REVIEW

The Columbia University
JOURNAL of
GLOBAL HEALTH

Artificial Intelligence Tools for Diabetic Retinopathy Screening in Low-Resource Environments: Review of Global Implementation and Challenges

Martena Grace[1], Amir A. Estil-las[2], Camelia Arsene, MD, PhD[3]

[1]Ross University School of Medicine, Miramar, Florida, USA
[2]Ross University School of Medicine, Miramar, Florida, USA
[3]Trinity Health Oakland, Pontiac, Michigan, USA

ABSTRACT Diabetic retinopathy (DR) remains a leading cause of preventable blindness worldwide, with the burden falling disproportionately on populations in low- and middle-income countries (LMICs), where access to timely screening is limited. Advances in artificial intelligence (AI) have enabled the development of automated DR screening tools with diagnostic accuracy comparable to expert graders, offering a promising solution to overcome the unique challenges LMICs face. This review examines the performance, global implementation and unique barriers of AI-based DR screening in low-resource environments, focusing on five leading systems: IDx-DR, EyeArt, Medios AI, Google's Automated Retinal Disease Assessment (ARDA) and Singapore Eye Lesion Analyzer Plus (SELENA+). Evidence shows these systems can increase detection rates, reduce referral delays and improve access to care. However, implementation faces significant challenges, including issues related to generalizability, infrastructure, regulation, and clinician and patient acceptance. Emerging strategies, such as federated learning, offline-capable devices, and more interpretable AI, may help overcome these barriers. Ultimately, AI-driven screening could play a critical role in reducing global vision loss from DR.

KEY WORDS Diabetic Retinopathy, AI-Screening, Artificial Intelligence

INTRODUCTION

Diabetic retinopathy (DR) is a leading cause of preventable blindness worldwide and disproportionately affects populations in low-resource settings. A meta-analysis performed by Teo et al. concluded that the global prevalence of DR was 22.27% with an estimated 103.12 million people affected in 2020.[1] That number is estimated to rise drastically in the coming decades due to the increasing prevalence of diabetes mellitus (DM).[2] DR is a progressive microvascular complication of DM that can lead to irreversible vision loss if not detected and treated early.

Despite its preventable nature, timely screening for DR remains severely limited in many low- and middle-income countries (LMICs). Early detection is paramount and strongly associated with better visual outcomes and quality

of life; however, adequate screening programs are limited and rarely feasible in resource-limited environments. Shortages of ophthalmologists, optometrists, retinal specialists and vision-care-related staff are particularly scarce in these regions. In sub-Saharan Africa, there are approximately 2.5 ophthalmologists per million people, compared with 76 per million in high-income countries.[3] Additionally, those who are able to assess and provide screening for DR are agglomerated in high-density urban centers, leaving rural populations underserved. Barriers such as transportation access, high travel costs and limited availability of reliable diagnostic equipment further delay diagnosis, leading to advanced disease at presentation and poorer prognosis.

Advances in artificial intelligence (AI) have created new opportunities to overcome these screening challenges. AI models trained on retinal fundus images have demonstrated diagnostic accuracy for DR comparable to expert graders.[4] These AI tools have the potential to be used by non-specialist healthcare workers, effectively expanding screening capacity in under-resourced areas. Notable examples include Google's Automated Retinal Disease Assessment (ARDA) and the now FDA-approved IDx-DR system.[5,6] Early results from these initiatives suggest that AI-assisted screening can substantially expand coverage, reduce delays in diagnosis and, ultimately, improve quality of life.

However, the implementation of AI for DR screening also faces unique challenges, including ensuring model generalizability across diverse populations, safeguarding data privacy and protection, complying with regulatory entities and establishing a secure and functional digital environment. Addressing these issues will require a multifaceted effort among governments, healthcare organizations, technology companies and local communities.

This review aims to explore the landscape of AI tools developed for DR screening and their performance in low-resource settings. Moreover, we aim to elucidate the potential AI models have for further implementation to overcome healthcare-gap-related challenges. We examine real-world applications, implementation strategies and reported outcomes from pilot programs. By synthesizing existing literature and case studies, this review seeks to inform future policy, explore clinical integration and elicit areas for further research needed to scale AI-driven DR screening in underserved populations.

LITERATURE REVIEW

Diabetic retinopathy screening

DR is a disease of the retina in patients with uncontrolled DM. In patients with DM, high levels of blood sugar can cause damage to the vessels of the retina. This occurs in two stages: first, in non-proliferative DR (NPDR), the retina begins to swell and small blood vessels leak fluid, blood and lipid deposits into the retina. This mechanism is responsible for the most common cause of vision loss; with enough time, the blood vessel leakage and swelling lead to macular ischemia, resulting in blindness. In the second and most advanced stage, proliferative DR (PDR), neovascularization occurs, in which new blood vessels form and grow sporadically in the retina. These new vessels may grow to eventually block all vision and potentially cause floaters and retinal detachment in addition to vision loss.[7] A study published in the Indian Journal of Ophthalmology predicts an increase in the number of people with DR from 126.6 million to 191.0 million and an increase in the number of individuals with vision-threatening DR (VTDR) from 37.3 million to 56.3 million between 2010 and 2030 if proper preventative action is not taken.[8]

