Artificial Intelligence in Optometry: Potential Benefits and Key Challenges: A Narrative Review

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***Abstract*—The integration of Artificial Intelligence (AI) into healthcare is transforming many medical fields, including optometry. This study provides a narrative review of the current applications and future potential of AI in optometric practice, emphasizing its role in automated screening and diagnosis, personalized treatment planning, and enhanced accessibility through tele-optometry. Alongside these opportunities, this study examines the technical, socioeconomic, ethical, legal, and professional challenges that limit the effective integration of AI in optometry practice. Focus is placed on concerns surrounding data privacy, patient autonomy, regulatory disparities, and practitioner resistance to adoption. Furthermore, this review highlights key research gaps, including the need for diverse training datasets, large-scale validation trials, and collaborative training between clinicians and AI developers. By resolving these challenges, AI has the potential to improve diagnostic accuracy, expand access to care, and enhance the quality of eye care services. By integrating the available evidence, this narrative review provides clinicians, policymakers, and researchers with a comprehensive overview of the benefits, challenges, and future directions of AI in optometry.**

Keywords*—*Artificial intelligence; automated screening; tele-optometry; eye care services; patient autonomy

I. Introduction

Artificial Intelligence (AI) is the ability of computer systems to perform tasks that normally require human intelligence, such as decision-making, pattern recognition, and problem-solving [1]. These processes include learning (the acquisition of information and rules for using this information), reasoning (the use of rules to arrive at precise or imprecise conclusions), and self-correction [2].

Machine Learning (ML), a subdivision of AI, primarily utilizes computer programming to execute tasks or forecast outcomes [3]. ML has shown significant promise in clinical decision support and machine translation [4]. Conventional ML algorithms rely on expert-selected variables as inputs and typically do not involve extensive neural networks. These algorithms include linear and logistic regression, support vector machines, decision trees, and random forests [5].

Deep Learning (DL), a subcategory of ML, can automatically derive rules from known data to evaluate unknown data without specialized programming, thus enabling it to handle more intricate data [6]. DL algorithms generally incorporate large-scale neural networks, including artificial, convolutional, and recurrent neural networks [5]. Recent advancements in AI, particularly ML and DL, have influenced the healthcare industry by increasing diagnostic efficiency, optimizing treatment, and lowering costs [7]. Fig. 1 shows the hierarchical relationship between AI, ML, and DL.

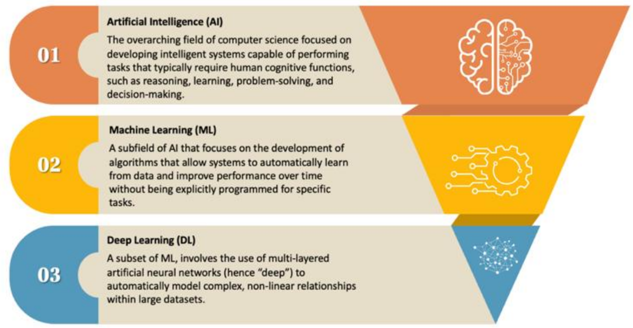

Fig. 1. Hierarchical relationship between Artificial Intelligence, Machine Learning and Deep Learning [3].

AI has demonstrated significant potential in clinical practice [8], particularly for improving diagnostic accuracy. The use of AI algorithms in the diagnosis of diseases such as cancer, heart disease, and neurological disorders has achieved an accuracy of 95% [9]. According to Ali et al. (2024), AI-powered algorithms demonstrated superior performance in detecting pneumonia from chest X-rays, achieving an accuracy rate of 92.7%, surpassing the diagnostic capabilities of human radiologists [10].

II. Background

The term "optometry" is derived from the Greek words "optos" meaning 'see' and "metron" meaning 'measure' and is concerned with the diagnosis and treatment of eye diseases and impaired vision. The field has undergone a significant transformation over the past century; in the early 1900s, visual optics was largely considered a philosophical study of light and vision.

