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Comparison of Digital Mammography Plus Full ABUS Review and Digital Mammography Plus Selective ABUS Review Guided by ABUS Artificial Intelligence–Computer-Aided Diagnosis for Breast Cancer Screening

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Objective: To compare two breast cancer screening strategies, digital mammography (DM) plus radiologist-interpreted automated breast ultrasound (ABUS) and DM plus selective ABUS review, in which only examinations positive for DM or flagged by ABUS artificial intelligence–computer-aided diagnosis (AI-CAD) were reviewed by radiologists.

Materials and Methods: This retrospective study included asymptomatic women who underwent DM and ABUS screening for breast cancer between March 2022 and March 2023. The radiologists' interpretations of DM and ABUS without AI assistance (DM + ABUS_radiologist) were collected from the clinical radiology reports. A selective DM plus ABUS reading strategy was simulated, in which only cases interpreted as positive in the radiologist's DM report or flagged by retrospectively applied ABUS AI-CAD were triaged for further evaluation through a full review by radiologists (DM + ABUS_AI-CAD). The cancer detection rate (CDR), sensitivity, specificity, and abnormal interpretation rate (AIR) were calculated and compared between DM + ABUS_radiologist and DM + ABUS_AI-CAD groups using the McNemar's test.

Results: Among 2,275 women (mean age, 56.1 ± 8.6 years), 12 cancers were diagnosed. The sensitivity, CDR and AIR for DM + ABUS_radiologist was 83.3% (10/12; 95% confidence interval [CI]: 51.6–97.9), 4.4 (10/2,275; 95% CI: 2.1–8.1) per 1,000 screening examinations and 16.7% (379/2,275; 95% CI: 15.1–18.3), respectively. DM + ABUS_AI-CAD triaged 84.0% (1,910/2,275) of the examinations as negative in both DM reports and retrospectively applied ABUS AI-CAD, requiring radiologist reassessment in only 16.0% (365/2,275). This approach reduced the AIR to 7.3% (167/2,275) and improved the specificity from 83.7% (1,894/2,263) to 93.1% (2,107/2,263) (all $P < 0.001$), while maintaining a CDR of 4.8 per 1,000 and a sensitivity of 91.7% (11/12) (all $P > 0.999$), compared to the DM + ABUS-radiologist.

Conclusion: An AI-CAD-assisted selective ABUS reading strategy reduces unnecessary recalls and improves specificity, which may help optimize reading priorities and reduce the reading workload while maintaining cancer detection performance.

Keywords: Automated breast ultrasound; Artificial intelligence; Abnormal interpretation rate; Computed aided diagnosis; Cancer detection rate; Specificity

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INTRODUCTION

Breast cancer screening plays a critical role in the early detection and management of breast cancer and significantly reduces mortality among women worldwide [1]. Mammography remains the gold standard; however, its limited sensitivity in women with dense breasts has led to the use of supplemental modalities, such as breast MRI or ultrasound (US), for high-risk patients [2].

In recent years, automated breast US (ABUS) has emerged as a promising supplemental screening tool that could potentially enhance the consistency and efficiency of breast cancer screening with improved reproducibility, reduced operator dependence, and standardized imaging compared to handheld US [3,4]. However, it is constrained by high recall and biopsy rates and a low positive predictive value similar to that of handheld US [4]. ABUS also produces hundreds of images, often prolonging the interpretation time, which varies according to radiologist's experience and case complexity [5-8].

Recent advances in artificial intelligence–computer-aided diagnosis (AI-CAD) have created opportunities to improve the diagnostic accuracy and efficiency of breast imaging [5,9-14]. In ABUS, AI-CAD may reduce interpretation time and workload, assist in detecting suspicious lesions, and lower false negatives and unnecessary biopsies [3,15]. Combining the standardized imaging of ABUS with the analytical capability of AI-CAD could enable more efficient and accurate screening. However, current evidence for AI-CAD in ABUS remains limited, as most studies have focused on diagnostic rather than screening use [5,13], and large-scale evaluations of its diagnostic performance and workflow impact are lacking.

Thus, this study aimed to compare the performance of digital mammography (DM) combined with radiologist-interpreted ABUS (DM + ABUS_radiologist) and DM combined with selective ABUS review guided by ABUS AI-CAD (DM + ABUS_AI-CAD), in which radiologists reviewed only cases with positive findings in DM reports or those flagged as suspicious by retrospectively applied ABUS AI-CAD.

MATERIALS AND METHODS

Study Population

This retrospective study was approved by the Institutional Review Boards and ethics committees of the two tertiary referral centers (IRB No. Seoul National University Hospital [Institution A]: 2304-149-1428; Kangbuk Samsung Hospital [Institution B]: 2023-06-001), and the requirement for written informed consent was waived. A database search from the two institutions identified consecutive asymptomatic women aged ≥40 years who underwent both DM and supplemental ABUS for breast cancer screening between March 2022 and March 2023. For both institutions, ABUS is indicated for the supplemental screening of asymptomatic women without a history of breast cancer. After the initial search, women without reference standards, defined as those with less than 12 months of follow-up or without histological data, were excluded.

Imaging Examinations

All imaging data were obtained prospectively as part of routine clinical practice and stored in a picture archiving and communication system. All standard two-view full-field DM of both breasts were acquired using two DM units (Selenia Dimensions, Hologic; Marlborough, MA, USA, Senographe Pristina, GE Healthcare, Chicago, IL, USA). All ABUS examinations were performed by trained technologists with 2–5 years of experience, using a dedicated ABUS system (Invenia ABUS; GE Healthcare). Details of the ABUS system and image acquisition are described in Supplement.