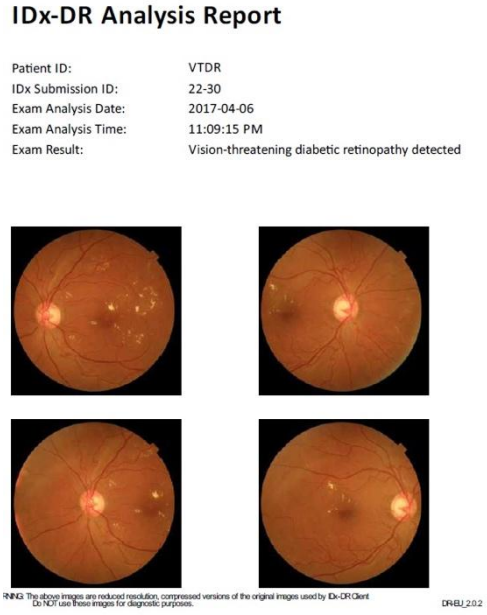
According to the American Diabetes Association as of 2025, adults with Type I DM should get a diabetic eye screening five years after initial diagnosis, while Type II DM should get a screening at the time of diagnosis. Additionally, both groups should have preventative comprehensive eye checks every one to two years. In the event that any degree of DR is detected, comprehensive eye exams visits should increase in frequency.[9] The gold standard screening for DR includes a dilated eye exam followed by slit lamp biomicroscopy to visualize the retina.[10,11] In low-resource areas where ophthalmologists and basic healthcare are scarce, screening is very limited, and DR does not get the preventative screening required. AI has enabled the identification of DR without the need for a specialist.

Most current AI systems for DR screening are based on convolutional neural networks (CNNs), a type of deep learning model designed to process and classify visual information. CNNs analyze the retinal fundus images by automatically learning and prioritizing important features, from simple edges and textures to complex pathological patterns including hemorrhages, microaneurysms and exudates. This framework allows the system to mimic certain aspects of the human visual recognition mechanism while maintaining high diagnostic accuracy, even in non-specialist settings.[12,13]

All five AI platforms reviewed in this paper—IDx-DR, EyeArt, MediosAI, Google's ARDA and Singapore Eye Lesion Analyzer Plus (SELENA+)—employ CNN-based frameworks. Despite the differences in each AI's training datasets, processing methods and deployment models, their shared CNN-based frameworks allow them to detect and grade DR lesions with improved accuracy.

IDx-DR is a fully automated AI software to test for and detect DR.[14] IDx-DR is currently FDA approved for DR and is used for screening in adults older than 22 with DM.[15] IDx-DR takes images of the retina and anterior chamber through a robotic non-mydriatic fundus camera called the Topcon TRC-NW400; within minutes, the software is able to detect if more than mild DR (mtmDR) is present (Figure 1).[15,16] According to a meta-analysis that included 13,233 patients, IDx-DR has a pooled sensitivity of 0.95 (95% CI: 0.82-0.99) and a pooled specificity of 0.91 (95% CI: 0.84-0.95), which is on par if not superior to the sensitivity and specificity of the gold standard screening method.[17] In addition to its robust sensitivity and specificity, IDx-DR is ideal for low-resource environments due to its relative affordability and accessibility. The robotic fundus camera, Topcon TRC-NW400, is an estimated one-time expense between $15,000 and $22,000, and patients are expected to pay $64.01 per eye evaluation.[15] Given IDx-DR's full automation, costs from payments to medical professionals are reduced. The limitations to this software include failure to successfully detect DR as well as the potential for overdiagnosis. In addition, diabetes often causes ocular problems other than retinopathy, which this software is unable to detect.[15] Still, in summary, IDx-DR is a very efficient tool to incorporate into low-resource settings to provide early detection, reduce vision loss and lessen healthcare costs.

FIGURE 1: Example of IDx-DR Analysis report Adapted from Healthvisors, 2018



EyeArt by Eyenuk is an FDA-approved AI tool for diagnosing DR, capable of detecting disease ranging from mild to vision-threatening stages. Similarly to IDx-DR, EyeArt uses an AI-powered software to analyze non-dilated images of the retina and automatically detects retinopathy within 60 seconds without human intervention.[18] EyeArt is able to utilize the same Topcon TRC-NW400 camera as IDx-DR but can also use other fundus cameras such as Canon CR-2 AF or CR-2 Plus AF.[18] This is highly advantageous, as the Canon CR-2 AF is portable and thus can be used in multiple primary care settings to lower patient travel burden in low-resource areas.[19] In a 2022 study conducted by Dr. Jennifer I. Lim, MD, Professor of Ophthalmology and Director of the Retina Service at the University of Illinois at Chicago, 521 participants underwent DR screening using EyeArt, a retina specialist exam and comprehensive ophthalmologist exam. Retina specialists had a sensitivity of 59.5%, correctly identifying 22 of 37 eyes as positive for retinopathy, and a specificity of 98.9%, correctly identifying 182 of 184 eyes as negative for mtmDR. The EyeArt AI system had a sensitivity of 97%, identifying 36 of 37 positive cases, and a specificity of 88%, correctly identifying 162 of 184 eyes as negative for mtmDR. General ophthalmologists had a sensitivity of 20.6%, correctly identifying 35 of 170 eyes as positive, and a specificity of

99.8%, correctly identifying 607 of 608 eyes as negative for mtmDR.[20] EyeArt has proven to be an effective and accessible solution in several healthcare scenarios.

