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Clinico-Pathological Correlation Between Pre-Operative Clinical Staging and Post-Operative Pathological Staging in Breast Cancer Patients

Abstract

Introduction: Breast cancer is the leading cause of cancer death among women worldwide. Staging guides treatment selection and prognosis; clinical staging precedes surgery, while pathological staging follows histological examination of the resected specimen. Any mismatch between the two can alter management.

Aim: To correlate pre-operative clinical staging with post-operative pathological staging in patients with carcinoma of the breast and to quantify the direction of stage change.

Materials and methods: This hospital-based, cross-sectional, observational study included 50 patients with histologically confirmed breast carcinoma who underwent surgery at a tertiary care hospital in western India over 18 months. Clinical stage was assigned from history, examination and routine investigations; pathological stage was assigned from the resected specimen using the AJCC 7th edition TNM system. Clinical and pathological stages were compared for the tumour (T) category, node (N) category and the overall stage, and were classified as concordant, upgraded or downgraded.

Results: The mean age was 50.9 years; 47 (94%) patients were women. A painless lump was the commonest presentation (72%), the upper outer quadrant was the commonest site (42%) and the right breast was slightly more often involved (56%). Grade II tumours predominated (58%). Overall clinical and pathological stages were concordant in 15 (30%) patients, while 26 (52%) were upgraded and 9 (18%) downgraded. Concordance was 46% for the T category and 38% for the N category, with nodal upgrading in 56%.

Conclusion: Clinical staging disagreed with pathological staging in roughly 70% of patients, with a clear tendency toward pathological upgrading, chiefly of nodal status. Careful pre-operative assessment of tumour size, fixity and nodal status is needed to narrow this gap and refine treatment planning.

INTRODUCTION

Breast cancer is the most frequently diagnosed cancer in women and the leading cause of cancer-related death in this group worldwide[1]. Its burden continues to rise, and public awareness of risk factors and management remains uneven, particularly in low- and middle-income settings[2]. In India the age-standardised incidence is lower than in high-income countries, yet a steady annual rise, especially among younger women, has been reported.

The disease is biologically heterogeneous, and its clinical behaviour varies widely between patients[3]. Molecular and immunohistochemical profiling has refined prognostication, and targeted and immune-based therapies now complement surgery, radiotherapy and cytotoxic chemotherapy[1]. Nodal involvement remains one of the strongest determinants of outcome, and the biology of lymphatic spread is increasingly well understood[4]. For locally advanced and inoperable disease, newer systemic and nanomaterial-based approaches are under active investigation[5], while curcumin-based nanomedicines illustrate the search for better-tolerated adjuncts[6].

Staging summarises disease extent using tumour size, nodal status and distant spread, and it underpins both treatment selection and prognosis[7]. Clinical staging, assigned before surgery from history, examination and imaging, must often guide the initial decision, including whether to offer neoadjuvant chemotherapy[8]. Response to such treatment varies, and residual disease after neoadjuvant therapy carries clear prognostic weight[8,9]; resistance mechanisms and multi-omic predictors of response are areas of intense study[10,11]. Serum markers such as CA 15-3 and CEA have also been examined for monitoring during chemotherapy[12].

Accurate staging depends heavily on imaging and pathology. Advances in computational analysis, radiomics and deep learning have improved lesion detection, nodal assessment and characterisation across mammography, ultrasound, magnetic resonance imaging and histopathology[13,14,15]. Deep-learning tools now assist in predicting nodal metastasis, interpreting longitudinal images and reducing false-positive readings[16,17,18,19], and artificial-intelligence systems have been integrated into sentinel-node assessment and broader diagnostic pathways[20,21,22,23]. Systematic evaluation confirms that diagnostic performance of these methods is approaching that of experts in selected tasks[24]. Foundation models, multimodal fusion strategies and weakly supervised approaches extend this work across imaging biomarkers and multiple tumour types[25,26,27], including nodal and outcome prediction in lung, gastric and colorectal cancer[28,29,30]. Comprehensive reviews summarise the growing role of artificial intelligence across cancer diagnosis[31,32].

Despite these advances, routine practice in many centres still relies on clinical examination and standard investigations for pre-operative staging, and definitive stage is only confirmed after surgery. Discordance between the two can change treatment recommendations. This study was undertaken to correlate pre-operative clinical staging with post-operative pathological staging in patients with carcinoma of the breast and to quantify the direction of any stage change.

