Communications Medicine

https://doi.org/10.1038/s43856-025-01342-3

Article in Press

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Received: 24 April 2025

Accepted: 15 December 2025

Cite this article as: Chua, B.N., Thng, D.K., Toh, T.B. *et al.* Artificial intelligence for breast cancer management. *Commun Med* (2025). https://doi.org/10.1038/s43856-025-01342-3

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Artificial Intelligence for Breast Cancer Management

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Abstract

Artificial intelligence is transforming breast cancer management through various machine learning applications. Artificial intelligence supports precision medicine by enhancing detection, diagnosis, prognosis, and treatment response prediction. It achieves this by analysing data from medical imaging, histopathology, genomics and multi-omics sources to improve patient recovery. This review summarises AI-driven advancements across the entire continuum of breast cancer management, spanning detection, diagnosis, prognosis, treatment and recovery. It evaluates their efficacy and limitations, explores their impact on healthcare costs and clinical practice, and addresses key challenges including generalisability, reproducibility and regulatory barriers. Evidence from recent studies highlights AI's role in improving breast cancer detection, molecular subtyping and prognostic accuracy. It also facilitates more patient-tailored therapeutic strategies and supports quality of life interventions. Nonetheless, the translation of these benefits into clinical practice requires rigorous validation, transparent model development, and equitable implementation.

Introduction

Breast cancer is the most commonly diagnosed cancer among women globally, with an estimated 2.3 million new cases reported in 2022. It is a complex and heterogeneous disease that can quickly develop into a metastatic, drug-resistant state[1]. Breast cancer is also the leading cause of cancer mortality among women with 666,000 deaths recorded in the same year[2].

Over recent decades, technological advancements have improved the detection and treatment of breast cancer. In particular, the adoption of artificial intelligence (AI) in medical imaging and therapeutics has enhanced breast cancer diagnosis and therapy planning, while reducing operational costs, time and labour[3–5]. AI refers to the use of computational methods that mimic human neural processes to process vast amounts of data and carry out tedious tasks, such as image recognition and predictive analyses. Within breast cancer care, the most widely applied techniques include machine learning, which builds predictive models by identifying patterns in data, and deep learning, which refers to a subset of machine learning that leverages neural networks to extract increasingly complex features from large datasets. These methods have demonstrated strength in medical imaging, pathology, and genomics, where high-dimensional inputs are difficult to interpret manually. A recent review encompassing more than 300 breast cancer AI studies has shown that performance varies substantially depending on algorithm

selection, with recurrent neural networks, transfer learning, and convolutional neural networks (CNNs) achieving higher accuracies compared to conventional machine learning methods, while decision trees often underperform due to overfitting[6].

In addition to machine learning and deep learning, which constitute the majority of current breast cancer AI research, it is important to note that generative AI represents a rapidly emerging field. Based on the input information it receives, generative AI can create new content, including text and images. To date, however, its applications in breast cancer care remain limited and largely restricted to diagnosis[7]. Several of its applications such as image augmentation[8,9] and drug discovery[10], also fall outside the primary scope of this review. Therefore, the use of generative AI tools is only briefly acknowledged within this review.

In the area of medical imaging, the use of AI in mammograms[11], tomosynthesis[12], magnetic resonance imaging (MRI)[13] and ultrasound[14] has improved the accuracy and speed of breast cancer detection, as compared to manual readings by radiologists. The use of AI in histopathology has also enhanced the grading and subtyping[15], and prognosis of breast cancer[16]. In the area of breast cancer therapeutics, AI has advanced the prediction of treatment response[17], the accuracy of precision medicine[18], and the recovery of patients[19].

Along with the numerous applications of AI in breast cancer management, it is also important to consider the impact of AI. Besides the direct impact of improving breast cancer diagnosis and therapy, AI is predicted to bring about significant cost savings in breast cancer management and in the healthcare industry as a whole[20,21]. The use of AI in breast cancer management will also affect the role of healthcare practitioners including

but not restricted to physicians and radiologists. At present, AI is not operating at a level where it can completely replace these healthcare practitioners. Instead, AI can complement them by performing specific time-consuming and tedious tasks, allowing healthcare practitioners to work more efficiently[22,23].

Our review provides a clinically focused synthesis of AI applications across the entire breast cancer care continuum, offering a holistic perspective that extends beyond what is typically available in domain-specific reviews. In addition to mapping this broad scope, we present a more methodologically transparent comparison of existing studies. Beyond performance outcomes, we also examine the datasets and strategies employed to train and validate the AI systems. We further assess whether the datasets and algorithms are publicly accessible or proprietary. By doing so, the review highlights issues of reproducibility and openness that are often overlooked. Finally, we expand the discussion beyond technical considerations to address barriers to implementation, including the challenges faced in low-resource settings. These contributions are summarised in **Box 1** and together, they provide an integrated and critically appraised perspective that offers clinicians, researchers, and policymakers a consolidated, practice-oriented resource for understanding how AI innovations can be translated into equitable and sustainable breast cancer care.

Treatment Phases

This review categorises the use of AI in breast cancer management into 3 phases – pre-treatment, treatment and post-treatment, as shown in **Fig. 1**. In the pre-treatment phase, detection, diagnosis, and prognosis represent distinct but interconnected phases of care. Detection refers to the identification of suspicious breast lesions, most commonly through

population-based screening modalities such as mammography. Diagnosis follows detection and involves confirming malignancy and characterising tumour grade and subtype through histopathology or molecular assays. Prognosis addresses the anticipated course of disease, including risk of recurrence, likelihood of treatment response and long-term survival outcomes. Specific uses of AI in the pre-treatment phase of breast cancer management are summarised in **Table 1** and **Supplementary Table 1**. In the second phase, patient samples may be obtained and tested with the goal of improving treatment. This testing can include predicting response to treatment and identifying precision medicine strategies. Specific uses of AI in the treatment phase of breast cancer management are summarised in **Table 2** and **Supplementary Table 2**. In the final phase, post-treatment focuses on the enhancement of patient recovery. This mainly involves interventions targeting quality of life (QoL) measures. Additionally, patient recovery can also be influenced by the aesthetic outcome of breast surgery. Specific uses of AI in the post-treatment phase of breast cancer management are summarised in **Table 3**. The process of selecting the studies to be included in this review is outlined in **Supplementary Methods** and **Supplementary Figure 1**.

Role of AI in Pre-treatment Phase

Detection

Early detection of breast cancer is crucial to plan timely treatment, prevent unnecessary biopsies, and reduce the mortality associated with this disease. The detection of breast cancer begins with non-invasive imaging techniques. Mammograms are the most commonly used imaging method for breast cancer screening and detection[24,25]. Mammography uses low dose X-rays to construct images of the breast, whereby

cancerous lesions appear as bright spots. Over time, mammograms have developed from 2-dimensional (2D) to 3-dimensional (3D) tomosynthesis, and from analogue screen-films to digital images. In traditional screening workflows, radiologists double-read mammograms, a process that is time-consuming and subject to reader variability, resulting in significant false positive and false negative rates[26,27]. AI-enhanced workflows, by contrast, offer automated triage, reduce unnecessary recalls, and shorten interpretation times, thereby alleviating workforce pressures while maintaining or improving accuracy.

Through the use of large datasets to train and test AI algorithms, these imaging techniques have been advanced and, in some cases, automated for the detection of breast cancer[28]. Initial attempts at automating mammograms involved using computer-aided detection (CADe) and computer-aided diagnosis (CADx) algorithms. These algorithms normalised images to a reference and identified suspected breast cancer lesions based on specific programmed-in features that were determined by human experts[29–36].

Currently, AI algorithms, specifically deep learning CNNs, have removed the need for human-determined programmed-in features[37]. By using large datasets of labelled mammogram images, supervised AI-based systems can train themselves to identify features that distinguish images with and without cancerous lesions, in the absence of explicit human guidance. These AI-based systems have been investigated in different formats such as reader replacements for radiologists or integrated decision support tools in standard double reading programs. Several retrospective studies evaluating the efficacy of these AI-based systems in mammography have shown that they can perform

on par or better than radiologists using metrics such as Area Under the Receiver Operating Characteristic Curve (AUROC), sensitivity and specificity[38–46]. In some cases, AI was shown to be able to detect interval cancers that were previously missed out by radiologists, demonstrating AI's superior performance[47–49]. However, as retrospective studies, the results from these studies do not directly benefit the women whose data was used to train and test the AI systems. More importantly, retrospective evidence cannot fully capture real-world effectiveness and thus, should be interpreted as proof-of-concept rather than definitive clinical validation[50].