By the mid-20th century, optometry had evolved into a clinical field, focusing on refractive errors and other ocular disorders, with corrective lenses serving as the primary method of management [11], [12]. Optometry practices manage a wide range of refractive and visual conditions, including myopia (near-sightedness), hyperopia (farsightedness), presbyopia (age-related farsightedness), astigmatism (vision distortion caused by an irregular corneal shape), anisometropia (unequal focal power between eyes), strabismus (squinting), and amblyopia (lazy eye) [11].

The integration of AI into optometry represents a game-changing development that fundamentally alters the approaches used by eye care specialists to detect and manage various eye disorders. This technological advancement is reforming optometric practice as the profession evolves, emerging as a transformative force in the diagnosis, treatment and management of diverse ocular conditions. By leveraging advanced algorithms and DL models, AI has introduced innovative approaches that enhance diagnostic accuracy and patient management and cover the system for personalized treatment, ultimately reshaping the future of eye care. According to a systematic review and meta-analysis published in 2024, the global incidence of myopia is anticipated to exceed 740 million cases by 2050 [13], with a significant increase particularly observed in the urban areas of East and Southeast Asia. Myopia currently affects approximately 30% of the population in North America and Europe, with rates approaching 80-90% in some parts of East Asia [14]. With the global prevalence of vision impairment increasing, an estimated 2.2 billion people are affected by some form of visual impairment worldwide [13], [14]. This trend has significantly increased the demand for innovative diagnostic and treatment methods in optometry [15]. One notable application of AI in this field is automated retinal image analysis, where algorithms can detect certain retinal diseases, such as diabetic retinopathy, with high sensitivity and specificity [16].

This study examines the opportunities and risks associated with the application of AI in optometry, as well as its practical implications. AI-driven technologies, such as diagnostic tools, treatment planning systems, and tele-optometry, are increasingly being integrated into optometric practice, offering the potential to improve the accuracy of diagnosis, quality of patient outcomes, and accessibility to eye healthcare.

III. Application of AI in Optometry

The role of AI in detecting, diagnosing, and treating several vision-related complications cannot be overstated, with the help of advanced ML and DL techniques. This section outlines the key applications of AI in optometry.

A. Diagnostic Tools and Image Analysis

AI has transformed diagnostic tools in optometry, particularly in the field of imaging. The automated diagnosis of retinal diseases using image recognition through AI systems has become a topic of interest. A systematic review and meta-analysis by Islam et al. (2020) indicated that DL algorithms trained on retinal fundus images can diagnose diabetic retinopathy with a sensitivity of 83% and a specificity of 92% [17].

Furthermore, AI has been utilized to identify age-related macular degeneration (AMD) and classify its stages by analyzing Optical Coherence Tomography scans with high accuracy [18]. The applications of DL to Optical Coherence Tomography in AMD were explored in a systematic review and meta-analysis conducted by Paul et al. [19]. They reported various applications, including disease diagnosis and classification, segmentation of retinal layers and biomarkers, prediction of disease progression and visual function, and determining the requirement for referral to a retinal specialist, with a performance comparable to that of human specialists.

The pattern recognition capabilities of DL have also been used to detect differences in corneal topographic patterns between normal individuals and those with keratoconus. For example, Kuo et al. proposed three Convolutional Neural Network (CNN) models, namely VGG16, InceptionV3, and ResNet152 [20]. These models were trained using topographic images without manual segmentation. All models achieved sensitivity, specificity, and area under the receiver operating characteristic curve (AUROC) values exceeding 90%, with the ResNet152 model reaching an AUROC of 0.995, indicating the high diagnostic accuracy of all models, with ResNet152 being superior. These results demonstrate the potential of AI-based approaches to enhance the detection and classification of keratoconus.

Moreover, ML and DL techniques have been applied to diverse image-based diagnostic and predictive solutions for myopia. AI tools have been developed for the detection, diagnosis, and prediction of myopia progression in children and adults [21], [22]. For instance, “DeepMyopia” is a DL system that was developed to detect and predict myopia onset in children at risk using retinal fundus images [23]. The system was trained on more than 1.6 million images and validated on different datasets from seven sites in China. The model showed a robust predictive performance, with AUCs ranging from 0.81–0.91 for 1- to 3-year onset prediction. DeepMyopia also successfully classified children into low- and high-risk groups, demonstrating its ability as a decision support tool.

