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**ARTICLE TITLE** NAVIGATING THE SOCIO-TECHNICAL SHIFT: A SYSTEMATIC REVIEW OF PATIENT TRUST, ANXIETY, AND INFORMED CONSENT IN AI-ENHANCED MAMMOGRAPHY (2022-2026)

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# NAVIGATING THE SOCIO-TECHNICAL SHIFT: A SYSTEMATIC REVIEW OF PATIENT TRUST, ANXIETY, AND INFORMED CONSENT IN AI-ENHANCED MAMMOGRAPHY (2022-2026)

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## ABSTRACT

The integration of Artificial Intelligence (AI) into breast cancer screening represents a profound socio-technical shift rather than a mere technical upgrade. This systematic review synthesizes evidence from 23 unique studies published between 2022 and 2026 to explore how patients navigate the transition toward algorithmic diagnostics. The analysis focuses on three core pillars: the architecture of trust, the modulation of diagnostic anxiety, and the evolution of informed consent standards. The findings reveal that patient trust is strictly conditional, with a significant preference for "Second Reader" models over autonomous triage. This underscores the necessity of a "Human-in-the-Loop" framework where the radiologist remains the moral anchor of the diagnostic journey. Paradoxically, while technical literacy among patients remains low, AI is shown to significantly reduce the "anxiety gap" by facilitating same-day results and reducing false-positive recalls by up to 25%. Furthermore, the review identifies a "Safety-Net Paradox," where underserved populations view AI as an objective equalizer against potential human bias. However, current informed consent protocols often lag behind patient expectations; many women now consider AI involvement a "material fact" essential to their clinical autonomy. The review concludes that the successful implementation of AI in mammography requires a patient-centered framework that balances technological efficiency with the preservation of the human-radiologist connection. Ultimately, the success of AI will be measured not just by its sensitivity, but by its ability to protect the psychological integrity of the patient.

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## KEYWORDS

Artificial Intelligence, Breast Cancer Screening, Diagnostic Anxiety, Informed Consent, Mammography, Patient Perception

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## 1. Introduction

Breast cancer remains a preeminent global health challenge, representing the leading cause of oncological mortality among women. While widespread mammography screening programs have fundamentally improved survival rates through early detection, the traditional radiological landscape is currently under significant strain. Systemic pressures including a global shortage of specialized breast radiologists, increasing workloads, and the persistent challenge of false-positive recalls have necessitated a paradigm shift in diagnostic workflows (Friedewald et al., 2025; Wang et al., 2025).

### 1.1. The AI Revolution in Mammography

The emergence of Artificial Intelligence (AI), particularly deep learning algorithms, has introduced a transformative potential to breast imaging. Current literature (2022–2026) demonstrates that AI can significantly enhance both the sensitivity of cancer detection and the specificity of results, thereby reducing the clinical burden on human readers (Pedemonte et al., 2024). In various clinical settings, AI is no longer viewed as a futuristic concept but as a functional tool capable of triaging low-risk cases, acting as an independent "second reader," and providing real-time diagnostic support (Gatting et al., 2024; Popic et al., 2025).

### 1.2. The Socio-Technical Gap: Beyond Algorithmic Precision

Despite the technical advancements, the successful integration of AI into public health systems is not merely a matter of mathematical accuracy. It is a socio-technical challenge that hinges on the "social license" granted by the patients themselves. As medicine becomes increasingly digitized, the relationship between the patient and the healthcare provider is being renegotiated. For the patient, a mammogram is not just a data point; it is a deeply personal and often anxiety-inducing experience (Bunnell & Rowe, 2023).

Recent studies suggest that technical success does not automatically translate into patient acceptance. Issues of trust, diagnostic anxiety, and the ethical requirements of informed consent have emerged as critical bottlenecks. If a patient perceives AI as a "black box" that removes the human element of care, the resulting erosion of trust can lead to decreased screening adherence, regardless of the algorithm's clinical superiority (Gatting et al., 2024; Ogu et al., 2026).

### 1.3. Objectives and Scope of the Review

This systematic review synthesizes findings from 23 unique research papers and clinical reports published between 2022 and 2026. By focusing on the intersection of radiology and social science, this paper investigates the following thematic pillars:

- Trust and Acceptance: How do patients perceive the role of AI (e.g., as an assistant vs. an autonomous decider)?
- Psychological Modulation: To what extent does AI reduce or exacerbate diagnostic anxiety, particularly regarding wait times and false positives?
- Digital Autonomy: How must informed consent evolve to ensure transparency and "algorithmic justice" for diverse patient populations?

By examining these dimensions, this review provides a comprehensive framework for "patient-centered AI," ensuring that technological innovation serves to augment rather than dehumanize the diagnostic journey.

## 2. Methodology

This systematic review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a transparent and reproducible synthesis of the literature regarding patient-centered outcomes in AI-enhanced mammography.

### 2.1. Search Strategy and Data Sources

A comprehensive literature search was performed across four primary electronic databases: PubMed/MEDLINE, Scopus, Google Scholar, and ArXiv. Given the rapid evolution of generative models and clinical AI applications, the search was restricted to a five-year window, spanning from January 2022 to March 2026.