Medios AI is an easy-to-use software reserved for severe referable DR. It is unique in that it is an AI that can be utilized completely offline. The Medios software is integrated into a smartphone-based nonmydriatic retinal imaging system (Figure 2).[21,22] After attaching the Remidio Fundus on Phone (FOP) camera to a smart phone, Medios captures two images: one is disc-centered and one is macula-centered.23 The AI software uses three neural networks in diagnosis—one to assess the quality of the images, prompting the user to retake images as needed, and two to detect DR lesions.[23] Using the FOP device, Rajalakshmi et al. (2018) conducted a pilot study evaluating the detection of DR and sight-threatening DR (STDR) by Medios in 296 patients against ophthalmologists' grading. The results were extremely promising: "DR was detected by the ophthalmologists in 191 (64.5%) and by the AI software in 203 (68.6%) patients while STDR was detected in 112 (37.8%) and 146 (49.3%) patients, respectively. The AI software showed 95.8% (95% CI 92.9-98.7) sensitivity and 80.2% (95% CI 72.6-87.8) specificity for detecting any DR and 99.1% (95% CI 95.1-99.9) sensitivity and 80.4% (95% CI 73.9-85.9) specificity in detecting STD."[24] For an offline AI that is portable and accessible, Medios can provide vision-saving detection in areas where an ophthalmologist is not accessible.

FIGURE 2: Medios AI user process, adapted from Negiloni et al., 2024

Google's ARDA system is a deep learning system validated and extensively tested for use in DR detection. In collaboration with Dr. Paisan Ruamviboonsuk, a retina specialist in India, ARDA was designed to identify referable DR and vision-threatening DR using standard non-mydriatic fundus photographs, without requiring specialist interpretation. The ARDA model was developed using a dataset of 128,175 retinal images obtained from clinical sites in the United States and India, each independently evaluated and graded by 54 licensed ophthalmologists or senior ophthalmology residents to identify pathologies such as microaneurysms and hemorrhages.[25] In a recent 2025 cohort study in India by Dr. Brant, 4,537 adjudicated images from >600,000 screenings across 45 Aravind centers were tested with ARDA, achieving 97.0% sensitivity and 96.4% specificity for severe non-proliferative DR (NPDR) and proliferative DR (PDR), with 95.9% sensitivity for sight-threatening DR. Impressively, it indicated an ophthalmology referral for 100% of patients with severe NPDR and PDR.5

SELENA+ is another deep learning AI system, developed by the Singapore National Eye Centre and Singapore Eye Research Institute, that can detect referable DR from non-mydriatic retinal fundus images. Additionally, SELENA + is capable of detecting glaucoma and age-related macular degeneration (AMD).[26] This system was trained extensively from datasets of about 500,000 retinal images, originating from multi-ethnic populations across various countries, to detect pathological features such as microaneurysms, hemorrhages, exudates and abnormal optic disc parameters. SELENA+ has demonstrated an ability to match or surpass human graders in detecting retinal abnormalities.[27] In a prospective pilot conducted by the Singapore Integrated DR Program (2024), SELENA+ was tested on 1,712 patients from multiple primary care clinics. It demonstrated a sensitivity

of 94.7% (95% CI: 88.0–98.3%) and a specificity of 82.2% for referable DR, closely approaching the benchmark performance of human graders, who showed sensitivities and specificities of 98.9% and 97.2%, respectively.[28] Additionally, SELENA+ achieved 90.5% sensitivity and 91.6% specificity for its detection of Diabetic Macular Edema (DME), which is often an early complication of DR.[29]

In Zambia, the availability of ophthalmologists is especially scarce. There are approximately three specialists per one million people in Zambia, compared to roughly 80 specialists per million people in high-income countries.[30] This severe shortage increases the risk of delayed DR detection and treatment, often resulting in irreversible vision loss. SELENA+ has been successfully evaluated as a practical DR-screening AI in Zambia, offering an effective approach to reducing DR-related blindness despite limited specialist resources. Its adaptability across diverse healthcare systems highlights its value, and ongoing initiatives aim to expand its capabilities while ensuring safe and effective implementation.

