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Australian healthcare workers' views on artificial intelligence in BreastScreen: Results of a mixed method survey study

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ABSTRACT

Introduction: The evolving role of Artificial Intelligence (AI) in medicine, particularly in radiology and population-based breast cancer screening programs, offers potential accuracy gains and efficiency improvements. However, successful implementation requires understanding of healthcare workers' views on AI, which this study aims to explore within the Australian BreastScreen program.

Methods: An online survey was distributed to clinical staff involved in breast imaging, collecting responses from November 2022 to April 2023. The survey encompassed demographic information, opinions, and experiences with AI in medical imaging, with questions covering various scenarios of AI integration in BreastScreen.

Results: Out of an estimated 350 professionals contacted, 95 responded, with 84.2 % (80/95) being radiologists. Less than half of respondents (44.9 %, 40/89) had worked with artificial intelligence for image classification previously. The majority of radiologists 74.2 % (46/62) thought that the use of AI in reading mammograms for BreastScreen would improve workflow. However, radiologists thought they would behave with increasing caution with scenarios where AI was more autonomous, with the majority of radiologists (63.3 %, 38/60) uncomfortable with holding accountability when the AI was used to triage and remove cases from the workflow. Notably, 60 % of radiologists (36/60) expressed concerns about accountability.

Discussion: The findings suggest an optimistic attitude towards AI among Australian healthcare workers, although when given hypothetical scenarios for the way AI could be integrated into BreastScreen, there was increasing caution with scenarios where AI was more autonomous. This study highlights understanding and concerns of healthcare professionals working in population screening which are important to address when implementing AI into the healthcare system.

1. Introduction

The application of artificial intelligence (AI) is rapidly evolving in the field of medicine, particularly in radiology. One area where the use of AI is surging is population-based breast cancer screening programs. Mammographic breast screening has been shown to reduce populationlevel breast cancer mortality by 22 % (Morrell et al., 2012). BreastScreen in Australia is a fully funded government program which actively invites women aged 50–74 to participate in free mammographic screening (with eligibility from age 40) (Australian Government Department of Health and Care, 2024). In BreastScreen Australia, two doctors (radiologist or breast physician) independently read all mammograms, with a third doctor arbitrating any discrepancies between the first two readers. Despite the multiread nature of the program, there are known challenges

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Received 30 June 2024; Received in revised form 20 October 2024; Accepted 21 October 2024 Available online 28 October 2024 2211-3355/© 2024 Published by Elsevier Inc. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/). with accuracy, client experience such as time to results and costs. AI integration has the potential to address these challenges faced by the BreastScreen program.

Several methods of AI implementation have been proposed for population-based breast cancer screening programs, including replacement of a reader, triaging of mammograms (first pass), and as a reading aid (Freeman et al., 2021). One study using AI in their breast cancer screening program demonstrated that replacing one radiologist resulted in a 4 % higher non-inferior cancer detection rate compared to radiologist double reading (Dembrower et al., 2023). In the literature, AI has been used to triage mammograms by pre-screening all mammograms and allocating patients at low risk to either single radiologist reading or no radiologist review (Dembrower et al., 2020; Lång et al., 2021). This has demonstrated the potential for up to 53 % of studies in low risk women to be ruled out of multireading with the potential to reduce radiologist workload by more than half (Freeman et al., 2021; Dembrower et al., 2020). When AI is used as an aid to mammography reading (decision support), it has been demonstrated that concurrent use of AI improves diagnostic performance without increasing radiologist reading time (Pacilè et al., 2020; Lång et al., 2023). Recently published research has demonstrated that diagnostic performance of AI was comparable with that of the average human reader (Chen et al., 2023). Within Australia, an AI algorithm developed by the Transforming Breast Cancer Screening with Artificial Intelligence (BRAIx) team evaluated three plausible AI integrated screening pathways on over 4 million images which demonstrated higher sensitivity and specificity than the BreastScreen Victoria two reader arbitration system (Frazer and Peña-Solorza, 2023). Beyond detection of cancer, AI has other potential applications, including mammographic quality evaluation, workflow prioritization as well as risk prediction and optimal time for mammographic follow up.