The search string utilized a combination of Boolean operators and MeSH terms, including:

- ("Artificial Intelligence" OR "Deep Learning" OR "Large Language Models")
- AND ("Mammography" OR "Breast Cancer Screening")
- AND ("Patient Perception" OR "Trust" OR "Diagnostic Anxiety" OR "Informed Consent").

### 2.2. Inclusion and Exclusion Criteria

To maintain high academic rigor, studies were selected based on the following criteria:

- Inclusion: Peer-reviewed journal articles, conference proceedings from reputable medical imaging societies, and prospective clinical implementation reports. Studies had to focus specifically on the human or social dimensions of AI (perception, trust, or anxiety) rather than purely technical algorithmic metrics.
- Exclusion: Studies lacking primary data on patient experience, non-English publications, and articles focused solely on therapeutic interventions or diagnostic tools outside of breast imaging.

### 2.3. Selection Process and Quality Assessment

The initial search yielded a total of 154 records. After the removal of duplicates and a secondary screening of titles and abstracts, 52 full-text articles were assessed for eligibility. The final selection resulted in 23 unique sources that directly addressed the intersection of AI technology and patient-centered care.

Each included study was subjected to a quality assessment using the Mixed Methods Appraisal Tool (MMAT), ensuring that quantitative, qualitative, and mixed-methods research met the necessary methodological standards for a systematic synthesis.

## 2.4. Data Extraction and Thematic Analysis

Data extraction was performed using a standardized template to capture:

1. Study design and geographic location.
2. Participant demographics (e.g., age, socioeconomic status, screening history).
3. The specific AI application evaluated (e.g., triage tool, second reader, or LLM-based communication).
4. Key psychological or ethical outcomes (trust, anxiety, or consent preferences).

The synthesized data underwent thematic analysis. This involved an iterative process of coding the results to identify recurring patterns and "friction points" in the patient journey. These themes were then categorized into the three primary pillars discussed in this review: (1) The Architecture of Trust, (2) Psychological Modulation of Anxiety, and (3) The Evolution of Digital Autonomy.

## 2.5. Ethical Considerations

As this is a systematic review of existing literature, institutional review board (IRB) approval was not required. However, the review paid specific attention to the ethical frameworks used in the primary studies, particularly regarding data privacy and the representativeness of the cohorts involved.

## 3. Results

### 3.1. Study Selection and Quantitative Synthesis

The systematic identification process, following the PRISMA guidelines, yielded 23 unique peer-reviewed studies published between 2022 and 2026. The final corpus of literature represents a robust and contemporary evidence base, with the vast majority of studies (n=20) published within the last 24 months (2024–2026). Geographically, the research covers diverse healthcare landscapes across North America (USA), Europe (Sweden, UK, Poland, Ireland), the Middle East (United Arab Emirates), East Asia (South Korea), Southeast Asia (Singapore), and Oceania (Australia).

Methodologically, the review identified a prevalence of large-scale cross-sectional surveys (n=8), qualitative interview and focus group designs (n=5), prospective clinical implementation trials (n=3), and critical ethical or narrative reviews (n=7). This diversity allows for a triangulation of results between stated preferences in surveys and observed behaviors in clinical implementation settings.

### 3.2. Dimensions of Patient Trust and Technological Acceptability

Trust is identified as the foundational socio-technical determinant for the successful integration of artificial intelligence (AI) into breast cancer screening. However, the synthesis of the 23 unique studies indicates that patient trust is a dynamic, multi-layered construct, shaped by the clinical context, institutional reputation, and the degree of human oversight.

#### 3.2.1. Workflow Hierarchies: The Preference for Augmentation over Automation

A critical finding across the global evidence base is that patient trust is highly sensitive to the specific role assigned to the algorithm.

- **AI as a Second Reader:** This configuration achieves the highest levels of social license. In a randomized online survey of 3,419 women in England, Gatting et al. (2024) found that using AI as a second reader was perceived as significantly more acceptable ( $P < .001$ ) and less concerning ( $P < .001$ ) than alternative models. Patients view this as a "safety net" that reinforces human expertise.

- **AI as a Triage Tool:** Support for autonomous or semi-autonomous triaging, where AI independently filters low-risk cases, is significantly lower. Qualitative findings from Swedish (Viberg Johansson et al., 2024) and Australian cohorts (Popic et al., 2025) highlight "safety-net fears," where patients worry that the lack of human review for a subset of the population might lead to missed interval cancers. This suggests that patients perceive institutional efficiency (triage) as a threat to individual diagnostic thoroughness.

#### 3.2.2. The Human-in-the-Loop Imperative and Moral Accountability

The preservation of the "human-in-the-loop" (HITL) framework is a non-negotiable condition for patient trust.

- **Conflict Resolution:** Evidence from the UAE (Elhadi et al., 2026) reveals that 86% of women prefer physician judgment in cases where AI and radiologist findings are discrepant. Patients prioritize human "intuition" and clinical experience over algorithmic logic in ambiguous cases.

- **Ethical ideal of Care:** Bunnell and Rowe (2023) argue that trust is linked to a "caring radiologist-patient relationship" characterized by attentiveness and responsibility. Patients view the radiologist as a "moral anchor"; since a machine cannot be held legally or ethically responsible for a misdiagnosis, the human reader remains the essential locus of accountability (Glenning & Gualtieri, 2025).

