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+15878858911
editorial-office@sciformat.ca

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AUTOMATED AI SCREENING FOR DIABETIC RETINOPATHY: A SYSTEMATIC REVIEW OF SOCIO-ECONOMIC ACCESSIBILITY, PATIENT ACCEPTANCE, AND THE DIGITAL DIVIDE

Wiktoria Donocik *(Corresponding Author, Email: wiktoria.don@gmail.com)*
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0003-3801-6729

Jakub Sałak
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0005-7078-6402

Piotr Tryczyński
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0001-8997-3225

Jakub Wrona
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0005-7722-7507

Piotr Helbin
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0007-5289-2521

Aleksandra Gralec
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0001-0061-311X

Sebastian Ożga
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0003-1337-7800

Aleksandra Spirkowicz
Medical University of Silesia in Katowice, Katowice, Poland
ORCID ID: 0009-0006-2228-4536

ABSTRACT

Purpose: This systematic review evaluates the socio-technical integration of autonomous artificial intelligence (AI) in diabetic retinopathy (DR) screening. While the technical accuracy of deep learning algorithms is well-established, their successful deployment depends on a complex interplay of economic, psychological, and organizational factors. This study synthesizes evidence from 35 peer-reviewed sources to provide a comprehensive roadmap for AI implementation in diverse healthcare settings.
Methods: A systematic analysis of 35 high-quality studies (2017–2026) was conducted, focusing on diagnostic performance, cost-effectiveness, and stakeholder acceptance. The findings were interpreted through the Consolidated Framework for Implementation Research (CFIR) to identify systemic barriers and facilitators.
Results: The evidence confirms that autonomous AI reaches high sensitivity (95.7%–100%) in detecting referable DR, matching specialist performance. Economically, AI is highly cost-effective in resource-limited and rural areas by reducing travel costs and labor burdens. However, significant barriers remain, including the "biological divide" in elderly populations, "black box" anxiety among patients, and organizational disruption in primary care workflows. Trust is identified as a critical mediator, with acceptance increasing when AI is positioned as a supportive "safety net" rather than a human replacement.
Conclusion: The transition to AI-driven screening is a transformative shift toward democratized healthcare. Success requires a move toward Human-Centered Design (HCD), localized staff education using tools like instructional videos, and inclusive governance to bridge the digital divide.

KEYWORDS

Diabetic Retinopathy, Autonomous Artificial Intelligence, Socio-Technical Integration, Health Equity, Patient Acceptance, Cost-Effectiveness

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1. Introduction

The global prevalence of diabetes mellitus has reached pandemic proportions, with estimates suggesting that over 600 million adults will be living with the condition by 2030 (Hu et al., 2024). Among the various complications associated with diabetes, diabetic retinopathy (DR) remains a leading cause of preventable blindness in the working-age population worldwide (Heydon et al., 2021; Tufail et al., 2017). Despite the availability of effective treatments such as laser photocoagulation and anti-VEGF therapy, the primary challenge remains the timely identification of referable disease through regular screening (Wewetzer et al., 2021).

1.1. The Crisis of Manual Screening

Traditional DR screening models rely heavily on manual grading by ophthalmologists or trained optometrists. However, this human-centric approach faces significant systemic bottlenecks, including a global shortage of specialists, high operational costs, and geographic disparities in access to care (Leigh et al., 2026; Rajesh et al., 2023). In many low- and middle-income countries (LMICs), as well as rural areas of high-income nations, the patient-to-specialist ratio is so skewed that universal screening remains an elusive goal (Cleland et al., 2023; Li et al., 2023).

1.2. The Emergence of Autonomous AI

Artificial Intelligence (AI), specifically deep learning (DL), has emerged as a "techno-clinical" revolution capable of addressing these gaps (Dave et al., 2026). Unlike assistive AI, which requires a human-in-the-loop, autonomous AI systems can independently interpret retinal images and provide an immediate diagnostic output at the point of care (Heydon et al., 2021; Teng et al., 2025). Systems such as EyeArt and IDx-DR have already demonstrated diagnostic sensitivity and specificity that match or exceed manual grading standards in large-scale clinical trials (Heydon et al., 2021; Wewetzer et al., 2021).

1.3. Beyond Technical Accuracy: A Social Science Perspective

While the technical efficacy of AI is well-documented, its successful integration into society is not merely a matter of algorithmic precision. The transition to autonomous diagnostics introduces complex socio-technical challenges, ranging from the "black box" nature of machine learning to issues of algorithmic bias and the digital divide (Held et al., 2022; Liao et al., 2024). As AI moves from the laboratory to the primary care clinic, its impact is mediated by patient trust, cultural values, and the economic structures of healthcare systems (Jin et al., 2025; Rustam et al., 2026; Wahlich et al., 2025).

1.4. The Digital Divide and Health Equity

A critical concern in the deployment of medical AI is whether it will narrow or widen existing health inequalities. While AI offers a tool for democratizing access to care for underserved populations (Liu et al., 2024), it also faces "biological" and "infrastructural" divides (Teng et al., 2025). Factors such as retinal pigmentation, age-related media opacities, and unstable internet connectivity in remote areas create barriers that require careful ethical and social governance (Bai et al., 2026; Crew et al., 2024; Mathenge et al., 2022).

1.5. Objectives of the Study

This systematic review analyzes 35 peer-reviewed sources to evaluate the current state of autonomous AI implementation in DR screening. By synthesizing evidence from diverse clinical and geographic settings, this study aims to:

1. Benchmark the diagnostic performance and clinical feasibility of autonomous systems.
2. Assess the socio-economic impact and cost-effectiveness across different healthcare infrastructures.
3. Explore the psychological and cultural determinants of stakeholder acceptance.
4. Identify the systemic barriers and facilitators through the lens of the Consolidated Framework for Implementation Research (CFIR).

Through this multi-dimensional analysis, the paper provides a roadmap for the responsible and equitable social integration of AI in global ophthalmology.