DM and ABUS Interpretation

DM and ABUS assessments were extracted from radiologic reports. All DM and ABUS images were prospectively interpreted as part of our routine clinical practice by one of 10 breast radiologists (2–31 years of experience in breast imaging). ABUS images were reviewed using a dedicated ABUS workstation (Invenia ABUS; GE Healthcare). When women were scheduled for both DM and ABUS on the same day, the radiologists reported the mammographic findings separately using the fifth edition of the American College of Radiology Breast Imaging Reporting and Data System (BI-RADS) (scores 0–5) [16] before ABUS interpretation, and subsequently interpreted ABUS and assigned BI-RADS categories independently in the radiologic reports. Cases assigned to BI-RADS categories 0, 3, 4, or 5 were considered positive, whereas those assigned to BI-RADS categories 1 or 2 were considered negative. The final combined recommendation was based on the more suspicious BI-RADS category between DM and ABUS. If ABUS shows a positive finding, the combined assessment is considered positive. If a positive DM finding corresponds to a benign lesion (BI-RADS 2) on ABUS, the combined assessment

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is considered negative. Otherwise, if no definite benign correlation is found on ABUS for a positive DM finding, or if both DM and ABUS demonstrated positive findings, the final combined assessment is considered positive. If the DM and ABUS are interpreted as negative or benign, the combined assessment is negative. A negative or benign final assessment results in the recommendation for routine screening. For lesions assessed as BI-RADS category 3, a 6-month follow-up was performed using either handheld US or ABUS depending on the clinician's preference. For lesions assessed as BI-RADS category 0 or 4, additional mammographic views, targeted handheld US or biopsies are recommended.

ABUS AI-CAD System

We used a commercially available ABUS AI-CAD system (MONCAD Version 2.15.0; Monitor Corporation, Seoul, South Korea) designed to assist radiologists in identifying suspicious regions in ABUS images. This system employs deep neural network techniques including vision transformers and convolutional neural networks [17-19]. Suspicious lesions in each scan were identified by transmitting the ABUS images to an AI workstation via the Digital Imaging and Communications in Medicine protocol. After processing the image volumes, the system generated a report that included detailed location information for each detected lesion, such as the clock-face position, nipple-to-lesion distance, and lesion depth relative to the skin surface.

Simulation of DM + ABUS_AI-CAD

To evaluate the feasibility of AI-CAD-triaged ABUS interpretation, we retrospectively applied AI-CAD to all ABUS images in the study cohort and identified the positive cases flagged by the system. Examinations without an ABUS

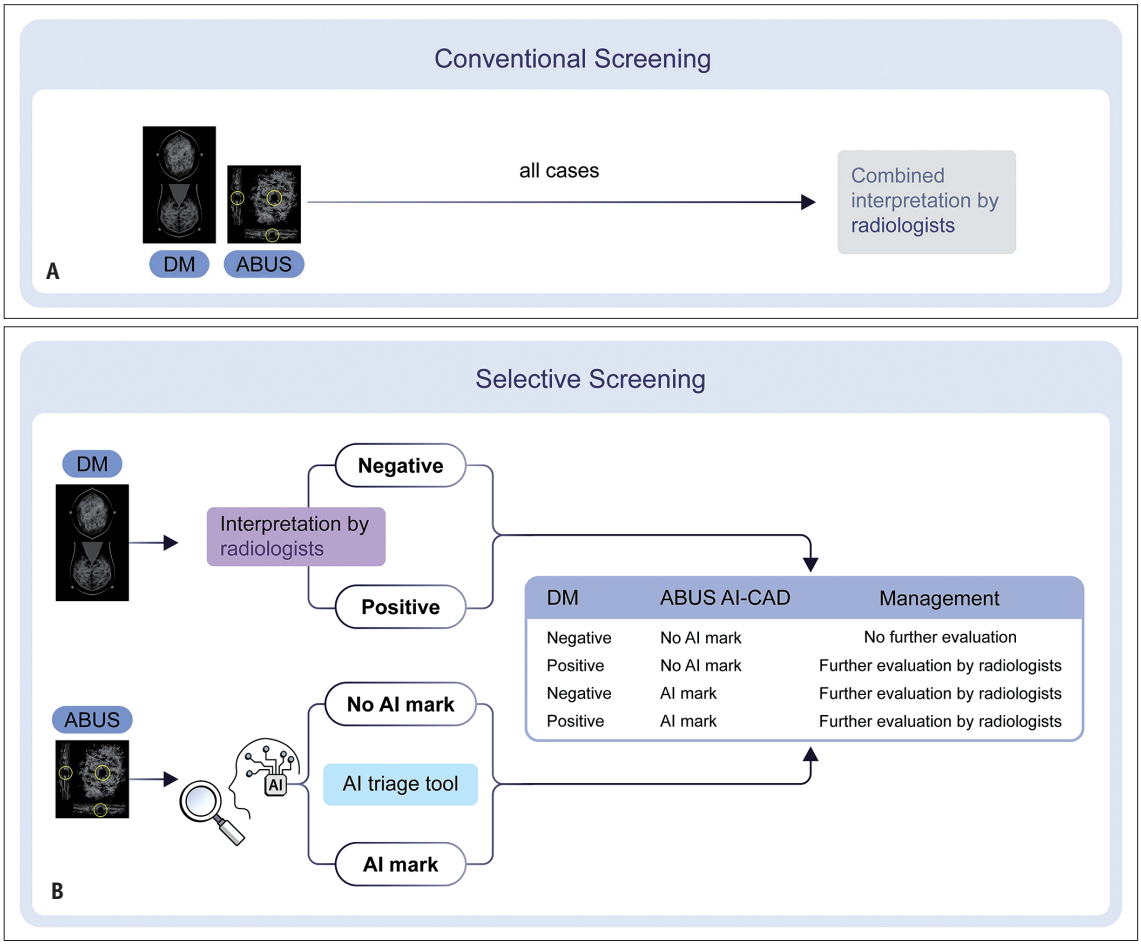

Fig. 1. Study overview comparing **(A)** conventional reading, in which all cases undergo both DM and ABUS with combined radiologist interpretation (DM + ABUS_radiologist), and **(B)** selective reading strategy, where DM is read by radiologists and ABUS is assessed by an AI-CAD triage tool (DM + ABUS_AI-CAD), with only positive cases from either modality undergoing radiologist reinterpretation. DM = digital mammography, ABUS = automated breast ultrasound, AI = artificial intelligence, CAD = computer-aided diagnosis

