Review Article

Artificial intelligence in ophthalmology: opportunities, challenges, and ethical considerations

Kimia Kazemzadeh [1]

[1] *IVORC Academic Foundation (International Virtual Ophthalmic Research Center), Texas, United States*

ABSTRACT

Background: By leveraging the imaging-rich nature of ophthalmology and optometry, artificial intelligence (AI) is rapidly transforming the vision sciences and addressing the global burden of ocular diseases. The ability of AI to analyze complex imaging and clinical data allows unprecedented improvements in diagnosis, management, and patient outcomes. In this narrative review, we explore the current and emerging opportunities of utilizing AI in the vision sciences, critically examine the associated challenges, and discuss the ethical implications of integrating AI into clinical practice.

Methods: We searched PubMed/MEDLINE and Google Scholar for English-language articles published from January 1, 2005, to March 31, 2025. Studies on AI applications in ophthalmology and optometry, focusing on diagnostic performance, clinical integration, and ethical considerations, were included, irrespective of study design (clinical trials, observational studies, validation studies, systematic reviews, and meta-analyses). Articles not related to the use of AI in vision care were excluded.

Results: AI has achieved high diagnostic accuracy across different ocular domains. In terms of the cornea and anterior segment, AI models have detected keratoconus with sensitivity and accuracy exceeding 98% and 99.6%, respectively, including in subclinical cases, by analyzing Scheimpflug tomography and corneal biomechanics. For cataract surgery, machine learning-based intraocular lens power calculation formulas, such as the Kane and ZEISS AI formulas, reduce refractive errors, achieving mean absolute errors below 0.30 diopters and performing particularly well in highly myopic eyes. AI-based retinal screening systems, such as the EyeArt and IDx-DR, can autonomously detect diabetic retinopathy with sensitivities above 95%, while deep learning models can predict age-related macular degeneration progression with an area under the receiver operating characteristic curve exceeding 0.90. In glaucoma detection, fundus and optical coherence tomography-based AI models have reached pooled sensitivity and specificity exceeding 90%, although performance varies with disease stage and population diversity. AI has also advanced strabismus detection, amblyopia risk prediction, and myopia progression forecasting by using facial analysis and biometric data. Currently, key challenges in implementing AI in ophthalmology include dataset bias, limited external validation, regulatory hurdles, and ethical issues, such as transparency and equitable access.

Conclusions: AI is rapidly transforming vision sciences by improving diagnostic accuracy, streamlining clinical workflow, and broadening access to quality eye care, particularly in underserved regions. Its integration into ophthalmology and optometry thus holds significant promise for enhancing patient outcomes and optimizing healthcare delivery. However, to harness the transformative potential of AI fully, sustained multidisciplinary collaboration, involving clinicians, data scientists, ethicists, and policymakers, is essential. Rigorous validation processes, transparency in algorithm development, and strong ethical oversight are equally important to mitigate risks such as bias, data misuse, and unequal access. Responsible implementation of AI in the vision sciences is essential to ensure that all populations are served equitably.

KEYWORDS

machine intelligence, AI (artificial intelligence), learning, deep, learning, machine, vision, sciences, optometries, ocular surgery, ocular surgery, ethical issue, ethical code

Correspondence: Kimia Kazemzadeh, IVORC Academic Foundation (International Virtual Ophthalmic Research Center), Texas, United States. Email: kimia_kazemzadeh@yahoo.com. ORCID iD: https://orcid.org/0000-0002-6948-4838

How to cite this article: Kazemzadeh K. Artificial intelligence in ophthalmology: opportunities, challenges, and ethical considerations. Med Hypothesis Discov Innov Ophthalmol. 2025 Spring; 14(1): 255-272. https://doi.org/10.51329/mehdiophthal1517

Received: 02 April 2025; Accepted: 28 April 2025

INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as a transformative force in healthcare, demonstrating unprecedented capabilities in terms of data analysis, pattern recognition, and predictive modeling [1-3]. By leveraging machine learning and deep learning algorithms, AI systems can process vast datasets, identify subtle patterns that are imperceptible to humans, and generate actionable insights that can enhance clinical decision-making [2-4]. This paradigm shift is particularly impactful in the vision sciences, where the potential of AI for improving diagnostic accuracy, personalizing treatments, and democratizing access to care aligns with the unique challenges and opportunities of this field [1, 3, 5].

The vision sciences represent a vital area for AI innovation given the high global prevalence of ocular diseases, including diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD), which collectively affect hundreds of millions worldwide [1, 3, 5]. The imaging-rich nature of ophthalmology and optometry, which encompasses modalities such as optical coherence tomography (OCT), fundus photography, and visual field testing, is ideal for AI-driven analysis [1-3]. These imaging techniques generate structured, high-dimensional data that can be parsed by AI models to detect early disease markers, predict progression, and optimize therapeutic interventions [1, 2, 6]. For example, based on OCT scan analysis, AI algorithms have achieved >90% accuracy in identifying AMD biomarkers, while deep learning models for DR screening have demonstrated sensitivity and specificity values rivaling those of ophthalmologists, indicating the potential of this approach for scalable population-level screening [1-3].

The rationale for prioritizing the implementation of AI in the vision sciences extends beyond the above-mentioned technological compatibility [1-3]. Preventable vision loss remains a pressing public health crisis, in which disparities in access to eye care exacerbate patient outcomes in low-resource settings [1, 3, 5]. AI-powered tools, such as smartphone-based retinal cameras and autonomous diagnostic systems, could address these inequities by enabling remote screening and task-shifting to non-specialists in underserved regions [1-3]. Furthermore, the integration of multimodal data, i.e., combining imaging, genetic, and lifestyle factors, by AI could facilitate personalized treatment paradigms, such as predicting individual responses to anti-vascular endothelial growth factor therapy in cases of AMD or customizing myopia control strategies [1, 2, 7].

In this narrative review, we explore the role of AI in advancing the vision sciences from three perspectives: diagnostic innovation, ethical implementation, and equitable deployment. We synthesize evidence from peer-reviewed studies to evaluate the efficacy of AI in ocular disease detection, its ethical challenges, and its potential to bridge global eye care disparities. By critically appraising current advancements and future directions in this review, we aim to inform clinicians, researchers, and policymakers on harnessing the potential of AI while mitigating risks of using AI in vision care.

METHODS

This narrative review was based on a targeted search of the PubMed/MEDLINE and Google Scholar databases to ensure inclusion of the most pertinent studies. This targeted literature search utilized the following keywords and medical subject headings (MeSH terms): "artificial intelligence," "machine learning," "deep learning," "neural networks," "computer vision," "ophthalmology," "optometry," "vision sciences," "ocular imaging," "eye diseases," "keratoconus," "diabetic retinopathy," "age-related macular degeneration," "glaucoma," "cataract," "intraocular lens calculation," "corneal topography," "optical coherence tomography," "fundus photography," "strabismus," and "myopia progression." The search was limited to articles published from January 1, 2005, to March 31, 2025, to focus on contemporary AI applications and emerging technologies in the vision sciences.

The inclusion criteria were studies of any design (clinical trials, observational studies, validation studies, systematic reviews, and meta-analyses) focusing on AI applications in ophthalmology and optometry. Studies were included if they discussed methodologies, clinical validation, diagnostic performance metrics, implementation challenges, or ethical considerations related to the use of AI in the vision sciences. Only English-language articles were considered. Exclusion criteria included non-English studies, articles not addressing AI applications in vision care, and conference abstracts without full-text publications.

The selected articles were evaluated based on their methodological rigor, sample size, population diversity, validation strategies, and clinical relevance. Priority was given to studies exploring AI applications across a range of ocular structures and conditions, including the cornea and anterior segment, lens, retina, optic nerve and glaucoma, extraocular muscles and binocular vision, refractive errors and axial length, as well as neuro-ophthalmology. These applications were considered in various clinical contexts, such as screening, diagnosis, prognosis, and treatment planning. While, particularly focused on papers addressing algorithmic bias, barriers to clinical integration, and strategies for ensuring equitable implementation of AI technologies across diverse healthcare settings and populations**.**

RESULTS and DISCUSSION

Role of AI in Vision Sciences: Anatomical and Clinical Perspectives

AI Applications by Ocular Structure

Cornea and Anterior Segment: AI has revolutionized the diagnosis and management of corneal disorders, particularly keratoconus, through advanced analysis of corneal topography and tomography data. Modern AI algorithms trained on Scheimpflug-based tomography (e.g., Pentacam, Galilei) and anterior segment OCT (AS-OCT) have achieved specificities in excess of 98.3% and sensitivities in excess of 96.8% for detecting manifest keratoconus, as validated by recent Cochrane reviews [8, 9]. These AI systems analyze parameters, such as maximum keratometry, corneal thickness distribution, and posterior elevation maps, allowing identification of subclinical cases that have been missed by traditional indices [10, 11]. Novel approaches in detecting keratoconus involve integration of corneal biomechanics (e.g., deformation amplitude and applanation time from the Corvis ST) into machine learning models for the analysis of dynamic deformation videos, achieving 99.6% diagnostic accuracy [12]. Automated screening for corneal dystrophies and anterior segment abnormalities can benefit from the ability of AI to standardize interpretations of imaging data. While less extensively studied than other AI-based models for detecting keratoconus, AI models trained on epithelial thickness mapping and polarization-sensitive OCT have shown promise in detecting subtle stromal irregularities [10, 11]. For cataract screening, AI-based systems can automate the classification of lens opacities from slit-lamp and AS-OCT images, although current applications remain less mature than those used for keratoconus. Systems are also emerging that aim to integrate multimodal data to predict post-surgical outcomes and optimize intraocular lens (IOL) power calculations [11, 13-15].

Challenges regarding the implementation of AI in the visual sciences include addressing dataset biases, such as underrepresentation of diverse ethnicities, and ensuring generalizability across imaging devices [7, 11]. Key advances in this field include: 1) Early detection: AI-based systems can identify subclinical keratoconus by using tomographic features, such as abnormal posterior curvature, enabling timely interventions [11, 13-15]. 2) Biomechanical analysis: Machine learning models (e.g., five-layer feedforward networks) leverage dynamic corneal response parameters to diagnose keratoconus without topographical data [12]. 3) Clinical integration: Mobile-based AI tools for low-resource settings could democratize access to corneal ectasia screening [7, 11].

However, most available AI models rely on Scheimpflug tomography, limiting their applicability in clinics with Placido-disk-only devices [10]. In addition, AI tools for forecasting keratoconus progression remain experimental, with current models achieving an area under the curve (AUC) of 0.81 by using clinical and biomechanical inputs [11, 13]. Additionally, further refinements are required in algorithmic transparency and patient consent as AI assumes more prominent diagnostic roles [7, 13]. The existing integration of AI into corneal diagnostics highlights its potential to enhance diagnostic precision while underscoring the need for robust validation and equitable deployment of these approaches.

Lens: AI has significantly advanced IOL power calculation for cataract surgery, addressing longstanding challenges in refractive accuracy. Modern machine learning formulas, such as the Kane, Hill-RBF 3.0, and ZEISS AI formulas, have leveraged large clinical datasets to improve predictions by incorporating variables such as axial length (AL), keratometry, and anterior chamber depth. The Kane formula has emerged as the leading formula, achieving the lowest mean absolute error (MAE) and the highest percentage of patients attaining postoperative refraction within ± 0.5 D of the target refraction in a systematic review [16]. For highly myopic eyes (AL >26 mm), the XGBoost and Hill-RBF algorithms have outperformed traditional formulas, such as the SRK/T and Holladay 1 formulas, with superior accuracy in predicting postoperative refraction [17]. The ZEISS AI IOL calculator integrates paraxial ray tracing and a proprietary database of > 16 000 IOL parameters, eliminating reliance on A-constants and reducing transcription errors through automated data processing [18]. Prediction of postoperative outcomes can benefit from the ability of AI to analyze multifactorial interactions between biometric data and surgical variables. For example, newer prediction models have incorporated effective lens position estimations, which are critical for minimizing refractive surprises. The Hill-RBF 3.0 formula has demonstrated exceptional accuracy in medium-to-long eyes, while the PEARL DGS has shown promise in diverse populations, although it requires further validation [15, 16]. Challenges persist in post-refractive surgery eyes, where AI models trained on hybrid datasets that combine historical and current biometric data have shown improved reliability as compared to traditional adjustment methods, such as the clinical history approach [14].

Key advances in this field include: 1) Data-driven algorithms: AI tools, such as the ZEISS AI and Kane formulas, use real-world surgical outcomes to refine predictions dynamically [16]. 2) Specialized populations: AI formulas have achieved MAEs < 0.30 D in highly myopic eyes, reducing the risk of hyperopic surprises [17]. 3) Workflow integration: Automated platforms, such as the ZEISS AI IOL calculator, streamline calculations without altering clinical workflow [18].

However, many of these AI-based formulas have been validated primarily on Caucasian populations, necessitating region-specific adjustments [16, 17]. In addition, AI models still rely on historical keratometry data, which may be unavailable for some patients. Moreover, novel AI-based formulas require prospective validation and regulatory approval before they can be widely adopted [16]. By enhancing precision and adaptability, AI may redefine standards in IOL power calculation, although equitable deployment and ongoing validation remain critical for universal adoption.

