Cancer Biol Med 2026. doi: 10.20892/j.issn.2095-3941.2025.0704

REVIEW

Artificial intelligence in breast cancer: applications and advancements

Jianbin Li[1,2], Zefei Jiang[1]

[1]Senior Department of Oncology, Chinese PLA General Hospital, Beijing 100071, China; [2]National Key Laboratory of Advanced Biotechnology, Academy of Military Medical Sciences, Beijing 100071, China

ABSTRACT Breast cancer is the most common malignant tumor among women globally and poses a major public health challenge due to limitations in traditional diagnostic and treatment processes, such as subjective interpretation biases and inefficient multi-dimensional data integration. Artificial intelligence (AI), particularly deep learning and machine learning technologies, has emerged as a transformative tool in addressing these issues. Clinically, AI has been widely applied in imaging screening to improve detection rates and reduce reading time, digital pathology for precise tumor typing and gene mutation prediction, treatment decision-support systems to enhance guideline compliance, and drug research and development to accelerate target identification and virtual screening. Despite these achievements, AI implementation faces challenges, such as data standardization issues, limited model generalization, low clinical accessibility, and unclear ethical-legal responsibilities, which require targeted solutions that include national data standards, multi-center training, hierarchical physician training, and explainable AI. Future directions involve multi-modal data integration, human-AI collaborative multidisciplinary team models, and extension to full-cycle health management from prevention-to-rehabilitation. This review provides a systematic overview of the role of AI in breast cancer care, offering insights for clinical practice and scientific research innovation, and supporting the transition toward personalized and intelligent medicine in oncology.

KEYWORDS Artificial intelligence; breast cancer; application; challenge

Introduction

The 2025 global cancer statistics show that breast cancer is the most common malignant tumor among women with greater than 2.3 million new cases and approximately 680,000 deaths each year[1]. Despite advances in diagnosis and treatment, breast cancer continues to pose a major public health challenge. Traditional diagnostic and treatment processes still depend heavily on human judgment. Radiologists interpret breast imaging based on personal experience, while pathologists face variability in tissue typing due to subjective factors. Treatment decisions also require the integration of large amounts of multi-dimensional clinical data. These complexities often result in inconsistent diagnostic accuracy and treatment outcomes across medical centers[2].

Artificial intelligence (AI) offers a new way to address these issues. Advances in deep learning (DL) and machine learning (ML) have enabled AI to assist in nearly every stage of breast cancer management. By 2025, more than 50 AI-based breast cancer systems have received certification worldwide. These technologies now support imaging screening, pathologic interpretation, and clinical decision-making. Some AI systems have shown performance comparable to that of experienced clinicians in validation studies. This article comprehensively reviews AI advances in breast cancer management from three aspects, providing a basis for clinical practice and scientific research innovation: technical principles; clinical applications; and challenges and prospects.

Iteration of medical models and evolution of AI technologies

Continuous innovation in medical diagnosis and treatment models has gradually promoted the integration of AI into healthcare. This evolution allows the development of medicine to be divided into four distinct eras[3].

Correspondence to: Zefei Jiang
E-mail: jiangzefei@csco.org.cn
ORCID ID: https://orcid.org/0000-0002-4295-0173
Received November 12, 2025; accepted February 5, 2026.
Available at www.cancerbiomed.org
©2026 The Authors. Creative Commons Attribution-NonCommercial 4.0 International License (CC BY-NC 4.0)

Empirical medicine era (before 2010)

Breast cancer diagnosis and treatment relied mainly on physical examination and basic imaging techniques, such as early mammography, during the empirical medicine era. Clinical judgment depends largely on personal experience and subjective interpretation. The rate of misdiagnosis was high. The lack of technological infrastructure and data limited the possibility of applying AI. As a result, a systematic approach to diagnosis and treatment had not been created.

Traditional machine learning era (2010–2015)

Clinical practice began to rely on diagnosis and treatment guidelines developed from randomized controlled trials during the traditional machine learning era. However, data processing still required manual work and AI was only used for basic probability modeling. Early expert systems, such as INTERNIST-I, attempted to organize medical knowledge for breast cancer diagnosis and treatment. Because these systems depended on manually built knowledge bases and were prone to logical errors, the expert systems could not fully meet clinical demands. Traditional regression models and Bayesian networks were gradually introduced for breast cancer risk prediction. These methods improved data processing efficiency but remained limited by small sample sizes and narrow feature dimensions, resulting in modest predictive accuracy.

Deep learning era (2016–2020)

Molecular typing began to guide personalized treatment for breast cancer during the deep learning era. The rapid growth of gene detection data pushed AI into a fully data-driven stage. As datasets expanded and computing power increased, deep learning technologies, especially convolutional neural networks (CNNs), achieved major breakthroughs. CNN-based systems automatically detected micro-calcifications and masses on mammograms. In pathology, whole-slide imaging (WSI) technology enabled automatic segmentation of tumor regions, creating a foundation for more precise classification. However, AI models of this era still faced notable limitations. Uneven data distribution reduced the generalizability and algorithmic bias risked widening disparities in diagnosis and treatment, which limited clinical adoption.

Large model and generalization era (2020s–present)

There is now an urgent need to integrate multi-omics data, including imaging, pathology, genetics, and clinical information. Emerging technologies, such as transformers and federated learning, have become increasingly mature and practical. Foundation models and large language models (LLMs) can process multi-modal data more effectively. For example, one model that combines multi-sequence breast magnetic resonance imaging (MRI) data with clinical text achieved a concordance index (C-index) of 0.82 in predicting the efficacy of neoadjuvant therapy, significantly outperforming single-modal models. Federated learning enables local training and parameter sharing across multiple centers. This approach not only protects data privacy but also enhances model adaptability across diverse patient populations[4] (**Figure 1**).

