RESEARCH PAPER

Implementing AI-Assisted Diabetic Retinopathy Screening: A Qualitative Evidence Synthesis of Data Governance, Trust and Equity

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ABSTRACT

Diabetic retinopathy can be screened (assisted by artificial intelligence) in primary care and underserved contexts, and technical accuracy is irrelevant to whether patients and practitioners consider the service a legitimate offer. This secondary qualitative research study explored how trust, data ownership and equity are formed in empirical descriptions of AI-assisted retinal screening. A systematic search found 35 sources from 2016–2026. The findings were based on sixteen major articles published since 2021, whereas a different body informed the introduction, theoretical framework, research gap, methods and discussion of literature. This yielded three themes suggested by reflexive thematic synthesis: trust as a relational goal and not an assurance of accuracy alone; retinal data ownership is an open relationship of governance; equity is a dilemma of increased access and risk redistribution. Speed, convenience, and instant outcomes were well-regarded by patients, although this consideration faded as AI seemed to substitute clinical elucidation or reuse of data was opaque. Practitioners were open to AI when accountability, escalation channels, and training could be perceived, but raised anxieties over consent, accountability, information security, and skewed model performance. The greatest gains in access were most effective when AI was integrated within attainable care pathways, though inaccessible images, referral failure, digital savvy, and subgroup bias could recreate disparity. The paper finds that reliable AI eye screening entails human-controllable communication, purpose-driven data stewardship, and equity considerations throughout the screening process, not just at the algorithmic endpoint. The analytic focus is therefore multi-actor and system-level, integrating patient experience with practitioner readiness, institutional accountability, data governance and referral capacity.

Keywords: Artificial Intelligence, Diabetic Retinopathy Screening, Patient Trust, Data Ownership, Health Equity, Ophthalmology, Qualitative Evidence Synthesis

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INTRODUCTION

One of the most notable clinical applications of artificial intelligence is in diabetic retinopathy screening, since retinal photographs can be taken outside specialist clinics and scored quickly by autonomous or assisted algorithms. The seminal test in an autonomous system showed that an algorithm (mainly in the primary care setting) could deliver a point-of-care diagnostic output to clinics, with later studies pushing ophthalmology as one of the most viable areas to implement an ophthalmology-focused deep learning system (Abràmoff et al., 2018; Ting et al., 2019). The African and Thai screening programmes also indicated that an automated grading system could alleviate specialist shortages and expand access among geographically scattered populations (Bellemo et al., 2019; Ruamviboonsuk et al., 2019). These successes have fostered a policy discourse where AI screening is referred to as an efficiency intervention as well as an equity intervention.

That is but half the story. The clinical adoption of the system will depend on whether patients are aware of what the system does and whether practitioners understand what the system does. They can explain and challenge its results, and institutions are accountable for how retinal images are stored, utilised, and commercialised. Even with high accuracy, AI implementation may fail due to a lack of workflow integration, accountability, and local clinical value (Kelly et al., 2019). Medical images are data assets as well, and they are resilient. They can be kept in case of quality control; they can be connected to another set of records, or they can be recycled to educate the college of business systems, creating a disconnect between the permission to subject to an eye examination and the authorization to broaden the extent of data use (Price & Cohen, 2019). Ethical issues are more to do with the wrong categorisation and also with the allocation of control, advantage, and risk.

The paper has the following question: How can patients and ophthalmic practitioners feel trusted, own their data and be part of equitable AI-assisted eye screening? It applies a secondary qualitative design to incorporate more modern primary evidence and maintain

an apparent distinction between the studies that will determine the literature background and those that will be analysed in the results. This is not aimed at concluding the acceptability of AI screening in the abstract. It is to determine when acceptance is justified, weak or unfair.

Accordingly, the unit of analysis in this synthesis is broader than the patient encounter alone. AI-assisted diabetic retinopathy screening is treated as an implementation system in which patients, ophthalmic practitioners, primary-care staff, institutions and technology providers distribute responsibility across image capture, algorithmic assessment, communication and referral. Rather than limiting analysis to patient acceptance or consent, this emphasis permits patient experience to be interpreted alongside practitioner readiness, institutional accountability and pathway capacity. It also makes governance analytically central: a technically accurate model may still be weakly implemented when staff cannot explain outputs, escalation is uncertain, secondary data use is opaque, or referral capacity is inadequate. The study therefore asks not only whether AI is acceptable, but how legitimacy is produced across the clinical and organisational relationships surrounding screening.

