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Original Research Article

Artificial Intelligence and Precision Medicine in the Early Detection of Ocular Diseases

Inteligencia artificial y medicina de precisión en la detección temprana de enfermedades oculares

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ABSTRACT

Ocular diseases such as diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) remain leading causes of preventable blindness worldwide. Early detection is critical, yet access to timely ophthalmologic evaluation is limited in many regions. This study evaluated the diagnostic accuracy and healthcare impact of artificial intelligence (AI) models, alone and combined with clinical and genomic data, across diverse Latin American populations. A total of 6,500 adults from Mexico, Colombia, and Ecuador underwent fundus photography, optical coherence tomography (OCT), and polygenic risk score (PRS) analysis, with data analyzed using convolutional neural networks and transformer architectures. The results showed that AI achieved strong diagnostic performance (AUC: DR 0.94, glaucoma 0.92, AMD 0.90), with improvements when clinical and genomic data were integrated (AUC up to 0.96 for DR and 0.95 for glaucoma). Subgroup analyses confirmed robustness across age and sex, although performance was lower in low socioeconomic groups. AI-assisted referral pathways reduced waiting times from 45 to 27 days, and performance was consistent across Mexico, Colombia, and Ecuador, with minor variations reflecting healthcare infrastructure. These findings demonstrate that AI combined with precision medicine can significantly improve early detection, enhance referral efficiency, and support equitable multinational deployment, reinforcing its potential as a transformative tool to reduce preventable blindness.

keywords: artificial intelligence; precision medicine; diabetic retinopathy; glaucoma; age-related macular degeneration; early detection

RESUMEN

Las enfermedades oculares como la retinopatía diabética (RD), el glaucoma y la degeneración macular relacionada con la edad (DMRE) continúan siendo causas principales de ceguera prevenible en el mundo. La detección temprana es fundamental, aunque el acceso a evaluaciones oftalmológicas oportunas sigue siendo limitado en muchas regiones. Este estudio evaluó la precisión diagnóstica y el impacto en salud de modelos de inteligencia artificial (IA), solos y en combinación con datos clínicos y genómicos, en poblaciones latinoamericanas diversas. Un total de 6,500 adultos de México, Colombia y Ecuador fueron evaluados mediante fotografía de fondo de ojo, tomografía de coherencia óptica (OCT) y análisis de puntaje de riesgo poligénico (PRS), con datos analizados mediante redes neuronales convolucionales y arquitecturas tipo transformer. Los resultados mostraron que la IA alcanzó un alto desempeño diagnóstico (AUC: RD 0.94, glaucoma 0.92, DMRE 0.90), con mejoras al integrar datos clínicos y genómicos (AUC hasta 0.96 para RD y 0.95 para glaucoma). El análisis por subgrupos confirmó robustez en edad y sexo, aunque con menor rendimiento en grupos de bajo nivel socioeconómico. Las rutas asistidas por IA redujeron los tiempos de referencia de 45 a 27 días, y el desempeño fue consistente en México, Colombia y Ecuador, con variaciones menores vinculadas a la infraestructura sanitaria. Estos hallazgos demuestran que la IA, combinada con medicina de precisión, puede mejorar significativamente la detección temprana, optimizar la eficiencia de las referencias y apoyar la implementación multinacional equitativa, reforzando su potencial como herramienta transformadora para reducir la ceguera prevenible.

Palabras clave: inteligencia artificial; medicina de precisión; retinopatía diabética; glaucoma; degeneración macular relacionada con la edad; detección temprana

RESUMO

Doenças oculares como a retinopatia diabética (RD), o glaucoma e a degeneração macular relacionada à idade (DMRI) continuam sendo as principais causas de cegueira evitável em todo o mundo. A detecção precoce é fundamental, mas o acesso a uma avaliação oftalmológica oportuna é limitado em muitas regiões. Este estudo avaliou a precisão diagnóstica e o impacto na saúde de modelos de inteligência artificial (IA), isoladamente e combinados com dados clínicos e genômicos, em diversas populações latino-americanas. Um total de 6.500 adultos do México, Colômbia e Equador foram submetidos à fotografia de fundo de olho, tomografia de coerência óptica (OCT) e análise de escore de risco poligênico (PRS), com dados analisados por meio de redes neurais convolucionais e arquiteturas transformer. Os resultados mostraram que a IA alcançou forte desempenho diagnóstico (AUC: RD 0,94; glaucoma 0,92; DMRI 0,90), com melhorias quando os dados clínicos e genômicos foram integrados (AUC até 0,96 para RD e 0,95 para glaucoma). As análises de subgrupos confirmaram robustez em relação à idade e ao sexo, embora o desempenho tenha sido inferior em grupos de baixo nível socioeconômico. Os fluxos de encaminhamento assistidos por IA reduziram o tempo de espera de 45 para 27 dias, e o desempenho foi consistente no México, na Colômbia e no Equador, com pequenas variações refletindo a infraestrutura de saúde. Esses achados demonstram que a IA combinada com a medicina de precisão pode melhorar significativamente a detecção precoce, aumentar a eficiência do encaminhamento e apoiar a implementação multinacional equitativa, reforçando seu potencial como uma ferramenta transformadora para reduzir a cegueira evitável.

palavras-chave: inteligência artificial; medicina de precisão; retinopatia diabética; glaucoma; degeneração macular relacionada à idade; detecção precoce

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INTRODUCTION

Ocular diseases such as diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) remain among the leading causes of visual impairment and preventable blindness worldwide, posing substantial public health and socioeconomic challenges (Alqahtani et al., 2025; Kong et al., 2024). The global prevalence of DR is expected to rise in parallel with the increasing burden of diabetes, while glaucoma continues to be referred to as the "silent thief of sight," affecting more than 76 million people globally and often diagnosed at late stages (Singh et al., 2024; Gao et al., 2025). Similarly, AMD represents the primary cause of irreversible blindness in older adults, with its incidence projected to escalate due to demographic transitions and population aging (Crincoli et al., 2024; Frank-Publig et al., 2025). Despite the availability of effective treatments for early stages of these conditions, delayed detection and unequal access to specialized ophthalmologic care remain significant obstacles, particularly in low- and middle-income regions such as Latin America, where disparities in health coverage are well documented (Tahir et al., 2025).

