Towards AI-enabled person centred care in breast imaging - A Scoping Review

Abstract

Aim: To overview Artificial Intelligence (AI) developments and applications in breast imaging (BI) focused on providing person-centred diagnosis and treatment for breast pathologies.

Methods: The scoping review was conducted in accordance with the Joanna Briggs Institute methodology. The search was conducted on MEDLINE, Embase, CINAHL, Web of science, IEEE explore and arxiv during June 2021 and included only studies published after 2016, in French and English. Combination of keywords and Medical Subject Headings terms (MeSH) related to breast imaging and AI were used. No keywords or MeSH terms related to patients, or the person centred care (PCC) concept were included. Three independent review authors screened all abstracts and titles, and all eligible full-text publications during a second stage.

Results: 2324 results were identified by the search strategy but only 79 studies met all criteria and were included. Seven themes relating to the AI-enabled PCC in BI were identified: treatment assessment (16%), individualised risk prediction/growth, prediction/false negative reduction (58%), unnecessary biopsies reduction (8%), specific populations (1%), patients' preferences (4%), tumour type prediction (5%) and other issues (9%). The main BI modalities explored in the included studies were mammography (34.2%), magnetic resonance imaging (MRI) (34.2%) and ultrasound (19%). The studies were predominantly retrospective, and some variations were present in the datasets used.

Conclusions: The AI tools for person-centered care are mainly designed for risk and cancer prediction and disease management to identify the most suitable treatment. However, further studies are needed for optimisation of image acquisition for different patient groups, improvement and customisation of patient experience and for communicating to patients options and pathways of disease management.

Introduction

Artificial intelligence (AI) is evolving lately at a fast pace, and it is being used in different domains to simplify processes and to improve quality of life using data produced by digital technologies. The medical field is no exception, especially in medical imaging, where several processes are being improved with AI, namely in scheduling patients, improving protocols for dose reduction and image optimisation and postprocessing, image interpretation, patient follow up, workflow efficiency optimisation, reduction of unnecessary biopsies and treatments (1–3). There are several AI tools available to improve cancer detection and diagnosis. The tendency is to integrate AI solutions to better

adapt diagnosis and treatment to each patient and to achieve better outcomes and consequently quality of life (2,4,5). Until now the available tools, such as computer aided detection (CAD) systems, used for image interpretation support, have resulted in increasing frequently recall rates due to the use of rules-based approach and domain knowledge incorporation (6–9).

Breast imaging is one of the most challenging domains in medical imaging with high false negative and false positive rates for breast cancer detection with an impact on patients' management and experience (10,11). Currently, available technologies for breast imaging are used to map structural or morphological differences in tumours, such as microcalcifications, tissue masses, angiogenesis, asymmetry, and architectural distortion. Some of the more recently developed techniques can provide information about the biological or functional differences between tumours and normal tissues. However, until now there is not one single modality that can simultaneously achieve all these anatomy-physiology and pathology-related goals (12,13) and, in addition, achieve risk prevention as well as personalised follow up. Considering the current limitations of breast imaging, AI can contribute to overcome interval cancers and minimise recall rates. AI tools can also provide customised recommendations for screening and follow up of breast diseases and treatment monitoring by combining different types of data (imaging features, radiomics and genomics) and patient preferences.

This study aimed to offer an overview of recent AI developments and applications in breast imaging focused on providing person centred diagnosis and treatment for breast pathologies.

Methodology

This scoping review was conducted in accordance with the Joanna Briggs Institute methodology for scoping reviews (14). Scoping reviews synthetise findings from various studies in a structured way to answer research questions and identify gaps in actual literature (15).

Inclusion criteria

This scoping review was performed to summarise the evidence in the use of AI in breast imaging to provide person centred care. A range of study types was included, considering different methodological designs, involving all breast imaging modalities and all relevant patient genders. Studies with patients were prioritised, instead of phantoms.

To be consistent with the concept of person-centered care (PCC), this review included studies considering patients preferences, and characteristics (age, gender, family history, breast density, risk factors, socioeconomic factors, human race, lifestyle) used to develop an AI toolfor improving individualized care.

This scoping review included quantitative, qualitative, and mixed methods studies. Systematic reviews, books articles or sections were excluded. Phantom studies were also excluded.

Search strategy

The search strategy (Appendix 1) included both published and unpublished primary studies using six databases: MEDLINE, Embase, CINAHL, Web of science, IEEE explore and arxiv searched during June 2021. Combination of keywords and Medical Subject Headings terms (MeSH) related to breast imaging and AI were used.

No keywords or MeSH terms related to patients, or the PCC concept were included in the search strategy as they introduced noise to the results after a first attempt. The selection on these criteria was carried out manually. Studies published from 2016 onwards in English or in French focused on technological advances in AI were included.

Study selection

All identified studies were uploaded into EndNote 20 and duplicates were removed by using the Bramer's method (16). Posteriorly, the references were imported into Rayyan, a free web-tool, to facilitate the selection of the studies. Titles and abstracts were screened in a first round by three independent reviewers for evaluation of their pertinence according to the criteria previously described. Eligible full-text articles were then retrieved and reviewed by the same three reviewers in a second round. Full-text studies not meeting the inclusion criteria and reasons for their exclusion are provided in *Figure 1*. Any disagreement between the reviewers was resolved by discussion and consensus.

Data extraction and analysis

Data were extracted using a pre-defined and tested extraction table by the three reviewers based on the following characteristics: country of study, aims, methodology, patients' gender, patients' specificities, patients' age, sample size, imaging modality, equipment type/model, acquisition parameters/image acquisition protocol, AI model, key findings. Seven themes relating to the PCC concept were identified: treatment assessment, risk prediction/growth prediction/false negative reduction, unnecessary biopsies reduction, specific population, patients' preferences, tumor type prediction and others. Each article was assigned in one of these categories.

Once the data was extracted, a discussion was conducted for the remaining studies not attributed to one category, achieving a consensus. A descriptive analysis with a narrative summary was performed to present the results.

Results

Search and study selection

After removing duplicates, 2324 results were identified by the search strategy. Of those 79 studies met all criteria and were included. The main reasons for exclusion were performance-related articles, no full text available, outcome not related to patient centred care and no breast imaging included (Figure 1).

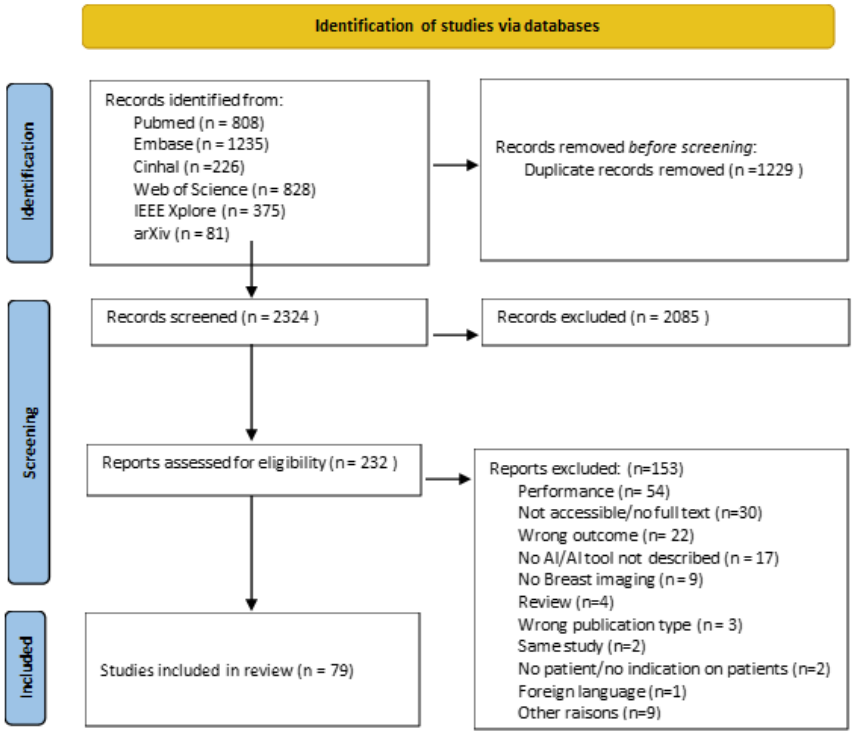

Figure 1: Search results and study selection and inclusion(17)

Included studies

Studies were published across 18 countries, with the majority in United States of America (30 out of 79) and China (21 out of 79). The main imaging modalities used in the studies were mammography (34.2%), magnetic resonance imaging (MRI) (34.2%) and ultrasound (US) (19%) but Breast CT, PET/CT, Thermography, Gama Camera, Contrast-Enhanced mammography and Tomosynthesis were also explored. The studies were predominantly retrospective (n= 65), using different datasets, some provided by the hospitals or open-source databases. Mainly studies focusing on women were included, with ages varying between 15-92 years. One study included male patients and another used patient and one included phantom. Sample sizes ranged from 28 to 164 444 patients. Six categories related to the PCC concept were identified: risk prediction/growth, prediction/false negative

reduction (52%), treatment assessment (18%), unnecessary biopsies reduction (7%), patients' preferences (4%), tumour type prediction (14%) and other issues (5%).