LITERATURE REVIEW

AI-assisted screening and the limits of technical validation

Studies of ophthalmic AI often have emphasised sensitivity, specificity, image gradability and comparisons with expert graders. These measures are indispensable, yet do not introduce clinical credibility. Ethical analysis has cautioned that machine learning systems can transfer responsibility without stipulating who should be accountable for mistakes, delayed referrals, or insufficient reassurance (Char et al., 2018; Vayena et al., 2018). Consort-human interaction Reporting standards like the CONSORT-AI and SPIRIT-AI address this issue by including more detailed descriptions of human interaction, error handling, and system changes during the trial (Cruz Rivera et al., 2020; Liu et al., 2020). However, transparent research reporting is not a guarantee of transparent patient encounters. Even when presented in a technical document, a system may be introduced with a consent process that substantially fails to provide interpretative meaning of automation or data reuse.

Trust, explainability, and professional mediation

Trust in clinical AI is generally considered an attitude that can be enhanced by interpreting model outputs. This is too narrow. Ghassemi et al. (2021) suggest that most existing explainable AI provides persuasive visualisations rather than proving causal reliability or clinical usefulness. Ethical reviews in ophthalmology also do not distinguish between accuracy, responsibility of clinicians, autonomy of patients, and regulatory matters as separate concerns (Abdullah et al., 2021). Trust is thus considered to be a judgement in respect of a sociotechnical arrangement. Patients can feel confidence in a screening pathway since a practitioner interprets the output to them, makes themselves available to queries, and can suppress or escalate the output. The same route might be trusted by practitioners since performance is proven locally, responsibility is shared, and failure is visible. Eliminating human elements can help make it faster and less reliant on relational evidence, where trust is established.

Data ownership, privacy, and data justice

The language of ownership can be legally inexact since health information can be dominated by cross-cutting rights, contracts, institutional obligations as well as intellectual property. But ownership language is a language that patients employ to represent legitimate issues of control, permission, benefit and future use. Price and Cohen (2019) demonstrate that traditional models of privacy fail when medical data is replicated, connected, and reused several times. AI exacerbates the moral issue since value is created based on aggregate information, and the subject matter might not be informed about downstream applications. The framework of data justice by Taylor (2017) can be applied to this situation, since it is not focused on privacy but on visibility, representation, and the ability to contribute to data decision-making. Mittelstadt et al. (2016) also show that algorithmic ethics are concerned with questions of epistemics and organisational structure, such as by whom acceptable outcomes are determined, and to whom a decision can be contested.

Equity and generalisability

AI can lessen the barriers of geography and workforce, yet it can also make decisions based on the prevailing inequalities. Norori et al. (2021) identify data-driven, algorithmic, and human sources of bias, demonstrating that underrepresentation, label construction, deployment issues, or selective access to subsequent care can cause inequity. Retinal AI surveys highlight that high average scores can mask ineffective generalisability between devices, populations, disease occurrence, and services (Daich Varela et al., 2023). Equity has thus to be considered throughout the entire journey, that is, invitation and image capture down to results communication and completed referral. An algorithm which enhances the screening uptake at the expense of more ungradable images in a disadvantaged group will reallocate, not remove, barriers.

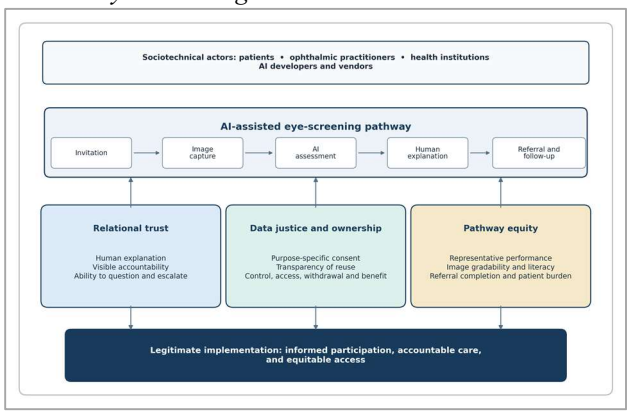
Theoretical framework

This paper integrates relational trust and data justice. Relational trust considers confidence as generated by holding to account the interaction of patient, practitioner, institution and technology. Data justice assesses how individuals are fairly represented, can know the use of the data, and have the ability to shape the decisions impacting them. The framework is also based on international AI ethics, and in this context, transparency, justice, non-maleficence, responsibility and privacy are repeated and interpreted differently in guidelines (Jobin et al., 2019). The combination of these opinions renders trust minimal to user satisfaction and equity minimal to identical