Applications of AI in breast cancer diagnosis and treatment

The introduction of AI has transformed every stage of cancer management, from screening and diagnosis-to-treatment and prognosis evaluation. Using algorithms, such as DL and ML,

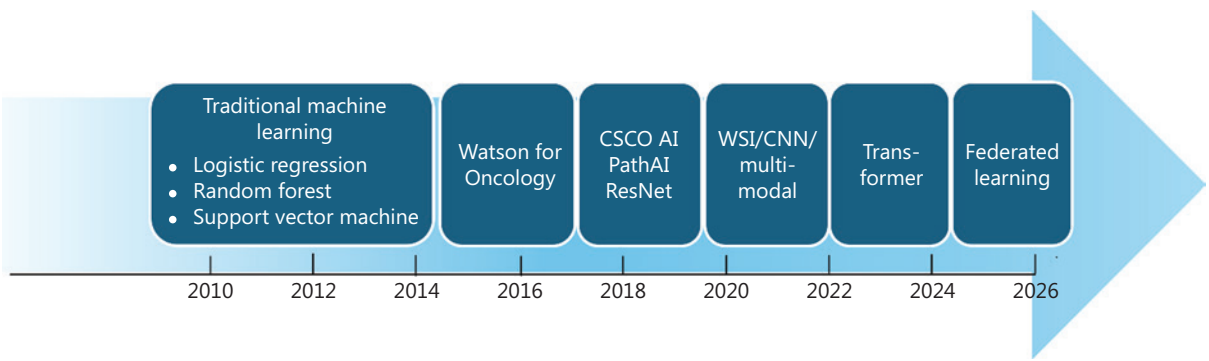


Figure 1 Timeline of core technological breakthroughs in AI-assisted breast cancer management from 2010 to 2025. Traditional ML (2010–2015): RCT-based guidelines; manual data processing; basic probability modeling; and limited by small samples/narrow features, modest accuracy. Deep learning (2016–2020): CNN for mammogram detection; WSI for pathology segmentation; and constrained by uneven data and algorithmic bias. Large model and generalization (2020s–present): multi-omics integration; transformers/LLMs/federated learning; and privacy-preserving, diverse population-adaptable, WSI, whole-slide imaging; CNN, convolutional neural network.

AI can analyze vast amounts of tumor data with speed and precision. These insights provide a stronger scientific basis for clinical decision-making in oncology and have greatly accelerated progress in cancer medicine.

Imaging

Breast imaging is the most established field for AI applications. Breast imaging covers screening, lesion characterization, and staging assessment, all of which greatly enhance diagnostic accuracy and efficiency.

Mammography (breast X-ray) remains the preferred method for breast cancer screening, but identifying microcalcifications continues to be difficult. Artificial neural networks are trained on tens of thousands of annotated mammograms and the accuracy improves through continuous optimization. Once trained, these models can analyze new images and generate predictions that assist radiologists in making diagnostic decisions. The PRAIM study reported that an AI-assisted double-reading approach achieved a breast cancer detection rate of 6.7%–17.6% higher than standard double reading (5.7%, 95% CI: 5.7%–30.8%) without increasing the recall rate[5,6]. Similarly, the ScreenTrustCAD study[7] found that replacing one radiologist with AI in double reading improved detection by 4% and reduced reading time by 30%. These findings demonstrate that AI can meaningfully enhance mammography screening performance and provide an effective strategy for strengthening screening capacity in primary hospitals.

MRI is the most sensitive imaging technique for detecting breast cancer. MRI has a key role in evaluating the efficacy of neoadjuvant therapy and identifying small lesions. However, interpreting multi-sequence MRI images is time-consuming and often subjective. AI can integrate multiple MRI parameters, such as T1-weighted, T2-weighted, and diffusion-weighted imaging (DWI), to improve diagnostic accuracy and reduce unnecessary biopsies. AI models have achieved an area under the curve (AUC) of 0.88 for predicting malignancy risk for patients classified as BI-RADS category 4, which allows up to 30% of low-risk patients to safely avoid biopsy[8]. AI can also predict the response to neoadjuvant therapy and support more individualized treatment decisions when MRI data are incorporated into a multivariable logistic regression model, ultimately improving patient prognosis[9].

Pathology

A pathologic diagnosis serves as the gold standard for tumor diagnosis. The accuracy and efficiency of a pathologic diagnosis directly influence treatment planning and prognosis evaluation. Traditional pathologic diagnosis relies on the subjective interpretation of stained sections and immunohistochemical results by pathologists, which is susceptible to factors, such as the pathologist's experience, staining quality, and sample heterogeneity. As a result, diagnostic consistency may be limited, small lesions can be overlooked, and biomarker prediction may be delayed. With the in-depth integration of digital pathology technology and AI, intelligent pathology systems now use deep learning algorithms to automatically segment tumor regions, perform quantitative molecular typing, and predict gene mutations. These capabilities address key limitations of traditional pathology and provide powerful technical support for more precise and efficient diagnosis.

Digital pathology converts traditional tissue slides into high-resolution digital images using advanced scanning technology[10]. This process enables digital storage, sharing, and analysis of pathologic data. The rise of digital pathology has laid a solid foundation for applying AI in diagnostic pathology, allowing computers to automatically detect and analyze key image features. In recent years, research in intelligent pathology has grown rapidly, showing remarkable value in solid tumors such as breast cancer and non-small cell lung cancer. AI models can now automate essential diagnostic tasks, including tumor grading, typing, and target detection. In studying the tumor microenvironment, AI has overcome the limitations of traditional qualitative assessments. Using graph neural networks and spatial transcriptomic analysis, AI can quantify immune cell density, spatial distribution, and interactions with tumor cells. AI can even identify subtle, visually indistinguishable patterns, such as clustered immune infiltration of immune cells and the blurring of the tumor-immune boundary, offering objective metrics for evaluating tumor immune activity. Furthermore, AI can integrate multi-modal data sources to improve the accuracy and efficiency of prediction models[11]. By combining pathologic features from whole slide imaging (WSI) with genomic and clinical data, researchers have developed multi-dimensional prediction models that achieve an AUC of 0.74–0.86 for predicting the objective response rate (ORR) to immunotherapy in non-small cell lung cancer. This performance is notably superior to the single PD-L1 CPS score, which has an AUC of 0.65–0.81[12].