Materials and Methods

Study design and setting: This was a hospital-based, cross-sectional, observational study conducted in the Department of General Surgery at a tertiary care teaching hospital in western India over a period of 18 months.

Study population: Fifty consecutive patients with histologically confirmed carcinoma of the breast who underwent surgery during the study period were included. The sample size of 50 was based on the prevailing case-load and the estimated number of eligible patients over the study period.

Inclusion criteria: All patients, male and female, aged over 18 years, with a diagnosis of breast carcinoma undergoing surgery were included.

Exclusion criteria: Patients who were medically or anaesthetically unfit for surgery, and those who declined to participate, were excluded.

Procedure: Patients presenting with a breast lump were assessed by detailed history, clinical examination and routine investigations, and a clinical TNM stage was assigned. After informed consent, patients underwent surgery, during which the tumour and, where indicated, axillary lymph nodes were excised. The specimen was examined histopathologically to determine tumour extent, nodal status and metastasis, and a pathological TNM stage was assigned. The AJCC 7th edition (2010) TNM system was used, and histological grade was assigned by the modified Scarff-Bloom-Richardson system.

Outcome and analysis: Clinical and pathological stages were compared separately for the T category, the N category and the overall stage. Each comparison was classified as concordant (clinical stage equal to pathological stage), upgraded (clinical stage lower than pathological stage) or downgraded (clinical stage higher than pathological stage). Data were summarised as frequencies and percentages, with mean and standard deviation for age.

Ethics: The study was conducted after institutional ethics committee approval, and written informed consent was obtained from every participant.

Results

Fifty patients with carcinoma of the breast were studied. The age ranged from 28 to 81 years, with a mean of 50.9 (SD 13.8) years. The 31-40 year band held the largest share of patients, and 47 (94%) were women. A painless breast lump was the commonest presenting complaint. The demographic and clinical profile is shown in [Table/Fig-1].

[Table/Fig-1]: Demographic and clinical profile of the study group (n=50)

Variable	Category	n (%)
Age group (years)	21-30	2 (4)
	31-40	17 (34)
	41-50	10 (20)
	51-60	10 (20)
	61-70	7 (14)
	71-80	3 (6)
	81-90	1 (2)
Sex	Female	47 (94)
	Male	3 (6)
Presenting complaint	Painless lump	36 (72)
	Painful lump	9 (18)
	Nipple discharge	4 (8)
	Wound/ulcer over breast	1 (2)
Laterality	Right breast	28 (56)
	Left breast	22 (44)

Note: Mean age 50.9 years (SD 13.8). Percentages are of the total group.

The upper outer quadrant was the commonest tumour site, and most tumours were of intermediate histological grade. Lymph nodal metastasis was present in the majority of specimens. Tumour characteristics are summarised in [Table/Fig-2].

[Table/Fig-2]: Tumour site, histological grade and nodal status (n=50)

Variable	Category	n (%)
Quadrant involved	Upper outer	21 (42)
	Upper inner	12 (24)
	Lower outer	7 (14)
	Central	7 (14)
	All quadrants	2 (4)
	Lower inner	1 (2)
Histological grade	Grade I	4 (8)
	Grade II	29 (58)
	Grade III	17 (34)
Axillary nodal status	Positive	34 (68)
	Negative	13 (26)
	Undetermined	3 (6)

Note: Grade assigned by the modified Scarff-Bloom-Richardson system.

Stage IIA was the commonest clinical stage, whereas stages IIB and IIIA were the commonest pathological stages. The distribution of clinical and pathological stages is compared in [Table/Fig-3].

[Table/Fig-3]: Distribution of clinical and pathological stage (n=50)

Stage	Clinical, n (%)	Pathological, n (%)
IA	3 (6)	2 (4)
IB	0 (0)	0 (0)
IIA	15 (30)	7 (14)
IIB	14 (28)	12 (24)
IIIA	9 (18)	12 (24)
IIIB	9 (18)	11 (22)
IIIC	0 (0)	6 (12)
IV	0 (0)	0 (0)
Total	50 (100)	50 (100)

On comparing the two staging systems, agreement was highest for the T category and lowest for the overall stage. Nodal status showed marked upward migration after pathological examination. The concordance analysis is presented in [Table/Fig-4].