algorithmic accuracy. Figure 1 presents the integrated framework used to interpret the screening pathway.

Figure 1

Integrated Theoretical Framework for Legitimate AI-Assisted Eye Screening



Note. The framework integrates relational trust, data justice, and pathway equity across the full screening process.

Research gap

The literature provides comprehensive explanations and descriptions of ethical principles and technical performance rather than lived performance. The discussion of trust, privacy, and fairness is usually presented in parallel, whereas empirical research usually explores acceptance, workflow, or accuracy individually. Few syntheses linking these concerns between patients and practitioners in actual screening encounters are available. Specifically, data ownership will be drowned in the general privacy discourse, and equality will be assumed based on expanded access, without reviewing referral completion, literacy, subgroup performance and institutional accountability. The present study fills this gap through a concentrated qualitative synthesis of recent primary studies.

An additional gap concerns the fragmentation of implementation evidence across stakeholder and organisational levels. Patient studies frequently describe convenience, willingness or satisfaction, whereas practitioner studies focus on workflow, liability, training and escalation, and ethics literature considers privacy, accountability and fairness at a more abstract level. Examining these bodies separately can obscure how one group's benefit may depend on another group's capacity to act. For example, rapid automated classification has limited practical value when practitioners lack a clear escalation route, while expanded screening access may reproduce inequity if image quality or referral completion differs between populations (Krogh, Hentze, et al., 2025; Nolan et al., 2023). This synthesis therefore connects patient, practitioner and service-level evidence within a single pathway perspective. Its contribution is an interpretation of how trust, data governance and equity interact as implementation conditions across the screening system.

METHODS

Design

A qualitative evidence synthesis was performed as a secondary synthesis. This design suited best, as the research question was about meanings, expectations, and implementation experiences that were heterogeneous and spanned qualitative, survey, observational, and pragmatic studies. Synthesizing qualitative evidence can produce a conceptually richer interpretation than adding results from a single study (Flemming & Noyes, 2021).

Search and selection

The search in PubMed, Google Scholar, and publisher repositories was organized using artificial intelligence, autonomous AI, diabetic retinopathy, retinal screening, patient perception, ophthalmologist, practitioner, trust, consent, privacy, data, bias, and equity. The limit was put on sources dating back to 2016 to July 2026. To maintain analytical distance, the works in the literature review were not included in the findings. The dataset of findings included 16 main empirical studies conducted since 2021 and investigated patients, clinicians, screening staff, implementation investigators, real-world use of services, or outcomes in subgroups. The findings did not include reviews, commentaries, protocols, and purely technical development studies.

Analysis

The findings of the study were synthesized into a grid encompassing setting, participants, technology, documented gains, worries, data customs, human supervision and equity implications. The analysis was guided by reflexive thematic principles, shifting descriptive codes to interpretive patterns, and the researcher's judgement was treated as part of the analytic process rather than an error to be overcome (Braun & Clarke, 2021). Speed and convenience, explanation, replacement anxiety, consent ambiguity, data protection, responsibility, ungradable images, subgroup bias, and referral continuity were initial codes. These codes were iteratively organised into three themes. The results of quantitative satisfaction and performance were construed as contextualized evidence rather than qualitative meaning. Since the synthesis was based on published reports, it was not possible to recapture unreported minority views or establish how authors represented participant accounts.

To maintain this system-level emphasis, the synthesis distinguished evidence about individual attitudes from evidence about organisational capability. Reports of willingness, satisfaction or perceived usefulness were interpreted as indicators of acceptance, whereas descriptions of training, responsibility, data handling, image gradability, escalation and referral completion were used to assess implementation conditions. Convergence between stakeholder groups was examined where possible, particularly when patient expectations for explanation or clinician access corresponded with practitioner concerns about liability, workflow and education. Divergence was also analytically important: high patient acceptance did not

automatically demonstrate informed data governance, and strong model performance did not demonstrate equitable pathway completion. This distinction prevented the themes from collapsing into a general account of patient sentiment and retained attention on the institutional mechanisms through which AI screening becomes trustworthy, governable and equitable.