Research has highlighted strabismus as another domain in which AI can provide valuable support. In 2021, a team led by Mao et al. established an AI-based platform that incorporated three DM systems [24]. This platform was designed to diagnose strabismus, assess angles, plan surgical interventions, and utilize corneal light-reflection images. The researchers trained and retrospectively validated the system using a historical development dataset. The results demonstrated that the AI-based screening method exhibited remarkable performance, with a sensitivity of 99.1%, specificity of 98.3%, area under the receiver operating characteristic curve (AUC) of 0.998, and matching accuracy of 99.0% in a retrospective evaluation. These metrics were comparable to or exceeded those of previously established automated techniques for strabismus identification. Building on such advancements, another study reported the development of a novel DL algorithm designed to objectively categorize eye versions from photographs of adult faces using a mobile application [25]. The model underwent initial training at nine gaze positions. Depending on the specific type of eye version, the application demonstrated an accuracy of 42 to 92% and precision of 28 to 84%. In a related effort, Zheng et al. developed an enhanced DL model trained on 7,026 images of children with primary horizontal strabismus [26]. The algorithm was evaluated on 277 images from a different dataset, achieving 95% accuracy, exceeding the performance of resident ophthalmologists. These innovations have led to faster and more accurate diagnoses, reduced clinicians’ workloads, and improved the overall quality of care. They are particularly valuable in emergency rooms and mass-screening initiatives.

B. Improved Accessibility and Screening through Tele-optometry

Tele-optometry refers to the delivery of optometric care through telehealth technologies, allowing optometrists to remotely evaluate and manage eye health [27]. AI-powered tele-optometry can facilitate the delivery of eye care services to underserved regions by analyzing patient-provided images, such as retinal scans and ocular images, to support early diagnosis and timely management [28]. During the COVID-19 pandemic in India, Karthikeyan et al. reported that 50.94% of optometrists relied on tele-optometry to provide their services, indicating its potential to remain a valuable component of eye care delivery beyond emergency settings [29]. Advances in DL further enhance this ability by enabling automated image analysis within tele-optometry platforms, supporting the remote management of posterior eye diseases, and referring cases to specialists when required, minimizing the need for face-to-face visits [30]. This technology not only improves the efficiency of eye care services but also alleviates the burden on overcrowded eye care clinics, allowing clinicians to prioritize urgent cases and minimize unnecessary referrals.

Another key advantage of AI-powered image analysis technology is its ability to remotely monitor chronic conditions, such as diabetic retinopathy and glaucoma. In particular, AI-based glaucoma screening can enhance the detection of moderate and advanced cases in primary care environments and help identify individuals at a higher risk of developing the condition [31]. This enables the early identification of disease progression, allowing timely intervention that may prevent further vision loss. Integrating AI with tele-optometry improves screening efficacy and optimizes the allocation of professional resources.

C. Personalized Care

AI supports individualized care in optometry, particularly in developing customized therapies for specific visual conditions. With access to vast pools of patient datasets, AI can develop tailored regimens based on visual characteristics, lifestyle, and other factors [11] [16]. Current AI-driven tools are used to design personalized contact lenses and eyeglasses by analyzing parameters such as visual acuity, astigmatism, eye structure, and even digital device usage patterns. This approach ensures more precise lens selection and recommendations, leading to effective and patient-centered solutions [32] [33].

AI is also advancing individualized care through the integration of CNNs in medical diagnostics. Hwang et al. trained an AI-based system to diagnose AMD using 35,900 Optical Coherence Tomography images, achieving over 90% accuracy, comparable to retinal specialists and outperforming medical students [34]. Beyond diagnosis, AI systems can provide appropriate treatment recommendations comparable to those of retinal specialists, demonstrating their potential for both remote and individualized care applications.

Moreover, AI systems show promise in complementing vision therapy, which is a core component of optometry care. Vision therapy involves structured exercises and activities designed to improve specific visual functions, such as eye movement coordination and binocular vision [35]. Vision therapy based on AI systems can continuously analyze patient data and assess their progress throughout the therapeutic process [36]. AI-enhanced vision therapy has the potential to optimize outcomes and improve patient adherence through continuous monitoring, follow-up care, and adaptive training. Fig. 2 provides a summary of the AI applications in optometry.