Presently, there have only been 4 prospective studies in Europe, which have shown that AI can improve detection in mammogram screening[51–54]. The Mammography Screening with AI (MASAI) trial (NCT04838756) reported a 44.3 % decrease in screen-reading workload with the Transpara AI-supported screening[51]. A study by Ng et al. showed 5 – 13 % relative increase in cancer detection rate, with minimal to no unnecessary recalls, using the Mia AI-assisted double reading[39]. The ScreenTrustCAD study (NCT04778670) reported a non-inferior cancer detection rate compared to radiologist double reading, with the Insight MMG AI-paired reading[53]. The Prospective Multicentre Observational Study of an Integrated AI System with Live Monitoring (PRAIM) showed a 17.6 % increase in cancer detection rate, using the Vara MG AI-supported double reading[54]. Despite these encouraging results, translating AI models into clinical practice remains challenging. Recent work shows that although deep learning tools can improve accuracy, external validation often reveals performance variability and difficulties in workflow integration[55]. Similarly, evaluations of AI-based breast density classification models highlight variability between radiologists and AI predictions, illustrating that consensus ground-truth and

prospective validation are essential before the widespread use of AI in breast imaging modalities[56].

In comparison to AI applications in mammography, there have been fewer AI-based systems developed for digital breast tomosynthesis[39]. This reflects the less common use of digital breast tomosynthesis in breast cancer screening. One main reason that accounts for this difference is the significantly longer reading time that is associated with digital breast tomosynthesis[57–60]. This has prompted studies to investigate the impact of AI-assisted digital breast tomosynthesis on reading times. Several retrospective studies have shown that AI-assisted digital breast tomosynthesis can achieve decreased reading times, ranging from 3 – 33.7 second-reductions, compared with unassisted digital breast tomosynthesis [61–65]. In addition to reducing reading times, AI in digital breast tomosynthesis has also shown other benefits such as increased accuracy in cancer detection, decreased workload, decreased recall rates and decreased radiation dose[66,67]. However, more prospective studies are needed to truly evaluate the impact of AI on digital breast tomosynthesis in breast cancer detection.

Besides the standard use of mammograms and tomosynthesis, other non-invasive imaging techniques such as MRI and ultrasound may be used for breast cancer detection. These techniques are usually used as supplemental methods when initial findings are inconclusive[68]. They are also used for women with very high risk of breast cancer or for women with dense breast tissue which could mask breast cancer lesions[69,70]. In contrast to mammography which uses ionising radiation, MRI employs a magnetic field and radio waves, and ultrasound employs sound waves.

As with the use of AI in mammograms, the use of AI in MRI seeks to enhance its performance[71]. Indeed, when compared to radiologists' readings, some AI-based MRI systems have been shown to possess greater accuracy. In a study by Jiang et al., radiologists guided with an AI system showed increased AUROC from 0.71 to 0.76 along with higher sensitivity[72]. Another study utilising a 3D CNN multimodal fusion framework, which processes all available MRI data instead of only a single volume, achieved an AUROC of 0.778[73]. Witowski et al. used a deep learning system which had higher AUROC than radiologists, 0.924 vs. 0.890 respectively[74]. This improvement in accuracy in turn, has the potential to reduce unnecessary biopsies. Besides improving accuracy, deep learning has been employed in an MRI CADe system to automate the breast cancer detection process with improved sensitivity, using only early-phase scans[75]. Deep learning has also enabled the simulation of contrast-enhanced T1-weighted breast MRI scans from 5 pre-contrast MRI sequences from a training set of 96 patients. A multi-reader study was used to validate 22 of the simulated MRI scans where all of them were assessed to look like a real MRI scan. This simulation removes the need of administering a gadolinium contrast agent and monitoring by a physician, while achieving the same accuracy as a real contrast-enhanced MRI[76]. While these retrospective evaluations demonstrate strong performance, methodological concerns must be acknowledged. Retrospective designs are limited by data insufficiency, lack of local annotations, and restricted generalisability, particularly in 3D imaging contexts such as MRI[77].

The use of AI in ultrasound imaging for breast cancer has seen similar effects in terms of non-inferior or improved performance compared to radiologists. For instance, deep learning CNNs have been used to develop a system with 97.18 % classification accuracy

in distinguishing breast ultrasonic images between normal, benign and malignant states[78]. Similarly, Yan et al. used deep learning to develop the Multimodal Ultrasound Prototype Network (MUP-Net) which distinguished between benign and malignant breast cancer with an AUROC of 0.902, sensitivity of 75.2 % and specificity of 91.8 %, which were comparable to radiologists' performance[79]. Among patients with benign breast lesions, deep learning has enabled more accurate sub-classification between high-risk and low-risk lesions. This is evidenced by higher AUROC using the Ensemble Deep Learning-Breast Cancer (EDL-BC) model compared to radiologists, 0.945 vs. 0.716[80]. This demonstrates the potential of an AI system to reduce the number of invasive biopsies in patients with benign breast lesions. Furthermore, deep learning in the form of Clearview Diagnostics' cCAD software, renamed to Koios DS, has also been used in automated breast ultrasound imaging to improve sensitivity and positive predictive value (PPV), and reduce inter-operator variability[81]. Comprehensively, the use of AI in mammograms, tomosynthesis, MRI and ultrasound imaging can improve the accuracy of breast cancer detection significantly in the clinic.

Diagnosis

After the detection of a cancerous breast lesion, breast cancer is diagnosed based on the tumour grade and subtype. This can be done using information obtained from genomic and transcriptomic profiling or from histopathology slides. With genomic and transcriptomic profiling, sequencing data or quantitative real-time reverse transcription polymerase chain reaction (qRT-PCR) data of breast cancer related genes can be obtained[82]. Such information can be fed into AI algorithms to distinguish between breast cancer subtypes. For instance, machine learning has been used to distinguish between

triple-negative breast cancer (TNBC) and non-TNBC with an accuracy of up to 86 %, based on the expression levels of 5502 genes[83]. However, genomic and transcriptomic profiling is costly and not routinely adopted in all clinical settings.

As a more common and affordable diagnostic method, histopathology slides are used. These slides can be analysed via hematoxylin and eosin (H & E) staining to assess tissue morphology, and immunohistochemistry (IHC) to characterise biomarker expression. Conventional histopathology depends heavily on manual microscopy which is not only time-consuming but also prone to inter-observer variability[84]. Both H&E and IHC slides are typically scanned into whole slide images (WSIs), which form the foundation of digital pathology. These digitised images can then be used for storage, sharing, and computational analysis. Furthermore, this has enabled AI-based digital pathology tools to assist pathologists by automating tasks. These tools have the capacity to accelerate slide review, support consistent grading and biomarker scoring, and enable integration of multi-omic data, which are difficult to synthesise manually[15].

One group developed a deep learning CNN approach to model the Predictor Analysis of Microarray 50 (PAM50) intrinsic molecular subtype using H & E-stained WSIs from a training set of 443 patients. They achieved an overall accuracy of 65.92 %, with a highest accuracy of 87 % for the basal subtype[85]. While there is room for improvement in terms of accuracy, this approach was able to detect multiple cases of significant intratumoural heterogeneity within a single WSI. This evidence of intratumoural heterogeneity could have different prognostic implications on survival for patients with the same breast cancer subtype.

Cruz-Roa et al. developed ConvNet classifier, an automated deep learning CNN approach to quantify the extent of invasive breast cancer in digitised WSIs. The ConvNet classifier was trained and tested on WSIs from 349 and 195 Estrogen Receptor (ER)-positive invasive breast cancer patients respectively[86]. The classifier possessed a PPV of 0.7162 and a negative predictive value (NPV) of 0.9977, compared to manual evaluation of invasive ductal carcinoma by pathologists, indicating high overall accuracy. However, some regions of *in situ* carcinoma were misclassified as invasive breast cancer, suggesting the classifier is not without its limitations.