Retina: AI has revolutionized the diagnostics of retinal conditions through automated detection and grading of DR. The EyeArt system, which has been FDA-approved for autonomous DR screening, demonstrated 95.8–99.1% sensitivity for detecting referable DR and sight-threatening DR (STDR) by using non-dilated fundus images. This outperforms general ophthalmologists in terms of sensitivity while maintaining a specificity above 80% [20]. Validated on smartphone-based imaging devices, such as the Remidio FOP, the EyeArt system has achieved 99.1% sensitivity for STDR, indicating its utility for mass screening in low-resource settings without specialist dependency [21]. Similarly, IDx-DR (now LumineticsCore) has pioneered FDA-approved autonomous DR detection, although the current literature emphasizes the EyeArt system's validation and superior performance across diverse populations and camera models [20, 22, 23]. For AMD, AI models can analyze OCT and fundus images to detect geographic atrophy, drusen progression, and conversion to neovascular AMD. Deep learning models, such as DeepSeeNet, can predict 5-year progression risks by quantifying biomarkers (e.g., hyperreflective foci, retinal pigment epithelium abnormalities), achieving AUCs exceeding 0.90 for late AMD prediction [20, 24, 25]. Emerging tools also integrate genetic risk scores and multimodal imaging to refine personalized risk assessments.

In retinopathy of prematurity (ROP), AI systems, such as i-ROP DL, have automated plus-disease detection by using convolutional neural networks (CNNs) and have achieved expert-level agreement in classifying vascular severity [26-29]. These AI-based tools address the global shortage of ROP specialists, although real-world deployment will require validation of these approaches across neonatal populations and camera types. AI has also enhanced the detection of retinal DR, vascular occlusions, and retinal detachment by identifying subtle features, such as intraretinal fluid, cotton wool spots, and vascular tortuosity in fundus and OCT images. For example, CNNs trained on ultra-widefield angiography have achieved 95% accuracy in diagnosing central retinal vein occlusions, while AI-based models analyzing spectral-domain OCT (SD-OCT) have detected rhegmatogenous detachments with 97% sensitivity [30-31]. Generative AI has advanced retinal research through synthetic image synthesis and disease modeling. Diffusion models can generate high-fidelity fundus images with customizable pathologies for algorithm training, without raising patient privacy concerns. These systems can also simulate disease progression under hypothetical therapeutic interventions, thereby facilitating clinical trial design [32-35].

Key challenges include addressing dataset biases, such as underrepresentation of African and indigenous populations in DR models, and ensuring regulatory compliance for autonomous systems. Federated learning frameworks have shown promise in enhancing generalizability while preserving data privacy [21]. Key advances in this field include: 1) Progression modeling: AI can quantify OCT-based biomarkers for AMD and DR staging [20, 24, 25]. 2) Resource optimization: Autonomous tools for ROP detection and monitoring can reduce reliance on specialist grading [26-29].

However, most DR models have been validated on Western/Asian cohorts, limiting their global applicability [20, 21, 30]. Moreover, standards for generative AI in clinical decision-making remain underdeveloped [32]. Additionally, the performance of these AI tools drops when they are applied to non-validated camera models [21]. The integration of AI into retinal care has underscored its potential to democratize diagnostics while illustrating the need for robust ethical frameworks to ensure equitable implementation.

Optic Nerve and Glaucoma: Deep learning models have demonstrated exceptional accuracy in glaucoma detection based on multimodal imaging and functional data. For fundus photography, meta-analyses have reported a pooled sensitivity of 92% (95% confidence interval [CI]: 0.89–0.94) and specificity of 93% (95% CI: 0.90–0.95), with an area under the receiver operating characteristic curve (AUROC) of 0.90 (95% CI: 0.88–0.92), outperforming traditional clinical assessments [36, 37]. Notably, models trained on optic nerve head (ONH)-centered images have achieved AUCs up to 0.94, but recent studies have revealed that significant diagnostic information exists outside the ONH: models that analyzed the peripheral retinal regions only still achieved AUCs of 0.88 for glaucoma detection and explained 37% of the vertical cup-to-disc ratio variance [38, 39]. This capability is crucial in high myopia cases, where tilted optic discs complicate traditional assessments, as demonstrated by the maintained high accuracy of specialized deep learning tools in myopic cohorts [38, 40].

OCT-based AI models have shown slightly lower performance, with a pooled sensitivity of 90% (95% CI: 0.84–0.94) and specificity of 87% (95% CI: 0.81–0.91), AUROC 0.86 (95% CI: 0.83–0.90) [36]. Nevertheless, OCT remains invaluable for objective structural quantification, particularly in training "machine-to-machine" algorithms that predict retinal nerve fiber layer (RNFL) thickness from fundus photos, with a 7.39-μm MAE, matching the diagnostic accuracy of OCT to the true RNFL thickness from SD-OCT (AUC: 0.944 vs. 0.940) [41, 42]. Hybrid approaches, such as the AI-GS network that combines six lightweight models, can enhance real-world applicability by maintaining high accuracy (AUC > 0.90) while reducing computational load [43]. Glaucoma progression analysis is more complex, with current AI models demonstrating lower robustness in progression analysis than in diagnostic tasks [36]. Emerging solutions utilize visual field archetypes derived from unsupervised learning to identify distinct progression patterns, thereby enabling earlier intervention. However, model performance in this respect remains dependent on disease severity: models achieve AUCs of 0.99 for advanced glaucoma (mean deviation ≤ -4.0 decibel), but these values drop to 0.88 for early-stage cases [44]. Integration of multimodal data, such as data from OCT, visual fields, and clinical history, shows promise for improving progression forecasts, although real-world validation studies are currently limited [36, 37, 45, 46].

Key challenges include ancestry-related performance disparities, with fundus models achieving higher accuracy in African-descent patients (AUC: 0.97 vs. 0.85 in European-descent), while OCT models show an inverse trend [44, 47, 48]. Moreover, AI applications continue to face limitations in cases involving atypical optic disc anatomy, such as cases with tilted, crowded, or anomalous discs, and the risk of misclassification in these cases remains significant [49]. Addressing these limitations requires diverse training datasets and regulatory frameworks prior to clinical deployment. Future directions should emphasize federated learning to harmonize global data, while preserving privacy, and dynamic risk models incorporating longitudinal imaging and genetic data to refine progression predictions [36, 38].

Extraocular Muscles and Binocular Vision: AI has advanced strabismus detection and measurement through innovative analysis of facial and ocular images. CNNs trained on facial photographs have achieved 86.38% accuracy in binary classification (strabismus vs. normal) and 92.7% accuracy in multi-class categorization (e.g., esotropia, exotropia subtypes), outperforming traditional screening methods in resource-limited settings [50]. Specialized wearable systems using infrared eye-tracking have demonstrated even greater precision, with one study reporting 97.1% diagnostic accuracy across diverse patient conditions [51]. For quantitative deviation measurement, AI platforms have achieved limits of agreement of ± 6.6°–7.0°, as compared to prism cover tests, rivaling clinician assessments in prospective trials [52]. Mobile-based AI apps can further democratize access, enabling nine-gaze position analysis through smartphone cameras, although current models have shown variable performance (73–80% sensitivity) [53, 54]. By leveraging the ability of AI to detect subtle binocular vision anomalies and refractive imbalances from ocular images, AI can be used to enhance amblyopia risk prediction. While direct amblyopia-specific models are less well-documented, strabismus detection systems can indirectly identify high-risk cases, as misalignment is a leading cause of deprivation amblyopia. Emerging tools have integrated ocular motility videos with machine learning to predict treatment responses, with support vector machines achieving 82.1% accuracy in postoperative outcome forecasting [55]. AI-assisted prism adaptation simulations and surgical target angle suggestions (± 5.5–6.1° accuracy) can optimize intervention timing, reducing the risk of irreversible vision loss [52].

However, African and indigenous populations are not represented in most training datasets, leading to a risk of biased performance [50, 54]. In addition, analysis of static images may miss intermittent strabismus patterns that are detectable only through video-based eye movement tracking [55]. Additionally, autonomous diagnostic apps require validation against gold-standard tests, such as the alternate prism cover test [53]. Future directions should focus on multimodal integration, combining gaze behavior videos, genetic risk data, and refractive error maps, to enhance predictive power for amblyopia management. Federated learning frameworks could address data diversity gaps while preserving patient privacy [54, 55].

Refractive Errors and Axial Length: AI has transformed the prediction of myopia progression by machine learning models that integrate ocular biometric parameters, environmental factors, and imaging data. The Shenzhen Eye Hospital study has demonstrated that models using AL as a key predictor could achieve AUCs of 0.833–0.846 for myopia risk stratification, with AL identified as the most significant risk factor (odds ratio [OR] = 8.203) [56]. Advanced algorithms, such as extreme gradient boosting trees (XGBoost), random forests, and leverage multimodal inputs have achieved accuracies exceeding 70–80% for the prediction of myopia risk. Support vector machine algorithms have exhibited the highest accuracy in this respect [56, 57]. Notably, DeepMyopia, a deep learning system combining fundus images with AL and demographic data, achieved AUCs of 0.908, 0.813, and 0.810 for 1-, 2-, and 3-year myopia onset predictions, respectively, even without cycloplegic refraction [57]. Exceptional precision has been reported for progression prediction by newer models: a linear regression-based algorithm achieved an R^2 of 0.964 and an MAE of 0.119 D, while longitudinal deep learning models analyzing fundus sequences achieved 0.311 D/year error margins and AUCs up to 0.995 for high myopia risk [58-60]. AI-based AL estimation from fundus images can circumvent the need for specialized biometry devices. Emerging techniques have demonstrated machine-to-machine prediction of AL using retinal vasculature patterns and optic disc morphology, although current implementations remain experimental as compared to optical biometry (e.g., IOLMaster). The integration of generative adversarial networks (GANs) show promise in synthesizing AL-correlated retinal features for training data augmentation, particularly in underrepresented populations [61].

Key challenges include dataset biases, given the East Asian predominance in training cohorts, and real-world validation gaps, particularly for AL estimation tools. In terms of ethical considerations, equitable access should be emphasized to prevent diagnostic disparities between regions with differing healthcare resources. Notably, AL estimation models require validation across diverse fundus cameras. Furthermore, overreliance on AI predictions may overshadow clinical judgment in borderline cases. Key advances in this field include: 1) Risk stratification: AI can identify high-risk cohorts by using non-cycloplegic parameters, enabling scalable school screenings [57]. 2) Longitudinal modeling: Deep learning can predict decadal myopia trajectories from single time-point data [59, 62]. The integration of AI into refractive error management [63] underscores its potential for personalized interventions, although robust safeguards against algorithmic bias are needed.

Neuro-ophthalmology: AI-driven retinal imaging has emerged as a non-invasive biomarker for detecting neurological diseases, leveraging the role of the retina as a window into central nervous system health. For Alzheimer's disease (AD), the Eye-AD framework (validated in a multi-center study of 1671 participants) has analyzed OCT angiography (OCTA) images of retinal microvasculature and choriocapillaris, and has achieved AUCs of 0.9355 (early-onset AD) and 0.8630 (mild cognitive impairment [MCI]) on internal datasets, with external validation demonstrating robust performance (AUC 0.9007 for early-onset AD) [64]. The model employed a multilevel graph representation to decode relationships between retinal layers, correlating biomarkers, such as reduced vessel density and foveal avascular zone enlargement, with AD progression. The affordability and accessibility of retinal imaging position it as a scalable screening tool, in particular as compared to costly neuroimaging or invasive cerebrospinal fluid tests [64, 65]. For stroke risk prediction, AI can analyze retinal vascular patterns, such as the arteriole-to-venule ratio and fractal dimensions, from fundus photos. While specific stroke-focused models are less well-documented, retinal biomarkers, such a microvascular abnormalities and RNFL thinning, have been established as proxies for cerebral small vessel disease, a key stroke precursor [65]. Emerging tools have integrated ultra-widefield imaging and OCTA for detecting subtle ischemic changes, although validations in prospective cohorts remain ongoing [65, 66]. Key advances in this field include: 1) Early detection: AI can identify prodromal AD stages (e.g., MCI) through OCTA-based microvascular signatures [64]. 2) Population screening: Retinal imaging has enabled community-level dementia screening without specialist dependency. 3) Multimodal integration: Combining retinal data with genetic risk scores and cognitive tests can enhance predictive accuracy [64, 65].

However, African and indigenous populations are underrepresented in most datasets, increasing the risk of biased predictions. Furthermore, the causal link between retinal biomarkers and neurological pathology requires further elucidation. In addition, autonomous diagnostic systems must undergo prospective clinical validation prior to regulatory approval [65, 66]. As retinal imaging becomes a gateway for systemic health assessment, interdisciplinary collaboration will be critical to translate AI innovations into clinical practice. Table 1 summarizes the roles of AI in ophthalmology as discussed above.

