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REVIEW

Artificial Intelligence in Breast Cancer Diagnosis and Surgical Decision-Making: An Updated and Comprehensive Overview of Precision and Personalization in Current Evidence

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Abstract: Breast cancer (BC) surgery has been advanced through artificial intelligence (AI), which helps surgeons to gain more accurate results and apply surgical procedures. Despite the increasing focus on AI in BC management, there are knowledge gaps in the current understanding that can be readily identified from the existing works of literature. This narrative review aims to provide an update on the influencing role of AI technologies in precise and personalized clinical decision-making in BC surgery. We included articles published in English during the past 5 years from the major databases. Furthermore, this review used appropriate keywords with and without Boolean operators like "AND", "OR" and "NOT". We considered three major aspects for surgical practice: preoperative planning, intraoperative decision-making, and postoperative outcomes, while interpreting the studies. We found that AI-assisted BC surgery has advanced through the development of a new real-time, accurate tumor identifier, margin assessment, and robotic-assisted surgeries. Moreover, AI-based algorithms are gradually incorporated into the evaluation of the postoperative probability of reoccurrence, complications, and patient satisfaction. It is documented that integrating AI technologies into BC care is inevitable and set to expand further in all aspects. Furthermore, this review identified some major challenges in the algorithm and ethical aspects. The limitations, such as lack of external validation, integration barriers, and the "black box" nature of some AI models, remain unresolved. To fully utilize AI's capabilities, it is recommended that surgeons, AI developers, and policymakers collaborate on more advanced AI that is enhanced for personalized care by including patients' genetics, medical history, and lifestyle factors. Additionally, future prospective and exploratory cost-effective analysis studies are to be done.

Keywords: breast cancer, personalized care, intraoperative, machine learning, deep learning

Introduction

Globally, breast cancer (BC) remains one of the important health challenges, as reported by the World Health Organization and the global cancer statistics. BC accounts for almost 2.3 million cases annually, rendering it the most prevalent cancer among adults.[1,2] In 95% of nations, BC ranks as the primary or secondary cause of mortality among female cancer patients.[2,3]

The management flow of BC includes risk reduction, screening, imaging, biopsy, treatment, and follow-up. There are various treatment modalities for BC, including surgical, radiotherapy, chemotherapy, and immunotherapy.[4,5] Despite the fact that new approaches for early diagnosis and management of BC have evolved over the past decade, the global BC statistics indicate the reality of persistent global obstacles in reducing the incidence and improving the survival of BC patients.[3,6,7] In recent years, artificial intelligence (AI) has emerged as a promising adjunct to conventional treatment approaches, particularly in enhancing the precision and personalization of surgical decision-making, for instance, in BC treatment.[8,9]

Among the available treatment approaches, surgical modalities (except in metastatic cancer) remain the first approach, followed by other therapies. The surgical options are lumpectomy (partial mastectomy) and mastectomy.

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Traditional methods often face limitations in terms of human variability, time constraints, and difficulty in interpreting complex, high-dimensional data. The surgeons may decide on further supplementary procedures, including sentinel lymph node biopsy, axillary lymph node dissection, and breast reconstructive surgery, according to the existing guidelines, the patient's condition and preference, and numerous other potential factors that can influence surgical decisions.[5,10] Nonetheless, it is stated that BC's surgical decision is moving away from "one size fits for all" to personalized and precision care.[11–13]

AI makes use of the most recent machine learning (ML) and deep learning (DL) algorithms and methods, including computer vision, among others (such as neural networks: convolutional, recurrent, and artificial and generative adversarial networks), to interpret sophisticated data. Large language models represent a category of AI that employs natural language processing techniques to analyze user prompts and provide human-like responses. DL involves multilayered neural networks for analyzing imaging data. Convolutional neural networks are a subset of DL specialized in medical image recognition. Reinforcement learning enables systems to improve decisions based on trial-and-error feedback. Natural language processing helps extract insights from clinical notes and medical literature.[14–16] The role of AI in BC care ranges from screening to predicting prognostic values.[9] For example, in BC screening, AI algorithms have the potential to significantly improve radiologists' workflow by offering quantitative assessments that are free from human bias, which might lead to data-driven recommendations for doubtful mammograms that could be interpreted in numerous ways. To provide patients with answers more quickly, AI-powered software can automate the interpretation of MRI, ultrasound, and breast mammography data.[17,18] Additionally, the role of AI in preoperative (surgical decision-making and patients' health education), intraoperative (margin evaluation and accurate tumor removal), and postoperative prediction (prognosis, complications, and survival rate) has been documented in recent studies. Kothari et al formed an integrated model (ML and Laser Raman spectroscopy) to accurately identify the cancer tissue margins, a crucial step in breast conservative techniques.[19] Similarly, Xu et al assessed the surgical decision-making model and found that about 5% of treating surgeons reworked their decisions after using this model.[20]