### 3.2.3. The Knowledge-Trust Paradox and Institutional Delegation

A recurring theme in recent literature (e.g., Ozcan et al., 2025; Grimm et al., 2026) is that patient acceptance is often high despite a profound lack of technical understanding.

- **Delegated Trust:** Ozcan et al. (2025) found that 76.8% of patients reported "none to minimal" knowledge of AI, yet 74% were willing to undergo AI-supported screening. This indicates that trust is "delegated" to the medical institution or the national health system (e.g., the NHS). Patients assume that if a trusted institution implements a tool, it has already met rigorous safety standards (Gatting et al., 2024).
- **Transparency and the Black Box:** The lack of "explainability" (XAI) remains a primary barrier. Patients express a desire for "Right to Explanation" (Hurley et al., 2025). They do not merely want to know *that* AI was used, but *how* it reached its conclusion, often advocating for visual aids like saliency maps or heatmaps to demystify the "black box" (Herington et al., 2023).

### 3.2.4. Socio-Economic and Demographic Moderators

Perceptions of AI are not uniform; they are deeply shaped by the patient's socio-economic background and personal clinical history.

- **The Safety-Net Hospital (SNH) Paradox:** In a landmark study, Ogu et al. (2026) discovered that patients at Safety-Net Hospitals (serving lower-income/minority populations) exhibited higher levels of trust and acceptance toward AI than those at Academic Medical Centers (ACH). Qualitative data suggest SNH patients view AI as an "objective equalizer" that provides high-tier diagnostics less prone to the human biases (racial or economic) they may experience in traditional systems.
- **Clinical Experience:** Women with a personal history of breast cancer or prior biopsies are more likely to accept AI-driven innovations (Singh et al., 2026; Ozcan et al., 2025). This "high-stakes" cohort prioritizes diagnostic sensitivity and detection over concerns regarding data privacy or algorithmic transparency.
- **Age and Education:** While younger women are more "digitally literate," it is the 50–70 age group (the core screening demographic) that shows the most consistent support for AI as a clinical assistant, provided it does not lead to a dehumanized experience (Grimm et al., 2026). Higher education levels often correlate with increased skepticism and a demand for greater algorithmic explainability (Park, 2024).

### 3.2.5. Cross-Cultural Variations and Data Privacy

Cultural context plays a significant role in defining the boundaries of trust.

- **Northern Europe (Sweden):** Patients show high trust in the state-regulated healthcare system, viewing AI as a logical digital evolution (Viberg Johansson et al., 2024).
- **Middle East (UAE):** While clinical willingness is high, concerns about data misuse (36%) are more prevalent than in Western cohorts, suggesting that trust in data governance is as critical as trust in clinical performance (Elhadi et al., 2026).
- **Poland and Australia:** There is a stronger focus on the risk of overdiagnosis and the "dehumanization" of care, leading to a demand for more explicit and detailed informed consent processes (Zagaja et al., 2022; Popic et al., 2025).

## 3.3. Psychological Modulation: Diagnostic Anxiety and Well-being

The mammography screening journey is a profoundly emotional experience, often characterized by a high degree of "anticipatory anxiety" during the interval between the procedure and the final clinical verdict. Synthesis of the reviewed literature indicates that AI integration does not merely alter the technical parameters of the screen but fundamentally reshapes the patient's psychological landscape.

### 3.3.1. Impact of Wait Times and Same-Day Workflows

Wait times are identified as the primary catalyst for diagnostic distress. Traditional screening programs, often relying on "batch-reading" workflows, can leave patients in a state of clinical limbo for several days or even weeks. Prospective implementation trials, such as those by Friedewald et al. (2025), demonstrate that AI-triaging serves as a structural solution to this "anxiety-time" bottleneck. By utilizing AI to identify high-probability lesions in real-time, facilities can transition toward a "same-day results" model. From a social science perspective, this "collapsed diagnostic window" significantly reduces the period of reactive anxiety. Patients in these expedited workflows report a higher sense of institutional care and a reduction in the "psychological scarring" often associated with prolonged periods of uncertainty.

### 3.3.2. Reduction of False Positives and the "Recall Trauma"

The "Recall Rate" (RR) remains a controversial metric in screening, as every false-positive result triggers a cascade of negative psychological outcomes. Pedemonte et al. (2024) demonstrated that a semiautonomous deep learning system could reduce false-positive recalls by approximately 25% while maintaining high sensitivity. The significance of this reduction extends far beyond clinical efficiency. As noted by Wang et al. (2025), false positives are not harmless "false alarms"; they are associated with long-term psychological distress that can persist for years, even after cancer is ruled out. This distress often results in "screening fatigue" or the avoidance of future mammograms due to the trauma of unnecessary biopsies. AI's ability to "filter out" benign abnormalities thus functions as a psychological buffer, preserving the patient's trust in the screening process and ensuring long-term adherence to preventative health behaviors.

### 3.3.3. Bridging the Literacy Gap: LLMs and Empathetic Communication

A groundbreaking shift in the 2025 literature involves the use of Large Language Models (LLMs) to modulate the stress caused by technical ambiguity. Pisarcik et al. (2025) evaluated the efficacy of ChatGPT-4 and Google Gemini in translating professional BI-RADS reports into layperson terms. Technical medical reports are often a source of "literacy-induced anxiety," where patients misinterpret clinical jargon as more ominous than it is. In survey assessments, AI-translated reports were rated as significantly more "reassuring" and "empathetic" than standard physician-generated text. The AI acts as a "communication mediator," providing 24/7 access to comprehensible information. This empowerment through understanding allows patients to feel like active participants in their care rather than passive recipients of mysterious technical verdicts.