The development of multi-modal pathologic AI models has greatly expanded the clinical value of pathology. These models enable a transition from traditional morphologic assessment to precise typing and prognosis prediction. Different models now perform specialized diagnostic and predictive tasks. The MUSK model[13], a vision-language foundation model based on the transformer architecture, was trained on 50 million pathologic images and 1 billion medical texts. The MUSK model uses mask modeling to learn cross-modal representations and optimizes the alignment between visual and language features through 1 million image-text pairs. In pan-cancer prognosis prediction, by analyzing WSI features and clinical follow-up data, MUSK achieved a C-index of 0.747 for predicting 5-year overall survival across 16 cancer types, which is significantly higher than traditional clinicopathologic models (C-index = 0.68). The model can also predict tumor-associated gene

mutations. The MUSK model reached an AUC of 0.768 for predicting PD-L1 expression status, offering a non-invasive tool for selecting immunotherapy regimens. The CHIEF model[14] integrates microscopic imaging with multi-modal information to enhance feature representation, thereby improving the accuracy of quantitative pathologic analysis. The CHIEF model was pre-trained on 60,530 WSIs from 14 research cohorts, covering cancer samples from 19 anatomic sites, including breast, endometrial, and esophageal cancers. The CHIEF model demonstrated excellent performance and was validated on 15 independent datasets, achieving a macro-average AUROC of 0.9397, which is approximately 10% higher than existing methods. The CHIEF model also accurately predicted survival outcomes for patients with 7 cancer types, distinguishing long-term from short-term survivors with an average C-index of 0.74 that was approximately 12% higher than previous approaches.

Intelligent pathology is evolving from a diagnostic support tool with continuous technological advances into a key driver of precision treatment. By integrating multi-omics data, such as single-cell sequencing and spatial transcriptomics, intelligent pathology will enable deeper connections between pathologic morphology, molecular mechanisms, and treatment responses in coming years. This integration will usher tumor pathology into a new era of precision, intelligence, and individualized care.

Decision-making

Treatment decisions for breast cancer require the integration of multiple types of information, including clinicopathologic features, imaging assessments, molecular typing, and genetic testing results. Traditional decision-making models rely heavily on physician experience and interpretation of clinical guidelines, which is easily influenced by regional variations in medical practice and delays in knowledge updates, which reduces the standardization of treatment for advanced breast cancer.

With the in-depth integration of AI into oncology, intelligent decision-support systems now enable personalized treatment recommendations and dynamic risk assessments. These systems provide a powerful technical solution to address the limitations of traditional decision-making processes by combining clinical guidelines with real-world data learning.

Watson for Oncology (WFO), the world's first AI system for breast cancer treatment decision-making, was jointly developed by IBM and the Memorial Sloan-Kettering Cancer Center (MSKCC). The design and performance provide important insights into the potential of AI in oncology. WFO integrated the MSKCC clinical practice guidelines, 1.5 million pages of medical literature, and over 3 million historical cases during 4 years of training to build the knowledge base. The WFO system covers the full spectrum of breast cancer management, including neoadjuvant, adjuvant, and advanced salvage therapy. The WFO system treatment recommendations were 93% consistent with expert multidisciplinary teams (MDTs) during clinical validation[15]. However, there are significant limitations in the clinical application of the WFO system in China. The consistency between WFO recommendations and physician decisions in China is only 56%[16]. Several factors contribute to this gap. First, the guideline adaptability is poor. The WFO system is trained primarily on national comprehensive cancer network (NCCN) guidelines, which differ in key areas from the national diagnosis and treatment standards in China. As a result, the system cannot adjust to local clinical practices. Second, there is a regional bias in the data. The training data are mainly derived from the European and American populations, which do not reflect the epidemiologic characteristics of Chinese patients, resulting in a consistency rate of only 48% for HER2-positive patients. Although, WFO is more helpful for the diagnosis and treatment decisions of HR-positive patients[17]. Third, the functionality of the WFO system is limited, mainly providing ranked treatment recommendations but lacking essential features, such as adverse event monitoring and dynamic prognosis evaluation. These shortcomings restrict the ability to support the full continuum of clinical care.

The Chinese Society of Clinical Oncology (CSCO) AI, the first breast cancer treatment decision-support system independently developed in China, was created by the CSCO in collaboration with several major hospitals nationwide. The training dataset of the system includes information from 80,346 Chinese breast cancer patients across 17 provinces and cities, comprising 68% early breast cancer (EBC) and 32% metastatic breast cancer (MBC) cases. This dataset closely reflects the real epidemiologic characteristics of breast cancer in China[18]. The CSCO AI is built primarily on the CSCO Breast Cancer Diagnosis and Treatment Guidelines[19], while also referencing the NCCN and european society for medical oncology (ESMO) guidelines to establish priority rules that align with local drug accessibility. In addition to the treatment recommendations, the CSCO AI includes modules for evidence tracing and adverse reaction management. For example, when recommending an aromatase inhibitor + CDK4/6 inhibitor regimen, the CSCO AI automatically cites data from the NATALEE study[20], showing a 5.1% absolute improvement in 5-year invasive disease-free survival (iDFS) among intermediate-risk HR-positive patients. The CSCO AI also reminds clinicians to monitor left ventricular ejection fraction every 3 months to reduce the risk of cardiotoxicity for patients receiving anthracycline chemotherapy.

The CSCO AI has undergone 4 phases of clinical research to verify safety and effectiveness. Phase I (2018, $n = 200$) focused on evaluating system integrity. The results showed that the availability of neoadjuvant, adjuvant, and first-line salvage treatment plans reached 100% with an overall guideline compliance rate of 88.2%. Most errors were linked to missing data, such as the Ki-67 index, which caused deviations in adjuvant chemotherapy recommendations. Phase II (2018–2019, *n*

= 500) further improved compliance by adding 2 new modules: one module for recording previous chemotherapy or targeted therapy history; and on module for specifying the cause of drug resistance (primary *vs.* secondary)[21]. Phase III (2019–2020, n = 1,200) was a multi-center, blinded study. The CSCO AI achieved a decision compliance rate of 95.8%, which was significantly higher than the initial decisions of the physicians (90.8%) and decisions made with guideline consultation (92.1%, $P < 0.01$; **Figure 2**). Stratified analysis revealed higher decision consistency for EBC (78.8%) than MBC (61.7%)[22]. The real-world data of Phase IV (2021–2025, n = 5,000+) provided real-world evidence. The CSCO AI had been implemented in > 500 hospitals across 30 provinces and cities by 2025. The average treatment decision-making time decreased from 30 min to 5 min. AI-generated alternative treatment plans helped identify and correct potential decision-making biases during MDT meetings in tertiary hospitals.