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AI-CAD mark on retrospectively applied ABUS images and with negative results in DM radiological reports were triaged as negative and excluded from the review. In contrast, examinations with positive findings in the DM reports by the initial interpreting radiologist or those flagged by retrospectively applied ABUS AI-CAD were referred for further evaluation with a combined DM and ABUS review (Fig. 1). Two radiologists (M.K. and S.M.H.; experience range: 7–11 years) reviewed the DM and full ABUS images of selected cases with positive findings in DM reports or ABUS AI CAD marks at the workstation, and determined the need for recall. Each radiologist independently assessed cases from their respective institutions, and the results were subsequently aggregated.

Data Collection

We collected identifiable clinical data from the medical records, including patient age, hormone replacement therapy status, and first-degree family history of breast cancer. DM and ABUS imaging data, including BI-RADS categories provided by the initial interpreting radiologists, mammographic density, biopsy method, and US background echotexture, were obtained from radiologic reports. Two breast imaging radiologists (I.Y. and J.M.C.; experience range: 13–18 years) retrospectively reviewed the cancer cases to determine whether an imaging abnormality could be identified using ABUS or DM. Cancers were categorized as those detected using DM alone, ABUS only, or both. The standalone ABUS AI-CAD results were also reviewed to assess whether AI-CAD correctly marked breast cancer regions. Histopathologic examination and ≥1 year follow-up data were used as the reference standard. Lesions diagnosed as invasive carcinoma or ductal carcinoma in situ (DCIS) via biopsy or surgery were classified as malignant. In patients without a history of biopsy or surgery, the reference standard was clinical follow-up for at least 12 months after the last imaging date. Follow-up examinations performed 11–15 months after the last imaging date were considered 12-month follow-ups, accounting for real-world variability in scheduling. For malignant lesions, pathologic invasive tumor size, nodal status, stage, and estrogen receptor, progesterone receptor, and human epidermal growth factor receptor 2 status were recorded (Supplement).

Statistical Analysis

All statistical analyses were conducted using individual examinations as the unit of analysis. Characteristics of the study sample at the two institutions were compared using the Student *t*-test for continuous variables and the chi-square (χ^2) test or Fisher's exact test for categorical variables. We calculated the performance metrics, including the cancer detection rate (CDR), sensitivity, specificity, and abnormal interpretation rate (AIR) for each breast cancer screening strategy (DM + ABUS_radiologist and DM + ABUS_AI-CAD). Subgroup analyses were performed to compare the outcomes stratified by breast density and institution. McNemar's test was used to compare paired proportions between DM + ABUS_radiologist and DM + ABUS _AI-CAD. We also calculated the number of examinations that were not subjected to further interpretation owing to negative findings in both the radiologists' DM report and ABUS AI-CAD results. The 95% confidence intervals (CIs) were estimated using the Clopper–Pearson exact method for proportions. All statistical analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA), and a two-sided $P < 0.05$ was considered statistically significant.

RESULTS

Patient and Lesion Characteristics

Among the 2,675 eligible women (897 from Institution A and 1,778 from Institution B), 400 (14 from Institution A and 386 from Institution B) were excluded because of a lack of reference standard data. Ultimately, 2,275 women (mean age, 56.1 years; range, 40–86 years) were included in the analysis (Fig. 2). DM and ABUS were performed on the same day in 2,037 women (n = 797 from Institution A and n = 1,240 from Institution B) and on different days in 238 women (mean interval of 156 days from Institution A and 93 days from Institution B). Among the 2,275 women, 12 cancers were diagnosed (mean invasive tumor size, 1.2 cm; range, 0.3–2.5 cm). The incidence of cancer was 0.5% (4/883) and 0.6% (8/1,392) in Institutions A and B, respectively. The 12 cancers consisted of 7 (58.3%) invasive ductal carcinomas, 2 (16.7%) DCIS, 1 (8.3%) invasive lobular carcinoma, 1 (8.3%) mixed ductal and lobular carcinoma, and 1 (8.3%) mucinous carcinoma. The detailed characteristics are presented in Table 1.