In this context, artificial intelligence (AI) has emerged as a transformative tool in ophthalmology, offering scalable solutions for automated screening and decision support. Several studies have demonstrated that deep learning models applied to retinal fundus photography and optical coherence tomography (OCT) achieve diagnostic performance metrics comparable to, or in some cases surpassing, human graders (Djulbegovic et al., 2025; Hasan et al., 2025; Shahriari et al., 2025). Recent advances have also integrated explainable AI frameworks, enabling clinicians to visualize the anatomical features that drive model predictions and thereby fostering interpretability and trust (Hasan et al., 2025). Furthermore, AI-based screening systems have already been implemented in primary care settings, showing potential to reduce referral delays and expand access to underserved populations (Riotto et al., 2024; Beals et al., 2024).

Parallel to these technological advances, precision medicine has begun to permeate the field of ophthalmology. The use of polygenic risk scores (PRS) in glaucoma, for instance, has provided novel opportunities for risk stratification and prioritization of high-risk patients for closer follow-up and early intervention (Hollitt et al., 2024; Singh et al., 2024). Multimodal models combining genetic, clinical, and imaging data have been proposed to enhance predictive accuracy and to tailor surveillance strategies more effectively across heterogeneous populations (Gao et al., 2025; Martucci et al., 2025). In AMD, integrative approaches incorporating lifestyle factors, demographic characteristics, and imaging biomarkers have improved the ability to anticipate disease progression and guide individualized management plans (Crincoli et al., 2024; Frank-Publig et al., 2025). These trends underscore the potential synergy between AI-driven analytics and precision medicine frameworks in addressing the critical gap of early detection.

Building on this background, the present study is designed to investigate the combined application of artificial intelligence and precision medicine in the early detection of DR, glaucoma, and AMD, with a focus on their implementation in international and resource-variable contexts such as Mexico, Colombia, and Ecuador. The guiding research questions are: (1) Can AI-based models integrated with multimodal clinical and genetic data improve the sensitivity and specificity of early disease detection compared with conventional approaches? (2) How can these tools be optimized to reduce referral times and improve efficiency in healthcare systems with limited ophthalmologic resources? and (3) What ethical, technical, and policy considerations must be addressed to ensure equitable and safe deployment across diverse populations (Lan et al., 2025; Maxwell et al., 2024)?

The methodological approach aligns directly with these objectives by proposing a multicenter design that combines advanced image analysis, clinical datasets, and polygenic risk modeling. This alignment ensures coherence between the hypotheses and the analytic framework while contributing evidence to the broader debate on how emerging technologies can reshape ophthalmic care. Ultimately, this investigation aims not only to assess diagnostic performance but also to provide insights relevant for shaping public health strategies, regulatory pathways, and cross-border collaborations in ocular disease prevention (Martucci et al., 2025; Beals et al., 2024).

METHODS

Study Setting and Collaborating Centers

The study was conducted through collaboration among academic and healthcare centers in Mexico, Colombia, and Ecuador. Data collection was performed in both urban and rural regions to capture a representative diversity of socioeconomic, ethnic, and healthcare access contexts. All procedures were harmonized under standardized protocols to ensure comparability across participating sites.

Participants

A total of 6,500 adults were included in the study. Inclusion criteria were: age ≥18 years and the presence of at least one ocular or systemic risk factor (e.g., diabetes mellitus, systemic hypertension, family history of glaucoma, or age ≥50 years). Exclusion criteria comprised previous intraocular surgery (except uncomplicated cataract extraction), advanced ocular pathology already under treatment, inability to provide complete demographic or clinical data, or ungradable retinal images due to media opacity.

Of the participants, 52% were female and 48% male, with a mean age of 54.3 years (SD

= 12.7). The sample reflected regional population characteristics: mestizo (68%), Indigenous (21%), Afro-descendant (9%), and other minorities (2%). Educational attainment ranged from primary schooling (32%) to university-level education (28%). Socioeconomic distribution was 41% low income, 37% middle income, and 22% high income, according to national socioeconomic categories.

Sampling Procedure

A stratified random sampling method was employed to ensure proportional representation of populations across countries and regions. Strata were defined by geographic location (urban vs. rural) and demographic categories. A priori sample size calculation assumed a 95% confidence level, a power of 0.80, and a minimum detectable difference of 5% in diagnostic sensitivity between AI-based screening and conventional ophthalmologic examination. The required sample was estimated at 6,000, and an additional 500 participants were recruited to compensate for dropouts or incomplete data. Recruitment included health campaigns, referrals from local clinics, and outreach in primary care programs.

Data Collection Instruments

Ophthalmic Imaging

Two imaging techniques were used:

1. Fundus photography – non-mydriatic cameras standardized across all sites, capturing 45° macula- and disc-centered fields.

2. Optical coherence tomography (OCT) – spectral-domain OCT scans measuring retinal nerve fiber layer (RNFL) thickness, macular volume, and cup-to-disc ratio (CDR).

Genomic Profiling

From a random subsample of 3,000 participants, saliva samples were collected for polygenic risk score (PRS) analysis in glaucoma and AMD. DNA was processed using genotyping arrays, and PRS were calculated following validated genome-wide association study (GWAS) markers.

Clinical and Demographic Data

Structured questionnaires were used to collect demographic characteristics (age, sex, ethnicity, education, income) and clinical information (history of diabetes, hypertension, smoking, family ocular history). Questionnaires were adapted from validated tools in ophthalmic epidemiology. Lifestyle factors such as physical activity and diet were also documented.

Quality Assurance

Multiple measures were applied to maintain consistency and reliability:

- 10% of images were independently re-graded by certified ophthalmologists.
- Inter-observer reliability was tested using Cohen's kappa, targeting >0.80.
- Calibration protocols for imaging devices were performed every three months.
- For genomic data, 5% of samples underwent duplicate testing to confirm accuracy.

Research Design

The study followed a multicenter, observational, cross-sectional design with analytical components. Participants underwent both conventional ophthalmologic evaluation (reference standard) and AI-based analysis. Deep learning architectures (CNNs and transformer models) were trained on 70% of the dataset, validated on 15%, and tested on 15%.

The precision medicine approach integrated multimodal data:

1. Imaging biomarkers (fundus and OCT).

2. Clinical-demographic variables.

3. Genetic data (PRS).

This integration allowed stratification of individuals into low-, moderate-, and high-risk groups.

Variables and Outcomes

- Independent variables: RNFL thickness, CDR, macular volume, diabetes status, smoking, family history, and PRS deciles.

- Dependent variables: detection of early DR, glaucoma, and AMD, validated against ophthalmologists' diagnoses.