More recent work has focused on the application of AI in reconstructive surgical treatment decision-making in the context of BC.[21,22] For instance, assessing ML methods for the prediction of donor-related complications in microsurgical breast reconstruction by Myung et al stated that using ML, the doctor can make a personalized surgical choice for better postoperative outcomes.[21] Despite the increasing focus on AI in BC management, there are knowledge gaps in the current understanding that can be readily identified from the existing works of literature. Several studies have been conducted with a small sample size and a retrospective nature. Although some reviews have been conducted on how artificial intelligence can be used in BC care, most of them have been restricted to either diagnostic imaging or early detection, with fewer reviews done on its overall contribution to the decision-making process of the surgery. Some recent reviews have targeted certain AI applications in the field of surgery, yet these did not encompass a wide range of technologies nor the implications for patients. Apart from that, there are other disadvantages to using AI in BC, including data protection, privacy, and ethical issues, which is less explored in previous reviews.[23,24] Finally, because of such dynamics and progressive changes in the application of AI in BC management in recent years, it is vital to obtain up-to-date information. Thus, the current narrative review seeks to provide a more holistic, up-to-date map of all applicable AI use cases in BC surgery decision-making and follow-up processes. Furthermore, the present review provides recommendations for future research directions to overcome the limitations and make use of AI efficiently in BC management.

Search Strategies

The present study included relevant literature published in the past five years (from January 2019 to September 2024). We used a diverse range of databases, namely, PubMed/Medline, Embase, Cochrane Library, Web of Science, Saudi Digital Library, IEEE Xplore, and Scopus, to find the latest published studies. This review used appropriate keywords with and without Boolean operators like "AND", "OR", and "NOT". The following keywords were used in the study: "Artificial Intelligence", "Breast Cancer", "Surgical Decision-Making", "Machine Learning", "Deep Learning", "Decision Support Techniques", "Treatment Outcome", "Patient Satisfaction", "Survival Rate", "Precision Medicine", "Surgical Outcomes". Moreover, the articles included were peer-reviewed with a digital object identifier (DOI) to ensure reliability and accessibility, even if the web address changed. This review excluded expert opinions, non-published

Table 1 Search Strategy for the Review

Components	Strategies/Details
Databases Searched	PubMed/Medline, Embase, Cochrane Library, Web of Science, Saudi Digital Library, IEEE Xplore, Scopus
Search Period	January 2019 to September 2024
Keywords Used	"Artificial Intelligence", "Breast Cancer", "Surgical Decision-Making", "Machine Learning", "Deep Learning", "Decision Support Techniques", "Treatment Outcome", "Survival Rate", "Precision Medicine", "Surgical Outcomes"
Search Operators	Boolean operators such as "AND" "OR", and "NOT"
Inclusion Criteria	- Peer-reviewed articles in English- Published studies with a digital object identifier (DOI)- Focus on AI in breast cancer surgical decision-making- Published between January 2019 and September 2024
Exclusion Criteria	- Expert opinions, case series, case reports- Studies not focused on AI in BC management- Non-English articles
Selection process*	- First-level screening by Anfal Mohammed Alenezi for relevance- Secondary review by Abdulaziz Khalid Alrasheed to ensure compliance with criteria - Conflicts resolved by Ashokkumar Thirunavukkarasu
Final included articles	116 (after applying inclusion/exclusion criteria)

Note: *The researchers involved in selection process are acknowledged in the acknowledgement section.

articles, case series, case reports, editorial comments, studies not focused on AI in BC management, and non-English articles. After applying all these inclusion and exclusion criteria, the final number of included articles in the present review's main text was 116. The search strategies are summarized in Table 1, and the study selection process in each stage is shown in a flow chart in Figure 1. Furthermore, the full database-specific search histories are presented as a supplementary file (Please find Appendix A – full search strategies by database for more information).

Main Text

This review's main text constitutes the discussion of AI applications in surgical decision-making (preoperative/intraoperative/postoperative), challenges and barriers to AI integration in clinical practice, and future directions and recommendations. The common AI models and their roles in BC surgical care are depicted in Figure 2.

AI Applications in Surgical Decision-Making

Role of AI in Preoperative BC Care

Some authors recently explored the significance of AI in preoperative BC care, and it was observed that AI could potentially transform and help in improving diagnostic precision, refining risk classification, and personalized care.[25,26] AI is now utilized in medical imaging and histopathology for breast diseases due to the latest developments in computer vision algorithms and expanding training datasets.[27,28] A prospective study by Dembrower et al 2023 reported that when AI replaced one radiologist to read screening mammograms independently, the non-inferior cancer detection rate was 4% higher than when two radiologists' reading was used. According to their research, AI has the potential to be used under controlled conditions in the study environment and performance monitoring in real-world scenarios. However, they also stated that the significant limitations were AI availability during consensus discussions, lack of real-time adjustment due to retrospective data, and generalizability of the findings due to specific workflow, equipment, and population studied.[17]