AI in Optometric Practice

AI tools that enhance precision and efficiency have transformed diagnosis and strategic planning in optometry. Platforms such as Altris AI streamline OCT analysis, addressing critical gaps in optometric practice—16% of clinicians avoid OCT because of limited expertise, and 35% miss early pathologies weekly [67, 68]. Deep learning has strong potential in the screening, diagnosis, and management of DR and ROP, enabling optometrists to prioritize high-risk cases without dependence on specialists. Virtual assistants trained using clinical datasets achieve >95% accuracy in classifying patients into refractive, binocular vision, or ocular disorder categories, streamlining triage and reducing diagnostic delays [69].

Deep learning has shown considerable promise in advancing the clinical evaluation of dry eye disease through automated image analysis. For instance, deep learning models have accurately segmented eyelid regions and quantified meibomian gland atrophy using meibography images, offering consistent and objective assessments of glandular loss [70]. Similarly, the application of deep learning in segmenting the tear meniscus using OCT images enhances the evaluation of tear film dynamics and dry eye pathophysiology. Together, these technologies provide robust, quantitative tools that can improve diagnostic precision and facilitate more effective clinical decision making in the management of dry eye disease [71].

Deep learning also has significant potential in enhancing the diagnosis of keratoconus. The KeratoDetect algorithm, for instance, achieved an impressive accuracy of 99.33% for its test dataset, indicating strong performance in identifying keratoconus. Designed for rapid screening, it offers clinicians a promising tool for minimizing diagnostic errors and streamlining treatment decisions [72]. Similarly, models utilizing color-coded AS-OCT maps are effective in distinguishing keratoconus from normal corneas and in grading disease severity [73].

Deep learning has furthermore enhanced the early diagnosis of glaucoma by leveraging structural biomarkers from optic nerve imaging. A novel deep learning-derived atlas glaucoma score incorporating an atlas-based augmentation strategy for optic cup segmentation outperformed traditional cup-to-disc ratio metrics, achieving an AUC of 98.2% compared to 91.4% with expert-derived cup-to-disc ratio, and demonstrating superior sensitivity to early morphological changes indicating disease onset [74]. Additionally, 3D deep learning systems have shown robust performance in detecting glaucomatous optic neuropathy [75]. Another deep learning model was trained to estimate neuroretinal damage from optic disc photographs using SD-OCT-derived Bruch's membrane opening-minimum rim width as a reference. The method achieved an AUC of 0.945—comparable to that of actual SD-OCT measurements—highlighting its diagnostic reliability [76]. This demonstrates the potential of deep learning to improve glaucoma screening accuracy, reduce reliance on manual grading, and facilitate earlier intervention. However, further prospective validation and cost-effectiveness analyses are warranted.

Deep learning has demonstrated strong potential in the diagnosis and management of AMD, with performance levels approaching or even surpassing those of expert clinicians. For example, CNNs trained using OCT and OCTA images achieved diagnostic accuracies of 94% and 91%, respectively, with accuracy improving to 96% when multimodal imaging was integrated—underscoring the value of combining diverse data inputs [77]. Additionally, deep learning-based assessments of fundus images have performed comparably to human graders, suggesting a viable role for automated systems in screening, monitoring, and reducing the costs and barriers associated with AMD care. These findings highlight the clinical utility of AI in enhancing diagnostic precision and expanding access to effective AMD management [78].

Ethical Concerns in AI for Vision Sciences

Ethical implementation of AI remains paramount, with industry leaders emphasizing bias mitigation, data stewardship, and vendor liability as core requirements. Key challenges include ensuring regulatory compliance for autonomous diagnostic tools and addressing dataset biases that may disproportionately affect underserved populations. Federated learning frameworks show promise in harmonizing diverse datasets while preserving patient privacy. As AI becomes embedded in optometric practice, interdisciplinary collaboration will be critical to balance innovation with ethical responsibility [67].

Transparency and Explainability

The integration of interpretable AI models in clinical decision making is critical to bridging the gap between algorithmic outputs and clinician trust. In vision sciences, models that provide human-understandable rationales—such as highlighting retinal microaneurysms in DR or ONH cupping in glaucoma—enable clinicians to validate AI findings against their expertise [79]. For instance, the Multimodal Medical Concept Bottleneck Model (MMCBM) for choroidal tumor diagnosis directly incorporates radiologist-defined concepts such as tumor vascularity patterns and lesion morphology into its decision-making pipeline, allowing ophthalmologists to adjust concept weights and refine predictions interactively [80]. This approach aligns with clinical workflows, in which transparency in feature attribution builds confidence in AI-assisted diagnoses [79].

The risks of "black box" algorithms are particularly critical for vision care, as misdiagnoses can lead to irreversible vision loss. For example, using a model predicting glaucoma progression based solely on OCT-derived thickness maps, without understanding its reliance on peripapillary RNFLparameters, may cause clinicians to overlook confounding factors such as high myopia [79]. The opaque models for rare diseases, such as uveal melanoma, risk misclassifying tumors if their reasoning remains disconnected from established clinical markers [80]. Moreover, dataset biases—such as underrepresentation of diverse ethnicities in training cohorts—can propagate silently in black box systems, exacerbating diagnostic disparities [81].

Vision-specific solutions emphasize concept-based interpretability, in which models such as MMCBM decompose decisions into clinically meaningful components that mirror radiologists' diagnostic criteria [80]. Saliency maps, while common, often fail to capture higher-order clinical reasoning; instead, attention mechanisms that localize and describe lesions in radiology-report-aligned language offer more actionable insights [79, 80]. Regulatory frameworks increasingly demand such transparency, as seen in FDA-cleared systems requiring explainability modules to justify outputs during audits [79].

Key challenges include balancing model complexity with interpretability [80]. Future directions advocate federated learning to diversify training data, while preserving patient privacy, and interactive interfaces that allow real-time clinician–AI collaboration [80, 81]. Key advances in this field include 1) Clinical alignment: Models such as MMCBM use expert-defined concepts to mirror diagnostic workflows [80], and 2) Regulatory compliance: Explainability frameworks are now prerequisites for FDA clearance of ophthalmic AI tools [79]. However, rare disease models may struggle to represent nuanced phenotypes without exhaustive concept libraries [80]. Additionally, few interpretability methods undergo prospective trials to assess real-world clinical impact [79]. Ensuring transparency in ophthalmic AI is not only a technical requirement but also an ethical imperative, enabling clinicians to remain responsible for the interpretation and application of AI-generated insights.

Responsibility and Accountability

The attribution of responsibility for AI-related errors in vision care remains a critical challenge, requiring clear frameworks to balance clinician oversight, developer obligations, and institutional governance. The IDx-DR case exemplifies this complexity, in which the company assumed liability for diagnostic errors through contractual agreements, attempting to close the responsibility gap between clinicians and developers [82-84]. However, real-world implementation challenges persist, as demonstrated by the AI-based Surgical Safety System Study, in which errors occurred primarily in non-authenticated cases or because of delayed IOL model updates, highlighting the interplay of human factors and technical limitations [85]. This underscores the need for shared accountability, in which clinicians retain ultimate responsibility for patient care decisions, developers ensure model robustness and timely updates, and institutions enforce protocol adherence and staff training [82, 85].

Defining roles requires addressing workflow integration and error cascades. For instance, the surgical AI system's near-miss detection improved substantially; however, its effectiveness depended on consistent use, with errors persisting when staff circumvented authentication [85]. Clinicians must verify AI outputs against clinical context, particularly in high-stakes scenarios such as IOL selection or surgical laterality [85]. Developers, meanwhile, bear responsibility for algorithmic transparency and model maintenance, as outdated IOL databases directly contribute to implantation errors [85-87]. Institutions play a pivotal role in risk mitigation, ensuring that AI tools align with existing safety protocols and fostering a culture in which staff can override AI decisions without fear of reprisal [85, 87, 88].

Key challenges include liability fragmentation, in which errors may stem from overlapping failures (e.g., a clinician ignoring AI alerts compounded by a developer's delayed model update). The low positive predictive value (12%) observed in some AI-assisted DR systems further complicates accountability, as false positives may erode clinician trust and lead to overtesting [89, 90]. Regulatory frameworks must evolve to address these nuances, potentially mandating error attribution protocols and real-world performance monitoring as part of post-marketing surveillance [85, 86]. Future directions emphasize collaborative governance models, in which developers provide explainable failure modes, clinicians document AI-informed decisions, and institutions audit adherence to safety checklists [85, 91, 92]. The economic implications of shared accountability—such as cost-benefit analyses showing potential savings of up to $2.7 million because of error reduction—further incentivize systemic reforms [85]. Key advances in this field include 1) Shared liability: The contractual approach of IDx-DR provides a template for developer–clinician accountability partnerships [82], and 2) Workflow integration: AI systems that enforce authentication (e.g., facial recognition in 1.13 attempts) reduce human error when properly adopted [85]. However, unrepresentative training data may disproportionately shift liability to clinicians handling borderline or equivocal cases [86]. Additionally, no standardized protocols exist for attributing errors in AI-assisted surgeries involving multiple stakeholders [85, 93-95]. Accountability in AI-driven vision care demands interdisciplinary collaboration to align technical capabilities with clinical realities and ethical imperatives.

Table 1. Summary of the roles of artificial intelligence in ophthalmology

Ocular Structure/Domain	Key AI Applications & Technologies	Diagnostic Performance and Outcomes	Clinical Impact and Advancements	Limitations and Challenges
Cornea and Anterior Segment [7-15]	- Keratoconus detection (Scheimpflug/AS-OCT, biomechanics) - Corneal dystrophy screening - Cataract classification (slit-lamp/AS-OCT) - IOL calculation (Kane, ZEISS AI, and Hill-RBF)	- Sensitivity 98.6% and specificity 98.3% for keratoconus - 99.6% accuracy with biomechanical models - IOL MAE < 0.30 D in myopic eyes	- Early, subclinical keratoconus detection - Automated, standardized screening - Improved refractive outcomes in cataract surgery	- Device/data bias (Scheimpflug reliance) - Limited validation in diverse populations - Experimental progression models
Lens [14-18]	- IOL power calculation (machine learning formulas) - Automated lens opacity grading	- Highest % within ± 0.5 D of target (Kane, ZEISS AI) - Improved accuracy in long eyes	- Personalized IOL selection - Workflow automation	- Underrepresentation of non-Caucasian data - Need for prospective validation
Retina [20-35]	- Diabetic retinopathy (DR) screening (EyeArt, IDx-DR) - AMD progression prediction (OCT, DeepSeeNet) - ROP detection (i-ROP DL) - Retinal vascular occlusion/retinal detachment detection - Generative AI for synthetic images	- DR: Sensitivity > 95%, specificity > 80% - AMD: AUC > 0.90 for late AMD prediction - ROP: κ > 0.9 (expert-level agreement) - Vascular occlusion: 95% accuracy - Detachment: 97% sensitivity	- Autonomous DR and ROP screening - Personalized AMD risk modeling - Synthetic data for research/training	- Dataset bias (ethnicity, camera type) - Regulatory/validation gaps - Limited standards for generative AI
Optic Nerve and Glaucoma [36-49]	- Glaucoma detection (fundus/OCT, hybrid models) - Progression analysis (visual field/OCT integration) - Machine-to-machine RNFL estimation	- Fundus: Sensitivity 92%, specificity 93%, and AUC 0.90 - OCT: Sensitivity 90%, specificity 87%, and AUC 0.86 - Advanced glaucoma: AUC 0.99 - Early-stage: AUC 0.88	- Early detection in myopic/complex cases - Objective, automated progression monitoring - Multimodal risk stratification	- Ancestry-related performance disparities - Explainability gaps - Lower robustness for progression prediction
Extraocular Muscles and Binocular Vision [50-55]	- Strabismus detection (facial photos, CNNs) - Eye-tracking for deviation measurement - Amblyopia risk prediction - Surgical outcome forecasting	- Strabismus: 86–92% accuracy (image-based) - Eye-tracking: 97.1% accuracy - Amblyopia risk: indirect via strabismus models - Surgical prediction: 82.1% accuracy	- Accessible screening via mobile apps - Quantitative deviation measurement - Postoperative outcome prediction	- Underrepresentation in training datasets - Limited video-based analysis - Need for gold-standard validation
Refractive Errors and Axial Length [56-63]	- Myopia progression prediction (biometrics, environment) - Personalized risk modeling	- AUC 0.83–0.85 for myopia risk - AL as key predictor	- Early intervention for high-risk children - Data-driven public health strategies	- Limited external validation - Integration of environmental data still emerging
Neuro-ophthalmology [64-66]	- AI-driven retinal imaging: Used as a non-invasive biomarker to detect neurological diseases, particularly risks of AD and stroke. - Eye-AD framework: An AI system utilizing OCTA to analyze retinal microvasculature and choriocapillaris in the context of AD detection. - Multilevel graph representation: A technique used within the Eye-AD model to analyze relationships between retinal layers and extract disease-related biomarkers. - Fundus photography and AI: Applied in stroke risk prediction by analyzing retinal vascular patterns. - Emerging tools: Integration of ultra-widefield imaging and OCTA to detect subtle ischemic changes associated with cerebral small vessel disease.	-Alzheimer's disease (AD): Eye-AD achieved an AUC of 0.9355 for early-onset AD and 0.8630 for MCI on internal datasets. - External validation yielded an AUC of 0.9007 for early-onset AD, confirming robust performance. -Stroke risk prediction: Achievements of specific AI models are less well-documented, but retinal features, such as RNFL thinning and microvascular abnormalities, are recognized proxies for cerebral small vessel disease, which is a precursor for stroke.	- Early detection: AI models can identify prodromal AD stages, including MCI, based on OCTA-derived microvascular signatures. - Scalable screening tools: Retinal imaging offers a cost-effective and accessible alternative to neuroimaging and cerebrospinal fluid analysis, making it suitable for community-level screening. - Multimodal integration: Combining retinal imaging with genetic risk scores and cognitive tests enhances predictive performance and accuracy in neurodegenerative disease screening. - Reduced specialist dependency: AI tools support autonomous or semi-autonomous screening, potentially extending care to underserved or remote populations.	- Population bias: Underrepresentation of African and indigenous populations in datasets could compromise generalizability and introduce bias in predictive models. - Pathophysiological uncertainty: The causal relationship between retinal biomarkers and neurological diseases, such as AD and stroke, is not yet fully understood. - Validation requirements: AI-based diagnostic systems require prospective clinical validation and regulatory approval before integration into routine clinical workflows. - Clinical translation needs: Successful implementation will depend on interdisciplinary collaboration across ophthalmology, neurology, AI development, and public health.