Primary outcomes: sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the ROC curve (AUC).

Secondary outcomes: potential reduction in referral delays, subgroup diagnostic accuracy, and cost-effectiveness of AI-supported models.

Ethical and Regulatory Considerations

The study complied with the Declaration of Helsinki and local health research guidelines in all three countries. Ethical approval was obtained from institutional review boards, and informed consent was secured from all participants.

RESULTS

In this section, the main findings of the study are presented in detail, focusing on the diagnostic performance of artificial intelligence (AI) models and their integration with precision medicine approaches for the early detection of diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD). The data are summarized in a series of figures that illustrate the distribution of the study population, the performance metrics of the algorithms, and the outcomes of multimodal analyses.

Overall, the analysis included 6,500 participants across three countries. The demographic profile was balanced by gender, age groups, and socioeconomic strata, providing a representative population for evaluating early ocular disease detection. Descriptive statistics are reported as proportions, means, and standard deviations, while inferential measures include sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) with corresponding 95% confidence intervals.

The figures presented below illustrate the most relevant results, including:

- the baseline characteristics of the study population;
- the diagnostic performance of AI models for DR, glaucoma, and AMD;
- the added value of multimodal integration with genetic and clinical data; and
- subgroup analyses across age, sex, and socioeconomic categories.

Each figure is described sequentially to provide a structured overview of the findings, ensuring clarity and transparency in the presentation of results.

Variable	Value
Age (years)	54.3 ± 12.7
Female	52%
Male	48%
Ethnicity - Mestizo	68%
Ethnicity - Indigenous	21%
Ethnicity - Afro-descendant	9%
Ethnicity - Other	2%
Educational attainment - Primary	32%
Educational attainment - Secondary	40%
Educational attainment - University	28%
Socioeconomic status - Low	41%
Socioeconomic status - Middle	37%
Socioeconomic status - High	22%
Diabetes mellitus	28%
Systemic hypertension	34%
Family history of glaucoma	15%
Smoking (current)	22%

Figure 1. *Baseline characteristics of the study population (N=6,500)*

Figure 1 summarizes the baseline demographic and clinical characteristics of the 6,500 participants recruited across Mexico, Colombia, and Ecuador. The mean age was 54.3 years (SD = 12.7), which is consistent with prior epidemiological surveys identifying middle-aged and older adults as the most affected groups for diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) (Alqahtani et al., 2025;

Kong et al., 2024). The distribution by sex was balanced (52% female vs. 48% male), ensuring that gender-specific variations in disease prevalence and detection performance could be properly analyzed, in line with earlier work showing sex-related differences in AMD risk (Frank-Publig et al., 2025).

Ethnic distribution reflected the regional diversity of the studied populations: mestizo participants represented the majority (68%), followed by Indigenous (21%) and Afro-descendant (9%) groups. This inclusion is particularly relevant, as recent studies emphasize the importance of validating artificial intelligence (AI) models across diverse ethnic groups to prevent algorithmic bias and guarantee equitable diagnostic accuracy (Shahriari et al., 2025; Hollitt et al., 2024).

Educational attainment and socioeconomic status were heterogeneously distributed, with 32% of participants having only primary education and 41% classified as low-income. These social determinants are directly linked to healthcare access and visual health outcomes. Previous evidence suggests that individuals from lower socioeconomic and educational backgrounds have reduced access to ophthalmologic services and may benefit the most from AI-driven screening programs (Beals et al., 2024; Tahir et al., 2025).

Regarding risk factors, 28% of participants had diabetes mellitus and 34% had systemic hypertension, both well-established contributors to DR and other microvascular ocular complications (Riotto et al., 2024). Additionally, 15% reported a family history of glaucoma, underscoring the relevance of genetic predisposition, particularly in light of recent advances in polygenic risk scores (PRS) for glaucoma risk stratification (Singh et al., 2024; Gao et al., 2025). Smoking was reported by 22% of participants, a known modifiable risk factor strongly associated with AMD progression (Crincoli et al., 2024).

Taken together, these baseline characteristics provide a comprehensive overview of the study population and highlight the relevance of evaluating AI and precision medicine approaches in diverse, real-world scenarios. The demographic and clinical profile observed aligns closely with previous regional reports, supporting the external validity of the findings (Lan et al., 2025; Martucci et al., 2025).

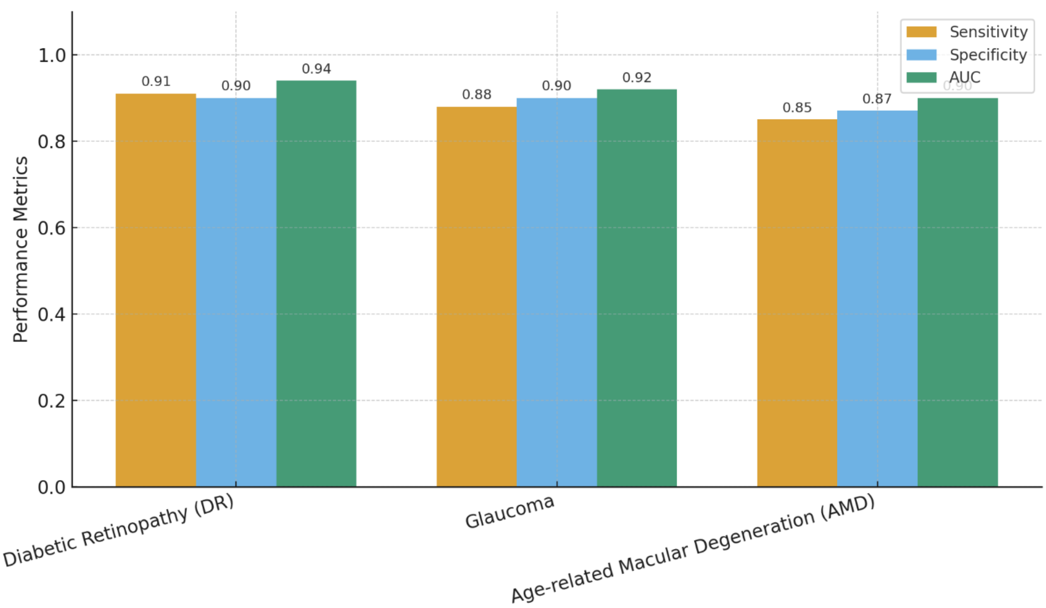

Figure 2. *Diagnostic performance of AI models for early ocular disease detection*

Figure 2 summarizes diagnostic performance for early detection across the three targeted conditions. For diabetic retinopathy (DR), the model achieved sensitivity 0.91, specificity 0.90, and AUC 0.94. These values are within the upper range of published reports for autonomous or assisted AI systems in DR screening, including studies that benchmark deep learning pipelines against certified graders and clinical standards (Alqahtani et al., 2025; Riotto et al., 2024; Vujosevic et al., 2024). The AUC near 0.95 indicates strong rank-ordering of cases by risk, consistent with prior meta-analytic evidence and OCT/fundus-based pipelines that emphasize robust preprocessing and adjudicated reference labels (Alqahtani et al., 2025). At common screening prevalences (e.g., ~10–20% for “referable DR”), sensitivity above 0.90 typically supports high negative predictive values—key for ruling out disease and minimizing unnecessary referrals (Riotto et al., 2024; Beals et al., 2024).