Although several studies have shown that adding AI to a populationbased screening program can be beneficial, successful implementation of AI in radiology depends on better understanding the potential users of the AI, including their past experience with AI, thoughts about AI, and preferences. Better understanding of the beliefs of end users of AI within the medical system allows for understanding and targeting of concerns which facilitates increased acceptance of the AI system when implemented. Collaboration with healthcare workers enables co-designing of services which incorporate AI and reduces barriers to adoption. Frameworks for AI tool deployment suggest understanding both the efficiency and productivity benefits from the AI upfront and quantifying these parameters in the applied clinical setting (Jindal et al., 2024). Collaboration with end users of the AI is crucial for understanding and quantifying these parameters. Enhancements in performance may not be sufficient for AI to be effectively utilized in daily clinical work. It is essential to explore the critical factors that influence clinicians' adoption behaviors regarding the use and interaction with these technologies. Security concerns, perceived risks, and trust have been identified as crucial factors influencing user acceptance behavior (Calisto et al., 2022).

Several studies have explored clinicians and radiologists' understanding, attitudes and experience with AI (Huisman et al., 2021; European Society of Radiology (ESR), 2022; Aquino et al., 2023). These studies demonstrate varying opinions both positive and negative towards AI, with many identifying the need to ensure careful and safe integration of AI into the healthcare system. Within Australia, surveys have been sent to imaging technologists and patients to better understand their views on AI in radiology (Currie et al., 2022; Clements et al., 2022). The views of radiologists working in population-based breast cancer screening programs are also largely positive, however there are uncertainties around risks and responsibilities with AI integration (Högberg et al., 2023). One survey of screen readers which explored potential use cases in population screening demonstrated that readers preferred AI as a partial replacement of human readers (de Vries et al. 2022). In Australia, the BRAIx project is exploring AI in the BreastScreen Australia program. BRAIx is a multi-institutional Medical Research Future Fund funded project between University of Melbourne, St. Vincent's Institute of Medical Research, St. Vincent's BreastScreen, BreastScreen Victoria and the Australian Institute of Machine Learning at the University of Adelaide which has developed an AI reading model to classify screening mammograms (BRAIx, 2021). This study, which is a sub-study of the BRAIx project, aims to investigate the opinions of healthcare workers in Australia regarding the implementation of AI in radiology and BreastScreen in Australia. This study specifically addresses the knowledge gap of participants' experience with AI, their perceived benefits and concerns of using AI in population breast screening in Australia.

2. Methods

2.1. Recruitment & data collection

An online survey was distributed to BreastScreen Victoria radiologists as well as distributed at the 13th General Breast Imaging Group meeting 2023 to radiologists, radiology technicians (radiographers and mammographers), breast surgeons and administrative staff. Responses were collected from November 2022 to April 2023. The chosen survey period provided respondents a reasonable amount of time to complete the survey, with follow up in person in March at the Breast Imaging Group meeting to maximize survey response. The survey was created using REDCap (Research Electronic Data Capture) which is a secure web application for building and managing online surveys and databases (Harris et al., 2009). Consent was obtained via REDCap after respondents were able to access the Participant and Information Consent Form. The survey was only distributed to healthcare workers involved with breast imaging who would be able to understand the context for the survey questions. Participation was voluntary and no incentivization was provided.

2.2. Survey domains

The survey contained a total of 27 questions covering demographic information, opinion and experience with artificial intelligence (AI) in medical imaging, opinion of AI in BreastScreen and how participants see themselves using AI. All questions within the survey were optional to answer.

