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Original Article

# Patient Confidence in Artificial Intelligence-Assisted Imaging Reports for Early Cancer Detection

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## ABSTRACT

Background: Artificial intelligence is increasingly used to support medical imaging, including cancer detection workflows. Although technical performance is important, patient confidence in AI-assisted imaging depends on how patients understand AI's role, whether clinicians remain responsible, and whether concerns about error, privacy, bias, and accountability are addressed. Qualitative evidence is needed to explore how patients interpret AI-supported imaging reports in emotionally sensitive cancer-related contexts. Objective: This study explored how adults with prior imaging exposure or cancer screening familiarity perceived AI-assisted imaging reports for early cancer detection, what increased or reduced their confidence, and what safeguards they considered necessary for acceptable use. Methods: An interpretivist qualitative study was conducted using semi-structured interviews with eight adult participants. Participants had experience of medical imaging or familiarity with cancer screening-related services. Interview data were analyzed using reflexive thematic analysis to identify patterns in perceived usefulness, concerns, trust conditions, and communication needs. Results: Eight themes were identified: AI as a supportive imaging tool, limited awareness and lack of disclosure, conditional confidence through human supervision, trust through reliability and approval, AI as a facilitator of earlier detection, fear of mistakes and overdiagnosis, ethical and social concerns, and assurance through clear communication. Participants viewed AI as useful when it acted as a second reader, but confidence depended on clinician verification, transparent disclosure, privacy protection, accountability, and simple explanations of AI's role and follow-up plans. Conclusion: Patient confidence in AI-assisted cancer imaging is conditional rather than automatic. AI may be acceptable when embedded in clinician-led care, supported by transparent communication, reliable governance, privacy safeguards, and clear responsibility for final interpretation.
Keywords: artificial intelligence; AI-assisted imaging; early cancer detection; patient confidence; medical imaging; radiology; patient-centered care.

**EDITORIAL INFORMATION**

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## INTRODUCTION

Cancer remains one of the most serious global health challenges because of its high incidence, mortality burden, emotional impact, and treatment cost. Global estimates for 2022 reported approximately 20 million new cancer cases and 9.7 million cancer deaths, reinforcing the continuing need for prevention, screening, timely diagnosis, and effective referral pathways [1]. Early cancer detection is clinically important because many cancers are more treatable when identified before advanced local invasion or metastatic spread. However, early detection is not determined by imaging access alone. Patients must understand why imaging is recommended, remain engaged after suspicious findings, tolerate diagnostic uncertainty, and trust that reports and subsequent clinical decisions are reliable, understandable, and safely managed [2].

Medical imaging is central to contemporary cancer detection and diagnostic pathways. Mammography can identify breast abnormalities before symptoms develop, low-dose computed tomography is used in selected lung cancer screening populations, and magnetic resonance imaging, ultrasound, computed tomography, and other modalities contribute to lesion detection, characterization, staging, and follow-up. In this context, imaging reports are not merely technical documents. For patients, they communicate risk, uncertainty, reassurance, possible malignancy, need for additional testing, and potential changes in family and treatment planning. A report suggesting possible cancer can generate fear, while a reassuring report can influence whether patients continue or discontinue care-seeking. Therefore, patient confidence in imaging depends not only on diagnostic performance but also on how findings are explained, who verifies them, and whether patients perceive the process as safe and accountable.

Artificial intelligence has increasingly entered radiology and medical imaging as a technology that may assist image interpretation, triage, prioritization, lesion detection, and reporting workflows. AI systems can be trained to recognize patterns in large imaging datasets, classify suspicious features, or highlight regions that require closer clinical attention. Reviews of AI in radiology describe its potential to improve detection, consistency, and workflow efficiency, but also emphasize that clinical value depends on validation, workflow integration, professional interpretation, and safe use in real-world settings [3]. These considerations are especially important in cancer imaging, where a false-negative result may delay diagnosis, while a false-positive or overdiagnosed abnormality may expose patients to anxiety, repeated investigations, biopsy, cost, and family distress.

Existing research has shown that AI can perform strongly in selected cancer imaging tasks. International evaluation of an AI system for breast cancer screening demonstrated promising diagnostic performance in mammography datasets [5], and deep learning approaches have also been explored for lung cancer screening using low-dose computed tomography [6]. AI-supported mammography screening has been investigated as a way to support detection while managing the workload of screen reading [7]. These studies demonstrate the technical and service-delivery potential of AI-assisted imaging. However, patient confidence cannot be inferred from algorithmic sensitivity, specificity, or reader-performance metrics alone. Most patients do not encounter AI as a model, dataset, or diagnostic statistic. They encounter it through a report, a consultation, a hospital system, and a clinician's explanation of what was found and what should happen next.