Imaging modalities play a critical role in the preoperative assessment of BC patients. The imaging studies include mammograms, ultrasound imaging, magnetic resonance imaging, and contrast-enhanced mammograms.[29,30] In 2023, on the evaluation of enhanced AI models, Zhu et al stated the significance of dataset-specific preprocessing methods and the capability of advanced AI models such as ViT and U-KAN to improve the precision of early BC diagnosis markedly.[31] MRI is especially important as it appears to be very sensitive to the detection of invasive neoplasms, making it a crucial technique for preoperative evaluation. There have been reports that MRI can be used to detect additional cancer foci that would have been overlooked either by clinical evaluation or other imaging modalities.[25] Being able to accurately depict

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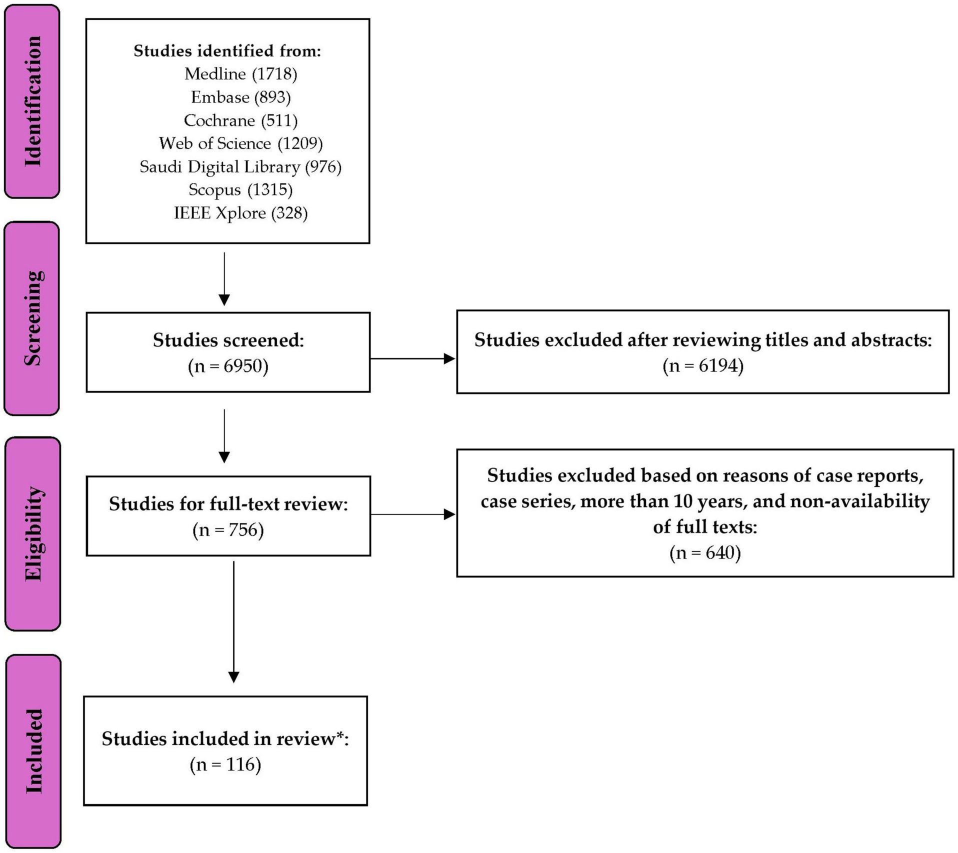

Figure 1 Diagram depicting the Flow of Study Screening and Selection Process.
Note: *Number of articles included in the main text.

the disease is a prerequisite for determining the surgical approach to be taken, particularly for patients who qualify for breast-conserving surgery. Such models help provide crucial information concerning tumor biology and help the surgeon decide whether surgery is warranted and to what degree. Nonetheless, Park et al stated that there is a lack of clarity on integrating the model into real-world screening programs.[32]

Additionally, using AI applications has been proven to reduce unnecessary biopsies, according to various studies. However, they are presented with some limitations, including the need for large datasets, lack of reproducibility, validation issues, integration into workflows, and resource constraints for smaller institutions.[30] For an enhanced computer vision, Kaffashbashi et al, in 2024, published an article that evaluated the ensemble learning (voting) model and found that the model (convolutional neural network) showed a 98% accuracy in BC images with varying magnification factors.[33] Considering the limitations of some of the AI models, such as convolutional neural network, recurrent neural network, and decision tree, Irshad Khan et al proposed a model (BC-AI) for the prompt and accurate diagnosis of BC, and their study reported more than 99% accuracy and sensitivity.[28] A study done by Ahmed et al evaluated BC risk prediction using six ML algorithms. They stated that Support Vector Machine had the highest prediction rate of about 97% with the lowest error rate.[34] Cè et al concluded that using AI algorithms, more complicated tasks in breast imaging, such as risk classifications and molecular characteristics of the tumor. However, these AI algorithms are limited by the need for large quantities of high-quality data.[30]

Recent advancements in predictive modeling (as documented by studies) using ML have emerged as significant developments in preoperative surgical decision-making. These models integrate clinical, pathological, and imaging data to determine the estimated course of the patient's condition, including the chance of lymph nodes being involved and the rate of the patient's overall survival.[35–37] A recent study (2024) by Liu et al explored that a radiomics-based model helped determine sentinel lymph node biopsy, which affects the decision-making for the need for axillary dissection.[38]