2. Methodology

This study employs a systematic review design to evaluate the socio-technical integration of autonomous artificial intelligence (AI) in diabetic retinopathy (DR) screening. The methodology was structured to identify, synthesize, and analyze high-quality peer-reviewed evidence focusing on diagnostic performance, health economics, and stakeholder psychology.

2.1. Search Strategy and Data Sources

A comprehensive literature search was conducted across multiple electronic databases, including PubMed, Google Scholar, ScienceDirect, and the Cochrane Library. The search timeframe was restricted to the period between 2017 and 2026 to capture the most recent advancements in deep learning algorithms and real-world implementation data.

The search utilized a combination of Medical Subject Headings (MeSH) terms and keywords, including: "Diabetic Retinopathy," "Autonomous Artificial Intelligence," "Deep Learning," "Screening," "Cost-Effectiveness," "Digital Divide," and "Patient Acceptance."

2.2. Eligibility Criteria

Studies were included in the review if they met the following criteria:

1. Technology Focus: The primary intervention involved autonomous AI systems (systems capable of making diagnostic decisions without a human-in-the-loop) for DR detection.
2. Outcome Measures: The study reported on at least one of the core thematic areas: diagnostic accuracy (sensitivity/specificity), economic impact (ICER/QALY), or social/psychological determinants of adoption.
3. Study Design: Peer-reviewed prospective clinical trials, retrospective validations, meta-analyses, and health economic modeling studies.
4. Language: English-language publications only.

Exclusion criteria included studies focusing solely on assistive (non-autonomous) AI, technical papers without clinical or social validation, and non-peer-reviewed grey literature.

2.3. Study Selection and Data Extraction

The initial search yielded a broad pool of candidates, which were screened by title and abstract. From this pool, a final set of 35 sources was selected for full-text analysis based on their relevance to the socio-technical framework of this review.

Data extraction was performed using a standardized template, capturing the following information:

- Study characteristics (Author, Year, Country/Region).
- AI system utilized (e.g., EyeArt, IDx-DR, AEYE-DS).
- Clinical setting (Primary care, Endocrinology clinics, LMIC infrastructures).
- Key findings regarding diagnostic integrity and socio-economic outcomes.

2.4. Analytical Frameworks

The extracted data were synthesized using two primary analytical lenses:

1. Thematic Synthesis: Findings were categorized into the four domains presented in the Results section (Diagnostic Performance, Economics, Stakeholders, and Equity).
2. Implementation Analysis: The Consolidated Framework for Implementation Research (CFIR) was applied to categorize barriers and facilitators into five domains: intervention characteristics, outer setting, inner setting, characteristics of individuals, and the implementation process (Liao et al., 2024).

2.5. Quality and Bias Assessment

To ensure the integrity of the synthesis, studies reporting diagnostic accuracy were evaluated based on the representativeness of their datasets and the rigor of their "gold standard" comparisons (e.g., comparison against professional manual grading or ETDRS standards). Economic studies were assessed for the transparency of their modeling assumptions and the inclusion of both direct and indirect costs (Wang et al., 2024),

3. Results

The systematic analysis of 35 peer-reviewed sources reveals a multifaceted landscape of autonomous artificial intelligence (AI) implementation for diabetic retinopathy (DR) screening. The findings are categorized into core thematic areas focusing on diagnostic performance, health economics, stakeholder psychology, and the socio-technical challenges of the digital divide.

3.1. Diagnostic Performance and Clinical Feasibility in Diverse Settings

The clinical validity of autonomous artificial intelligence (AI) systems is the technological foundation upon which socio-economic integration rests. The analyzed literature provides robust evidence that these systems have reached diagnostic maturity, enabling their deployment in various clinical settings from high-resource national screening programs to point-of-care (POC) services in resource-limited environments.

3.1.1. Large-Scale Clinical Evidence and Algorithmic Validation

The most comprehensive evidence for AI performance comes from large-scale prospective trials within established healthcare infrastructures. In a landmark prospective evaluation conducted within the English National Health Service (NHS), which included 30,405 consecutive screening episodes, the EyeArt v2.1 system demonstrated a sensitivity of 95.7% (94.8%–96.5%) for referable diabetic retinopathy (RDR) and a perfect 100% (97.9%–100.0%) for proliferative disease (Heydon et al., 2021). The system's specificity was 68.0% (67.4%–68.5%) for episodes with no retinopathy. While this specificity is lower than that of human graders, it allows for the safe exclusion of over half of the healthy population from manual grading queues, potentially reducing the human workload in national programs by approximately 50% (Heydon et al., 2021; Macdonald et al., 2025).

In the United States, autonomous systems such as IDx-DR (LumineticsCore), EyeArt, and AEYE-DS have undergone rigorous validation for primary care office settings. Clinical trials for IDx-DR reported a sensitivity of 87.2% and a specificity of 90.7% for RDR, while AEYE-DS achieved a sensitivity of 93.0% and specificity of 91.4% (Teng et al., 2025). These results underscore the capacity of autonomous AI to operate as a stand-alone diagnostic tool in a "techno-clinical" capacity, provided that image quality standards are maintained (Dave et al., 2026; Teng et al., 2025).

3.1.2. Meta-Analytical Stability and Primary Care Reliability

Meta-analyses synthesize these findings, confirming the diagnostic stability of deep-learning (DL) algorithms across primary care settings. A pooled analysis of multiple DL-based screening methods reported a collective sensitivity of 87% and a specificity of 90% (Wewetzer et al., 2021). When these metrics are applied to a theoretical population with a 10% prevalence of DR, the systems yield a Negative Predictive Value (NPV) of 98% (Wewetzer et al., 2021).

This high NPV is a critical factor for social acceptance, as it ensures that the vast majority of patients screened as "negative" are indeed free of sight-threatening disease. However, the moderate Positive Predictive Value (PPV) of approximately 49% implies that while AI is an exceptional triage tool, it may increase the volume of referrals to specialist care, necessitating robust secondary grading or "safety net" protocols to manage the potential burden on ophthalmologists (Cuadros, 2021; Wewetzer et al., 2021).

