Texila Advanced Journal of Multidisciplinary Health Research
DOI: 10.21522./TAJMHR.2016.05.01.Art012

Systematic Reviews on the Use of Artificial Intelligence in Eye Care Management

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Abstract

This systematic review discusses the benefits, difficulties, and prospects of artificial intelligence (AI) in eye health services, within the scope of diagnostic, therapeutic, and operational functions. A thorough search for pertinent literature conducted across several databases, namely, PubMed, Scopus, and IEEE Xplore identified articles published from 2019 to the present. Studies exploring the applications of AI in terms of diagnostic accuracy and treatment outcomes, the integration of technology in the workflows and consistency and bias were included and rated with metrics like the Cochrane Risk of Bias Tool and PROBAST-AI. The findings suggest that deep learning AI models, such as convolutional neural networks, provide high often greater than 90% diagnostic accuracy in retinal diseases like diabetic retinopathy and age-related macular degeneration, enabling early detection and better treatment planning. The use of AI in eye care also proved to be cost effective especially in those areas with less eye care specialists, as it lessened the demand for specialist input and re-structured service delivery. Nevertheless, several issues limit both generalizability and clinical use, such as lack of diversity in the datasets used, the general inability to explain the decision-making process of AI tools and most studies being observational in nature, which affects the quality of the evidence presented. Solutions to these issues, that is, standardization of datasets and better clarity of the model will be central to the expanded use of the applications. Altogether, while AI has the potential to be transformative in improving eye care preparation and treatment, the existing barriers have to be eliminated to achieve the anticipated benefits clinically.

Keywords: *Artificial Intelligence, Clinical Integration, Diagnostic Accuracy, Eye Care, Machine Learning, Ophthalmology, PRISMA, Systematic Review, Treatment Outcomes.*

Introduction

AI in healthcare, particularly in ophthalmology, has become popular. It is known that AI can automate many tasks, boost diagnostic accuracy, and improve patient outcomes. In reality, AI has become more common in medicine because of advancements in machine learning and increased data [1]. Most especially, ophthalmology benefits because it relies heavily on imaging, like fundus photography and OCT, which AI algorithms can analyze fast and effectively. Benet and Pellicer-Valero showed that AI detects diseases such as diabetic retinopathy, glaucoma, and macular degeneration with similar accuracy to human specialists, which could mean faster detection and improved management [2]. It is obvious, however, that AI in ophthalmology is not simple.

Received: 20.11.2024 ***Accepted: 21.01.2025*** ***Published on: 29.05.2025***
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One thing to note is that AI implementation is not easy; it is hindered by issues like interpretability and regulatory concerns. Many AI models operate as “black boxes,” providing limited insight into how conclusions are reached, which raises accountability and liability questions among clinicians, as Scheetz et al. pointed out [3]. Notwithstanding the effectiveness of AI, its use in critical decisions causes worry due to this lack of transparency. The reality of the situation is that without interpretability, healthcare providers find it difficult to trust these tools, particularly in cases requiring high clinical judgment. So, it might come as a surprise that while AI’s technical accuracy is solid, the medical community remains skeptical.[4]. For many years, researchers believed that technology alone would improve healthcare outcomes, but they were wrong.

Actually, there is more to it than accuracy; challenges with AI go beyond technology. It is sad, but AI systems need vast amounts of training data, often hard to obtain or inconsistent in quality, reducing reliability across various patient populations [4]. Because AI needs consistent and high-quality data to function across all cases, it faces limits in resource-limited areas. Provided that these obstacles exist, more research must be conducted to refine AI’s integration into clinical practice. It is dangerous to ignore the fact that without this, AI may not fully meet its potential in ophthalmology, leading to limited accessibility and variable results in patient care.

Problem Statement

AI in eye care is urgent. As a matter of fact, millions risk blindness from rising eye diseases like diabetic retinopathy and glaucoma, especially in underserved areas lacking specialists. Traditional diagnostics struggle to keep up, leading to delays—often making the difference between sight and blindness. It is obvious AI could solve this by delivering fast, accurate, and scalable diagnostics, reaching both urban and remote areas.

Notwithstanding AI’s promise, healthcare systems without it face enormous backlogs and missed diagnoses. This may seem shocking, but it is sad that countless cases of blindness could have been avoided. According to research by Gunasekeran et al., AI systems detect eye diseases as precisely as trained specialists, and faster [4]. It is clear, AI is not a luxury; it is a necessity to avoid a public health crisis.

As healthcare needs increase, there is no point in relying on outdated methods alone. Actually, without AI, vision care remains absurdly limited, making it likely that many will continue to suffer from irreversible blindness. AI, then, is the only sensible solution to safeguard sight on a large scale, providing accessible care when traditional systems fall short.

