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A Study on the Challenges Faced by Clinical Engineers in the Use of AI-Based Mammography Devices in Mongolia

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Abstract

Since 2020, Mongolia has begun developing phased policies and recommendations to implement artificial intelligence (AI) technology across education, healthcare, and business. In the health sector, international policy documents on the introduction of AI were developed by the World Health Organization (WHO) and the United Nations Educational, Scientific, and Cultural Organization (UNESCO) between 2019 and 2021, providing guidelines and recommendations for its use, application, and ethical standards. These policy documents emphasize that AI in healthcare should not replace doctors, but rather serve as a tool to support clinical decision-making in diagnosis and treatment, with the final decision always being made by the physician [1, 2]. After World War II, a group of people began working independently to create intelligent machines. In 1947, British mathematician Alan Turing presented his first research. He concluded that it was better to study AI through computer programming rather than by building machines. By the late 1950s, many people were studying AI, mostly based on computer programming [3].

Keywords: Artificial Intelligence, Machine Learning, Digital Mammography, Automatic Exposure Control

Introduction

Among the many types of cancers, such as lung, stomach, liver, pancreas, and colorectal cancers, breast cancer ranks first in Mongolia and second worldwide [4]. In 2022, there were 2,296,840 new cases of breast cancer globally, resulting in 666,103 deaths. China (26%), the United States (20%), and India (14%) account for the highest number of breast cancer cases. Regionally, Asia accounts for 47% of cases, Europe 24%, North America 13%, and Africa 9%. Due to population growth and aging, by 2040, the annual number of new breast cancer cases is expected to exceed 3 million, with 1 million deaths, representing a 22.2% increase in new cases and a 35.2% increase in deaths [5, 6]. In Mongolia, by 2025, the number of breast cancer cases is expected to rise sharply, with 250–300 new cases diagnosed annually, more than 70% of which are detected at an advanced or terminal stage. As of 2023, there were a total of 2,438 registered breast cancer cases nationwide, with 344 new cases diagnosed that year, compared to 244 in 2020, 278 in 2021, and 283 in 2022. Between 2019 and 2023, there were 488 deaths from breast cancer in Mongolia. Based on statistics of 10 cases per 100,000 people annually, comparing data from 2020 to 2023, breast cancer in Mongolia has increased by 5%. While it mainly affected those aged 40–60 in the past, in recent years it has become more common among women aged 30–40, accounting for 25–30% of all female cancer cases [7]. Since 2020, the main goal of introducing artificial intelligence in the healthcare sector has been to improve the quality, speed, and accuracy of diagnosis and treatment, increase the accessibility of healthcare services, reduce the workload of doctors and nurses, decrease costs and clinical errors, and ultimately improve disease prevention and early detection. In particular, policy-level recommendations to use AI in diagnostic imaging and auxiliary diagnostic systems have begun to be implemented in practice [5, 6]. With the introduction of AI in healthcare, new professions and roles, such as clinical data analyst and healthcare AI engineer, have emerged. However, in Mongolia, the training system for specialists in these fields is not yet fully developed, so clinical engineers are forced to fulfill these roles as well. As a result, specific issues and challenges related to the use, maintenance, data management, software updates, and safety of AI-based medical equipment have begun to emerge in practice [7].

Research Objective

This research aims to study and develop the use of AI-based mammography devices for the detection, identification, evaluation, and diagnosis of breast cancer and other breast pathologies; to investigate the challenges faced by clinical engineers in this context; and to implement solutions at a certain level.

Research Tasks

1. To assess the current state of utilization of AI-based mammography devices in the healthcare sector.
2. To study the components of the infrastructure of AI mammography devices.
3. To identify and analyze the technical knowledge, skill requirements, data, and system compatibility challenges clinical engineers face during the use of AI mammography devices, as well as to determine the needs for training and support to enhance their capacity.

Research Methods and Methodology

This study is a cross-sectional survey designed to identify the challenges encountered in using AI mammography devices. The questionnaire will be developed based on international research, recommendations from the World Health Organization (WHO) and UNESCO regarding artificial intelligence, and the professional functions of clinical engineers. The survey will consist of 3 main sections with 40 questions: a general section (8 questions), a section to identify the conditions and challenges of using AI-based medical equipment (24 questions), and a section to assess the knowledge, skills, and training needs (8 questions). The questionnaire will be designed using a 5-point Likert scale and completed by participants themselves. The survey data will be coded and used solely for research purposes, ensuring the confidentiality of participants' personal information.

Scope of the Research

This study covers clinical engineering activities related to the use of AI mammography devices in secondary and tertiary public healthcare institutions in Ulaanbaatar (e.g., AI-based image processing/diagnostic support systems, smart monitoring, AI modules integrated with PACS/RIS/HIS, etc.). The research will involve clinical engineers (medical equipment utilization engineers) who are directly engaged in the installation, operation, maintenance, data/system compatibility, and safety of AI mammography devices at these institutions.

Research Ethics

Written informed consent will be obtained from all participants voluntarily. The names of the participants and institutional information will be kept confidential, and ethical principles will be followed to ensure participants are not exposed to psychological or professional risks during the research process.