Beyond its current role in detecting DR and other eye pathologies, SELENA+ is being developed to extend its analysis to additional conditions. Ongoing research is investigating whether retinal imaging biomarkers can be used to estimate cardiovascular risk.[27] Subtle changes in retinal blood vessel structure may indicate early signs of systemic vascular disease. If these findings are validated, SELENA+ may have the capability to function not only as a highly specialized ophthalmic screening tool but also as part of a wider strategy for chronic disease prevention and management.[27]

To facilitate direct comparison between the AI systems reviewed, Table 1 summarizes their key properties, including sensitivity and specificity, deployment status, low-resource suitability, speed of results, upgradable detection and AI model type.

Having outlined the core AI systems used for DR screening, we now turn to their real-world deployment. Multiple countries have integrated these tools into screening programs, offering valuable insights into their implementation and feasibility.

TABLE 1: Comparison chart of the Diabetic Retinopathy AI software Image Credit : Martena Grace, Amir Estil-las

Tool	Developer	Input Modality	Sensitivity (rDR)	Specificity (rDR)	Regulatory Status / Deployment	Low-Resource Suitability	Speed of Results	Upgradable Image Detection	AI Model Type
IDx-DR	Digital Diagnostics	Non-mydriatic fundus camera	87%	90.7%	FDA-approved (2018) autonomous DR screening	Moderate (requires specific camera, cloud connectivity)	Immediate (cloud-based)	Limited	Proprietary deep learning
EyeArt	Eyenuk Inc.	Fundus camera (2-field)	97%	88%	FDA-cleared (2020), CE marked	High (fast, point-of-care; minimal training)	Immediate (automated)	Yes (cloud updates)	Deep learning
Medios AI	Remidio Innovative Solutions (Fundus-on-Phone)	Smartphone-based fundus camera	96%	80.2%	CDSCO-approved (India), CE marked; offline operation	Very high (portable, offline analysis; low training needed)	Instant (offline processing)	No (offline)	Ensemble of DL models
Google ARDA	Google Health / Verily	Non-mydriatic fundus camera	97%	96.4%	CE mark; deployed in India & Thailand (600K+ screenings)	High (edge/cloud support; integrates into primary care)	Seconds (edge/cloud hybrid)	Yes (frequent updates)	CNN-based deep learning
SELENA+	SNEC / SERI / EyRIS	Standard fundus photographs	94.7%	82.2%	Integrated in Singapore's national DR program (SiDRP)	High (non-mydriatic, local processing; multi-site use)	Fast (point-of-care)	Yes (hospital-linked upgrades)	Hybrid deep learning

GLOBAL IMPLEMENTATION

United States

In 2018, the FDA granted authorization to IDx-DR, the first autonomous AI system cleared for DR screening in primary care offices.[31] The pivotal trial for IDx-DR demonstrated a sensitivity greater than 87% and a specificity of 90%.[32] Van der Heijden et al. (2018) tested the accuracy of IDx-DR in the Hoorn Diabetes Care System and reported sensitivity and specificity similar to the original trials.[33] Due to its success and routine usage, Centers for Medicare & Medicaid Services (CMS) established a unique Current Procedural Terminology (CPT) code for AI usage in 2019.[34] Alongside IDx-DR, EyeArt and AEYE-DS are similar systems employed to screen for DR, and they are all FDA approved and widely utilized in ophthalmology and endocrinology clinics in the United States.[35]

Singapore

In 2019, the Health Sciences Authorities of Singapore approved the Singapore Eye Lesion Analyser (SELENA+) AI platform for autonomous detection of DR, glaucoma suspects and early AMD.[25,26] Historically, Singapore utilized the Singapore Integrated Diabetic Retinopathy Program (SiDRP), a tele-ophthalmology platform that captured eye images from multiple centers and processed them in a central location, setting the stage for autonomous AI tools like SELENA+.[36] During the first year of development, SELENA+ processed 38,215 retinal photographs across six public polyclinics with accuracy similar to expert readers. The system has since been implemented nationally within the SiDRP, which screens over 100,000 patients annually, and is projected to reduce grading workload by approximately 50%.[25,36,37]

India

Aravind Eye Care System is a renowned eye-care network in India, marked by its extensive use of routine tele-ophthalmology.[38] Aravind partnered with Google/Verily to integrate the ARDA algorithm directly into its vision-care network, progressing from a pilot study to routine day-to-day clinical use.[5] Between 2019 and 2023, ARDA screened about 600,000 patients across 45 sites.[5] Images are taken at remote vision centers and uploaded via secure VPN to Aravind's reading hubs. Severe cases are triaged by ARDA so that sight-threatening disease can be rapidly assessed and managed, while less-threatening diseases can be followed up by routine care.[5,39,40] This workflow model demonstrates the crucial role AI can play in reducing the care gap in ophthalmology. It dramatically shortens the bench-to-bedside gap for patients, increases access to routine ophthalmologic screening and decreases the risk of vision loss from potentially urgent ophthalmic pathologies.

AI utilization in low-resource settings

Low-resource environments entail unique implementation challenges that higher-income countries have either already addressed or have not had to consider. The specifics of these limiting factors will be discussed in the following section, but several AI models have already demonstrated success by overcoming infrastructure connectivity and workforce constraints. Adapting these workflow frameworks to the needs of specific regions can significantly reduce the global burden of preventable ophthalmologic disease, extending high-quality screening at volumes that exceed human capacity.