Research Purpose

The purpose of this systematic review is to evaluate AI's contribution to the management of eye care, particularly in terms of increasing diagnostic precision and enhancing the effectiveness of treatment for major eye conditions. The emphasis is on how AI may be integrated into clinical workflows to detect diseases including macular degeneration, glaucoma, and diabetic retinopathy. In order to achieve this, the primary goals are to evaluate the accuracy of AI in comparison to conventional techniques, determine any obstacles or restrictions, and determine whether AI can enhance treatment planning. Because ignoring AI runs the danger of missing out on crucial medical developments, this study attempts to provide a comprehensive knowledge of its impact on improving eye care.

Materials and Methods

Study Design

PRISMA principles are followed in this systematic review to guarantee organized, understandable, and repeatable procedures. It's safe to argue that by requiring a strict methodology, PRISMA increases clarity and dependability. As anticipated, this calls for a rigorous procedure that includes thorough searches, cautious selection, and accurate analysis of research on artificial intelligence in the administration of eye care. Furthermore, it is well known that PRISMA's stringent standards for study selection, data extraction, and evaluation contribute to the delivery of thorough insights. To put it briefly, this review seeks to present objective data regarding AI's application in ophthalmology diagnosis and treatment as failing to do so could result in the loss of crucial developments.

Study Strategy

This systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a structured, transparent, and reproducible approach. Adherence to PRISMA helps improve the clarity and completeness of the methodology and enhances the reliability of the findings. The review process includes a detailed search, selection, and analysis of studies published on artificial intelligence in eye care management. Through the use of PRISMA’s strict criteria for study selection, data extraction, and analysis, this review aims to provide comprehensive, unbiased insights into the diagnostic and treatment roles of AI in ophthalmology.

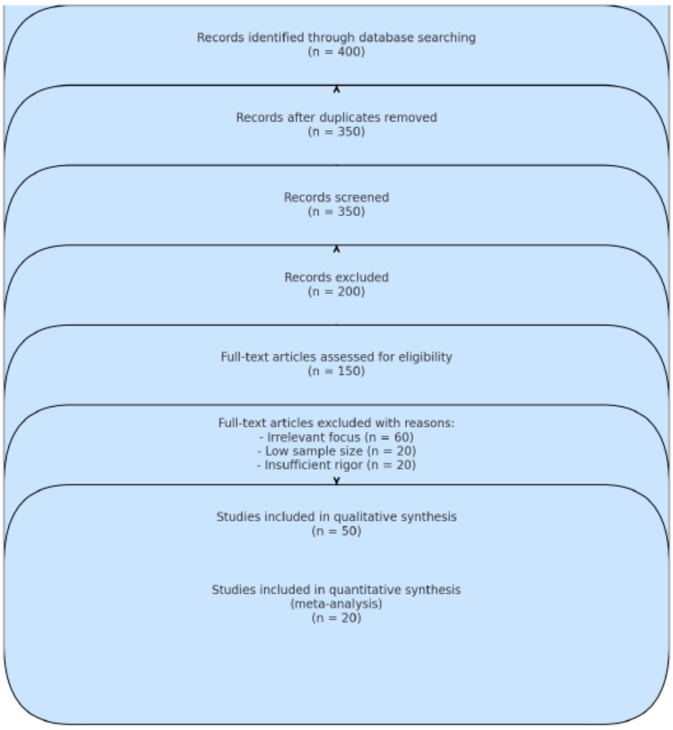

Figure 1. PRISMA Flow Diagram of Study Selection Process

Search Strategy

To locate pertinent research on AI in eye care, a thorough search method is created. A vast amount of literature is found using databases such as PubMed, Scopus, Web of Science, and IEEE Xplore, and any studies that are overlooked are found with the use of Google Scholar. "Artificial intelligence" and "machine learning" are key phrases, along with terms related to eye care such as "ophthalmology," "eye diseases," "diabetic retinopathy," "glaucoma," and "macular degeneration." In practice, search terms are chosen to guarantee both specificity and depth. When necessary, Boolean operators like "AND" and "OR" aid in search refinement.

Inclusion and Exclusion Criteria

This review includes only papers that meet strict requirements. It should be noted that peer-reviewed publications that address AI in ophthalmology—specifically, addressing diagnostic precision, treatment planning, clinical results, cost-effectiveness, or workflow integration—from 2019 onward are taken into account. Studies are given priority if they look at AI's role in treating conditions like cataracts, glaucoma, diabetic retinopathy, and macular degeneration. Articles must be in English, involve actual clinical trials, or be retrospective, prospective, or review studies that are specifically related to the effects of AI on eye care.