Risk prediction/growth, prediction/false negative reduction

From the 41 studies investigating risk prediction, 20 were conducted in the USA, 10 in China and 3 in Sweden, 8 in other countries (Table 1). Studies were predominantly retrospective using institutional image datasets or screening country's datasets. Only one study (18) was prospective using a small institutional sample of 37 women with advanced cancer. However, some retrospective studies included larger samples namely Schmidt et al. (19) using 46158 images, Eriksson et al. (20) with 45417 images, Yala et al.(21) with 39558 images and Akselrod-Ballin et al.(22) with 52936 images acquired in 13234 women. Only women taking part in a screening program (9 studies) or as diagnostic examination were included.

Most studies included women of an age range that made them eligible to participate in screening programs. However, younger women were also included in some studies aging between 18 and 30 years old (23–29).

Most of the time, the images used were acquired in a single institution. Nine studies (28,30,31) used images from 2 clinical settings; 2 included images from 4 settings (20,32); one (22) from 5; one from 9 (33) and one from 10 settings (34).

In the included studies, none was conducted combining populations from different countries, but they included women from different ethnicities, namely Caucasian (Australia) & Japanese American (Hawaii) women (19); other heterogenous samples involved non-Hispanic White (36.7%), non-Hispanic Black (11.6%), Hispanic or Latina (36.4%), Asian (5.7%), and others (9.4%) (26). None of the studies explored if these differences had an impact in the outcomes.

Some papers described the sample as heterogeneous due to the use of imaging devices from different manufacturers. Eriksson et al. (20) used images acquired with 6 different mammography manufacturers, Guo et al.(30) and Moon et al.(35) explored 2 different types of US, Braman et al.(27) included 2 different MRI devices; Zhou et al.(28) included 3 different US manufacturers, Zhu et al.(36) explored 4 different types of MRI from the same vendor, and Lång et al. (32) included 2 mammography vendors.

The risk prediction was mostly explored using one imaging modality: analogue or digital Mammography (n=18 articles), MRI (n=13), US (n=5), Gamma camera (n=1), Tomographic diffuse optical spectroscopy imaging (n=1). In three studies multimodalities were used, one (37) with images from mammography and MRI; other (38) mammography and US; and finally other (29) with thermal images, mammography and US.

Nearly half (20 out of 41) of the studies predicting risk used patient features specially the Tyrer-Cuzick scores in addition to image features. Manley et al.(26) added patients with alcohol habits and He et al. (38) complemented with skin change, palpable lump and nipple discharge.

The AI techniques applied in the studies were heterogeneous but convolutional neural networks (CNN) were the most predominant (Table 1). Some studies added natural language processing (38) or transfer learning (33,36,39,40). In the risk prediction category, most of the studies used AI for risk model prediction for development of breast cancer in the short term (n=14). Some explored more specifically Ductal Carcinoma in Situ (DCIS) or Invasive ductal carcinoma (IDC) grade (n=5), axillary lymph node metastasis prediction (n=5), breast density estimation (n=4), interval cancer risk prediction (n=2), screening selection according to age or risks (n=2), other issues (n=3).

Treatment assessment

Under the category of "treatment assessment" 19 articles were included (Table 2). AI tools were used mainly to predict the response of chemotherapy as neoadjuvant treatment (NAC). Two studies (41,42) explored respectively breast cancer surgery (BCS) and not any other specific treatment; two (43,44) used an evaluation during the treatment to predict the final response using quantitative ultrasound (QUS). CNN and SVM classifiers were the major AI tools used for the treatment assessment and more specifically for the prediction of final treatment response. Different modalities, like PET/CT, MRI, US or mammography shown to be useful for the assessment of treatments although US and MRI images seemed to be most appropriate due to not using ionising radiation. The number of subjects ranged from 37 to 288 aging from 18 to 85 years old. Most of the studies (13 out of 19) axed their research in patients with locally advanced breast cancer (LABC), 4 studies used patients with multiple cancer subtypes, one (42) evaluated the response for triple negative breast cancer (TNBC) and the last integrated only patients with HER+ subtype. Two studies (43,45) included respectively 2 and 1 male in their data.

Table 1: Studies focusing on the use of AI for risk prediction/growth, prediction/false negative reduction