Couture et al. developed a deep learning CNN approach to predict several factors such as breast cancer grade, intrinsic subtype, histologic subtype, ER status, and risk of recurrence score using H & E-stained histologic images[87]. This approach achieved at least 75 % accuracy across all the classifications, with 82 % accuracy for low-intermediate vs. high tumour grade, and 77 % accuracy for basal-like vs. non-basal-like subtype. Similarly, Bae et al. developed a deep learning-based platform, 3DHistoNet, to predict breast cancer subtype by identifying 5 biomarkers – Ki-67 index, ER, Progesterone Receptor (PR), Androgen Receptor (AR) and Human Epidermal Growth Factor Receptor 2 (HER2) from z-stacked H & E-stained WSIs from 401 breast cancer patients. This 3D platform possessed a higher AUROC compared to a 2D model, 0.75 – 0.91 vs. 0.67 – 0.83[88]. By incorporating AI in the analysis of H & E-stained slides, these methods can also save the time and cost associated with IHC staining.

In invasive breast cancer cases, machine learning has also been used to automate the detection of HER2 amplification in chromogenic *in situ* hybridization (CISH) WSIs. This approach required less labour and time, while maintaining the same level of accuracy as

manual quantification by pathologists[89]. However, this system was only tested on 22 cases so further testing with a larger dataset is needed to validate the findings.

Apart from the standard diagnostic methods using genomic testing and histopathology slides, novel innovative approaches are being explored for breast cancer diagnosis. One such method is the integration of AI algorithms with nanotechnology and nanomedicine[90]. For example, Yang et al. has developed an electric nose composed of carbon nanotube sensors to detect volatile metabolites from patients' breath. These metabolites differ between patients with breast cancer, patients with other types of cancers and healthy individuals. In combination with random forest modelling, the electric nose showed a 91 % accuracy in diagnosing breast cancer non-invasively[91]. Alafeef et al. has developed a carbon nanoparticle platform with multifarious surface chemistries[92]. The different structural properties of the nanoparticles led to different cellular internalisation responses by breast cancer cells. Consequently, different breast cancer cell types showed different responses to the nanoparticle platform. In combination with an artificial neural network algorithm, the platform showed an accuracy of 98.1 % in distinguishing between 5 breast cell lines. With more clinical testing and fine-tuning, these innovative approaches have the potential to simplify the diagnosis of breast cancer.

Prognosis

Prognosis not only complements the diagnosis of breast cancer, it also provides more information about the likely progression or relapse of the disease. Prognostic evaluation has traditionally relied on clinicopathological features and gene expression panels, whereas AI approaches can incorporate histopathology slide images, radiomics, and multi-omics to provide more granular and scalable predictions of recurrence risk.

Morphological features of both the tumour cells and the cells in the tumour microenvironment (TME) can be identified and analysed by computerised systems to provide prognostic information. For example, a deep learning model, DeepGrade (DG), was developed to analyse H & E-stained WSIs of breast cancer patients with Nottingham histological grade (NHG) 2 prognostic grading[93]. NHG 2 represents an intermediate risk group in which patients have moderately differentiated cancer cells, prompting further risk stratification by Wang et al. The model showed that the DG2-high group possessed a higher risk of recurrence compared to the DG2-low group, with a hazard ratio (HR) of 1.91 and 2.94 in 2 separate test groups.

Deep learning was also used to assess the nuclear morphology of epithelial and stromal cells from ER-positive breast cancer histopathology slides[94]. Subsequently, machine learning was used to categorise the images using a predicted Oncotype DX risk score, which indicates the risk of recurrence. With a classification accuracy of 76 – 85 %, this predicted risk score could aid in deciding whether to prescribe adjuvant chemotherapy for ER-positive breast cancers.

Using a similar approach, Li et al. utilised a deep learning model to identify nuclei in WSIs of ductal carcinoma *in situ*. Based on histomorphometry features such as shape, arrangement and texture of the identified nuclei, machine learning was used to predict the Oncotype DX risk scores of the images[95]. With AUROC of 0.57 – 0.68, this prognostic model has potential but can be developed further to improve its accuracy.

Additionally, Romo-Bucheli et al. used a deep learning model to quantify mitotic nuclei in WSIs of ER-positive breast cancer[96]. Based on the quantified mitotic count, a support vector machine classifier was subsequently used to categorise the images into low and

high predicted Oncotype DX risk scores. This classifier possessed an accuracy of 83.19 %, demonstrating its prognostic value in advising treatment selection for patients with different risk scores.

In ductal carcinoma in situ (DCIS), nuclear morphology is also often used to characterise disease stage and determine prognosis. However, DCIS patients exhibit heterogeneity in terms of nuclear shape and tissue morphology which limit the reliability of nuclear morphology as a prognostic biomarker. To address this limitation, Zhang et al. utilised unsupervised representation learning on a tissue microarray of Hoechst-stained chromatin images[97]. They identified 8 distinct cell states which were present in both normal and cancerous breast tissues. Interestingly, the proportion and spatial organisation of these 8 cell states were found to be predictive of disease stage, illustrating the potential of using chromatin images as a prognostic biomarker in DCIS.

Besides using nuclear morphology as the main input factor, Ki-67 index has also been used to predict Oncotype DX risk scores in early stage, hormone receptor-positive, HER2-negative breast cancer. Thakur et al. utilised an automated image analysis system to score Ki-67 in H & E-stained slides, followed by a machine learning model to predict the Oncotype DX risk score[98]. The automated scoring system showed high concordance with manual scoring by a pathologist and the model had a 97 % accuracy, 98 % sensitivity and 80 % specificity in distinguishing low-risk and high- risk patients.

In a study by Basavanhally et al., it was demonstrated that machine learning can be used to identify and grade the degree of lymphocytic infiltration in HER2-positive breast cancer histopathology slides[99]. With a 90 % accuracy, this system could potentially be used to

stratify for HER2-positive breast cancer patients with low lymphocytic infiltration and poor prognosis.

Another way that AI algorithms have been used in breast cancer prognosis is by analysing existing genomic, transcriptomic and metabolomic data. For instance, machine learning was used to develop a breast cancer stem cell (BCSC)-related risk score, based on prognostic BCSC genes[100]. In combination with clinical factors such as age, cancer stage and gender, the BCSC risk score had AUROC of 0.746 – 0.805 for predicting survival. Furthermore, the model showed that a subpopulation of BCSCs, $CD79A^{+}CD24^{-}PANCK^{+}$-BCSCs, was associated with poor prognosis. This subpopulation of BCSCs could potentially exhaust neighbouring $CD8^{+}FOXP3^{+}$ T cells, thereby creating an immunosuppressive TME that contributes to reduced survival. Accordingly, this specific BCSC-T cell axis could be targeted to sensitise breast cancer patients with a high $CD79A^{+}CD24^{-}PANCK^{+}$-BCSC subpopulation to immunotherapy.

In a study by Xiao et al., machine learning was applied on metabolomic data to develop a risk model to stratify patients with basal-like immune-suppressed (BLIS) TNBC into high or low recurrence risk groups[101]. Within the high-risk group, further experiments showed that N-acetyl-aspartyl-glutamate was a potential therapeutic target. Together, these prognostic AI models demonstrate the potential to enhance patient stratification for subsequent treatment planning.

Role of AI in Treatment Phase

Prediction of Treatment Response

Beyond diagnosis and prognosis, treatment planning is a key component of breast cancer care. In predicting treatment response, traditional workflows rely on clinicopathological markers such as tumour size, nodal involvement, grade, and receptor status to guide therapeutic decisions. While these indicators are clinically useful, they lack precision at the individual level, often resulting in overtreatment or undertreatment. AI-enhanced workflows, by contrast, integrate clinical, demographic, digital pathology, genomic, transcriptomic and treatment type data to build predictive models that estimate the likelihood of pathological complete response or residual disease with greater accuracy (**Fig. 2A**). These approaches enable more individualised therapy selection, reducing unnecessary toxicity for non-responders and optimising outcomes for patients most likely to benefit. By leveraging on AI systems, several studies have shown adequate performance in predicting pathologic complete response to neoadjuvant therapy in breast cancer, measured by AUROC of 0.74 – 0.93[102], 0.83 – 0.87[103], 0.87[104], 0.896 – 0.903 for a deep learning radiomics nomogram (DLRN-PCR)[105] and 0.91 for SimBioSys' TumorScope Predict platform[106].