Theoretical Framework

A mammography device is designed to examine the breast's soft tissue and mammary glands by taking X-ray images using minimal radiation exposure (Figure 1.1). This device can capture images in both vertical and horizontal positions. It is equipped with a component known as the "C-arm," which rotates along the horizontal axis (Figure 1.2). The breast typically has a base diameter of 10–12 cm, a thickness of 2.5–3 cm, and consists of 15–25 lobes. The structure of the breast is composed of three parts: connective tissue, glandular tissue, and adipose (fatty) tissue. In premenopausal women, the breast ducts are primarily composed of connective and glandular tissues, whereas after menopause, the connective and glandular tissue decreases, and fatty tissue increases. The most radiation-sensitive tissue, and thus the most susceptible to cancer, is the glandular tissue. Mammography examinations are performed for two main purposes: screening and diagnostic. By further developing the imaging systems of mammography X-ray devices, image quality can be improved while reducing patient dose. The "dose given to the patient" refers to the amount of X-ray radiation absorbed by the patient. Mammography devices typically use radiation in the range of 25–50 kV, and even slight changes in kV can result in maximum image contrast. When performing exposures in 1 kV increments from 15–40 kV, with an exposure time ranging from 0.01 to 6 seconds, a current of up to 6000 mAs is used for diagnostic mammography examinations [8]. AI consists of five main components: data collection, reasoning, problem solving, data integration, and data processing [10, 11]. The operating principle of AI consists of five factors: input, processing, output, adjustment, and evaluation [12]. Inputs: the data and information the AI system analyzes and processes. Inputs can include text, images, audio, video, and sensor data, and they play a key role in determining the system's operational performance. Processing: Using software, data is processed, analyzed, interpreted, classified, regressed, clustered, and predicted with AI algorithms. Output: The output of an AI system is the solution or interpretation derived from the input data. The outcome of such work can be difficult to predict in advance, depending on the specific problem or objective of the system. It may show either successful or unsuccessful results. Adjustment: Adjustment is often used to determine the AI system's ability to focus on data, learn, adapt, and improve based on user feedback. AI systems typically include mechanisms that enable them to update their models or parameters, learn from past experiences, and self-improve rather than repeating errors. Adjustments can include retraining machine learning models, fine-tuning algorithms, updating decision-making procedures, or executing specific processes. Evaluation: This refers to assessing the results of analysis and data processing. AI is generally divided into two main categories: hardware-based AI and function-based AI. Hardware-based AI includes Narrow AI, General AI, and Strong AI, while function-based AI consists of reactive machines, limited memory, theory of mind, and self-awareness [13].

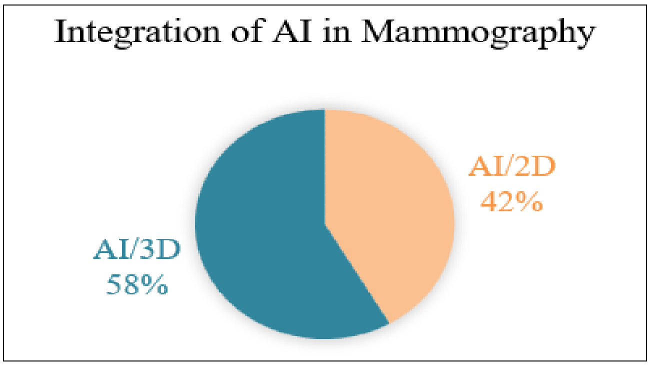
The use of AI in departmental units within the healthcare sector is 87% in pathology and 71% in radiology. AI is most widely used, with an average of 72%, for tasks such as diagnosing, predicting, and analyzing suspicious cases, including various diseases and cancers. (See Table 1) Since 2024, companies supplying medical equipment in Mongolia have started integrating AI into diagnostic imaging devices. In a study on medical equipment using AI, a total of 12 hospitals participated, of which 58% were private hospitals, and 42% were public hospitals. (See Table 2) 2D mammography captures images from the front and side, creating a single projection or image and showing whether breast tissue overlaps. This device is intended for screening examinations, especially in cases with low breast density and high fat content. The 3D mammography device, on the other hand, produces 15–30 projections from multiple angles and displays each 1-mm layer of breast tissue, making it suitable for diagnosing dense and firm breasts. (See Table 2).

Table 2: Study of Some Mammography Devices Used in Mongolia

S. No	Name	Mammography Device in Use	Integrated with Artificial Intelligence	Brand
1	Mongolia-Japan Hospital	3D	+	Fujifilm
2	Erdenet Medical	3D	+	Fujifilm
3	Ekh Narya National Center for Maternal and Child Health	2D	+	DRTech
4	Breast Clinic of UB	2D	+	DRTech
5	National Cancer Center	2D	+	DRTech
6	Chingeltei Health Center	2D	-	DRTech
7	IT Laboratory	2D	+	DRTech
8	UB Med	2D	+	DRTech
9	Songinokhairkhan General Hospital	2D	-	DRTech
10	Ulaanbaatar Songdo	2D	-	DK
11	Second State Central Hospital	3D	-	Sono Crystal
12	Nura Center	3D	+	Fujifilm

Source: Khosbayar, 2026, p. 15

As of 2025, among the 12 hospitals participating in the study on early detection of breast cancer, 53% widely use 2D mammography and 47% use 3D mammography, with an average of 20–26 patients undergoing mammography per day. Fig 1.