Screening Outcomes of DM + ABUS_Radiologist

The CDR for DM + ABUS_radiologist was 4.4 (10 of 2,275; 95% CI: 2.1–8.1) per 1,000 examinations. The sensitivity, specificity and AIR were 83.3% (10 of 12; 95% CI: 51.6–

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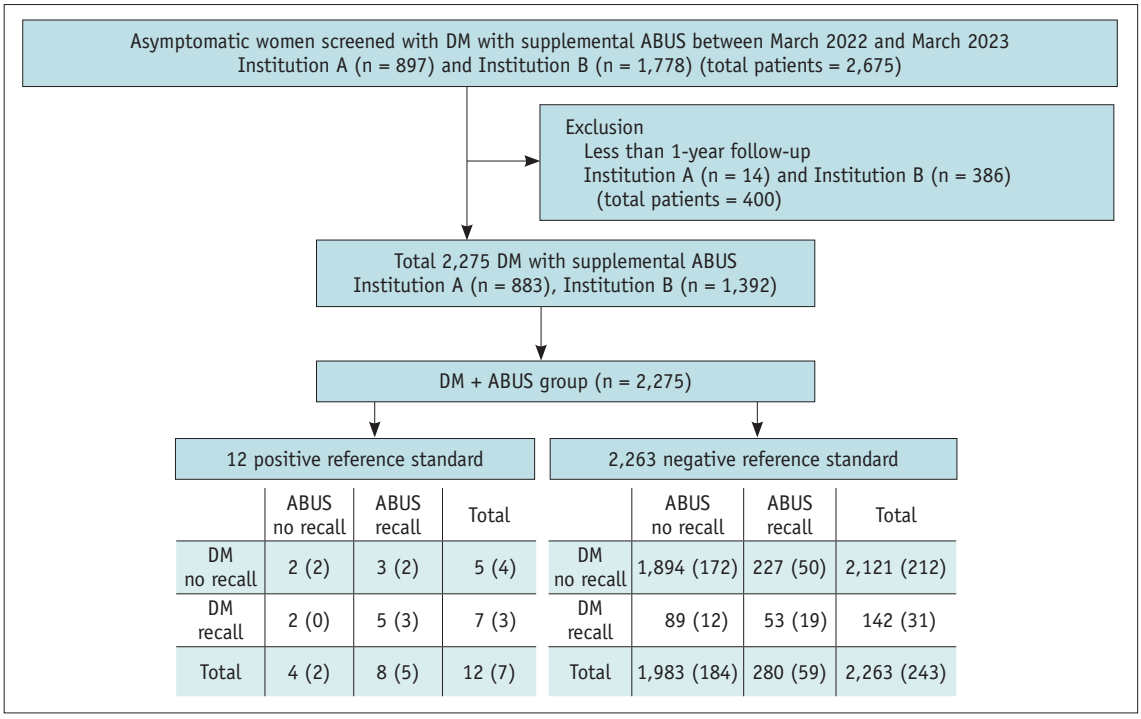

	ABUS no recall	ABUS recall	Total
DM no recall	2 (2)	3 (2)	5 (4)
DM recall	2 (0)	5 (3)	7 (3)
Total	4 (2)	8 (5)	12 (7)

	ABUS no recall	ABUS recall	Total
DM no recall	1,894 (172)	227 (50)	2,121 (212)
DM recall	89 (12)	53 (19)	142 (31)
Total	1,983 (184)	280 (59)	2,263 (243)

Fig. 2. Flowchart showing the study inclusion and exclusion criteria. Numbers in parenthesis are number of cases recalled by standalone ABUS AI-CAD. ABUS = automated breast ultrasound, AI = artificial intelligence, CAD = computer-aided diagnosis, DM = digital mammography

97.9), 83.7% (1,894 of 2,263; 95% CI: 82.1–85.2) and 16.7% (379 of 2,275; 95% CI: 15.1–18.3), respectively (Table 2). Among the 12 diagnosed cancers (Supplementary Fig. 1), seven were seen as masses (n = 1), calcification (n = 2), and asymmetry (n = 4) on DM, and eight were seen as masses (n = 8) on ABUS. ABUS detected three cancers that were missed by DM in women with dense breasts: two invasive ductal carcinomas (0.3 cm and 1.8 cm) and one mucinous carcinoma (1.8 cm). DM detected two DCIS manifesting as calcifications that were missed on ABUS. Two cancers, 1.8 cm invasive ductal and 2.5 cm invasive lobular carcinomas, were missed by both DM and ABUS but were evident on ABUS as masses retrospectively and were diagnosed on subsequent US 13 and 13.5 months after screening (Table 3).

Performance of Standalone ABUS AI-CAD

In our retrospective AI-CAD application to ABUS images, standalone ABUS AI-CAD demonstrated a CDR of 3.1 per 1,000 examinations (7 of 2,275; 95% CI: 1.2–6.3), sensitivity of 58.3% (7 of 12; 95% CI: 27.7–84.8), specificity of 89.3% (2,020 of 2,263; 95% CI: 87.9–90.5), and AIR of 11.0% (250 of 2,275; 95% CI: 9.7–12.3). Standalone ABUS AI-CAD detected seven cancers (five invasive ductal carcinomas, one invasive lobular carcinoma, and one mixed ductal and lobular carcinoma [size range: 0.3–2.5 cm]) (Fig. 3). Details of the five cancers missed by ABUS AI-CAD are summarized in Table 3: two were detected by both DM and ABUS-radiologist without AI-CAD (0.6 cm and 0.9 cm invasive ductal carcinomas), one was detected only by ABUS- radiologist without AI-CAD (1.8 cm mucinous carcinoma; Fig. 4), and two were detected only by DM (Table 3, Supplementary Fig. 1).