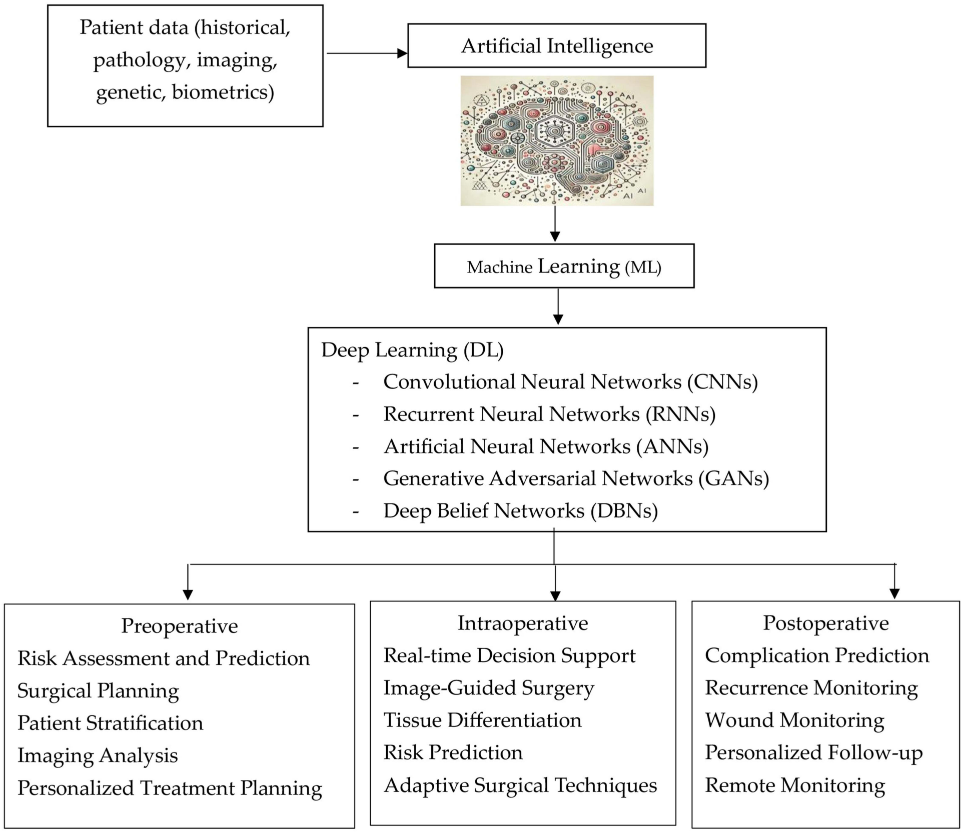

Figure 2 AI models and their roles in BC surgical care.

The preoperative evaluation of axillary lymph nodes is crucial in managing BC as it helps tailor the treatment and the subsequent expected patient outcome. In 2024, Qian et al stated that DL -and radionics-based ultrasound nomograms could precisely predict axillary lymph node status in metastatic BC patients, and which can support personalized patient care and improvement in quality of life among patients.[39]

Biopsy is the gold standard for pathological assessment of several malignancies, including BC, and pathologists are dedicated to helping surgeons manage BC precisely. Hence, for personalized treatment, an accurate diagnosis is very important.[40–42] Some recent studies described in their paper that AI algorithms can allocate patients for cancer assessment in BC clinics based on various clinical findings.[43]

As AI becomes more widely used in breast pathology, it helps with pathology diagnosis to increase accuracy and lessen pathologists' burden, and offers fresh insights into prognosis and treatment response prediction. Recent studies, including a study by Shen et al in 2021, stated that the use of AI models reduces the false positives of breast imaging studies and the need for biopsies. The AI system achieved a sensitivity of 94.5% at the average radiologist's specificity, representing a 4.4% absolute increase over human readers, who averaged 90.1% sensitivity.[44] Aljondi et al explored an instance where AI was able to assist in breast cancer diagnosis. In their study, the AI detection agreed with the histopathological result was 91.3%, while the radiologist's interpretation agreed with the pathology report was 73.8%.[45] Using an ML model, Rao et al found that AI with neural network algorithms is efficient enough to identify patients who require biopsy. Their retrospective study was conducted among 794 cases who were assessed for their breast symptoms.[46] This is important considering the global scenario of BC is changing, and incidence in women with fewer risk factors and in young women is expected to increase further. Hence, it is important to refine referral guidelines as AI can help identify patients needing biopsies promptly, potentially leading to earlier diagnosis and treatment. That is to say, AI has the potential to decrease the false negative rate in BC diagnosis, which improves the reliability of biopsy results. Furthermore, AI models can process imaging data to help identify critical areas that may need several interventions, such as a biopsy.[47,48] This is a logical conclusion as combining AIs and human experts will enable better judgment on whether the lesion should be biopsied or not, increasing the diagnostic capability as well as the outcome of the patients.[48,49] However, some authors are concerned about the black-box limitations associated with the AI models, especially in DL.[50,51]