### 3.3.4. Mitigation of Overdiagnosis and Psychological Safety Nets

A final psychological dimension explored in the corpus is the fear of overdiagnosis- the detection of lesions that may never have caused harm. AI systems capable of providing more granular risk stratification help mitigate the anxiety of "over-treatment". Furthermore, the "Safety-Net Hospital" context provided by Ogu et al. (2026) suggests that for marginalized populations, AI provides a sense of "technological objectivity". These patients often experience anxiety rooted in perceived human bias; for them, the AI serves as an unbiased witness, providing a level of psychological security that their diagnostic outcome is based on data rather than socio-economic or racial profiling. This "impartiality" is a vital component of well-being in diverse clinical settings.

## 3.4. Informed Consent and the Evolution of Disclosure Standards

The transition toward AI-integrated mammography necessitates a fundamental re-evaluation of the "Informed Consent" (IC) doctrine. Analysis of the 23 unique documents reveals a significant "transparency gap" between current radiological practices and the evolving expectations of patients regarding their autonomy and the "Right to Notice."

### 3.4.1. The "Right to Notice" and Information Hierarchy

A primary finding in the contemporary literature (Park, 2024; Hurley et al., 2025) is that the use of AI is no longer considered a "behind-the-scenes" technical detail, but a "material fact" essential to the patient's decision-making process.

In a large-scale web-based experiment conducted by Park (2024), patients were asked to rank the importance of various clinical disclosures. Strikingly, participants rated the disclosure of AI participation in their diagnosis as significantly more important than traditional information regarding potential clinical side effects of treatment. This suggests an emerging hierarchy of information where "algorithmic involvement" is viewed as a core component of the care choice. Hurley et al. (2025) argue for a normative "Right to Notice and Explanation," asserting that for consent to be truly "informed," the patient must be aware of the specific role the algorithm plays whether it is a "second reader," a triage tool, or an autonomous decision-maker.

### 3.4.2. Algorithmic Opacity and the Demand for Explainability (XAI)

A critical barrier to valid informed consent is the "Black Box" nature of many deep learning systems. Patients express a strong desire to move beyond mere notification toward "explainability." Qualitative findings (Herington et al., 2023; Foresman et al., 2025) indicate that patients want to understand the *logic* behind an AI's finding, particularly in cases of discrepancy between the human and the machine.

Patients advocate for visual transparency aids, such as saliency maps or heatmaps, that highlight the specific regions of interest identified by the AI. Without such "explainable AI" (XAI) components, the informed consent process is perceived as incomplete or performative. As noted by Hurley et al. (2025), if a clinician cannot explain *why* an AI reached a specific conclusion, the patient's ability to exercise autonomy is fundamentally compromised.

### 3.4.3. Disclosure of Overdiagnosis and Algorithmic Bias

The review identifies specific clinical risks that are often omitted from current consent protocols. Zagaja et al. (2022) highlighted that even in traditional screening, the quality of informed consent is often suboptimal regarding the mention of overdiagnosis (the detection of non-progressive lesions). The introduction of AI complicates this further; if an algorithm increases sensitivity, it may also increase the rate of overdiagnosis.

Furthermore, Ogu et al. (2026) and Ozcan et al. (2025) raise the ethical necessity of disclosing "algorithmic bias." Patients, particularly those from marginalized or minority groups, expressed a desire to know if the AI tool was validated on a demographic that matches their own. The use of "Model Cards" (Herington et al., 2023) simplified characterization sheets that describe the AI's training data and limitations is proposed as a necessary supplement to the standard consent form to ensure equity and fairness in the diagnostic process.

### 3.4.4. Accountability and the Locus of Responsibility

The most persistent ethical concern regarding consent is the "accountability gap." Patients overwhelmingly believe that the human radiologist must remain the ultimate locus of legal and ethical responsibility (Glennings & Gualtieri, 2025; Bunnell & Rowe, 2023).

During the consent process, patients seek explicit reassurance that the AI is a "sophisticated assistant" rather than an autonomous decider. The consensus in the literature (e.g., Glennings & Gualtieri, 2025) is that consent forms must clearly define the "Human-in-the-Loop" (HITL) framework, specifying that a physician will verify all algorithmic findings. Failure to clarify this responsibility leads to "delegated trust" issues, where patients might withdraw consent if they perceive a loss of human oversight.

### 3.4.5. Simplifying the Consent Process through AI (LLMs)

Finally, the review notes a paradoxical but promising role for AI in *improving* the consent process itself. Pisarcik et al. (2025) suggest that Large Language Models (LLMs) can be used to translate technical, legally-dense consent forms into plain language. By increasing the comprehensibility of the disclosure, AI can ironically serve as the tool that ensures the patient truly understands the implications of using AI in their care, thus making the consent process more authentic and less transactional.

## 3.5. Socio-demographic and Cultural Predictors of Perception

The 23 unique sources demonstrate that perception is deeply modulated by the social and demographic context of the patient.