Screening Outcomes of DM + ABUS_AI-CAD

In a triaged reading workflow, 1,910 of 2,275 examinations (84.0%) were classified as negative by both DM reports and retrospectively applied ABUS AI-CAD, while 365 examinations were triaged to the review study based on positive findings from either the DM report (n = 149, 40.8%), retrospectively applied ABUS AI-CAD (n = 250, 68.5%), or both DM and ABUS AI-CAD (n = 34, 9.3%). Among the 12 detected cancers, one mucinous carcinoma (Fig. 4) was triaged into the negative group, while the remaining 11 were included in the re-evaluation group. For DM + ABUS_AI-CAD, the CDR was 4.8 per 1,000 examinations (11 of 2,275; 95% CI: 2.4–8.6), with a sensitivity of 91.7% (11 of 12; 95% CI: 61.5–99.8), specificity of 93.1% (2,107 of 2,263; 95% CI: 92.0–94.1), and AIR of 7.3% (167 of 2,275; 95% CI: 6.3–8.5). When the DM + ABUS_AI-CAD

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Table 1. Patient and lesion characteristics

Characteristics	Total (n = 2,275)	Institution A (n = 883)	Institution B (n = 1,392)	*P*
Patient variables				
Age, yr				<0.001
Mean ± SD	56.1 ± 8.6	57.1 ± 9.2	55.5 ± 8.3	
Median (IQR)	56 (48–62)	57 (51–63)	55 (49–61)	
Hormone replacement therapy				<0.001
No	1,285 (56.5)	473 (53.6)	812 (58.3)	
Yes	436 (19.2)	372 (42.1)	64 (4.6)	
Unknown	554 (24.4)	38 (4.3)	516 (37.1)	
1st family history of breast cancer				<0.001
No	1,590 (69.9)	816 (92.4)	774 (55.6)	
Yes	191 (8.4)	67 (7.6)	124 (8.9)	
Unknown	494 (21.7)	0 (0)	494 (35.5)	
Screening rounds				<0.001
Prevalence screen	99 (4.4)	99 (11.2)	0 (0)	
Incidence screen	2,176 (95.6)	784 (88.8)	1,392 (100)	
Mammography density				<0.001
Almost entirely fatty	34 (1.5)	19 (2.2)	15 (1.1)	
Scattered fibroglandular density	473 (20.8)	154 (17.4)	319 (22.9)	
Heterogeneously dense	1,302 (57.2)	453 (51.3)	849 (61.0)	
Extremely dense	466 (20.5)	257 (29.1)	209 (15.0)	
Ultrasound echotexture				<0.001
Homogeneous background echotexture-fatty	105 (4.6)	37 (4.2)	68 (4.9)	
Homogeneous background echotexture-fibroglandular	1,128 (49.6)	749 (84.8)	379 (27.2)	
Heterogeneous background echotexture	1,042 (45.8)	97 (11.0)	945 (67.9)	
Mammography finding				<0.001
Negative (BI-RADS 1, 2)	2,126 (93.5)	860 (97.4)	1,266 (90.9)	
Positive (BI-RADS 0, 3, 4, 5)	149 (6.5)	23 (2.6)	126 (9.1)	
Ultrasound finding				0.13
Negative (BI-RADS 1, 2)	1,987 (87.3)	783 (88.7)	1,204 (86.5)	
Positive (BI-RADS 0, 3, 4, 5)	288 (12.7)	100 (11.3)	188 (13.5)	
Lesion variables				
Lesion biopsy method				0.01
Ultrasound guided core needle biopsy	107 (91.5)	31 (81.6)	76 (96.2)	
Mammography guided biopsy	10 (8.5)	7 (18.4)	3 (3.8)	
Benign	2,263 (99.5)	879 (99.5)	1,384 (99.4)	0.03
Columnar cell change	23 (1.0)	8 (0.9)	15 (1.1)	
Fibrocystic change	51 (2.3)	12 (1.4)	39 (2.8)	
Intraductal papilloma	4 (0.2)	4 (0.5)	0 (0)	
Sclerosing adenosis	2 (0.1)	1 (0.1)	1 (0.1)	
Atypical ductal hyperplasia	1 (0.1)	1 (0.1)	0 (0)	
Fibroadenomatoid change	3 (0.1)	1 (0.1)	2 (0.1)	
Stromal fibrosis	13 (0.6)	3 (0.3)	10 (0.7)	
Fibroadenoma	8 (0.4)	4 (0.5)	4 (0.3)	
Stable follow-up	2,158 (95.4)	845 (96.1)	1,313 (94.9)	>0.99
Malignant	12 (0.5)	4 (0.5)	8 (0.6)	0.55
Ductal carcinoma in situ	2 (16.7)	1 (25.0)	1 (12.5)	
Invasive ductal carcinoma	7 (58.3)	3 (75.0)	4 (50.0)	
Invasive lobular carcinoma	1 (8.3)	0 (0)	1 (12.5)	
Mixed invasive ductal and lobular	1 (8.3)	0 (0)	1 (12.5)	
Mucinous carcinoma	1 (8.3)	0 (0)	1 (12.5)	

Data are presented as the number of patients or lesions, with percentages in parentheses unless otherwise specified.
SD = standard deviation, IQR = interquartile range, BI-RADS = Breast Imaging Reporting and Data System

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Table 2. Screening outcomes of DM + ABUS_radiologist vs. DM + ABUS_AI-CAD