One proven approach is the offline or edge-computing model, in which AI analysis occurs on portable devices without the need for an internet connection. Medios AI, together with the FOP device, exemplifies this strategy. Its smartphone-mounted fundus camera enables point-of-care screening—diagnostic testing performed directly at the patient's location—in rural settings, achieving a 95.8% sensitivity for any DR and 99.1% sensitivity for vision-threatening cases.[24] This portability allows screening to be brought directly to underserved communities, bypassing the need for patients to travel to centralized clinics.

For settings with intermittent or unreliable internet connectivity, hybrid models can maximize coverage. EyeArt, for example, can function locally for image capture and initial assessment using cameras such as the Topcon TRC-NW400 or portable cameras like the Canon CR-2AF, uploading data to cloud-based servers when connectivity is available. This approach reduces dependence on continuous internet access while enabling centralized quality control and analysis and long-term data storage.

In regions where resources allow clinic-based implementation, systems such as IDx-DR and SELENA+ have proven to be reliable and effective. IDx-DR can seamlessly integrate into existing primary care settings to provide immediate DR detection without specialist analysis. SELENA+, deployed nationally in Singapore's Integrated Diabetic Retinopathy Program, allows for processing of large volumes of non-mydriatic fundus images across various clinics. This framework greatly reduces grading workload without sacrificing high diagnostic accuracy.
Google ARDA exemplifies the value of large-scale integration into existing tele-ophthalmology networks. In India, ARDA has screened over 600,000 patients across 45 Aravind Eye Care System sites, allowing for the successful triage of sight-threatening DR for urgent referral and routine follow-up for non-critical cases. This model illustrates how AI can be embedded within national screening programs to expand coverage and prioritize high-risk patients.

Beyond deployment logistics, explainability and trust are critical for successful adoption into clinical practice. Incorporating visual overlays, such as lesion heatmaps highlighting microaneurysms and hemorrhages, can help healthcare providers interpret AI analyses and foster clinician confidence. Equally important to the analysis is data privacy. Many low-resource settings face both regulatory and cultural barriers when transferring patient

images across regions or to servers. Federated learning offers a sustainable solution: instead of sharing patient images, each clinic or testing site trains a local copy of the AI model on its own data. Only model parameters, instead of the images themselves, are combined into a central model. This process protects patient privacy and complies with common data protection laws like HIPAA and GDPR, all while having the added benefit of training the AI continuously by learning from diverse populations, including under-represented groups in rural or LMIC settings. For DR screening, this means the model can adapt to local imaging devices, lighting conditions, and population-specific disease presentations without risking sensitive patient health data.

In summary, DR-specific AI tools can be effectively adapted to a variety of low-resource environments. Offline devices like Medios AI excel in rural outreach, hybrid systems like EyeArt address the challenges of intermittent and unreliable internet connectivity, clinic-integrated solutions like IDx-DR and SELENA+ streamline high-volume screening and large-scale deployments like Google ARDA show the potential for nationwide coverage. When combined with local community engagement, effective education, transparent communication, federated learning frameworks and sustainable financing, these systems have the potential to dramatically reduce the burden of vision loss from DR in underserved populations.

Challenges to the implementation of AI

Although AI-based systems for DR screening have demonstrated impressive diagnostic accuracy and the potential to transform screening access in low-resource settings, several challenges continue to limit their widespread adoption. Another challenge is ensuring that AI models trained predominantly on datasets from high-income countries perform reliably in low-resource settings, where differences in retinal pigmentation, comorbidities, image quality and device types may reduce generalizability. Differences in lighting, operator skill and resolution introduce statistical noise that reduces diagnostic accuracy, particularly for early disease detection. Without continuous training on locally acquired images, AI performance may degrade over time.

Navigating regulatory approval is another significant hurdle. In the United States, the FDA has established a framework that medical devices must comply with prior to their implementation in routine care. Software as a Medical Device (SaMD) is defined by the International Medical Device Regulators Forum (IMDRF) as "software intended to be used for one or more medical purposes that perform these purposes without being part of a hardware medical device."[41] The SaMD framework ensures that medical devices, including AI, are safe, efficacious and beneficial. However, this process alone is costly and may delay implementation until all testing is complete. European countries employ similar standards by marking healthcare products as "European CE," which certifies that a healthcare product has met EU health, safety and environmental requirements, ensuring the safety of consumers.[42] Even after clearance by regulatory committees, AI tools face uncertainty regarding reimbursement. The healthcare environment is still in its early stages of implementing AI-assistance, and there are very limited Current Procedural Terminology (CPT) codes used for billing in the setting of AI. Moreover, regulators and healthcare providers will have evolving post-market requirements that call for ongoing performance monitoring and training regimens, creating a necessary long-term financial burden. Solutions to these unique hurdles include collaborative multidisciplinary pilot programs involving government bodies, hospital systems, healthcare committees and clinicians. These programs can carefully analyze the effectiveness of particular AI systems for their region's needs.