Study first author	Year	Country (where the study was conducted)	Purpose or Aim(s)	Study design	Imaging modality	Number of subjects or images (N)	Subjects' mean, median or range age	Subjects' or machine specificities	Clinical (patient) features	AI information's	Key findings	Keywords/categorization
Hao [?]	2020	China	To explore the potential of magnetic resonance imaging (MRI)radiomics-based machine learning to improve assessment and diagnosis of contralateral Breast Imaging Reporting and Data System (BI-RADS) category 4 lesions in women with primary breast cancer.	Retrospective	MRI (3.0T/breast dynamic MRI)	178	50.7±11.5 25-78	Chinese Women with BI-RADS 4 lesion	Age-Menopause Status-Family History-Breast density	Machine learning: SVM	MRI radiomics-based machine learning model can assess lesion in contralateral BI-RADS 4 women. T2 and T1 + C features are useful in discriminating benign and malignant contralateral BI-RADS 4 lesions.	Contralateral assessment-diagnosis
Aghaei [?]	2016	USA	To develop and test a new computerized model for predicting near-term breast cancer risk based on quantitative assessment of bilateral mammographic image feature variations in a series of negative full-field digital mammography (FFDM) images.	Retrospective	Full-field digital mammography	335	51 42-71	American women taking part in screening program (using 4 different views)	Age-Density/ BIRADs-Family History-Age at menarche-Parous (age at first birth) -Menopausal status	Machine learning: SVM	This study demonstrated a positive association between the risk scores generated by a bilateral mammographic feature difference-based risk model and an increasing trend of the near-term risk for having mammography-detected breast cancer.	Short term BC/risk score prediction
Wang [?]	2017	Japan	To estimate volumetric breast density from Full-field digital mammograms on Japanese women with and without breast cancer.	Retrospective	Full-field digital mammography + MRI only in patient with invasive carcinoma	99	47-72	Japanese women with and without invasive carcinoma	Age- Age at menarche-Menopausal Status-Parity status-BMI	ANN	The proposed ANN calibrated model appears to produce reasonable measures of mammographic density that are validated with breast tissue composition phantoms, associated with existing qualitative and quantitative measures of breast density, and associated with classical biomarkers of breast cancer as previously reported.	Volumetric breast density estimation
Lång [?]	2021	Sweden	To investigate whether artificial intelligence can reduce interval cancer in mammography screening.	Retrospective	Digital mammography	429	58 39-76	Sweden women (4 sites) taking part in screening program 2 vendors	BI-RADS Screening prevalence Time from screening to IC Prior breast surgery (breast reduction) Best implants	Deep-learning CNN	The use of AI in screen reading has the potential to reduce the rate of interval cancer without supplementary screening modalities. an AI system detected 19% of interval cancers at the preceding screening mammograms. these cancers were correctly located and classified as high risk by AI, thus obviating supplementary screening modalities.	IC reduction-prediction
Schmidt [?]	2018	Australia/ Hawai	To apply machine learning to find a novel breast cancer predictor based on information in a mammogram	Retrospective	Digitized film mammography	46158 images	47.5 & 67.2 according to cohort	Caucasian (Australia) & Japanese American (Hawaii) women	Age-BMI-Density	Machine learning	A fully automated personal risk measure created from the combination of textural image features is better at predicting breast cancer risk than conventional mammographic density risk measures. Cirrus can be used as one of the strongest known risk factors for breast cancer	BC risk Prediction
Carter [?]	2019	USA	To develop and validate a deep learning model using image convolution to automatically categorize background parenchyma uptake on molecular breast imaging	Retrospective	Gamma camera (Tc99m sestamibi)	3919 exams in 3919 unique patients	56 ± 10.9	Not specified	-	CNN Deep learning	A CNN was successfully developed and validated for the automatic classification of background parenchyma uptake in women undergoing supplemental screening using molecular breast imaging. Additional research to determine if these automatic classifications add to risk stratification and breast cancer risk prediction is warranted.	Classification of uptake
Dembrower [?]	2020	Sweden	To develop a risk score that is associated with future breast cancer and compare it with density-based models	Retrospective	Digital mammography	2283 (4 images per patient)	40-74	Swedish screening-aged women	Age	Deep neural network (ResNet-v2)	the performance of a deep learning–based risk model trained on mammographic images was better than that of density-based models. It showed better performance for more aggressive cancers, without decreasing. The risk model should be trained on further cancer cases from multiple institutions and combined with another model predicting the risk of mammographic masking.	Risk score prediction
Zhao [?]	2017	China	To develop a valid predictive mathematical model for selecting high-risk groups eligible for mammography examinations and cost-effective strategies for breast cancer screening among Chinese women	Cross-sectional	Mammography	13355	30-65	Chinese women	Age-BMI-Reproductive factors Personal & family disease history	BP-ANN	A BP-ANN model using age, BMI, reproductive factors, and disease history factors can be a valuable tool with the capacity to preselect women for recommended mammography screenings. BP-ANN model followed by MAM for Chinese women aged 40–49, and mammography alone for screening women aged 50–65.Further research is needed to determine the optimal screening strategy for women younger than 40 in China.	Screening selection according to age
Eriksson [?]	2018	Sweden	To present a new algorithm which measures density on all type of images, regardless of vendor, and controls for non-biological differences seen in time series of mammograms from the same women	case-control retrospective	Analog and digital mammography	45417	57.4 ± 9.2	Swedish women from 4 units and 9 different types of mammograms from 6 vendors (3 studies samples)	Age-Density-Ever use of HRT-Postmenopausal-Family history of cancer	Machine learning (Stratus)	Measures mammographic density from mammograms obtained from a variety of sources (raw and processed digital images, analogue films). The added alignment feature provided by STRATUS improves longitudinal measurements of mammographic density. STRATUS-derived mammographic density can become a useful tool for risk prediction and treatment response in research and clinical praxis.	Density measurement for risk prediction
Moon [?]	2018	Republic of Korea	To develop a computer-aided prediction model as well as the tumor features for ALN metastasis in breast cancers using breast ultrasound images	Retrospective	US	247	55±11 20–84	Korean women with breast cancer 2 different vendors	-	Computer-aided prediction (CAP) (backward feature selection)	The proposed CAP model based on combining morphological and textural features of primary tumours can be useful to determine the ALN status in patients with newly diagnosed breast cancer. In clinical use, this CAP model can be helpful to provide consistent and objective recommendations to radiologists on the ALNs status in the preoperative staging of breast cancer	ALN prediction
Ha [?]	2019	USA	To propose a novel convolutional neural network derived pixel-wise breast cancer risk model using mammographic dataset to stratify patients into personalized breast cancer risk categories beyond just breast density.	case-control retrospective	Mammogram	Case: 210 Control: 527	Case: 57.4 ± 10.4 / Control 58.2 ± 10.9	American women	Age-Density	A fully convolutional neural network	The novel pixel-wise mammographic breast evaluation using a CNN architecture can stratify breast cancer risk, independent of the mammographic BD. The CNN risk model [OR = 4.42 (95% CI, 3.4-5.7)] showed greater predictive potential compared to mammographic BD [OR = 1.67 (95% CI, 1.41.9)]. The CNN risk model achieved an overall accuracy of 72% (95%CI, 69.8-74.4) in predicting patients in the case group. Validation by a prospective randomized study is needed to potentially implement our individualized risk stratification scheme into screening and chemoprevention guidelines.	Stratification BC risk prediction
Zhu [?]	2019	USA	To determine whether deep learning-based algorithms applied to breast MR images can aid in the prediction of occult invasive disease following the diagnosis of ductal carcinoma in situ (DCIS) by core needle biopsy	Retrospective	MRI (dynamic contrast-enhanced)	131	With invasive: 50.5 (32–73) / without invasive: 53.4 (31–75)	American women with a core needle biopsy-confirmed diagnosis of ductal carcinoma in situ. With and without invasive carcinoma 4 different types from same vendor	-	Deep learning-based approach: by exploring two methods: transfer learning approach and deep features approach	A deep learning-based model based on MR imaging showed moderate predictive power for identifying occult invasive cancer in patients diagnosed with ductal carcinoma in situ using core needle biopsy but needs further investigation to be clinically relevant. Specifically, the deep features approach with Google Net (AUC =0.70, 95% CI: 0.58–0.79) demonstrated superior performance compared to the transfer learning approach (AUC=0.68, 96% CI: 0.57-0.77).	Invasive cancer prediction
Yala [?]	2019	USA	To develop a mammography-based DL breast cancer risk model that is more accurate than established clinical breast cancer risk models	Retrospective	Digital mammograms	39558	56.20 ± 10.04	American screening examinations	Traditional risk factor information	Hybrid deep learning model that used full-field mammograms in addition to traditional risk factor information to assess breast cancer risk	A hybrid deep learning model that directly leverages full-field mammograms in addition to traditional risk factors AUC (0.70) outperforms the Tyrer-Cuzick model (version 8) by a large margin (0.62; P, .001) and RF-LR (0.67; P = .01); this improvement is consistent across demographic subgroups. These models have the potential to replace conventional risk prediction models.	BC prediction