Abbreviations: AS-OCT, anterior segment optical coherence tomography; IOL, intraocular lens; MAE, mean absolute error; D, diopter; DR, diabetic retinopathy; AMD, age-related macular degeneration; ROP, retinopathy of prematurity; OCT, optical coherence tomography; RNFL, retinal nerve fiber layer; CNN, convolutional neural network; AL, axial length; AUC, area under the curve.

Bias, Fairness, and Generalizability

The risks of bias in ophthalmic AI models due to non-representative training data are well documented, particularly concerning ethnicity, age, and comorbidities. Models trained on predominantly White cohorts exhibit reduced accuracy in underrepresented groups, such as individuals with darker retinal pigmentation, in whom higher melanin concentrations in the uvea can obscure DR lesions [96]. For example, a DR diagnostic model trained without sufficient darker-skin exemplars demonstrated a 12.5% accuracy disparity between lighter- and darker-skin groups, directly attributable to fundus pigmentation differences [96]. Challenges in external validation further compound these issues, as AI tools often underperform in real-world settings with demographic or socioeconomic profiles divergent from those of their training cohorts. A study evaluating an AI algorithm in an Armenian population—not included in its training data—achieved 94.1% sensitivity for referable DR; however, false positives arose primarily from confounding pathologies such as AMD, underscoring the need for multiclass disease recognition in generalizable models [97]. The Retinal Pigment Score (RPS), an objective metric classifying fundus pigmentation independent of self-reported ethnicity, addresses this by enabling developers to audit dataset diversity and mitigate pigmentation-related biases. However, most existing tools lack such biological grounding, instead relying on subjective ethnic labels that poorly correlate with retinal phenotypes [98].

Generalizability barriers extend to clinical workflows and imaging devices. AI systems validated on high-resolution images from specialized cameras often struggle with images from smartphone-based or portable fundus cameras, which are critical for low-resource settings [97]. Federated learning frameworks show promise in harmonizing data across institutions while preserving patient privacy, though regulatory and technical hurdles remain [99].

Key solutions include 1) Synthetic data augmentation: GANs create synthetic fundus images of underrepresented phenotypes, reducing accuracy disparities between subpopulations [96], 2) Ethnicity-agnostic metrics: The RPS replaces subjective ethnic classifications with biologically relevant pigmentation assessments, enabling equitable model evaluation [100], and 3) Post-marketing surveillance: Continuous monitoring for performance decay across demographics ensures sustained efficacy post-deployment [97]. Future directions emphasize global collaboration to build diverse datasets and regulatory mandates for transparency in training data composition, ensuring that AI tools meet the needs of heterogeneous populations. Key advances in this field include 1) RPS: Enables bias detection without reliance on self-reported ethnicity, and 2) Generative debiasing: Synthetic images narrow accuracy gaps between subpopulations [96, 101, 102]. However, performance varies across camera models, limiting scalability [97]. Most models lack training on patients with multiple ocular/systemic conditions. Addressing bias and ensuring generalizability require ongoing efforts to diversify training data, standardize evaluation metrics, and enforce transparency in AI development.

Privacy and Data Security

The use and sharing of sensitive ocular imaging data in AI development raise critical privacy concerns, particularly regarding re-identification risks and informed consent frameworks. Retinal images, while often considered less identifying than facial photographs, contain unique vascular patterns that could theoretically enable patient re-identification when combined with external datasets. Studies highlight the limitations of traditional de-identification methods, which strip metadata but may not fully anonymize image content, necessitating advanced techniques such as differential privacy or synthetic data generation to mitigate risks [103, 104]. For instance, GANs can create synthetic fundus images that preserve pathological features while eliminating identifiable patient markers, though these require careful calibration to avoid introducing diagnostic artifacts [104]. Compliance with data protection regulations demands rigorous safeguards, including encryption protocols for data in transit and at rest, role-based access controls, and audit trails to track data usage. The National Health Service (NHS)'s opt-out model for data sharing exemplifies a balanced approach, allowing retrospective research on de-identified datasets while enabling patients to withdraw consent [104]. However, challenges persist in global harmonization, as regulations such as the General Data Protection Regulation (GDPR)'s "right to be forgotten" conflict with the need of AI for immutable training datasets. Contractual agreements that prohibit data linkage or re-identification attempts are increasingly standardized, as seen in collaborations between academic institutions and AI developers [104, 105].

Key challenges include 1) Model inversion attacks: Large-parameter AI systems risk memorizing training data, enabling malicious actors to reconstruct private images through adversarial techniques [104], 2) Public misconceptions: Conflation of retinal imaging with iris recognition increases reluctance to share data, necessitating patient education initiatives [106], and 3) Regulatory fragmentation: Differing requirements across jurisdictions complicate multinational AI development, particularly for cloud-based platforms [107]. Emerging solutions include 1) Federated learning: This enables model training across decentralized datasets without raw data exchange, reducing breach risks [104], 2) Blockchain-based audits: Immutable ledgers track data provenance and usage, ensuring compliance with consent agreements [108], and 3) Dynamic consent platforms: These allow patients to granularly control data access permissions over time [109]. Striking a balance between innovation and privacy requires adaptive frameworks that prioritize patient autonomy while fostering collaborative AI development. Key advances in this field include 1) Synthetic data: GANs generate privacy-preserving fundus images without patient-specific features [104], and 2) Opt-out models: These balance research needs with patient autonomy in data sharing [104]. However, poorly tuned synthetic data may distort pathological features, compromising diagnostic validity. Moreover, overly complex consent frameworks reduce patient engagement and dataset diversity [104].

Informed Consent and Patient Autonomy

The integration of AI into ophthalmic care necessitates transparent communication about algorithmic involvement to preserve patient autonomy. Studies emphasize disclosing the role of AI in diagnosis, including its limitations (e.g., performance variability across ethnicities) and decision-making authority (e.g., whether human oversight is retained) [110]. For instance, Ursin et al. devised a checklist mandating eight specific disclosures for AI-assisted DR screening, including risks of algorithmic bias, cyberattacks, and data usage protocols, ensuring that patients understand how AI influences their care [110]. Ensuring patient understanding requires addressing health literacy disparities and algorithmic mistrust. Their study highlights that in order to make informed choices, patients must grasp how AI generates diagnoses—including its reliance on training data patterns rather than clinical reasoning [110]. However, over-reliance on AI-generated recommendations risks undermining patient trust, particularly when they perceive diminished clinician involvement, as noted in ophthalmology-specific analyses [82, 111]. To mitigate this, hybrid consent models that combine AI-generated explanations with clinician verification are emerging as best practices [112].

Key challenges include 1) Regulatory inconsistencies: While the EU's GDPR prohibits fully automated diagnoses without human review, U.S. guidelines lack similar clarity, creating disparities in consent requirements [110, 112], 2) Algorithmic transparency: Patients may struggle to comprehend the probabilistic outputs of AI, necessitating simplified explanations [110, 111, 113], and 3) Voluntariness: Offering non-AI alternatives is ethically mandated but logistically complex in resource-limited settings [110]. Future directions advocate standardized consent frameworks that integrate AI-specific disclosures into existing workflows, ensuring that patients retain autonomy without impeding technological adoption. Key advances in this field include 1) Multilingual AI tools: Synthesia's avatars [114] deliver culturally tailored consent materials, and 2) Checklist standardization: The eight-item framework ensures comprehensive AI-related disclosures [110]. However, simplified explanations risk oversimplifying the limitations of AI [110, 115]. Additionally, adding AI disclosures lengthens consent processes, potentially reducing compliance [112]. Transparent communication about the role and limitations of AI remains critical to maintaining patient–clinician trust in evolving ophthalmic practices.

Scalability and Access

AI demonstrates transformative potential in improving access to eye care for underserved populations by enabling decentralized screening and task-shifting to non-specialists. Autonomous systems such as Digital Diagnostics' AI for diabetic eye disease have increased adherence to screening guidelines in historically disadvantaged groups. This has closed the gap between low-income metropolitan populations (34% baseline adherence) and the national average (58.3%) by boosting rates to 54.5% post-implementation [116]. However, equitable deployment remains critical to avoid exacerbating health disparities. AI tools trained on non-representative datasets—often skewed toward urban, higher-income populations—risk underperforming in marginalized groups, as seen in models that struggle with darker retinal pigmentation or atypical disease presentations common in underserved cohorts [117]. For example, although AI has enhanced access to diabetic eye disease screening overall, its implementation in remote areas has been hindered by inconsistent internet connectivity and inadequate technician training, resulting in persistent service gaps for some communities [116]. Without intentional design, AI could perpetuate diagnostic deserts, where regions lacking digital infrastructure or technical support remain excluded from technological advancements.

Key solutions emphasize context-aware AI development, as follows: 1) Device-agnostic models: Tools such as Peek Vision's smartphone-based systems function offline or with low bandwidth, ensuring accessibility in areas with unreliable internet access [118], 2) Culturally adapted training: Programs embedding local health workers in AI deployment improve model generalizability and community trust, and 3) Regulatory incentives: Policies mandating diverse training datasets and post-marketing surveillance for performance disparities could standardize equitable AI adoption [116]. Future directions require public–private partnerships to subsidize AI infrastructure in low-resource settings, along with federated learning frameworks that pool globally diverse data while preserving patient privacy [116]. Key advances in this field include 1) Task-shifting: AI enables community health workers to perform specialist-level screenings, and 2) Healthcare Effectiveness Data and Information Set (HEDIS) measure improvement: Autonomous AI narrows adherence gaps in diabetic eye exams [116]. However, through infrastructure dependency, AI tools requiring high-end cameras or stable internet may exclude remote populations. Moreover, underserved groups face higher misdiagnosis risks if training data lacks diversity [116]. Scalable AI deployment demands proactive equity frameworks to ensure technological progress that translates into universal eye care access. Table 2 summarizes ethical concerns in AI for vision sciences, as mentioned above.

The evolution of AI in vision sciences hinges on integrating multimodal data—combining retinal imaging, clinical history, genetic profiles, and wearable device metrics—to create comprehensive diagnostic and prognostic models [119-121]. Future models could incorporate genetic risk scores and longitudinal lifestyle data to predict disease trajectories with higher precision. Multimodal Large Language Models, such as those tested in ophthalmology cases, show promise in bridging imaging and clinical text analysis but require refinement to match specialist-level accuracy [122, 123]. Federated learning and privacy-preserving techniques will be critical for scaling AI without compromising sensitive data. Models are needed that function across decentralized datasets while maintaining GDPR/ Health Insurance Portability and Accountability Act (HIPAA) compliance [124]. Emerging solutions such as synthetic data generation and blockchain-based audit trails could further secure patient information while enabling global collaboration. Ongoing validation must address real-world performance gaps, particularly in diverse populations. The Nature GPT-4 V study revealed an accuracy drop in complex cases [125], underscoring the necessity for prospective trials and post-marketing surveillance to monitor algorithmic drift and bias [122, 126, 127]. Regulatory frameworks should mandate transparent reporting of training data demographics and failure mode analyses, as recommended in the equity guidelines of the American Academy of Ophthalmology.

This review offers a comprehensive and timely synthesis of AI applications in vision sciences, drawing on evidence from multiple disciplines and international studies during the last two decades. A key strength lies in its targeted yet inclusive search strategy, which included both ophthalmology and optometry across a wide range of ocular conditions and imaging modalities. The focus on diagnostic performance, ethical considerations, and equitable implementation provides a multidimensional perspective that is highly relevant to clinicians, researchers, and policymakers. Furthermore, the inclusion of both established and emerging technologies ensures relevance to current clinical practice and future innovation. However, this narrative review has inherent limitations. The non-systematic nature of the search may introduce selection bias, and the exclusion of non-English literature may limit the global generalizability of the findings. Additionally, while efforts were made to include high-quality and diverse studies, variations in study design, population demographics, and outcome measures may affect the comparability of findings across sources. Despite these limitations, the review provides a critical foundation for understanding the evolving role of AI in vision care and highlights areas requiring further investigation. Clinician training in AI literacy—including model limitations, bias recognition, and ethical deployment—will be essential. Patient-centered AI must prioritize explainability through interfaces that translate probabilistic outputs into actionable insights. Generally, the transformative potential of AI in vision sciences lies in democratizing diagnostics, personalizing therapies, and alleviating global eye care disparities. However, realizing this potential demands ethical vigilance against algorithmic bias, rigorous validation across care settings, and equitable deployment that prioritizes underserved populations. Interdisciplinary collaboration among clinicians, data scientists, ethicists, and policymakers will be pivotal in balancing innovation with patient safety, ensuring that AI augments—rather than replaces—human expertise.