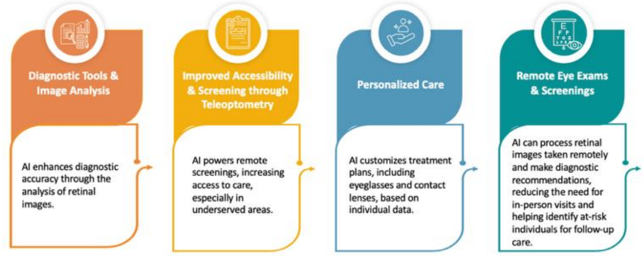

Fig. 2. Application of artificial intelligence in optometry.

III. Challenges of AI in Optometry

While AI presents significant opportunities for enhancing optometric care, its implementation in clinical practice is accompanied by several key challenges that must be overcome. These challenges extend beyond technical limitations, including socioeconomic issues, ethical considerations regarding patients' rights and data use, regulatory and legal complexities, and resistance from practitioners and patients. The following sections outline the main challenges that need to be addressed for the successful integration of AI in optometry, along with the current strategies that have been proposed to address them.

A. Technical Challenges

One of the major challenges in the application of AI in optometry is the methodological complexity of designing effective and precise models. DL-based AI systems, in particular, require extensive amounts of high-quality labeled data for effective training and performance [37]. Parmar et al. (2024) indicated that the performance of AI algorithms in identifying retinal diseases was greatly dependent on the quality of the training datasets. Models trained on biased or limited data may produce inaccurate or non-generalizable results when applied to diverse patient populations [38].

Another critical technical challenge is the "black box phenomenon", which refers to the lack of interpretability of AI models. Various DL models, particularly CNNs, are described as "black boxes" because their decision-making processes are challenging for clinicians to fully understand. This lack of transparency can undermine trust in AI systems, especially when they are used to make life-and-death clinical decisions [39]. To address this, explainable AI (XAI) strategies have been introduced to provide clearer insights into the decision-making process and enhance the overall transparency of AI models. For example, the OptiDex model was developed to enhance the detection and categorization of diabetic retinopathy. An XAI framework was incorporated using gradient-weighted class-activation maps. The model achieved a high diagnostic accuracy of 97.65% and provided visual heatmaps that explained how decisions were made [40]. This clarity improved clinician trust by indicating which retinal regions affected the output of the system. These examples emphasize how XAI can reduce the gap between accuracy and interpretability, improving both the confidence and adoption of AI in clinical optometry.

Furthermore, implementing and maintaining AI systems can be challenging because of their technical complexity, which often requires specialized expertise and continuous support from the organization. Although it is crucial to smoothly incorporate these systems into existing clinical practices and electronic health record platforms, this integration process remains technically demanding.

B. Socioeconomic Challenges

The adoption of AI in optometry has emerged along with pressing socioeconomic challenges, particularly those associated with cost, accessibility, and healthcare equity. Among these, cost remains the most significant challenge, as AI integration involves expensive imaging machinery, advanced software, and considerable investments in staff training and resources. Muradov (2024) estimated the cost of the initial setup of the AI-based Retinal disease screening system to be between $30,000 and $50,000 [41]. Most of these costs are not covered by current reimbursement schemes; therefore, clinics in rural or low-income areas may not be able to afford such technologies. Continuous updates and maintenance contribute to the overall cost of implementing AI systems. The substantial upfront costs may place these technologies beyond the reach of smaller practices, potentially creating disparities between well-funded and under-resourced environments. To ensure the fair distribution of AI-enabled tools across all optometric practices, cost-reduction strategies, such as cloud-based alternatives or shared resources, should be explored.