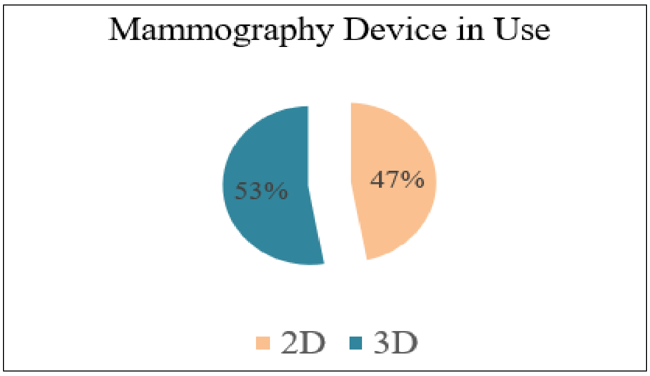
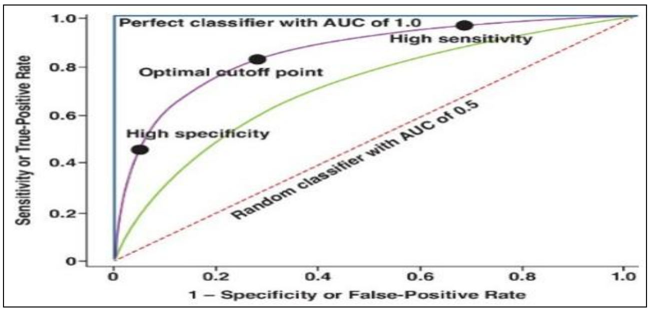


Fig 1: Graphical Representation of Mammography Usage and AI Integration

Between 2016 and 2020, mammography devices from Germany's Siemens, Japan's Fujifilm, the United States' GE, and South Korea's DR TECH were installed in Mongolia. Among them, the AIDIA model from South Korea is the most widely used, accounting for 65% usage. (See Figure 1.10) This device features 2D imaging and is suitable for screening examinations, particularly for the early detection of breast cancer. It is a mammography device integrated with AI. What distinguishes this device from others is its high image resolution, the use of cesium iodide (CsI) material in its detector—which allows the conversion of X-rays into light energy—a fast image processing speed (10 seconds), and the shortest breast compression time (3.5 seconds) compared to brands from other companies. Due to common errors in both 2D and 3D mammography, the need and demand for AI integration in mammography devices is increasing.

These include technical errors: wear and tear on components, loss of X-ray tube calibration, deterioration of filters, and artifacts on the screen, which can degrade image quality. Magnification errors: Technicians often set the image magnification to 0.3 mm for greater precision, shifting the original focal point by 0.1 mm. As a result, unnecessary image regions are excluded, and the suspicious area needs to be magnified. There is a high probability that the technician may overlook suspicious findings in the excluded parts of the image. This is one reason early-stage (stages 1 and 2) cancers may go undetected. Even a slight change in the focal point can greatly impact image accuracy. Adjustment errors: kV and mA directly affect image quality, radiation dose, and patient safety. kV improves image contrast, while mA reduces image noise. Whether the image appears faint or clear depends greatly on component wear and kV and mA settings. Software errors: Under heavy workloads, the software may freeze or slow down, adversely affecting image analysis and processing. Motion errors: Compressing the breast with the compression plate improves image quality. However, movement caused by pain or discomfort during compression can lead to blurred or scattered images. Therefore, AI technology is fully capable of reprocessing blurred and scattered images caused by technical, technician, adjustment, software, and motion errors, as well as detecting and analyzing suspicious cases of breast cancer. With the involvement of doctors and technicians, it is possible to detect breast cancer early with up to 96% accuracy, reduce the incidence of cancer cases, and correct or improve errors caused by technical factors and image processing. Records of both scheduled and unscheduled inspections and maintenance performed on mammography devices are promptly entered into the technical passport. Scheduled maintenance is conducted once every three months, while unscheduled maintenance is carried out immediately in the event of equipment malfunction or failure, restoring the device to normal operation.

The performance of AI is evaluated using the ROC curve. The performance of AI is evaluated using the ROC curve. The ROC curve consists of perfect classification, high sensitivity, the optimal cut-off point, high specificity, and a random classifier. See Fig 2. The confusion matrix allows readers to understand how the artificial intelligence algorithm is functioning easily. The ROC curve consists of perfect classification, high sensitivity, the optimal cut-off point, high specificity, and a random classifier. Fig 2 The confusion matrix allows readers to easily understand how the artificial intelligence algorithm is functioning [14].



Source: (J. H. a. E.-K. K. Yoon, "Deep Learning-Based Artificial Intelligence for Mammography," %1-д *Korean Journal of Radiology, vol. 22*, 8, Aug. 2021, p. 1225–1239) [14].