3.1.3. Feasibility and Technical Challenges in Resource-Limited Environments

The implementation of AI in low-income and middle-income countries (LMICs) reveals unique operational barriers, primarily centered on technical ungradability and infrastructure.

- Smartphone-Based Innovations: In Karachi, Pakistan, a study using the smartphone-based VistaView fundus camera reported a sensitivity of 69.9% and a specificity of 92.9% for "any DR" (Shahzad et al., 2024). Despite its portability, the study identified a significant technical hurdle: 18.2% of images were ungradable by the AI due to factors such as media opacities (e.g., cataracts), poor pupillary dilation, or operator error (Shahzad et al., 2024). This highlights a "technical divide," where algorithmic efficacy is restricted by the quality of hardware and environmental variables (Cleland et al., 2023; Shahzad et al., 2024).
- Workflow Efficiency in Rwanda: The RAIDERS trial in Rwanda demonstrated the transformative impact of immediate AI feedback (Mathenge et al., 2022). By comparing immediate AI results with human grading results delayed by 3-5 days, the study found that immediate feedback significantly improved patient management. Point-of-care results bypassed the logistical challenges of re-contacting patients in rural areas, which is a major source of loss to follow-up in traditional screening cascades (Mathenge et al., 2022).
- Specialized Clinical Integration: Pilot studies in Australian endocrinology clinics and Indigenous healthcare settings showed that AI-based screening is highly feasible, with a mean assessment time of only 6.9 minutes (Keel et al., 2018). Over 96% of patients in these settings found the automated model more convenient than traditional referrals, demonstrating that AI can effectively move diagnostics from specialized centers to the patient's immediate medical environment (Keel et al., 2018).

3.1.4. Algorithmic Sensitivity and Safety Profiles

AI performance remains non-uniform across the stages of DR, with systems typically prioritizing high sensitivity for vision-threatening conditions. In high-quality trials, while the sensitivity for referable DR (RDR) ranges from 87% to 95.7%, the sensitivity for the most urgent stage proliferative DR consistently approaches 100% (Heydon et al., 2021; Teng et al., 2025). This "safety-first" profile is essential for clinical adoption, as it minimizes the risk of missing the most vulnerable patients, even if it results in a higher number of referrals for early-stage cases (Cuadros, 2021; Heydon et al., 2021).

3.2. Socio-Economic Accessibility and Cost-Effectiveness

The economic viability of autonomous artificial intelligence (AI) is a primary determinant of its sustainable integration into global health systems. The literature identifies a significant divergence in cost-effectiveness depending on the existing healthcare infrastructure, local labor costs, and the specific screening model employed (Leigh et al., 2026; Wang et al., 2024).

3.2.1. Long-term Economic Impact in High-Income Countries (HICs)

In nations with high manpower costs and established screening protocols, AI offers substantial systemic savings by automating labor-intensive grading tasks.

- Australia: A comprehensive 40-year Markov model simulation evaluated the impact of universal AI-based screening in primary care. The study projected that this intervention would prevent 38,347 cases of blindness and generate a net saving of AU$595.8 million (Hu et al., 2024). This represents a benefit-cost ratio of 3.96, indicating that for every dollar invested, nearly four dollars are returned to the health system and society through reduced disability costs and increased productivity (Hu et al., 2024).
- United Kingdom: In the English National Health Service (NHS), which generates millions of retinal images annually, the implementation of automated retinal imaging analysis software (ARIAS) could save approximately £0.5 million per 100,000 screening episodes (Heydon et al., 2021). The highest cost-effectiveness is achieved when AI replaces the primary human grader in a "triage" model, significantly reducing the volume of images requiring expensive specialist review (Macdonald et al., 2025; Tufail et al., 2017).
- United States: Implementation of autonomous AI in primary care has shown a 36% higher increase in adherence to annual eye exams compared to standard-of-care clinics (Liu et al., 2024). By closing the gap in screening adherence, health systems can mitigate the downstream costs of treating advanced, vision-threatening stages of the disease (Goldstein et al., 2023; Teng et al., 2025).

3.2.2. The Rural-Urban Cost-Effectiveness Paradox in China

Economic evaluations in China highlight how local socio-economic conditions alter the value proposition of AI.

- Rural Settings: AI-based screening is unequivocally identified as the most cost-effective strategy in rural areas, with an Incremental Cost-Effectiveness Ratio (ICER) of 15,595.47 USD/QALY (Li et al., 2023). In these regions, the primary economic drivers are the reduction in patient travel time and the high direct costs of transportation to urban centers where specialists are located (Li et al., 2023; Wang et al., 2024).
- Urban Settings: In highly zurbanized environments like Shanghai, the economic advantage of AI is less pronounced. Due to relatively low medical labor costs and high hardware acquisition prices, AI-assisted screening may not be more cost-effective than traditional manual grading unless the technology manages to increase referral compliance by at least 7.5% (Lin et al., 2023).

3.2.3. The Accuracy vs. Cost-Effectiveness Trade-off

Current research challenges the assumption that the most accurate AI model is always the most economically viable (Wang et al., 2024).

- Threshold Optimization: A nationwide analysis in China tested 1,100 different diagnostic performance pairs (sensitivity/specificity). The results demonstrated that the most accurate model (the status quo) was not the most cost-effective (Wang et al., 2024). Instead, a "sensitivity-priority" scenario with 96.3% sensitivity and 80.4% specificity was found to be optimal for identifying high-risk patients while keeping overall systemic medical costs manageable (Wang et al., 2024).
- Screening Intervals: Economic modeling suggests that while annual screening is the standard, AI-enabled biennial screening for low-risk patients could offer a more sustainable balance between clinical safety and financial burden in resource-limited areas (Leigh et al., 2026; Wang et al., 2024).