Qualitative inquiry is needed because confidence in AI-assisted imaging is socially and emotionally constructed. Patients may interpret AI through prior experiences of illness, trust in clinicians, fear of cancer, concerns about privacy, expectations of human care, and beliefs about whether machines can make safe decisions. Patient confidence may also be shaped by disclosure, institutional reputation, perceived accountability, explainability, and whether AI is presented as a replacement for radiologists or as a supervised second reader. Previous studies on patient and public attitudes toward clinical AI indicate that people may accept AI when it improves care, but remain concerned about loss of human interaction, reduced safety, lack of control, and unclear responsibility [8,9]. Patient apprehensions about AI in healthcare also include depersonalization, error, opacity, and uncertainty regarding who is accountable when harm occurs [10].

The implementation literature further indicates that safe clinical AI use requires external validation, regulatory assessment, workflow integration, human factors evaluation, and ongoing monitoring [11]. Methodological guidance on diagnostic AI cautions that performance metrics must be interpreted in relation to clinical outcomes and real-world application rather than laboratory performance alone [12]. Concerns about bias and fairness are also central, because AI systems trained on unrepresentative datasets may perform unequally across populations, imaging devices, cancer types, ethnic groups, age categories, or local healthcare contexts [13,14]. These concerns matter directly to patients, who may reasonably ask whether an AI-supported report is accurate for people like them, whether their data are protected, and whether a clinician remains responsible for the final interpretation.

In cancer screening and early diagnosis, the balance between benefit and harm is particularly sensitive. Screening can reduce mortality for some cancers but can also produce false positives, false negatives, overdiagnosis, unnecessary procedures, and psychological distress [15]. AI-assisted imaging may modify this balance by detecting subtle abnormalities earlier, but it may also increase uncertain findings if not carefully integrated into clinical pathways. Patient confidence therefore depends on whether healthcare professionals can explain not only what AI identified, but also what the finding means, what remains uncertain, whether a clinician confirmed it, and what follow-up is appropriate.

Radiology-specific studies suggest that patients are generally more accepting of AI when it is supervised by radiologists and used as an assistive technology rather than as an autonomous substitute for clinical judgement [16,17]. This aligns with broader trust-in-automation literature, which emphasizes that safe reliance requires calibrated trust rather than blind acceptance or complete rejection [18,19]. Ethical and regulatory literature similarly stresses transparency, accountability, privacy, inclusiveness, human wellbeing, and meaningful explanation in AI-supported healthcare [20–24]. Taken together, this evidence suggests that patient confidence in AI-assisted cancer imaging is best understood as a conditional judgement shaped by perceived usefulness, human oversight, communication, ethical safeguards, and institutional credibility.

Using a SPIDER-oriented qualitative framing, the sample for this study comprised adults with prior exposure to medical imaging or cancer screening-related services; the phenomenon of interest was confidence in AI-assisted imaging reports for early cancer detection; the design involved semi-structured qualitative interviews; the evaluation focused on perceived benefits, concerns, safeguards, and conditions for trust; and the research type was interpretivist qualitative inquiry. This study therefore aimed to explore how adults with imaging-related experience understand AI-assisted imaging, what factors increase or reduce their confidence in AI-supported reports for early cancer detection, and what forms of clinician involvement, disclosure, communication, privacy protection, and accountability they consider necessary for acceptable implementation.

## MATERIALS AND METHODS

This study used an interpretivist qualitative design based on semi-structured individual interviews and reflexive thematic analysis. The design was selected because the objective was not to measure diagnostic accuracy, estimate prevalence of confidence, or test a predictive model, but to understand how participants made meaning of AI-assisted imaging in relation to early cancer detection. An interpretivist approach was appropriate because patient confidence was treated as a relational and context-dependent judgement shaped by prior imaging experience, perceived usefulness, fear of cancer, communication, clinician oversight, trust in institutions, and ethical concerns. The study was informed by the Technology Acceptance Model, particularly the concepts of perceived usefulness and understandability, and by broader technology acceptance scholarship emphasizing that acceptance of health technologies depends on social trust, perceived conditions of use, and confidence in the surrounding clinical system rather than technical performance alone [25,26].