Portnoi [?]	2019	USA	To develop an image-based deep learning (DL) model to predict the 5-year risk of breast cancer based on a single breast MR image from a screening examination	Retrospective	Contrast enhanced screening MRI	1623 exams in 1164 women	Not specified <40 to >80	American screening examinations	Tyrer-Cuzick score: age-height and weight-breast density-history and results of breast biopsies-personal history of breast or ovarian cancer-family history of breast or ovarian cancer history of hormone use Ashkenazi Jewish heritage Trusted Source-age when the person had their first menstrual period-age when the person first gave birth, age at menopause, age of cancer diagnosis	Deep learning	Our DL model can assess the 5-year cancer risk based on a breast MR image alone, and it showed improved individual risk discrimination when compared with a state-of-the-art risk assessment model. These results offer promising preliminary data regarding the potential of image-based risk assessment models to support more personalized care	5-year cancer risk Prediction
Arefan [?]	2020	USA	To investigate two deep learning-based modeling schemes for predicting short-term risk of developing breast cancer using prior normal screening digital mammograms	Retrospective	Mammography	226 women (50% case 50% control)	50-71.5	American screening women with and without cancer	-	End-to-end deep learning model and a Google Net-LDA model	CC view was consistently more predictive than MLO view in both deep learning models (Google Net-LDA and end-to-end Google Net model), regardless of the input subregions. Both models exhibited superior performance than the percent breast density (AUC=0.54; 95% CI: 0.49–0.59). Both deep learning models can predict short-term breast cancer risk using normal mammograms.	Short-term BC prediction
Hinton [?]	2019	USA	To determine if mammographic features from deep learning networks can be applied in breast cancer to identify groups at interval invasive cancer risk.	Retrospective	Mammography	182 interval and 173 screen-detected cancers	45-69	American screening women	Bi-RADS density or deep-learning network prediction or both	Deep learning network architecture (ResNet50) with ImageNet transfer learning weights	Better discrimination than BI-RADS breast density for classifying interval cancer versus screen-detected cancer with a 75% classification accuracy; pre-cancerous mammograms contain imaging information beyond breast density that can be used to predict the probability of breast cancer detection	IC prediction
Zheng [?]	2020	China	To evaluate the diagnostic performance of clinical parameter combined DLR on conventional US images and SWE images of breast cancer in predicting the extent of ALN involvement in patients with early-stage breast cancer	Retrospective	Ultrasound with Elastography	584	50 26-83	Chines women with malignant breast lesions	-	ResNet50, ResNet101, Inception V3, and VGG19	Development and validation of a clinical parameter combined DLR method based on breast conventional US and SWE images for preoperative prediction of ALN status in patients with clinical T1 or T2 breast cancer.	ALN prediction
Guo [?]	2020	China	To identify as many high-risk (HR) patients as possible to ensure an appropriately reduced in over-treatment without adverse impacts on survival	Retrospective	Ultrasound	937	41-63	Chinese women from 2 sites	-	Two Deep Learning Radiomics models	DLRU predicts the risk of SLN involvement. that it may offer a simple preoperative tool to promote personalized axillary management of breast cancer.	Prediction high risk patients
Sun [?]	2020	China	To assess how deep convolutional neural network (CNN) performed compared with radiomics analysis in predicting ALN metastasis using breast ultrasound, and to investigate the value of both intratumorally and peritumoral regions in ALN metastasis prediction	Retrospective	Ultrasound	79 patients with 479 breast tumors (136 positive and 343 negative ALN)	36-60	Chinese women	-	Three image-only CNN models, including the intra tumoral CNN, the peritumoral CNN and the combined-region CNN, were built with the DenseNet based on the intratumor	The major findings of this study were that deep CNN, built by combining intra tumoral and peritumoral regions in breast ultrasound images, outperformed radiomics models in predicting ALN metastasis. "Helps to avoid axillary overtreatment and reduce associated serious complications."	ALN prediction
He [?]	2019	USA	To apply machine learning to find a novel breast cancer predictor based on information in a mammogram	Retrospective	FFDM & Ultrasound	5147	N/A	American women with BI-RADS 4	Patient demographic variables, and pathology result: Age-dead-race-height-weight-BMI-Insurance-Menopause-Family history- Previous breast cancer, other cancer, skin change, palpable Lump, nipple Discharge,	Natural language processing and deep learning methods	We defined five diagnosis types from the biopsy report: benign, atypia, lobular carcinoma in situ, ductal carcinoma in situ (DCIS), and carcinoma. Invasive breast cancer or DCIS were considered positive results. Any other pathology diagnosis was considered as free of breast cancer and as a negative result. BRISK was able to categorize abnormal mammogram findings into subtypes (benign, atypia, lobular carcinoma in situ, DCIS, and carcinoma) and improve the biopsy endorsement compared with BI-RADS 4 recommendations, with high specificity and sensitivity. We have validated the tool with data from thousands of BI-RADS 4 patients.	BC prediction
Haji Maghsoudi [?]	2018	USA	To estimate breast percentage density (PD) from digital mammograms	Retrospective	Mammography	15661 images from 4437 women	N/A	American women from 2 sites	-	Deep-learning (U-Net 2 CNN)	Deep-LIBRA can provide breast segmentation by separating the dense from the non-dense tissues within the breast region. The method included two major steps: the segmentation of the breast region and the estimation of PD. It employed some pre-processing steps, two CNNs (the modified U-Net architecture), super pixels, extracting texture features, and SVM to accomplish the PD estimation.	Breast density estimation
Ciritsis [?]	2018	Switzerland	To develop a deep convolutional neural network (dCNN) for the automatic classification of breast density based on the mammographic appearance of the tissue according to the ACR -BIRADS	Retrospective	Mammography	20,578 single view from 5,221 patients	47-69	Swiss women	-	Deep convolutional neural network	The model computations for the MLO and CC projection were completed in 20.3 and 21.6 hours, respectively. In the differentiation between fatty (ACR A/B) and dense breasts (ACR C/D), the agreement reached 99% for the MLO and 96% for the CC projections, respectively.	Breast density classification
Yuan [?]	2020	China	The objective of this study is to investigate the use of texture analysis (TA) of magnetic resonance image (MRI) enhanced scan and machine learning methods for distinguishing different grades in breast invasive ductal carcinoma (IDC). Preoperative prediction of the grade of IDC can provide reference for different clinical treatments, so it has important practice values in clinic.	Retrospective	MRI	28	29-63	Chinese women from one hospital	-	Machine learning	Our model can distinguish these two grades of tumors; he best classification result is obtained by selecting 3 or 8 key features; Because of the small amount of data collected, the result of CNN classification is very poor.; Experiments show that the classification effect of the Gabor wavelet combined with SVM is better than that of CNN and other classification methods; Our model is not combined with other common medical image data such as CT and DR. There are some uncertainties in our model; we developed a prediction system for the grades of IDC with the highest accuracy of 81.33%. Our model inputs the MRI of patients with IDC before operation, and the output of the model is the possible grade of IDC predicted.	Preoperative distinction of breast IDC grade
Manley[?]	2021	USA	To investigate whether our convolutional neural network (CNN)-based breast cancer risk model is modifiable by testing it on women who underwent risk reducing chemoprevention treatment.	Retrospective cohort	Mammography	541	27-90	Sample was racially and ethnically diverse with 36.7% non-Hispanic white, 11.6% non-Hispanic black, 36.4% Hispanic or Latina, 5.7% Asian, and 9.4% Other.	Age- race and ethnicity-menopausal status-BMI-hormone therapy use-alcohol use-	CNN risk model	The group of patients that underwent chemoprevention treatment had significant decrease in breast cancer risk compared to the group of patients that did not undergo treatment.; The modifiability of our risk model has a potential to be used as a Journal Pre-proof assessment tool to measure effectiveness of known chemoprevention agents as well as for use in testing novel chemoprevention strategies;	Risk model prediction
Pérez-Benito [?]	2019	Spain	To improve the rate of risk breast cancer estimation from healthy mammograms.	Case control	Mammography	1563 (808 cases &755 control)	45-70	Spanish women from 10 different sites	Percentage of breast density	DM-Scan: computer-assisted tool for segmentation and random forest for risk model prediction	After calculating the PDROC curve for both views in the test set (391patients,202 of which developed cancer and 189 were controls), we obtain AUCs of 0.559 and 0.551 for CC view and MLO view respectively; possible contribution to a better estimate of cancer risk compared to PD; better performance o fG-HOGH in our dataset	Breast cancer risk estimation
Fan [?]	2019	China	To investigate the accuracy of multiparametric image fusion with T2W- and DCE-MRI-based radiomic features by CCA for the prediction of histological grade in IDC	Retrospective cohort	MRI	167	51.9 28-83	Chinese women from 1 site	-	Segmentation: spatial fuzzy C-means (FCM) algorithm	SVM-based recursive feature elimination (SVM-RFE) was adopted to identify the optimal features for prediction. The areas under the ROC curves (AUCs) for the T2W images and the DCE-MRI series of pre-contrast, intermediate and last postcontrast images were 0.750±0.047, 0.749±0.047, and 0.788±0.045, respectively, for the development cohort and 0.715±0.068, 0.704±0.073, and 0.744±0.067, respectively,	Histopathological grade for IDC prediction

											for the validation cohort. After the CCA-based fusion of features from the DCE-MRI series and T2W images, the AUCs increased to 0.751±0.065, 0.803±0.0600 and 794±0.060 in the validation cohort. Moreover, the method of fusing features between DCE-MRI and T2W images using CCA achieved better performance than the concatenation-based feature fusion or classifier fusion methods. Our results demonstrated that anatomical and functional MR images yield complementary information, and feature fusion of radiomic features by matrix transformation to optimize their correlations produced a classifier with improved performance for predicting the histological grade of IDC.	
Fan [?]	2020	China	To improve prediction accuracy of these clinical indicators (Histologic grade and Ki-67 proliferation status) based on tumor radiomic analysis.	Retrospective	MRI	144	51.9 28-83	Chinese women from 1 site	Histologic grade Ki-67 status	Segmentation: spatial fuzzy C-means (FCM) algorithm	Joint prediction of Ki-67 status and tumor grade on MR images using the MTL achieved performance improvements over that of single-task-based predictive models. Similarly, for the prediction tasks of Ki-67 and tumor grade, the MTL for combined pre contrast and apparent diffusion coefficient (ADC)images achieved AUCs of 0.811 and 0.816, which were significantly better than that of the single-task-based model with p values of 0.005 and 0.017, respectively	Clinical indicators prediction
Zhou [?]	2020	China	To determine the feasibility of using a DL approach to predict clinically negative axillary lymph node metastasis from US images in patients with primary breast cancer.	Retrospective	US	680	24-82	Chinese women from 2 sites 3 vendors	-	Three different convolutional neural networks (CNNs) of Inception V3, Inception-ResNet V2, and ResNet-101 architecture	The best-performing CNN model, Inception V3, achieved an AUC of 0.89 (95% confidence interval [CI]: 0.83, 0.95) in the prediction of the final clinical diagnosis of axillary lymph node metastasis in the independent test set. The deep learning models achieved good performance in predicting lymph node metastasis with the use of the primary breast cancer US images of test set A, with AUCs of 0.90 (95% CI: 0.84, 0.95) for the Inception V3 model, 0.89 (95% CI: 0.83, 0.94) for the Inception-ResNet V2 model, and 0.87 (95% CI: 0.82, 0.93) for the ResNet-101 model (P = .44, .33, and .38 for Inception V3 vs Inception-ResNet V2, Inception V3 vs ResNet-101, and Inception-ResNet V2 vs ResNet-101, respectively. To achieve individualized and precise minimally invasive treatment, an increasing number of studies have focused on how to select an axillary management strategy to reduce the use of axillary lymph node dissection for positive sentinel lymph nodes and how to provide an option to avoid sentinel lymph node biopsy for clinically lymph node–negative breast cancer	ALN prediction
Bhattarai [?]	2019	USA	To identify predictors of BC in vivo growth rate	Retrospective	Mammography	114	50-70	American women from 1 site discovery cohort (unique and rare cohort because the second mammogram illuminated that the tumor was indeed “missed” during the first mammogram)	-	Machine learning	model (Surr-INVIGOR) that can predict a gross scale (fast versus slow) in vivo growth rate accurately in routine practice, and its medicolegal consequences	Predictors identification for BC in vivo rate
Saha [?]	2019	USA	To determine if algorithmically extracted imaging features of BPE on screening breast MRI in high-risk women are associated with subsequent development of cancer	retrospective study (Case–control study)	MRI	133 (46 cancer & 87 control patients)	50 27-76	High risk women taking part in screening breast MRI	-	Machine Learning-Based Models Using Computer-Extracted Features (multivariate logistic regression model)	The imaging features remained independently predictive of subsequent development of cancer (P< 0.003) when compared with the subjective BPE assessment of the readers	Imaging features prediction
Teja Kakileti [?]	2019	India	New personalized risk framework called Thermalytix Risk Score (TRS) to identify a high-risk target population for regular screening and enable early-stage breast cancer detection at scale	Retrospective	thermal image (+ mammo & US)	769	18-82	four breast cancer screening facilities.	Dataset without info as family history, race, age at menarche…	Cascaded CNN architecture	Effectiveness of TRS in stratifying the screening population into four different risk levels. These four risk levels might be further used to create a personalized screening regime	High-risk women prediction
Yu [?]	2021	China	To investigate whether radiomics classifiers from mammography can help predict tumor-infiltrating lymphocyte (TIL) levels in breast cancer	Retrospective	Mammography	121	50	Chinese women	-	Machine learning	Radiomics from digital mammograms not only predicts the TIL levels in breast cancer patients, but can also serve as non-invasive biomarkers in precision medicine, allowing for the development of treatment plans	Tumor-infiltrating lymphocyte prediction
Akselrod-Ballin [?]	2019	Israel	To evaluate the accuracy and efficiency of a combined machine and deep learning approach for early breast cancer detection applied to a linked set of digital mammography images and electronic health records	Retrospective	Mammography	13234 patients (52936 images)	56	Israeli women from 5 sites with many clinical features included	Age-BMI-gynecologic history (age first menstruation, age last menstruation, postmenopausal, menstruation years, pregnancies count, past pregnancies, breastfeeding, number of children breastfed, hormone replacement therapy status), cancer history (family cancer first degree, family cancer breast or ovarian, and number relatives, family cancer minimum age, any personal cancer history), symptoms, breast radiology history.	Combination of machine-learning and deep-learning approaches	The algorithm has the potential to substantially reduce missed diagnoses of breast cancer: it predicted breast malignancy detected within 12 months from the index examination and identified in 34 of 71 women with negative cancer but diagnosed within a year	BC prediction
Hou [?]	2019	USA	To improve the prediction of pure DCIS (negative) versus upstaged DCIS (positive) cases	Retrospective	Mammography	335	40-86	American women from 1 site with microcalcifications only	Shape. Topology, texture	Transfer learning	The prediction performance of DCIS upstaging by embedding two related pathology classes in different training phases was improved and outperformed the baseline model	Ductal carcinoma in situ or IDC prediction
Liu [?]	2020	USA	To explore whether the multiparametrci-MRI based model, which employs deep CNNs and transfer learning methods, can serve as a noninvasive preoperative prediction method of Ki-67 status in patients with breast cancer	Retrospective	MRI	328	51.1	American women from 1 site with multiple lesions	-	Deep CNN + Transfer learning	Noninvasive approach improves the performance of radiomics in preoperative prediction of Ki-67 status extracting breast cancer specific structural and functional features from mp-MRI images obtained from conventional scanning sequences using the advanced deep learning methods. This could further personalize medicine and computer aided diagnosis	Preoperative prediction