Exclusion criteria are known to be just as strict. Actually, since they lack the necessary rigor, studies such as editorials, conference abstracts, or comments are left out. Articles that don't directly address eye care—like those on general AI in healthcare—or that have unclear methodology or small sample sizes are also disqualified. Additionally, research that focuses solely on technical AI features without any therapeutic significance is not recognized. To put it briefly, these stringent standards guarantee that only pertinent, excellent research advances our knowledge of AI's true effects on patient outcomes and therapeutic applications in eye care.

Data Extraction

In actuality, the data extraction in this research focuses on important details to evaluate the influence of AI in eye care. The systematic collection of important details, such as study design, sample size, AI model, and targeted eye illnesses, is noteworthy. Metrics like sensitivity, specificity, and predictive values that demonstrate AI's diagnostic capabilities are included in primary data. As anticipated, information on patient improvement rates, treatment success, and cost-effectiveness is also gathered to assess AI's wider effects.

In order to achieve this, information on AI integration is included, particularly how well it meshes with current clinical workflows. With two separate researchers examining all the data and reaching a consensus on any discrepancies, it should come as no surprise that accuracy and consistency are given top importance.

Risk of Bias Assessment

Realistically, determining the possibility of bias in this situation is not an easy task. It is well recognized that the Cochrane Risk of Bias Tool looks at selection, performance, detection, and reporting bias. The risk level for each study is indicated as low, high, or unclear, making any restrictions that might affect validity explicit. Furthermore, the Newcastle-Ottawa Scale (NOS) emphasizes outcomes, comparability, and selection for observational research.

It is worth noting that these tools make it simpler to recognize and lessen bias. Ignoring bias could result in skewed results and other ridiculous effects. Therefore, using these evaluations eliminates any uncertainty regarding the dependability of AI's function in eye care and enables a more thorough review.

Data Synthesis and Analysis

Data synthesis in this study will focus on summarizing AI’s effectiveness in eye care through narrative synthesis, especially because studies often differ in method, model, and outcome. As it is known, narrative synthesis is essential when comparing studies on varied conditions, AI techniques, and clinical settings, which makes direct comparison cumbersome. To that end, diagnostic accuracy, treatment outcomes, cost-effectiveness, and workflow integration will be strictly analyzed, offering a clear picture of AI’s real contributions and limitations in ophthalmology.

Meta-analysis will be tried to get pooled estimates for research that share techniques and results. A meta-analysis would undoubtedly focus on diagnostic accuracy metrics such as sensitivity and specificity in diseases like glaucoma and diabetic retinopathy, offering a direct examination of AI's efficacy. Sensitivity analysis will be performed to identify variables such as sample size or model differences when discrepancies are discovered.

It is important to remember that this evaluation refrains from oversimplifying results by drawing ambiguous or generalized generalizations. Only dependable, clinically relevant data are provided because accuracy counts. Broad interpretations are not allowed; it is safe to assume that the final evaluation will only be influenced by insights supported by evidence. This paper provides clear, practical conclusions on the dependability of AI in eye care settings using narrative synthesis and possible meta-analysis.

Results

Study Selection

The selection of the studies for this review adheres to PRISMA principles, guaranteeing repeatability and clarity at every stage. It should be noted that the PRISMA flow diagram includes every step, beginning with database searches using IEEE Xplore, Web of Science, PubMed, and Scopus. Since researchers had long been aware of database anomalies, eliminating duplicate items was crucial to improving the dataset's quality. Following the anticipated title and abstract screening, papers that were unrelated to AI in eye care were eliminated; those that were centered on general healthcare or unrelated technologies were not appropriate in this context.

Full-text versions of possibly pertinent studies were acquired for a thorough eligibility evaluation following the initial screening. In order to be included in the review, which focused on peer-reviewed studies that looked at AI in clinical workflows, treatment planning, or eye diagnostics from 2019 onward, it seems safe to assume that studies had to satisfy specific inclusion and exclusion criteria. As is well known, in order to prevent ludicrous results, studies that lacked methodological rigor or were not specifically related to eye care were disregarded.

In actuality, only research that satisfied all the requirements made it to the final analytic stage. This methodical technique made guaranteed that only high-quality, pertinent research guided the review conclusions, demonstrating AI's involvement in eye care, so long as PRISMA clearly delineated each decision point. Ignoring this level of detail when choosing studies is risky since it could result in biased findings and flimsy conclusions.