The study included eight adult participants who had undergone medical imaging or had sufficient familiarity with cancer screening or imaging services to discuss their perceptions of AI-assisted imaging. Participants varied by age, gender, educational background, occupation, and imaging experience, including exposure to ultrasound, aspiration, computed tomography, mammography, and magnetic resonance imaging. Direct prior receipt of an AI-assisted imaging report was not required, because AI involvement in imaging reports is not always disclosed to patients and many patients form confidence through explanation, expectation, perceived safeguards, and trust in clinician-led systems. The study therefore explored anticipated and conditional confidence in AI-assisted imaging rather than restricting participation to patients with documented personal exposure to AI-generated or AI-supported reports.

Participants were recruited using a purposive sampling approach intended to capture variation in imaging experience and background characteristics relevant to confidence in AI-supported reporting. The final manuscript should specify the recruitment source, who approached potential participants, whether recruitment occurred through clinical services, community networks, or researcher contacts, and whether any eligible individuals declined participation. Inclusion criteria were adult status, ability to provide informed consent, and prior exposure to imaging or cancer screening-related services sufficient to discuss the study topic. Exclusion criteria should be stated explicitly in the final version if applied, particularly for individuals unable to provide informed consent or those for whom discussion of cancer-related imaging could cause undue distress. The authors should also clarify whether any participant had a prior personal or professional relationship with the interviewer, as this is required for transparent qualitative reporting.

Data were collected using semi-structured individual interviews. Semi-structured interviewing was selected because it allowed the same core areas to be explored across participants while giving participants flexibility to describe uncertainty, fear, conditional trust, expectations of human supervision, and concerns about error, privacy, bias, and accountability. The interview guide covered awareness of AI-assisted imaging, prior knowledge of AI in healthcare, perceived usefulness of AI for early cancer detection, conditions that would increase or reduce confidence, concerns about false positives, false negatives and overdiagnosis, privacy and data protection, preference for AI-only, clinician-only, or combined interpretation, and the type of information participants expected from healthcare professionals. The development of the interview guide was informed by qualitative interviewing principles and by the need to maintain both comparability and depth across interviews [27,28]. The final manuscript should report whether the guide was piloted, whether it was revised after pilot testing, and whether participants were invited to add issues not covered by the guide.

The final manuscript should provide full procedural details for data collection in line with COREQ and SRQR. These include the interview setting, mode of interview, language used, interview duration, privacy arrangements, whether anyone else was present, whether interviews were audio-recorded, whether field notes were taken, and whether participants were offered transcript review. If interviews were conducted in a language other than English, the transcription and translation process should be described, including whether translations were checked for meaning and whether culturally specific expressions were preserved during analysis. If interviews were not audio-recorded, the manuscript should state how data accuracy was protected, for example through detailed contemporaneous notes, participant confirmation, or interviewer memos.

Ethical approval was obtained from Prima University, Indonesia. Written informed consent was obtained from all participants before participation. The final manuscript should add the full ethics committee name, approval number, approval date, and any institutional permission details if available. Participants should be informed that participation was voluntary, that they could decline to answer questions or withdraw according to the approved protocol, and that their responses would be anonymized. Because the interview topic involved cancer detection and possible diagnostic error, the manuscript should also state whether any safeguarding procedure was available if participants became distressed during discussion. All participant identifiers should be removed from transcripts and quotations, and quotations should be labeled using anonymized participant IDs and relevant non-identifying descriptors such as imaging experience where appropriate.

Data management procedures should be described explicitly. Interviews should be transcribed verbatim where recordings were available, de-identified before analysis, and stored in a secure password-protected location accessible only to the research team. If translation was required, the manuscript should specify whether translation occurred before or after coding and whether translated transcripts were checked against original-language data. The final manuscript should also state how long data will be retained, who has access to the data, and under what conditions de-identified data may be shared. The current data availability statement indicates that data are available from the corresponding author on reasonable request; this should be reconciled with participant consent and confidentiality safeguards.

Reflexivity was an important methodological consideration because participants' responses may have been influenced by how the interviewer explained AI, cancer detection, error, or privacy. The final manuscript should identify the interviewer's professional background, training in qualitative interviewing, relationship to participants, assumptions about AI-assisted imaging, and steps taken to reduce bias. Such steps may include use of a semi-structured guide, neutral prompts, reflexive memoing, team discussion of emerging interpretations, and attention to deviant or contrasting cases. If the researchers had clinical, radiological, academic, or technical expertise related to AI, this should be disclosed because it may influence questioning, interpretation, and participant responses.