Other types of post-treatment outcome metrics have also been used in AI-based predictive models in breast cancer. In addition to predicting pathologic complete response, Gu et al. also developed a deep learning radiomics nomogram to predict lymph node metastasis (DLRN-LNM) in response to neoadjuvant therapy, with AUROC of 0.853 – 0.863[105]. Another study developed a survival prediction model with AUROC of 0.98 and a half-maximal inhibitory concentration (IC_{50}) drug response prediction model with mean square error (MSE) of 1.154 and an overall regression value of 0.92[107]. Park et al. developed a deep learning model, Nested Systems in Tumours-Visible Neural Network

(NeST-VNN), to predict sensitivity to CDK4/6 inhibitor treatment. For patients treated with a CDK4/6 inhibitor such as palbociclib, those who were predicted to be sensitive showed a longer duration of survival than those who were predicted to be strongly resistant, with a HR of 0.21[108]. A model to predict cardiotoxicity in response to anthracycline treatment was also developed by a separate study. The model showed AUROC of 0.66 for predicting breast cancer therapy-related cardiac dysfunction and 0.81 for predicting symptomatic heart failure with reduced ejection fraction[109]. Altogether, these various predictive models illustrate the therapeutic potential to guide treatment planning for breast cancer with increased accuracy.

Precision Medicine

Given the complex and heterogeneous nature of breast cancer, treating patients safely and effectively remains a challenge. As a result, it is common in clinical settings to see patients coming back with refractory metastatic breast cancer after several lines of treatment, especially for patients with the TNBC subtype[110]. One emerging strategy to address this challenge is to use precision medicine. Conventional approaches in precision medicine are anchored in targeted biomarker testing and fixed gene expression panels such as Oncotype DX, which stratify recurrence risk and inform therapeutic decisions. Although effective, these tools assess a limited number of molecular features and provide static insights that may not fully capture tumour heterogeneity. Beyond interrogating a patient's unique genetic and molecular signatures[111], AI-enhanced precision medicine leverages empirical data from ex vivo drug testing to predict drug sensitivity, identify novel therapeutic combinations, and adapt treatment strategies in real time. This shift allows for

a more dynamic and comprehensive personalisation of care, ensuring that treatment is tailored to each patient (**Fig. 2B & C**).

Many studies have developed and investigated the use of AI-based models to optimise drug combination selection[112]. The purpose of identifying effective drug combinations is to leverage the potentially synergistic effects between the drugs, overcoming resistance to monotherapy, leading to lower doses and toxicity[113]. The various machine learning algorithms that have been used to determine the best drug combinations include random forest[114], extreme gradient boosting[115,116], extremely randomised tree[117], tensor factorisation[118], feed-forward neural networks[119–122], autoencoder[123], stacked restricted Boltzmann machine[124] and graph convolutional networks[125,126]. However, these studies were mostly conducted using breast cancer cell lines and therefore, are not specific to individual patients.

Moving from the use of cell lines to patient samples, several AI-based models have been developed to predict the best drug combination to treat cancers. One example is the computational-experimental Drug Combination Prediction and Testing (DCPT) platform[127]. To predict synergistic drug combinations, DCPT utilises exome sequencing data, RNA sequencing data, single drug responses in ex vivo patient samples and a network pharmacology-based machine learning model. In 3 patients with T-cell prolymphocytic leukemia, 10 out of 24 DCPT-predicted synergistic drug combinations were experimentally validated using ex vivo patient samples. However, there is currently no reported evidence that the DCPT platform has been used for breast cancer patients.

Another example of a patient-centric AI-based prediction model is Quadratic Phenotypic Optimization Platform (QPOP), which uses an orthogonal-array composite design, a

linear regression model and minimal tumour biopsy samples. This model has optimised effective drug combinations in ex vivo patient samples in hepatocellular carcinoma[128] and multiple myeloma[129]. Moreover, the results from this model have also been translated to the clinic. 6 patients with refractory lymphoma who were treated with the QPOP-guided drug combination subsequently experienced a complete response[130,131]. Currently, there is a phase I clinical trial (NCT05177432) to determine the feasibility of using QPOP to guide drug combination treatment in breast cancer patients.

To personalise treatment dosages, an AI-based prediction model called CURATE.AI has been developed. Unlike most other AI-based prediction models, CURATE.AI does not require a large patient dataset for training. Instead, it only requires the pre-existing drug dose information from an individual patient to generate a personalised treatment profile. Using quantifiable biomarker levels such as tumour size and circulating tumour DNA, CURATE.AI can determine the optimal drug dose while minimising toxicity[132]. Furthermore, this N-of-1 model is dynamic which means that it can be used to adjust dosage levels during the course of treatment. To date, CURATE.AI has been investigated in several clinical trials involving cancer patients (NCT04522284, NCT05175235 and NCT03759093). Notably, it was successfully used to adjust the drug doses of enzalutamide and ZEN-3694 for a patient with metastatic prostate cancer, resulting in reduced prostate-specific antigen levels and lesion size[133]. Furthermore, CURATE.AI-guided dosing also demonstrated reduced adverse events, suggesting improved safety and drug tolerance. In the context of breast cancer, a clinical trial (NCT05381038) evaluating the use of QPOP in combination with CURATE.AI is currently in progress.

Apart from optimising drug treatment, AI can also be used to aid in genetic testing for breast cancer patients. Results from genetic testing can greatly impact subsequent treatment options. This makes pre-test genetic education or counselling important to ensure that patients can make informed treatment decisions. In addition, genetic education can help to advise patients on the potential implications for family members who share the same genes. Experts at Johns Hopkins University and OptraHEALTH developed an AI conversational virtual assistant on the HealthFAX platform to provide tailored genetic education to patients[134]. To study the performance of this AI tool, 39 patients who were receiving active treatment for breast cancer used the tool at home. All the patients reported that the tool provided valuable information and was easy to use. However, there was no comparison to in-person genetic education.

A study by Al-Hilli et al. went a step further by comparing their genetic counselling AI chatbot to a certified genetic counsellor in a randomised controlled trial[135]. 37 newly diagnosed breast cancer patients took part in this study. The results revealed that there was no significant difference in the patient satisfaction score and the knowledge score between the AI chatbot and the genetic counsellor. This indicated that the AI chatbot performed on par with the genetic counsellor in terms of patient satisfaction and comprehension, demonstrating the potential of AI to provide precise genetic education or counselling during breast cancer treatment.

Role of AI in Post-treatment Phase

Patient Recovery

In patient recovery, standard workflows depend on periodic follow-up visits and clinician-reported outcomes, which can delay recognition of complications or declines in quality of life between scheduled assessments. AI-enhanced recovery workflows incorporate wearable sensors, mobile health platforms, and conversational agents to continuously monitor physiological and behavioural signals, detect emerging QoL issues, and provide personalised recommendations. This proactive model enables earlier interventions, reduces unplanned hospital visits, and empowers patients to play a more active role in managing their recovery trajectory.

After treatment, some breast cancer patients may respond successfully and consequently be in remission or cancer-free. However, these patients still need to recover from the physical, psychiatric and emotional effects of surgery and drug treatment. These effects may be detrimental to the patients' QoL, especially when they are not adequately addressed[136]. Currently, there are many web-based and app-based digital therapeutics being developed to aid in patient recovery and improve QoL[19]. These digital therapeutics recommend and provide lifestyle interventions to patients in the form of physical activity[137–139], support for anxiety[140], depression[141], mental and sexual health[142] or a combination of physical and psychological interventions[143,144]. However, most of these digital therapeutics do not incorporate AI in their software. As such, the potential benefits of AI-based digital therapeutics remain largely untapped.

One potential benefit of AI-based digital therapeutics may be observed in the Artificial intelligence Supporting Cancer Patients across Europe (ASCAPE) clinical trial (NCT04879563). Based on breast cancer patient data from apps, questionnaires, medical records and wearables, the ASCAPE platform utilises machine learning algorithms to predict 15 QoL issues such as anxiety, depression, negative body image and sexual health[145]. Furthermore, the ASCAPE platform also recommends interventions to clinicians based on these QoL predictions. The results of this study are currently unavailable as the trial is still ongoing. Therefore, more time is needed before accurate conclusions can be made about this platform.