Moreover, AI-based tele-optometry relies on a stable Internet connection and high-quality imaging, both of which are often limited in rural areas, limiting the application of AI in such regions [42]. Another key issue is the underrepresentation of specific population groups in the training datasets, which can result in biased AI algorithms and, therefore, provide less accurate outcomes for these groups. Such algorithmic bias perpetuates existing health disparities among different races, ethnicities, and socioeconomic levels [43]. Addressing these socioeconomic and equity-related challenges requires novel approaches to make AI both accessible and comprehensive.

One promising example is the work of Vohra et al. (2025), who developed an AI system capable of analyzing fundus images captured with cost-effective equipment using CNNs for the diagnosis of AMD, diabetic retinopathy, and glaucoma [44]. With the implementation of AI technology and cloud-based accessibility, the system achieved an accuracy exceeding 96.5%. Such efforts emphasize the potential of affordable and scalable AI solutions to bridge gaps in access and make advanced healthcare systems more widely available.

Another practical cost-reduction approach involves shifting from on-site infrastructure to cloud-based platforms. In the radiology field, healthcare organizations implementing cloud solutions have recognized up to 30% savings in infrastructure and overhead costs [45]. This strategy can also benefit optometry clinics that implement AI-driven diagnostic tools.

C. Ethical Concerns

The three major ethical issues related to the use of AI in optometry are confidentiality, security, and independence of the data. AI models rely on medical images and patient information for training and operation, raising significant concerns regarding patient privacy. The incorporation of personal health data into AI training models increases the risk of privacy infringement, data breaches, and the misuse of sensitive health information [46]. Williamson (2024) indicated that while AI offers beneficial opportunities for enhancing healthcare, inadequate protection in handling sensitive health records can undermine patient trust and compromise confidentiality, creating a conflict between innovation and privacy. Given the sensitive nature of patient information used in AI model training and operations, robust security measures are necessary to ensure data protection, maintain confidentiality, and inhibit unauthorized access or breaches.

Furthermore, the issue of informed consent for the use of AI in optometric care is a considerable ethical concern. As the application of AI systems in clinical practice increases, patients may not be fully aware of the extent to which AI technologies contribute to the diagnosis and treatment of their conditions, especially if such systems are used to provide recommendations or even make decisions on their behalf [47]. Li et al. (2021) noted that patients may lose confidence in their care if they are being treated by an algorithm rather than a clinician, raising critical concerns about patient empowerment and the ethical use of AI in healthcare [48].

D. Regulatory and Legal Barriers

The utilization of AI in optometry is associated with legal and regulatory challenges that vary significantly across geographical areas. Considerable regional regulatory disparities exist, with the European Union (EU) requiring more comprehensive protections, such as the General Data Protection Regulation (GDPR) and the AI Act, compared to the United States Food and Drug Administration (FDA)'s softer, sector-specific approach. Palaniappan et al. (2024) pointed out that the EU has adopted a stricter, risk-based framework that classifies AI in healthcare as a high-risk group, thus requiring stringent conformity evaluations, transparency responsibilities, and post-market monitoring [49]. In contrast, the FDA mainly regulates AI as part of medical devices under the present frameworks, which stress safety and efficacy but do not insist on the same level of oversight on problems such as algorithmic bias, transparency, or international data transfer. These regulatory disparities complicate the global implementation of AI in optometry.

Nevertheless, there are rising questions regarding the regulation of AI, as regulatory bodies have struggled to keep pace with its fast development, resulting in delayed approval and the establishment of clear legal standing for AI implements [50]. In addition to slowing the clinical adoption of AI, this misalignment raises uncertainty among clinicians and patients regarding the safety, reliability, and legal accountability of AI-powered services.

Moreover, legal concerns and issues of responsibility arise when an AI system provides a misdiagnosis or recommends inappropriate treatment. Uncertainty persists over whether responsibility should fall on AI developers, healthcare professionals who rely on the system, or equipment manufacturers [51]. To address these challenges, comprehensive and effective regulations must be established through collaboration among major stakeholders, including AI developers, eye care professionals, policymakers, and patient advocacy organizations. These regulations should achieve a careful balance between utilizing AI's potential benefits of AI and protecting patient rights while ensuring ethical and responsible implementation.