In addition to optimizing treatment selection, the CSCO AI can accurately predict recurrence risk and treatment-related adverse reactions through multi-dimensional data modeling, further improving the safety and effectiveness of decision-making. AI builds predictive models based on the toxicity profiles of different therapies for early warning of adverse events. For example, the CSCO AI system integrates patient age, co-morbidities, and baseline left ventricular ejection fraction (LVEF) during anthracycline chemotherapy to assess the risk of cardiotoxicity. The CSCO AI can also predict the likelihood of chemotherapy-induced leukopenia and vomiting, enabling clinicians to implement preventive measures and early interventions.

Drug research and development

Drug screening is a critical step in new drug research and development but faces major challenges under traditional methods. Large compound libraries, low screening efficiency, and poor clinical translation rates often lead to long development cycles and high costs. With the in-depth integration of AI technology and pharmaceutical engineering, technologies such as machine learning, deep learning, and generative AI are now being applied to key stages including target identification, virtual screening, and molecular design. These approaches have greatly improved both the efficiency and accuracy of drug discovery.

AI enables precise target identification in the target screening stage by integrating multi-omics data, which overcomes the limitations of traditional experimental screening. Wu et al.[23] used AI to analyze single-cell transcriptomic data from 44 treatment-naïve triple-negative breast cancer (TNBC) patients to assess immunotherapy resistance. The analysis identified antigen-presenting mast cells (apMCs) as a novel therapeutic target capable of enhancing the efficacy of anti-PD-1 therapy. Validation in an independent cohort of 484 TNBC patients confirmed that TNBC patients with high apMC expression had a significantly higher objective response rate (ORR) to anti-PD-1 treatment (50.0% *vs.* 10.0%). This study demonstrated that AI can rapidly identify promising therapeutic targets from large-scale biological datasets, shorten the validation cycle, and provide new directions for drug development in refractory cancers.

AI significantly reduces the number of compounds requiring experimental testing in the virtual screening stage and lowers research and development costs by building molecular docking models and activity prediction algorithms. Traditional virtual screening methods, such as structure-based drug design (SBDD), depend on manually constructed pharmacophore models, which are time-consuming and subjective. In contrast, AI models can automatically learn the relationships between molecular structures and biological activity by analyzing large datasets of compound-target interactions. The Genotype-Drug Diffusion (G2D-Diff) model that was

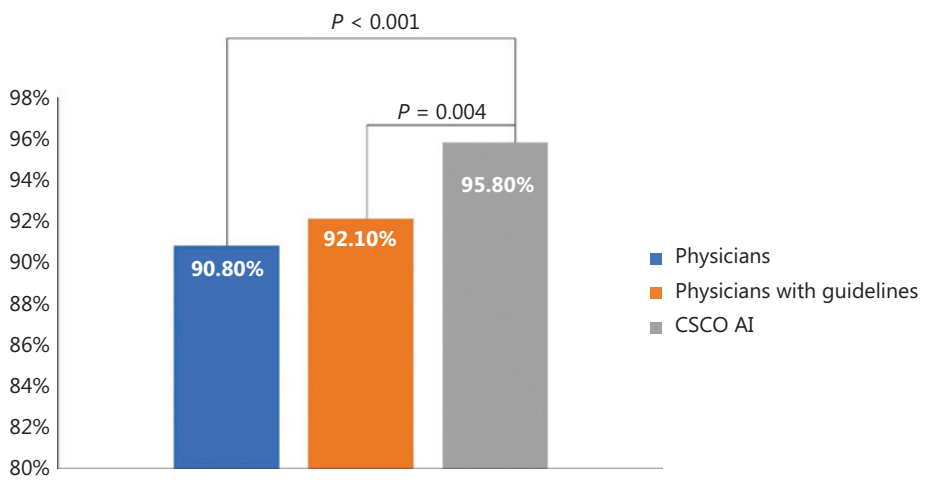


Figure 2 The conformity of decisions made by the CSCO AI, physicians, and physicians with guidelines.

developed by Kim et al.[24] can generate targeted small-molecule compounds based on tumor genotypes. The G2D-Diff model demonstrated strong performance in virtual screening. The generated molecules achieved druggability scores (QED > 0.8 and SAS < 4.5) comparable to the druggability scores in the ChEMBL database, while showing significantly lower *in vivo* toxicity than known active compounds ($P < 0.01$). Molecular docking validation further confirmed that the binding affinities of the generated TNBC-S1/S2 compounds to PI3Kα and HDAC1 were comparable to binding affinities of approved clinical drugs, such as fimepinostat and dinaciclib.

The clinical transformation value of AI in drug screening has been verified through several practices. A study conducted by the Boston Consulting Group reported that AI can increase the overall success rate of drug development from 5%–10% to 9%–18%. The success rate of Phase I can reach 80%–90% and 40% in Phase II clinical trials, while the duration of trials are shortened by 50%–60%[25]. AI also improves clinical trial design. By integrating electronic medical records and drug response data through knowledge graph technology, AI enables precise patient stratification and reduces the number of ineligible or low-value enrollments.

Challenges and countermeasures in implementing AI

Although the value of AI in breast cancer diagnosis and treatment has been increasingly confirmed in clinical practice, several major challenges remain. Current AI technologies still face issues, such as poor data standardization, limited model generalization, low clinical accessibility, and unclear definitions of ethical and legal responsibility during clinical translation. Addressing these problems requires targeted strategies to guide the standardized and sustainable development of AI in oncology.