The concern over the workload and efficiency of pathologists has been heightened in recent times due to the increased number of BC biopsies carried out. AI could be useful to pathologists by reducing the time needed to diagnose and automating the analysis of the biopsy samples, thus improving the consistency of interpretation.[52–54] Sandbank et al undertook a study in which they validated a computer-assisted algorithm for the detection of breast cancer in the biopsy specimen, and the authors proved its usefulness in clinical practice. The AI algorithm differentiates the different types of carcinoma with high sensitivity and specificity (more than 90%).[48] As noted in the studies, the AI was able to make quality and timely diagnoses with high accuracy and the identification of cancers initially missed by the reviewing pathologist. Thus, it can address the concerns of the pathologists' workload. However, being a single-center study and lacking external validations were significant limitations in implementing the proposed AI models from previous studies.[17,54]

As discussed earlier, AI models can help with surgical decision-making in numerous ways. By offering the possibility of more accurate evaluations of the problems related to the tumor, its characteristics, and its nature of metastases, AI is able to suggest the most appropriate surgical strategies to the surgeon.[8,51,55] For example, AI-imaging techniques that enable the detection of other noticeable cancers may, in some instances, result in the move from breast conservative surgeries to mastectomy to improve patient care. Also, AI tools that are able to estimate postoperative complications and survival rates are useful in preoperative counseling and shared management and decision-making by the patients and their doctors as they play a role in predicting outcomes.[56,57]

The applicability of such models in routine practice has been endorsed by several studies, which have recommended their incorporation together with biomarkers into clinical guidelines for managing BC patients. These areas are still developing, and one can anticipate an even more active integration of these technologies into treatment protocols and the improvement of standard care for BC patients.[22,32,58,59]

The AI helps the patients to make the right choice when it comes to treatment options. One example is AI-powered 3D imaging and augmented reality, which lets patients glimpse what may happen during breast augmentation or reconstruction. The personalized approach sets up patient engagement and satisfaction while setting realistic expectations of the surgical process and fostering trust in the process. In addition, natural language processing tools woven into patient education platforms use pre-existing text repositories to deliver custom information to address an individual's concerns and clarify the complexities of medical procedures.[60–63]

Role of AI in Intraoperative BC Care

AI has made important advances in the area of surgical oncology, including decision support for BC surgery.[35,64] Many of the aforementioned approaches, such as ML techniques, including DL, convolutional neural network, artificial neural network, and reinforcement learning, are useful in resolving intraoperative issues from different perspectives and creating opportunities to better the outcomes of BC surgery.[14]

ML, as a subset of multiple other AI domains, assists in predicting patient outcomes and increasing tumor localization efficiency during procedures such as BC surgery. Intraoperative complications can be predicted by ML models, which analyze patients, tumor characteristics, and historical data.[59,65] Furthermore, ML can adjust the analyses based on age, genetics, and size of the tumor and predict complications like bleeding, infection, and extended recovery. With integration into real-time imaging analysis, for example, ultrasound or MRI, ML makes it easier for surgeons to differentiate between normal tissues and malignant ones, which largely decreases the chances of missing tumor tissues or the need to perform surgeries on the same site (reoperation).

DL is the latest branch of ML where multiple neural networks are cascaded to work over large amounts of data to provide efficiency with image work tasks in BC surgery. DL models provide detailed information on imaging data that can improve the evaluation of tumor margins and help with surgical navigation hand in hand.[54,66–68] This is, in particular, significant in breast conservative surgeries. For example, a study published by Veluponnar et al in 2023 evaluated an AI model based on pre-trained neural networks. Comparing the segmentation results to the histology data, the authors able to predict a close margin with a sensitivity of 96% and a specificity of 76%. The authors described that the developed model could be further enhanced by algorithm changes, identifying the artifacts (such as hematomas), and further validation of real-time margin assessment is required. Sub-analyses on tumor characteristics and clinical workflow integration are needed for broader application.[67] Pradipta augmented reality et al also proposed the necessity of more advanced AI models that help in real-time intraoperative management of breast margins in live tissues.[69] Convolutional neural networks are composed of several layers of neuron cells where each layer focuses on image pixels, and through pattern recognition, they identify features sometimes impossible for the human eye to detect. Research shows that samples taken from breast tissue put through a convolutional neural network, which was trained on histopathologic data, are able to detect cancerous cells; this, in return, aids the surgeon in getting a clear margin, hence reducing the chances of reoperation. Such a level of automation is helpful during BC surgery, where severe attention is required for the amount of tumor tissues being scraped off and healthy ones being spared.[70–72] In addition, DL models with augmented reality functionality can help guide the surgeon to enhance his visibility and aid in the performance of the surgery by anchoring the data on the particular areas in the surgical field that are to be operated on. For example, a 3D model of a breast cancerous tumor may be created from preoperative MRI scans and displayed on the surgical field during the surgery. For instance, a randomized controlled trial conducted by Lee et al in 2024 reported better safety, outcome, and reliability in the augmented reality localization group. Hence, they concluded that augmented reality localization can be another option for tumor localization.[73] However, the lack of detailed demographic characteristics limits their study findings. This model, complemented with DL, makes it easy for surgeons to dissect difficult regions of the body precisely, thus shortening surgical time and improving patients' outcomes.[27,73,74] However, cost, accessibility, and adequate training were the major challenges encountered in implementing real-world scenarios.