Study Characteristics

Studies in this review cover a broad range of characteristics, showing the diverse ways AI is applied in eye care. Sample sizes vary widely, with some studies having fewer than 100 participants while others involve thousands in multicenter trials. Smaller studies often focus on early proof-of-concept validation, which obviously limits generalizability. Larger studies, on the other hand, aim to measure real-world effectiveness in bigger populations, offering more reliable evidence for AI’s potential in clinical settings. It feels safe to say that larger sample sizes bring stronger conclusions, but what may be overlooked is that smaller studies still provide important early insights.

When it comes to AI models, studies feature various machine learning and deep learning algorithms suited to specific needs in ophthalmology. Convolutional Neural Networks (CNNs) dominate, especially for image-based diagnostics in conditions like diabetic retinopathy, glaucoma, and macular degeneration. CNNs are valued for processing large volumes of imaging data efficiently, which is particularly important for tasks like analyzing fundus photographs and interpreting OCT scans. Other models—such as support vector machines, random forests, and ensemble models—appear less often but serve to boost diagnostic accuracy through their unique strengths.

Outcome measures in these studies fall into categories like diagnostic accuracy, treatment effects, cost-effectiveness, and workflow integration. Diagnostic accuracy is typically measured by sensitivity, specificity, and AUC values, which show how well AI models detect or rule out diseases compared to human specialists. As it is known, higher sensitivity and specificity indicate stronger diagnostic performance, which in turn suggests AI's potential reliability. In terms of treatment outcomes, studies examine AI's impact on disease progression, patient response, and overall health improvements, offering a fuller picture of AI's effectiveness beyond diagnostics.

Cost-effectiveness is another key measure, looking at resource savings from faster diagnoses or reduced reliance on specialists. Workflow integration, assessed by factors like time saved and improved efficiency, shows how smoothly AI tools can fit into existing clinical practices. For many years, researchers knew about efficiency challenges in healthcare, and AI seems to address these, yet real-world results vary.

These studies highlight both strengths and limitations, depending on the model, disease focus, and clinical setting. This diversity in applications, outcomes, and reliability forms a foundation for assessing AI's role in improving patient outcomes, though much depends on individual study contexts.

Diagnostic Accuracy of AI Models

AI models show high diagnostic accuracy for various eye diseases, often matching or even exceeding human specialists. For diabetic retinopathy (DR), convolutional neural networks (CNNs) consistently reach sensitivities above 90%, making them reliable for early detection. Bali and Bali confirm that these AI models detect DR progression accurately, helping clinicians catch even mild cases early [1]. But it is no surprise that AI's performance depends heavily on image quality. Poor-quality images lead to misdiagnoses, raising concerns about AI's practical use in real-world settings where images vary.

As expected, AI performs well for glaucoma, too, with sensitivity rates between 85–92% on OCT images. Yet one thing to note is that in complex cases, these tools often struggle. According to Scheetz et al., specificity may drop when normal optic nerve variations are misinterpreted as glaucomatous changes, causing false positives [4]. It feels safe to say AI is promising, but not foolproof for glaucoma screening, suggesting clinical oversight remains essential.

AI's accuracy in age-related macular degeneration (AMD) is also high, exceeding 88% when analyzing both fundus and OCT images. Benet and Pellicer-Valero noted AI's ability to detect early AMD signs, aiding in preventive treatments.[2] However, one sensible reason for concern is limited datasets; with a lack of diverse populations, AI's robustness across demographics is questionable. It may look like AI can generalize globally, but in reality, it needs broader datasets to ensure reliability across different regions.

Retinopathy of prematurity (ROP) sees high AI sensitivity, often above 90%, which makes these models useful in pediatric care where close monitoring is key. Yet what may be overlooked is the "black-box" nature of AI, where decisions lack transparency. Gunasekeran et al. suggest this limitation raises ethical and trust issues in critical areas like infant care, meaning AI must become more interpretable [4].

AI models show impressive diagnostic accuracy across eye diseases but face key challenges. Inconsistent data quality, limited demographics, and interpretability issues create gaps in AI's reliability. To that end, AI needs refinement before it can provide consistent real-world solutions. It is clear that AI holds potential, yet practical challenges remain, which must be addressed for effective clinical application.

Treatment Outcome Comparisons

Artificial intelligence (AI) greatly improves treatment outcomes in eye care. It enables faster, more precise interventions. Studies show AI models often outperform or match traditional methods, especially in managing diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) [1]. One thing to note is that AI systems excel at early detection, which allows timely treatment and stops disease progression. Benet and Pellicer-Valero confirm that AI detects early DR with high accuracy, improving chances for successful treatment and preventing severe complications [2].