Data standardization and quality control

As the foundation of AI model training and application, the standardization and quality of data directly determine the accuracy and reliability of AI-driven decisions. Current data-related challenges mainly fall into three categories in breast cancer applications. First, data formats are inconsistent. DICOM files produced by imaging equipment vary across hospitals in parameters, such as slice thickness, matrix size, window width, and window level, resulting in poor generalization of AI models to generalize across devices. Second, key clinical information is often missing. Electronic medical record systems in many primary hospitals remain incomplete and 30%–40% of breast cancer cases lack full documentation of treatment history, making it impossible for AI to generate comprehensive treatment recommendations. Third, data privacy poses significant risks. Genetic, imaging, and pathologic data are highly sensitive forms of personal information. Legal and policy restrictions on cross-institutional data sharing make multi-center AI model training difficult to implement.

There are three countermeasures. First, national data standards should be established. Government-led initiatives, developed in collaboration with academic and clinical institutions, should create unified data standards for AI applications. These standards should harmonize imaging parameters, pathologic staining procedures, and key fields within electronic medical records to ensure interoperability and consistency across medical centers[26]. Second, dual quality control should be implemented. A combined system of AI-based automatic verification and manual review can enhance data reliability. For example, the CSCO AI database evaluates the completeness of each case, deducting 20 points for every missing key data item and rejecting cases scoring < 60. Routine data cleaning should also be performed to remove duplicates and correct logical inconsistencies, ensuring high data integrity. Third, privacy protection technologies should be adopted. Techniques, such as federated learning and differential privacy, can safeguard sensitive information. Data remain stored locally at each institution in this framework, while only model parameters are shared, avoiding direct transmission of original datasets. For highly sensitive data, such as genomic information, differential privacy methods can introduce controlled noise to protect individual identity while maintaining overall data utility for statistical analysis[27].

Model generalization and clinical adaptability

The generalization and clinical adaptability of AI models directly determine the practical value across different medical settings and patient populations. Current AI systems for breast cancer still face three major challenges. First, regional and population differences limit model adaptability. Most AI models are trained on data from tertiary hospitals, whereas patients in primary hospitals are typically older, have more co-morbidities, and present in more advanced disease stages. Consequently, model performance often declines significantly in primary care settings. Second, guideline updates do not keep up with clinical needs. AI model updates generally occur every 6–12 months, while breast cancer diagnosis and treatment guidelines are revised 1–2 times per year. This mismatch prevents AI systems from promptly incorporating the latest treatment recommendations. Third, AI models struggle with complex cases. For rare subtypes or patients with multi-line drug resistance, the guideline compliance rate of AI-generated treatment plans is markedly lower than the guideline compliance rate of common subtypes. This limitation arises because such cases are underrepresented in training datasets, preventing the model from fully learning their clinical characteristics.

There are three countermeasures. First, data sources should be expanded. Multi-center, stratified model training should be conducted to improve the representation of key populations, including patients from primary hospitals, elderly individuals, and advanced cases. Transfer learning should be applied to adapt model parameters trained on tertiary hospital data to primary hospital data, enhancing model performance in real-world primary care settings. Second, real-time linkage should be established between guidelines and algorithms. Collaboration with guideline development organizations should occur to build a structured, machine-readable interface. AI systems can automatically convert new recommendations into executable logic rules *via* API integration when guidelines are updated, ensuring real-time synchronization between clinical standards and AI algorithms. Third, a complex case database should be developed. Rare cases should be collected, such as inflammatory breast cancer and multi-line drug-resistant disease, and data augmentation should be used to expand sample size. Data from related cancers should be leveraged through multi-task learning to enhance model robustness and improve the accuracy of decision-making for complex or low-frequency cases[28].

Clinical accessibility and user acceptance

The clinical accessibility of AI technology and the acceptance of physicians are crucial for large-scale adoption in breast cancer care. However, current applications still face two major barriers. First, the technical threshold remains high. Physicians in primary hospitals often lack adequate training in AI operation and interpretation. As a result, physicians may find it difficult to understand the evidence cited by AI systems or interpret the quantitative outputs related to lesion features. Moreover, some AI platforms have complex user interfaces that require familiarity with specialized terminology, further increasing the operational difficulty for non-specialist clinicians. Second, physician trust in AI is limited. Many clinicians worry that AI systems may rigidly apply clinical guidelines while neglecting patient-specific factors. In addition, the high hardware requirements of AI systems, such as the need for powerful computing servers, exceed the technical and financial capacity of many primary hospitals, further restricting accessibility[29].

There are three countermeasures. A hierarchical training system should be established. Standardized training programs that combine AI operation skills with clinical interpretation for physicians in primary hospitals should be developed. The training should include online theoretical courses and offline practical sessions with system access granted only after passing assessments. In addition, an intelligent interpretation module should be developed to translate AI-cited research evidence into plain language and provide real-time explanations for specialized medical terms, improving usability and comprehension. A human–AI collaborative decision-making model should be built. AI should be clearly defined as an assistive tool within the clinical workflow. The AI system can generate three alternative treatment plans, each annotated with corresponding benefits, risks, and levels of evidence. Physicians then tailor the final plan based on the individual patient's condition, while the system records the rationale for any adjustments. This creates the following closed feedback loop, which maximizes AI efficiency while preserving the clinician's authority and autonomy: AI recommendation → physician decision → feedback optimization. Third, policy and infrastructure support should be enhanced. The use of cloud-based AI platforms led by tertiary hospitals should be promoted to reduce the adoption barrier. Primary hospitals can upload imaging and pathology data to the cloud platform *via* the internet, allowing centralized AI analysis and feedback without the need for costly local hardware. This approach lowers implementation costs and strengthens technical collaboration and guidance between higher-level and primary medical institutions.