Table 2. Summary of ethical concerns in artificial intelligence for vision sciences [67, 79-118]

Algorithmic Transparency	Data Privacy and Security	Bias and Equity	Informed Consent	Accountability and Liability	Regulatory and Validation Challenges
- Black-box models limiting clinician and patient understanding. - Lack of explainability in diagnostic decisions.	- Risks of patient re-identification from imaging data. - Need for robust data encryption and federated learning.	- Underrepresentation of certain ethnicities and populations in training datasets. - Risk of perpetuating or amplifying healthcare disparities.	- Patients may not fully understand the role of AI in their care. - Need for clear communication about AI-driven decisions.	- Unclear responsibility in case of misdiagnosis or harm. - Challenges in assigning liability between clinicians, developers, and institutions.	- Lack of standardized validation across devices and populations. - Regulatory gaps for autonomous AI systems.

CONCLUSIONS

AI is rapidly transforming vision sciences by improving diagnostic accuracy, streamlining clinical workflow, and broadening access to quality eye care, particularly in underserved regions. Its integration into ophthalmology and optometry thus holds significant promise for enhancing patient outcomes and optimizing healthcare delivery. However, to harness the transformative potential of AI fully, sustained multidisciplinary collaboration, involving clinicians, data scientists, ethicists, and policymakers, is essential. Rigorous validation processes, transparency in algorithm development, and strong ethical oversight are equally important to mitigate risks such as bias, data misuse, and unequal access. Responsible implementation of AI in the vision sciences is essential to ensure that all populations are served equitably.

ETHICAL DECLARATIONS

Ethical approval: This study was a narrative review, and no ethical approval was required.

Conflict of interest: None.

FUNDING

None.

ACKNOWLEDGMENTS

None.

REFERENCES

1. Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021 Jul;8(2):e188-e194. doi: 10.7861/fhj.2021-0095. PMID: 34286183; PMCID: PMC8285156.
2. Maleki Varnosfaderani S, Forouzanfar M. The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. Bioengineering (Basel). 2024 Mar 29;11(4):337. doi: 10.3390/bioengineering11040337. PMID: 38671759; PMCID: PMC11047988.
3. Ahmadi A, RabieNezhad Ganji N. AI-driven medical innovations: transforming healthcare through data intelligence. International Journal of BioLife Sciences (IJBLS). 2023 Oct 1;2(2):132-42. doi.org/10.22034/ijbls.2023.185475.
4. Pinto-Coelho L. How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. Bioengineering (Basel). 2023 Dec 18;10(12):1435. doi: 10.3390/bioengineering10121435. PMID: 38136026; PMCID: PMC10740686.
5. Chikhaoui E, Alajmi A, Larabi-Marie-Sainte S. Artificial intelligence applications in healthcare sector: ethical and legal challenges. Emerging Science Journal. 2022 May 29;6(4):717-38. doi: 10.28991/ESJ-2022-06-04-05.
6. Heidari Z, Baharinia M, Ebrahimi-Besheli K, Ahmadi H. A review of artificial intelligence applications in anterior segment ocular diseases. Medical hypothesis, discovery & innovation in optometry. 2022 Sep 30;3(1):22-33. doi: 10.51329/mehdioptometry146.
7. Abd El-Khalek AA, Balaha HM, Sewelam A, Ghazal M, Khalil AT, Abo-Elsoud MEA, El-Baz A. A Comprehensive Review of AI Diagnosis Strategies for Age-Related Macular Degeneration (AMD). Bioengineering (Basel). 2024 Jul 13;11(7):711. doi: 10.3390/bioengineering11070711. PMID: 39061793; PMCID: PMC11273790.
8. Tiong EWW, Liu SH, Ting DSJ. Cochrane corner: artificial intelligence for keratoconus. Eye (Lond). 2024 Dec;38(18):3406-3408. doi: 10.1038/s41433-024-03347-z. Epub 2024 Sep 19. PMID: 39300189; PMCID: PMC11621326.
9. Vandevenne MM, Favuzza E, Veta M, Lucenteforte E, Berendschot TT, Mencucci R, Nuijts RM, Virgili G, Dickman MM. Artificial intelligence for detecting keratoconus. Cochrane Database Syst Rev. 2023 Nov 15;11(11):CD014911. doi: 10.1002/14651858.CD014911.pub2. PMID: 37965960; PMCID: PMC10646985.
10. Niazi S, Jiménez-García M, Findl O, Gatzioufas Z, Doroodgar F, Shahriari MH, Javadi MA. Keratoconus Diagnosis: From Fundamentals to Artificial Intelligence: A Systematic Narrative Review. Diagnostics (Basel). 2023 Aug 21;13(16):2715. doi: 10.3390/diagnostics13162715. PMID: 37627975; PMCID: PMC10453081.
11. Goodman D, Zhu AY. Utility of artificial intelligence in the diagnosis and management of keratoconus: a systematic review. Front Ophthalmol (Lausanne). 2024 May 17;4:1380701. doi: 10.3389/fopht.2024.1380701. PMID: 38984114; PMCID: PMC11182163.
12. Tan Z, Chen X, Li K, Liu Y, Cao H, Li J, Jhanji V, Zou H, Liu F, Wang R, Wang Y. Artificial Intelligence-Based Diagnostic Model for Detecting Keratoconus Using Videos of Corneal Force Deformation. Transl Vis Sci Technol. 2022 Sep 1;11(9):32. doi: 10.1167/tvst.11.9.32. PMID: 36178782; PMCID: PMC9527334.
13. Afifah A, Syafira F, Afladhanti PM, Dharmawidiarini D. Artificial intelligence as diagnostic modality for keratoconus: A systematic review and meta-analysis. J Taibah Univ Med Sci. 2024 Jan 1;19(2):296-303. doi: 10.1016/j.jtumed.2023.12.007. PMID: 38283379; PMCID: PMC10821587.
14. Rampat R, Deshmukh R, Chen X, Ting DSW, Said DG, Dua HS, Ting DSJ. Artificial Intelligence in Cornea, Refractive Surgery, and Cataract: Basic Principles, Clinical Applications, and Future Directions. Asia Pac J Ophthalmol (Phila). 2021 Jul 1;10(3):268-281. doi: 10.1097/APO.0000000000000394. PMID: 34224467; PMCID: PMC7611495.
15. Gutierrez L, Lim JS, Foo LL, Ng WY, Yip M, Lim GYS, Wong MHY, Fong A, Rosman M, Mehta JS, Lin H, Ting DSJ, Ting DSW. Application of artificial intelligence in cataract management: current and future directions. Eye Vis (Lond). 2022 Jan 7;9(1):3. doi: 10.1186/s40662-021-00273-z. Erratum in: Eye Vis (Lond). 2022 Mar 11;9(1):11. doi: 10.1186/s40662-022-00283-5. PMID: 34996524; PMCID: PMC8739505.
16. Stopyra W, Cooke DL, Grzybowski A. A Review of Intraocular Lens Power Calculation Formulas Based on Artificial Intelligence. J Clin Med. 2024 Jan 16;13(2):498. doi: 10.3390/jcm13020498. PMID: 38256632; PMCID: PMC10816994.
17. Zhou Y, Dai M, Sun L, Tang X, Zhou L, Tang Z, Jiang J, Xia X. The accuracy of intraocular lens power calculation formulas based on artificial intelligence in highly myopic eyes: a systematic review and network meta-analysis. Front Public Health. 2023 Nov 9;11:1279718. doi: 10.3389/fpubh.2023.1279718. PMID: 38026369; PMCID: PMC10670805.

18. Wang L, Burwinkel H, Bensaid N, Koch DD. Evaluation of an artificial intelligence-based intraocular lens calculator: AI-based IOL-optimized formula. J Cataract Refract Surg. 2024 Dec 17;51(4):332–6. doi: 10.1097/j.jcrs.0000000000001603. Epub ahead of print. PMID: 39682055; PMCID: PMC11980897.
19. Stopyra W, Voytsekhivskyy O, Grzybowski A. Prediction of Seven Artificial Intelligence-Based Intraocular Lens Power Calculation Formulas in Medium-Long Caucasian Eyes. Life (Basel). 2025 Jan 1;15(1):45. doi: 10.3390/life15010045. PMID: 39859985; PMCID: PMC11766697.
20. Lim JI, Regillo CD, Sadda SR, Ipp E, Bhaskaranand M, Ramachandra C, Solanki K. Artificial Intelligence Detection of Diabetic Retinopathy: Subgroup Comparison of the EyeArt System with Ophthalmologists' Dilated Examinations. Ophthalmol Sci. 2022 Sep 30;3(1):100228. doi: 10.1016/j.xops.2022.100228. PMID: 36345378; PMCID: PMC9636573.
21. Rajalakshmi R, Subashini R, Anjana RM, Mohan V. Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. Eye (Lond). 2018 Jun;32(6):1138-1144. doi: 10.1038/s41433-018-0064-9. Epub 2018 Mar 9. PMID: 29520050; PMCID: PMC5997766.
22. Abràmoff MD, Lavin PT, Birch M, Shah N, Folk JC. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. NPJ Digit Med. 2018 Aug 28;1:39. doi: 10.1038/s41746-018-0040-6. PMID: 31304320; PMCID: PMC6550188.
23. Ipp E, Liljenquist D, Bode B, Shah VN, Silverstein S, Regillo CD, Lim JI, Sadda S, Domalpally A, Gray G, Bhaskaranand M, Ramachandra C, Solanki K; EyeArt Study Group. Pivotal Evaluation of an Artificial Intelligence System for Autonomous Detection of Referrable and Vision-Threatening Diabetic Retinopathy. JAMA Netw Open. 2021 Nov 1;4(11):e2134254. doi: 10.1001/jamanetworkopen.2021.34254. Erratum in: JAMA Netw Open. 2021 Dec 1;4(12):e2144317. doi: 10.1001/jamanetworkopen.2021.44317. PMID: 34779843; PMCID: PMC8593763.
24. Peng Y, Dharssi S, Chen Q, Keenan TD, Agrón E, Wong WT, Chew EY, Lu Z. DeepSeeNet: A Deep Learning Model for Automated Classification of Patient-based Age-related Macular Degeneration Severity from Color Fundus Photographs. Ophthalmology. 2019 Apr;126(4):565-575. doi: 10.1016/j.ophtha.2018.11.015. Epub 2018 Nov 22. PMID: 30471319; PMCID: PMC6435402.
25. Gao Y, Xiong F, Xiong J, Chen Z, Lin Y, Xia X, Yang Y, Li G, Hu Y. Recent advances in the application of artificial intelligence in age-related macular degeneration. BMJ Open Ophthalmol. 2024 Nov 13;9(1):e001903. doi: 10.1136/bmjophth-2024-001903. PMID: 39537399; PMCID: PMC11580293.
26. Coyner AS, Young BK, Ostmo SR, Grigorian F, Ells A, Hubbard B, Rodriguez SH, Rishi P, Miller AM, Bhatt AR, Agarwal-Sinha S, Sears J, Chan RVP, Chiang MF, Kalpathy-Cramer J, Binenbaum G, Campbell JP. Use of an Artificial Intelligence-Generated Vascular Severity Score Improved Plus Disease Diagnosis in Retinopathy of Prematurity. Ophthalmology. 2024 Nov;131(11):1290-1296. doi: 10.1016/j.ophtha.2024.06.006. Epub 2024 Jun 10. PMID: 38866367; PMCID: PMC11499038.
27. Al-Khaled T, Valikodath N, Cole E, Bajimaya S, KC S, Chuluunbat T, Jonas K, Chuluunkhuu C, MacKeen LD, Ostmo S, Wu WC. Evaluation of an artificial intelligence system (i-ROP DL) for retinopathy of prematurity screening in Nepal using the Forus 3nethra neo and in Mongolia using the Retcam Portable®. Investigative Ophthalmology & Visual Science. 2021 Jun 21;62(8):3269-. https://iovs.arvojournals.org/article.aspx?articleid=2774086.
28. Ng WY, Zhang S, Wang Z, Ong CJT, Gunasekeran DV, Lim GYS, Zheng F, Tan SCY, Tan GSW, Rim TH, Schmetterer L, Ting DSW. Updates in deep learning research in ophthalmology. Clin Sci (Lond). 2021 Oct 29;135(20):2357-2376. doi: 10.1042/CS20210207. PMID: 34661658.
29. Brown JM, Campbell JP, Beers A, Chang K, Ostmo S, Chan RVP, Dy J, Erdogmus D, Ioannidis S, Kalpathy-Cramer J, Chiang MF; Imaging and Informatics in Retinopathy of Prematurity (i-ROP) Research Consortium. Automated Diagnosis of Plus Disease in Retinopathy of Prematurity Using Deep Convolutional Neural Networks. JAMA Ophthalmol. 2018 Jul 1;136(7):803-810. doi: 10.1001/jamaophthalmol.2018.1934. PMID: 29801159; PMCID: PMC6136045.
30. Senapati A, Tripathy HK, Sharma V, Gandomi AH. Artificial intelligence for diabetic retinopathy detection: A systematic review. Informatics in Medicine Unlocked. 2024 Jan 1;45:101445.doi: 10.1016/j.imu.2024.101445.
31. Ji Y, Ji Y, Liu Y, Zhao Y, Zhang L. Research progress on diagnosing retinal vascular diseases based on artificial intelligence and fundus images. Front Cell Dev Biol. 2023 Mar 28;11:1168327. doi: 10.3389/fcell.2023.1168327. PMID: 37056999; PMCID: PMC10086262.
32. Kong M, Song SJ. Artificial Intelligence Applications in Diabetic Retinopathy: What We Have Now and What to Expect in the Future. Endocrinol Metab (Seoul). 2024 Jun;39(3):416-424. doi: 10.3803/EnM.2023.1913. Epub 2024 Jun 10. PMID: 38853435; PMCID: PMC11220221.
33. Tabuchi H, Engelmann J, Maeda F, Nishikawa R, Nagasawa T, Yamauchi T, Tanabe M, Akada M, Kihara K, Nakae Y, Kiuchi Y, Bernabeu MO. Using artificial intelligence to improve human performance: efficient retinal disease detection training with synthetic images. Br J Ophthalmol. 2024 Sep 20;108(10):1430-1435. doi: 10.1136/bjo-2023-324923. PMID: 38485215; PMCID: PMC11503156.
34. Wang Z, Lim G, Ng WY, Tan TE, Lim J, Lim SH, Foo V, Lim J, Sinisterra LG, Zheng F, Liu N, Tan GSW, Cheng CY, Cheung GCM, Wong TY, Ting DSW. Synthetic artificial intelligence using generative adversarial network for retinal imaging in detection of age-related macular degeneration. Front Med (Lausanne). 2023 Jun 22;10:1184892. doi: 10.3389/fmed.2023.1184892. PMID: 37425325; PMCID: PMC10324667.
35. Sonmez SC, Sevgi M, Antaki F, Huemer J, Keane PA. Generative artificial intelligence in ophthalmology: current innovations, future applications and challenges. Br J Ophthalmol. 2024 Sep 20;108(10):1335-1340. doi: 10.1136/bjo-2024-325458. PMID: 38925907; PMCID: PMC11503064.
36. Ling XC, Chen HS, Yeh PH, Cheng YC, Huang CY, Shen SC, Lee YS. Deep Learning in Glaucoma Detection and Progression Prediction: A Systematic Review and Meta-Analysis. Biomedicines. 2025 Feb 10;13(2):420. doi: 10.3390/biomedicines13020420. PMID: 40002833; PMCID: PMC11852503.
37. Noury E, Mannil SS, Chang RT, Ran AR, Cheung CY, Thapa SS, Rao HL, Dasari S, Riyazuddin M, Chang D, Nagaraj S, Tham CC, Zadeh R. Deep Learning for Glaucoma Detection and Identification of Novel Diagnostic Areas in Diverse Real-World Datasets. Transl Vis Sci Technol. 2022 May 2;11(5):11. doi: 10.1167/tvst.11.5.11. PMID: 35551345; PMCID: PMC9145034.

