistent with the findings reported by Wang *et al*. [24]. The analysis suggests that calcifications may be associated with tumor necrosis and fibrosis, which are likely related to rapid tumor growth and invasive behavior. Moreover, calcifications may also influence the tumor microenvironment, thereby promoting tumor recurrence. Prior research has suggested that ER/PR negativity is typically associated with more aggressive tumor biology [25]. In this study, ER/PR negativity was identified as an independent predictor of postoperative recurrence in breast cancer. This may be attributed to the fact that patients not only have a higher degree of tumor malignancy but also exhibit poor sensitivity to chemotherapy and endocrine therapy, thereby increasing the risk of postoperative recurrence. Investigations have suggested that SWV reflects tissue stiffness, and its higher values in the recurrence group may be associated with fibrous tissue proliferation in tumors [26]. This study demonstrated that SWV was an independent predictor of postoperative recurrence in breast cancer. This may be because increased tumor stiffness essentially reflects changes in the microenvironment. The pathological findings in the recurrence group showed significant fibrous tissue proliferation and collagen fiber deposition, which led to increased tissue stiffness. These changes may alter the tumor microenvironment, promoting the survival and proliferation of tumor cells, thereby increasing the risk of recurrence. In this study, tumor diameter >5 cm, clinical stage III, vascular invasion, and HER2 positivity were correlated with recurrence in univariate analysis but did not emerge as independent predictive factors. This may be because tumor size and clinical staging have already been integrated into histological grading, with grade III tumors more likely to grow rapidly to a larger size and exhibit lymph node metastasis and recurrence [27]. Although tumor size is an important clinical indicator, in models that incorporate other

pathological factors, it may not be an independent predictor. Vascular invasion was collinear with histological analysis, as poorly differentiated tumors are more prone to vascular invasion. In recent years, improvements in adjuvant chemotherapy regimens for breast cancer have gradually mitigated the impact of HER2 positivity on chemosensitivity [28].

In this study, multivariate analysis was used to identify the most predictive independent factors (histological grade, calcification, ER/PR status, and SWV), based on which a nomogram prediction model was constructed and externally validated. The AUC values for the training and validation sets were 0.789 (95% CI: 0.729–0.850) and 0.728 (95% CI: 0.615–0.841), respectively. These results suggest that the model possesses strong discriminative power, effectively differentiating patients with a high risk of recurrence from those with a low risk. The calibration curves revealed a close match between the predicted probabilities and the actual recurrence probabilities, highlighting the model's accuracy and reliability. DCA further demonstrated that the model has certain clinical utility. The strengths of this study lie in the integration of traditional clinicopathological features with VTIQ. As a non-invasive imaging technique, VTIQ provides quantitative information on tissue stiffness, thereby complementing the limitations of traditional pathological examinations. Moreover, the independent predictive factors identified through logistic regression analysis further enhanced the accuracy and reliability of the model. In clinical practice, patients identified as high-risk should be offered intensified surveillance and considered for more aggressive adjuvant therapy to maximize the chance of preventing recurrence.

There are also several limitations in this study that need to be considered. Firstly, the retrospective study design may be affected by selection bias and information bias. Secondly, the relatively short follow-up period of 3 years may not fully reflect the long-term recurrence pattern, and postoperative adjuvant therapy was not included in the analysis. Future studies should focus on conducting prospective research and consider the impact of postoperative treatment by conducting longer follow-up to further verify the predictive efficacy of this model. Moreover, although the overall sample size (n = 420) is moderate, the number of events (recurrences, n = 76) remains limited. This low event-to-variable ratio may compromise model stability and generalizability and increase the risk of over-fitting. To address this limitation, we performed both internal and external validation together with calibration analyses; the results confirm that the model maintains consistent performance and has practical clinical value.

5. Conclusions

This study successfully developed and preliminarily validated a nomogram model integrating VTIQ with clinicopathological features to assess the risk of postoperative recurrence in breast cancer patients. The model showed strong predictive accuracy, calibration, and clinical applicability, offering valuable prognostic stratification for postoperative recurrence risk.

Availability of Data and Materials

Data supporting this study are available from the corresponding author upon reasonable request.

Author Contributions

SD: Conceptualization, validation, data curation, writing—review and editing. CZ: Conceptualization, methodology, software, formal analysis, investigation, writing—original draft preparation. XC: Investigation, data curation, writing—review and editing. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study was approved by the ethics committee of Wuxi People's Hospital Affiliated to Nanjing Medical University (Ethics Approval Number: KY23040), and written informed consent was obtained from all patients. All procedures complied with institutional ethics guidelines and the Declaration of Helsinki.

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Conflict of Interest

The authors declare no conflict of interest.

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