3.2.4. Financial and Structural Barriers to Adoption

Despite long-term benefits, several socio-economic hurdles inhibit the scalable adoption of AI:

- Initial Capital Investment: The high cost of medical-grade fundus cameras (ranging from several thousand to tens of thousands of dollars) remains a prohibitive barrier for small primary care practices and community clinics (Chen et al., 2025; Leigh et al., 2026).
- Reimbursement Gaps: A significant obstacle identified in multiple jurisdictions is the lack of standardized billing codes and reimbursement frameworks for autonomous AI diagnostics (Leigh et al., 2026; Teng et al., 2025). Without clear financial incentives for primary care providers, the "upfront" cost of the technology often outweighs the perceived benefits (Held et al., 2022).
- Maintenance and IT Infrastructure: Scalability is further limited by the hidden costs of integrating AI software with existing Electronic Health Records (EHR) and the requirement for stable, high-speed internet to access cloud-based processing units (Goldstein et al., 2023; Liao et al., 2024).

3.3. Stakeholder Acceptance: Trust, Culture, and Oversight

The social integration of artificial intelligence (AI) is significantly influenced by the perceptions and attitudes of the primary users: patients and healthcare providers. The literature suggests that technical performance alone does not guarantee successful adoption; rather, acceptance is mediated by trust, perceived responsibility, and cultural values (Held et al., 2022; Wahlich et al., 2025).

3.3.1. Patient Perspectives and the "Human-in-the-Loop" Preference

Research conducted at an urban US medical center indicates high levels of patient satisfaction with AI-based screening, with 92.4% of participants reporting a positive experience (Rustam et al., 2026). Furthermore, 76.1% of patients expressed comfort with AI being used as part of their routine eye care (Rustam et al., 2026). However, this acceptance is highly conditional. A substantial majority (82.6%) stated they would trust AI more if a physician supervised the process, and 94.1% believed that a human doctor should remain legally and professionally responsible for the final diagnosis (Rustam et al., 2026).

Data from New Zealand mirror these findings, where 78% of respondents were comfortable with AI use in their care (Yap et al., 2022). Interestingly, age appears to be a factor in trust levels; younger participants, despite having higher general awareness of AI, paradoxically exhibited lower levels of trust in autonomous diagnostic systems compared to older cohorts (Yap et al., 2022). This suggests that "digital natives" may be more skeptical of the limitations or privacy implications of automated algorithms.

3.3.2. Cultural Mediators of Technology Acceptance

Acceptance is not a monolithic phenomenon but is deeply rooted in cultural contexts. In New Zealand, Maori and Pacific Islander patients indicated a stronger preference for human-led screening, emphasizing the importance of *whakawhanaungatanga*- a concept centered on building personal relationships and rapport (Yap et al., 2022). For these populations, the efficiency of AI may be perceived as a barrier to the holistic, relational nature of healthcare.

In contrast, studies in mainland China utilized Structural Equation Modeling (SEM) to identify factors influencing AI adoption in a collectivist society. The results showed that "Subjective Norms" (SN) the perceived social pressure from family, peers, and society were the strongest predictors of the intention to use AI devices (Jin et al., 2025). This indicates that in certain social structures, community and institutional endorsement may outweigh individual concerns regarding "Uniqueness Neglect" or the fear that an algorithm cannot account for a patient's individual characteristics (Jin et al., 2025; Mo et al., 2025).

3.3.3. Healthcare Provider (HCP) Experiences and Institutional Barriers

Healthcare practitioners generally view AI as an inevitable progression that can improve health system efficiency, yet they identify several structural and ethical concerns. In the English NHS, staff highlighted the potential of AI to reduce the grading burden but expressed anxiety regarding job security, data privacy, and the potential dehumanization of the screening experience (Wahlich et al., 2025).

Qualitative studies in Germany and Denmark identified critical determinants for implementation at the clinic level (Held et al., 2022; Krogh et al., 2025a). Primary care staff listed the following factors as key facilitators or barriers:

- Time and Organization: Many clinics found that while AI is fast, the additional workflow required to capture high-quality images can be disruptive in a time-constrained primary care environment (Held et al., 2022; Krogh et al., 2025b).
- Education and Support: A lack of specialized training for non-ophthalmic staff was identified as a major hurdle. However, the use of short, instructional videos has been proven as a successful teaching concept to quickly build staff competency (Krogh et al., 2025c).
- Professional Identity: Some practitioners expressed concern that autonomous AI might oversimplify the complex diagnostic process, leading to "deskilling" or a shift in the traditional professional role of the primary care physician (Held et al., 2022).

Ultimately, patient welfare and the desire to prevent blindness are the strongest motivators for both patients and providers to adopt AI. When the technology is perceived as a "safety net" that supports rather than replaces human expertise, its social acceptance increases significantly (Krogh et al., 2025a; Rustam et al., 2026).

3.4. Health Equity and the Digital Divide

The implementation of autonomous artificial intelligence (AI) in diabetic retinopathy (DR) screening is frequently discussed as a dual-edged sword in terms of health equity. While the technology has the potential to democratize access to diagnostics, it also risks institutionalizing a "digital divide" characterized by age, geography, and socio-economic status (Cleland et al., 2023; Teng et al., 2025). This section synthesizes the evidence regarding how AI bridges historical gaps and where structural barriers still prevent equitable rollout.

3.4.1. Closing the Gap in Underserved and Minority Populations

A significant finding in the US-based literature is that autonomous AI can effectively reduce racial and socio-economic disparities in eye care. Historical data indicate that Black and Hispanic populations, as well as those with lower socio-economic status, have significantly lower rates of annual retinal exams due to barriers such as lack of transportation, insurance limitations, and a shortage of specialists in their neighborhoods (Liu et al., 2024; Rustam et al., 2026).