Findings

Table 1 summarizes the interpretive structure of the three findings themes.

Table 1

Thematic Synthesis of Trust, Data Ownership, and Equity

Theme	Core evidence pattern	Patient and practitioner meaning	Implementation implication
1. Relational, conditional, human-mediated trust	Convenience and rapid results encouraged acceptance, but trust weakened when AI appeared to replace explanation, accountability, or clinician access.	Patients valued human interpretation and the ability to ask questions. Practitioners required clear workflows, escalation routes, training, and shared responsibility.	Deploy AI as decision support within a visible care relationship, not as an independent authority.
2. Data ownership as an ongoing governance relationship	Consent to screening did not clarify image retention, secondary use, model training, commercial access, or inferential risks within retinal data.	Ownership language expressed expectations of permission, transparency, control, withdrawal, oversight, and fair distribution of benefit.	Separate consent by purpose and disclose retention, reuse, access, model development, and withdrawal arrangements.
3. Equity gains with redistributed pathway risk	Primary-care deployment improved access, yet ungradable images, subgroup bias, staffing limits, literacy barriers, and incomplete referral could recreate inequality.	Access was meaningful only when screening results led to understandable communication and achievable follow-up care.	Audit equity across invitation, imaging, model performance, referral completion, treatment access, and patient burden.

Note. Themes were generated through reflexive thematic synthesis of the primary studies reserved for the findings dataset.

Theme 1: Trust was relational, conditional, and human-mediated

In patient studies, acceptance tended to be high when AI was felt to be a convenient source of extended care. In rural Maine, local patient screening and provision were appreciated, and implementation was anticipated to be better, even though the workflow did not allow it (Nolan et al., 2023). Even Indian participants expressed that they were quite willing to use AI-based retinal screening. In many cases, they even believed that it made them better understand their ocular health (Shah et al., 2022). Real-world screening revealed positive attitudes even without previous experience with AI in Brazil, showing that acceptance can arise after a positive experience even in the case of low technical literacy (Malerbi et al., 2024). This is also applicable to Danish patients, as the majority expressed a desire to use AI-assisted screening in primary care in the future. Yet, distrust towards AI remained measurable alongside acceptance (Krogh, Nielsen, et al., 2025).

These findings are contrary to the belief that willingness is equal to trust. The structural equation modelling results indicated a mutual interaction of usefulness, social influence, risk perception, and trust that is effective in constructing acceptance, implying that patients draw on more extensive mental processes for the service than on claims of accuracy (Jin et al., 2025). In an urban medical centre in the US, patients were open to autonomy in screening and still appreciated face-to-face communication and access to clinicians (Rustam et al., 2026). The English NHS research was significant, especially due to the notion of acceptable AI among people living with diabetes and practitioners who believed that professional care could be assisted by AI and not substituted. Anxiety escalated around the idea of automation posing a threat to explanation, accountability, or the status quo screening relationship (Wahlich et al., 2025).

This relational interpretation was supported by practitioner evidence. According to general practice staffing in Denmark, AI screening was only feasible when the workflow features, issues of trouble, and referrals were understood (Krogh, Hentze, et al., 2025). International ophthalmologists were optimistic and lacked familiarity and routine adoption, whereas Swiss practitioners noted liability, informed consent, data protection, and lack of education as key barriers (Ferro Desideri et al., 2025; Tappeiner, 2025). The attitudes of Pakistani medical workers were quite positive and unequal in terms of knowledge, which means that zeal without skills might result in shallow rather than justified trust (Habib et al., 2024). Reliability thus relied on human agency in visual display, as opposed to introducing AI as an independent authority.