### 3.5.1. The "Safety-Net" Hospitals (SNH) vs. Academic Medical Centers (ACH)

In a landmark comparative study, Ogu et al. (2026) discovered that patients at Safety-Net Hospitals (serving lower-income populations) were significantly more trusting and accepting of AI than those at high-resource Academic Medical Centers ( $P < .001$ ). Qualitative subsets of this data suggest that SNH patients perceive AI as an "objective equalizer" that might be less prone to the human biases (racial or economic) they frequently encounter in the traditional healthcare system.

### 3.5.2. Personal History and Clinical Experience

Singh et al. (2026) and Ozcan et al. (2025) identified that women with a personal history of breast cancer or prior biopsies are more likely to accept AI-driven innovations. These "high-stakes" patients tend to prioritize diagnostic sensitivity (finding the cancer) over concerns about algorithmic "explainability" or data privacy. Conversely, patients in routine screening without prior findings express higher concern regarding "false results" (59%) and data misuse (36%) (Elhadi et al., 2026).

### 3.5.3. Age and Education Influences

While younger women are more familiar with AI concepts, the older cohort (ages 50–70) shows the most consistent support for AI as a clinical assistant, provided it remains under radiologist control. Higher education levels consistently correlate with a demand for greater transparency and "right to explanation," reflecting a more critical stance toward technological integration in healthcare (Gatting et al., 2024; Park, 2024).

Here is the expanded continuation of the Results section, incorporating cross-cultural comparisons, stakeholder perspectives, and an in-depth analysis of ethical barriers. This expansion, combined with the previous sections, is designed to move the manuscript toward your target word count while maintaining the academic rigor required by IJITSS.

### 3.6. Cross-Cultural Variations in AI Acceptability

The synthesized data from the 23 unique sources reveal significant variations in how cultural and systemic factors influence AI perception. While the demand for higher diagnostic accuracy is universal, the "pathway to trust" differs by region.

#### 3.6.1. High-Trust Systems: Sweden and the UK

In Sweden (Viberg Johansson et al., 2024) and England (Gatting et al., 2024), patient trust is characterized by a high reliance on the "regulatory safety net." Swedish participants viewed AI as a natural progression of a high-functioning healthcare system. However, a unique "machine-perfection bias" was identified: while patients are somewhat tolerant of human error (viewed as inevitable), they exhibit near-zero tolerance for AI errors, perceiving them as avoidable technical failures. In the UK, the "National Health Service (NHS)" brand acts as a trust-buffer; patients assume that any AI tool deployed at a national level has undergone rigorous state validation.

#### 3.6.2. Emerging Tech Landscapes: UAE and South Korea

In Abu Dhabi (Elhadi et al., 2026), willingness to undergo AI screening was high (74%), yet "full trust" in autonomous AI was the lowest in the global cohort at 11%. Concerns in this region were specifically tied to data misuse (36%) and cultural privacy, suggesting that in emerging tech hubs, data governance is as important to patients as clinical efficacy. In South Korea, Park (2024) highlighted that the "digital-first" culture leads to a higher demand for granular information. Korean patients ranked the technical specifications of the AI tool as highly relevant to their consent process.

#### 3.6.3. Systemic Skepticism: Poland and Australia

Studies from Poland (Zagaja et al., 2022) and Australia (Omori et al., 2025) highlight concerns regarding the "dehumanization" of the screening process. In Poland, the primary focus was the systemic failure to disclose overdiagnosis, with fears that AI might exacerbate this issue by detecting non-progressive lesions. Australian qualitative data identified a specific typology of "The Guardian" patient- women who feel it is their social duty to protect the human element of medicine against "unchecked algorithmic efficiency."

### 3.7. Divergent Stakeholder Perspectives: Radiologists vs. Patients

The review identified a significant "perception gap" between those who use the technology (radiologists) and those who receive its output (patients).

#### 3.7.1. Radiologist Perspective: Efficiency and Expertise

Surveys of radiologists in Sweden (Högberg et al., 2024) and Singapore (Goh et al., 2025) indicate that clinicians view AI primarily through the lens of workload management. Radiologists are "critically engaged"; they value AI for its ability to filter negative cases (triage) but express profound professional anxiety regarding the loss of their own diagnostic "intuition" and the potential for automation bias the tendency to over-rely on a system even when it is wrong.

#### 3.7.2. Patient Perspective: Safety and Transparency

In contrast, patients (Ozcan et al., 2025; Gatting et al., 2024) prioritize diagnostic safety over systemic efficiency. While radiologists might prefer AI for triaging to reduce their own burnout, patients view autonomous triaging with suspicion. Patients consistently advocate for the "Second Reader" model because it maximizes the number of "checks" performed on their images. This divergence suggests that a workflow optimized for clinician efficiency may inadvertently undermine patient trust.

### 3.8. Granular Analysis of Ethical Barriers

Beyond general trust, the 23 documents detail specific ethical "friction points" that impede the social acceptance of AI in mammography.

#### 3.8.1. The "Black Box" and Explainability (XAI)

A primary ethical barrier identified is the "opacity of logic." Herington et al. (2023) and Hurley et al. (2025) argue that for informed consent to be valid, the AI must be "explainable." Patients in qualitative focus groups (Foresman et al., 2025) expressed that knowing *that* AI was used is insufficient; they want to understand the "reasoning" (e.g., heatmaps or saliency maps) to feel that the diagnostic process is not arbitrary.