Table 2: Studies focusing the use of AI for treatment assessment

Study first author	Year publication	Purpose or aim(s)	Study design	Imaging modality	Number of subjects or images (N)	Subjects' mean, median or range age	Subjects' specificities/ cancer type	Treatment type	AI information's	Key findings	Keywords/categorization
Li	2020	To determine if we could identify radiomic predictors from PET/CT in breast cancer Patient therapeutic efficacy prior to NAC	retrospective	PET/CT	100 (50 Pathologic complete response & 50 without)	26-76	Chinese/ all subtype	Neoadjuvant chemotherapy (NAC)	Unsupervised and supervised machine learning	Predicting model development for pathologic complete response prior to neoadjuvant chemotherapy using radiomic PET/CT features from a single pre-treatment and patient age	treatment assessment
Aghael	2020	To develop a new quantitative global kinetic breast MRI features analysis scheme and assess its feasibility to assess tumor response to neoadjuvant chemotherapy.	retrospective	DCE-MRI	151 (63: complete response & 88: partial response)	25-76	American/ all subtype	NAC	artificial neural network and a Wrapper Subset Evaluator	quantitative analysis of global kinetic features computed from breast MR images acquired pre-chemotherapy has potential to generate a useful clinical marker that is associated with tumor response to neoadjuvant chemotherapy	treatment assessment
Gangeh	2016	To develop a noninvasive computer-aided-theragnosis (CAT)system for the early therapeutic cancer response assessment in patients with locally advanced breast cancer treated with neoadjuvant chemotherapy.	prospective	US (baseline, week 1,4 and 8 after beginning pre-ttt NAC, last scan pre-operatively 4 to 6 weeks after the completion of 2–4 months of chemotherapy administration).	56	26-67 (mean:49 +/-9)	Canadian / LABC	NAC	Advanced machine learning techniques. kernel-based metric named maximum mean discrepancy and supervised learning	The proposed CAT system thus establishes a noninvasive framework for monitoring cancer treatment response in tumors using clinical ultrasound imaging in conjunction with machine learning techniques. Such a framework can potentially facilitate the detection of refractory responses in patients to treatment early on during a course of therapy to enable possibly switching to more efficacious treatments	treatment assessment
Choi	2020	to investigate the predictive efficacy of positron emission tomography/computed tomography (PET/CT) and magnetic resonance imaging (MRI) for the pathological response of advanced breast cancer to neoadjuvant chemotherapy (NAC).	retrospective	PET/CT and MRI	56 patients were selected	26-66	Korean/ LABC	NAC	Cubic-shaped ROIs were used for image cropping for deep learning. The CNN structure arranges the input layers in a geometric pattern consisting of rows and columns of the image matrix12. It was based on Alexnet (version 2012, ImageNET large scale visual recognition challenge), using Python language (version 3.6.0), and the machine learning framework known as Tensorflow, to classify the patients into responders and non-responders.	The sensitivity increased significantly after augmentation; application of the CNN method improved the accuracy of prediction. Among the conventional imaging parameters, ΔSUV exhibited the best results with a sensitivity of 83% and specificity of 68% among the PET and MRI data. the performance of ADC in evaluating pathological responses had a sensitivity of 83% and a specificity of 72%. Subgroup analysis according to the molecular subtype revealed that all the changes in PET and ADC data were statistically significant in predicting the pathologic response in the HER2-negative group but not in the triple-negative group.	treatment assessment
Dashevsky	2018	to predict resectability of HER2+ breast cancer at breast conservation surgery (BCS) utilizing features identified on preoperative breast MRI	retrospective study	MRI	109	30-79	American / HER2+	Breast cancer surgery (BCS)	SVM classifier	We found 55% of patients that required one re-excision had multifocal or multicentric disease, compared to only 24% of patients who had successful initial BCS	treatment assessment
Ha	2018	to better predict post-NACaxillary response using a breast MRI dataset	retrospective study (feasibility study)	MRI	127	23-82	American / LABC	NAC	CNN with 4 block and 10 CL	accuracy of 83% in predicting NAC response in patients with node-positive breast cancer	treatment assessment
Ha	2018	to develop a novel CNN to predict NAC response using a baseline breast MRI tumor dataset and pathological confirmation of treatment response	retrospective study using retrospective review of our database	MRI	141	not specified	American / LABC	NAC	CNN	It is feasible for current deep CNN architectures to be trained to predict NAC treatment response using a breast MRI dataset obtained prior to initiation of chemotherapy.Larger dataset will likely improve our prediction model	treatment assessment
Czarnota	2018	to demonstrate the clinical utility of pre-ttt and early stage treatment QUS texture features in predicting the response of breast cancer patients to NAC	prospective study	US	100	29-82	Canadian / LABC	NAC	SVM classifier	highly accurate algorithms able to detect tumour response prior to treatment and early after starting NAC	treatment assessment
Gangeh	2016	to propose a new and improved approach for the QUS prediction of breast tumor response to neoadjuvant chemotherapy.	Prospective study	US	58	29-67	Canadian / LABC	NAC	KNN classifier ? And SVM ?	multi-parametric QUS applied at a clinically relevant frequency range (<10 MHz) can be used to non-invasively predict breast tumor response to NAC as early as after 1-2 cycles (1-4 weeks) with reasonable accuracy (80%), whereas RECIST-based tumor size change is only 52% accurate in predicting response at week 4 with a 30% threshold.	treatment assessment
DiCenzo	2020	to develop a model for predicting response to neoadjuvant chemotherapy (NAC) in patients with locally advanced breast cancer (LABC) using pre-treatment quantitative ultrasound (QUS) radiomics	prospective observational study	US	82 (80W & 2M)	27-74	Canadian / LABC	NAC	SVM classifier	QUS-based radiomics can predict response to NAC based on pretreat-ment features with acceptable accuracy	treatment assessment
Jiang	2020	To develop and validate a radiomics-based nomogram with texture features from mammography for the prognostic prediction in patients with early-stage triple-negative breast cancer (TNBC)	retrospective study	mammography	200	mean = 49	Chinese / (triple negative) TNBC	Not specific	deep-learning strategies (not really specified)	the radiomics nomogram adds more net benefit than the "treat all" or "treat none" strategies without limitation on the threshold probability	treatment assessment
Quiaoit [?]	2020	To investigate the utility of quantitative ultrasound(QUS) carried out during NAC to predict the final tumour response in a multi-institutional setting	Prospective observational study	US	59 (58 W & 1 M)	27-73	Canadian / LABC	NAC	SVM	QUS data obtained during NAC reflect the ongoing treatment-related changes during chemotherapy and can lead to better classifier performance in predicting the ultimate pathologic response to treatment compared to baseline features alone.	Treatment assessment
Tahmassebi [?]	2019	To assess the potential of machine learning with multiparametric magnetic resonance imaging (mpMRI) for the early prediction of pathological complete response (pCR) to neoadjuvant chemotherapy (NAC) and of survival outcomes in breast cancer patients	Retrospective	MRI	38	25-70	American	NAC	ML – 8 classifiers	For prediction of RCB class, RFS, and DSS, qualitative and quantitative features from all mpMRI sequences, that is, T2-weighted, DCE, and DWI, were necessary. The most relevant features for prediction of RCB class were qualitative features including changes in lesion size (RL, craniocaudal, and AP) and complete pattern of shrinkage on DCE-MRI, quantitative pharmacokinetic features including mean transit time with DCE-MRI, peritumoral oedema onT2-weighted imaging, and minimum ADC with DWI. Machine learning with mpMRI allowed prediction of pCR (best/mean AUC, 0.94/0.86) and survival outcomes (RFSbest/mean AUC, 0.83/0.77; DSS best/mean AUC, 0.92/0.91) with high accuracy. Qualitative and quantitative features from all MRI sequences were necessary for prediction of RCB class, RFS, and DSS, thus supporting the use of an mpMRI	Treatment assessment