Given the rapid development of AI technology and the evolving ethical landscape, it is crucial to conduct regular assessments and updates of the current guidelines. Implementing well-defined legal and regulatory frameworks can enhance trust and confidence in the application of AI in healthcare, encouraging its broader adoption while addressing potential risks.

E. Resistance to Adoption

Resistance to adoption by both optometrists and patients is a major problem in the implementation of AI in optometry. Some optometrists expressed concerns that AI could limit their professional role or reduce their control over patient care. A recent web-based survey of optometrists revealed that while many appreciate the potential of AI in enhancing diagnostic precision, a considerable number expressed concerns that AI systems cannot imitate human clinical judgment and patient-centered decision-making applied by clinicians [52].

Some optometrists are concerned about the potential of AI to lead to job displacement as more tasks become automated. Although AI is not expected to replace human optometrists entirely, it may streamline routine processes, such as image analysis, potentially resulting in job changes or the necessity for specific technical positions, thereby creating pressure for workforce adaptation and retraining. Nevertheless, AI is more likely to complement rather than replace human clinicians by alleviating routine tasks and enabling them to focus on complex cases and patient-centered care. Addressing these issues requires practical workforce planning and targeted educational initiatives. Training programs can assist eye care professionals in adjusting to the evolving demands of their field and equip them with the skills required to collaborate effectively with AI technology. Emphasizing workforce upskilling can transform the role of optometrists, allowing them to undertake advanced and specialized responsibilities in the field.

IV. Ethical Considerations of AI in Optometry

The integration of AI into optometric practice raises significant ethical concerns (Table I).

A. Patient Autonomy and AI Decision-Making

Patient autonomy refers to the right of individuals to make informed decisions regarding healthcare. One of the key ethical challenges of AI is its potential impact on autonomy, particularly when AI systems provide diagnostic or treatment recommendations. Wang et al. (2023) indicated that patients often experience discomfort when AI systems make decisions without human supervision. Although AI can be used to detect diseases such as diabetic retinopathy, the ultimate decision-making should remain with the clinician to ensure that patient values and preferences are considered [11]. In addition, patients should be well informed about AI integration into their care, including the use of their personal health data [53]. Maintaining patient autonomy not only protects personal rights but also strengthens trust and acceptance of AI integration in optometric practice.

TABLE I. Ethical Considerations of AI in Optometry

Ethical concern	Description	Implications
Patient Autonomy	Ensuring patients can make informed decisions, even with AI involvement.	AI should support, not replace, clinical judgment. Patients must be informed about the role of AI and allowed to opt out if desired [2],[3].
Bias and Fairness	AI may be biased if trained on non-representative data, affecting accuracy for certain population groups.	Models must be trained on diverse and representative data to minimize bias, ensure accuracy, and promote equitable care [4–6].
Transparency in AI	AI decision-making processes are often opaque, hindering trust and understanding.	AI systems should provide explainable outputs, allowing clinicians to understand the rationale behind AI-driven decisions [7].

B. Bias and Fairness

AI bias is a major issue because of the lack of diversity in the training datasets. Many AI models have been developed and trained based on data obtained mainly from high-income urban populations, which limits their usefulness for patients from other demographic groups [54]. For example, Jacoba et al. (2023) reported that AI systems designed to diagnose retinal diseases may be less accurate in rural or minority populations, resulting in healthcare inequalities [55]. To this end, AI models should be trained on quantitative and qualitative datasets that represent individuals across diverse age groups, ethnicities, and socioeconomic backgrounds. Addressing these challenges requires a shift toward developing robust, interpretable, and unbiased AI models. |Equally critical is the comprehensive validation of these systems across a diverse spectrum of patient demographics to ensure their efficacy and universal applicability to all patients.

To alleviate data scarcity while maintaining patient privacy, multi-center federated learning has recently emerged as a promising approach in the development of medical AI. This collaborative strategy enables training on diverse datasets distributed across institutions without transferring sensitive patient data by exchanging model updates rather than raw data. Various studies have shown its efficacy and privacy benefits. For example, Linardos et al. (2022) simulated federated learning across four cardiac imaging centers and found that models trained in a distributed, privacy-preserving mode performed competitively with traditional centralized approaches, even with limited datasets (180 subjects) [56]. A novel adaptive aggregation framework for federated learning was proposed by Haripriya et al. (2025), enhancing collaborative model training across multiple medical centers without exposing patient data [57]. These findings emphasize the potential of federated learning to overcome data scarcity and enhance model generalizability across heterogeneous patient populations.