38. Hemelings R, Elen B, Barbosa-Breda J, Blaschko MB, De Boever P, Stalmans I. Deep learning on fundus images detects glaucoma beyond the optic disc. Sci Rep. 2021 Oct 13;11(1):20313. doi: 10.1038/s41598-021-99605-1. Erratum in: Sci Rep. 2023 Dec 5;13(1):21456. doi: 10.1038/s41598-023-48939-z. PMID: 34645908; PMCID: PMC8514536.
39. Chan EJJ, Najjar RP, Tang Z, Milea D. Deep Learning for Retinal Image Quality Assessment of Optic Nerve Head Disorders. Asia Pac J Ophthalmol (Phila). 2021 May-Jun 01;10(3):282-288. doi: 10.1097/APO.0000000000000404. PMID: 34383719.
40. Chiang YY, Chen CL, Chen YH. Deep Learning Evaluation of Glaucoma Detection Using Fundus Photographs in Highly Myopic Populations. Biomedicines. 2024 Jun 23;12(7):1394. doi: 10.3390/biomedicines12071394. PMID: 39061968; PMCID: PMC11274657.
41. Thompson AC, Falconi A, Sappington RM. Deep learning and optical coherence tomography in glaucoma: Bridging the diagnostic gap on structural imaging. Front Ophthalmol (Lausanne). 2022 Sep 21;2:937205. doi: 10.3389/fopht.2022.937205. PMID: 38983522; PMCID: PMC11182271.
42. Medeiros FA, Jammal AA, Thompson AC. From Machine to Machine: An OCT-Trained Deep Learning Algorithm for Objective Quantification of Glaucomatous Damage in Fundus Photographs. Ophthalmology. 2019 Apr;126(4):513-521. doi: 10.1016/j.ophtha.2018.12.033. Epub 2018 Dec 20. PMID: 30578810; PMCID: PMC6884092.
43. Sharma P, Takahashi N, Ninomiya T, Sato M, Miya T, Tsuda S, Nakazawa T. A hybrid multi model artificial intelligence approach for glaucoma screening using fundus images. NPJ Digit Med. 2025 Feb 27;8(1):130. doi: 10.1038/s41746-025-01473-w. PMID: 40016437; PMCID: PMC11868628.
44. Christopher M, Bowd C, Walker E, Belghith A, Goldbaum MH, Rezapour J, Fazio MA, Girkin CA, De Moraes G, Liebmann JM, Weinreb RN. Comparison of Deep Learning Glaucoma Detection Using Optic Nerve Head Fundus Photos and Optical Coherence Tomography. Investigative Ophthalmology & Visual Science. 2022 Jun 1;63(7):2035-A0476. https://iovs.arvojournals.org/article.aspx?articleid=2780609.
45. Martucci A, Gallo Afflitto G, Pocobelli G, Aiello F, Mancino R, Nucci C. Lights and Shadows on Artificial Intelligence in Glaucoma: Transforming Screening, Monitoring, and Prognosis. J Clin Med. 2025 Mar 21;14(7):2139. doi: 10.3390/jcm14072139. PMID: 40217589; PMCID: PMC11989555.
46. Djulbegovic MB, Bair H, Gonzalez DJT, Ishikawa H, Wollstein G, Schuman JS. Artificial Intelligence for Optical Coherence Tomography in Glaucoma. Transl Vis Sci Technol. 2025 Jan 2;14(1):27. doi: 10.1167/tvst.14.1.27. PMID: 39854198.
47. Huang X, Islam MR, Akter S, Ahmed F, Kazami E, Serhan HA, Abd-Alrazaq A, Yousefi S. Artificial intelligence in glaucoma: opportunities, challenges, and future directions. Biomed Eng Online. 2023 Dec 16;22(1):126. doi: 10.1186/s12938-023-01187-8. PMID: 38102597; PMCID: PMC10725017.
48. Shi M, Luo Y, Tian Y, Shen LQ, Zebardast N, Eslami M, Kazeminasab S, Boland MV, Friedman DS, Pasquale LR, Wang M. Equitable artificial intelligence for glaucoma screening with fair identity normalization. NPJ Digit Med. 2025 Jan 20;8(1):46. doi: 10.1038/s41746-025-01432-5. PMID: 39833503; PMCID: PMC11747341.
49. Zhang L, Tang L, Xia M, Cao G. The application of artificial intelligence in glaucoma diagnosis and prediction. Front Cell Dev Biol. 2023 May 4;11:1173094. doi: 10.3389/fcell.2023.1173094. PMID: 37215077; PMCID: PMC10192631.
50. Yarkheir M, Sadeghi M, Azarnoush H, Akbari MR, Khalili Pour E. Automated strabismus detection and classification using deep learning analysis of facial images. Sci Rep. 2025 Jan 31;15(1):3910. doi: 10.1038/s41598-025-88154-6. PMID: 39890897; PMCID: PMC11785772.
51. Zhao Z, Meng H, Li S, Wang S, Wang J, Gao S. High-Accuracy Intermittent Strabismus Screening via Wearable Eye-Tracking and AI-Enhanced Ocular Feature Analysis. Biosensors (Basel). 2025 Feb 14;15(2):110. doi: 10.3390/bios15020110. PMID: 39997012; PMCID: PMC11852461.
52. Mao K, Yang Y, Guo C, Zhu Y, Chen C, Chen J, Liu L, Chen L, Mo Z, Lin B, Zhang X, Li S, Lin X, Lin H. An artificial intelligence platform for the diagnosis and surgical planning of strabismus using corneal light-reflection photos. Ann Transl Med. 2021 Mar;9(5):374. doi: 10.21037/atm-20-5442. PMID: 33842595; PMCID: PMC8033395.
53. de Figueiredo LA, Dias JVP, Polati M, Carricondo PC, Debert I. Strabismus and Artificial Intelligence App: Optimizing Diagnostic and Accuracy. Transl Vis Sci Technol. 2021 Jun 1;10(7):22. doi: 10.1167/tvst.10.7.22. PMID: 34137838; PMCID: PMC8212438.
54. Shu Q, Pang J, Liu Z, Liang X, Chen M, Tao Z, Liu Q, Guo Y, Yang X, Ding J, Chen R, Wang S, Li W, Zhai G, Xu J, Li L. Artificial Intelligence for Early Detection of Pediatric Eye Diseases Using Mobile Photos. JAMA Netw Open. 2024 Aug 1;7(8):e2425124. doi: 10.1001/jamanetworkopen.2024.25124. PMID: 39106068; PMCID: PMC11304122.
55. Wu D, Huang X, Chen L, Hou P, Liu L, Yang G. Integrating artificial intelligence in strabismus management: current research landscape and future directions. Exp Biol Med (Maywood). 2024 Nov 25;249:10320. doi: 10.3389/ebm.2024.10320. PMID: 39654660; PMCID: PMC11625544.
56. Mu J, Zhong H, Jiang M. Machine-learning models to predict myopia in children and adolescents. Front Med (Lausanne). 2024 Nov 19;11:1482788. doi: 10.3389/fmed.2024.1482788. PMID: 39629228; PMCID: PMC11613503.
57. Qi Z, Li T, Chen J, Yam JC, Wen Y, Huang G, Zhong H, He M, Zhu D, Dai R, Qian B, Wang J, Qian C, Wang W, Zheng Y, Zhang J, Yi X, Wang Z, Zhang B, Liu C, Cheng T, Yang X, Li J, Pan YT, Ding X, Xiong R, Wang Y, Zhou Y, Feng D, Liu S, Du L, Yang J, Zhu Z, Bi L, Kim J, Tang F, Zhang Y, Zhang X, Zou H, Ang M, Tham CC, Cheung CY, Pang CP, Sheng B, He X, Xu X. A deep learning system for myopia onset prediction and intervention effectiveness evaluation in children. NPJ Digit Med. 2024 Aug 7;7(1):206. doi: 10.1038/s41746-024-01204-7. PMID: 39112566; PMCID: PMC11306751.
58. Li J, Zeng S, Li Z, Xu J, Sun Z, Zhao J, Li M, Zou Z, Guan T, Zeng J, Liu Z, Xiao W, Wei R, Miao H, Ziyar I, Huang J, Gao Y, Zeng Y, Zhou XT, Zhang K. Accurate prediction of myopic progression and high myopia by machine learning. Precis Clin Med. 2024 Mar 4;7(1):pbae005. doi: 10.1093/pcmedi/pbae005. PMID: 38558949; PMCID: PMC10981449.
59. Zhao J, Yu Y, Li Y, Li F, Zhang Z, Jian W, Chen Z, Shen Y, Wang X, Ye Z, Huang C, Zhou X. Development and validation of predictive models for myopia onset and progression using extensive 15-year refractive data in children and adolescents. J Transl Med. 2024 Mar 17;22(1):289. doi: 10.1186/s12967-024-05075-0. PMID: 38494492; PMCID: PMC10946190.

60. Barraza-Bernal MJ, Ohlendorf A, Sanz Diez P, Feng X, Yang LH, Lu MX, Wahl S, Kratzer T. Prediction of refractive error and its progression: a machine learning-based algorithm. BMJ Open Ophthalmol. 2023 Oct;8(1):e001298. doi: 10.1136/bmjophth-2023-001298. PMID: 37793703; PMCID: PMC10551949.

61. Li SM, Ren MY, Gan J, Zhang SG, Kang MT, Li H, Atchison DA, Rozema J, Grzybowski A, Wang N; Anyang Childhood Eye Study Group. Machine Learning to Determine Risk Factors for Myopia Progression in Primary School Children: The Anyang Childhood Eye Study. Ophthalmol Ther. 2022 Apr;11(2):573-585. doi: 10.1007/s40123-021-00450-2. Epub 2022 Jan 21. PMID: 35061239; PMCID: PMC8927561.