Fig 2: ROC Curve Figure

ROC analysis is commonly used to evaluate the performance of clinical epidemiological diagnostic tests. The ROC curve is a plot of the true positive rate (TPR) against the false positive rate (FPR) at each threshold. The ROC curve depends on the false positive rate.

Table 3: The ROC curve displays the positive and negative values of a binary classification

S. No	Actual	Test Result Positive	Test Result Negative
1	Condition Positive	True Positive	False Positive
2	Condition Negative	False Positive	True Positive

Source: Khosbayar, 2026, p. 28

Here is the English translation of your text:

A. The number of actual positive cases in the data.
B. The test result that correctly indicates the presence of a condition or characteristic.
C. Type II error: The test result that incorrectly indicates the absence of a specific condition or characteristic.
D. The number of actual negative cases in the data.
E. The test result that correctly indicates the absence of a condition or characteristic.
F. Type I error: The test result that incorrectly indicates the presence of a specific condition or characteristic.

Row ratios: True Positive Rate (TPR) = (TP/(TP+FN)), also known as sensitivity or recall. This represents the proportion of the population with the condition for whom the test result is correct. Additionally, False Negative Rate (FNR) = (FN/(TP+FN)). True Negative Rate (TNR) = (TN/(TN+FP)), also known as specificity (SPC), which is the complement of the False Positive Rate (FPR) = (FP/(TN+FP)), and is considered prevalence-independent.

Column ratios: Positive Predictive Value (PPV, also known as precision) = (TP/(TP+FP)). This is the proportion of correct results among all positive test outcomes. False Discovery Rate (FDR) = (FP/(TP+FP)). Negative Predictive Value (NPV) = (TN/(TN+FN)). Additionally, the False Omission Rate (FOR) = (FN/(TN+FN)) and is also referred to as prevalence-dependent.

AI-Based Mammography Imaging Diagnosis

AI-based mammography is built on machine learning, deep learning, and neural network algorithms, and mammography devices are classified into three types: 2D, 3D, and AI-based mammography. Specifically, 2D mammography devices capture images of each breast from the front and side, producing one image per breast, which can show whether breast tissue overlaps. 3D mammography devices, on the other hand, take multiple images of each breast from different angles, displaying each layer of breast tissue. These images are combined on a computer to create a 3D image of the breast. Due to this precise visualization, 3D mammography can detect many hidden cancers that might otherwise go unnoticed.

AI-based mammography is highly important for early disease detection and for quickly confirming accurate diagnoses. The use of artificial intelligence in breast cancer diagnosis enables tests to be completed 30 times faster and with 99% accuracy, reducing the need for unnecessary biopsies. AI algorithms analyze vast amounts of medical images, identify patterns that may be difficult for radiologists to detect, improve diagnostic accuracy, accelerate interpretation, reduce errors, measure tumor size, detect changes in breast structure, and assess blood flow patterns. They also perform medical image segmentation, which involves dividing an image into different regions or objects. Medical image segmentation is useful for identifying specific structures such as tumors, blood vessels, and organs, and for outlining their boundaries. AI algorithms can perform medical image segmentation quickly and accurately, improving the diagnosis and treatment of various diseases. Mammography devices process breast tissue images in two color tones—black and gray—and technicians acquire and analyze mammograms based on the following four factors. AI-based mammography, using a wide range of data, can further analyze and reprocess mammogram images produced by the device, identifying suspicious cases of breast cancer through color differentiation and quantitative metrics. Mammography technicians analyze mammogram images based on the following four factors:

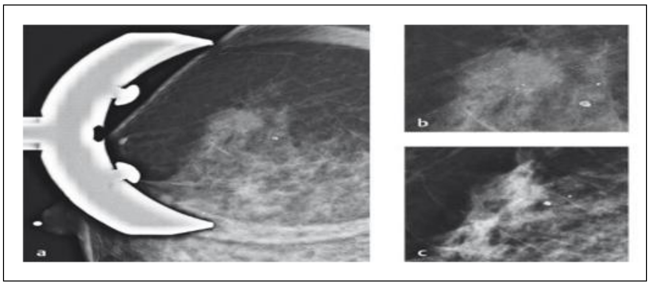


Fig 3: a) Original version, b, c) non-essential areas removed, highlighting cancer cells

a) Magnification Imaging: By magnifying a specific region of the image, non-essential areas are excluded, allowing for a more detailed and precise view of the area of interest. Cancerous tissue in the breast can vary in size, and during preventive screenings, it is often necessary to magnify any suspicious images. b) Magnification imaging with focus point selection: Magnifying the image and selecting the focal point has a significant effect on detecting cancer cells and any abnormalities. Typically, the focus point is set to 0.3 mm when capturing the image, and the original position can be adjusted by up to 0.1 mm. Even a very small change in the focal point can greatly affect image resolution. (Fig 4). c) Factors Affecting the Image: In mammography, technical parameters are adjusted depending on how much the breast is compressed (fatty or muscular mass). For example, factors such as the type of filter, current, voltage, and contrast agent all affect the quality of the X-ray image. Fig 5.