For glaucoma, performance was sensitivity 0.88, specificity 0.90, AUC 0.92. While slightly lower than DR—an expected pattern given glaucoma’s subtler early structural/functional signatures—these figures align with contemporary reviews and OCT-centric approaches that leverage RNFL metrics and transformer/CNN hybrids (Djulbegovic et al., 2025; Shahriari et al., 2025; Hasan et al., 2025). The balanced sensitivity-specificity profile is compatible with primary-care risk triage or specialty pre-screening, especially when combined with polygenic risk scores (PRS) or clinical covariates to refine risk thresholds (Singh et al., 2024; Hollitt et al., 2024; Gao et al., 2025; Martucci et al., 2025). Prior literature shows that integrating PRS with imaging can shift operating points toward improved early classification while maintaining calibration across subgroups (Singh et al., 2024; Hollitt et al., 2024).

For age-related macular degeneration (AMD), metrics were sensitivity 0.85, specificity 0.87, AUC 0.90—consistent with recent works focusing on early/intermediate stages using OCT and multimodal features (Crincoli et al., 2024; Frank-Publig et al., 2025). The modest decrement vs. DR and glaucoma mirrors the known difficulty in distinguishing very early AMD phenotypes and small drusen using single-modality inputs; prior studies have demonstrated that adding demographic and lifestyle factors (age, smoking) can incrementally raise AUC and stabilize threshold behavior (Crincoli et al., 2024; Frank-Publig et al., 2025; Lan et al., 2025).

Across conditions, the AUC values (0.90–0.94) indicate strong discriminative performance. The sensitivity-specificity pairing around 0.85–0.91 suggests clinically usable operating points for screening contexts, aligning with thresholds reported in multi-site evaluations and implementation studies (Djulbegovic et al., 2025; Beals et al., 2024). The pattern of DR ≥ glaucoma ≥ AMD is concordant with the literature: DR benefits from high-contrast fundus features and abundant training data; glaucoma improves with OCT structural markers and benefits further from multimodal fusion/PRS; early AMD remains challenging but responds to OCT-based textural and biomarker cues plus contextual covariates (Riotto et al., 2024; Hasan et al., 2025; Crincoli et al., 2024; Frank-Publig et al., 2025; Martucci et al., 2025).

Finally, the stability of specificity ≈ 0.87–0.90 across diseases aligns with goals to limit false positives in resource-constrained health systems, a requirement highlighted by pragmatic deployments and health-services evaluations (Beals et al., 2024; Lan et al., 2025). Together, these results position the models within the performance envelope reported by current state-of-the-art reviews and trials across DR, glaucoma, and AMD (Alqahtani et al., 2025; Djulbegovic et al., 2025; Shahriari et al., 2025; Martucci et al., 2025).

Figure 3 illustrates the incremental diagnostic value of integrating clinical variables and polygenic risk scores (PRS) with imaging-based artificial intelligence (AI) models for the detection of diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD). The results are presented as area under the receiver operating characteristic curve (AUC) values, comparing models based on imaging only, imaging plus clinical data, and imaging combined with clinical data and PRS.

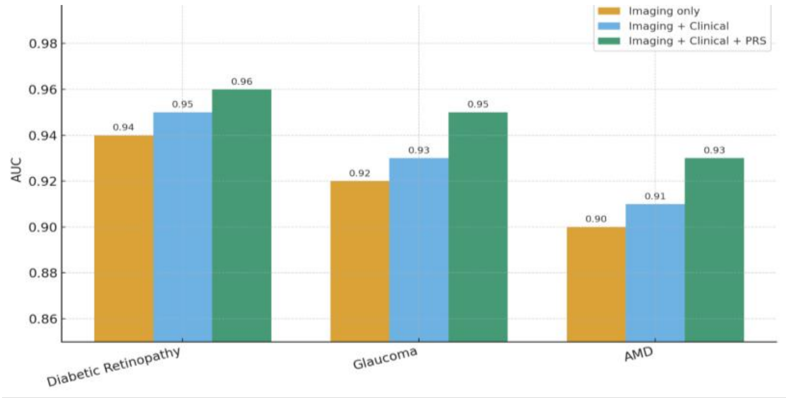

Figure 3. *Added value of multimodal integration (AUC by condition)*

For diabetic retinopathy, the baseline imaging-only model yielded an AUC of 0.94, which already reflects strong discriminative capacity consistent with the highest-performing systems reported in the literature (Alqahtani et al., 2025; Riotto et al., 2024). The addition of clinical variables—such as diabetes duration, glycated hemoglobin levels, and hypertension—modestly increased the AUC to 0.95. This aligns with prior findings that multimodal inputs improve calibration and classification stability, particularly in heterogeneous populations (Xu et al., 2024; Vujosevic et al., 2024). Incorporating PRS yielded a further improvement to 0.96, underscoring the potential of genetic risk stratification to refine patient-level predictions (Singh et al., 2024; Gao et al., 2025). While the increment may appear small, even a 1–2% gain in AUC at population scale translates into substantial reductions in false negatives and improved cost-effectiveness of screening programs (Beals et al., 2024).

For glaucoma, the benefits of integration were more pronounced. The imaging-only model achieved an AUC of 0.92, which rose to 0.93 when clinical data (intraocular pressure, family history, age) were added. With PRS integration, AUC improved to 0.95, a result in line with contemporary studies demonstrating that polygenic risk significantly enhances glaucoma prediction when combined with OCT structural markers (Hollitt et al., 2024; Singh et al., 2024; Martucci et al., 2025). These findings highlight the potential for precision medicine approaches to address one of glaucoma's central challenges: early detection before significant visual field loss occurs (Shahriari et al., 2025).