As mentioned previously, image quality is a key factor that introduces noise to AI analysis. Reliable technology and hardware may be needed for some of the AIs to properly function, which imposes a significant upfront financial burden. Additionally, if the AI is based on analyzing images, there needs to be an adequate location for safe storage and reliable recall of data. Some of the current storage solutions include cloud-based storage, in which adequate bandwidth and resources for maintenance are necessary—this is especially difficult in remote regions of the world and low-resource settings. Physical storage solutions are also an option but are costly and must comply with regulatory committees to ensure protection of sensitive patient data.

Despite their benefit in screening for ophthalmological pathologies, for AIs to be welcomed by eye-care professionals, they must not be burdensome to implement in current healthcare systems. Adding another user interface to which users must adapt may require additional training and costs. AI systems often provide statistics like sensitivity, specificity and confidence intervals. Users will have to be trained on specific cut-off values to make a diagnosis, and unintentional disagreement may be created if thresholds are not clearly defined. Furthermore, clear imaging protocols may not always be followed by every user, introducing distortions into data analysis. Ensuring that AI systems are as autonomous and as simple as possible will most likely lead to high rates

of acceptance and utilization among healthcare providers.

Assuming eye-care providers adopt AI systems for screening, patients must also feel comfortable with AI assisting in or even making diagnostic recommendations. Transparent communication between patient and provider is necessary to avoid confusion, and conversations about AI's efficacy must happen. Partnering with community representatives and even advocacy groups may help optimize deployment strategies that respect the local cultural and privacy standards.

Although the obstacles to adopting AI in ophthalmologic screening are substantial, each obstacle also points towards a concrete mitigation strategy. Multi-center data centers and continuous-learning frameworks can frequently update the AI's accuracy and reliability while maintaining patient privacy. Early collaboration with regulators and investors via pilot programs will be able to generate the real-world safety, efficacy and health-economic evidence needed to streamline the approval and reimbursement of screening AI. Product bundles including hardware and software packages can bridge the connectivity gap present in low-resource settings. AI user interfaces must be created with the users in mind as a clinician-centered design and targeted training initiatives will permit smoother integration and less disruption in healthcare. Open conversations must be held in the rapidly changing field of healthcare, with patients and providers, to ensure appropriate respect and trust.idx

FUTURE PERSPECTIVES

As AI tools for DR screening continue to evolve, future efforts will likely focus on enhancing adaptability and permitting algorithms to maintain consistent and reliable performance across varied imaging devices, patient populations and clinical environments. Approaches like federated learning and feedback-based model updates offer pathways for continuous improvement with minimal added costs to already existing systems.

Improving the usability and ease of interpretation of AI systems will also be a crucial area of growth. Simplified interfaces, clearer diagnostic output and better integration into existing clinical workflows may help reduce training barriers and increase acceptance among all users throughout the healthcare field. These improvements are particularly important in low-resource and LMIC settings, where demand for ophthalmologic care far exceeds personnel capacity.

Additionally, long-term sustainability will require coordinated development of supportive infrastructure and reimbursement mechanisms. Continuous evaluation in real-world environments, including cost-effectiveness analyses and implementation studies, will help determine which models are most feasible for scalable deployment. With sustained collaboration between health systems, policymakers, and AI developers, AI-assisted DR screening can transition from pilot projects to reliable, routine tools of global eye-care.

CONCLUSION

AI has emerged as a transformative tool for DR screening, particularly in low-resource settings where shortages of trained vision-care personnel and limited access to diagnostic infrastructure hinder timely detection. AI systems including IDx-DR, EyeArt, Medios AI, Google ARDA, and SELENA+ have demonstrated diagnostic performance comparable, and in some cases superior to, expert human graders. Their integration into diverse healthcare environments, from rural outreach programs to national screening networks, highlights their potential to close the screening gap in underserved populations.

Realizing the full potential of these AI systems requires overcoming significant and unique challenges, including ensuring model generalizability, complying with regulatory requirements, addressing connectivity and infrastructure limitations, developing sustainable funding mechanisms and building trust among healthcare providers and patients. Emerging approaches like federated learning, offline deployment and insightful AI interfaces offer promising solutions to many of these barriers.

Multidisciplinary collaboration among governing bodies, healthcare systems, technology developers and local communities are required for successful implementation. Policies that support equitable access, investment in infrastructure, AI integration into preexisting systems and ongoing evaluation of clinical and economic impact will be essential. By addressing these barriers proactively, AI-driven DR screening can move beyond pilot programs to become a sustainable and essential part of global eye health.

Ultimately, the successful deployment of AI for DR screening has the potential to dramatically reduce preventable

blindness, improve quality of life and extend the reach of preventive healthcare services to millions of people worldwide who would otherwise remain unscreened.