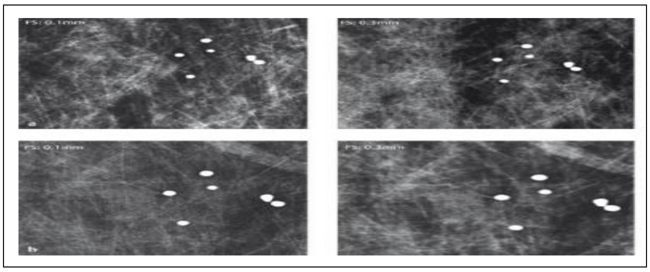


Fig 4: Focusing on the density of cancer cells at 0.1 mm

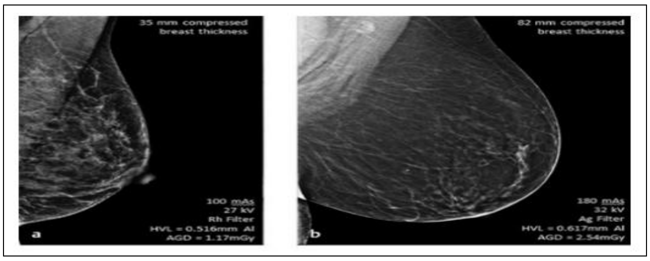


Fig 5: Influence of Breast Characteristics on Imaging 3D Digital Tomosynthesis

Tomosynthesis imaging creates a three-dimensional image of the breast by acquiring and processing X-ray images at angles ranging from 15 to 30 degrees. Unlike 2D mammography, this technology captures multiple images from multiple angles around the object in incremental steps, enabling more detailed reconstruction. Fig 6.

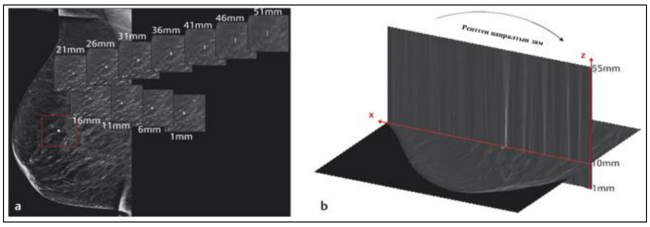


Fig 6: Tomosynthesis Mammography

AI-Based Mammography Device

AI-based mammography can diagnose tumors at all stages, saving time for doctors, medical staff, and patients and reducing hospital workload by providing rapid results. Furthermore, in developed countries, AI mammography is advancing rapidly and is now able to calculate the probability of breast cancer with high precision. The image processing of AI-based mammography devices uses computer assistance to detect breast cancer with color differentiation—blue, green, red, and orange shades. Blue-green colors indicate benign tumors, while red-orange shades indicate invasive or malignant tumors, with probabilities ranging from 0% to 100%. This information is used to assist doctors. (Fig 7).

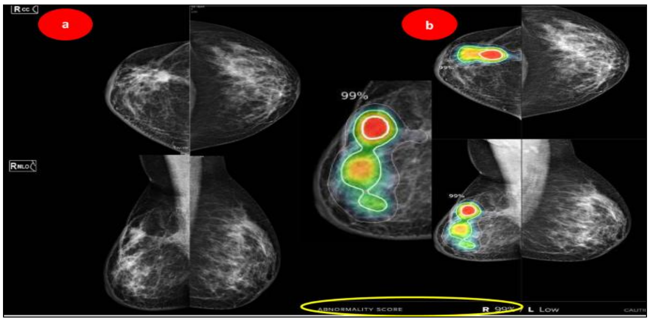


Fig 7: Postoperative follow-up of a 40-year-old female patient after right breast-conserving surgery

a. Mammography (CC, MLO) shows postoperative changes in the right upper outer quadrant (UOQ) of the breast, with a suspicious, indeterminate, partially obscured dense mass lesion (BI-RADS 4). b. The AI-identified suspicious lesion in the right UOQ appears larger (orange-colored) than what is seen on the mammogram and is marked with a 99% risk of malignancy by a "yellow circle" (according to our calculated margin value, considered malignant at 51.5%). After biopsy, the lesion was confirmed as invasive ductal carcinoma. Thus, artificial intelligence not only detected the suspicious lesion visible on mammography but also identified the extension of the affected tissue [10, 13].

The accuracy of mammographic images is directly influenced by factors such as radiation dose, imaging angle, X-ray absorption, resolution, contrast agent dose, body density (muscle, fat), and the degree of breast compression. While digital mammography magnifies images and eliminates unnecessary parts for diagnosis, it can detect stage 3 and 4 breast cancers with 65% accuracy. In contrast, AI-based mammography can detect stage 1, 2, 3, and 4 breast cancers with 96% accuracy. (Table 4).