										approach. Of all machine learning classifier models, the XGBoost classifier model outperformed all other models in the prediction of pCR and DSS. Only for RFS, the LR classifier model showed a slightly better accuracy (~3%) yet the XGBoost model is more stable.	
Braman [?]	2017	To predict pathological complete response (pCR) to neoadjuvant chemotherapy (NAC) using dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI)	Retrospective	MRI	117	23-79	American / multiple subtypes	NAC	SVM	Among all patients, a combined intratumoral and peritumoral radiomic feature set yielded a maximum AUC of 0.78 ± 0.030 within the training set and 0.74 within the independent testing set using a diagonal linear discriminant analysis (DLDA) classifier. Receptor status-specific feature discovery and classification enabled improved prediction of pCR, yielding maximum AUCs of 0.83 ± 0.025 within the HR+, HER2−group using DLDA and 0.93 ± 0.018within the TN/HER2+group using a naive Bayes classifier. In HR+, HER2−breast cancers, non-pCR was characterized by elevated peritumoral heterogeneity during initial contrast enhancement. However, TN/HER2+tumors were best characterized by a speckled enhancement pattern within the peritumoral region of non-responders. Radiomic features were found to strongly predict pCR independent of choice of classifier, suggesting their robustness as response predictors. our findings suggest that the radiomic features most predictive of response vary across different receptor subtypes	treatment assessment
Sutton [?]	2020	To develop and validate a radiomics classifier that classifies breast cancer pCR post-NAC on MRI priorto surgery USA	Retrospective	MRI	273	Mean=51.8	American/ all subtypes	NAC	ML classifier	The model 1 RFE-RF classifier identified 19 different features including pre-contrast and first post-contrast MRI intensity features from post-NAC and difference from the post-NAC to pre-NAC mean intensities. Model 2 identified 12 radiomics features and molecular subtype as relevant for pCR classification. Model 3 identified 11 radiomics features, of which delta pre-contrast MRI homogeneity, delta pre-contrast MRI contrast, and delta first post-contrast MRI Gabor (90, 14.14) energy were significantly different between pCR and no CR.	treatment assessment
El Adoui [?]	2020	To present a new deep learning (DL) model predicting the breast cancer response to NAC based on multiple MRI inputs	Retrospective	MRI	42	Mean=55	Belgian / LABC	NAC	CNN	Using gradient class activation maps to localize tumor regions of interest relevant to the CNN predictions is a unique strength of this work and imparts greater interpret-ability than DL approaches with no visualized decision-making component.	treatment assessment
Tran [?]	2017	To evaluate texture features of pretreatment DOS functional maps for predicting LABC response to NAC	Prospective	Tomographic diffuse optical spectroscopy imaging	37	18-85	American / LABC	NAC	Machine learning	The novel machine learning algorithms, especially XGBoost, can be used to develop breast cancer prediction models to help identify women at high risk for breast cancer in developing countries	treatment assessment
Liu [?]	2020	To apply our convolutional neural network (CNN) algorithm to predict neoadjuvant chemotherapy (NAC) response using the ISPYTRIAL breast MRI dataset	Retrospective	MRI	131	Mean=48.3	American / LABC	NAC	CNN	Utilizing a publicly available breast MRI dataset from the ISPY-Trial, our CNN algorithm was able to achieve an overall accuracy of72.5% in predicting patients with pCR following NAC	treatment assessment
Hope Cain [?]	2018	To determine whether a multivariate machine learning-based model using computer-extracted features of pre-treatment dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) can predict pathologic complete response (pCR) to neoadjuvant therapy (NAT) in breast cancer patients	Retrospective	MRI	288	24-76	American / invasive	NAC	multivariate models (both SVM and logistic regression)	validate tool for specific subpopulation. We found a significant association between our multivariate models and pCR in TN/HER2+ patients. These findings are important because TN/HER2+ patients achieve higher rates of pCR compared to HR+/HER2- cancers and have improved disease free and overall survival after a pCR	treatment assessment

Unnecessary biopsies reduction

Six studies explored the possibility of reducing unnecessary biopsies, one (46) from Canada was prospective, and the other 5 were retrospective (2 Americans (47,48) and 3 Chinese (49–51). The sample size was small varying from 100 to 167 patients, except for Zhang et al (50) study which included 2822 images from 1820 patients. The women age ranged between 15 and 92 years old. The images used were acquired in a single institution except for of study Zhang (50) that included women's data from 2 different sites. Destrempes et al (46) used images acquired with equipment from two US vendors. No other specific characteristics of the women were described except that for BI-RADS 4 and 5 category patients were the most explored (46).

Most of the studies (n=4) used US images while one used mammography and another MRI. Two used contrast-enhanced images, one was contrast-enhanced digital mammography, and the other was CE-US. The AI techniques were heterogeneous, but the results showed AI tool as having potential to reduce unnecessary biopsies in a short period, improving the times allocated to manage the disease. The invasive biopsies require more time to have the results (46–49), more costs and pain for the patient and the healthcare system.

Patients' preferences

The 3 studies showed that women in a screening age had high levels of trust in AI tools and were ready to accept the use of them in clinical practice. However, the results showed a preference in use of AI tool as co-actor in the decision, with the clinician have the ultimate decision making role. Understanding the technology seems to be a key point for the confidence, being linked to the responsibility when diagnostic errors happen. Another aspect to consider for patients' comfort and control of their anxiety was the reduction of waiting time between the examination acquisition and the receipt of the final diagnostic report.

Tumour type prediction

Eleven retrospective studies were categorised under "tumour type prediction" (Table 3). Most imaging modalities were used to acquire the images used in the studies included in this category (MRI=5, US=3, Mammography=1, PET/CT=1 and multimodality MRI & mammography=1).

Most studies were conducted in China (n=6) and the age range of women included in these studies varied between 18 and 89 years old). Five out of 11 studies included young women not participating in a screening programme. In this category, several studies (5 out of 11) used patients' samples with different characteristics, namely different race, age, equipment utilised and sites. Castaldo et al (52) had used an available American database combining data from 5 sites.