Performance	DM + ABUS_radiologist	DM + ABUS_AI-CAD	*P*
Total (n = 2,275)			
CDR	4.4 (10/2,275) [2.1, 8.1]	4.8 (11/2,275) [2.4, 8.6]	>0.999
Sensitivity	83.3 (10/12) [51.6, 97.9]	91.7 (11/12) [61.5, 99.8]	>0.999
Specificity	83.7 (1,894/2,263) [82.1, 85.2]	93.1 (2,107/2,263) [92.0, 94.1]	<0.001
AIR	16.7 (379/2,275) [15.1, 18.3]	7.3 (167/2,275) [6.3, 8.5]	<0.001
Dense breast (n = 1,768)			
CDR	3.4 (6/1,768) [1.2, 7.4]	4.0 (7/1,768) [1.6, 8.1]	>0.999
Sensitivity	75.0 (6/8) [34.9, 96.8]	87.5 (7/8) [47.3, 99.7]	>0.999
Specificity	81.5 (1,434/1,760) [79.6, 83.3]	91.9 (1,617/1,760) [90.5, 93.1]	<0.001
AIR	18.8 (332/1,768) [17.0, 20.7]	8.5 (150/1,768) [7.2, 9.9]	<0.001
Nondense breast (n = 507)			
CDR	7.9 (4/507) [2.2, 20.1]	7.9 (4/507) [2.2, 20.1]	>0.999
Sensitivity	100 (4/4) [39.8, 100]	100 (4/4) [39.8, 100]	>0.999
Specificity	91.5 (460/503) [88.7, 93.7]	97.4 (490/503) [95.6, 98.6]	<0.001
AIR	9.3 (47/507) [6.9, 12.1]	3.4 (17/507) [2.0, 5.3]	<0.001
Institution A (n = 883)			
CDR	3.4 (3/883) [0.7, 9.9]	4.5 (4/883) [1.2, 11.6]	>0.999
Sensitivity	75.0 (3/4) [19.4, 99.4]	100 (4/4) [39.8, 100]	>0.999
Specificity	88.2 (775/879) [85.8, 90.2]	95.8 (842/879) [94.2, 97.0]	<0.001
AIR	12.1 (107/883) [10.0, 14.5]	4.6 (41/883) [3.4, 6.2]	<0.001
Institution B (n = 1,392)			
CDR	5.0 (7/1,392) [2.0, 10.3]	5.0 (7/1,392) [2.0, 10.3]	>0.999
Sensitivity	87.5 (7/8) [47.3, 99.7]	87.5 (7/8) [47.3, 99.7]	>0.999
Specificity	80.9 (1,119/1,384) [78.7, 82.9]	91.4 (1,265/1,384) [89.8, 92.8]	<0.001
AIR	19.5 (272/1,392) [17.5, 21.7]	9.1 (126/1,392) [7.6, 10.7]	<0.001

CDR is presented as per 1,000 examination, and all other results are presented as percentages. The raw numerator/denominator values and the 95% confidence interval are presented in parentheses and brackets, respectively.
The McNemar's test was used to compare paired proportions.
DM = digital mammography, ABUS = automated breast ultrasound, AI = artificial intelligence, CAD = computer-aided diagnosis, CDR = cancer detection rate, AIR = abnormal interpretation rate

results were compared with the DM + ABUS_radiologist results, a notable reduction in AIR with improved specificity (all $P < 0.001$) was noted without a decrease in CDR and sensitivity (all $P > 0.999$). A similar performance trend with improved specificity and AIR and comparable CDR was consistently observed when the outcomes were stratified by breast density and institution (Table 2).

DISCUSSION

In this study, we simulated a combined DM and selective ABUS screening strategy guided by ABUS AI-CAD, in which cases with negative DM reports and no mark on ABUS AI-CAD were excluded from the review, eliminating the need for full ABUS evaluation in 84.0% (1,910/2,275) of the cases. Reviewing positively assessed cases based on either DM or ABUS AI-CAD results increased specificity and lowered AIR compared to the conventional workflow, in which all ABUS were interpreted by radiologists without AI-CAD assistance, highlighting its potential to offset ABUS's specificity limitations.

Adding ABUS to DM in women with dense breasts or elevated cancer risk doubled the CDR from 3.6 to 7.2 per 1,000, but also raised the recall rates from 4.2% to 9.6% [20]. The SomoInsight study found that ABUS in 15,318 women with dense breasts increased the CDR by 1.9 per 1,000, with a 13.4% increase in the recall rate [21]. Similar results were observed in an Asian cohort (n = 2,785), where the CDR rose from 6.5 to 9.3 per 1,000 and the specificity decreased [22].

Recent studies have demonstrated that AI systems in mammography can enhance screening specificity without sacrificing sensitivity [23,24]. Building on this, we applied an AI-based triage model to ABUS, and this selective ABUS

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Table 3. Characteristics of cancers

Age	DM density	DM BI-RADS	DM finding	ABUS BI-RADS	ABUS finding	DM + ABUS_ radiologist	Standalone ABUS AI-CAD*	DM + ABUS_ AI-CAD	Pathology	Invasive cancer size (cm)	Lymph node	Stage	Molecular subtype
50	c	1	Negative	1	Negative	Negative†	Positive	Positive	IDC	1.8	Negative	I	Luminal
47	c	3	Calcification	1	Negative	Positive	Negative	Positive	DCIS	0	Negative	0	Luminal
46	c	1	Negative	4	Mass	Positive	Positive	Positive	IDC	1.8	Negative	II	Tripe negative
62	c	5	Mass	5	Mass	Positive	Positive	Positive	IDC	1.5	Negative	I	Luminal
61	b	0	Asymmetry	3	Mass	Positive	Positive	Positive	IDC	NA	NA	NA	Luminal
62	b	0	Asymmetry	4	Mass	Positive	Negative	Positive	IDC	0.6	Negative	I	Luminal
46	d	1	Negative	1	Negative	Negative‡	Positive	Positive	ILC	2.5	Negative	II	Luminal
54	c	1	Negative	4	Mass	Positive	Positive	Positive	IDC	0.3	Negative	I	Luminal
49	b	4	Calcifications	1	Negative	Positive	Negative	Positive	DCIS	0	NA	0	Luminal
54	c	4	Asymmetry	4	Mass	Positive	Negative	Positive	IDC	0.9	Negative	I	Luminal
71	b	5	Asymmetry	5	Mass	Positive	Positive	Positive	Mixed	1.5	Negative	I	Luminal
62	c	1	Negative	3	Mass	Positive	Negative	Negative	Mucinous	1.8	Negative	I	Luminal