Demographic questions had categorical responses. Questions relating to participants' opinion and experience with AI had Likert-scale response options (Strongly disagree, Disagree, Neither agree nor disagree, Agree and Strongly agree). A question relating to the participants' expected behavior change in reading with different hypothetical scenarios of AI integration had three options (More cautious, Less cautious, Neutral). Two questions only had a free-text response option. One free-text response question asked participants to provide a response for their reasoning on their expected behavior change in each AI integration scenario. The other free-text response question was "What do you think the role for AI in personalized or risk-based screening would be?". Six questions also had "other" as an option which could be selected and a free-text response could be provided by the participant.

Participants were asked their opinion on how they viewed the use of AI in medical imaging as well as specifically in BreastScreen. Options for the potential role of AI in mammographic reading were provided to the participants including AI as an aid alongside the radiologist, AI replacing the first or second reader, AI replacing the third reader or AI used as a first pass filter (triage), where the AI evaluates all mammograms first and clears a subset of normal mammograms.

The full survey is attached in Appendix 1.

2.3. Data analysis

Results were analysed using descriptive statistics and are presented in frequencies and percentages. Free-text responses were qualitatively analysed and grouped into themes. As non-radiologist healthcare workers were also invited to participate, questions relating to radiologist specific activities such as reading of mammograms were analysed within the radiologist subgroup only. The participants' responses were collated and analysed using Python 3.

2.4. Ethics

The study was approved by The University of Melbourne Office of Research Ethics and Integrity. Reference number 2021-22029-20158-4. All participants consented at the time of completing the survey.

3. Results

A total of 95 participants responded to the survey from approximately 350 people contacted (response rate 27.1 %). All questions were optional with 100 % (95/95) of respondents completing the first question, whilst only 63.2 % (60/95) completed the final question.

3.1. Participant demographics

Demographics are summarized in Table 1. 84.2 % of respondents were radiologists (80/95) and 12.6 % were radiographers or mammographers (12/95). The majority of radiologists (77.9 %, 60/77) had over 10 years of experience with only 9.0 % of radiologists with less than

Table 1

Descriptive statistics of Australian survey respondents, including breast radiologists, collected between November 2022 and April 2023.

Characteristic	N (%)
Professional Title	N = 95
Radiologist	80 (84.2)
Radiographer or mammography	12 (12.6)
Clinical Director	1 (1.1)
Breast Physician	1 (1.1)
Executive officer	1 (1.1)
Experience in breast radiology*	
> 20 years	39 (49.3)
16-20 years	6 (7.8)
11–15 years	16 (20.1)
5–10 years	10 (13.9)
< 5 years	7 (9.0)
No response	3 (3.8)
Percentage of work in breast radiology*	
> 75	28 (36.3)
51–75	20 (26.0)
26–50	16 (20.8)
< 25	13 (16.9)
No response	3 (3.8)
Length of time working at BreastScreen	<i>N</i> = 66
> 20 years	24
16–20 years	9
11–15 years	15
5–10 years	9
< 5 years	9
Percentage of clinical work in BreastScreen*	N = 57
> 75	N = 37 7 (12.3)
51–75	7 (12.3)
26–50	19 (33.3)
< 25	24 (42.1)

Only radiologists included in this count.

5 years experience (7/77). Most radiologists (83.1 %, 64/77) do more than 25 % of their radiology work in the subspecialty of breast radiology. 72.5 % (66/91) of participants work in BreastScreen in Australia.

3.2. Opinion and experience of participants with AI in medical imaging

Less than half of respondents (44.9 %, 40/89) had worked with artificial intelligence for image classification previously. Only 28.1 % (25/89) had actively sought learning and development opportunities in AI. The majority of respondents (87.6 %, 78/89) were interested or excited about the role of AI in medical imaging and 79.8 % (71/89) had either a highly or somewhat favorable opinion about working with AI in medical imaging. In individuals who had used AI in their clinical work, 29.3 % (17/58) agree that it resulted in time saving, 34.5 % (20/58) neither agree nor disagree and 36.2 % (21/58) disagree.