C. Transparency in AI Algorithms

Ensuring transparency in AI algorithms is crucial for promoting confidence among clinicians and patients. CNNs and many other AI models are often called "black boxes" because their decision-making processes are not easily interpretable [58]. Roy et al. (2023) stressed the growing importance of XAI, which can provide clinicians with insights into how AI systems arrive at their conclusions [59]. For instance, in the diagnosis of diabetic retinopathy, an XAI should be able to visually highlight the retinal features that lead to a diagnosis. Such transparency is important for improving clinical accountability and empowering clinicians to integrate AI technology responsibly into patient care, thereby improving both trust and clinical adoption [60].

V. Current Research Gaps and Future Directions

Current research on AI applications in optometry focuses on addressing several key gaps that are critical for improving the accuracy, reliability, and integration of AI technologies into clinical practice. One major research gap is the lack of diverse and representative training datasets. As AI systems are highly dependent on the data used for training, many existing optometry datasets are limited in terms of demographic diversity and clinical variability. Studies have shown that AI models trained predominantly on data from high-income urban populations may exhibit biases when applied to rural or minority populations [55]. This limitation hinders the applicability of AI systems and may result in healthcare service inequalities. Thus, it is crucial to develop datasets that include a wide range of ethnicities, age groups, and clinical conditions to ensure fair and equitable performance. Furthermore, the creation of standardized datasets for AI model training and evaluation is essential to ensure the reproducibility and reliability of AI-driven diagnostic systems in clinical practice. This process involves addressing challenges, such as data variability, and ensuring that the datasets used to train AI models reflect the diverse populations they are intended to serve.

Another critical gap is the limited validation and scarcity of large-scale clinical studies investigating the effectiveness of AI in optometry. Although several studies have reported promising findings when AI models are applied under controlled conditions, their real-world integration into clinical practice remains unexplored. Shen et al. (2019) indicated that to assess the safety and efficacy of AI systems in the diagnosis of retinal diseases and guiding the treatment, it is necessary to conduct large-scale, multi-center clinical trials [61]. Such trials would not only provide evidence of clinical usefulness but also ensure regulatory compliance and readiness for integration into routine clinical practice. Therefore, robust validation is a prerequisite for promoting clinical confidence and enhancing the safe adoption of AI in optometry.

Furthermore, providing collaborative training opportunities for AI developers and clinicians is crucial for narrowing this gap. The active involvement of optometrists in the development and adoption of AI systems ensures their alignment with existing workflows and clinical requirements [62]. Continuous training programs are important to ensure that healthcare providers are well placed to deliver care using new AI technologies, [1]. Such programs should focus on enhancing competencies in the effective use of AI systems while preserving the human touch in patient interactions. Professional associations and academic institutions play a key role in preparing optometrists for this evolving field by offering curricula that involve both technical components of AI and its ethical and clinical implications. This includes guidance on analyzing AI-produced outcomes, recognizing potential biases, and effectively conveying insights to patients. Ongoing education will enable optometrists to remain updated on the latest developments in AI technology and adopt the best practices for its clinical integration.

VI. Conclusion

AI has considerable potential to transform optometry by improving diagnostic accuracy, enhancing patient care, and expanding access to vision care services. AI-integrated innovations encompass several tools, including image analysis, tele-optometry, and personalized treatment plans, representing significant advancements in the field. However, the effective implementation of these AI technologies requires careful consideration of technical, socioeconomic, ethical, and legal challenges. Major barriers include the lack of diverse datasets for training, insufficient large-scale validation studies, and the need for stronger cooperation between AI developers and clinicians. Overcoming these challenges is essential to enhance optometric practices and ensure equitable, high-quality eye care services for all patients.

Acknowledgment

The author thanks the Deanship of Scientific Research and the Research Support and Services Unit (RSSU) at King Saud University for their technical support.

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