Table 4: Probability of Diagnosis Percentage

S. No	Device Name	Cancer Stage	Probability of Diagnosis
1	AI-Based Mammography	Stages 1, 2, 3, 4	96%
2	Digital Mammography	Stages 3, 4	65%

AI 96% Diagnostic Accuracy – Research Results Study 1. In 2018–2019, Ribli and Ruiz used a deep CNN on 2,949 digital mammography cases to distinguish malignant from benign lesions, achieving an AUC of 0.95. This study confirmed that Deep CNN AI detects breast cancer with 90% accuracy. (AUC is a statistical indicator expressed in tables to show the performance of diagnostic tests and AI training models.) In a test of 546 cases comparing the performance of mammography technicians with and without AI using Deep CNN AI, 110 cases of breast cancer were detected, with an AUC=0.89. It was confirmed that technicians' performance with AI was 0.89 higher than that of technicians without AI, indicating good diagnostic outcomes. See Table 5 for an explanation of AUC values.

Table 5: Statistical Indicators of AUC Results [14]

S. No	AUC Value	Quality	Description
1	0.9–1.0	Excellent	Detects cancer with 90% accuracy
2	0.8–0.9	Good	Suitable for use in cases requiring attention
3	0.7–0.8	Fair	Additional testing is required
4	0.5–0.7	Poor	Slightly better than random guessing
5	0.5	Useless	Only performs random guessing

Study 2. The research results show the improvement in the detection performance of suspicious cases when 14 radiologists used AI with mammography devices. The AUC increased from 0.87 to 0.89, and the statistical significance was p = 0.02. A comparison of these results can be seen in Fig 8.

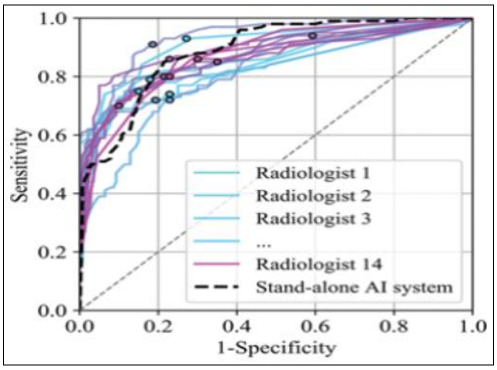


Fig 8: Comparison of AI-CAD and Non-AI-CAD Examinations

Study 3. The AI manufacturer Lunit analyzed a case of late-diagnosed breast cancer in a 59-year-old woman using Deep AI. The patient's cancer was not detected in preliminary mammography screenings in 2013 and 2014, nor in follow-up screenings in 2015 and 2016. In 2017, the cancer was diagnosed at a late stage with 65% probability as malignant. According to AI analysis, the probability of detection in the initial screening would have been 16.7% in 2013, 43.1% in 2014, 61.9% in 2015, and 90.7% in 2017, indicating that the suspicious cancer case could have been detected much earlier [15].

Results of AI Utilization in Mammography Devices

Detection of suspicious cancer cases is improved. As shown in "Figure 2.20," the preliminary predictions made by 31 radiologists in identifying tumor sites without AI assistance are illustrated using the ROC curve. Since it is difficult for radiologists to pinpoint the exact location of the tumor, breast cancer is often diagnosed at a late stage (stage 3 or 4), a trend observable from the ROC curve graph. In image (a), it can be seen that 6 radiologists, with the help of AI, were able to preliminarily detect the tumor site earlier and in a shorter time. The ROC curve is a statistical method for evaluating the diagnostic accuracy of tests. The sensitivity and specificity used here help determine the optimal point with the highest probability of being a tumor site.

Using AI improves physicians' image interpretation skills. When AI is integrated into mammography devices, physicians' ability to interpret images is enhanced. For example, a study involving 24 technicians compared the reading times of mammograms with and without AI support. The results showed that reading time improved with AI support, and the average time to make a diagnosis without AI decreased by 35 seconds. Each blue line represents an individual reader. Only one reader (the leftmost bar) had a 1.4-second increase in reading time when using AI support [15]. Fig 9.

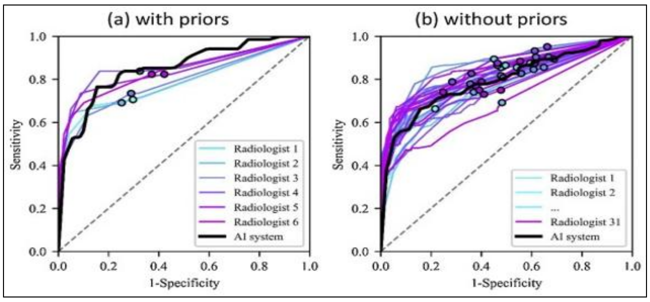


Fig 9: Comparison of AI-CAD and Non-AI-CAD Examinations

Software improvements in mammogram analysis AI-based mammography devices use computer assistance to detect breast cancer with color differentiation—blue, green, red, and orange. Blue-green colors indicate benign tumors, while red-orange colors indicate invasive or malignant tumors, with probabilities ranging from 0% to 100% for physician reference. This helps to detect cancer on mammogram images more effectively. Fig 10.