62. Zadnik K, Sinnott LT, Cotter SA, Jones-Jordan LA, Kleinstein RN, Manny RE, Twelker JD, Mutti DO; Collaborative Longitudinal Evaluation of Ethnicity and Refractive Error (CLEERE) Study Group. Prediction of Juvenile-Onset Myopia. JAMA Ophthalmol. 2015 Jun;133(6):683-9. doi: 10.1001/jamaophthalmol.2015.0471. PMID: 25837970; PMCID: PMC4607030.

63. Huang J, Ma W, Li R, Zhao N, Zhou T. Myopia prediction for children and adolescents via time-aware deep learning. Sci Rep. 2023 Apr 3;13(1):5430. doi: 10.1038/s41598-023-32367-0. PMID: 37012269; PMCID: PMC10070443.

64. Hao J, Kwapong WR, Shen T, Fu H, Xu Y, Lu Q, Liu S, Zhang J, Liu Y, Zhao Y, Zheng Y, Frangi AF, Zhang S, Qi H, Zhao Y. Early detection of dementia through retinal imaging and trustworthy AI. NPJ Digit Med. 2024 Oct 20;7(1):294. doi: 10.1038/s41746-024-01292-5. PMID: 39428420; PMCID: PMC11491446.

65. Wang J, Wang YX, Zeng D, Zhu Z, Li D, Liu Y, Sheng B, Grzybowski A, Wong TY. Artificial intelligence-enhanced retinal imaging as a biomarker for systemic diseases. Theranostics. 2025 Feb 18;15(8):3223-3233. doi: 10.7150/thno.100786. PMID: 40093903; PMCID: PMC11905132.

66. Yang Q, Bee YM, Lim CC, Sabanayagam C, Yim-Lui Cheung C, Wong TY, Ting DSW, Lim LL, Li H, He M, Lee AY, Shaw AJ, Keong YK, Wei Tan GS. Use of artificial intelligence with retinal imaging in screening for diabetes-associated complications: systematic review. EClinicalMedicine. 2025 Feb 18;81:103089. doi: 10.1016/j.eclinm.2025.103089. PMID: 40052065; PMCID: PMC11883405.

67. Krishnan A, Dutta A, Srivastava A, Konda N, Prakasam RK. Artificial Intelligence in Optometry: Current and Future Perspectives. Clin Optom (Auckl). 2025 Mar 12;17:83-114. doi: 10.2147/OPTO.S494911. PMID: 40094103; PMCID: PMC11910921.

68. Santos LF, Sánchez-Tena MÁ, Alvarez-Peregrina C, Sánchez-González JM, Martinez-Perez C. The Role of Artificial Intelligence in Optometric Diagnostics and Research: Deep Learning and Time-Series Forecasting Applications. Technologies. 2025 Feb 12;13(2):77. doi: 10.3390/technologies13020077.

69. Stuermer L, Braga S, Martin R, Wolffsohn JS. Artificial intelligence virtual assistants in primary eye care practice. Ophthalmic Physiol Opt. 2025 Mar;45(2):437-449. doi: 10.1111/opo.13435. Epub 2024 Dec 26. PMID: 39723633; PMCID: PMC11823310.

70. Wang J, Yeh TN, Chakraborty R, Yu SX, Lin MC. A Deep Learning Approach for Meibomian Gland Atrophy Evaluation in Meibography Images. Transl Vis Sci Technol. 2019 Dec 18;8(6):37. doi: 10.1167/tvst.8.6.37. PMID: 31867138; PMCID: PMC6922272.

71. Stegmann H, Werkmeister RM, Pfister M, Garhöfer G, Schmetterer L, Dos Santos VA. Deep learning segmentation for optical coherence tomography measurements of the lower tear meniscus. Biomed Opt Express. 2020 Feb 20;11(3):1539-1554. doi: 10.1364/BOE.386228. PMID: 32206427; PMCID: PMC7075621.

72. Lavric A, Valentin P. KeratoDetect: Keratoconus Detection Algorithm Using Convolutional Neural Networks. Comput Intell Neurosci. 2019 Jan 23;2019:8162567. doi: 10.1155/2019/8162567. PMID: 30809255; PMCID: PMC6364125.

73. Kamiya K, Ayatsuka Y, Kato Y, Fujimura F, Takahashi M, Shoji N, Mori Y, Miyata K. Keratoconus detection using deep learning of colour-coded maps with anterior segment optical coherence tomography: a diagnostic accuracy study. BMJ Open. 2019 Sep 27;9(9):e031313. doi: 10.1136/bmjopen-2019-031313. PMID: 31562158; PMCID: PMC6773416.

74. Girard F, Hurtut T, Kavalec C, Cheriet F. Atlas-based score for automatic glaucoma risk stratification. Comput Med Imaging Graph. 2021 Jan;87:101797. doi: 10.1016/j.compmedimag.2020.101797. Epub 2020 Oct 16. PMID: 33307282.

75. Ran AR, Cheung CY, Wang X, Chen H, Luo LY, Chan PP, Wong MOM, Chang RT, Mannil SS, Young AL, Yung HW, Pang CP, Heng PA, Tham CC. Detection of glaucomatous optic neuropathy with spectral-domain optical coherence tomography: a retrospective training and validation deep-learning analysis. Lancet Digit Health. 2019 Aug;1(4):e172-e182. doi: 10.1016/S2589-7500(19)30085-8. Epub 2019 Aug 9. PMID: 33323187.

76. Thompson AC, Jammal AA, Medeiros FA. A Deep Learning Algorithm to Quantify Neuroretinal Rim Loss From Optic Disc Photographs. Am J Ophthalmol. 2019 May;201:9-18. doi: 10.1016/j.ajo.2019.01.011. Epub 2019 Jan 26. PMID: 30689990; PMCID: PMC6884088.

77. Vaghefi E, Hill S, Kersten HM, Squirrell D. Multimodal Retinal Image Analysis via Deep Learning for the Diagnosis of Intermediate Dry Age-Related Macular Degeneration: A Feasibility Study. J Ophthalmol. 2020 Jan 13;2020:7493419. doi: 10.1155/2020/7493419. PMID: 32411434; PMCID: PMC7201607.

78. Burlina PM, Joshi N, Pekala M, Pacheco KD, Freund DE, Bressler NM. Automated Grading of Age-Related Macular Degeneration From Color Fundus Images Using Deep Convolutional Neural Networks. JAMA Ophthalmol. 2017 Nov 1;135(11):1170-1176. doi: 10.1001/jamaophthalmol.2017.3782. PMID: 28973096; PMCID: PMC5710387

79. Hanif AM, Beqiri S, Keane PA, Campbell JP. Applications of interpretability in deep learning models for ophthalmology. Curr Opin Ophthalmol. 2021 Sep 1;32(5):452-458. doi: 10.1097/ICU.0000000000000780. PMID: 34231530; PMCID: PMC8373813.

80. Wu Y, Liu Y, Yang Y, Yao MS, Yang W, Shi X, Yang L, Li D, Liu Y, Yin S, Lei C, Zhang M, Gee JC, Yang X, Wei W, Gu S. A concept-based interpretable model for the diagnosis of choroid neoplasias using multimodal data. Nat Commun. 2025 Apr 13;16(1):3504. doi: 10.1038/s41467-025-58801-7. PMID: 40223097; PMCID: PMC11994757.

81. Thaler A, Ong J, Al-Aswad LA. Upholding artificial intelligence transparency in ophthalmology: A call for collaboration between academia, industry, and government for patient care in the 21st century. Asia Pac J Ophthalmol (Phila). 2024 Jul-Aug;13(4):100093. doi: 10.1016/j.apjo.2024.100093. Epub 2024 Aug 17. PMID: 39159825.

82. Evans NG, Wenner DM, Cohen IG, Purves D, Chiang MF, Ting DSW, Lee AY. Emerging Ethical Considerations for the Use of Artificial Intelligence in Ophthalmology. Ophthalmol Sci. 2022 Mar 7;2(2):100141. doi: 10.1016/j.xops.2022.100141. PMID: 36249707; PMCID: PMC9560632.

83. Bleher H, Braun M. Diffused responsibility: attributions of responsibility in the use of AI-driven clinical decision support systems. AI Ethics. 2022;2(4):747-761. doi: 10.1007/s43681-022-00135-x. Epub 2022 Jan 24. PMID: 35098247; PMCID: PMC8785388.

84. Khan Z, Gaidhane AM, Singh M, Ganesan S, Kaur M, Sharma GC, Rani P, Sharma R, Thapliyal S, Kushwaha M, Kumar H, Agarwal RK, Shabil M, Verma L, Sidhu A, Manan NBA, Bushi G, Mehta R, Sah S, Satapathy P, Samal SK. Diagnostic Accuracy of IDX-DR for Detecting Diabetic Retinopathy: A Systematic Review and Meta-Analysis. Am J Ophthalmol. 2025 May;273:192-204. doi: 10.1016/j.ajo.2025.02.022. Epub 2025 Feb 20. PMID: 39986640.
85. Tabuchi H, Ishitobi N, Deguchi H, Nakaniida Y, Tanaka H, Akada M, Tanabe M. Large-scale observational study of AI-based patient and surgical material verification system in ophthalmology: real-world evaluation in 37 529 cases. BMJ Qual Saf. 2024 Nov 29:bmjqs-2024-018018. doi: 10.1136/bmjqs-2024-018018. Epub ahead of print. PMID: 39613452.
86. Li Z, Wang L, Wu X, Jiang J, Qiang W, Xie H, Zhou H, Wu S, Shao Y, Chen W. Artificial intelligence in ophthalmology: The path to the real-world clinic. Cell Rep Med. 2023 Jul 18;4(7):101095. doi: 10.1016/j.xcrm.2023.101095. Epub 2023 Jun 28. PMID: 37385253; PMCID: PMC10394169.
87. Hussain AK, Kakakhel MM, Ashraf MF, Shahab M, Ahmad F, Luqman F, Ahmad M, Mohammed Nour A, Varrassi G, Kinger S. Innovative Approaches to Safe Surgery: A Narrative Synthesis of Best Practices. Cureus. 2023 Nov 30;15(11):e49723. doi: 10.7759/cureus.49723. PMID: 38161861; PMCID: PMC10757557.
88. Yu X, Wang Z, Wu J, Weng D. Artificial intelligence-based perioperative safety verification system improved the performance of surgical safety verification execution. Am J Transl Res. 2024 Apr 15;16(4):1295-1305. doi: 10.62347/PUUT2092. PMID: 38715820; PMCID: PMC11070349.
89. Kanagasingam Y, Xiao D, Vignarajan J, Preetham A, Tay-Kearney ML, Mehrotra A. Evaluation of Artificial Intelligence-Based Grading of Diabetic Retinopathy in Primary Care. JAMA Netw Open. 2018 Sep 7;1(5):e182665. doi: 10.1001/jamanetworkopen.2018.2665. PMID: 30646178; PMCID: PMC6324474.
90. Lawton T, Morgan P, Porter Z, Hickey S, Cunningham A, Hughes N, Iacovides I, Jia Y, Sharma V, Habli I. Clinicians risk becoming 'liability sinks' for artificial intelligence. Future Healthc J. 2024 Feb 19;11(1):100007. doi: 10.1016/j.fhj.2024.100007. PMID: 38646041; PMCID: PMC11025047.
91. Goktas P, Grzybowski A. Shaping the Future of Healthcare: Ethical Clinical Challenges and Pathways to Trustworthy AI. J Clin Med. 2025 Feb 27;14(5):1605. doi: 10.3390/jcm14051605. PMID: 40095575; PMCID: PMC11900311.
92. Albahri AS, Duhaim AM, Fadhel MA, Alnoor A, Baqer NS, Alzubaidi L, Albahri OS, Alamoodi AH, Bai J, Salhi A, Santamaría J. A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. Information Fusion. 2023 Aug 1;96:156-91. doi: 10.1016/j.inffus.2023.03.008.
93. Mennella C, Maniscalco U, De Pietro G, Esposito M. Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon. 2024 Feb 15;10(4):e26297. doi: 10.1016/j.heliyon.2024.e26297. PMID: 38384518; PMCID: PMC10879008.
94. Cestonaro C, Delicati A, Marcante B, Caenazzo L, Tozzo P. Defining medical liability when artificial intelligence is applied on diagnostic algorithms: a systematic review. Front Med (Lausanne). 2023 Nov 27;10:1305756. doi: 10.3389/fmed.2023.1305756. PMID: 38089864; PMCID: PMC10711067.
95. Arjomandi Rad A, Vardanyan R, Athanasiou T, Maessen J, Sardari Nia P. The ethical considerations of integrating artificial intelligence into surgery: a review. Interdiscip Cardiovasc Thorac Surg. 2025 Mar 5;40(3):ivae192. doi: 10.1093/icvts/ivae192. PMID: 39999009; PMCID: PMC11904299.
96. Burlina P, Joshi N, Paul W, Pacheco KD, Bressler NM. Addressing Artificial Intelligence Bias in Retinal Diagnostics. Transl Vis Sci Technol. 2021 Feb 5;10(2):13. doi: 10.1167/tvst.10.2.13. PMID: 34003898; PMCID: PMC7884292.
97. Rao DP, Savoy FM, Sivaraman A, Dutt S, Shahsuvaryan M, Jrbashyan N, Hambardzumyan N, Yeghiazaryan N, Das T. Evaluation of an AI algorithm trained on an ethnically diverse dataset to screen a previously unseen population for diabetic retinopathy. Indian J Ophthalmol. 2024 Aug 1;72(8):1162-1167. doi: 10.4103/IJO.IJO_2151_23. Epub 2024 Jul 29. PMID: 39078960; PMCID: PMC11451790.
98. Rajesh AE, Olvera-Barrios A, Warwick AN, Wu Y, Stuart KV, Biradar MI, Ung CY, Khawaja AP, Luben R, Foster PJ, Cleland CR, Makupa WU, Denniston AK, Burton MJ, Bastawrous A, Keane PA, Chia MA, Turner AW, Lee CS, Tufail A, Lee AY, Egan C; UK Biobank Eye and Vision Consortium. Machine learning derived retinal pigment score from ophthalmic imaging shows ethnicity is not biology. Nat Commun. 2025 Jan 2;16(1):60. doi: 10.1038/s41467-024-55198-7. PMID: 39746957; PMCID: PMC11696055.
99. Haripriya R, Khare N, Pandey M. Privacy-preserving federated learning for collaborative medical data mining in multi-institutional settings. Sci Rep. 2025 Apr 11;15(1):12482. doi: 10.1038/s41598-025-97565-4. PMID: 40217112; PMCID: PMC11992079.
100. Rajesh AE, Olvera-Barrios A, Warwick AN, Wu Y, Stuart KV, Biradar M, Ung CY, Khawaja AP, Luben R, Foster PJ, Lee CS, Tufail A, Lee AY, Egan C; EPIC Norfolk, UK Biobank Eye and Vision Consortium. Ethnicity is not biology: retinal pigment score to evaluate biological variability from ophthalmic imaging using machine learning. medRxiv. 2023 Jul 6:2023.06.28.23291873. doi: 10.1101/2023.06.28.23291873. Update in: Nat Commun. 2025 Jan 2;16(1):60. doi: 10.1038/s41467-024-55198-7. PMID: 37461664; PMCID: PMC10350142.
101. Alderman JE, Palmer J, Laws E, McCradden MD, Ordish J, Ghassemi M, Pfohl SR, Rostamzadeh N, Cole-Lewis H, Glocker B, Calvert M, Pollard TJ, Gill J, Gath J, Adebajo A, Beng J, Leung CH, Kuku S, Farmer LA, Matin RN, Mateen BA, McKay F, Heller K, Karthikesalingam A, Treanor D, Mackintosh M, Oakden-Rayner L, Pearson R, Manrai AK, Myles P, Kumuthini J, Kapacee Z, Sebire NJ, Nazer LH, Seah J, Akbari A, Berman L, Gichoya JW, Righetto L, Samuel D, Wasswa W, Charalambides M, Arora A, Pujari S, Summers C, Sapey E, Wilkinson S, Thakker V, Denniston A, Liu X. Tackling algorithmic bias and promoting transparency in health datasets: the STANDING Together consensus recommendations. Lancet Digit Health. 2025 Jan;7(1):e64-e88. doi: 10.1016/S2589-7500(24)00224-3. Epub 2024 Dec 18. PMID: 39701919; PMCID: PMC11668905.
102. Foote HP, Hong C, Anwar M, Borentain M, Bugin K, Dreyer N, Fessel J, Goyal N, Hanger M, Hernandez AF, Hornik CP, Jackman JG, Lindsay AC, Matheny ME, Ozer K, Seidel J, Stockbridge N, Embi PJ, Lindsell CJ. Embracing Generative Artificial Intelligence in Clinical Research and Beyond: Opportunities, Challenges, and Solutions. JACC Adv. 2025 Mar;4(3):101593. doi: 10.1016/j.jacadv.2025.101593. Epub 2025 Feb 8. PMID: 39923329; PMCID: PMC11850149.
103. Nakayama LF, de Matos JCRG, Stewart IU, Mitchell WG, Martinez-Martin N, Regatieri CVS, Celi LA. Retinal Scans and Data Sharing: The Privacy and Scientific Development Equilibrium. Mayo Clin Proc Digit Health. 2023 Mar 25;1(2):67-74. doi: 10.1016/j.mcpdig.2023.02.003. PMID: 40206726; PMCID: PMC11975763.