The practicality of reinforcement learning in fine-tuning and optimizing surgical skills in the context of BC surgery seems reasonable, considering that reinforcement learning is a subfield of ML where algorithms learn maximum reward through different experimentations. RL algorithms solve several possible situations that might occur during the tumor removal process to develop the best strategy for removing the tumor. Such algorithms are quite flexible since they rely on current data; therefore, they enhance intra-operative accuracy while avoiding undue risks and play a significant role in precision oncology.[75–77] A deep reinforcement model was developed by Almutairi et al using two big data sets, stating that their proposed model achieved high accuracy in comparison to the traditional techniques. This can help the surgeons to identify precise margins, which, in turn, can help in decision-making during surgical procedures.[78] The application of Generative Adversarial Networks in the field of DL can assist in generating models where synthetic data is sparse and thereby assist models in BC surgery. AI models created using Generative Adversarial Networks can create and supplement existing datasets with synthetic images to increase the accuracy and performance of convolutional neural networks in identifying BC tissue images. This is especially significant in BC surgery, where large amounts of data with corresponding labels are hard to come across, and the data created using Generative Adversarial Networks aids in improving the generalizability of the AI models.[79–82] Apart from data generation, GANs can also be used to build 3-dimensional (3D) models of tumors and other relevant tissues, which can be used for surgical simulation, where complex surgical resections can be practiced in virtual reality.[83–85]

Role of AI in Postoperative BC Care

In the context of BC surgery, AI improves the management of care after discharge from the hospital by monitoring recovery processes, preventing or predicting complications, and adjusting the follow-up depending on the patient's needs.[86–89] Patients' imaging studies, wearable devices, electronic health records, and work as AI models that assist in patient data analysis. This part of the review focuses on the importance of several AI models, including but not limited to ML, DL, convolutional neural networks, reinforcement learning, and natural language processing, in improving overall postoperative BC care.[86,90–92] ML models are used to correlate potential postoperative complications with intraoperative factors like length of surgery, blood loss, weight, and additional illnesses such as obesity.

In 2023, Zuo et al, developed a prediction model using eleven different ML-based models that evaluated the possibility of BC recurrence among the patients. Their retrospective study generated a model (AdaBoost) that was based on the patients' clinical and laboratory parameters using ML algorithms.[93] They reported that the AdaBoost algorithm model consistently forecasts the likelihood of BC recurrence. The authors cautioned about the limitations, including sample size, lack of external validation, and the necessity of further clinical details for making valuable personalized care. A retrospective cohort study by Mansour et al in 2024 reported that using AI models in analyzing helped in postoperative imaging accuracy and ruled out the recurrence of BC.[94] These AI models not only improve clinical outcomes by out, enabling postoperative monitoring, but also assist with patient satisfaction. Because potential complications may be predicted with the aid of intelligent models, patients become less anxious, having been made aware of this feature.[86,89,95] DL models, especially those focused on the analysis of postoperative histopathological tissues and imaging data, are also important in determining cancer recurrence cases. DL in oncological follow-up aids tumor recurrence risk assessment by reviewing previous expectative data and postoperative tumor samples. This also allows for the planning of care time in future follow-ups by oncologists.[96–98] This helps patients' contentment as it provides them with tailored plans, ensuring that the plans for recovery and monitoring are within their specific risks.

Another recently concluded cross-sectional study that was conducted among 66 female patients who had undergone breast conservative surgeries by Eissa et al 2024 stated that AI-augmented mammograms enhanced the ability to rule out postoperative malignancy with 100% sensitivity.[99] Nonetheless, the smaller sample size, lack of accountability of the AI algorithm with clinical characteristics, and lack of long-term follow-up data were the limitations of their study findings. Both imaging analysis in the search for recurrence and monitoring of the wound during the postoperative phase of BC patients utilize convolutional neural networks. Such models are very effective in the region of postoperative mammography, MRI, and ultrasound images, as well as those looking for chances of recurrence through abnormal body tissues.[100,101] Regarding wound monitoring, convolutional neural networks help analyze clear pictures of surgical wounds and can determine postoperative infection, necrosis, or dehiscence.[102,103] Remote monitoring via AI platforms is useful in BC postoperative care as it reduces physical visits to the hospital. Wound images can also be taken at home by the patients, and patients can receive expert feedback when the images do not require immediate attention; this eases the worry created by the procedure and promotes effective injury healing, better care, and improved quality of life.[104,105] Besides, AI wearable devices and mobile health applications also achieve remote, uninterrupted monitoring of patient vital signs and activity levels, thereby interpreting recovery trends. The patients can wear sensors capable of measuring heart rate, temperature, and movement, and ML models process these parameters to detect outliers in expected recovery stage characteristics. This increases patient satisfaction since it provides safety without requiring numerous clinical appointments.[106–108] A recent study by Cloß et al stated that the available evidence of the use of wearable devices is higher in BC care than in other types of cancers, indicating the growing importance of these devices in BC management.[109]