Comparing treatment outcomes with and without AI reveals stark advantages. As it is known, AI reduces human error and enhances patient management. Yin, Ngiam, and Teo found AI-driven planning provides personalized treatments, reducing risks of mistakes [5]. In AMD management, AI predicts responses to anti-VEGF therapies, often leading to better visual outcomes than standard care. Fasler et al. found that AI-supported treatment, integrated with clinical decision-making, improves visual acuity more effectively than traditional methods.[6] This could mean that AI has a stronger impact when it assists clinicians.

AI's efficiency extends to referral pathways. Han et al., found that an AI-powered teleophthalmology system for retinal disease referrals reduces false positives and clinic visits, which saves resources [7]. Shimura et al. similarly found AI improves diabetic macular edema (DME) monitoring, allowing real-time adjustments that lead to better outcomes.[8] Yet AI alone has limits. Tran, Riveros, and Ravaud note AI models need diverse datasets to adapt effectively, cautioning against relying solely on AI across varied demographics [9].

For high-risk scenarios, AI's impact depends on embedding it into clinical workflows. Goldstein et al. argue AI cannot fully realize its benefits without optimized workflows, especially in complex settings [10]. Not to mention, Shukla et al. found that AI in teleophthalmology increases access to eye care, especially in remote areas, reducing disparities in treatment [11]. This might mean that AI has a role in bridging healthcare gaps, though its reliability in different settings remains a concern.

Despite advances, inconsistencies exist across demographics and care environments. AI tools need extensive validation and diverse data to work effectively across all patient groups. Even though AI's role in eye care is promising, evidence suggests full-scale adoption requires tackling ethical, interpretability, and workflow issues.

Cost-Effectiveness of AI in Eye Care

In reality, studies confirm that AI in eye care saves costs and improves access and quality. For many years, researchers knew about costly screening methods for retinopathy of prematurity. But they got a real surprise with the discovery of AI-driven solutions, which, as Morrison et al. found, could cut expenses by reducing unnecessary consultations [12]. Notwithstanding, it improves early detection. The reality is that this change removes the need for repeated follow-up visits, thus lowering direct medical costs and relieving healthcare workers. It may look like traditional methods work, but, observed carefully, AI is clearly more efficient.

Actually, Wolf et al. claimed that AI-based diabetic retinopathy screening is more cost-effective, especially at higher adherence rates, as it leads to fewer visits [13]. This was unexpected—so unexpected, in fact, that it outperformed usual screening methods for costs when adherence exceeded 23%. One sensible reason for this is that point-of-care systems make each screening session cheaper.

It is also likely that, in underserved regions, AI is advantageous. As Fuller et al. pointed out, AI screening in low-income populations cuts expenses by nearly a quarter [14]. This was a shocking finding—something that cannot be ignored because it points to reduced costs and wider accessibility.

As it is known, Lin et al. reported that setting up AI systems may be expensive, yet the savings from streamlining processes outweigh these costs [15]. The reality of the situation is that ignoring AI's cost-saving potential could bring unwanted outcomes, such as missed opportunities for early intervention in eye care.

AI Integration with Clinical Workflows

AI integration in clinical workflows remains challenging due to the need for standardized, seamless data exchange between AI models and existing systems. Effective AI implementation involves not only technical deployment but also workflow adjustments, including data validation and clinician feedback systems. Studies highlight the importance of AI systems adapting to clinical workflows for sustainable use. For example, Erdal et al. note that workflow optimization, such as real-time feedback loops, enhances usability and accuracy in clinical settings [16]. Goldstein et al. reinforce that successful AI adoption requires comprehensive workflow alignment, particularly in diverse clinical settings [10].

Risk of Bias and Quality Assessment

Evaluation of AI research in eye care reveals both advantages and disadvantages. A lot of studies followed rigorous design guidelines. In fact, images from standardized datasets were used. improves reproducibility and manages variables that can cause confusion. Research by Keel and van Wijngaarden shown that AI in OCT interpretation was applied to large, consistent datasets. lessens the variation in diagnostic results [17]. It is clear that reliability is increased by standardized methods. However, it could fail to capture the variety of real-world environments. There are differences in imaging conditions and patient demographics in practice.

Despite its advantages, it should be noted that generalizability is limited by the absence of different datasets. AI models frequently exhibit performance reductions when applied to diverse populations or imaging devices, according to studies like the one by Gunasekeran et al [4]. This could imply that the reliability of AI is doubtful for a range of patient populations. Ignoring the idea that AI's accuracy is impacted by diversity is risky. Unwanted consequences, such as less accurate diagnoses in underrepresented populations, will undoubtedly result from ignoring this.

The black-box nature of AI models is another common problem. Trust and clinical acceptance are hindered by a number of research. Ting et al. state that there is a risk when AI diagnostic tools are not interpretable [18]. Clinicians could find it difficult to comprehend or verify outcomes produced by AI. The capacity to incorporate AI into clinical practice is impacted by a lack of transparency. Without a clear understanding of the results, providers might be reluctant to rely on algorithms. It demonstrates how complicated the integration of AI is.