Another potential benefit of AI-based digital therapeutics may be observed in the Cuidados Más Allá del Cáncer-Mama (CUMACA-M) randomised controlled trial (NCT05322460). CUMACA-M is a web program that utilises AI to provide personalised interventions to long-term breast cancer survivors[146]. These interventions aim to improve the spiritual, physical, social and psychological aspects of QoL, as well as self-management of cancer sequelae. However, the results of this trial have not been published since its estimated completion date in June 2024. As such, the true efficacy of this program in improving QoL remains questionable.

Another aspect of patient recovery is patient satisfaction with the aesthetic outcome of breast surgery. Depending on the severity of the cancer and other risk factors, patients may be offered different treatment choices, including the type of surgery – mastectomy, lumpectomy (standard breast-conserving surgery), or oncoplastic breast-conserving surgery, which maintains the natural breast contour. While standard breast-conserving surgery offers safer margins than oncoplastic breast-conserving surgery, it is also

associated with poorer patient satisfaction in terms of aesthetic outcome[147]. This may lead to patients experiencing a negative body image and lowered QoL[148]. To help patients decide on the type of treatment, the Comparing Decision on Aesthetics After Breast Cancer Locoregional Treatment (CINDERLLA) clinical trial (NCT05196269) was established. The CINDERELLA trial employs an AI web-based platform that provides patients with information regarding the different treatments and surgeries offered. Using the patients' own pre-treatment images, it also generates the possible aesthetic outcomes associated with each treatment[149]. With an estimated study completion date in 2026, it is currently too early to ascertain if this platform can effectively assist patients in making more informed decisions about their treatment, improve QoL and decrease the need for supplementary breast surgeries to improve aesthetic outcome.

Breast reconstruction surgery is another important factor that is associated with body image and QoL. This surgery helps patients to achieve a more satisfactory post-treatment aesthetic outcome, which contributes to enhanced recovery. There are several breast reconstruction surgeries available, including the deep inferior epigastric artery perforator (DIEP) flap, which is the most common free flap method. In preoperative planning, computed tomography angiography (CTA) images of the vascular anatomy of the DIEP are taken. However, analysing these images is a time-consuming and labour-intensive process even for experts[150]. AI has the potential to improve the pre-operative planning of DIEP flap surgery. By using computer vision techniques to automate the detection of perforator vessels in CTA images, Mavioso et al. have reduced the analysis time from 2 hours to 30 minutes[151]. This demonstrates the ability of AI to decrease the workload of healthcare professionals, allowing them to provide better care to patients. With further

applications, AI could potentially improve the accuracy and robustness in the preoperative planning of breast reconstruction surgeries.

Impact of AI on the Cost of Healthcare

In this review, we have shown that various AI applications have been developed and tested for use in breast cancer management. This extensive use of AI can be largely attributed to the attractive benefit of improved accuracy in detection and treatment. In addition, other benefits of AI include reductions in analysis times, labour-intensive processes and invasive procedures such as biopsies. In theory, these benefits should translate to cost savings for both healthcare providers as well as patients. Accenture, a global professional services company, estimated that AI could save up to US$150 billion in the US healthcare industry annually by 2026[21]. Furthermore, the US National Bureau of Economic Research estimated even greater cost savings of US$200 billion to US$360 billion annually from 2019 in the US healthcare industry[20].

More specifically, in areas that are related to breast cancer management, AI has been predicted or modelled to achieve cost savings in mammogram screening[152–154], MRI[155], avoiding unnecessary biopsies[156], diagnosis and treatment[157], as detailed in **Table 4**. For instance, traditional mammograms are prone to false positive results, which incur additional costs due to follow-up testing. Chubak et al. reported the cost of breast-care services for each false positive case to be $507 in 2010[158] while Ong and Mandl reported it to be $852 in 2015[159]. Furthermore, in the US, the cost of false positive mammograms and subsequent overdiagnoses has been estimated to be $4 billion annually[159]. With more accurate AI-based mammograms and detection systems, false positive cases can potentially be reduced, leading to significant cost savings.

Despite these estimated and predicted figures, there is a lack of information available about the real cost savings that AI provides in the overall healthcare industry and in breast

cancer management. In fact, a systematic review by Wolff et al. in 2020 showed that only 6 out of 66 identified publications assessed the economic impact of AI in healthcare settings[160]. Additionally, these 6 studies did not include information about the initial investment in the AI system, the operational costs of AI system and any alternatives to the AI system used.

Impact of AI on Healthcare Practitioners

The increasing use and evolution of AI has sparked discussions over its potential impact on jobs. Specifically, in the healthcare industry, there are major concerns regarding the impact of AI on the role of healthcare practitioners such as doctors, nurses and pathologists[22,23,161,162]. Initially, it was broadly speculated that AI would replace healthcare practitioners. Instead, with the current state of AI, it is more widely held that healthcare practitioners who use AI would replace those who do not use AI. By collaborating together, AI and healthcare practitioners have immense potential to improve outcomes for patients[163]. AI can complement healthcare practitioners by being used to analyse large datasets with greater speed and accuracy[164]. In addition to accuracy, the way AI communicates its findings to clinicians has a significant impact on adoption. A recent study on personalised AI communication in breast cancer imaging showed that assertiveness-based AI agents reduced diagnostic time by over a third and lowered error rates, particularly among less experienced clinicians, without compromising accuracy[165]. Clinicians also expressed a preference for AI systems that provide detailed contextual explanations rather than numerical outputs, underscoring the importance of adaptive communication styles for building trust, reducing cognitive load, and streamlining clinical workflows.

Healthcare practitioners would then come in to monitor the AI systems and interpret the results in the relevant context[166]. Next, healthcare practitioners would need to communicate the results to patients. This communication process involves a unique human touch encompassing empathy and nuance, which is difficult for AI to emulate[167,168]. Importantly, healthcare practitioners should provide oversight by looking out for errors and providing feedback to improve the performance of the AI systems. In resource-poor settings where there is a lack of trained and skilled healthcare practitioners, AI systems could serve as a useful tool to enable more inclusive access to healthcare[169]. Ultimately, healthcare regulatory organisations should be responsible for ensuring that adequate training and infrastructure are in place to facilitate effective collaboration between man and machine[170].

Similarly, the use of AI in imaging technologies has prompted discourse on the role and relevance of radiologists. At first glance, a commonly held notion is that radiologists would be made redundant and that AI would replace them in detecting cancers or diseases in general[171–173]. Upon closer inspection, the current consensus is that AI would not replace radiologists but instead serve as a complementary tool alongside radiologists[174–179]. AI would likely alter how radiologists practice their work and reshape their role in the healthcare industry. For example, instead of having 2 independent radiologists interpret an image, 1 radiologist may be aided with an AI decision support system to do the same job more quickly and accurately[79]. Alternatively, AI may be used as an initial triage method to screen mammogram images and radiologists would follow up on positive or uncertain cases[46]. Just as how radiology images developed from analogue to digital forms in the past, this change can be regarded as the next step of technological advancement in

radiology. Radiologists who embrace AI and adapt to the associated changes will likely be in a better position than radiologists who are sceptical and show reluctance towards AI.

Challenges

While there are several advantages of using AI in breast cancer management, such as higher accuracies and accelerated analysis times, the pitfalls of AI should also be weighed when considering its implementation (**Fig. 3**). AI algorithms usually require large and diverse training datasets to be sufficiently representative of a given population[161,162,164]. Without such datasets, AI would encounter generalisation challenges, especially for groups that are underrepresented in the training datasets, potentially leading to widening health inequalities[170]. Addressing this challenge will require not only prospective validation in multi-centre trials, but also intentional inclusion of diverse patient populations in training datasets to ensure equitable applicability across global breast cancer care. Taking into consideration data privacy and consent issues from patients, obtaining such datasets in the form of sensitive health information may also pose a challenge[168,180].