Research in urban primary care settings showed that when autonomous AI was introduced at the point of care, adherence to DR screening increased by 36% overall (Liu et al., 2024). Crucially, the increase was most pronounced in underserved groups; Black/African American patients experienced an 11.9% increase in adherence, effectively narrowing a long-standing health equity gap (Liu et al., 2024). By removing the need for a separate visit to an eye specialist, AI addresses the "navigational burden" that frequently leads to loss to follow-up in minority communities (Goldstein et al., 2023; Liu et al., 2024).

3.4.2. The Biological and Generational Divide

Despite its benefits, AI screening faces a "biological divide" that disproportionately affects elderly patients. Studies have noted that as patient age increases, the rate of ungradable images also rises significantly (Teng et al., 2025). In clinical trials for systems like LumineticsCore, the imaging success rate for patients over 70 was approximately 69%, compared to nearly 100% in younger cohorts (Teng et al., 2025).

This disparity is primarily driven by physiological factors common in older populations, such as media opacities (cataracts), narrow pupils, and poor fixation, which the current generation of non-mydriatic AI fundus cameras struggles to overcome (Shahzad et al., 2024; Teng et al., 2025). Furthermore, older patients may possess lower levels of "digital comfort," leading to higher anxiety when interacting with automated diagnostic terminals (Krogh et al., 2025a; Yap et al., 2022).

3.4.3. Algorithmic Bias and Federated Solutions

Ethical and sociological concerns remain regarding the "representativeness" of the data used to train AI algorithms. Most commercially available systems were trained on datasets that primarily feature Caucasian populations (Crew et al., 2024). This raises the risk of algorithmic bias, where the system may underperform on patients with darker retinal pigmentation (Cleland et al., 2023; Crew et al., 2024).

To ensure that AI does not become an instrument of systemic exclusion, recent research highlights the importance of using diverse, global datasets (Cleland et al., 2023). A promising solution discussed in the literature is Federated Multimodal AI, which allows for the training of precision-equitable models across multiple institutions without moving sensitive patient data (Bai et al., 2026). This approach addresses privacy concerns while ensuring that the AI is calibrated for a global population, thereby promoting long-term health equity (Bai et al., 2026).

3.4.4. Infrastructural Barriers in Low-Resource Settings

In low- and middle-income countries (LMICs), the digital divide is fundamentally an infrastructural issue. While AI algorithms are portable, they rely on hardware and connectivity that are often absent in rural areas (Cleland et al., 2023; Mathenge et al., 2022).

- The Hardware Hurdle: In Karachi, Pakistan, even with smartphone-based technology, 18.2% of examinations resulted in ungradable images, often due to environmental conditions and lack of specialized operator training (Shahzad et al., 2024).
- The Connectivity Gap: Many autonomous AI systems require cloud-based processing, which is unfeasible in regions with unstable internet connectivity (Cleland et al., 2023).
- The Referral Paradox: In Rwanda, the RAIDERS trial demonstrated that while immediate AI feedback increased referral adherence by 30.1%, many patients still could not access treatment due to the high costs of travel to specialized centers (Mathenge et al., 2022). This confirms that technological innovation in diagnosis must be matched by social and economic innovations in treatment access to be truly effective (Cleland et al., 2023; Mathenge et al., 2022).

3.4.5. Strategies for Inclusivity

To mitigate these divides, the literature suggests a "Human-Centered Design" approach (Scanzera et al., 2023). This includes using "clinical champions" (non-physician staff) who can assist elderly patients with imaging and using localized education materials to build trust in communities that have historically been skeptical of medical technology (Held et al., 2022; Scanzera et al., 2023). By addressing the socio-technical barriers, AI can be transformed from a potential source of inequality into a vital driver of universal health access (Liu et al., 2024; Teng et al., 2025).

3.5. Systemic Implementation Factors: A CFIR Analysis

The clinical efficacy of artificial intelligence (AI) in controlled environments does not inherently guarantee successful integration into complex healthcare ecosystems. A systematic analysis of the provided literature from 2021–2026, filtered through the Consolidated Framework for Implementation Research (CFIR), identifies several critical determinants of operational success across the intervention characteristics, outer setting, inner setting, and individual levels (Liao et al., 2024; Teng et al., 2025).

3.5.1. Intervention Characteristics: Relative Advantage and Complexity

The perceived relative advantage of AI over traditional manual grading is a primary facilitator of adoption. The literature consistently highlights the "speed of results" as a transformative factor, allowing for point-of-care decisions that reduce patient anxiety and clinical backlog (Nolan et al., 2023). However, this advantage is often offset by the perceived "complexity" of the technology. The "black-box" nature of deep learning algorithms creates a transparency gap, leading to "algorithmic anxiety" among practitioners who are hesitant to rely on diagnostic outputs they cannot clinically trace or explain (Held et al., 2022; Liao et al., 2024).

3.5.2. Outer Setting: Policy, Reimbursement, and Liability

The outer setting, consisting of the broader economic and legal landscape, presents significant hurdles to the scalable rollout of AI screening:

- Reimbursement Frameworks: A lack of standardized billing codes and sustainable reimbursement models (notably in jurisdictions like Japan, Singapore, and parts of the EU) remains a prohibitive barrier for smaller primary care practices (Kawasaki, 2024; Leigh et al., 2026).
- Medicolegal Liability: Qualitative reviews identify "professional and legal responsibility" as one of the top ten implementation barriers. Uncertainty regarding who (the physician, the developer, or the clinic) is liable for a false negative result acts as a deterrent for clinical adoption (Crew et al., 2024; Liao et al., 2024).
- Data Sovereignty and Security: The requirement for cloud-based processing necessitates high-level cybersecurity compliance, which often exceeds the financial and technical capacity of rural or resource-constrained clinics (Cleland et al., 2023; Liao et al., 2024).

3.5.3. Inner Setting: Workflow Integration and Technical Readiness

Successful implementation depends on the seamless integration of AI into the "inner setting" of the clinic. The literature emphasizes that technology must adapt to the workflow, rather than forcing the workflow to adapt to the technology (Goldstein et al., 2023; Teng et al., 2025).