REFERENCES

1. Teo, Z. L., Tham, Y.-C., Yu, M., Chee, M. L., Rim, T. H., Cheung, N., et al. (2021). Global prevalence of diabetic retinopathy and projection of burden through 2045: Systematic review and meta-analysis. Ophthalmology, 128, 1580–1591. https://doi.org/10.1016/j.ophtha.2021.04.027
2. Eisma, J. H., Dulle, J. E., & Fort, P. E. (2015). Current knowledge on diabetic retinopathy from human donor tissues. World Journal of Diabetes, 6(2), 312–320. https://doi.org/10.4239/wjd.v6.i2.312
3. 3. ESCRS. (2025, July 13). A force for good in global eye care. https://www.escrs.org/eurotimes-articles/a-force-for-good-in-global-eye-care/
4. Alqahtani, A. S., Alshareef, W. M., Aljadani, H. T., Hawsawi, W. O., & Shaheen, M. H. (2025). The efficacy of artificial intelligence in diabetic retinopathy screening: A systematic review and meta-analysis. International Journal of Retina and Vitreous, 11, 48. https://doi.org/10.1186/s40942-025-00670-9
5. Brant, A., Singh, P., Yin, X., Yang, L., Nayar, J., Jeji, D., et al. (2025). Performance of a deep learning diabetic retinopathy algorithm in India. JAMA Network Open, 8, e250984. https://doi.org/10.1001/jamanetworkopen.2025.0984
6. Google. (2024, October 17). How AI is making eyesight-saving care more accessible in resource-constrained settings. https://blog.google/around-the-globe/google-asia/arda-diabetic-retinopathy-india-thailand/
7. American Academy of Ophthalmology. (2024, October 11). Diabetic retinopathy: Causes, symptoms, treatment. https://www.aao.org/eye-health/diseases/what-is-diabetic-retinopathy
8. Zheng, Y., He, M., & Congdon, N. (2012). The worldwide epidemic of diabetic retinopathy. Indian Journal of Ophthalmology, 60, 428–431. https://doi.org/10.4103/0301-4738.100542
9. American Diabetes Association Professional Practice Committee. (2023). 12. Retinopathy, neuropathy, and foot care: Standards of care in diabetes—2024. Diabetes Care, 47(Suppl. 1), S231–S243. https://doi.org/10.2337/dc24-S012
10. vmc. (2011, July 4). Diabetes symptoms: Non-proliferative retinopathy information. Healthengine Blog. https://healthinfo.healthengine.com.au/diabetic-eye-disease-non-proliferative-diabetic-retinopathy
11. National Eye Institute. (2025, July 19). Get a dilated eye exam. https://www.nei.nih.gov/learn-about-eye-health/healthy-vision/get-dilated-eye-exam
12. Abràmoff, M. D., Lavin, P. T., Birch, M., Shah, N., & Folk, J. C. (2018). Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. npj Digital Medicine, 1, 39. https://doi.org/10.1038/s41746-018-0040-6
13. Alyoubi, W. L., Abulkhair, M. F., & Shalash, W. M. (2021). Diabetic retinopathy fundus image classification and lesions localization system using deep learning. Sensors, 21, 3704. https://doi.org/10.3390/s21113704
14. Docwire News. (2025, July 20). IDx-DR, the first FDA-approved AI system, is growing rapidly. https://www.docwirenews.com/post/idx-dr-the-first-fda-approved-ai-system-is-growing-rapidly
15. Savoy, M. (2020). IDx-DR for diabetic retinopathy screening. American Family Physician, 101, 307–308.
16. Healthvisors. (2025, August 13). IDx-DR. https://www.healthvisors.com/en/idx-dr/
17. Khan, Z., Gaidhane, A. M., Singh, M., Ganesan, S., Kaur, M., Sharma, G. C., et al. (2025). Diagnostic accuracy of IDx-DR for detecting diabetic retinopathy: A systematic review and meta-analysis. American Journal of Ophthalmology, 273, 192–204. https://doi.org/10.1016/j.ajo.2025.02.022
18. Eyenuk, Inc. (2020, April 14). EyeArt. https://www.eyenuk.com/us-en/products/eyeart/
19. Canon Medical Systems USA. (2025, July 20). CR-2 AF digital non-mydriatic retinal camera. https://us.medical.canon/products/eye-care/cr-2-af/
20. Lim, J. I., Regillo, C. D., Sadda, S. R., Ipp, E., Bhaskaranand, M., Ramachandra, C., et al. (2023). Artificial intelligence detection of diabetic retinopathy: Subgroup comparison of the EyeArt system with ophthalmologists' dilated examinations. Ophthalmology Science, 3. https://doi.org/10.1016/j.xops.2022.100228
21. Natarajan, S., Jain, A., Krishnan, R., Rogye, A., & Sivaprasad, S. (2019). Diagnostic accuracy of community-based diabetic retinopathy screening with an offline artificial intelligence system on a smartphone. JAMA Ophthalmology, 137, 1182–1188. https://doi.org/10.1001/jamaophthalmol.2019.2923
22. Negiloni, K., Rao, D. P., Savoy, F. M., & Sivaraman, A. (2025). Enhancing comprehensive diabetic care: A smartphone fundus camera with an offline AI-powered diabetic retinopathy screening solution for physicians. International Journal of Diabetes in Developing Countries, 45, 736–738. https://doi.org/10.1007/s13410-024-01393-7
23. Sosale, B., Aravind, S. R., Murthy, H., Narayana, S., Sharma, U., Gowda, S. G. V., et al. (2020). Simple, mobile-based artificial intelligence algorithm in the detection of diabetic retinopathy (SMART) study. BMJ Open Diabetes Research & Care, 8, e000892. https://doi.org/10.1136/bmjdrc-2019-000892
24. Rajalakshmi, R., Subashini, R., Anjana, R. M., & Mohan, V. (2018). Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. Eye, 32, 1138–1144. https://doi.org/10.1038/s41433-018-0064-9
25. Ong, S. S., & Varghese, J. S. (2025). Closing gaps in diabetic retinopathy screening in India using a deep learning system. JAMA Network Open, 8, e250991. https://doi.org/10.1001/jamanetworkopen.2025.0991
26. Synapxe. (2025, July 22). SELENA+. https://www.synapxe.sg/healthtech/health-ai/selena
27. Khoo, N. (2024, September 19). Beyond what meets the eye: How SELENA+ is revolutionizing the detection of eye diseases. https://itif.org/publications/2024/09/19/beyond-what-meets-the-eye-how-selena-is-revolutionizing-the-detection-of-eye-diseases/
28. Gunasekeran, D. V., Miller, S., Hsu, W., Lee, M. L., Wong, H. T., Lee, M. T., et al. (2024). National use of artificial intelligence for eye screening in Singapore. NEJM AI, 1, AIcs2400404. https://doi.org/10.1056/AIcs2400404
29. Ting, D. S. W., Cheung, C. Y.-L., Lim, G., Tan, G. S. W., Quang, N. D., Gan, A., et al. (2017). Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. JAMA, 318, 2211–2223. https://doi.org/10.1001/jama.2017.18152
30. Wong, D. C. S., Kiew, G., Jeon, S., & Ting, D. (2021). Singapore Eye Lesions Analyzer (SELENA): The deep learning system for retinal diseases. In Artificial intelligence in ophthalmology (pp. 177–185). Springer. https://doi.org/10.1007/978-3-030-78601-4_13
31. Niederhauser, O. (2019, November 12). LumineticsCore® (formerly known as IDx-DR), the first FDA-approved AI system, is growing rapidly. Digital Diagnostics. https://www.digitaldiagnostics.com/lumineticscore-formerly-known-as-idx-dr-the-first-fda-approved-ai-system-is-growing-rapidly/
32. U.S. Food & Drug Administration. De Novo Summary 180001. https://www.accessdata.fda.gov/cdrh_docs/reviews/DEN180001.pdf
33. van der Heijden, A. A., Abràmoff, M. D., Verbraak, F., van Hecke, M. V., Liem, A., & Nijpels, G. (2018). Validation of automated screening for referable diabetic retinopathy with the IDx-DR device in the Hoorn Diabetes Care System. Acta Ophthalmologica, 96, 63–68. https://doi.org/10.1111/aos.13613
34. American Academy of Ophthalmology. (2019, March 18). CPT code for new technology IDx-DR. https://www.aao.org/practice-management/news-detail/cpt-code-new-technology-idx-dr
35. Athenaeum Publications. (2023). Artificial intelligence systems for diabetic retinopathy screening: Appraisal on the 3rd US FDA-approved algorithms — AEYE-DS. https://athenaeumpub.com/artificial-intelligence-systems-for-diabetic-retinopathy-screening-