Additionally, AI algorithms often represent a 'black box', generating outputs without interpretable reasoning. These algorithms may not be understood by end-users or may not be disclosed due to commercial interests[161,166,181]. Reproducibility remains a critical challenge in AI research. Many AI models are trained on proprietary or non-public datasets, and clinically deployed systems are often closed source, limiting opportunities for independent validation. Similarly, while some datasets, such as The Cancer Genome Atlas (TCGA) and the Molecular Taxonomy of Breast Cancer International Consortium (METABRIC), are publicly available, many large screening repositories remain under

controlled access, reinforcing inequities in research capacity. This raises barriers to transparency and clinical trust, and stresses the importance of open-access resources, standardised reporting, and reproducible pipelines to ensure that AI findings can be independently verified and applied across different healthcare settings.

In the US, several mammography AI tools, such as Lunit INSIGHT MMG, DeepHealth's Saige-Q and ScreenPoint Medical's Transpara, have obtained FDA clearance as decision-support systems for breast cancer screening. Lunit INSIGHT MMG, for example, received FDA 510(k) clearance in 2021 as an adjunctive tool for mammography interpretation, reflecting the most common approval pathway for breast imaging AI. The 510(k) route requires developers to demonstrate that their device is substantially equivalent to an already approved predicate device, typically involving analytical validation and clinical performance studies, followed by an FDA review that may span several months to over a year. In contrast, AI systems for which no suitable predicate exists must undergo the De Novo classification process, a lengthier and more evidence-intensive pathway that establishes a new device category and generally requires more rigorous clinical data. While these regulatory frameworks aim to ensure safety and reliability, they also introduce practical challenges for AI adoption. Many breast cancer AI tools do not fit neatly into existing device categories, suitable predicates may be lacking and the need for extensive evidence can slow innovation. As a result, navigating these regulatory frameworks remain a significant barrier to the timely integration of AI technologies into breast cancer care[161,168,180].

Beyond technical opacity, recent work has shown that AI systems in medicine can introduce bias from multiple sources, including data bias, development bias, and

interaction bias, which may result in model overfitting, unfair or even harmful outcomes if unaddressed[181,182]. In medical imaging, this is particularly concerning as AI systems may inherit demographic underrepresentation from training datasets[183]. Emerging work also shows that models validated on limited datasets may underperform on minority or underrepresented groups, risking the exacerbation of health disparities[184]. Apart from assessing performance and safety, a comprehensive evaluation framework is required to assess ethics and bias from model development through to clinical deployment, ensuring that AI systems remain fair, transparent, and beneficial in diverse patient populations.

Widespread clinical adoption of AI in breast cancer management depends on substantial non-technical infrastructure and governance that are currently unevenly available. Practical barriers include the need for robust IT infrastructure, clinical workflow integration, long-term maintenance and model updating[181]. Regulatory hurdles including device classification, pre-market clinical evidence requirements, post-market surveillance such as monitoring for performance drift, reporting safety events and periodically reassessing model outputs, further slow translation from research to routine care[181,185]. These processes are increasingly important as regulators consider how to oversee adaptive AI models that continue to learn from new data after deployment, which current approval pathways are not yet fully equipped to manage. These challenges are amplified in low-resource settings where imaging equipment, secure data pipelines, trained personnel, and reimbursement mechanisms may be limited[181,186]. Without targeted investments in infrastructure, regulatory harmonisation, and capacity building, AI risks being adopted unevenly and could exacerbate rather than reduce disparities.

Regulatory agencies also need to ensure that the sensitive health information used in AI systems is adequately secured to prevent breaches in patients' privacy[162,181,187]. While large, diverse datasets are essential for model generalisability, they raise concerns around patient consent, data ownership, and risk of re-identification. Ensuring compliance with regulatory frameworks, while enabling secure data sharing and federated training, is critical to balancing innovation with patient protection. From a legal perspective, it is also important to decide which party – healthcare practitioner or AI system developer, should be liable if there are adverse effects to patients due to errors or failure of the AI systems[162,180,181]. This could deter healthcare practitioners from accepting the AI systems if they perceive the level of liability on them to be unfair.

The cost of AI in breast cancer management is also an important factor to consider. On the one hand, it is possible for AI to result in cost savings by improving accuracy and reducing time-consuming manual processes. On the other hand, the AI systems themselves may be expensive and they may incur additional costs if they require novel technical expertise, training and infrastructural modifications[161,168,187]. This could limit the use of AI in breast cancer management to resource-rich institutions in developed countries.

Another concern is how the use of AI would affect the long-term health of breast cancer patients. The impact of AI systems on long-term health outcomes such as progression-free survival and life expectancy are presently not well-studied[166]. Most studies evaluating the use of AI in breast cancer management are retrospective studies[180]. This provides limited evidence to show that AI can help make patients healthier or save more lives[161]. More comparative prospective studies and randomised controlled trials are needed to

accurately investigate the long-term health effects of AI applications. All these issues must be critically evaluated to ensure that the use of AI in breast cancer management is safe, effective and affordable for patients.

Conclusion

With increasing applications in image recognition and making predictions, the use of AI has pervaded multiple aspects of breast cancer management. This review offers a comprehensive and critically appraised synthesis of how AI is reshaping breast cancer care, from early detection to post-treatment recovery, by evaluating its clinical performance, translational potential, and systemic implications, while underscoring the infrastructural, ethical, and regulatory challenges that must be addressed for equitable implementation. In general, there are more applications of AI in the pre-treatment phase of breast cancer management compared to the treatment and post-treatment phases. Although this trend may lead to the earlier and more accurate detection of breast cancer cases, it is equally important that AI can benefit breast cancer cases which fall through the cracks and are detected at late stages.

Acknowledgements

All figures were created on https://BioRender.com. This work was supported by funding from the WisDM Seed Fund (WisDM/Seed/002/2021, NUS).

Author Contributions

BNC, DH and TBT conceptualised the review. DH and TBT were responsible for the acquisition of funding for the study. BNC wrote and edited the manuscript. BNC, DKHT and TBT reviewed the manuscript. All the authors read and approved the final manuscript.

Competing Interests

Authors declare no competing interests.

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Box 1. Integrating AI in breast cancer management.

- AI is being applied across the full breast cancer care continuum, including detection, diagnosis, prognosis, treatment response prediction, precision medicine and patient recovery, showing improvements in accuracy, efficiency and clinical decision support.
- Performance of AI systems varies widely depending on algorithm choice, dataset size, validation strategy and population diversity, underscoring the need for rigorous, transparent evaluation.
- Many AI models rely on proprietary algorithms and non-public datasets, which limits reproducibility and raises concerns about fairness, generalisability and clinical trustworthiness.
- AI influences healthcare practitioners by shifting rather than replacing clinical roles, automating labour-intensive tasks, reducing cognitive load, and potentially improving workflow efficiency, while also raising training and oversight demands.
- AI has the potential to reduce healthcare costs through more accurate triage, reduced unnecessary imaging, and improved resource allocation, though widespread cost benefits depend on scalable deployment and supportive infrastructure.
- Implementation barriers, including IT infrastructure, workflow integration, regulatory requirements and disparities in resource availability, continue to constrain real-world adoption of AI.

Figure Captions

Figure. 1. The comprehensive and multidisciplinary applications of AI in different phases of breast cancer management. AI is used in the pre-treatment, treatment and post-treatment phases of breast cancer management. The pre-treatment phase consists of detection, diagnosis (grading and subtyping) and prognosis. AI is used in imaging tools such as mammography, DBT, MRI and ultrasound to identify women with breast cancer. AI is also applied to genomic and transcriptomic profiling as well as histopathological analysis to provide more information about the cancer. The treatment phase consists of prediction of treatment response and precision medicine. Using genomic, transcriptomic and other pathological information, AI can be used to predict a variety of outcomes in response to drug treatment. Additionally, AI is applied to drug sensitivity testing in patient samples to predict personalised effective treatments. The post-treatment phase mainly focuses on patient recovery. Using medical records, questionnaires and wearables, AI can be used to recommend lifestyle interventions to address quality of life issues in breast cancer patients. AI is also used in pre-operative imaging and patient education to improve the aesthetic outcome of breast surgery. DBT = digital breast tomosynthesis and MRI = magnetic resonance imaging.