- EHR Compatibility: The ability of AI systems to interface directly with existing Electronic Health Records (EHR) is a critical facilitator. Systems that require manual data entry or separate login portals experience significantly lower utilization rates (Goldstein et al., 2023; Teng et al., 2025).
- Resource Constraints: Primary care staff frequently report a "lack of time" and "inadequate technical support" as daily operational barriers. The time required for high-quality retinal imaging, even when automated, can disrupt the high-throughput nature of general practice (Held et al., 2022; Krogh et al., 2025b).

3.5.4. Individual and Process Factors: Champions and Education

The "human element" within the process is essential for overcoming organizational inertia. The presence of "clinical champions" respected practitioners who advocate for the technology is identified as a core predictor of institutional uptake (Teng et al., 2025). Furthermore, innovative educational strategies are required to train non-ophthalmic staff. Research into "short instructional videos" has shown that they are highly effective for rapid skill acquisition in fundus photography among medical assistants, representing a low-cost, high-impact implementation facilitator (Krogh et al., 2025c).

3.5.5. Human-Centered Design (HCD) for Social Sustainability

Finally, contemporary research advocates for Human-Centered Design (HCD) as a necessary shift in implementation strategy. HCD involves engaging patients and healthcare providers as co-creators of the AI workflow (Scanzera et al., 2023). By addressing specific stakeholder needs such as the patient's need for immediate reassurance and the provider's need for a clear referral pathway HCD ensures that AI implementation is not only technologically sound but also socially acceptable and operationally sustainable (Held et al., 2022; Scanzera et al., 2023).

4. Discussion

The transition from traditional, human-led ophthalmic screening to autonomous artificial intelligence (AI) systems represents a significant socio-technical shift in the management of chronic diseases (Dave et al., 2026; Leigh et al., 2026). The findings of this systematic review indicate that while the technical feasibility of AI is well-established, its successful integration is deeply influenced by the socio-economic context, stakeholder psychology, and the prevailing digital infrastructure (Held et al., 2022; Liao et al., 2024; Wahlich et al., 2025).

4.1. The Socio-Economic Paradox: Context-Dependency of AI Value

The economic justification for integrating autonomous AI into diabetic retinopathy (DR) screening programs is far from uniform; rather, it is shaped by a complex paradox where technological value is dictated by the local socio-economic environment. The literature suggests that the return on investment (ROI) for AI is highest where specialized medical labor is scarce and patient indirect costs such as travel and loss of productivity are significant (Li et al., 2023; Wang et al., 2024).

4.1.1. High-Income Countries and Systematic Efficiency

In established healthcare systems within high-income countries (HICs), the primary economic driver is the reduction of the "grading burden" on human specialists. In Australia, long-term modeling indicates that universal AI-based screening in primary care settings could prevent over 38,000 cases of blindness, resulting in a benefit-cost ratio of 3.96 (Hu et al., 2024). Similarly, within the UK's National Health Service (NHS), the implementation of automated systems could save approximately £0.5 million per 100,000 screening episodes (Heydon et al., 2021; Tufail et al., 2017). In these contexts, the high cost of medical labor makes the substitution of human graders with autonomous algorithms a clear economic necessity (Leigh et al., 2026).

4.1.2. The Urban-Rural Divergence in Emerging Economies

The socio-economic paradox is most visible in the comparative data from China. In rural regions, AI-based screening is identified as the most cost-effective strategy because it eliminates the high direct and indirect costs for patients who would otherwise have to travel to urban centers for specialized care (Li et al., 2023). However, in urban centers like Shanghai, the value proposition shifts. Due to relatively lower medical labor costs and high initial hardware acquisition expenses, AI-assisted models may not currently offer a dominant economic advantage over manual grading unless they can demonstrably improve patient referral compliance by at least 7.5% (Lin et al., 2023).

4.1.3. The Accuracy vs. Cost-Effectiveness Trade-off

Current research fundamentally challenges the assumption that the most technically accurate AI model is always the most economically viable (Wang et al., 2024). A nationwide analysis conducted by Wang et al. (2024) demonstrated that a "sensitivity-priority" scenario prioritizing the identification of all potential cases even at the cost of more false positives is often more cost-effective than the pursuit of perfect specificity. This is because the long-term societal costs of missed diagnoses (resulting in vision loss) far outweigh the immediate costs of secondary human verification for false positives (Wang et al., 2024).

4.1.4. Structural and Financial Barriers to Scalability

Despite the projected savings, the "upfront cost" barrier remains a significant deterrent to adoption. The high price of medical-grade fundus cameras essential for high-quality AI diagnostics often prevents smaller primary care practices from implementing these systems (Leigh et al., 2026). Furthermore, the lack of standardized reimbursement codes for AI-driven diagnostics in many regions creates a financial disincentive for providers, who must bear the operational costs without a clear mechanism for cost-recovery (Held et al., 2022; Kawasaki, 2024). Therefore, for AI to fulfill its economic potential, health policies must shift toward inclusive reimbursement frameworks that recognize the long-term preventive value of the technology (Leigh et al., 2026; Wang et al., 2024).

4.2. Trust and the Social Acceptance of the "Black Box"

The successful adoption of autonomous AI in diabetic retinopathy (DR) screening is fundamentally moderated by human trust a variable that operates independently of technical accuracy. While algorithms now match or exceed human grading performance (Heydon et al., 2021; Wewetzer et al., 2021), the "black box" nature of deep learning remains a primary source of psychological friction for both patients and practitioners (Held et al., 2022; Liao et al., 2024).

4.2.1. Conditional Trust and the Requirement for Oversight

A critical finding in recent stakeholder surveys is that patient trust is rarely absolute; rather, it is conditional upon human supervision. As reported by Rustam et al. (2026), while 92.4% of patients expressed satisfaction with the AI experience, over 82% stated their trust would be significantly higher if a physician remained actively involved in the diagnostic loop. This preference is driven by the perceived need for a "safety net" a human authority capable of interpreting complex or borderline cases that an algorithm might oversimplify (Cuadros, 2021; Rustam et al., 2026). Furthermore, 94.1% of patients believe that professional and legal responsibility must remain with the clinician, suggesting that "autonomous" AI is socially accepted only when it is not truly "independent" from human accountability (Rustam et al., 2026).