Data were analyzed using reflexive thematic analysis. The analytic process involved familiarization with the dataset through repeated reading, generation of initial codes, comparison and refinement of codes, development of candidate themes, review of themes against the coded data and full dataset, naming and defining themes, and production of the analytic narrative. Reflexive thematic analysis was appropriate because it supports identification of patterned meanings across qualitative data while preserving the interpretive complexity of participants' explanations [29]. Initial codes included AI as computer support, second reader, lack of disclosure, doctor confirmation, approval, hospital reputation, subtle detection, false positive, false negative, privacy, bias, accountability, and simple explanation. These codes were organized into eight themes: AI as a supportive imaging tool, limited awareness and lack of disclosure, conditional confidence through human supervision, trust through reliability and approval, AI as a facilitative instrument for early detection, fear of mistakes and overdiagnosis, ethical and social concerns, and assurance through effective communication.

To improve analysis transparency, the final manuscript should specify the number of coders, whether coding was conducted independently or collaboratively, whether a codebook was developed, whether qualitative software was used, and how differences in interpretation were resolved. If only one researcher coded the data, this should be stated transparently and strengthened through reflexive memoing, audit trail documentation, and team review of themes. If more than one researcher coded the data, the manuscript should describe whether coding comparison was used for interpretive discussion rather than statistical intercoder agreement, which is not always required or conceptually appropriate in reflexive thematic analysis. The manuscript should also explain how final themes were checked against the research questions and participant quotations.

Trustworthiness was addressed through use of direct participant quotations, attention to contrasting views, documentation of analytic decisions, and maintenance of an audit trail linking research questions, codes, candidate themes, final themes, and illustrative data extracts [30]. Credibility should be strengthened by showing clear theme–quote linkage and, if applicable, by describing transcript checking, peer debriefing, or participant feedback. Dependability should be supported through a transparent description of recruitment, data collection, and analytic procedures. Confirmability should be supported through reflexive memoing and audit trail documentation. Transferability should be supported by reporting participant characteristics and imaging experiences in sufficient non-identifying detail so readers can judge relevance to other settings. The final results section should include a theme table and a quote table, with representative quotations labeled by participant ID and relevant imaging context.

No statistical analysis, inferential testing, p-values, confidence intervals, confounder adjustment, or missing-data imputation was performed because the study was qualitative and did not aim to estimate quantitative associations. Findings were reported as themes and subthemes supported by illustrative quotations. Where magnitude language is used in the results, it should remain qualitative and transparent, such as "most participants," "several participants," or "one participant," and exact counts should be used only when clearly traceable to the dataset.

## RESULTS

The analysis generated eight interrelated themes describing how participants understood and evaluated AI-assisted imaging reports for early cancer detection. Across the dataset, confidence was not expressed as unconditional acceptance of AI, but as a cautious and relational judgement shaped by human verification, institutional reliability, disclosure, privacy protection, and the quality of communication. Participants generally viewed AI as potentially useful when positioned as a supportive second reader, but they did not want it to replace radiologists or treating clinicians in cancer-related interpretation. Their confidence increased when AI was described as clinically tested, professionally supervised, explained in simple language, and embedded within a clear pathway for follow-up care.

*Table 1. Theme Matrix Showing Qualitative Strength, Analytic Meaning, and Illustrative Quote IDs*

| Theme | Qualitative strength | Analytic meaning | Illustrative quote IDs |
|---|---|---|---|
| **AI as a supportive imaging tool** | Frequent | Participants accepted AI most readily when it was framed as a tool that assists clinicians by highlighting suspicious findings or providing an additional review, rather than replacing professional judgement. | P1 |
| **Limited awareness and lack of disclosure** | Moderate | Several participants had heard about AI from general sources but were unsure whether it had been used in their own imaging care. Disclosure was linked directly to trust. | P1, P8 |
| **Conditional confidence through human supervision** | Frequent | Confidence depended strongly on radiologist or doctor verification. Participants wanted the final report to remain clinician-led, especially because cancer-related imaging carries emotional and clinical consequences. | P2, P5 |
| **Trust through reliability, approval, and hospital reputation** | Moderate | Participants wanted assurance that AI systems had been clinically tested, approved, monitored, and used in reputable institutions under professional supervision. | P4, P8 |
| **AI as a facilitator of earlier detection** | Moderate | Participants perceived AI as potentially helpful for identifying subtle abnormalities, supporting busy clinicians, and acting as a safety net in image review. | P1, P6 |
| **Fear of mistakes, false results, and overdiagnosis** | Moderate | Participants were concerned about false positives, false negatives, unnecessary anxiety, avoidable tests, and the possibility that AI may highlight abnormalities that are not clinically harmful. | P2, P3 |
| **Ethical and social concerns** | Moderate | Privacy, bias, accountability, and unequal access shaped acceptability. Participants wanted to know who would be responsible if AI contributed to an incorrect report. | P4, P6, P8 |
| **Assurance through clear communication and patient education** | Frequent | Participants wanted simple explanations of what AI did, what the clinician confirmed, whether the data were safe, and what the next step would be. Communication functioned as a central condition of confidence. | P5, P8 |