Figure. 2. Comparison of conventional breast cancer treatment with AI-guided breast cancer treatment. (A) Conventional treatment operates based on expert analysis and recommendations by doctors and pathologists. However, they are prone to personal bias and inter-observer variability which could negatively impact their decisions. Additionally, this process is labour-intensive and time-consuming, potentially reducing productivity. In contrast, AI-guided treatment utilises results from multi-omics data analysis for decision-making. This makes the treatment decisions less subjective and prone to human error. The automated aspect of AI also helps to save manpower and time. (B) The information that is used to guide conventional treatment is derived from the patient's medical history. Such information may be recorded differently over time by different healthcare professionals. Moreover, patients may not accurately recall and report their own information when questioned by healthcare professionals. Comparatively, AI-guided treatment uses data from patient samples such as breast tumour biopsy samples to inform treatment decisions. The patient samples may be experimentally analysed in a standardised manner to provide empirical evidence that is fed into computerised AI models. (C) Conventional treatment routinely provides the standard of care especially as the initial line of treatment. This often proves to be ineffective as breast cancer is a heterogeneous disease and manifests differently in different patients. In comparison, AI-guided treatment can incorporate precision medicine approaches to personalise drug combinations and dosages for individual patients.

Figure. 3. Challenges of using AI in breast cancer management. There are five main challenges to recognise and address when using AI systems and applications – the generalisability of AI models, the AI 'black box' problem, regulation, cost and long-term health impact. To be generalisable to broader patient populations, AI algorithms require large and diverse datasets. However, certain groups are often underrepresented in datasets, partially due to patient consent and privacy issues. The AI 'black box' problem can hinder the acceptance of AI due to a lack of understanding and transparency of how the AI systems work. This also limits the reproducibility of AI applications particularly when non-public datasets are used. The regulation of AI is an immense task as it encompasses minimising biases, overcoming infrastructural barriers and ensuring that AI systems perform effectively while protecting patient safety and privacy. AI applications may lead to cost savings as a result of improved accuracy and faster analyses, or higher costs due to additional training and infrastructural modifications to adopt the new AI systems. To better understand the long-term health impact of AI, such as progression-free survival and life expectancy, more prospective studies and randomised controlled trials should be conducted.

Table 1. Overview of selected studies evaluating AI applications in the pre-treatment phase – detection, diagnosis and prognosis, of breast cancer management. The table summarises datasets (source, size, population-based vs. multi-institutional vs. single institution and accessibility), performance metrics, validation strategies (prospective vs. retrospective and internal vs. external), model accessibility (open source vs. closed source vs. commercially available), and reported clinical outcomes, providing a consolidated view of current evidence and translational potential. More studies are summarised in Supplementary Table 1. AUROC = area under the receiver operating characteristic curve, DG2 = digital grade 2, HR = hazard ratio, NPV = negative predictive value, PAM50 = Predictor Analysis of Microarray 50, PPV = positive predictive value, TCGA = The Cancer Genome Atlas and WSI = whole-slide image.

Purpose	Application	Dataset	Key Performance Metrics	Validation Strategy	Model Accessibility	Outcome	Reference
Detection	Mammogram	BreastScreen Victoria, Australia; ~1M	Sensitivity, specificity & workload reduction	Retrospective & external	Closed source	1.9 - 2.5% ↑ sensitivity, 0.3 - 0.6% ↑ specificity & 48	[38]

		mammograms; population-based; controlled access				- 80% ↓ in human reads	
		Systematic review of 13 studies	Pooled estimates of AUROC, sensitivity & specificity	Not applicable	Not applicable	Sensitivity 75.8 - 80.8% vs. 72.4 - 72.6% (radiologists)	[39]
Diagnosis	Histopathology	TCGA; ~1.1k WSIs; multi-institutional; publicly available	Accuracy	Retrospective & internal	Closed source	65.92% accuracy predicting PAM50 subtype	[85]
		US; 349 patients; multi-institutional; controlled access except for TCGA	PPV & NPV	Retrospective & external	Closed source	PPV 0.7162 & NPV 0.9977	[86]
Prognosis	Histopathology	Sweden & US; ~1.5k patients; multi-institutional; controlled access except for TCGA	HR	Retrospective & external	Closed source	HR 1.91 - 2.94 for recurrence (DG2-high vs DG2-low)	[93]
		US; 178 WSIs; multi-institutional;	Accuracy	Retrospective & external	Closed source	75 - 86% accuracy	[94]

		available on request				predicting Oncotype DX	

Table 2. Overview of selected studies evaluating AI applications in the treatment phase – prediction of treatment response and precision medicine, of breast cancer management. The table summarises datasets (source, size, multi-institutional vs. single institution and accessibility), performance metrics, validation strategies (prospective vs. retrospective and internal vs. external), model accessibility (open source vs. closed source vs. commercially available), and reported clinical outcomes, providing a consolidated view of current evidence and highlighting the potential of AI to guide therapeutic decision-making. More studies are summarised in Supplementary Table 2. AUROC = area under the receiver operating characteristic curve.

Purpose	Application	Dataset	Key Performance Metrics	Validation Strategy	Model Accessibility	Outcome	Reference

Prediction of Treatment Response	Predict pathologic complete response to neoadjuvant therapy	US; 117 patients; multi-institutional; available on request	AUROC	Retrospective & internal	Closed source	AUROC 0.74 - 0.93	[102]
		China; 335 patients; multi-institutional; controlled access	AUROC	Retrospective & external	Open source	AUROC 0.83 - 0.87	[103]
	Predict lymph node metastasis in response to neoadjuvant therapy	China; 297 patients; multi-institutional; controlled access	AUROC	Retrospective & external	Closed source	AUROC 0.853 - 0.863	[105]
	Quadratic Phenotypic Optimization Platform (QPOP)	Singapore; single institution; ongoing	Personalised drug combination	Prospective & ongoing	Closed source	Ongoing clinical trial to determine the effective drug combinations for breast cancer patients	NCT05177432
	CURATE.AI	Singapore; single institution; ongoing	Personalised drug dosing	Prospective & ongoing	Closed source	Ongoing clinical trial to determine the optimal drug dosing for	NCT05381038

						breast cancer patients	
	Conversational virtual assistant on HealthFAX platform	US; 51 patients; single institution; available on request	Personalised education	Prospective	Closed source	Provided easy-to-use and valuable genetic education	134

Table 3. Overview of studies evaluating AI applications in the post-treatment phase – patient recovery, of breast cancer management. The table summarises datasets (source, size, multi-institutional vs. single institution and accessibility), performance metrics, validation strategies (prospective vs. retrospective), model accessibility (open source vs. closed source vs. commercially available), and reported clinical outcomes, with a focus on platforms supporting quality of life interventions and preoperative planning. CTA = computed tomography angiography, DIEP = deep inferior epigastric perforator and QoL = quality of life.

Purpose	Application	Dataset	Key Performance	Validation Strategy	Model Accessibility	Outcome	Reference

			Metrics				
Patient Recovery	Artificial intelligence Supporting CAncer Patients across Europe (ASCAPE) platform	Greece, Spain & Sweden; multi-institutional; ongoing	QoL	Prospective, randomised & ongoing	Closed source	Ongoing trial to predict 15 QoL issues & recommended interventions	[145] NCT04879563
	CUidados Más Allá del Cáncer-Mama (CUMACA-M) web program	Spain; multi-institutional; unknown	QoL	Prospective & randomised	Closed source	Unknown but aims to provide personalised interventions to improve QoL & self-efficacy in the management of cancer sequelae	[146] NCT05322460
	Comparing Decision on Aesthetics After Breast Cancer Locoregional Treatment (CINDERELLA) web platform	Germany, Israel	QoL	Prospective &	Closed source	Ongoing trial to provide treatment information & predict post-surgery aesthetic outcomes	[149] NCT05196269