Ethical and legal responsibility definition

The ethical compliance and legal responsibility of AI technologies are essential to ensuring safe and trustworthy application in clinical practice. Current ethical and legal challenges in breast cancer care mainly arise in three areas[30,31]. First, the division of responsibility remains unclear. Without definitive legal guidelines, especially under the regulatory framework in China, liability for patient harm caused by inappropriate AI recommendations is ambiguous (physician, hospital, or developer). Several related medical disputes have already emerged. Second, algorithm transparency is insufficient. The black box feature of DL models prevents physicians from fully understanding the rationale behind AI-generated recommendations. This lack of interpretability not only limits physicians' ability to evaluate the appropriateness of AI decisions but also undermines patients' informed consent. Third, fairness risks persist. Models trained on urban-dominated datasets may underperform for rural patients or those with rare subtypes, which are common gaps in Chinese clinical data.

There are three countermeasures. First, the liability of Chinese regulations should be clarified. Specific regulations that define the allocation of responsibility in AI-related medical decisions should be developed. The AI developer should bear compensation liability if patient harm results from model defects. Conversely, the physician should assume primary responsibility if a physician adopts AI recommendations without considering the patient's actual condition. Medical institutions should be required to record in medical charts if AI recommendations were considered and document any modifications, providing a clear basis for liability assessment. Second, algorithm transparency should be enhanced. Explainable AI (XAI) methods, such as local Interpretable model-agnostic explanations (LIMEs) and SHAP value analysis, should be

applied to improve interpretability[32]. The AI system should display the key decision factors when presenting treatment options and provide a visualized decision path, allowing clinicians to trace and understand the logic behind AI judgments. The authorized AI devices should provide visualized decision paths, aligning with the transparent and traceable requirements in China. Third, fairness should be ensured by integrating data from diverse Chinese regions. Breast cancer patient data should be incorporated from diverse races, regions, age groups, and molecular subtypes into model training. Routine fairness assessments should be performed to detect and correct biases, ensuring equitable decision accuracy across all patient populations[33].

The future development direction of AI

AI in breast cancer care is expected to overcome current limitations and evolve from single-step assistance to comprehensive, full-cycle intelligent management with ongoing advances in multi-omics technologies, human-AI collaboration models, and emerging algorithms.

Multi-modal data integration and multi-task learning

Traditional AI models for breast cancer primarily rely on single-modal data, making it difficult to fully capture tumor heterogeneity and individual patient differences. The deep integration of multi-omics data has therefore become a key direction for developing AI systems that support precise clinical decision-making. Systematic integration of multi-modal information provides a new paradigm for accurate tumor classification and outcome prediction. The Anhui Provincial Hospital research team developed the Tumor Invasion Margin Evaluation System (TIMES) by combining spatial transcriptomics, proteomics, and multiplex immunohistochemistry (IHC) data using AI technology[34]. The system focuses on molecular differences between the tumor invasion front and the central region. The ability of TIMES to predict 1-year postoperative recurrence risk achieved an AUC of 0.822, significantly outperforming traditional TNM staging (AUC = 0.685). Similarly, the Fudan University Shanghai Cancer Center team created the Clinical–Immune–Metabolic–Proteomic–Transcriptomic–Genomic–Viral (CIMPTGV) multi-omics model for HR+/HER2− breast cancer. By integrating seven data types, including clinical, metabolomic, and genomic information[35], the model accurately predicts 5-year invasive disease-free survival, with a C-index of 0.871, compared to 0.763 for single-gene testing models. Notably, the CIMPTGV multi-omics model successfully identifies 74.2% of patients at potential risk of recurrence. Looking forward, AI will evolve toward panoramic decision-making systems that integrate imaging, pathology, genetic, and clinical data. These systems will enhance prediction accuracy, identify patient subgroups most likely to benefit from specific treatments, and reduce ineffective therapies through the collaborative analysis of multi-modal features.

In addition, multi-task learning (MTL) will further improve the efficiency and cost-effectiveness of AI models. MTL enables one model to perform multiple diagnostic and therapeutic tasks simultaneously, unlike traditional single-task frameworks. For example, an MTL model using multi-phase dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) can predict histologic grade and Ki-67 status in breast cancer[36]. MTL improves model generalization, while reducing hardware resource consumption by sharing feature representations across tasks. This approach is particularly valuable for primary hospitals, where one AI system is allowed to support multiple diagnostic and treatment functions, lowering equipment investment costs and enhancing clinical accessibility.

Popularization of human-machine collaborative MDT model

The MDT model is the cornerstone of standardized diagnosis and treatment for breast cancer. However, widespread implementation remains limited by the shortage of MDT resources and the low consistency of expert opinions, particularly in primary hospitals. AI is expected to become a core auxiliary member of the MDT team, helping to optimize workflows and promote treatment standardization across institutions. Notably, based on the CSCO AI, we have established the CSCO breast cancer database. This database not only enables us to better grasp patients' dynamic clinical conditions for more targeted MDT discussions but also serves as a valuable resource for data analysis. Discrepancies in diagnosis and treatment practices can be identified across different regions or institutions through in-depth mining of this database, as well as tracking advances in clinical management, thereby providing data-driven evidence to further refine MDT protocols and clinical guidelines[18].

AI can also support a closed-loop process that includes treatment plan recommendations, adverse reactions prediction, and individualized plan adjustments. MDT members can tailor treatment strategies according to the patient's clinical condition, tolerance, and financial situation based on AI-generated recommendations and risk assessments. This approach not only ensures adherence to clinical standards but also allows flexibility for personalized care. The promotion of remote MDT models offers a promising solution to the shortage of high-quality medical resources in primary hospitals. Primary hospitals can upload patient imaging, pathology, and genetic data to a cloud-based MDT platform

with the integration of AI and 5G technologies. AI systems perform preliminary analyses using both real-time patient data and aggregated insights from the database, then generate baseline treatment recommendations, which are reviewed and refined online by specialists from tertiary hospitals. These analyses establish a collaborative workflow encompassing local data collection, AI-assisted analysis, and expert remote consultation.

Medical data can now be processed efficiently with advances in cloud computing at the point of care before being uploaded to the central server, improving system responsiveness and decision accuracy. This approach not only offers logistic, economic, and environmental benefits by reducing data loss, lowering maintenance costs, and minimizing bandwidth dependence but also integrates hospital data at the local, regional, and national levels. The result is a comprehensive digital medical ecosystem that enables more precise treatment optimization, real-time monitoring of patient outcomes, and continuous feedback for clinical decision-making. Ultimately, this model extends high-quality medical services to remote regions, enhancing healthcare equity and patient benefit[37].