3.3. Opinion of AI in BreastScreen

Just under half of respondents (49.3 %, 36/73) thought that AI will be used in screening programs within the next 4 years, whilst 39.7 % (29/73) thought that it will be used within the next 5–10 years. 1 (1.4 %) respondent thought that AI would never be used in the screening program. Most respondents (83.6 %, 61/73) would like to know more about AI prior to implementation, with the majority of respondents wanting to learn more about performance (sensitivity and specificity) as well as explainability (what the AI is looking at in the image). Other items that respondents would like to better understand prior to AI implementation include understanding liability and accountability.

When radiologists were asked to select from a list of what they considered to be potential advantages of using AI in mammography reading (a multi-select question), the most commonly selected options were: 'Improved efficiency in workflow' (68.0 %, 51/75), 'Consistent breast density measurements' (60.0 %, 45/75), 'Dealing with workforce shortages' (57.3 %, 43/75) and 'Less interval cancers' (57.3 %, 43/75). The option selected as the most important advantage of implementing AI in mammography screening was 'Less interval cancers'. In regards to the disadvantages for mammography reading, the most common selected options were 'Lack of accountability if an error in reading occurs' and 'Deskilling of the workforce'. The option selected as the most important disadvantage of implementing AI in mammography was 'Deskilling of the workforce'. Other themes that arose in the free-text option included the cost for development, implementation and training as well as inefficient information technology systems and support.

Most radiologists (85.7 %, 54/63) strongly agree or agree that AI to interpret radiology in the future is a certainty, with most (74.2 %, 46/62) either strongly agreeing or agreeing that the use of AI in reading mammograms for BreastScreen will improve workflow. Under half of the radiologists surveyed (46.0 %, 29/63) either strongly agree or agree that AI performance for mammographic reading would be similar to an experienced breast radiologist. Just over half of the radiologists (50.8 %, 32/63), disagree that AI would pose a risk to job security, whilst 15.0 % (10/63) agree that AI would pose a risk to job security (Fig. 1). 60 % of radiologists (36/60) are concerned about who is at fault if AI makes a mistake.

3.4. How radiologists see themselves using AI in BreastScreen

Most radiologists (74.6 %, 53/71) selected AI used as an aid to support radiologist reading to be a potential role of AI in mammographic reading followed by AI replacing the first or second reader (59.2 %, 42/71). In all scenarios where AI would be implemented, most radiologists selected they would be as cautious in reading as they would be without AI. Radiologists were more likely to select that they would be more cautious in scenarios where AI was used as first pass to clear a subset of normal mammograms or when AI was used to replace the third reader (Fig. 2).

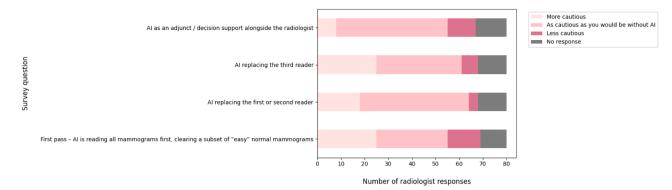


Fig. 1. Distribution of Australian radiologists' levels of caution when using AI in mammogram reading across various roles.

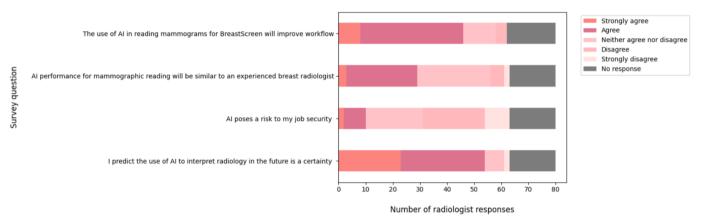


Fig. 2. Distribution of Australian radiologists' opinion of reading behaviors with different implementations of AI.