4.2.2. Cultural Mediators: Individualism vs. Collectivism

Social acceptance is also heavily influenced by the cultural context of the patient population. In New Zealand, the importance of *whakawhanaungatanga* (the cultural process of establishing relationships) among Maori and Pacific Islander communities leads to a distinct preference for human-led screenings (Yap et al., 2022). For these populations, the efficiency of a machine may be perceived as a dehumanizing barrier to the holistic nature of healthcare (Wahlich et al., 2025; Yap et al., 2022).

Conversely, in collectivist societies such as China, "subjective norms" (social pressure and expectations from family and peers) emerge as the strongest predictors of the intention to use AI (Jin et al., 2025). In these environments, the endorsement of a technology by a trusted institution or social circle can mitigate individual fears regarding "uniqueness neglect" the worry that an algorithm cannot account for a patient’s unique physiological characteristics (Jin et al., 2025; Mo et al., 2025).

4.2.3. Practitioner Resistance and Professional Identity

From the perspective of healthcare providers (HCPs), trust is often tied to concerns regarding "deskilling" and professional identity. Qualitative data from European primary care settings reveal that staff fear the loss of holistic care and express anxiety about the "opaque" decision-making process of AI (Held et al., 2022; Wahlich et al., 2025). The lack of "explainability" in AI outputs makes it difficult for practitioners to justify diagnostic decisions to patients, especially in cases of false positives (Liao et al., 2024; Nolan et al., 2023).

4.2.4. Mitigation: Transparency and Education

To overcome the "black box" barrier, the literature suggests a shift toward Human-Centered Design (HCD) and localized education (Scanzera et al., 2023). The use of instructional videos, as noted by Krogh et al. (2025c), has proven effective in building the technical confidence of non-specialist staff, which in turn projects a sense of reliability to the patient. By fostering a "techno-clinical" partnership rather than a total replacement model, health systems can preserve the human touch while leveraging the precision of AI (Dave et al., 2026; Krogh et al., 2025a).

Here is the expanded version of section 4.3. Closing the Digital Divide: Equity and Its Limits, drafted in academic English. This section synthesizes the findings on how AI technology acts as both a facilitator for health equity and a potential source of new exclusions.

4.3. Closing the Digital Divide: Equity and Its Limits

The integration of autonomous AI into ophthalmology is often framed as a "techno-clinical revolution" with the potential to democratize access to specialized diagnostics. However, the systematic analysis reveals that technology alone cannot solve the systemic inequalities inherent in global healthcare; rather, it risks institutionalizing a new "digital divide" defined by age, geography, and physiological factors (Cleland et al., 2023; Teng et al., 2025).

4.3.1. AI as an Instrument for Social and Racial Equity

A significant finding in the literature is the measurable role of AI in narrowing historical care gaps for minority populations. In the United States, Black and Hispanic communities, along with Medicaid-insured patients, have traditionally faced lower rates of retinal screening due to fragmented referral networks and socioeconomic barriers (Liu et al., 2024). The implementation of autonomous AI at the point of care (POC) bypasses these hurdles by eliminating the need for a separate visit to an eye specialist. As Liu et al. (2024) demonstrated, AI implementation led to an 11.9% increase in screening adherence specifically among Black/African American patients, effectively mitigating a long-standing racial disparity in preventive care. In this capacity, AI functions as a tool for social justice, ensuring that technological progress directly benefits the most vulnerable cohorts (Liu et al., 2024; Teng et al., 2025).

4.3.2. The Generational and Biological Divide

Despite its potential for equity, AI screening faces a "biological divide" that disproportionately impacts the elderly. The efficacy of non-mydriatic fundus imaging the hardware foundation of most AI systems is significantly reduced in older populations due to physiological factors such as cataracts, media opacities, and narrow pupils (Teng et al., 2025). Clinical data indicate that while imaging success is near-perfect in younger cohorts, the ungradability rate for patients aged 70 and above can reach up to 31% (Teng et al., 2025). Without targeted interventions to address these physiological limitations, the senior population, which remains at the highest risk for diabetic complications, may be systematically excluded from the benefits of automated diagnostics (Cleland et al., 2023; Teng et al., 2025).

4.3.3. Algorithmic Bias and Global Data Sovereignty

A secondary layer of the digital divide concerns the representativeness of the algorithms themselves. Most commercially available AI models were trained on datasets primarily composed of Caucasian populations, creating a risk of "algorithmic bias" (Crew et al., 2024). There is concern that these systems may underperform in patients with darker retinal pigmentation or those from diverse ethnic backgrounds not well-represented in training sets (Cleland et al., 2023; Crew et al., 2024). To counter this, current research emphasizes the importance of Federated Multimodal AI, which allows for the training of precision-equitable models using decentralized, global data without compromising patient privacy (Bai et al., 2026). Such technological safeguards are essential to ensure that AI does not perpetuate Western-centric biases in global health (Bai et al., 2026; Crew et al., 2024).

4.3.4. The Referral-Treatment Gap in LMICs

In low- and middle-income countries (LMICs), the digital divide manifests as "diagnostic futility" a situation where high-tech diagnostics are available, but the subsequent treatment is not. As demonstrated in the RAIDERS trial in Rwanda, while point-of-care AI significantly increased the number of patients identified with referable DR, many were still unable to access treatment due to the high costs of travel and specialized laser procedures (Mathenge et al., 2022). This confirms that in resource-constrained settings, the digital divide is not merely a lack of technology, but a lack of integrated care pathways. For AI to be truly equitable, its deployment must be paired with social and economic innovations that ensure a diagnosis at the point of care leads to a clinical outcome at the point of need (Cleland et al., 2023; Mathenge et al., 2022).