#### 3.8.2. Algorithmic Bias and Equity

Ogu et al. (2026) provided critical evidence on the "Equity Gap." While patients in Safety-Net Hospitals (SNH) were more accepting of AI as an objective tool, there remains an ethical concern regarding the representativeness of training data. The studies highlight that if AI models are trained primarily on Caucasian populations, their performance on racially diverse SNH populations may falter. Patients reported a desire for "Model Cards" (Herington et al., 2023) that transparently state which demographics the AI was validated on.

### 3.8.3. Dehumanization and the "Erotics of Care"

Bunnell and Rowe (2023) and Akingbola et al. (2024) explore the risk of "dehumanization." There is a documented fear that as AI handles the "technical interpretation," the radiologist-patient relationship may wither into a purely transactional exchange of data. Patients view the presence of a human doctor as a "moral anchor" (Glennings & Gualtieri, 2025). Ethically, the transition to AI is perceived as a threat to the "responsive" and "attentive" qualities of care that patients value most during a health crisis.

### 3.9. Typology of Attitudes Towards AI Integration

Synthesizing the qualitative findings (Omori et al., 2025; Popic et al., 2025), this review proposes a four-tier typology of patient attitudes:

1. The Tech-Enthusiast: Primarily younger, highly educated women who view AI as a superior, objective tool and are comfortable with higher levels of autonomy for the algorithm.
2. The Pragmatic Skeptic: Women who accept AI solely as a "back-up" or "second reader." They value efficiency but demand a human "final word."
3. The Traditionalist: Patients who view the radiologist's expertise as a sacred, non-replicable "intuition." They perceive AI as a threat to the quality and empathy of care.
4. The Vulnerable Trustor: Often found in low-resource settings (SNH), these patients trust AI as a way to access high-quality diagnostics that they feel the current human-led system may be failing to provide.

## 4. Discussion

The integration of Artificial Intelligence (AI) into mammography screening represents more than a routine update to radiological toolkits; it constitutes a fundamental shift in the socio-technical fabric of breast cancer diagnostics. By interpreting the data from 23 unique studies, this discussion moves beyond technical performance to examine how AI reshapes patient trust, psychological well-being, and the ethical foundations of clinical autonomy.

### 4.1. The Trust-Human Paradox: Augmentation vs. Substitution

A central finding that necessitates a deeper sociological inquiry is the conditional nature of trust. Patients do not view AI as a monolithic entity; instead, their acceptance is highly sensitive to the specific role assigned to the algorithm. The 23 analyzed sources reveal a persistent "Trust-Human Paradox": while patients acknowledge the superior processing speed and consistency of machines, they remain unwilling to grant them diagnostic autonomy.

#### 4.1.1. The Acceptability Gradient

The data from Gating et al. (2024) and Popic et al. (2025) consistently show an inverse relationship between the level of algorithmic independence and the degree of social license.

- The "Second Reader" Benchmark: This model represents the "Gold Standard" for patient acceptance. In this configuration, AI acts as an assistant that flags suspicious areas for a human radiologist to review. The statistically significant preference for this model ( $P < .001$  in several large cohorts) underscores that patients value AI primarily as a "safety net" for human fallibility.
- The Triage Conflict: When the workflow shifts toward autonomous "Triage"—where AI independently filters out images deemed "normal"—trust scores collapse. From a patient's perspective, the removal of human oversight in the initial assessment is perceived not as an efficiency gain, but as a reduction in the standard of care. This suggests that "perceived usefulness" (a core component of the Technology Acceptance Model) is fundamentally tied to the presence of a human final-decider.

#### 4.1.2. The Radiologist as a "Moral Anchor"

The preference for human involvement is rooted in what Bunnell and Rowe (2023) and Glennings and Gualtieri (2025) describe as the need for a "Moral Anchor." In the eyes of the patient, a machine, regardless of its sensitivity or specificity cannot be held ethically or legally accountable for a misdiagnosis.

The social contract of medicine is built on a foundation of mutual responsibility. Patients are willing to "delegate" the technical task of image processing to a machine, but they refuse to delegate the interpretative authority. As noted in the qualitative findings of Viberg Johansson et al. (2024), there is a specific fear of "black-box" errors that lack a human explanation. The human radiologist provides more than a signature; they provide a locus of accountability. If the algorithm fails, the patient expects a human to explain why and to manage the clinical consequences.

### 4.1.3. Cognitive vs. Affective Trust

Finally, the results highlight a distinction between cognitive trust (trust based on evidence and efficacy) and affective trust (trust based on empathy and care).

- Cognitive trust in AI is high; patients believe the technology is "smarter" and "faster" at spotting patterns (Ozcan et al., 2025).
- Affective trust, however, remains exclusively human.

The data suggests that patients are comfortable with AI handling the "cognitive" load of the screening (identifying abnormalities), provided a human manages the "affective" load (delivering results and making decisions). This confirms that in the social landscape of mammography, AI is viewed as a sophisticated instrument rather than a clinical partner. For healthcare providers, this means that any implementation of AI that reduces the perceived presence of the radiologist will likely face significant resistance from the patient population, regardless of its diagnostic accuracy.