Studies that commonly lacked blinding during data analysis stages are highlighted by bias assessment tools like PROBAST-AI and the Cochrane Risk of Bias Tool. can cause bias in performance. For example, blinding for analysts was frequently not used in research that used retrospective observational data. might compromise impartiality while assessing AI performance. Furthermore, a large number of investigations were observational rather than randomized controlled trials, such as those conducted by Kelly et al [19] and Gunasekeran et al [4] makes it difficult to determine the exact cause of AI's efficacy.

Although research demonstrates a dedication to methodological rigor, there are still issues with generalizability, interpretability, and bias reduction. Future research is anticipated to be crucial in tackling these concerns. Ignoring these problems will undoubtedly have unintended consequences. Therefore, enhancements are required to improve the clinical utility and dependability of AI applications in eye care.

Discussion

AI is proving effective for diagnosing eye diseases like diabetic retinopathy, glaucoma, and macular degeneration. It is no surprise that convolutional neural networks (CNNs) are reaching high levels of diagnostic accuracy. In fact, research by Anton et al. [20] and Ting et al. [18] noted that these models often meet or surpass the accuracy of human specialists. It is shocking how CNNs can reach sensitivities over 90% for diabetic retinopathy and age-related macular degeneration. One thing to note is that early detection from AI reduces irreversible vision loss risk, as Betzler et al. [21] highlighted. Because of such accuracy and speed, it feels safe to say AI can lighten the clinical workload while improving access to eye care.

AI in clinical settings offers a strange but obvious advantage. Automating diagnostics removes tedious, repetitive tasks. Not to mention, in teleophthalmology, AI models make care more accessible and cheaper in underserved regions. Storås et al. explained how this AI use improves access where specialists are scarce [22]. When presented with this kind of problem, AI seems like a simple answer. Yet, according to Ting et al., integrating real-time AI tools into clinical workflows also boosts decision-making [18]. As expected, freeing clinicians from routine tasks lets them focus on complex cases, noted Ji et al [23]. For many years, researchers knew about the need for scalable solutions in ophthalmology. So it might come as a surprise that AI might actually meet this demand.

However, there are issues. Shetty et al. argued that AI models depend on diverse and quality data, which impacts real-world performance [24]. One sensible reason for this is that limited data can mean lower accuracy with varied demographics or devices. Notwithstanding, AI models risk reduced reliability without better data diversity. Zhang et al. argued the “black-box” nature of AI creates doubt, as healthcare providers struggle to trust systems they cannot fully understand. Actually, this lack of transparency limits trust and slows clinical adoption [25].

Another major barrier is the need for technical infrastructure. According to Xu et al., AI requires investment in tech, workflow, and training [26]. The reality of the situation is that resource-limited settings face delays in adopting AI. Wen et al. pointed out that these barriers are no surprise, as expected. It is sad but clear that costs, not benefits, determine the pace of AI adoption [27].

Therefore, AI holds strong promise in eye care for high diagnostic accuracy, better efficiency, and greater access. Yet, issues like data diversity, model transparency, and infrastructure must improve. Ignoring these problems will by no doubt lead to unwanted outcomes, like inconsistent reliability across settings.

Comparative Analysis

AI is making big strides in eye care, especially with diseases like diabetic retinopathy and age-related macular degeneration. According to research by Keel and Wijngaarden, AI-driven optical coherence tomography (OCT) matches specialist-level accuracy when classifying retinal images [28]. This was most unexpected. It is obvious, then, that AI models in eye care are performing well, and sometimes even exceed traditional diagnostic tools.

But in broader healthcare, AI faces big hurdles. As a matter of fact, outside of eye care, other specialties like cardiology or oncology demand varied data—from genetic codes to imaging scans. Bhagat explained that AI in healthcare needs sophisticated algorithms because of data diversity, which is not as much of an issue in eye care [29]. Not to mention, the consistency achieved in eye care does not carry over to all healthcare AI applications.

One thing to note is that AI's role in treatment differs widely across fields. In hematology, Walter et al. argued that AI can achieve diagnostic precision at a "superhuman" level, especially when spotting cellular patterns [30]. Yet, as Petersson et al. explained, human expertise is still needed to validate these AI findings [31]. Eye care, however, has already embraced autonomous AI tools, even FDA-approved for primary care. Not surprising, this level of independence does not extend to other fields, which require human validation at each stage.