Extension from treatment to full-cycle health management

The current application of AI in breast cancer primarily focuses on diagnosis and treatment. In the future, AI is expected to expand across the entire continuum of care, from prevention and screening to diagnosis, treatment, and rehabilitation, forming an integrated, intelligent health management system[38]. AI can integrate genetic background, lifestyle factors, and imaging data in primary prevention to build individualized risk prediction models. These models enable personalized prevention strategies for high-risk populations, improving screening efficiency, while avoiding unnecessary medical interventions. AI can continuously monitor patient recovery indicators through wearable devices during postoperative rehabilitation and combine these data with clinical follow-up information to generate tailored rehabilitation plans. The ability to conduct self-monitoring *via* wearables, such as smart bras, unlocks novel opportunities for early disease detection and holistic management. The integration of these technologies into current healthcare frameworks presents a dual landscape of prospects and obstacles. Smartphone-enabled systems can capitalize on pre-existing infrastructure, while AI-driven interpretation modules offer the advantage of streamlining diagnostic workflows and boosting efficiency.[39] The system can automatically produce progress reports, allowing physicians to adjust treatment strategies in real time. This process establishes a closed-loop model of precise rehabilitation, dynamic monitoring, and outcome evaluation. Traditional methods, such as periodic imaging or tumor marker testing, often fail to detect early signs of recurrence in long-term follow-up. AI addresses this limitation by constructing recurrence risk prediction models based on longitudinal patient data. These systems can send automated alerts through mobile applications or text messages, enhancing patient adherence to follow-up and enabling earlier clinical intervention.

Conclusions

The application of AI in breast cancer has entered a pivotal phase, transitioning from technical exploration to clinical implementation. The clinical value of AI has been demonstrated across multiple domains, including intelligent imaging diagnosis, digital pathology, treatment decision optimization, and prognosis prediction. AI is expected to extend across the entire continuum of breast cancer care with the in-depth use of technological innovation and growing clinical validation and cover the full cycle of breast cancer prevention, screening, diagnosis, treatment, and rehabilitation. AI will serve as a driving force in transforming breast cancer management in the long term, from standardized care to truly personalized and intelligent medicine. AI will have a key role in advancing national health goals and supporting the realization of the "Healthy China 2030" strategy by reducing disease incidence, improving survival outcomes, and enhancing quality of life.

Grant support

This work was supported by the National Natural Science Foundation of China (Grant No. 82404074) and the Science and Technology Major Project (Grant No. 2024ZD0519805).

Conflict of interest statement

No potential conflicts of interest are disclosed.

Author contributions

Conceived and designed the analysis: Zefei Jiang, Jianbin Li.
Collected the data: Jianbin Li.
Contributed data or analysis tools: Jianbin Li.
Performed the analysis: Jianbin Li.
Wrote the paper: Zefei Jiang, Jianbin Li.

Data availability statement

The data generated in this study are available upon request from the corresponding author.