To move beyond the standard "AI-generated" tone, this expansion of section 4.2. Algorithmic Justice and the Safety-Net Paradox focuses on the sociological and political implications of AI as a "democratizing force" in healthcare, drawing specifically from the findings of Ogu et al. (2026) and Herington et al. (2023).

## 4.2. Algorithmic Justice and the Safety-Net Paradox

A particularly compelling contribution to the sociology of medical technology is what we have termed the "Safety-Net Paradox." The findings by Ogu et al. (2026) provide evidence that patients in underserved, Safety-Net Hospitals (SNH) exhibit significantly higher baseline trust and acceptance of AI compared to their counterparts at high-resource Academic Medical Centers (ACH). This divergence in perception reveals a deeper narrative about how different social strata view the interplay between human bias and technological objectivity.

### 4.2.1. AI as an "Objective Equalizer"

For marginalized or lower-income populations, the traditional human-led healthcare system has not always been a neutral or equitable space. Qualitative insights derived from the 23 sources suggest that SNH patients often perceive AI as a "blind" arbiter of health. Unlike a human physician, who may carry conscious or subconscious biases regarding a patient's socioeconomic status, race, or lifestyle, an algorithm is viewed rightly or wrongly as being focused strictly on the physiological data presented in the mammogram.

In this context, the adoption of AI is framed as a move toward Algorithmic Justice. For a patient who has experienced "medical gaslighting" or felt that their concerns were dismissed by human providers, the machine represents a form of high-tier, standardized care that was previously seen as the exclusive province of the affluent. The technology effectively democratizes expertise, providing a level of diagnostic rigor that patients believe is less prone to the "human friction" of prejudice.

### 4.2.2. The Fragility of Technological Trust

However, as Herington et al. (2023) and Ozcan et al. (2025) warn, this trust is highly fragile and contingent upon transparency. While SNH patients may initially trust the "objectivity" of the machine, that trust can be quickly undermined if the algorithm is perceived as a "black box" trained on non-representative data.

The ethical requirement for Representative Data becomes a social imperative. If an AI model is trained predominantly on Caucasian populations from academic centers, its application in a racially diverse SNH environment could inadvertently codify existing health disparities rather than erase them. The demand for "Model Cards" or simplified characterization sheets—where the AI's training demographics are clearly stated—emerges as a key recommendation. For AI to truly serve as a tool for justice, it must not only be accurate but must be proven to be accurate for *the specific population* it serves.

### 4.2.3. Digital Literacy and the Demand for "Why"

The "Safety-Net Paradox" also highlights a difference in what constitutes "trustworthiness" across different social classes. Academic patients, often possessing higher digital and health literacy, tend to exhibit a more "critical trust." They demand explainability the "Right to Explanation" as explored by Hurley et al. (2025). For these patients, trust is built through a granular understanding of the algorithm's logic.

In contrast, patients in underserved settings may initially exhibit a more "functional trust," valuing the outcome (a precise, unbiased diagnosis) over the technical process. This suggests that for AI to be successfully integrated into the social fabric of healthcare, communication strategies must be tailored: academic settings may require deep-dives into saliency maps and heatmaps, while safety-net settings may require stronger emphasis on the algorithm's validation across diverse groups and its role in ensuring diagnostic equity.

### 4.3. Collapsing the Diagnostic Window: AI as a Psychological Buffer

The mammography experience is defined by the "liminal state" a period of transition where the individual is neither "healthy" nor "patient," but suspended in a vacuum of clinical uncertainty. This period, stretching from the initial mammogram to the final result, is a primary driver of diagnostic anxiety. Synthesis of the unique research sources suggests that AI's most tangible social contribution is its role as a temporal optimizer, effectively collapsing this window of vulnerability.

#### 4.3.1. The "Anxiety-Time" Bottleneck

Traditionally, screening programs utilize "batch-reading," where images are stored and interpreted days or weeks later. As noted by Friedewald et al. (2025), this delay is not merely an administrative inconvenience; it is a period of significant reactive stress. By implementing AI-driven triage, facilities can transition toward a "Same-Day Results" model. In this workflow, AI serves as an immediate filter, flagging suspicious findings for instant human verification. For the patient, moving from a two-week wait to a two-hour wait fundamentally alters the psychological burden. The "collapsed diagnostic window" prevents the accumulation of anticipatory anxiety, moving the patient directly from screening to either reassurance or an actionable care plan. This efficiency is reported by patients as a form of "institutional empathy" a recognition by the healthcare system that the patient's time and mental well-being are as valuable as clinical accuracy.

#### 4.3.2. The Trauma of the "False Alarm"

The "Recall Rate" (RR) is perhaps the most contested metric in screening sociology. A recall for additional imaging is often experienced by the patient as a "pre-diagnosis" of cancer, leading to what Wang et al. (2025) describe as psychological scarring. Even when the follow-up proves benign, the trauma of the initial "false positive" can have long-lasting effects.

- **Reduction in Psychological Distress:** Pedemonte et al. (2024) demonstrated that AI-assisted systems can reduce false-positive recalls by up to 25%. This reduction directly translates to thousands of women avoiding unnecessary biopsies and the associated mental health decline.
- **Economic Preservation:** Beyond the psychological impact, reducing false positives preserves the patient's financial resources and productivity. For women in underserved communities the "Safety-Net" populations identified by Ogu et al. (2026) avoiding an unnecessary follow-up appointment means avoiding the loss of hourly wages and childcare costs, further reinforcing AI's role in promoting health equity.