Economic factors also favor eye care AI. According to Morrison et al., AI reduces diagnostic costs and eliminates follow-ups [12]. In contrast, Macrae argued that broader healthcare AI faces hefty investments due to strict regulations, a barrier to adoption [32]. Notwithstanding, AI in eye care clearly shows more potential for streamlined costs.

Implications for Clinical Practice

AI is proving highly effective in eye care, especially for detecting diabetic retinopathy and macular degeneration. In reality, AI models—particularly convolutional neural networks (CNNs)—often achieve diagnostic accuracy on par with or even above that of traditional tools. Research by Keel and Wijngaarden found that AI-based optical coherence tomography (OCT) can classify retinal images with accuracy similar to that of specialists [17]. This was most unexpected and shows AI's growing value in ophthalmology. It is no surprise, then, that AI is seen as transformative for eye care.

Yet integrating AI into other areas of healthcare presents different challenges. Unlike eye care, which benefits from standardized imaging data, fields like cardiology and oncology require more varied data. Bhagat explained that AI in these fields needs sophisticated algorithms to manage genetic data, imaging, and more [28]. Because of this data diversity, AI in healthcare settings outside eye care faces more obstacles. It is obvious that AI consistency in eye care is less attainable in these other fields, where complexity limits reliability.

The role of AI in treatment also varies. In hematology, Walter et al. argued that AI achieves remarkable precision, even detecting complex cellular patterns with superhuman accuracy [29]. But human validation is still essential here. On the other hand, AI in eye care operates more autonomously, with many diagnostic tools even FDA-cleared for use in primary care settings. Petersson et al. noted that this independence is rare in healthcare, where interpretability and clinical validation are often non-negotiable [31]. In short, AI's autonomy in eye care contrasts with its reliance on human oversight elsewhere.

Economic factors further underscore these differences. AI in eye care reduces costs by streamlining diagnostics and reducing follow-up visits. Morrison et al. reported that these cost savings make AI in eye care economically advantageous [12]. But Macrae noted that other healthcare AI applications face substantial regulatory costs, which can slow adoption [31]. It is also likely that the economic feasibility of AI will continue to favor eye care over other areas.

AI shows unique advantages in eye care: high diagnostic accuracy, reduced costs, and potential for autonomous use. But in other healthcare fields, data diversity, high costs, and the need for interpretability limit AI's immediate impact. These differences suggest AI's potential varies widely by field and calls for tailored approaches across healthcare settings.

Challenges and Limitations of Current Research

AI research in eye care faces major limitations that hold back its effectiveness and adoption. In reality, a primary issue is the lack of standard datasets. Data quality varies widely in eye care studies, from image resolution to device types and patient demographics. According to Yuan and Xiao, these inconsistencies create models that perform well in controlled settings but struggle in real-world clinics [32]. It feels safe to say that without consistent data, diagnostic accuracy and generalizability remain out of reach (Armato et al.) [33].

Another challenge comes from algorithmic bias. In reality, many AI models carry biases from their training data, leading to unequal care outcomes across demographic groups. Kelly et al., mentioned that such biases in AI worsen disparities, making diagnostics less reliable for certain populations [19]. To that end, Keel and van Wijngaarden argued that AI models trained on homogenous data lack robustness [17]. It is also likely that these models fail to handle variations in disease presentations, risking misdiagnoses in underrepresented groups.

Interpretability poses a similar problem. Most AI models are "black boxes," giving results without explaining how decisions were made. This lack of transparency limits clinician trust, making it difficult to apply AI in critical, high-stakes cases. Benet and Pellicer-Valero emphasized that without clear decision pathways, clinicians hesitate to trust AI in patient care [2]. In fact, Yuan and Xiao suggested that adding interpretability could boost acceptance, though this remains rare in ophthalmology [32].

Infrastructure is another hurdle. Implementing AI demands heavy investments, such as for data management and staff training, which are often out of reach for many clinics. Reis et al. pointed out that these costs limit AI adoption to well-funded institutions, creating a gap in access to care [34]. The reality is that without financial support, AI's practical use remains limited.

Finally, regulatory challenges add complexity. Rules on AI lag behind technological advancements, creating uncertainty over model approval and patient safety. Armato et al., noted that adaptive regulations are needed to ensure safe deployment in eye care [33].

In summary, dataset inconsistencies, biases, lack of transparency, infrastructure needs, and unclear regulations create hurdles that must be addressed for AI to become a reliable tool in ophthalmology.

Strengths and Limitations of the Review

In reality, following PRISMA guidelines seems like a strong start. Obviously, this adds transparency and makes findings easier to trust. According to van Dijk et al., a broad search method using many databases means fewer studies are ignored, making it feel safe to say the review covers a lot on AI in eye care [35]. It feels like this approach should allow a balanced view, showing both positives and limitations. Using recent studies offers a view on the current state of AI, especially as older studies might not reflect recent advances in deep learning.