*Table 2. Representative Quotations Mapped to Themes and Subthemes*

| Theme | Subtheme | Representative quotation |
|---|---|---|
| **AI as a supportive imaging tool** | AI as an additional opinion | "I do not think AI will replace the doctor; however, I think it will help the doctor by providing an extra opinion." — P1 |
| **Limited awareness and lack of disclosure** | Awareness from media rather than clinical care | P1 described awareness of AI in healthcare mainly through social media and news, but did not report being told that AI had been used in their own imaging care. |
| **Limited awareness and lack of disclosure** | Disclosure as a condition of trust | P8 emphasized that patients should know when AI is used because hidden use may create trust problems. |
| **Conditional confidence through human supervision** | Doctor review as reassurance | P2 stated that confidence would depend on the doctor reviewing the report. |
| **Conditional confidence through human supervision** | Resistance to machine-only reporting | P5 explained that a machine should not deliver such a critical result alone and that reassurance would increase if the doctor explained that AI had assisted the review. |
| **Trust through reliability, approval, and hospital reputation** | Clinical testing and supervision | P4 indicated that confidence would increase if the AI system had undergone clinical testing and was used under medical supervision. |
| **Trust through reliability, approval, and hospital reputation** | Rejection of novelty alone | P8 stated that AI should not be used simply because it is modern, but should be tested and supervised. |
| **AI as a facilitator of earlier detection** | Detection of subtle changes | P1 stated that AI could detect slight changes that might otherwise escape attention, especially when doctors are busy. |
| **AI as a facilitator of earlier detection** | AI as backup | P6 described AI as a backup that could detect something difficult to notice. |
| **Fear of mistakes, false results, and overdiagnosis** | Emotional harm from false positives | "When AI informs a patient that he/she is a cancer patient and by the time that the test results are discovered to be false, the patient and his/her family will be mentally impacted." — P2 |
| **Fear of mistakes, false results, and overdiagnosis** | Concern about overdiagnosis | P3 noted that a small abnormality may not be dangerous but may become a source of stress when highlighted by AI. |
| **Ethical and social concerns** | Bias, false results, and privacy | P4 identified algorithmic bias, false positives, false negatives, and data privacy as important concerns. |

| Theme | Subtheme | Representative quotation |
|---|---|---|
| **Ethical and social concerns** | Accountability for error | "Who will we blame in case the AI makes a mistake: the hospital, the doctor or the software company?" — P6 |
| **Ethical and social concerns** | Equity in access | P8 expressed concern that poorer patients might receive lower-quality AI-supported services than wealthier patients. |
| **Assurance through clear communication and patient education** | Explanation of AI role and next steps | P8 wanted to know why AI was used, what it found, whether the doctor agreed, and what the next plan would be. |
| **Assurance through clear communication and patient education** | Simple explanation from doctor | "I would insist on having the doctor explain in basic terms what AI did and what the doctor discovered." — P5 |

The first theme, AI as a supportive imaging tool, showed that participants were most comfortable with AI when it was framed as assisting, rather than replacing, clinical judgement. The dominant interpretation was that AI could function as an additional layer of review by helping doctors identify suspicious areas in imaging studies. This framing reduced resistance because it preserved the clinician's role as the final interpreter. P1 captured this position by stating, "I do not think AI will replace the doctor; however, I think it will help the doctor by providing an extra opinion." This theme suggests that participants' confidence began from a cautious but practical understanding of AI as a second reader rather than an autonomous diagnostic authority.

The second theme, limited awareness and lack of disclosure, reflected the difference between general awareness of AI and informed awareness of AI use in personal healthcare. Some participants had encountered AI through news, social media, or general discussion, but this did not mean they knew whether AI had influenced their own imaging reports. P1 described awareness of AI in healthcare mainly through social media and news, but did not report being told that AI had been used in their own imaging care. P8 linked disclosure directly to trust, emphasizing that patients should be informed when AI is involved because hidden use may create suspicion. This pattern indicates that confidence is weakened when AI operates as an invisible technical layer within a diagnostic pathway.

The third theme, conditional confidence through human supervision, was one of the strongest patterns in the findings. Participants did not reject AI-assisted imaging, but their confidence depended on confirmation by a doctor or radiologist. P2 stated that confidence would depend on the doctor reviewing the report. P5 similarly expressed discomfort with a machine delivering a critical cancer-related result independently and reported that reassurance would increase if a doctor explained that AI had assisted the review. This theme shows that human supervision was not viewed as a minor procedural detail; it was central to perceived safety, responsibility, and emotional reassurance.