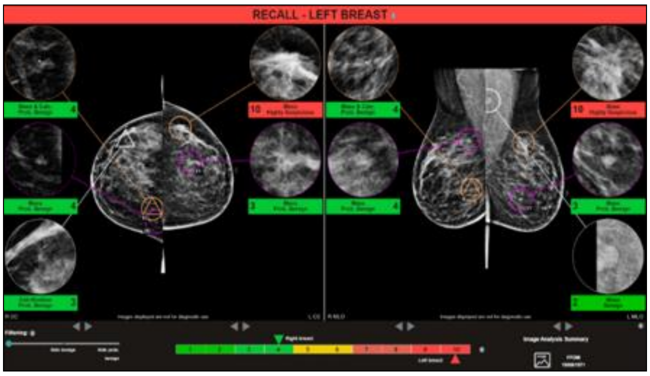


Fig 10: AI System Differences Between Mammography and AI-Based Mammography Devices

The differences between conventional mammography and AI-based mammography devices lie in imaging technology, image processing, diagnostic accuracy, speed, data storage and reuse, radiation dose, technological advancements, and operational costs.

Research Results

A total of n = 68 clinical engineers participated in the study, of whom 66.7% work in public hospitals and 33.3% in private hospitals. In terms of work experience, 71.6% of the engineers have more than three years of experience.

Table 6: Level of AI Mammography Utilization

S. No	Level of Utilization	Percentage (%)
1	Regularly used	58.3
2	Occasionally used	26.7
3	At the experimental level	15.0

As shown in Table 6, the majority of clinical engineers—58.3%—regularly use AI-based mammography devices, indicating that this technology has been integrated into clinical practice to a certain extent. Meanwhile, 26.7% use it occasionally, indicating that the application of this technology is inconsistent and depends on specific circumstances. Additionally, 15.0% use it at the experimental level, suggesting that some institutions are still in the early stages of AI implementation.

Table 7: Assessment of Challenges

S. No	Type of Challenge	Mean	Standard Deviation
1	Technical malfunction	4.05	± 0.74
2	Software	4.28	± 0.63
3	System compatibility	4.46	± 0.59
4	Lack of training	4.21	± 0.66

As seen in Table 7, system compatibility (Mean = 4.46 ± 0.59) was identified as the most significant challenge faced by clinical engineers, receiving the highest rating. This is followed by software issues (Mean = 4.28 ± 0.63) and lack of training (Mean = 4.21 ± 0.66), both of which received high ratings. Although technical malfunctions (Mean = 4.05 ± 0.74) were rated somewhat lower, they still represent a considerable challenge.

Table 8: Common Challenges

S. No	Issue	Percentage (%)
1	PACS/RIS connection issues	73.3
2	Software crashes	68.3
3	Data format incompatibility	65.0
4	Lack of understanding of AI	61.7
5	Insufficient knowledge of maintenance	59.2

As shown in Table 8, the most common challenge among clinical engineers is difficulty connecting PACS/RIS systems (73.3%), indicating a lack of interoperability among healthcare information systems. This is followed by software crashes (68.3%) and data format incompatibility (65.0%), which highlight challenges related to software and data compatibility in AI-based devices. In addition, a lack of understanding of AI (61.7%) and insufficient knowledge of maintenance (59.2%) reflect gaps in professional skills and the need for further training among clinical engineers.

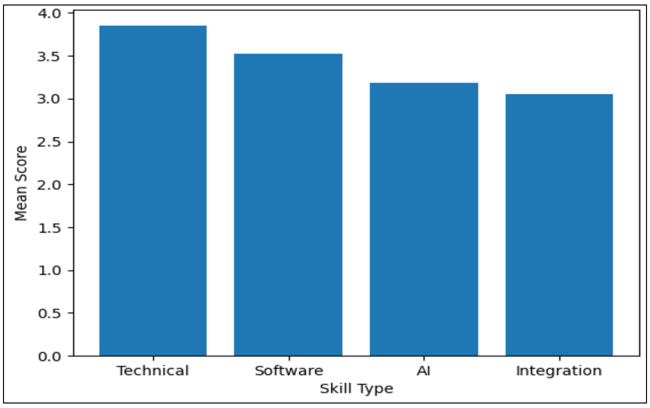


Fig 11: Assessment of Clinical Engineers' Skills (Average Score)

As illustrated in the figure, the skill levels of clinical engineers vary considerably. Technical operation skills (Mean = 3.85) received the highest average score, indicating that engineers have a strong grasp of basic equipment operation. Software operation skills (Mean = 3.52) are at a moderate level. In contrast, understanding of AI (Mean = 3.18) and system integration (Mean = 3.05) received the lowest scores, highlighting that clinical engineers have relatively limited knowledge and skills in artificial intelligence and information systems integration.

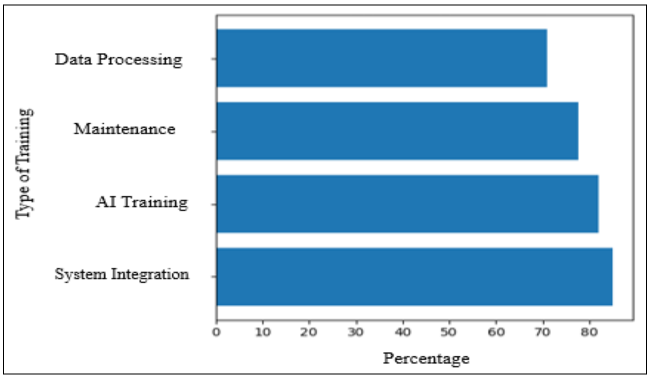


Fig 12: Training Needs of Clinical Engineers (%)

According to the research findings, the training needs of clinical engineers are shown in Fig 2. System integration training (85.0%) is in the highest demand, followed by AI training (82.0%), maintenance (77.5%), and data processing training (70.8%). The figure demonstrates that training needs are directly related to challenges in system compatibility and skill gaps, indicating the necessity to enhance the professional capacity of clinical engineers.