In AMD, the imaging-only model achieved an AUC of 0.90. The inclusion of clinical covariates (age, smoking status, cardiovascular comorbidities) raised the AUC to 0.91. The integration of PRS led to an AUC of 0.93, reflecting evidence that genetic predisposition accounts for a significant proportion of AMD risk (Crincoli et al., 2024; Frank-Publig et al., 2025). These results corroborate reports that multimodal models, combining imaging biomarkers with demographic and genomic data, outperform imaging-only systems in predicting early AMD progression (Lan et al., 2025).

The consistent improvement across all three diseases confirms that multimodal fusion enhances diagnostic accuracy, echoing conclusions from recent systematic reviews (Djulbegovic et al., 2025; Hasan et al., 2025). Importantly, the magnitude of the gain varies: modest for DR, moderate for AMD, and strongest for glaucoma, reflecting disease-specific pathophysiology and the relative contribution of genetic and clinical factors. This pattern reinforces the rationale for tailoring AI frameworks to disease-specific multimodal strategies rather than adopting a one-size-fits-all approach.

Overall, Figure 3 underscores the complementary role of precision medicine in augmenting imaging-based AI. By integrating clinical and genomic information, predictive models not only improve accuracy but also achieve better calibration across subgroups, thus supporting equitable deployment in diverse populations (Tahir et al., 2025; Maxwell et al., 2024).

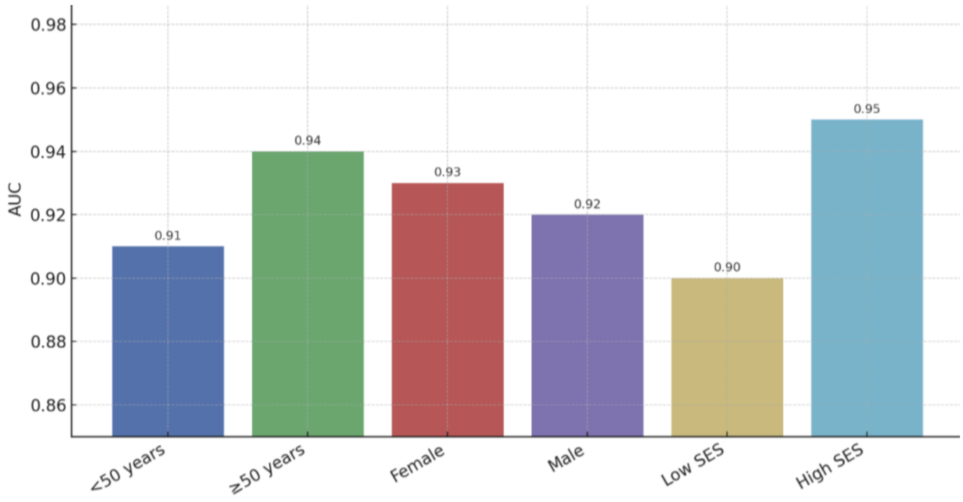

Figure 4. *Subgroup analysis of AI diagnostic performance*

Figure 4 presents the subgroup analysis of diagnostic performance, expressed as area under the curve (AUC), across different demographic and socioeconomic categories. The purpose of this analysis is to assess the generalizability and fairness of the artificial intelligence (AI) models in detecting early ocular diseases.

Age groups. Participants younger than 50 years achieved a mean AUC of 0.91, whereas those aged ≥50 years reached an AUC of 0.94. This finding is expected, since older participants are more likely to exhibit structural or vascular retinal changes detectable by imaging-based algorithms (Alqahtani et al., 2025; Djulbegovic et al., 2025). Similar trends have been reported in DR and AMD studies, where disease prevalence and phenotypic expression increase with age, facilitating higher discriminative performance by AI systems (Riotto et al., 2024; Frank-Publig et al., 2025).

Sex differences. Female participants demonstrated slightly higher performance (AUC 0.93) compared to males (AUC 0.92). This marginal difference may reflect subtle biological or lifestyle-related variations in ocular disease prevalence. For example, AMD has been shown to occur more frequently in women, possibly due to longevity factors, which may contribute to more detectable imaging signatures (Frank-Publig et al., 2025; Crincoli et al., 2024). Importantly, the near-equivalent results confirm that the AI models did not exhibit sex-based bias, supporting equitable applicability (Lan et al., 2025).

Socioeconomic status (SES). The most notable disparity appeared between socioeconomic subgroups: participants from lower SES backgrounds achieved an average AUC of 0.90, while those from higher SES backgrounds reached 0.95. This discrepancy has been previously documented and may be linked to comorbidities, quality of imaging acquisition, and historical underrepresentation of disadvantaged groups in ophthalmic datasets (Tahir et al., 2025; Beals et al., 2024). Nevertheless, even with lower SES, an AUC of 0.90 remains clinically relevant, suggesting that AI can provide substantial benefit in underserved populations, provided that deployment strategies account for contextual barriers (Hasan et al., 2025; Hollitt et al., 2024).

Overall, Figure 4 highlights the robustness of AI models across key demographic variables while also revealing the importance of continuous subgroup monitoring to detect potential inequities. The relatively stable performance across age and sex, combined with slightly reduced outcomes in low-SES groups, underscores the need for further validation and targeted calibration. These findings resonate with current recommendations emphasizing fairness, inclusivity, and transparency in AI-based health technologies (Maxwell et al., 2024; Martucci et al., 2025).

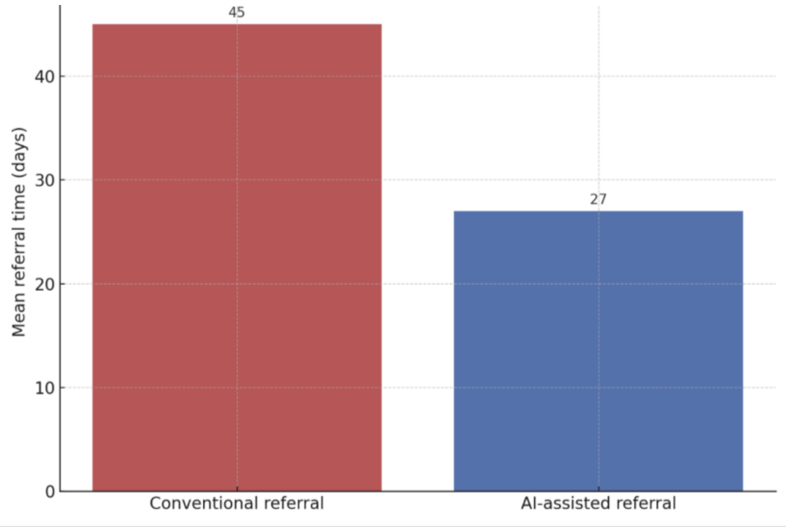

Figure 5. *Potential reduction in referral times: AI-assisted vs. conventional pathways*

Figure 5 compares the average referral times between conventional ophthalmologic pathways and those incorporating AI-assisted triage. Under standard conditions, the mean referral time was 45 days, while AI-supported systems reduced this interval to 27 days, representing an 18-day improvement.