Theme 2: Data ownership was experienced as a governance relationship, not a consent checkbox

The key literature was often silent about patients' direct ownership of retinal images. Still, it was the question of ownership enactment in the form of questions of permission, further use, commercial use, and responsibility. In a national programme, Wahlich et al. (2025) established that stakeholders demanded transparency on the use of data and their governance before implementation. Likewise, Tappeiner (2025)

documented a significant worry among ophthalmologists regarding whether the data protection and informed consent are sufficient. These results imply that a conventional clinical consent form might be lacking in responding to the question that patients are implicitly asking: what will become of my image after this screening today, who will use it and could I deny secondary uses without losing care?

According to the implementation investigators, AI trials have raised unusually complex issues of consent and fairness due to systems being potentially subject to change, reusing data, and risk variation across underrepresented groups (Youssef et al., 2024). Whether de-identification takes place is not the ethical issue per se. Retinal images contain strong biological data and can support inferences beyond the initial purpose of screening. Coyner et al. (2023) demonstrated that AI was able to predict self-reported race based on retinal vessel maps, which were created to eliminate overt race information. This discovery unsettles claims that constrained or mollified photos are required to be impartial. It also demonstrates why data governance cannot be limited to explicit identifiers.

The patient-satisfaction literature was sparse in detailing the use of secondary data, analytically important in its own right. Rural Maine, India, Brazil, Denmark, the United States, and Australia had mostly high levels of satisfaction in terms of convenience, comfort, speed, and readiness to rescreen (Joseph et al., 2026; Malerbi et al., 2024; Nolan et al., 2023; Rustam et al., 2026; Shah et al., 2022). These steps cannot determine informed consent to image retention, model training or provider access. Ownership of data was thus not so much an established legal right as an ongoing rule. Individuals and practitioners seemed to be better accepting of data use as purpose, access, oversight and benefit were clarified.

Theme 3: Equity gains were real, but risk was redistributed across the pathway

When AI screening transferred eye examinations to places patients already frequented, it had a positive effect on access. The ACCESS randomised trial enhanced diabetic eye examination attendance and follow-up in an ethnically and racially diverse youth group, highlighting the ability of point-of-care autonomous AI to address a feasible gap in care (Wolf et al., 2024). Additionally, the rural implementation improved local access, and the Australian pragmatic trial reported high patient and provider satisfaction regarding true screening in primary care and endocrinology services (Joseph et al., 2026; Nolan et al., 2023). Subgroup comparison of EyeArt with ophthalmologists demonstrated high sensitivity for more-than-mild diabetic retinopathy, which suggests the use of EyeArt as a scalable screening tool (Lim et al., 2023).

But based on availability alone, equity could not be deduced. Staffing, camera operation, timing, and referral coordination were deemed to be limiting, especially among providers in rural and general practice settings, and tend to have a disproportionate impact on under-resourced clinics (Krogh, Hentze, et al., 2025; Nolan et al., 2023). Ungradeable images and false-positive referrals might also impose more appointments, travel, and anxiety on patients who already experience barriers.

The most profound equity issue was retinal AI's ability to encode socially patterned information. Coyner et al. (2023) showed that even biomarker representations can include race-related cues. In contrast, Youssef et al. (2024) determined that researchers do not consider choosing participants fairly and cannot estimate the risks and benefits of these underrepresented groups. Surveys in practice indicated that insufficient training and institutional preparedness might further concentrate benefits in well-resourced services (Ferro Desideri et al., 2025; Habib et al., 2024; Tappeiner, 2025). AI-aided eye screening thus posed an equity paradox. It might reduce the distance and deficit of specialists and create new reliance on data quality, digital literacy, vendor infrastructure, and quality referral methods.

DISCUSSION

The synthesis displays that there is no independent implementation domain of trust, ownership and equity. They go hand in hand as conditions of legitimacy. Patients were comfortable with AI when it decreased inconvenience and was associated with human care, but acceptance did not reduce the necessity of explanation. This aligns with ethical explanations that place responsibility in the clinical system, rather than in the algorithm per se (Char et al., 2018; Vayena et al., 2018). It also qualifies the vow suggested in ophthalmics AI reviews. Technical capability may provide access, and clinical value depends on whether institutions are capable of maintaining communication, escalation, and follow-up (Kelly et al., 2019; Ting et al., 2019).