References

1. Kim J, Harper A, McCormack V, Sung H, Houssami N, Morgan E, et al. Global patterns and trends in breast cancer incidence and mortality across 185 countries. Nat Med. 2025; 31: 1154-62.
2. Zeng H, Ran X, An L, Zheng R, Zhang S, Ji JS, et al. Disparities in stage at diagnosis for five common cancers in China: a multicentre, hospital-based, observational study. Lancet Public Health. 2021; 6: e877-87.
3. Howell MD, Corrado GS, DeSalvo KB. Three epochs of artificial intelligence in health care. JAMA. 2024; 331: 242-4.
4. Singhal K, Tu T, Gottweis J, Sayres R, Wulczyn E, Amin M, et al. Toward expert-level medical question answering with large language models. Nat Med. 2025; 31: 943-50.
5. Lotter W, Hassett MJ, Schultz N, Kehl KL, Van Allen EM, Cerami E. Artificial intelligence in oncology: current landscape, challenges, and future directions. Cancer Discov. 2024; 14: 711-26.
6. Eisemann N, Bunk S, Mukama T, Baltus H, Elsner SA, Gomille T, et al. Nationwide real-world implementation of AI for cancer detection in population-based mammography screening. Nat Med. 2025; 31: 917-24.
7. Dembrower K, Crippa A, Colón E, Eklund M, Strand F. Artificial intelligence for breast cancer detection in screening mammography in Sweden: a prospective, population-based, paired-reader, non-inferiority study. Lancet Digit Health. 2023; 5: e703-e11.
8. Luo L, Wu M, Li M, Xin Y, Wang Q, Vardhanabhuti V, et al. A large model for non-invasive and personalized management of breast cancer from multiparametric MRI. Nat Commun. 2025; 16: 3647.
9. Ramtohul T, Lollivier D, Spriet J, Jin M, Djerroudi L, Gaillard T, et al. Posttreatment MRI to predict pathologic complete response of triple-negative breast cancer to neoadjuvant chemoimmunotherapy. Radiology. 2025; 316: e243824.
10. Prelaj A, Miskovic V, Zanitti M, Trovo F, Genova C, Viscardi G, et al. Artificial intelligence for predictive biomarker discovery in immuno-oncology: a systematic review. Ann Oncol. 2024; 35: 29-65.
11. Vanguri RS, Luo J, Aukerman AT, Egger JV, Fong CJ, Horvat N, et al. Multimodal integration of radiology, pathology and genomics for prediction of response to PD-(L)1 blockade in patients with non-small cell lung cancer. Nat Cancer. 2022; 3: 1151-64.
12. Rakaee M, Tafavvoghi M, Ricciuti B, Alessi JV, Cortellini A, Citarella F, et al. Deep learning model for predicting immunotherapy response in advanced non-small cell lung cancer. JAMA Oncol. 2025; 11: 109-18.
13. Xiang J, Wang X, Zhang X, Xi Y, Eweje F, Chen Y, et al. A vision-language foundation model for precision oncology. Nature. 2025; 638: 769-78.
14. Wang X, Zhao J, Marostica E, Yuan W, Jin J, Zhang J, et al. A pathology foundation model for cancer diagnosis and prognosis prediction. Nature. 2024; 634: 970-8.
15. Somashekhar SP, Sepulveda MJ, Puglielli S, Norden AD, Shortliffe EH, Rohit Kumar C, et al. Watson for oncology and breast cancer treatment recommendations: agreement with an expert multidisciplinary tumor board. Ann Oncol. 2018; 29: 418-23.
16. Xu F, Sepúlveda MJ, Jiang Z, Wang H, Li J, Yin Y, et al. Artificial intelligence treatment decision support for complex breast cancer among oncologists with varying expertise. JCO Clin Cancer Inform. 2019; 3: 1-15.
17. Xu F, Sepúlveda MJ, Jiang Z, Wang H, Li J, Liu Z, et al. Effect of an artificial intelligence clinical decision support system on treatment decisions for complex breast cancer. JCO Clin Cancer Inform. 2020; 4: 824-38.
18. Li J, Zhou J, Wang H, Liu Z, Fan Z, Liu Y, et al. Trends in disparities and transitions of treatment in patients with early breast cancer in China and the US, 2011 to 2021. JAMA Netw Open. 2023; 6: e2321388.
19. Li J, Hao C, Wang K, Zhang J, Chen J, Liu Y, et al. Chinese Society of Clinical Oncology (CSCO) breast cancer guidelines 2024. Transl Breast Cancer Res. 2024; 5: 18.
20. Slamon D, Lipatov O, Nowecki Z, McAndrew N, Kukielka-Budny B, Stroyakovskiy D, et al. Ribociclib plus endocrine therapy in early breast cancer. N Engl J Med. 2024; 390: 1080-91.
21. Li J, Jiang Z. Establishment and its application of Chinses society of clinical oncology artificial intelligence decision system (CSCO AI). Chin J Med. 2020; 100: 411-5.
22. Li J, Yuan Y, Bian L, Lin Q, Yang H, Ma L, et al. A comparison between clinical decision support system and clinicians in breast cancer. Heliyon. 2023; 9: e16059.
23. Wu SY, Jin X, Liu Y, Wang ZY, Zuo WJ, Ma D, et al. Mobilizing antigen-presenting mast cells in anti-PD-1-refractory triple-negative breast cancer: a phase 2 trial. Nat Med. 2025; 31: 2405-15.
24. Kim H, Bae B, Park M, Shin Y, Ideker T, Nam H. A genotype-to-drug diffusion model for generation of tailored anti-cancer small molecules. Nat Commun. 2025; 16: 5628.
25. Kp Jayatunga M, Ayers M, Bruens L, Jayanth D, Meier C. How successful are AI-discovered drugs in clinical trials? A first analysis and emerging lessons. Drug Discov Today. 2024; 29: 104009.
26. Lekadir K, Frangi AF, Porras AR, Glocker B, Cintas C, Langlotz CP, et al. FUTURE-AI: international consensus guideline for trustworthy and deployable artificial intelligence in healthcare. BMJ. 2025; 388: e081554.
27. Teo ZL, Jin L, Li S, Miao D, Zhang X, Ng WY, et al. Federated machine learning in healthcare: a systematic review on clinical applications and technical architecture. Cell Rep Med. 2024; 5: 101419.
28. Wu BR, Ormazabal Arriagada S, Hsu TC, Lin TW, Lin C. Exploiting common patterns in diverse cancer types via multi-task learning. NPJ Precis Oncol. 2024; 8: 245.
29. Fang H, Zhang H, Vargas Bustamante A, Luo S, Chen X, Gao Y, et al. Regional disparities, economic development, and neonatal mortality and hospital delivery in China. JAMA Netw Open. 2024; 7: e2443423.
30. Abdulnour RE, Gin B, Boscardin CK. Educational strategies for clinical supervision of artificial intelligence use. N Engl J Med. 2025; 393: 786-97.

31. Reddy S. Generative AI in healthcare: an implementation science informed translational path on application, integration and governance. Implement Sci. 2024; 19: 27.
32. Subramanian HV, Canfield C, Shank DB. Designing explainable AI to improve human-AI team performance: a medical stakeholder-driven scoping review. Artif Intell Med. 2024; 149: 102780.
33. Yu KH, Healey E, Leong TY, Kohane IS, Manrai AK. Medical artificial intelligence and human values. N Engl J Med. 2024; 390: 1895-904.
34. Jia G, He P, Dai T, Goh D, Wang J, Sun M, et al. Spatial immune scoring system predicts hepatocellular carcinoma recurrence. Nature. 2025; 640: 1031-41.
35. Zhang H, Yang F, Xu Y, Zhao S, Jiang YZ, Shao ZM, et al. Multimodal integration using a machine learning approach facilitates risk stratification in HR+/HER2- breast cancer. Cell Rep Med. 2025; 6: 101924.
36. Sun R, Li X, Han B, Xie Y, Nie S. Multi-task learning for joint prediction of breast cancer histological indicators in dynamic contrast-enhanced magnetic resonance imaging. Comput Methods Programs Biomed. 2025; 267: 108830.
37. Putzier M, Khakzad T, Dreischarf M, Thun S, Trautwein F, Taheri N. Implementation of cloud computing in the German healthcare system. NPJ Digit Med. 2024; 7: 12.
38. Maddox TM, Embí P, Gerhart J, Goldsack J, Parikh RB, Sarich TC. Generative AI in medicine – evaluating progress and challenges. N Engl J Med. 2025; 392: 2479-83.
39. Aboagye SO, Hunt JA, Ball G, Wei Y. Portable noninvasive technologies for early breast cancer detection: a systematic review. Comput Biol Med. 2024; 182: 109219.

Cite this article as: Li J, Jiang Z. Artificial intelligence in breast cancer: applications and advancements. Cancer Biol Med. 2026; 23: 363-373. doi: 10.20892/j.issn.2095-3941.2025.0704