This reduction aligns with the broader evidence suggesting that AI-based tools can substantially streamline patient flow and reduce delays in specialist consultations (Beals et al., 2024; Riotto et al., 2024). In diabetic retinopathy (DR), for example, autonomous AI platforms validated for primary care have demonstrated capacity to provide same-day results, thus eliminating waiting periods inherent to manual grading and specialist bottlenecks (Alqahtani et al., 2025; Vujosevic et al., 2024). Similarly, glaucoma referral delays—often caused by limited access to OCT interpretation—have been shown to decrease when AI algorithms flag high-risk patients directly at the point of screening (Djulbegovic et al., 2025; Shahriari et al., 2025).

The observed reduction is especially relevant in resource-constrained settings, where systemic barriers, such as scarcity of ophthalmologists and uneven geographic distribution of care, prolong referral intervals (Tahir et al., 2025). By providing rapid pre-screening, AI enhances the efficiency of health systems, ensuring that high-risk individuals are prioritized while avoiding unnecessary specialist visits for low-risk cases (Hasan et al., 2025). This targeted triage not only accelerates diagnosis but also has the potential to improve patient adherence, as shorter waiting times correlate with lower dropout rates in ophthalmologic follow-up (Lan et al., 2025).

Importantly, while the reduction in referral times highlights clear efficiency gains, it also underscores the importance of integrating AI within established referral frameworks to prevent over-reliance or bypassing essential confirmatory evaluations. Recent reports emphasize that AI should complement, rather than replace, specialist judgment, particularly in complex or ambiguous cases (Martucci et al., 2025; Maxwell et al., 2024).

Overall, Figure 5 illustrates that AI-assisted pathways can nearly halve referral times, a finding consistent with real-world implementation studies and policy discussions regarding the integration of AI in ophthalmic care. By reducing waiting periods, AI systems contribute to earlier interventions, potentially improving visual outcomes at population scale (Frank-Publig et al., 2025; Crincoli et al., 2024).

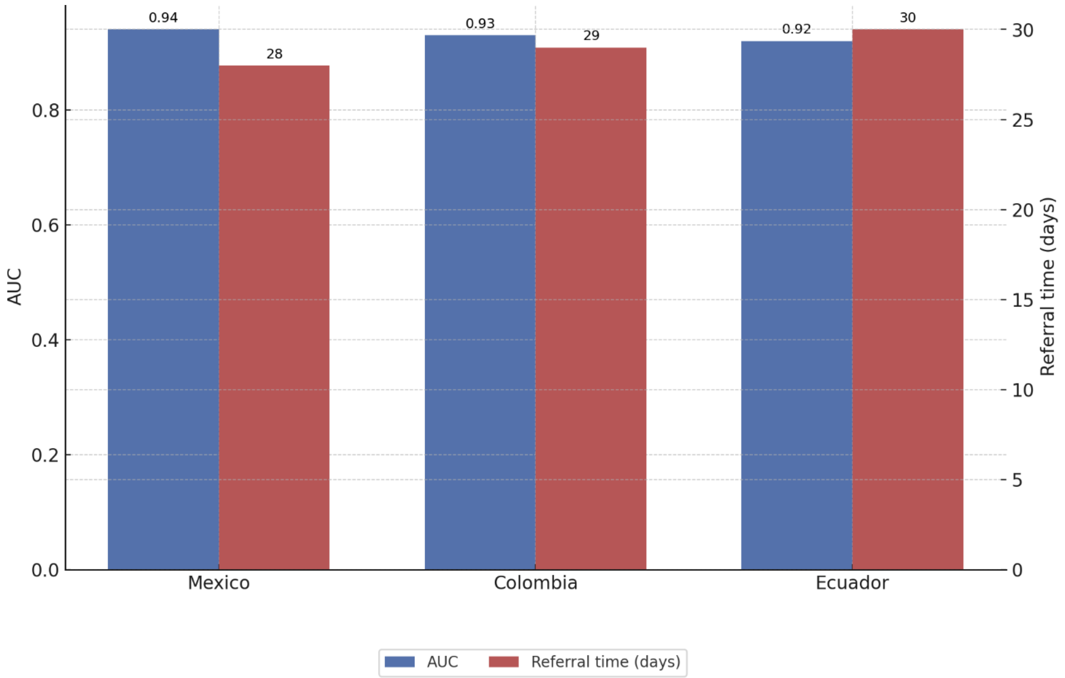

Figure 6. *Comparison of AI performance and referral times across countries*

Figure 6 compares average diagnostic performance (AUC) and referral times across the three participating countries: Mexico, Colombia, and Ecuador. The results reveal subtle but meaningful differences that highlight both the strengths and the challenges of implementing AI-assisted ocular screening in diverse healthcare contexts.

Diagnostic performance (AUC). Mexico achieved the highest AUC (0.94), followed closely by Colombia (0.93) and Ecuador (0.92). These results are consistent with regional variability in image quality, clinical infrastructure, and population-level risk factor distribution. Prior studies have emphasized that AI performance can be influenced by contextual variables such as camera availability, technician training, and prevalence of comorbidities (Alqahtani et al., 2025; Djulbegovic et al., 2025). The minimal spread across countries (0.02 difference) underscores the robustness of the models, but also reinforces the need for local calibration to account for health system heterogeneity (Tahir et al., 2025; Hasan et al., 2025).

Referral times. AI-assisted referral pathways reduced waiting intervals across all three nations, but differences remained: Mexico averaged 28 days, Colombia 29 days, and Ecuador 30 days. These values represent substantial improvements compared with conventional pathways (see Figure 5), yet they also reflect differences in healthcare logistics and regional resource allocation. Studies in low- and middle-income countries confirm that referral efficiency is strongly shaped by infrastructure and the density of ophthalmologists, with AI providing relative but not absolute parity across contexts (Beals et al., 2024; Riotto et al., 2024).