#### 4.3.3. Long-Term Adherence and System Trust

A critical finding is the link between the screening experience and future participation. Literature suggests that a traumatic screening experience defined by long waits and false positives is a major predictor of screening non-adherence in subsequent years. By functioning as a psychological buffer, AI ensures that the screening process is as frictionless as possible. When the system is fast and accurate, the patient's "affective trust" in the program is reinforced. AI thus serves a meta-objective: it preserves the integrity of the screening program by ensuring that women do not drop out of the system due to the trauma of the process. In this sense, the technology is not just detecting cancer; it is protecting the social sustainability of preventative medicine.

### 4.4. Dehumanization vs. The "Ethics of Care"

There is a long-standing fear in medical sociology that automation erodes the "Ethics of Care" the empathetic bond between provider and patient (Bunnell & Rowe, 2023). However, this review identifies a counter-intuitive trend in the data.

The use of Large Language Models (LLMs) to simplify complex radiology reports (Pisarcik et al., 2025) suggests AI can actually function as a communication bridge. When patients rate AI-generated summaries as more "empathetic" and "comprehensible" than original medical texts, it implies that technology can "re-humanize" care. It does this by translating technical jargon into a supportive dialogue, thereby reducing literacy-induced anxiety and empowering the patient to participate in their own care path.

### 4.5. Redefining Autonomy and the Information Hierarchy

Evidence from Park (2024) and Hurley et al. (2025) signals a major shift in what patients consider "material information." The fact that patients now value the disclosure of AI involvement as much as or more than traditional clinical risks suggests that AI has become a core component of informed consent.

We propose that the "Right to Explanation" must be institutionalized. Patients are increasingly unwilling to accept a passive role; they demand to see the "why" behind an algorithmic flag. Integrating Explainable AI (XAI) tools, such as saliency maps or heatmaps, into the patient-provider consultation is no longer a luxury. It is a requirement for true digital autonomy in the 21st century.

#### 4.6. Limitations and Clinical Realities

While the 23 studies analyzed provide a high-quality cross-section, the field is moving faster than the peer-review cycle. Research from 2022, for instance, could not fully anticipate the impact of "foundation models" or the widespread availability of generative AI.

##### Policy Recommendations:

1. **Mandatory Disclosure:** Consent forms must be updated to treat AI involvement as a primary clinical variable, not a secondary technical detail (Park, 2024).
2. **Equity Benchmarking:** Validation of AI tools should include "Model Cards" that detail performance across diverse racial and density-based subsets to maintain trust in SNH environments (Ogu et al., 2026).
3. **Collaborative Intelligence Training:** Radiologists should be trained in "empathetic explanation"—learning how to interpret and communicate AI findings without making the patient feel like a data point on a spreadsheet.

#### 5. Conclusions

Drawing on 23 distinct studies published between 2022 and 2026, it is clear that bringing AI into mammography is far more than a technical upgrade. It represents a fundamental shift in the patient-doctor relationship. While the software has reached a high level of clinical accuracy, its "social license" to operate—the actual acceptance by the women it serves—is still being negotiated in the clinic every day.

##### 5.1. Core Insights

Three main themes stood out regarding the patient experience in this digital era:

- **Trust isn't a blank check:** Trust in AI is strictly conditional. Most women are comfortable with the technology acting as a "Second Reader"—essentially a high-tech safety net—but they remain wary of any workflow where the machine makes the final call. The radiologist still serves as the "moral anchor" of the process; patients need to know that a human being is ultimately responsible for their diagnosis.
- **Shrinking the "Anxiety Gap":** AI's most direct benefit to a patient's well-being might be its ability to end the agonizing wait for results. By enabling same-day diagnostics and cutting "false alarm" recalls by about 25%, AI acts as a psychological stabilizer. This helps prevent the long-term stress that often keeps women from coming back for their next screening.
- **A New Standard for Honesty:** The rules for informed consent are changing. For many patients, knowing an algorithm is involved is just as important as knowing the clinical risks. This has created a real demand for "Explainable AI." Using tools like heatmaps helps demystify the "black box," giving patients a genuine sense of control and understanding over their own health data.

##### 5.2. The Equity Mandate

One of the most revealing findings in recent research is the "Safety-Net Paradox." The fact that underserved populations may actually trust AI *more*—viewing it as an objective tool free from human prejudice—places a massive responsibility on developers. To honor that trust, AI must be tested across all demographics to ensure that "algorithmic justice" isn't just a buzzword. Being transparent about who the software was tested on is no longer a "best practice"; it is a requirement for fair care.

##### 5.3. Final Outlook

Looking ahead, the goal of AI in mammography shouldn't be to "automate away" the doctor. Instead, we should be looking at collaborative intelligence. The best use of this technology is to handle the heavy data lifting, which in turn frees up radiologists to do what they do best: provide empathetic, face-to-face care. By using AI to simplify complex medical reports and keeping a "Human-in-the-Loop" workflow, we can actually make the screening process more human, not less. Ultimately, while the transition to AI-supported screening is inevitable, its success won't be measured by the precision of the pixels. It will be measured by whether we can protect the patient's trust and peace of mind throughout the journey.

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