Table 9: Reliability Analysis

S. No	Indicator	Value
1	Reliability coefficient of the questionnaire/test used in the study	0.88
2	Level of reliability	High

As shown in the table, the reliability coefficient of the questionnaire and test used in the study is 0.88, indicating that the survey instrument is highly reliable.

Table 10: Reliability Analysis

S. No	Correlation	Correlation Coefficient	Statistical Significance Level
1	Skills and equipment usage	0.64	<0.05
2	Training and performance	0.71	<0.01

As shown in the table, there is a moderate positive correlation ($r = 0.64$, $p < 0.05$) between skills and equipment usage. Additionally, a strong positive correlation ($r = 0.71$, $p < 0.01$) was observed between training and performance, indicating that training significantly impacts performance.

Table 11: Group Difference Analysis

S. No	Group	Mean Value	Significance
1	Received training	4.18	
2	Did not receive training	3.42	<0.01

As shown in the table, there is a statistically significant difference ($p < 0.01$) in performance between clinical engineers who received training and those who did not receive training. This confirms that engineers who received training perform better.

Improving the Capacity of Clinical Engineers Based on Identified Issues

This study comprehensively identified the technical and professional skill challenges that clinical engineers face when using AI-based mammography systems and evaluated their interrelationships using statistical methods. Among participants, 58.3% use AI systems regularly, indicating that this technology has been integrated into the healthcare sector to some extent. However, the remaining 41.7% use it irregularly, reflecting uneven implementation, system readiness, and varying user competency levels [17].

The highest-rated challenge was system compatibility (Mean = 4.46 ± 0.59), indicating inadequate integration between health information systems, such as PACS (Picture Archiving and Communication System) and RIS (Radiology Information System). Specifically, PACS/RIS connection issues were observed in 73.3% of cases, which can disrupt data transmission, storage, image processing, and adversely affect the normal operation of AI algorithms. International studies have also highlighted that the effectiveness of AI systems directly depends on data standardization (DICOM), interoperability protocols (HL7), and system compatibility [17, 18]. Software issues (Mean = 4.28 ± 0.63) were the next most important challenge, with 68.3% reporting software crashes and system slowdowns. This can be linked to multiple factors, including the computational load of AI algorithms, server capacity, network speed, and data volume. The research found that the reliability of AI systems depends not only on algorithm accuracy but also on technical and infrastructure readiness [19]. Lack of training (Mean = 4.21 ± 0.66) clearly points to challenges in human resource capacity. Clinical engineers' understanding of AI (Mean = 3.18) and knowledge of system integration (Mean = 3.05) received the lowest scores, indicating that current engineering training does not fully meet the new requirements of AI and digital health. WHO reports have also emphasized that human resource capacity and training are the most critical factors for successful AI technology implementation [20].

Correlation analysis confirmed these findings: a moderate positive correlation was observed between skills and device usage ($r = 0.64$, $p < 0.05$), whereas a strong positive correlation was observed between training and performance ($r = 0.71$, $p < 0.01$), demonstrating that training is a key driver of improved performance. There was also a statistically significant difference ($p < 0.01$) in performance between engineers who received training and those who did not, clearly showing the impact of training. This is consistent with previous research, which found that continuous training increases the effective use of AI technology [21]. Therefore, to successfully implement AI mammography systems, it is necessary to comprehensively address not only technological solutions but also human resources, training, and system integration.

Training and Capacity Building System: To improve the professional skills of clinical engineers, a tiered, continuous training system is needed, including:

Basic level: Fundamentals of AI, machine learning, and image processing.

Intermediate level: DICOM standard, HL7 protocol, PACS/RIS integration.

Advanced level: AI system diagnostics, troubleshooting, and data analysis.

The study results show that system integration (85%) and AI training (82%) are in the highest demand, indicating that training in these areas should be prioritized [18, 20].

Technical Infrastructure and Support:

- High-capacity servers and network infrastructure
- Regular software updates
- Remote monitoring and diagnostic systems
- Direct connection with manufacturers
- These measures will reduce system failures and increase the reliability of AI systems [20].

System Compatibility Policy

- Full compliance with DICOM and HL7 standards
- Unified data format and exchange policy
- Improved interoperability of health information systems
- International experience shows that system integration is the key determinant for successful AI implementation [18].

Organizational and Policy Level:

- Consistent funding for training
- Establishment of a professional grading system
- Performance-based evaluation
- Policies to specialize engineers in AI

In the future, there will be a need for clinical engineers to become:

- AI + Health IT integration specialists
- Clinical data analysts

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