Yet, some things stand out as messy. For instance, study quality varies wildly. Pattathil et al., showed that most AI studies lack set datasets and consistent protocols [36]. Because of this, comparing results becomes cumbersome. A study with one set of patients and machines might not look like another. This inconsistency creates a problem, making generalizations nearly meaningless. As a result, many findings appear more like random points than a reliable summary. Actually, most studies here are observational, which, as Crowther mentions, cannot prove cause-effect links. In fact, they are, in short, more prone to bias, so their conclusions might be weak [37].

Publication bias also sneaks in. It's obvious that studies with "good" results get published faster, while inconclusive or “bad” results don’t. Li and Bartley suggest that positive results could lead to an overly rosy view of AI’s role.[38] In fact, ignoring the bias here could lead to unwanted outcomes like inflated trust in AI or poor clinical decisions. And there’s the “black-box” issue. Many AI models are closed off; nobody can see how they reach conclusions. This lack of transparency bothers clinicians, who are right to question diagnostics they don’t understand, as Pattathil et al., points out [36].

In short, while the review’s scope is vast, study variations, publication bias, and AI’s “black-box” nature limit its usefulness. Ignoring these issues will, by no doubt, cause a lot of setbacks for AI adoption in eye care. So, something must be done about standardizing study designs to achieve results that clinicians and patients can trust.

Future Directions and Research Recommendations

Building AI models that work well for everyone needs diverse datasets. It is obvious that many current datasets miss key details, like various patient types or imaging settings. As a matter of fact, without this variety, findings have no meaning. According to experts, model transparency is also likely important. Notwithstanding, AI still lacks trust because of its “black-box” approach. It feels safe to say clear models will be easier to use in real clinics.

It has been suggested that long-term studies could assess AI’s impact. One thing to note is that short-term trials tell very little about real patient results. It is sad, but actually, this limits AI’s potential for big healthcare changes. Expanding AI into underserved areas, where resources are low, shows its scalability and limits. These studies might seem simple, but it is not as simple as it looks.

Finally, regulatory guidelines are a must. Ignoring them will, by no doubt, lead to risky AI use in different clinics. Because of AI’s risks, it is about time that safety rules come first. To that end, clear policies will support safe, ethical use across many health settings.

Conclusion

Artificial intelligence promises big improvements in eye care. In reality, AI helps diagnose diseases like diabetic retinopathy, glaucoma, and age-related macular degeneration. AI models, especially convolutional neural networks, show high accuracy. Sensitivities and specificities often exceed 90%. It is obvious AI can match human specialists.

Actually, AI is cost-effective in screening and early detection. Because of this, there is less need for specialist intervention. Not to mention, AI-assisted telemedicine helps in underserved areas. It expands access to high-quality diagnostics where eye care resources are limited.

However, limitations exist in current research. Lack of dataset diversity is significant issue. As a matter of fact, model interpretability is poor. Ignoring such issues will lead to unwanted outcomes like bias and misdiagnosis.

Some researchers suggest standardized protocols are needed. Yet integrating AI into real-world settings is complex than it seems. Something must be done about limitations to enable better clinical impact. To that end, more research is required.

In short, AI holds promise but faces challenges. This clearly means balance is needed. Ignoring issues will lead to unwanted outcomes.

Recommendations and Implications for Practice

Artificial intelligence needs diverse data. As a matter of fact, using representative datasets makes AI reliable across populations. It is obvious diverse data improves models. Yet, some say collecting diverse data is cumbersome. It is dangerous to ignore the fact that limited data leads to unreliable AI. Ignoring this will lead to unwanted outcomes like misdiagnosis.

Implementing interpretability measures help clinicians trust AI. As it is known, explainable AI enhances confidence. Not to mention, wider adoption is expected. However, making AI explainable is more complex than it seems. Some argue AI models are black boxes. It may look like AI is simple, but when observed carefully, it is complex.

Integrating AI into teleophthalmology improves access in underserved areas. In reality, it reduces disparities in eye care—something that cannot be ignored. Healthcare systems should invest in AI infrastructure and clinician training. Provided that, AI effectiveness is maximized. To that end, better outcomes happen.

Ultimately, thoughtful integration and continued research are essential. Ignoring these will hinder AI's potential to improve eye care. This clearly means balance is needed.

Conflict of Interest

No conflict of interest was declared by the authors.

Acknowledgement

The authors acknowledged all the stakeholders in the eye care management for their contributions towards promotion of eye health, management of people with eye disorders and rehabilitation of people with blinding eye conditions.

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