*Positive was defined when AI-CAD marked the breast cancer regions, †Diagnosed on subsequent US 13 months after screening, ‡Diagnosed on subsequent US 13.5 months after screening. AI = artificial intelligence, CAD = computer-aided diagnosis, US = ultrasound, DM = digital mammography, BI-RADS = Breast Imaging Reporting and Data System, ABUS = automated breast ultrasound, IDC = invasive ductal carcinoma, DCIS = ductal carcinoma in situ, NA = not applicable, ILC = invasive lobular carcinoma

interpretation, guided by DM and ABUS AI-CAD reduced the need for full ABUS review by 84.0%, lowered AIR, and improved specificity, while maintaining a CDR of 4.8 per 1,000 and sensitivity of 91.7%. Indeed, our strategy may preserve the benefits of supplemental ABUS screening while improving its efficiency. This allows us to focus on more suspicious findings and support as second readers in the single-reading ABUS practice, particularly in low-prevalence, incidence-screening populations like ours. This approach yielded consistent results across institutions despite differences in patient age, hormone therapy, family history, screening type, and breast composition. However, our results were simulated by retrospectively applying an AI-based triaging model to ABUS, and its effectiveness in higher-prevalence settings remains uncertain. Notably, the ABUS recall rate was relatively high at 12.7%, compared to the 4% reported in a previous study [25], which may be attributed to the fact that interpretations were made by a single radiologist in clinical practice. A reduction in the recall rate may be achieved through double-reading approaches.

Despite a promising workflow, standalone ABUS AI-CAD missed 5 of the 12 cancers. Of the five cancers missed by AI-CAD, two DCIS were also missed by the radiologists. The remaining three—two small invasive ductal carcinomas (0.6 cm and 0.9 cm) and one mucinous carcinoma (1.8 cm)—were detected by radiologists. These results suggest that small size and isoechogenicity may contribute to false negatives in AI-CAD, and underscore the continued value of human oversight [15]. Furthermore, because AI-CAD and radiologists missed different cancers, refining AI-CAD decision thresholds and training with diverse US-detected cancers is essential to enable safe standalone use. A previous preoperative ABUS CAD study reported a false-negative rate of 16%, with higher rates in asymptomatic patients and associations with small lesions, posterior depth, indistinct or angular margins, and a lack of architectural distortion [26]. Improved AI-CAD performance could enhance the feasibility of ABUS as a primary screening tool for breast cancer in low-resource settings [27]. In addition to the false-negative issue in ABUS AI-CAD, before the clinical implementation of a standalone ABUS AI-CAD system for screening, a more practical and effective approach would be to integrate AI as an interactive tool to assist radiologists during ABUS interpretation. Furthermore, because a substantial number of cancers are detected only in the DM, mammography should still be performed concurrently when using standalone ABUS AI-CAD as a primary screening

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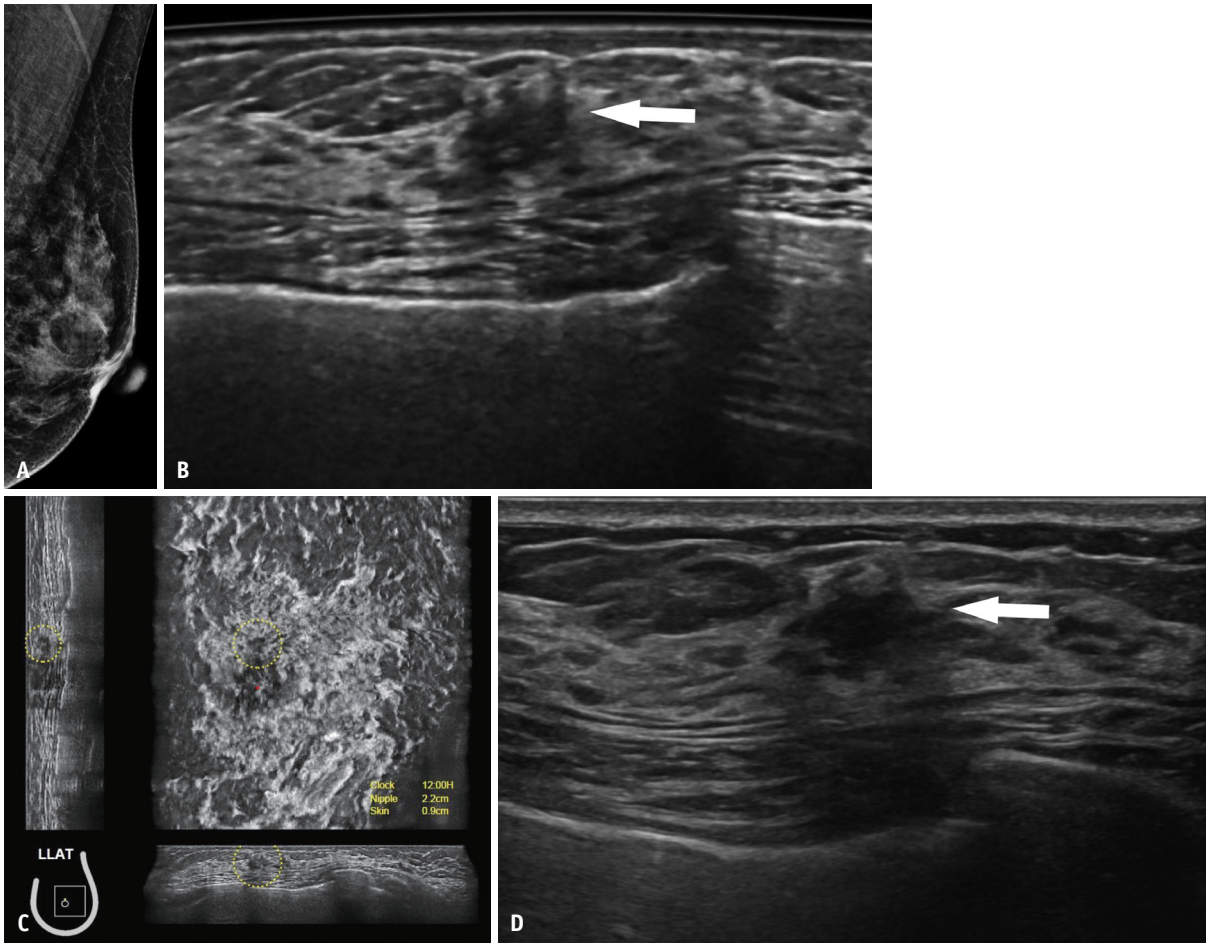