The fourth theme, trust through reliability, approval, and hospital reputation, showed that participants connected confidence with governance and institutional credibility. AI was considered more acceptable when associated with clinical testing, approval, monitoring, and reputable healthcare settings. P4 indicated that confidence would increase if the AI system had undergone clinical testing and was used under medical supervision. P8 similarly emphasized that AI should not be adopted simply because it is modern, but should be tested and supervised. These accounts show that participants distinguished technological novelty from trustworthy implementation. For them, innovation required evidence, oversight, and credible institutional use.

The fifth theme, AI as a facilitator of earlier detection, reflected participants' cautious optimism about the clinical value of AI. Participants perceived AI as potentially useful for identifying subtle abnormalities, acting as a safety net, and supporting doctors who manage heavy imaging workloads. P1 stated that AI could detect slight changes that might otherwise escape attention, especially when doctors are busy. P6 described AI as a backup that could detect something difficult to notice. However, this optimism remained conditional. Participants did not interpret earlier detection as automatically beneficial unless AI-supported findings were clinically verified and communicated clearly.

The sixth theme, fear of mistakes, false results, and overdiagnosis, captured the emotional and practical risks participants associated with AI-assisted cancer imaging. Their concerns were not limited to technical error; they focused on the consequences of error for patients and families. P2 explained the emotional

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harm of a false positive by stating, "When AI informs a patient that he/she is a cancer patient and by the time that the test results are discovered to be false, the patient and his/her family will be mentally impacted." P3 raised the related issue of overdiagnosis, noting that a small abnormality may not be dangerous but may become stressful if highlighted by AI. These accounts show that participants evaluated AI through the lived consequences of cancer-related uncertainty, not simply through diagnostic performance.

The seventh theme, ethical and social concerns, demonstrated that privacy, bias, accountability, and equity were integral to confidence. P4 identified algorithmic bias, false positives, false negatives, and data privacy as important concerns. P6 raised the question of responsibility by asking, "Who will we blame in case the AI makes a mistake: the hospital, the doctor or the software company?" P8 was concerned that poorer patients might receive lower-quality AI-supported services than wealthier patients. These findings suggest that participants viewed trust in AI-assisted imaging as inseparable from wider questions of governance, responsibility, fairness, and access.

The eighth theme, assurance through clear communication and patient education, showed that communication was a core mechanism through which confidence could be built. Participants wanted to know why AI was used, what it found, whether the doctor agreed with its output, how their data were protected, and what follow-up steps were required. P8 wanted an explanation of why AI was used, what it found, whether the doctor agreed, and what the next plan would be. P5 stated, "I would insist on having the doctor explain in basic terms what AI did and what the doctor discovered." These responses indicate that communication was not an optional supplement to AI implementation. It was a necessary condition for patient confidence.