[Table/Fig-4]: Concordance between clinical and pathological staging (n=50)

Comparison	Concordant, n (%)	Upgraded, n (%)	Downgraded, n (%)
T category	23 (46)	16 (32)	11 (22)
N category	19 (38)	28 (56)	3 (6)
Overall stage	15 (30)	26 (52)	9 (18)

Note: Upgraded = clinical stage lower than pathological stage; downgraded = clinical stage higher than pathological stage.

Overall, clinical and pathological stages agreed in only 15 (30%) patients. Of the 35 discordant patients, most were upgraded on pathology, driven chiefly by nodal upstaging.

Discussion

In this series of 50 patients, clinical and pathological stages agreed in only 30% of cases, while 52% were upgraded and 18% downgraded after surgery. This high discordance, with a clear tendency toward upgrading, is the central finding and carries direct implications for treatment planning, because clinical stage often dictates the initial decision, including whether neoadjuvant chemotherapy is offered[8].

The demographic profile matched regional patterns. The mean age of about 51 years and the marked female preponderance (94%) are consistent with earlier Indian and international series. A painless lump was the dominant presentation (72%), the upper outer quadrant was the commonest site (42%), and grade II tumours predominated (58%). These features reflect the heterogeneous biology of the disease, in which tumour size, nodal status and grade remain the principal prognostic factors[3,7].

Nodal status showed the greatest migration: agreement was only 38% for the N category, and 56% of patients were upstaged on pathology. This is expected, because clinical examination underestimates microscopic nodal disease, and lymphatic spread is a key driver of outcome[4]. The difficulty of assessing nodes clinically has motivated a large body of work on imaging- and pathology-based prediction of nodal metastasis, including deep-learning models applied to mammograms and to sentinel-node histology[14,20]. Such tools, together with artificial-intelligence systems that reduce false-positive imaging findings and assist longitudinal assessment, may in future narrow the gap between clinical and pathological nodal staging[16,18,19].

Agreement was higher for the T category (46%) than for the overall stage, indicating that primary tumour size is estimated more reliably at the bedside than nodal or composite stage. Even so, one third of T assessments were discordant, underlining the value of accurate measurement of tumour size and fixity. Improved imaging and computational analysis of tumour extent, including radiomics and multimodal fusion, are being developed to support this[13,15,25].

Comparison with a large registry analysis of over 400,000 patients is instructive. That study reported far higher concordance (68% overall, 87% for T and 80% for N) with a tendency toward downgrading, the opposite of the upgrading seen here. The difference most likely reflects the resource setting: later clinical presentation, limited access to high-resolution pre-operative imaging and reliance on clinical examination lead to systematic underestimation of stage in our population. Where routine practice cannot yet incorporate advanced imaging or artificial-intelligence support[21,22,24], meticulous clinical assessment remains the main safeguard against understaging.

These findings also bear on treatment. Systemic therapy is increasingly tailored to disease extent and biology, from neoadjuvant regimens and their multi-omic response predictors[10,11] to residual-disease-guided prognostication[8,9], targeted and immune-based agents[1], serum-marker monitoring[12], and emerging nanomaterial-based delivery for advanced disease[5,6]. Reliable staging is the entry point to all of these decisions, and comprehensive reviews of artificial intelligence in oncology emphasise that data quality and accurate ground-truth staging underpin any computational gain[17,23,31,32]. The broader literature on outcome prediction across tumour types further shows how histopathology- and imaging-derived models depend on well-characterised stage[26,27,28,29,30].

The main limitations are the small single-centre sample, the observational cross-sectional design and the absence of formal agreement statistics such as the kappa coefficient, which reflects the descriptive scope of the source data. Reliance on the AJCC 7th edition also limits direct comparison with studies using the 8th edition. Larger, multicentre studies with standardised imaging and formal agreement analysis would strengthen these observations.

Conclusion

Clinical staging disagreed with pathological staging in about 70% of patients with breast cancer, with most tumours upstaged on pathology and nodal status accounting for the largest shift. Because clinical stage guides early treatment decisions, this degree of discordance is clinically important. Careful pre-operative assessment of tumour size, fixity and nodal status is essential to reduce understaging and to support sound treatment planning, particularly where advanced imaging and computational tools are not yet routinely available.

Declarations

Ethics approval: The study was approved by the Institutional Ethics Committee of Sumandeep Vidyapeeth, and written informed consent was obtained from all participants.

Conflicts of interest: The authors declare no conflict of interest.

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Authors' contributions: All the authors contributed to the study concept, data acquisition, analysis, drafting and critical revision of the manuscript, and approved the final version.

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