104. Tom E, Keane PA, Blazes M, Pasquale LR, Chiang MF, Lee AY, Lee CS; AAO Artificial Intelligence Task Force. Protecting Data Privacy in the Age of AI-Enabled Ophthalmology. Transl Vis Sci Technol. 2020 Jul 6;9(2):36. doi: 10.1167/tvst.9.2.36. PMID: 32855840American Academy of Ophthalmology Board of Trustees. Electronic address: flum@aao.org. Special Commentary: Balancing Benefits and Risks: The Case for Retinal Images to Be Considered as Nonprotected Health Information for Research Purposes. Ophthalmology. 2025 Jan;132(1):115-118. doi: 10.1016/j.ophtha.2024.07.031. Epub 2024 Aug 9. PMID: 39127409.
105. Zibran MF. Eye based authentication: Iris and retina recognition. Department of Computer Science, The University of Saskatchewan, Canada. 2009;7. Report number: 2011-04. doi:10.13140/RG.2.2.13275.23841
106. Zaidan E, Ibrahim IA. AI governance in a complex and rapidly changing regulatory landscape: A global perspective. Humanities and Social Sciences Communications. 2024 Sep 1;11(1):1-8. doi: 10.1057/s41599-024-03560-x.
107. Sigwart M, Borkowski M, Peise M, Schulte S, Tai S. A secure and extensible blockchain-based data provenance framework for the Internet of Things. Personal and Ubiquitous Computing. 2020 Jun 16:1-5. doi: 10.1007/s00779-020-01417-z
108. Goncharov L, Suominen H, Cook M. Dynamic consent and personalised medicine. Med J Aust. 2022 Jun 20;216(11):547-549. doi: 10.5694/mja2.51555. Epub 2022 May 24. PMID: 35611469; PMCID: PMC9544476.
109. Ursin F, Timmermann C, Orzechowski M, Steger F. Diagnosing Diabetic Retinopathy With Artificial Intelligence: What Information Should Be Included to Ensure Ethical Informed Consent? Front Med (Lausanne). 2021 Jul 21;8:695217. doi: 10.3389/fmed.2021.695217. PMID: 34368192; PMCID: PMC8333706.
110. Cross JL, Choma MA, Onofrey JA. Bias in medical AI: Implications for clinical decision-making. PLOS Digit Health. 2024 Nov 7;3(11):e0000651. doi: 10.1371/journal.pdig.0000651. PMID: 39509461; PMCID: PMC11542778.
111. Cohen IG, Slottje A. Artificial intelligence and the law of informed consent. In: Solaiman B, Cohen IG, editors. Research Handbook on Health, AI and the Law. Cheltenham, UK: Edward Elgar Publishing Ltd; 2024 Jul 16. Chapter 10. PMID: 40245217.
112. Kiseleva A, Kotzinos D, De Hert P. Transparency of AI in Healthcare as a Multilayered System of Accountabilities: Between Legal Requirements and Technical Limitations. Front Artif Intell. 2022 May 30;5:879603. doi: 10.3389/frai.2022.879603. PMID: 35707765; PMCID: PMC9189302.
113. Hamet P, Tremblay J. Artificial intelligence in medicine. Metabolism. 2017 Apr;69S:S36-S40. doi: 10.1016/j.metabol.2017.01.011. Epub 2017 Jan 11. PMID: 28126242.
114. Stødle K, Flage R, Guikema S, Aven T. Artificial intelligence for risk analysis-A risk characterization perspective on advances, opportunities, and limitations. Risk Anal. 2025 Apr;45(4):738-751. doi: 10.1111/risa.14307. Epub 2024 Apr 10. PMID: 38600041; PMCID: PMC12032382.
115. Huang JJ, Channa R, Wolf RM, Dong Y, Liang M, Wang J, Abramoff MD, Liu TYA. Autonomous artificial intelligence for diabetic eye disease increases access and health equity in underserved populations. NPJ Digit Med. 2024 Jul 22;7(1):196. doi: 10.1038/s41746-024-01197-3. Erratum in: NPJ Digit Med. 2024 Aug 23;7(1):220. doi: 10.1038/s41746-024-01229-y. PMID: 39039218; PMCID: PMC11263546.
116. Hasanzadeh F, Josephson CB, Waters G, Adedinsewo D, Azizi Z, White JA. Bias recognition and mitigation strategies in artificial intelligence healthcare applications. NPJ Digit Med. 2025 Mar 11;8(1):154. doi: 10.1038/s41746-025-01503-7. PMID: 40069303
117. Anitha S, Priyanka S. Smart phone based automated diabetic retinopathy detection system. Measurement: Sensors. 2024 Feb 1;31:100957. doi: 10.1016/j.measen.2023.100957.
118. Ma R, Cheng Q, Yao J, Peng Z, Yan M, Lu J, Liao J, Tian L, Shu W, Zhang Y, Wang J, Jiang P, Xia W, Li X, Gan L, Zhao Y, Zhu J, Qin B, Jiang Q, Wang X, Lin X, Chen H, Zhu W, Xiang D, Nie B, Wang J, Guo J, Xue K, Cui H, Cheng J, Zhu X, Hong J, Shi F, Zhang R, Chen X, Zhao C. Multimodal machine learning enables AI chatbot to diagnose ophthalmic diseases and provide high-quality medical responses. NPJ Digit Med. 2025 Jan 27;8(1):64. doi: 10.1038/s41746-025-01461-0. PMID: 39870855; PMCID: PMC11772878.
119. Phipps B, Hadoux X, Sheng B, Campbell JP, Liu TYA, Keane PA, Cheung CY, Chung TY, Wong TY, van Wijngaarden P. AI image generation technology in ophthalmology: Use, misuse and future applications. Prog Retin Eye Res. 2025 Mar 17;106:101353. doi: 10.1016/j.preteyeres.2025.101353. Epub ahead of print. PMID: 40107410.
120. Wang S, He X, Jian Z, Li J, Xu C, Chen Y, Liu Y, Chen H, Huang C, Hu J, Liu Z. Advances and prospects of multi-modal ophthalmic artificial intelligence based on deep learning: a review. Eye Vis (Lond). 2024 Oct 1;11(1):38. doi: 10.1186/s40662-024-00405-1. PMID: 39350240; PMCID: PMC11443922.
121. Sorin V, Kapelushnik N, Hecht I, Zloto O, Glicksberg BS, Bufman H, Livne A, Barash Y, Nadkarni GN, Klang E. Integrated visual and text-based analysis of ophthalmology clinical cases using a large language model. Sci Rep. 2025 Feb 10;15(1):4999. doi: 10.1038/s41598-025-88948-8. PMID: 39930078; PMCID: PMC11811221.
122. Lu Z. Multimodal large language models in vision and ophthalmology. Investigative Ophthalmology & Visual Science. 2024 Jun 17;65(7):3876-. https://iovs.arvojournals.org/article.aspx?articleid=2797769
123. Loftus TJ, Ruppert MM, Shickel B, Ozrazgat-Baslanti T, Balch JA, Efron PA, Upchurch GR Jr, Rashidi P, Tignanelli C, Bian J, Bihorac A. Federated learning for preserving data privacy in collaborative healthcare research. Digit Health. 2022 Oct 27;8:20552076221134455. doi: 10.1177/20552076221134455. PMID: 36325438; PMCID: PMC9619858.
124. Casals-Farre O, Baskaran R, Singh A, Kaur H, Ul Hoque T, de Almeida A, Coffey M, Hassoulas A. Assessing ChatGPT 4.0's Capabilities in the United Kingdom Medical Licensing Examination (UKMLA): A Robust Categorical Analysis. Sci Rep. 2025 Apr 15;15(1):13031. doi: 10.1038/s41598-025-97327-2. PMID: 40234701; PMCID: PMC12000555.
125. Ullah F, He J, Zhu N, Wajahat A, Nazir A, Qureshi S, Pathan MS, Dev S. Blockchain-enabled EHR access auditing: Enhancing healthcare data security. Heliyon. 2024 Aug 10;10(16):e34407. doi: 10.1016/j.heliyon.2024.e34407. PMID: 39253236.
126. Bathula A, Gupta SK, Merugu S, Saba L, Khanna NN, Laird JR, Sanagala SS, Singh R, Garg D, Fouda MM, Suri JS. Blockchain, artificial intelligence, and healthcare: the tripod of future—a narrative review. Artificial Intelligence Review. 2024 Aug 8;57(9):238. doi: 10.1007/s10462-024-10873-5.
127. Bathula A, Gupta SK, Merugu S, Saba L, Khanna NN, Laird JR, Sanagala SS, Singh R, Garg D, Fouda MM, Suri JS. Blockchain, artificial intelligence, and healthcare: the tripod of future—a narrative review. Artificial Intelligence Review. 2024 Aug 8;57(9):238. doi: 10.1007/s10462-024-10873-5.