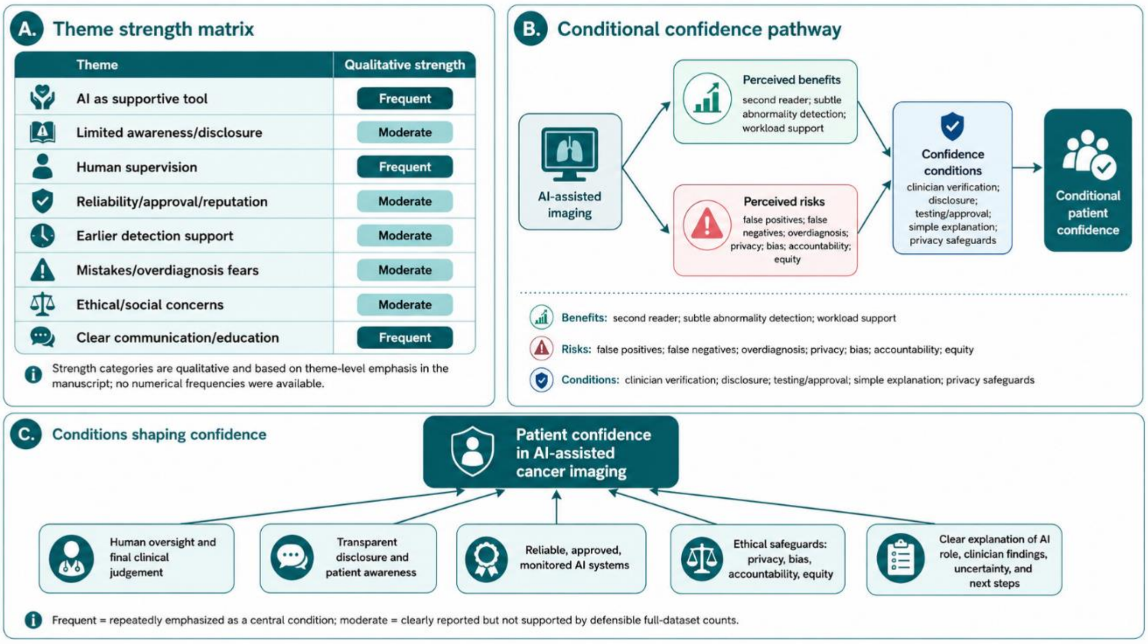


*Figure 1. Panelled qualitative model of conditional patient confidence in AI-assisted imaging for early cancer detection.*

*Panel A presents the theme strength matrix derived from the qualitative findings. Panel B illustrates how perceived benefits and perceived risks of AI-assisted imaging converge through confidence conditions to shape conditional patient confidence. Panel C summarizes the main conditions that participants associated with confidence, including human oversight, transparent disclosure, reliable and monitored AI systems, ethical safeguards, and clear explanation of AI's role, clinician findings, uncertainty, and next steps. Strength categories are qualitative only: frequent indicates themes repeatedly emphasized as central in the manuscript, while moderate indicates themes clearly reported but not supported by defensible full-dataset numerical counts. No inferential statistics or fabricated frequencies were used.*

Overall, the findings indicate that participants' confidence in AI-assisted imaging for early cancer detection was best understood as conditional confidence. AI was acceptable when it strengthened clinician-led interpretation, supported earlier detection, and operated within a transparent and accountable system. Confidence was reduced when AI was hidden, autonomous, poorly explained, weakly governed, or associated with unclear responsibility. Across themes, participants placed the greatest trust not in AI alone, but in a diagnostic process where AI assistance, radiologist verification, institutional reliability, ethical safeguards, and patient-centered explanation worked together.

## DISCUSSION

This qualitative study shows that patient confidence in AI-assisted imaging reports for early cancer detection is conditional, relational, and ethically shaped rather than determined by technical performance alone. Participants did not reject AI as a tool for cancer imaging, but they consistently positioned it as an assistive technology that should support, not replace, radiologists or treating clinicians. AI was viewed as potentially useful when it acted as a second reader, highlighted subtle abnormalities, reduced the risk of oversight in busy imaging settings, and contributed to earlier identification of suspicious findings. However, confidence depended on the presence of human verification, clear explanation, institutional reliability, and ethical safeguards. This finding is consistent with previous work showing that patients and the public may accept clinical AI when it is perceived to improve care, but remain concerned about safety, accountability, loss of human interaction, and reduced control over clinical decisions (8,9).

The strongest condition for confidence was clinician oversight. Participants were more willing to trust AI-assisted imaging when the final interpretation remained the responsibility of a doctor or radiologist. This finding aligns with radiology-specific patient-attitude studies indicating that acceptance of AI increases when AI is supervised by radiologists and used as an assistive rather than autonomous diagnostic tool (16,17). It also reflects broader trust-in-automation theory, which emphasizes calibrated trust rather than blind reliance or complete rejection (18,19). In the context of cancer imaging, this distinction is particularly important because a report suggesting possible malignancy has emotional, practical, and family-level consequences. Participants associated clinicians with judgement, explanation, empathy, and responsibility, while AI was associated with speed, pattern recognition, and additional image review. Confidence therefore emerged from the integration of machine assistance with human interpretation rather than from AI performance in isolation.

Disclosure was another major condition shaping trust. Participants indicated that they wanted to know when AI contributed to imaging interpretation, even if they did not require detailed technical explanations of model architecture or algorithmic design. This suggests that transparency should be meaningful and proportionate. Patients do not necessarily need to understand the computational structure of an AI system, but they do need to know whether AI was used, what role it played, whether a clinician verified its output, and how the final report should be interpreted. This finding is consistent with ethical guidance emphasizing transparency, autonomy, accountability, and human wellbeing in the use of health AI (20,21). Hidden or poorly explained AI use may weaken trust, particularly if patients later discover that algorithmic assistance contributed to a cancer-related report without prior explanation.