Natural language processing facilitates the analysis of unstructured data embedded in electronic health records regarding the measures of a patient's recovery. It can analyze determinants from reports and documents that have been associated with specific events or negative outcomes through patterns established within the interference of physicians' notes and patient reports. As the networks generate more synthetic data, they, in turn, help the AI models make better postoperative prediction models. This serves as a complication in training datasets, which give the network information on rare complications.[110,111] With the increased data, trained models will be better equipped for AI tools to predict patient complications accurately across diverse populations. In the realm of BC postoperative assistance, the particularity of an AI in formulating algorithm-driven individual follow-up schedules, as well as monitoring in distant locations, is indispensable. The follow-up schedule is determined by analyzing the patient-outlined data with a view of the postoperative complications. Hence, personalized follow-up plan strategies can be formulated by the treating surgeons.[107,109,112]

In summary, postoperative BC care AI enhances the outcome by providing more personalized, faster, and easier service. With predictive modeling, recurrence monitoring, wound assessment, and management, wound healing supportive attention, and remote monitoring, AI paves the way for a more patient-centered postoperative process that meets the medical and psychological aspects of the patients. As AI technology advances, the effectiveness of patient' satisfaction and the quality of postoperative care are likely to improve, which gives a bright hope for more individualized BC care in the future.[113,114] For example, in a Korean hospital study where breast cancer patients' cases were discussed by a multidisciplinary team using Watson for Oncology, 86.8% of patients in the AI-assisted group reported a positive change in their perception of the hospital's care, compared to 71.2% in the non-AI group.[113]

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Table 2 Comparative Summary of AI Models in Breast Cancer Surgery

AI Model	Application	Strengths	Limitations
Machine Learning (ML)	Predictive modeling (eg, recurrence risk)	Easy to implement; interpretable results	Performance depends on data quality and feature selection
Deep Learning (DL)	Imaging interpretation, tumor classification	High accuracy with large datasets; automates feature extraction	Requires large datasets; black-box nature
Reinforcement Learning (RL)	Surgical planning, adaptive decision-making	Learns optimal strategies over time	Complex; needs real-time feedback and large simulations
Generative Adversarial Networks (GANs)	Synthetic image generation, data augmentation	Effective for training models with limited data	Risk of generating misleading or unrealistic data

The outline of some important research related to AI and its applications and limitations in all stages (preoperative, postoperative, and intraoperative) in BC surgical decision-making is depicted in Appendix B–Supplementary Table Also, a comparative summary of most common AI Models in BC surgery is depicted in Table 2.

Challenges and Barriers to AI Integration in Surgical Practice Related to BC

The present review noted that AI plays a crucial role in the personalized and precision care of BC. Nonetheless, implementing these innovations is not easy without limitations. The most prominent example of this scenario revolves around the ML and DL architectural models that largely depend on adequate and robust datasets to operate.[25,115,116] For example, missing data can significantly decrease the full potential of the use of AI models. Some of those elements are histopathological slides, imaging, and the patient's ends, which are often stored in separate institutions with different standards.[30,117] In addition, several countries, such as the USA, restrict data sharing due to patients' safety and confidentiality.[118,119]

Another clear barrier is the "black-box" character of many AI models, particularly those based on configurations like DL, as they often find it difficult to account for how their decisions evolve throughout the use of the system.[50,120] In high-stakes situations like BC surgery, clinicians need AI systems that provide clear and interpretable outputs to ensure trust and reliability. The issue of AI models and lack of transparency in such elaborate algorithms are further aggravated in situations of trust once the nature of AI and AI recommendations for surgery are taken into account, as data scarcity limits the use of AI.[103,121,122] Also, ethical issues stem from the data used to create and train AI systems. In instances where the training data consists of the same age group or race, then the resulting model or AI system is going to be less effective on patients of older age or other different races than those of the mixed-race sample population used to create that AI model.[123,124] Such issues are very pertinent in BC treatment as in BC, the disease and treatment response vary for genetic and heterogeneous reasons, and BC treatment's biased AI systems provide unequal treatment recommendations.[125–127]

AI integration often faces dramatic obstacles, as it requires altering the existing surgical systems, such as accepting and enhancing the knowledge of the practitioners.[128] Some AI algorithms, such as convolutional neural networks, lack transparency (as some models use secondary data).[72] Therefore, some surgeons may hesitate to use AI. The use of AI in BC surgeries requires standardized training. Therefore, the utilization varies between those with adequate training and those without.[129,130] Similar to other technologies, there is a possibility of commercialization in the healthcare industry of AI marketing. However, structural factors, such as regulatory and legal requirements, still play a huge role in constraining the operational potential of AI.[131,132] In this landscape, the role of an AI developer, a hospital, or a surgeon becomes unclear, which further complicates the adoption of AI tools in surgical units. Financial constraints could be another challenge in implementing AI in surgical practice. AI also uses and requires a steady supply of hardware, software, and maintenance, which often does not make financial sense. Hence, the country's healthcare policy and economic situation also play a role in implementing AI in BC surgical care.[133]

A few studies have found an improved return on investment in AI systems in BC surgery, but few have also found the investment to be too high without sufficient long-term funding support.[132,134] Finally, continuously updated data is critical, and the AI models based on older databases will be out of date and will no longer be accurately predictive of future events.[135,136] Any of these problems will make it impossible to solve these issues without a broad and unified strategy throughout the fundamental research, as well as the law and practice. If there are no targeted measures to boost the quality of data, raise openness, create ethical and legal structures, and prove profitability, the dream of artificial intelligence cutting-edge solutions in transforming BC surgical practice will remain just that a dream.