appraisal-on-the-3rd-us-fda-approved-algorithms-aeye-ds-2/
36. Ta, A. W. A., Goh, H. L., Ang, C., Koh, L. Y., Poon, K., & Miller, S. M. (2022). Two Singapore public healthcare AI applications for national screening programs and other examples. Health Care Science, 1, 41–57. https://doi.org/10.1002/hcs2.10
37. Ministry of Health. (2025, July 22). Efficacy of the SELENA+ system. https://www.moh.gov.sg/newsroom/efficacy-of-the-selena-system/
38. Aravind Eye Care System. (2025, July 23). Home — Aravind Eye Care System. https://aravind.org/
39. Li, J.-P. O., Liu, H., Ting, D. S. J., Jeon, S., Chan, R. V. P., Kim, J. E., et al. (2021). Digital technology, tele-medicine and artificial intelligence in ophthalmology: A global perspective. Progress in Retinal and Eye Research, 82, 100900. https://doi.org/10.1016/j.preteyeres.2020.100900
40. Aravind Eye Care System. Aravind telemedicine manual. https://www.v2020eresource.org/content/files/Aravindtele.pdf
41. U.S. Food & Drug Administration. (2022, July 21). Global approach to software as a medical device. https://www.fda.gov/medical-devices/software-medical-device-samd/global-approach-software-medical-device
42. European Commission. (2025, August 1). CE marking. https://single-market-economy.ec.europa.eu/single-market/goods/ce-marking_en