The findings also show that participants evaluated AI through both perceived benefit and perceived harm. AI was considered promising because it might detect slight abnormalities, support busy clinicians, and provide a safety net in image review. These perceptions are consistent with imaging studies showing the potential role of AI in breast and lung cancer screening workflows (5–7). However, participants also worried about false positives, false negatives, and overdiagnosis. Their concerns were not abstract statistical concerns; they were linked to anxiety, family distress, unnecessary investigations, delayed treatment, financial burden, and loss of trust in healthcare. This is consistent with cancer-screening literature showing that early detection may offer clinical benefit but can also create harms through false alarms, missed disease, overdiagnosis, and unnecessary intervention (15). Therefore, communication around AI-assisted imaging should avoid presenting AI as simply “more accurate” or “more advanced” and should instead explain uncertainty, confirmation processes, and follow-up pathways.

Ethical and social concerns were central to acceptability. Participants raised issues of data privacy, algorithmic bias, accountability, and unequal access. These concerns are supported by broader literature showing that AI systems can reproduce or intensify health disparities when trained on unrepresentative data or implemented outside the populations and settings in which they were validated (13,14). In cancer imaging, fairness concerns may involve differences in age, ethnicity, scanner type, breast density, tumour characteristics, local care pathways, and access to specialist review. Participants' questions about responsibility also reflect ongoing legal and ethical uncertainty about whether accountability lies with clinicians, hospitals, regulators, developers, or software vendors when AI contributes to an incorrect result (22). These findings suggest that patient confidence requires governance structures that are visible enough to reassure patients that AI is validated, monitored, and professionally accountable.

The study also highlights communication as a mechanism of confidence. Participants wanted simple explanations of what AI did, what the doctor found, whether the AI output and clinician interpretation agreed, how privacy was protected, and what the next step would be. This supports explainability literature arguing that technical explanations alone are insufficient in healthcare; patients need clinically meaningful explanations that connect AI output to diagnosis, uncertainty, and care decisions (23). In cancer imaging, communication must also respond to fear. A technically accurate report may still fail patients if it is delivered without emotional sensitivity, contextual explanation, or a clear follow-up plan. AI-assisted imaging should therefore be implemented as part of a patient-centered diagnostic communication process, not merely as a back-end reporting tool.

The practical implication is that AI-assisted imaging for early cancer detection should be introduced through clinician-led, transparent, and ethically governed pathways. Imaging centers should use validated AI systems, monitor performance after implementation, train radiologists and clinical staff in appropriate use, and provide patient-facing explanations that clarify AI's role. Reports or consultations should make clear that AI assistance does not remove clinician responsibility for final interpretation. Where uncertainty exists, patients should be told what is uncertain, what has been checked, and what follow-up is recommended. These findings support a model in which AI contributes to diagnostic safety and workflow support while the clinician remains responsible for interpretation, explanation, and care planning.

This study has limitations. The sample was small and qualitative, so the findings should not be interpreted as population-level estimates of confidence or acceptance. Participants did not necessarily have direct experience of receiving an AI-assisted imaging report; therefore, several responses reflect anticipated or hypothetical confidence rather than post-exposure evaluation. Social desirability may have influenced participants to express balanced or clinician-approved views. If participants were recruited through healthcare-related networks, their responses may also have been shaped by trust in medical institutions. The study may be affected by translation or wording loss if interviews were conducted in a language different from the reporting language. The absence of full demographic, recruitment, and interview-context details also limits assessment of transferability. Nevertheless, the study provides useful qualitative insight into how patients reason about AI-assisted imaging when cancer detection is emotionally and clinically significant.

The findings should therefore be interpreted as an exploratory account of conditional patient confidence. The main contribution is not that patients simply accept or reject AI, but that they define acceptable AI-assisted imaging through a set of conditions: human supervision, transparent disclosure, institutional reliability, privacy protection, accountability, equity, and clear communication. These conditions should guide future patient-centered implementation studies, larger qualitative inquiries, and mixed-methods evaluations of AI-supported cancer imaging pathways.

## CONCLUSION

Patient confidence in AI-assisted imaging reports for early cancer detection was shaped by perceived usefulness, human oversight, communication, and ethical safeguards. Participants viewed AI as potentially valuable when it functioned as a second reader that could support clinicians, identify subtle abnormalities, and strengthen the imaging review process. However, confidence depended on clinician verification, transparent disclosure, reliable and approved systems, privacy protection, accountability, and clear explanation of what AI contributed and what the doctor confirmed. The findings suggest that AI-assisted imaging should be implemented as a clinician-led and patient-centered process rather than as an invisible or autonomous reporting mechanism. Sustainable acceptance will require practical safeguards, including patient-facing explanations, continued radiologist responsibility, monitoring of AI performance, protection against bias, and clear follow-up pathways. The study does not establish population-level acceptance or diagnostic benefit, but it shows that patients' confidence in AI-assisted cancer imaging must be earned through trustworthy technology, responsible governance, and communication that recognizes the emotional significance of possible cancer detection.

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