Table 3: *Studies focusing the use of AI for tumour type prediction*

Study first author	Year	Country	Purpose or Aim(s)	Study design	Imaging modality	Nbr subjects or images	Subjects' mean, median or range age	Subjects' or machine specificities	Clinical (patient) features	AI information's	Key findings
Sutton [?]	2016	USA	To use features extracted from magnetic resonance (MR) images and a machine-learning method to assist in differentiating breast cancer molecular subtypes.	Retrospective	MRI (1.5 or 3.0T)	178	28-76	American women with invasive ductal carcinoma and preoperative breast MRI	Age-Menopausal Status-Pathologic tumor size-Histologic grade-nuclear grade-Axillary lymph-node status	Multiclass SVM	This machine-learning-based predictive model using features extracted from MRI can distinguish IDC subtypes with an overall accuracy on LOOCV of 83.4%. The model's accuracy was increased when pathologic data were incorporated. Computer-derived imaging features of the different subtypes were also significantly different, suggesting that image-based biomarkers may define behavior and determine treatment.
Krajnc [?]	2021	Austria	To establish prediction models for breast cancer detection and the identification of breast cancer receptor status, proliferation rate, and molecular subtypes from [18F] FDG-PET/CT images with ML, (b) To investigate the effect of data pre-processing on breast tumor characterization ML models, and (c), To compare ML-based prediction models with conventional SUV-based approaches.	Retrospective	PET/CT [18F] FDG	170	57.6 (18-86)	Austrian women	Age-Weight/Height-BMI	Machine learning	Predictive models based on [18F] FDG-PET/CT images in combination with advanced data pre-processing steps aid in breast cancer diagnosis and in ML-based prediction of the aggressive triple negative breast cancer subtype. However, radiomics analysis of [18F] FDG-PET/CT is limited in value for the prediction of individual receptor status and proliferation rate.
Ha[?]	2019	USA	To develop a novel CNN algorithm to predict Oncotype DX recurrence score using a breast MRI tumor dataset.	Retrospective	MRI (1.5 or 3.0T)	134	55.9 ± 11	American women	Age	CNN	In a relatively small sample size, we were able to predict Oncotype Dx RS based on an MRI tumor dataset with an accuracy of up to 84%. Future research with a prospective randomized study is needed to validate the potential of predicting Oncotype Dx RS, as well as directly correlating MRI with clinical outcome.
Jiang[?]	2021	China	To evaluate the prediction performance of deep convolutional neural network (DCNN) based on ultrasound (US)images for the assessment of breast cancer molecular subtypes.	Retrospective	US	4828 images from 1275 patients	26-74	Chinese women 4 vendors	Pathology subtype annotation	ResNet50 as the basal DCNN classification model to train the deep learning algorithm, in which image input features are mapped to the corresponding output label	Automatic breast cancer phenotyping allows for a more detailed analysis of pretreatment US images, which would provide complementary information for individualized treatment plan options without increasing the time burden. Although analyzing breast cancer molecular subtypes based on US images is a relatively new area of exploration, there is some evidence to support an ultrasonic and biological basis for our findings. For example, significant differences in shear wave velocity values among different molecular subtypes were detected. Our results demonstrated that DCNN derived from US data enables the identification of molecular subtypes with accuracy. The computer algorithm may therefore provide helpful prognostic information based on the pretreatment tumor image.
Saha [?]	2018	USA	To present a comprehensive analysis of associations of MRI-based imaging phenotypes of breast tumors with breast cancer molecular, genomic, and related characteristics	Retrospective heterogenous cohort	MRI	922	52.25 21.75-89.49	American heterogeneous women from 1 site (race white, black and others)	-	Fuzzy C-means	Our additional analysis on subgroups formed using different scanner manufacturers, races, and menopausal status of the patients did not demonstrate major differences in the performance of the trained models most of the tasks. Regarding molecular subtypes, the highest performance was obtained for the models distinguishing Luminal A from other subtypes with AUC=0.697 (95% CI: 0.647–0.746, p< 1.24e−11) and TNBC from the other subtypes AUC=0.654 (95% CI:0.589–0.720, p< 1.42e−05). The performances for distinguishingHER2 from other subtypes and for Luminal B from other subtypes were somewhat lower and did not reach statistical significance (p=0.03 and p=0.13, respectively). Regarding individual molecular markers, the

											models showed significant prognostic value for distinguishing ER+from ER−patients (p< 4.2e−06), PR+fromPR−patients (p< 1.93e−04). The model for predicting high vs low proliferation (Ki-67) showed AUC=0.624 with ap-value on the margin of significance (p=0.01)
Wu [?]	2018	China	To evaluate the potential of machine learning with quantitative ultrasound image features for the diagnosis of TN breast cancer	Retrospective	US	140	50.3 ± 9.6	Surgically confirmed breast cancer in Chinese women	-	Machine learning	The analysis of breast ultrasound images by machine learning achieves high level of differentiation between the TN and NTN subtypes, exceeding the diagnostic performance by standard visual assessments of the images
Guo [?]	2017	China	To assess the associations between quantitative ultrasound feature and biological characteristics	Retrospective	US	215	52.53 & 50.94	Chinese women (HER-2 neg and triple negative) 2 vendors	-	SVM	Strong correlation between receptor status and subtypes (p<0.05, AUC=0.760). Hormone receptor-positive, HER2-negative cancers have different ultrasound appearances from Triple-negative cancers.
Zhou [?]	2019	China	To evaluate the HER-2 status in breast cancer patients using mammography(MG) radiomics features	Retrospective	Mammography	306	49.5	Chinese women with onvasive ductal carcinoma of no special type	-	SVM	Radiomics features could be an efficient tool for the preoperative evaluation of HER-2 status inpatients with breast cancer. ng the SVM andlogistic regression models built from radiomics features from CC viewsalone, MLO views alone and CC and MLO views in combination, thelogistic regression model built from a combination of features from CCviews and MLO views showed the optimal performance for distin-guishing HER-2 status.
Zhang [?]	2020	China	To apply deep learning algorithms using a conventional convolutional neural network (CNN) and a recurrent CNN to differentiate three breast cancer molecular subtypes on MRI	Retrospective	MRI	244	33-72	Chinese women from 2 sites	-	CNN and transfer learning	How the AI methods developed using one training dataset can be implemented in a different clinical setting, e.g., images acquired using different protocols, different scanners, or in different hospitals
Wu [?]	2019	China	To develop and validate an interpretable and repeatable machine learning model approach to predictmolecular subtypes of breast cancer from clinical metainformation together with mammography and MRI images	Retrospective	Mammography & MRI	363	21-77	Chinese women from 1 site	Breast cancer family-oral contraceptive history-reproductve & breastfeeding history-multiple aborption history-breast prosthesis implantation-nipple discharge-skin abnormalita-Age	Decision tree (machine learning)	A complete“white box”machine learning method to predict the molecular subtype ofbreast cancer based on the BI-RADS feature description in a multi-modal setting.
Castaldo	2020	Italy	To evaluate the effect of several normalization techniques to predict four clinical phenotypes such as ER,PR,HER2 and TN status by quantitative features	Retrospective	MRI	91	29-82	The cancer Genome Atlas database American women from 5 sites	-	Three advanced ML techniques (Support Vector Machine,Random Forest and Naïve Bayesian)	Radiomic features enable to discriminate major breast cancer molecular subtypes and may yield a potential imaging biomarker for advancing precision medicine

Other issues

Four 4 articles were identified as not being directly related to one of the 6 categories identified above. Two of these were about image quality assessment, as they addressed breast positioning in mammography (53,54). The other two studies were performed on a dedicated breast-CT and focused specifically image reconstruction and glandular dose estimation for optimisation. While Teuwen et al. (55) performed their study using a dataset of 3D breast phantoms images to estimate the actual breast density or patient specific dose, Cong et al. (56) used an available dataset from the company that manufactured the dedicated breast CT system to achieve a radiation dose reduction of 6mGy per cone-beam CT scan.

Discussion

The aim of this study was to identify AI tools facilitating person centred care for diagnostic and treatment of breast diseases, and according to the findings, there are six different categories of AI tools. Most of these categories are dedicated to cancer prediction and disease management. For all these categories, the AI algorithms were in stage of internal validity, using mainly retrospective study designs and small samples. Furthermore, the samples were relatively heterogenous (females of different ages, races, and ethnicities and some have even included images acquired with different equipment). But to the best of our knowledge, none of them have studied the influence of these variables on the results.

In addition, only two studies included 1 or 2 males in their samples. Although breast cancer affects mostly women, it can happen also in males (57,58), as well as in people transitioning genders, due to the use of hormones, which can promote an increase on breast dense tissues and consequently an increase of BC risk (59–61).

A valid, clinically applicable external model should be applied to prospective data using direct raw data and applicable to all patients' specificities without variability by acquisition or treatment protocol. This is to study whether these algorithms can be generalised across other clinical situations and contexts. This step is essential if the algorithm is to be adopted and implemented clinically (62).

The advantage of AI tools is their ability to integrate data from various sources, both in terms of imaging modality and patient information for direct precision medicine (63). However, only few studies (6 out of 79) have combined data from different imaging modalities, which could be improved especially since a multitude of imaging modalities are available and integrated in the diagnosis and follow-up of breast diseases. Regarding the inclusion of patient features, heterogeneity was observed probably due to the need to include different factors for a better risk prediction. While some studies used known models such as the Tyrer-Cuzick score, others included just some of the patient features

or no features at all. Due to the preliminary phase of AI tool development (mostly retrospective studies, homogenous population and single field strength), an approach fully oriented to radiomics seem to be still far away because those limits restrict their wider applicability and generalizability at present (64). Radiomics have the potential to facilitate the integration of quantitative information with clinical, histological, and genomic data and to give robustness to the decision and promote precision medicine and personalised care (65). The radiogenomics (combination of radiomic and genomic) could help in the prediction of breast cancers molecular profile and contribute to the establishment of the best patient management (66).

Moreover, the use of actual statistical and evidence data in combination of specific patient data could help on reducing recall rate, misdiagnosis, overdiagnosis as well on offering a personalised prognosis and consequently more adapted treatment as shown on the studies about NAC (44,67,68).