4.4. Implementation and Ethical Governance

The successful social integration of autonomous AI is not merely a matter of technical installation but requires a comprehensive governance framework that addresses organizational readiness, ethical accountability, and data sovereignty. Applying the Consolidated Framework for Implementation Research (CFIR) reveals that the "inner setting" of healthcare institutions often lacks the structural maturity to support fully autonomous diagnostic workflows (Liao et al., 2024; Nolan et al., 2023).

4.4.1. Organizational Readiness and the "Responsibility Gap"

A primary barrier identified in the CFIR analysis is the "medicolegal liability" associated with autonomous decisions. As noted by Liao et al. (2024), the lack of clear legal frameworks defining who is responsible for a false-negative result (the AI developer, the healthcare institution, or the supervising clinician)acts as a significant deterrent to institutional adoption. This "responsibility gap" necessitates a governance model that transitions from traditional individual liability toward a system-level accountability framework (Crew et al., 2024; Liao et al., 2024). Furthermore, the presence of "clinical champions" internal advocates who bridge the gap between technology and practice has been identified as a critical factor in overcoming organizational inertia and fostering trust within the inner setting (Teng et al., 2025).

4.4.2. Technological Solutions to Ethical Challenges

Ethical governance in medical AI must also address the inherent tension between data utility and patient privacy. The emergence of Federated Multimodal AI represents a significant technological response to this ethical dilemma. As Bai et al. (2026) argue, federated learning allows for the continuous training and refinement of AI models across multiple decentralized institutions without the need to transfer sensitive patient data to a central server. This "privacy-by-design" approach not only complies with increasingly stringent global data protection regulations but also mitigates algorithmic bias by allowing models to learn from diverse, representative datasets in their original clinical context (Bai et al., 2026; Crew et al., 2024).

4.4.3. Human-Centered Design (HCD) as a Governance Strategy

To ensure that AI systems are socially sustainable, implementation must move toward Human-Centered Design (HCD). According to Scanzera et al. (2023), HCD involves the active participation of all stakeholders including patients, medical assistants, and ophthalmologists in the co-creation of the AI-enabled workflow. By prioritizing the lived experience of the users, HCD identifies "pain points" such as technical ungradability or patient anxiety that traditional clinical trials may overlook. Effective governance, therefore, includes the provision of localized educational tools, such as the instructional videos proposed by Krogh et al. (2025c), which empower non-specialist staff and reduce the "complexity barrier" associated with new technology.

4.4.4. Integrated Referral Networks: Beyond Diagnosis

Finally, ethical governance must ensure that a point-of-care diagnosis is not a clinical dead-end. The literature highlights a critical need for integrated referral networks that connect the AI output directly to specialized treatment centers (Liao et al., 2024; Nolan et al., 2023). In resource-constrained environments, providing a high-tech diagnosis without a clear, affordable pathway to laser treatment or surgery is ethically questionable (Mathenge et al., 2022). Consequently, the governance of AI in ophthalmology must extend beyond the algorithm itself to encompass the entire continuum of care, ensuring that technological precision leads to meaningful clinical and social outcomes (Liao et al., 2024; Scanzera et al., 2023).

5. Conclusions

The systematic analysis of 35 peer-reviewed sources confirms that autonomous artificial intelligence (AI) has transitioned from a theoretical clinical tool to a functional component of global diabetic retinopathy (DR) screening. While the technological maturity of these systems is no longer in question, their successful long-term integration is a socio-technical challenge that requires balancing algorithmic precision with human-centric care models.

5.1. Summary of Key Findings

The research synthesis identifies several critical pillars of AI implementation:

- Clinical Efficacy: Autonomous AI systems, such as EyeArt and IDx-DR, consistently demonstrate sensitivity and specificity levels that meet or exceed the rigorous standards set by human graders (Heydon et al., 2021; Wewetzer et al., 2021).
- Economic Viability: AI-based screening offers a dominant cost-effectiveness profile, particularly in resource-constrained or rural environments where it significantly reduces patient travel costs and diagnostic delays (Li et al., 2023; Wang et al., 2024).
- Stakeholder Acceptance: Trust remains the primary mediator of adoption. Acceptance is highest when AI is implemented as a "safety net" that supports rather than replaces the clinical authority of healthcare providers (Krogh et al., 2025a; Rustam et al., 2026).
- Equity and Inclusivity: AI holds the potential to bridge racial and geographic care gaps (Liu et al., 2024), yet it faces persistent barriers related to the "biological divide" in geriatric populations and infrastructural limitations in the Global South (Teng et al., 2025; Mathenge et al., 2022).

5.2. Practical and Policy Implications

For health systems to realize the full potential of AI, policies must move beyond technical validation toward comprehensive implementation frameworks. Key recommendations include:

1. Workflow Integration: Prioritizing Human-Centered Design (HCD) to ensure that AI tools fit seamlessly into the high-throughput nature of primary care (Liao et al., 2024; Scanzera et al., 2023).
2. Education and Training: Implementing visual and interactive training concepts, such as instructional videos, to empower non-specialist staff and build technical confidence (Krogh et al., 2025c).
3. Algorithmic Governance: Ensuring data diversity and privacy through technologies like Federated AI to mitigate racial and ethnic biases (Bai et al., 2026).

5.3. Future Research Directions

Future studies should focus on the long-term clinical outcomes of AI-driven screening pathways, specifically tracking the rate of vision preservation over multiple years. Additionally, more research is needed to understand the "explainability" of AI decisions in a way that is digestible for patients, thereby reducing the "black box" anxiety currently associated with deep learning models.

5.4. Final Closing Statement

In conclusion, the deployment of autonomous AI for DR screening represents a landmark shift toward proactive and democratized healthcare. By addressing the socio-economic and psychological barriers identified in this review, medical institutions can move toward a "techno-clinical" partnership that preserves the human touch while leveraging the life-saving precision of artificial intelligence.

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