The availability of AI systems in healthcare and the growing use of practical implementations beyond theoretical models invite us to expect their use in real-time clinical decision-making. The AI tool could provide precise localization of tumors, predict complications, and propose tailored surgical strategies to individual patients, thereby increasing accuracy and efficiency in delivering care by surgeons. In addition, AI can dramatically enhance healthcare disparities by closing resource-poor distances where no specialists may be present. Besides practical medical use, AI can also serve as an educational aid and let surgeons cultivate their skills using AR-based training modules and simulations. Together, these will collectively lead to AI's transition from a promising innovation to a pillar of modern care for BC patients.

Unique Contributions and Strengths of This Review

This review article presents a comprehensive overview of the clinical use of AI in BC surgical decision-making in all stages, offering several distinct contributions to what is currently available in the literature. The key strengths and unique aspects of this work are summarized as follows:

a. Inclusion of the Latest Advancements: This review incorporated studies published up to that date (past 5 years) in order to include the most recent updates on AI applications for BC surgery. Reading materials include exploring emerging technologies like DL models (eg, convolutional neural networks and generative adversarial networks) and augmented reality integration for intraoperative tumor localization. Hence, surgeons and other readers can interpret the state of the art in AI driving innovation. Also, clinicians can be aware of the limitations of the latest AI models before they use them in their clinical practice.
b. Identification of Knowledge Gaps: While previous studies have covered AI applications broadly, this work identifies and addresses specific gaps in the literature. Furthermore, the review included some of the under-explored/unexplored AI technologies to keep readers informed.
c. Practical Recommendations: The manuscript provides practical recommendations to all stakeholders (clinicians, policymakers, and developers). These recommendations are derived from recent evidence. So that clinicians can apply AI effectively to surgical decision-making workflows in all stages, make recommendations for developing AI guidelines, and train healthcare professionals to use AI appropriately and intelligently for policymakers. This review also explored issues like cost, accessibility, and interoperability in clinical environments.
d. Real-World Case Studies: Real-world examples with more detailed explanations of included studies (like country, funding sources, external validation, etc)., including their limitations in practical use, are included to enhance the practical relevance of this review. Therefore, the lessons derived from other settings can guide the future use of AI in various clinical settings.
e. The review discussed ethical aspects in detail to provide a holistic view of AI applications. Furthermore, the discussion of black-box concepts, which are discussed in very few manuscripts, added more novelty to the present review.
f. Future Research Directions: The present review recommends forward-looking ideas, proposing a roadmap for advancing AI in breast cancer surgery. This includes developing AI models to overcome the "black box" issue and encouraging large multicenter studies for external validation so that this futuristic technology can be used effectively on a wider basis.

Limitations

This review was made with the standard method. However, some limitations that should be acknowledged. Firstly, this review's findings were synthesized based only on English-language articles, which may introduce language bias and exclude valuable evidence from non-English-speaking countries. Similarly, we did not include grey literature and unpublished studies. Secondly, we relied on studies with varying designs and sample sizes, which may affect the generalizability and strength of the evidence synthesized from the present review. Next, there was also variability in the AI methodologies used across studies, including differences in model training, validation techniques, and outcome measures. Thus, making direct comparison challenging. Finally, the heterogeneity in clinical settings, patient populations, and institutional resources may limit the applicability of some AI tools across diverse healthcare systems.

Conclusion

The present review observed that AI has a significant scope in the surgical decision-making process in all stages. However, numerous challenges are present in implementing AI on a broader and more regular basis. First, using AI systems as black boxes, as in many systems (such as DL and convolutional neural networks), increases concerns regarding privacy, accountability, and clinical relevance. There are still no uniform and clear laws around liability, and the lack of a transparent accountability model does not encourage wider adoption. Hence, making reliable and secure data-sharing policies for the concerned authorities is critical. The high costs involved in use and maintenance further constrain small organizations, especially in resource-limited settings. While advanced AI tools may enhance decision-making and surgical precision, there is a risk of widening disparities across countries. Therefore, ensuring equitable access requires investments in infrastructure, clinician training, and the development of inclusive, multiethnic datasets. Additionally, future prospective and exploratory cost-effective analysis studies are to be done. Furthermore, economic viability and the ability to devise efficient AI systems for the variable dynamics involved in BC surgery are also important. Only in that way can the complete potential of AI be harnessed so that the clinical results of BC surgery and the quality of care of patients with BC can be improved.

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