The screening of breast cancer can be also personalised to respond to the individual needs. Currently, in most of the countries having a breast cancer screening program, there is harmonisation of the program regarding the age of the participants, the examinations performed and the screening interval (69,70). One of the exceptions to the standard screening is for women at elevated risk based on *BRCA1/2* mutation carriers, a strong family history of BC, or several genetic syndromes, such as Li-Fraumeni syndrome or Cowden disease (71). In these situation a MRI is being recommended as the screening test (72–74). However, with a combination of the AI tools for risk prediction as well as the tools for breast density assessment, a personalized screening, instead of program where “one size fits all”, can be achieved (20,38,75,76). A recommendation for a pathway can be presented to each person considering their age, the family history, and their individual risk factors , since these parameters can vary from an individual to another (77). Some current guidelines (78,79) present already pathways for different groups of patients but still not individualised enough by combining all required data.

As artificial intelligence applications aim mainly to imitate and learn complex, time-consuming cognitive human tasks, the emotions, pain and stress management is limited by these applications. The healthcare professionals are critical to overcome these limitations and since AI is focussing on technical aspects, the professionals have more time to focus their attention on patients’ needs and become the advocates and facilitators of person centred care.

AI, despite limitations, can still help on on emotions’ and pain management, indirectly, namely if for example a biopsy can be avoided. Avoiding unnecessary biopsies reduces the pain and stress experienced by patients, typically associated with invasive procedures (47–51).

The unnecessary biopsy reduction can also have positive impact on workload and workflow of medical imaging departments, since fewer examinations are required, and the patients' pathway can be improved and adapted to their needs.

None of the included studies have addressed the topic of "conversational agents (chatbot)" that could be used to speak to the patients to try to reduce anxiety, to improve technology confidence or treatment adherence. As example, a tool named *Vik* developed in France (80) has demonstrated that chatbot could improve support and medication adherence rate for patients with breast cancer.

The patient preferences were explored in 3 studies, but none mentioned if the patient choices are included as criteria in the decision-making process. Currently, the treatment options are presented by the relevanthealthcare professionals to the patients, and decisions are made jointly. However, with AI contribution more variables can be integrated to achieve the personalisation of disease management, including the patients' preferences and demographics (81)(82). This should be included at the beginning of the tool's development, during in the training and validation phase, and be constantly updated for different patient cohorts.

Confidence in and acceptability of technology, the use and the sharing of patient clinical data are all key aspects to consider in the AI tools development. Indeed, as large prospective datasets are proving challengingto collect and as individual data belong to the patient, it seems essential to develop trust with the patients in order for them to allow access to personal information. Explanations of how the AI algorithm, known as black box, makes its predictions can influence the confidence of patients and thus the clinical deployment of these algorithms. Explainable AI (XAI) provides an understanding and explanation of the decision, prediction and execution process (83). This ensures that the patients are involved, that AI transforms into collective intelligence and can help in the acceptability of this new technology (84). Appropriately trained healthcare professionals, who can help explain the basics, risks and benefits of AI applications to patients in relation to their specific imaging pathway, can be instrumental in AI integration in clinical practice.

Only 4 studies focused a better patient management at the time of the imaging examination by exploring the optimisation of the examination, by studying patient positioning or delivered dose. However, several elements can affect the outcomes of breast imaging namely organisational issues such as the time allocated to the examination which can promote high levels of stress as well as work-related musculoskeletal disorders, promoting a risk of impacting the examination outcome (85,86).

Aspects related to the patient (age, the volume of the breast, breast density, previous interventions, capability of collaboration) (87–89), the equipment, the acquisition techniques (exposure parameters, breast compression and breast positioning) (89–94) and the quality assurance/control practices have a role to play as well (95,96). AI tools integrated in practice to help on patients' management with solutions to adapt technique to each individual, for compression, positioning and preferences, presenting possible approaches to overcome even the individual limitations that may exists to acquire the imaging. The image quality evaluation can also be improved with the support of AI tools since the algorithms can detect artifacts that sometimes are not visible to the human eyes, mainly when blur exists due to inadequate breast compression in mammography and the monitors are not suitable for image assessment (97,98).

Breast Tomosynthesis is also an imaging modality available for BC screening in some European countries such as Norway and United Kingdom (36,99). However, it remains an optional extra tool in the assessment of breast abnormalities and not as a routine screening in UK) even with evidence about the benefits for women with denser breasts, recall rates reduction and increase on cancer detection (36,99–101). Currently, AI is being applied to tomosynthesis, mainly to reduce the reading time and lesion detection (102–104) but other roles can be played namely on adapting the patients' pathway, breast compression and positioning, exposure parameters optimisation with a special attention to dose reduction while keeping image quality.

There are some limitations to our scoping review; the quality of included studies was not evaluated in accordance to the scoping review methodology. To consider only recent AI developments, the studies included were only published after 2016 and not before. The PCC concept is really vast developing so it was hard to attempt a shared vision and mental model, which could impact the first stage screening of studies' selection. The exclusion of studies using phantoms could also impact the lack of data in terms of dose and image quality.

From this research, it seems important to further explore the role of AI for different patient population profiles/characteristics, so it is in the future better integrated into effective personalised care, by considering the idiosyncracies of each race and gender. There is a lack of studies that provide better management of patients at the time of imaging acquisition to improve their experience including positioning, compression, optimization quality/dose received, faster acquisitions or personalised techniques. Male and transgender women studies are still scarce and those are populations that may also experience from breast pathologies. The explainability of AI tools and the inclusion of patient's preferences in the management of breast disease are needed to be further developed, studied and explored in the future to ensure a balanced integration of AI in breast imaging.

Conclusions

The use of AI for person-centered care is mainly focused on risk and cancer prediction and disease management. It seems that AI brings the possibility of personalised screening taking into consideration the specific risks, as well as the identification of the most suitable treatment by analysing multi data and multi-imaging modalities. However, AI tools are mainly designed for imaging assessment and less for the optimisation of image acquisition, improvement of patient experience and to explain to patients the possible impacts and pathways of disease management.

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Appendix 1 Search strategy: 23.06.2021

PubMed

("Mammography"[MeSH Terms] OR "breast neoplasms/diagnostic imaging"[MeSH Terms] OR "Breast/diagnostic imaging"[Mesh] OR "mammograph*"[Title/Abstract] OR "breast cancer screening"[Title/Abstract] OR "breast screening"[Title/Abstract] OR "breast imaging"[Title/Abstract]) AND ("Artificial Intelligence"[MeSH Terms] OR "Artificial Intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract]) AND (2016:2021[pdat])

Nombre de références: 808

Embase.com

('mammography'/exp OR mammograph*:ti,ab,kw OR 'breast cancer screening':ti,ab,kw OR 'breast screening':ti,ab,kw OR 'breast imaging':ti,ab,kw) AND ('artificial intelligence'/exp OR 'machine learning'/exp OR 'artificial intelligence':ti,ab,kw OR 'machine learning':ti,ab,kw OR 'deep learning':ti,ab,kw) AND [2016-2021]/py

Nombre de références : 1235

CINAHL (ebsco)

(MH "Mammography" OR MH "Breast Neoplasms+/DI/US/RA" OR MH "Breast+/US/RA" OR TI mammograph* OR AB mammograph* TI "breast cancer screening" OR AB "breast cancer screening" OR TI "breast screening" OR AB "breast screening" OR TI "breast imaging" OR AB "breast imaging") AND (MH "Artificial Intelligence+" OR TI "Artificial Intelligence" OR AB "Artificial Intelligence" OR TI "machine learning" OR AB "machine learning" OR TI "deep learning" OR AB "deep learning") AND PY 2016-3000

Nombre de références : 226

Web of Science

Web of Science Core collection (indexes=SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI)

TS=(mammograph* OR "breast cancer screening" OR "breast screening" OR "breast imaging") AND TS=("artificial intelligence" OR "machine learning" OR "deep learning") AND PY=2016-2100

Nombre de références : 828

IEEE Xplore https://ieeexplore.ieee.org/Xplore/home.jsp

("All Metadata":mammograph* OR "All Metadata":"breast cancer screening" OR "All Metadata":"breast screening" OR "All Metadata":"breast imaging") AND ("All Metadata":"artificial intelligence" OR "All Metadata":"machine learning" OR "All Metadata":"deep learning")

Filters Applied: 2016 - 2021

Nombre de références : 375

arXiv.org https://arxiv.org/

Advanced search :

All fields : mammograph* OR "breast cancer screening" OR "breast screening" OR "breast imaging"

AND
All fields :"artificial intelligence" OR "machine learning" OR "deep learning"
Query: order: -announced_date_first; size: 50; date_range: from 2016-01-01 to 2021-12-31; include_cross_list: True; terms: AND all=mammograph* OR "breast cancer screening" OR "breast screening" OR "breast imaging"; AND all="artificial intelligence" OR "machine learning" OR "deep learning"

Nombre de références : 81