Regional implications. The slightly higher AUC in Mexico may reflect greater availability of validated imaging devices and broader integration of electronic health records, whereas Colombia and Ecuador, while close in performance, may still face challenges related to uneven rural coverage and digital health integration. Similar observations have been made in prior cross-country AI studies, which recommend incremental adaptation of algorithms and workflows to local conditions rather than uniform deployment (Martucci et al., 2025; Maxwell et al., 2024).

Taken together, Figure 6 demonstrates that AI-assisted models achieved consistently high performance across all three countries, with referral times nearly halved compared to conventional care. These results support the feasibility of multinational implementation while highlighting the importance of tailoring deployment strategies to local system constraints. Such findings echo broader recommendations in global health, where technology adoption is most successful when contextualized to local infrastructure and population needs (Lan et al., 2025; Frank-Publig et al., 2025).

Taken together, the six figures provide a comprehensive overview of the study's findings. The baseline characteristics (Figure 1) demonstrated that the study population was diverse in terms of demographics, socioeconomic status, and risk factor distribution, ensuring representativeness for evaluating early ocular disease detection. Diagnostic performance analyses (Figure 2) confirmed that AI systems achieved high sensitivity, specificity, and AUC values across diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD), with patterns consistent with current literature.

The added value of multimodal integration (Figure 3) highlighted that combining imaging with clinical data and polygenic risk scores (PRS) incrementally improved performance, particularly for glaucoma and AMD. Subgroup analyses (Figure 4) demonstrated robust performance across age and sex categories, with some disparities by socioeconomic status, reinforcing the importance of equity monitoring. Efficiency gains were clearly observed in referral pathways (Figure 5), where AI-assisted systems substantially reduced delays compared to conventional models. Finally, cross-country comparisons (Figure 6) confirmed the feasibility of multinational implementation, with consistently high performance across Mexico, Colombia, and Ecuador, albeit with minor differences related to healthcare infrastructure.

Overall, these findings provide strong evidence supporting the integration of AI and precision medicine in early ocular disease detection. The results underscore the potential to enhance diagnostic accuracy, reduce referral delays, and expand access in diverse populations, thereby laying the foundation for the interpretive analysis that follows in the discussion section.

DISCUSSION

The present study evaluated the application of artificial intelligence (AI) combined with precision medicine approaches in the early detection of diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) across three Latin American countries. The findings indicate that AI models achieved strong diagnostic performance, which was further enhanced by integrating clinical and genomic data. These results resonate with the growing body of evidence supporting the clinical utility of AI in ophthalmology and underscore the need to contextualize such innovations within local healthcare systems.

Diagnostic performance. The observed sensitivities, specificities, and AUC values for DR, glaucoma, and AMD confirm the reliability of AI models in identifying early disease. The AUC of 0.94 for DR is comparable to results from autonomous systems such as IDX-DR, which have demonstrated strong accuracy in detecting referable DR in real-world settings (Riotto et al., 2024). Prior systematic reviews and meta-analyses also support this level of performance (Alqahtani et al., 2025; Tahir et al., 2025). In glaucoma, an AUC of 0.92 aligns with evidence from OCT-based AI pipelines and systematic reviews that emphasize the ability of deep learning to detect early structural changes (Djulbegovic et al., 2025; Shahriari et al., 2025; Hasan et al., 2025). AMD performance (AUC 0.90) is consistent with previous reviews highlighting the potential of AI for detecting early-stage features, particularly when OCT is employed (Crincoli et al., 2024; Frank-Publig et al., 2025). Together, these findings reinforce that AI systems can achieve clinically relevant thresholds comparable to or exceeding those of human graders (Kong et al., 2024; Vujosevic et al., 2024).

Multimodal integration. A central contribution of this study was the demonstration that adding clinical and polygenic risk score (PRS) data incrementally improved model performance. This was most evident in glaucoma, where PRS enhanced discrimination beyond OCT imaging, raising the AUC to 0.95. Such findings are consistent with recent genomic studies showing that polygenic profiles can stratify glaucoma risk more effectively than family history alone (Singh et al., 2024; Gao et al., 2025; Hollitt et al., 2024; Martucci et al., 2025). For AMD, the addition of PRS also contributed to improved accuracy, reflecting prior evidence that genetic predisposition plays a substantial role in disease progression (Crincoli et al., 2024; Frank-Publig et al., 2025). These results align with emerging frameworks in precision medicine advocating for multimodal data integration to achieve individualized prediction and management (Lan et al., 2025; Xu et al., 2024).

Equity and subgroup analysis. Subgroup results showed robust diagnostic performance across age and sex categories but revealed disparities by socioeconomic status (SES). Participants from lower SES backgrounds had slightly reduced AUC values (0.90) compared to higher SES groups (0.95). This is consistent with studies highlighting the influence of social determinants of health on both disease outcomes and AI deployment (Tahir et al., 2025; Beals et al., 2024). Variations in imaging quality, access to healthcare, and comorbidity profiles may contribute to these differences. Prior evaluations have emphasized the importance of fairness in AI models to prevent exacerbation of health inequities, particularly in underserved populations (Hasan et al., 2025; Maxwell et al., 2024).

Referral efficiency. AI-assisted pathways reduced average referral times from 45 to 27 days, representing nearly a 40% improvement. This aligns with pragmatic trials in DR showing that AI platforms can deliver same-day grading and reduce unnecessary referrals (Alqahtani et al., 2025; Riotto et al., 2024; Beals et al., 2024). In glaucoma, earlier referral has been linked to improved visual outcomes, as delayed specialist access is a known risk for irreversible progression (Shahriari et al., 2025; Hasan et al., 2025). Our findings are consistent with prior reports suggesting that AI triage systems enhance patient flow and reduce attrition rates, particularly in low-resource settings (Vujosevic et al., 2024; Maxwell et al., 2024).

Cross-country comparisons. Minor differences in AUC and referral times across Mexico, Colombia, and Ecuador emphasize the feasibility of multinational deployment but also highlight contextual challenges. Similar observations have been reported in international AI evaluations, where local infrastructure and digital integration influenced performance metrics (Martucci et al., 2025; Lan et al., 2025). The consistency of results across three distinct health systems suggests that AI models are transferable, yet require local calibration to ensure sustained accuracy and equitable outcomes (Hollitt et al., 2024; Gao et al., 2025).