The limitation of explainability as an elaborate solution is revealed in the former theme too. The practitioners and patients did not just demand more model detail. They asked for a trustworthy relationship in which someone would be able to interpret the outcome, respond to questions, and take responsibility. This aligns with Ghassemi et al. (2021), who warn that post hoc explanations may build confidence but not reliability. Factually, procedural explanations (what the system reviews, uncertainty treatment, failure reviewer and outcome) might be most meaningful.

The second theme is an extension of the debate on privacy, given that it reveals the reasoning behind why the language of ownership continues. With medical big data, it can be copied and used in new ways that require a single authorization (Price & Cohen, 2019). Data justice introduces a more impactful layer of questioning: can patients view, challenge, and gain advantage from the data associations made about them (Taylor, 2017)? The fact that there is a possibility to determine race using retinal representations shows that eliminating visible markers does not eliminate social content. Governance then needs to state the principal use of screening, quality assurance, model development, commercial availability, retention and withdrawal individually. Only the repeated principles

that Jobin et al. (2019) discovered can be plausible when expressed into the following operational choices.

The equity theme also speaks against a performance frame. Experiments in Africa and Thailand have indicated that AI can operate within the context of a limited number of specialists (Bellemo et al., 2019; Ruamviboonsuk et al., 2019), but recent primary research indicates that access is under the condition of trained personnel, image quality, referral capacity, and patient comprehension. Norori et al. (2021) define bias as something produced by data, algorithms, and human systems. The current synthesis has contributed that a failure of pathways is an equity mechanism itself. When referral is not accessible for a screening outcome, a highly sensitive system will add load by doing nothing, whereas false positives are not clustered in disadvantaged populations.

Taken together, the findings support a multi-actor interpretation of implementation. Trust is not located solely in the patient's attitude toward an algorithm; it is produced through the visible ability of practitioners and institutions to explain, question, override and escalate AI outputs (Char et al., 2018; Vayena et al., 2018). Data governance extends beyond the consent encounter because decisions about retention, model development, third-party access and withdrawal are shaped by institutional and vendor arrangements (Price & Cohen, 2019). Equity is also a property of the pathway rather than a single performance statistic. It depends on who receives an invitation, whose images are gradable, whether subgroup performance is monitored, and whether a positive result leads to reachable follow-up (Norori et al., 2021). This perspective distinguishes successful deployment from simple acceptance: an AI service can be popular yet poorly governed, accurate yet operationally fragile, or accessible at screening while inequitable at referral. Implementation evaluation should therefore combine patient experience with practitioner preparedness, governance transparency and pathway-level monitoring.

The research has several limitations, such as the usage of published reports, methodological heterogeneity and the fact that most of the evidence was found in diabetic retinopathy. Dissent is also likely to be underreported in satisfaction surveys, and national and cultural differences limit transferability. However, the distinction between the findings of studies and the literature review minimized the extent of circularity and permitted recent primary evidence to challenge, rather than reiterate, held ethical assertions.

CONCLUSION

AI-aided eye screenings are most credible when introduced as a responsible care pathway, rather than an independent technical occurrence. Patients and practitioners prized the convenience, fast outcome and increased access, yet they needed human clarification, seen responsibility and believable referent schemes. Ownership of retinal data was ambiguous because consent to be screened did not specify how the data could be used in the future or how it would benefit commercially. The increase in equity was real, especially in primary care and underserved settings, but subgroup bias, ungradable images, insufficient training and missing follow-up could undermine it. Reliable implementation thus entails oversight throughout the entire workflow.

Implications

Health services are supposed to have a named clinician or trained practitioner who may interpret AI results, express doubt, and escalate. Consent materials must differentiate clinical screening and image retention, quality assurance, research, model training, and third-party access. The plain-language explanations to patients on the retention duration of the images, the possibility of withdrawal, and its subsequent benefits should be as pledged.

Performance should be checked before deployment across pertinent demographic stratifications, camera types, disease prevalence, and image-quality circumstances. Invitation measurement, successful imaging, ungradable rates, positive results, completed referrals, treatment initiation, and patient burden are some of the measurements of equity audits. It is necessary to have procurement contracts that mandate access to Subgroup performance, Incident reporting, model updates, and data-use terms. Lastly, professional education must not only be focused on how to use the device, but also on consent, bias, liability, communication and the boundaries of algorithmic explanations. Such measures would transform abstract ethical commitments into real protections for patients and practitioners.

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