Most radiologists (61.7 %, 37/60) would be comfortable holding accountability for AI when used as an aid or adjunct to reading (strongly agree or agree). Less radiologists were comfortable holding accountability with increasing AI autonomy, such as when the AI was used as a first or second reader in parallel with human reader (28.3 %, 17/60) and even less when the AI acted as a first pass clearing a subset of normal mammograms first prior reading (18.3 %, 11/60) (Fig. 3). Free-text responses as to why respondents selected their choices in this question were variable, with several stating that they viewed "AI as an adjunct tool, not a replacement" with many wanting to better understand performance of the AI as it may "change the degree of caution and trust".

Radiologists believed that an AI with performance equal to an experienced breast radiologist was the most important performance indicator, with many radiologists also selecting high sensitivity and high specificity as an important performance indicator. Most radiologists would like to see a confidence score (73.4 %, 47/64) or heat map (68.8 %, 44/64) showing the region of interest if they were to work with AI in their practice. When respondents were asked about the role of AI in personalized or risk-based screening, most thought that AI could assist in risk-based screening through the use of family history, personal history and breast density.

4. Discussion

This study explores the opinions of radiologists and radiology technicians on the use of AI in radiology and BreastScreen in Australia. The majority of respondents had a positive view of AI, with most radiologists believing that AI could improve mammographic reading workflow, which is consistent with other recent studies (Pacilè et al., 2020). Respondents highlighted the importance of high sensitivity and specificity

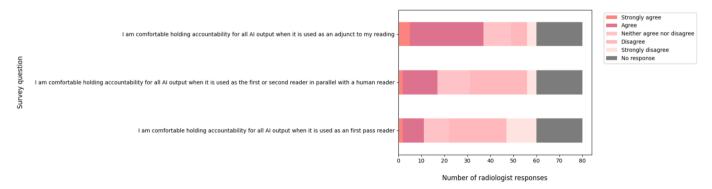


Fig. 3. Distribution of Australian radiologists' opinion of accountability with different implementations of AI.

for integration into population screening to ensure appropriate recall of patients.

Despite positive views and expectations towards AI, the responses to perceived behavior changes with AI integration suggests that scenarios with increasing AI autonomy are associated with decreased levels of comfort and perceived increased caution. Radiologists selected that they would behave more cautiously when AI acted more autonomously, such as clearing a subset of normal mammograms or replacing the third arbitration read. Most radiologists felt that AI as an aid to support radiological reading was a likely potential application of AI in BreastScreen which is consistent with most radiologists feeling more comfortable with holding accountability for the AI output when used as an adjunct to reading and feeling less comfortable in scenarios where a radiologist is replaced by the AI.

Slightly less than half of the radiologists believed that performance of an AI would be equal to that of a radiologist. This may provide some insight as to why radiologists selected that they would behave more cautiously in scenarios where the AI was more autonomous as they may have beliefs that the AI performance is not at the same standard as a radiologist. Several radiologists stated that their trust level and responses would depend on the performance of the AI. Although the performance of the AI was not specified in the question, it would be interesting to explore the radiologists' responses at different sensitivity and specificity levels in the future.

Although almost all radiologists stated that AI to interpret radiology in the future was a certainty, most radiologists were concerned as to who would be at fault if there is an AI related error with a perceived disadvantage being deskilling of radiologists. These concerns are not only limited to the breast screen workflow but are also relevant to other population based screening and diagnostic radiology practices. Concerns raised around deskilling of radiologists may relate to a perceived dependency or over-reliance of the AI, which needs to be further explored. Understanding the potential impacts to workflow from AI implementation and expected performance metrics from a radiologist and system perspective would be beneficial in ensuring smooth integration and acceptance of AI in any practice.