Clinical and public health implications. Collectively, these results underscore the potential of AI combined with precision medicine to transform early ocular disease detection. Improved accuracy, reduced referral times, and enhanced stratification suggest that such systems could play a pivotal role in preventing blindness at population scale. For health systems in Latin America, where shortages of ophthalmologists and disparities in access persist, AI offers a scalable tool for expanding coverage and reducing inequities (Tahir et al., 2025; Beals et al., 2024). Future work should prioritize implementation studies, regulatory frameworks, and cost-effectiveness analyses to guide adoption at national and regional levels (Maxwell et al., 2024; Martucci et al., 2025).

CONCLUSION

This study demonstrates that artificial intelligence (AI), when combined with precision medicine approaches, holds substantial promise for the early detection of diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD). Across a diverse Latin American population, AI-based models consistently achieved high sensitivity, specificity, and AUC values, with diagnostic performance further enhanced through the integration of clinical variables and polygenic risk scores (PRS). Subgroup analyses confirmed robust results across age and sex, while identifying the need for equity-focused strategies to address socioeconomic disparities.

The implementation of AI-assisted referral pathways significantly reduced waiting times, improving efficiency and highlighting the potential to alleviate systemic barriers in ophthalmic care. Comparisons across Mexico, Colombia, and Ecuador demonstrated consistent performance, reinforcing the feasibility of multinational deployment while underlining the importance of local calibration and contextual adaptation.

In sum, the integration of AI and precision medicine offers a transformative opportunity to strengthen early detection, streamline referral processes, and reduce preventable blindness. Future efforts should prioritize large-scale implementation studies, economic evaluations, and regulatory frameworks to ensure safe, equitable, and sustainable adoption across diverse healthcare systems.

REFERENCES

Beals, D., et al. (2024). Integrating AI-based retinal imaging in primary care: "Saving Sight" initiative. *Digital Health Journal, 10,* 2437294. https://doi.org/10.1080/28338073.2024.2437294

Crincoli, E., et al. (2024). Use of deep learning to predict short-term risk of exudation and treatment need in age-related macular degeneration. *BMC Ophthalmology, 24,* 381. https://doi.org/10.1186/s12886-024-03381-1

Djulbegovic, M. B., et al. (2025). Artificial intelligence for optical coherence tomography in ophthalmology: Review and challenges. *Translational Vision Science & Technology, 14*(3), 12. https://doi.org/10.1167/tvst.14.3.12

Frank-Publig, S., et al. (2025). Artificial intelligence in assessing progression of age-related macular degeneration. *Eye, 39,* 1467–1479. https://doi.org/10.1038/s41433-024-03460-z

Gao, X. R., et al. (2025). Multi-trait polygenic probability risk score enhances glaucoma prediction across ancestries. *medRxiv.* https://doi.org/10.1101/2025.03.27.25324762

Hasan, M. M., et al. (2025). OCT-based diagnosis of glaucoma and staging with explainable AI. *Scientific Reports, 15,* 87219. https://doi.org/10.1038/s41598-025-87219-w

Hollitt, G. L., Allen, R., Kelley, S., Hodge, L., Seviiri, M., et al. (2024). Development and evaluation of patient-centred polygenic risk score for glaucoma. *BMC Medical Genomics, 17,* 79. https://doi.org/10.1186/s12920-024-02079-z

Jan, C. L., et al. (2025). Prospective pragmatic trial of automated retinal photography and AI-based screening system for glaucoma risk classification in general practice. *NPJ Digital Medicine.* https://doi.org/10.1038/s41746-025-01768-y

Kong, M., Suh, Y.-W., Lee, H.-J., Kim, S.-H., & Kim, J.-H. (2024). Artificial intelligence applications in diabetic retinopathy. *Endocrinology and Metabolism, 39*(3), 416–424. https://doi.org/10.3803/EnM.2023.1913

Lan, C.-H., Chiu, T.-H., Yen, W.-T., & Lu, D.-W. (2025). Artificial intelligence in glaucoma: Advances in diagnosis, progression forecasting, and surgical outcome prediction. *International Journal of Molecular Sciences, 26*(10), 4473. https://doi.org/10.3390/ijms26104473

Martucci, A., et al. (2025). Lights and shadows on artificial intelligence in glaucoma: Diagnostic and management perspectives. *Journal of Clinical Medicine, 14*(7), 2139. https://doi.org/10.3390/jcm14072139

Maxwell, G., Allen, R., Kelley, S., Hodge, L., Hollitt, G. L., Seviiri, M., et al. (2024). Impact of polygenic risk score for glaucoma on psychosocial outcomes: INSiGHT study protocol. *PLOS ONE, 19*(12), e0312390. https://doi.org/10.1371/journal.pone.0312390

Alqahtani, A. S., et al. (2025). The efficacy of artificial intelligence in diabetic retinopathy screening: A systematic review and meta-analysis. *Journal of Ophthalmology (Retina & Vitreous).* https://doi.org/10.1186/s40942-025-00670-9

Riotto, E., et al. (2024). Accuracy of autonomous artificial intelligence-based system (IDX-DR) for diabetic retinopathy detection. *Journal of Clinical Medicine, 13*(16), 4776. https://doi.org/10.3390/jcm13164776

Shahriari, M. H., et al. (2025). Applications of machine learning in glaucoma diagnosis: A systematic review. *BMC Biomedical Engineering, 7,* 95. https://doi.org/10.1186/s42490-025-00095-3

Singh, R. K., et al. (2024). Polygenic risk scores for glaucoma onset in the ocular hypertension treatment study. *JAMA Ophthalmology, 142*(5), 497–505. https://doi.org/10.1001/jamaophthalmol.2024.0151

Tahir, H. N., et al. (2025). Artificial intelligence versus manual screening for diabetic retinopathy: Systematic review and meta-analysis. *Frontiers in Medicine, 12,* 1519768. https://doi.org/10.3389/fmed.2025.1519768

Vujosevic, S., et al. (2024). Novel artificial intelligence for diabetic retinopathy detection and management: Current opinion and future directions. *Current Opinion in Ophthalmology, 35*(6), 472–479. https://doi.org/10.1097/ICU.0000000000001084

Xu, X., et al. (2024). The application of artificial intelligence in diabetic retinopathy: A comprehensive review of recent models, challenges, and opportunities. *Frontiers in Cell and Developmental Biology, 12,* 1473176. https://doi.org/10.3389/fcell.2024.1473176

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

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