		, Italy, Poland & Portugal; multi-institutional; ongoing		randomised			
	Preoperative planning of DIEP flap surgery	Portugal; 40 patients; single institution; contr	Analysis time	Prospective	Closed source	↓ CTA analysis time 2 hrs to 30 mins	151

		oll ed ac ce ss					

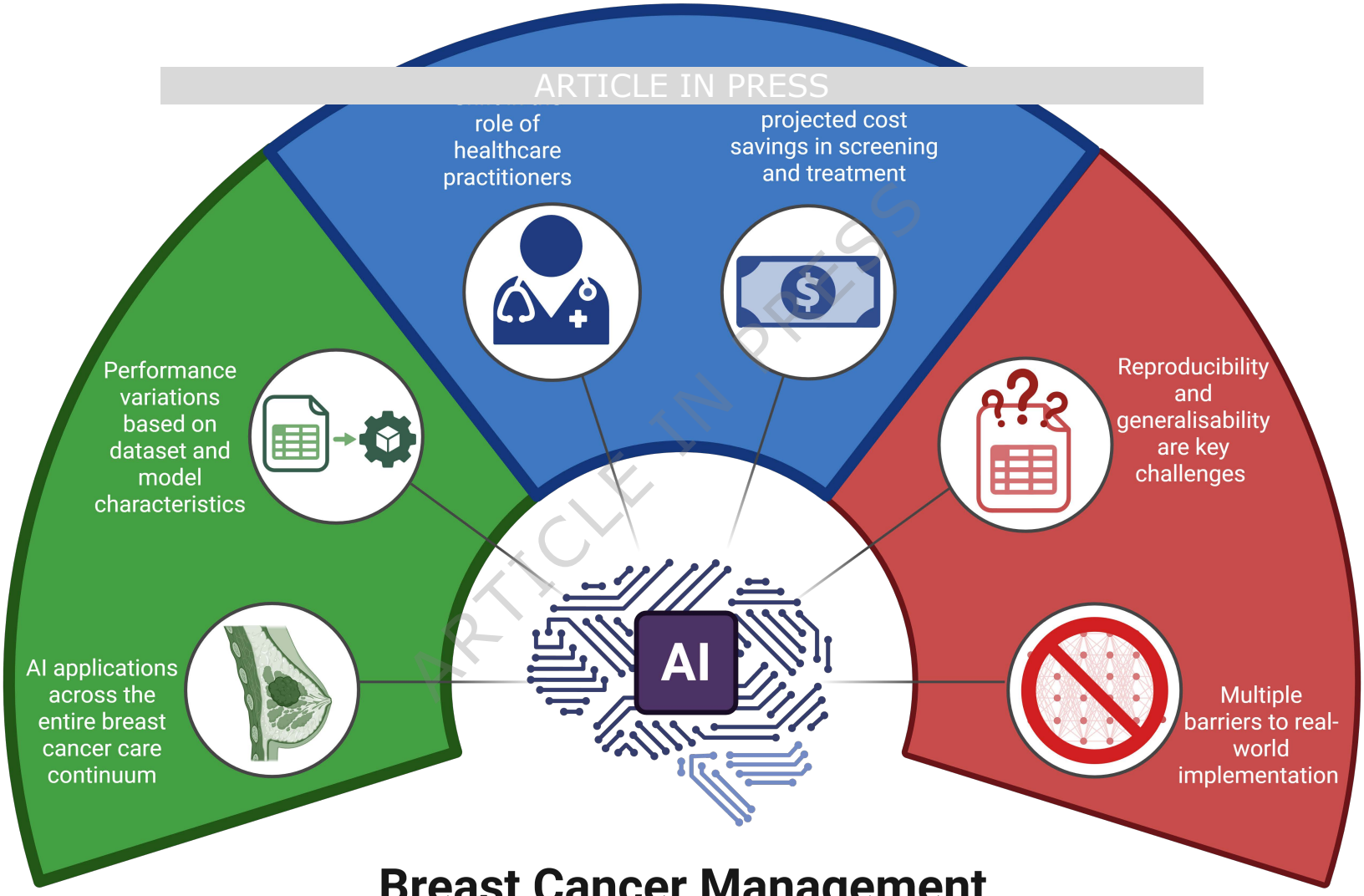
Table 4. Estimated and predicted cost savings of AI applications in healthcare and breast cancer management.

Area of Healthcare	Cost Savings Metric	Estimated & Predicted Cost Savings	Reference
Entire healthcare industry	Total cost	$200 billion - 360 billion annually from 2019 in the US	[20]
		$150 billion annually by 2026 in the US	[21]
Mammogram screening	Incremental Cost Effectiveness Ratio (ICER)	ICER of $23,755 per Quality-adjusted Life Year (QALY) gained (below the threshold of $100,000)	[152]
	Incremental Net Monetary Benefit (INMB)	Positive INMB of £2.70	[153]
	Net Monetary Benefit (NMB)	NMB of £60.4 million - 85.3 million (assuming QALY = £20 000 and £30 000 respectively)	[154]
MRI	Time and total cost	€399,000 ↓ in hospital annual examination costs vs. acquiring an additional MRI scanner, ↓ appointment times & ↑ 20 - 32 % scanner capacity	[155]
Breast cancer biopsy	Total cost	>$420 million by obviating unnecessary biopsies	[156]
Diagnosis and treatment	Time and cost per day per hospital	Diagnosis: 3.33 - 15.17 h and $1666.66 - 17,881 per day per hospital (at the initial year and 10 years respectively) Treatment: 21.67 - 122.83 h and $21,666.67 - 289,634.83 per day per hospital (at the initial year and 10 years respectively)	[157]

ed summary

Chu et al., discuss how artificial intelligence is transforming breast cancer care by improving detection, diagnosis, prognosis, treatment planning, and patient recovery through advanced machine learning and deep learning applications. They emphasise that widespread adoption faces challenges such as data diversity, reproducibility, regulatory hurdles, infrastructure limitations, and ethical concerns around transparency and bias.

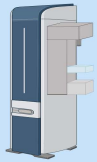
Peer review information: *Communications Medicine* thanks Francisco Maria Calisto and Asim Waqas for their contribution to the peer review of this work.

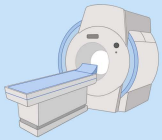


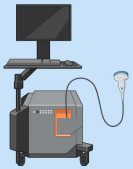
Pre-treatment

Detection

Mammogra



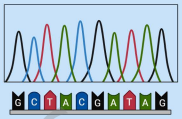




Outcome:
Identify breast tumour

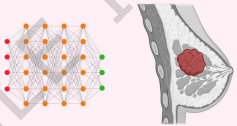
Diagnosis & Prognosis

stopathology



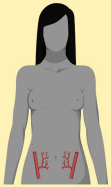
Outcome:
Determine tumour grade, subtype, likely progression and risk of relapse

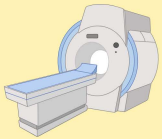
AI in Breast Cancer Management



Patient Recovery (II)

Pre-operative imaging





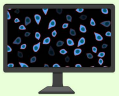
Outcome:
Achieve satisfactory aesthetic outcome

Prediction of Treatment Response

Genome

Transcriptome

Digital pathology



Outcome:
Predict drug response, pathologic complete response, metastasis, survival and toxicity

Patient Recovery (I)

Medical records

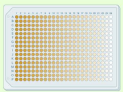
Questionnaires

Wearables

Outcome:
Improve quality of life

Precision Medicine

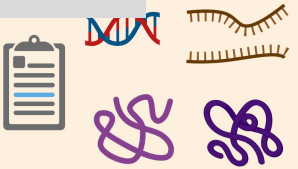
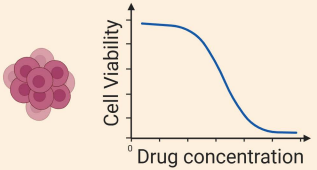
Empirical data from patient samples



Outcome:
Predict effective drug combination & dose

Post-treatment

Treatment

Conventional Treatment	AI-guided Treatment
(A) 	
👎 Subjective & based on experience level 👎 Inter-observer variability 👎 Labour-intensive & time-consuming	👍 Objective analysis 👍 Less human error 👍 Capital-intensive & time-saving
(B) 	
Medical history of patient 👎 Different standards of data recording between institutions/professionals 👎 Prone to recall bias and inaccurate reporting by patients	**Empirical data from patient samples** 👍 Standardised data recording 👍 Uniform digitised reporting
(C) 	
Standard of care 👎 One-size-fits-all approach is not patient-specific	**Precision oncology** 👍 Drug combination and dose are tailored to individual patients