In addition to addressing concerns about accountability and deskilling, it is essential to engage more extensively with the ethical implications of AI integration, particularly in scenarios where AI operates autonomously. Other healthcare systems have approached these challenges by developing ethical frameworks and guidelines to mitigate risks associated with AI deployment, for example, the European Union's Ethics Guidelines for Trustworthy AI (European Commission, 2019). By adopting similar frameworks, we can address issues of transparency, accountability, and patient safety. Furthermore, expanding co-design and collaboration efforts with radiologists and other stakeholders is crucial for the smooth integration of AI technologies. Such collaborative approaches ensure that AI solutions are aligned with clinical needs and workflows, thereby offering practical solutions to the concerns raised by participants in our study.

As it may be difficult for radiologists to understand the different hypothetical scenarios for AI integration prior to implementation it is important to continue to understand the impacts of radiologist behavior in prospective trials as AI becomes increasingly utilized. The integration of AI into population based breast cancer screening programs have already been demonstrated in prospective trials implementing AI into screening workflows (Dembrower et al., 2023; Lång et al., 2023). The BRAIx program will shortly be conducting a randomized control trial with the AI reader as a second reader replacement (primary readers blinded, arbitration radiologist unblinded) in keeping with BreastScreen Australia policy. Research has similarly demonstrated diverse views in regards to the proper extent of AI-enabled automation and what roles AI should have in healthcare (Aquino et al., 2023).

The study had several limitations. Firstly, the sample size was small and only included radiologists and other breast screening healthcare workers, with no representation from radiology trainees who may have a different level of exposure to AI. Although the response rate of 27.1 % in this survey was lower than that of a similar survey of breast radiologists in another country, which had a response rate of 44.8 %, the total number of respondents in this survey (95) was higher than in the previous survey (47) (Högberg et al., 2023). Secondly, there was not enough diversity in the respondents to identify statistical differences in responses by years of experience. Thirdly, the questions were not compulsory, which led to variability in the number of questions answered, and respondent fatigue was demonstrated with fewer responses to the last question than the first question. Finally, given the use of specific terminology to describe the application of AI, it would have been beneficial to explain the terminology before the survey to ensure that everyone had the same understanding of each scenario, although this would have increased the time to complete the survey and could have increased respondent fatigue.

5. Conclusion

This study has shown radiologists are motivated to learn more about AI and want to understand the performance of an AI algorithm prior to implementation. Further work needs to be done to better understand how trust in an AI system differs with differing AI performance and implementation. This study emphasizes that radiologists believe they are likely to exercise greater caution in situations where AI operates with more autonomy. Radiologists were also less likely to feel comfortable to take accountability in scenarios where AI functioned more autonomously. Respondents felt that a major disadvantage of AI implementation was a lack of accountability which is a multifaceted topic that requires transparency and could be pivotal in adoption and acceptance of AI in the clinical workflow. It suggests that initial integration and acceptance of AI may occur when it serves as an adjunct, followed by scenarios where AI functions more independently. Moving forward, research should focus on how AI can be designed and implemented to enhance radiologists' confidence, particularly by ensuring transparency in decision-making processes and clarifying lines of accountability. Investigating strategies for collaboration between AI and radiologists could improve safety and comfort levels during the transition to more autonomous AI systems. Additionally, it is essential to study how AI may impact clinical skills over time, including concerns about de-skilling, and how this might affect the acceptance of AI tools in practice. Additionally, given the rapid growth of AI in population-based screening programs, it would be interesting to repeat the survey in the future to see if there is a change in opinion. Understanding the opinions of radiology trainees would be particularly important, as they will be the main users of AI in the future.

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CRediT authorship contribution statement

Jennifer SN Tang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. Helen ML Frazer: Writing – review & editing, Supervision. Katrina Kunicki: Writing – review & editing, Funding acquisition. Prabhathi Basnayake: Writing – review & editing, Methodology, Investigation. Maho Omori: Writing – review & editing. Jocelyn Lippey: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2024.102917.

Data availability

Data will be made available on request.

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