Fig. 3. A 54-year-old woman with invasive ductal carcinoma. **A:** Left mediolateral oblique view of digital mammography shows heterogeneously dense breast with no definite suspicious lesion. **B:** Automated breast ultrasound axial view reveals a 1.3-cm irregular hypoechoic mass (arrow). The radiologist assessed the lesion as Breast Imaging Reporting Data System category 4. **C:** Retrospectively applied artificial intelligence–computer-aided diagnosis output display also marked the lesion (dotted yellow circles). **D:** On handheld breast ultrasound for biopsy, an irregular hypoechoic mass was identified (arrow). Surgical histopathology revealed invasive ductal carcinoma (Stage I, T1N0M0, estrogen receptor positive, progesterone receptor positive, human epidermal growth factor 2 negative).

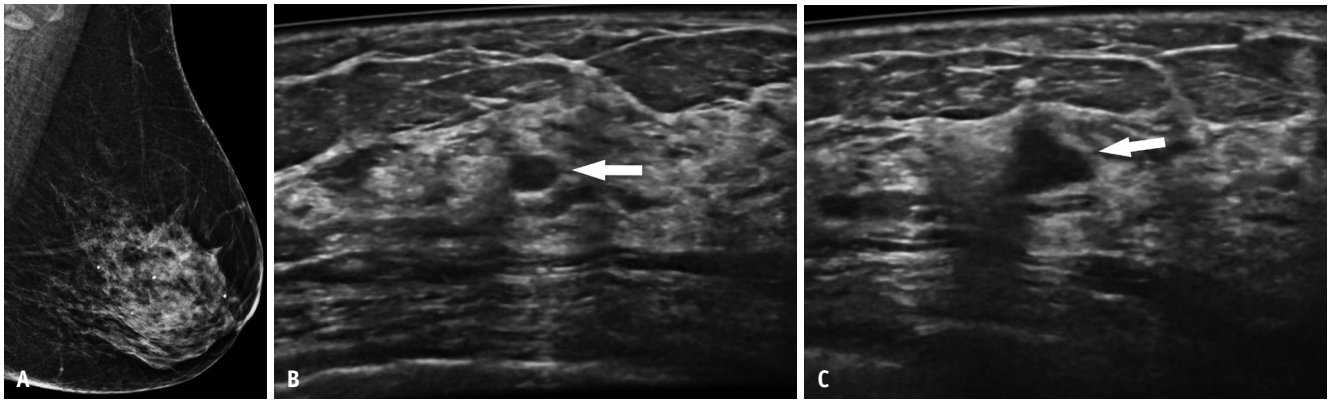

Fig. 4. A 62-year-old woman with mucinous carcinoma. **A:** Left mediolateral oblique view of digital mammography shows heterogeneously dense breast with no definite suspicious lesion. The ABUS artificial intelligence–computer-aided diagnosis output displayed no mark (not shown). **B:** ABUS axial view reveals a 0.5-cm round hypoechoic mass (arrow). The radiologist assessed the lesion as Breast Imaging Reporting and Data System category 3. **C:** After 15.6 months, the mass increased in size (arrow) and surgical histopathology revealed a 1.8-cm mucinous carcinoma (Stage I, T1N0M0, estrogen receptor positive, progesterone receptor positive, human epidermal growth factor 2 negative). ABUS = automated breast ultrasound

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modality.

This study has several limitations. First, the small number of cancer cases (n = 12) reflects the screening population prevalence but limits statistical power and may overestimate sensitivity. Indeed, the low CDR DM + ABUS_radiologist (4.4/1,000) may have resulted from the high proportion of incidence screen (95.6%) in the study population. Second, our triage strategy was based on a retrospective review of selected DM- or ABUS-CAD-positive cases, whereas all DM + ABUS_radiologist assessments were retracted from the radiologist reports. Factors such as radiologist confidence and institutional workflow may influence real-world effectiveness. In addition, the follow-up period was relatively short. Prospective studies with longer follow-up periods are needed to validate the integration of the DM and AI-CAD triage systems in clinical practice. Third, only one commercial AI-CAD algorithm was used. Fourth, there were differences in the patient characteristics between the two institutions. Nevertheless, a consistent trend in diagnostic performance was observed across both institutions. Finally, our study population was comprised of Asian women, most of whom had dense breast tissue [28].

In conclusion, our simulated selective ABUS reading strategy, triaged by positive findings on DM or ABUS AI-CAD, reduced unnecessary recalls and improved specificity for breast cancer screening, which may optimize reading priorities and workload while preserving cancer detection performance.

Supplement

The Supplement is available with this article at https://doi.org/10.3348/kjr.2025.1335.

Availability of Data and Material

The datasets generated or analyzed during the study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors have no potential conflicts of interest to disclose.

Author Contributions

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