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Review

Integration of smartphone technology and artificial intelligence for advanced ophthalmic care: A systematic review

Kai Jin[a,1], Yingyu Li[a,1], Hongkang Wu[a], Yih Chung Tham[b,c,d,e], Victor Koh[b,c], Yitian Zhao[f,g,h,i], Ryo Kawasaki[j,k], Andrzej Grzybowski[l], Juan Ye[a,*]

[a] Eye Center, The Second Affiliated Hospital of Zhejiang University School of Medicine; Zhejiang Provincial Key Laboratory of Ophthalmology; Zhejiang Provincial Clinical Research Center for Eye Diseases; Zhejiang Provincial Engineering Institute on Eye Diseases, Hangzhou, China
[b] Centre for Innovation and Precision Eye Health, National University of Singapore, Singapore
[c] Department of Ophthalmology, National University of Singapore, Singapore
[d] Singapore Eye Research Institute, Singapore National Eye Centre, Singapore
[e] Ophthalmology and Visual Science Academic Clinical Program, Duke-NUS Medical School, Singapore
[f] Cixi Institute of Biomedical Engineering, Ningbo Institute of Materials Technology and Engineering, Chinese Academy of Sciences, Ningbo, China
[g] Ningbo Eye Hospital, Ningbo, China
[h] Zhejiang International Scientific and Technological Cooperative Base of Biomedical Materials and Technology, Ningbo Institute of Materials Technology and Engineering, Chinese Academy of Sciences, Ningbo, China
[i] Zhejiang Engineering Research Center for Biomedical Materials, Ningbo Institute of Materials Technology and Engineering, Chinese Academy of Sciences, Ningbo, China
[j] Division of Public Health, Department of Social Medicine, Graduate School of Medicine, Osaka University, Osaka, Japan
[k] Artificial Intelligence Center for Medical Research and Application, Osaka University Hospital, Osaka, Japan
[l] Institute for Research in Ophthalmology, Foundation for Ophthalmology Development, Poznan, Poland

A R T I C L E I N F O

Keywords:
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Telemedicine
Ocular disease management

A B S T R A C T

Background: The convergence of smartphone technology and artificial intelligence (AI) has revolutionized the landscape of ophthalmic care, offering unprecedented opportunities for diagnosis, monitoring, and management of ocular conditions. Nevertheless, there is a lack of systematic studies on discussing the integration of smartphone and AI in this field.
Main text: This review includes 52 studies, and explores the integration of smartphones and AI in ophthalmology, delineating its collective impact on screening methodologies, disease detection, telemedicine initiatives, and patient management. The collective findings from the curated studies indicate promising performance of the smartphone-based AI screening for various ocular diseases which encompass major retinal diseases, glaucoma, cataract, visual impairment in children and ocular surface diseases. Moreover, the utilization of smartphone-based imaging modalities, coupled with AI algorithms, is able to provide timely, efficient and cost-effective screening for ocular pathologies. This modality can also facilitate patient self-monitoring, remote patient monitoring and enhancing accessibility to eye care services, particularly in underserved regions. Challenges involving data privacy, algorithm validation, regulatory frameworks and issues of trust are still need to be addressed. Furthermore, evaluation on real-world implementation is imperative as well, and real-world prospective studies are currently lacking.
Conclusions: Smartphone ocular imaging merged with AI enables earlier, precise diagnoses, personalized treatments, and enhanced service accessibility in eye care. Collaboration is crucial to navigate ethical and data security challenges while responsibly leveraging these innovations, promising a potential revolution in care access and global eye health equity.

* Corresponding author.
E-mail address: yejuan@zju.edu.cn (J. Ye).
[1] Both authors contributed equally to this article.

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1. Introduction

The convergence of smartphone technology and artificial intelligence (AI) has ushered in new opportunities to disrupt current delivery of ophthalmic care.[1] The ubiquitous presence of smartphones, coupled with their ever-evolving capabilities, has surpassed their conventional utility as communication devices, transforming them into powerful tools for medical diagnostics and patient care.[2] Simultaneously, the rapid advancements in AI algorithms have revolutionized the interpretation of ocular images and clinical data, transforming the landscape of ophthalmology.[3]

The amalgamation of smartphones and AI holds immense promise for addressing the burgeoning global burden of ocular diseases. According to the World Health Organization (WHO), visual impairments affect over 2.2 billion people worldwide, with conditions such as diabetic retinopathy (DR), glaucoma, and age-related macular degeneration (AMD) posing significant threats to vision health.[4] However, the conventional barriers to access specialized ophthalmic care, especially in remote or underserved regions, have hindered early detection and timely intervention, exacerbating the impact of these ocular conditions.[5] In remote or underserved regions, undiagnosed ocular conditions prevail, impeding timely interventions and escalating their burden, as highlighted by recent studies, emphasizing the critical need for enhanced accessibility to eye screenings.[6]

This review explores the synergy between smartphone technology and AI in ophthalmology, elucidating their collective potential to revolutionize screening methodologies, disease diagnosis, telemedicine initiatives, and personalized patient management. It explores the utilization of smartphone-based imaging modalities, ranging from fundus photography to anterior segment imaging, enhanced by AI-driven algorithms for efficient and accurate detection of ocular pathologies.[7,8] Moreover, the integration of AI with smartphone platforms has not only facilitated remote consultations but also empowered patients to actively engage in their eye health management.

While the prospects of leveraging these technologies for enhancing ophthalmic care are promising, various challenges such as data security, algorithm validation, ethical considerations, regulatory frameworks, and real-world implementation necessitate thorough consideration and discussion. This systematic review aims to comprehensively summarize the current landscape, discuss existing challenges, and outline future prospects for integrating smartphone technology and AI to advance ophthalmic care.

2. Methods

2.1. Study selection and search strategy

This is a systematic review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) guidelines (Fig. 1). Extensive searches were conducted across electronic databases including PubMed, Web of Science (WOS), Scopus and Google Scholar databases. Keywords were selected from three aspects: ophthalmology-related terms

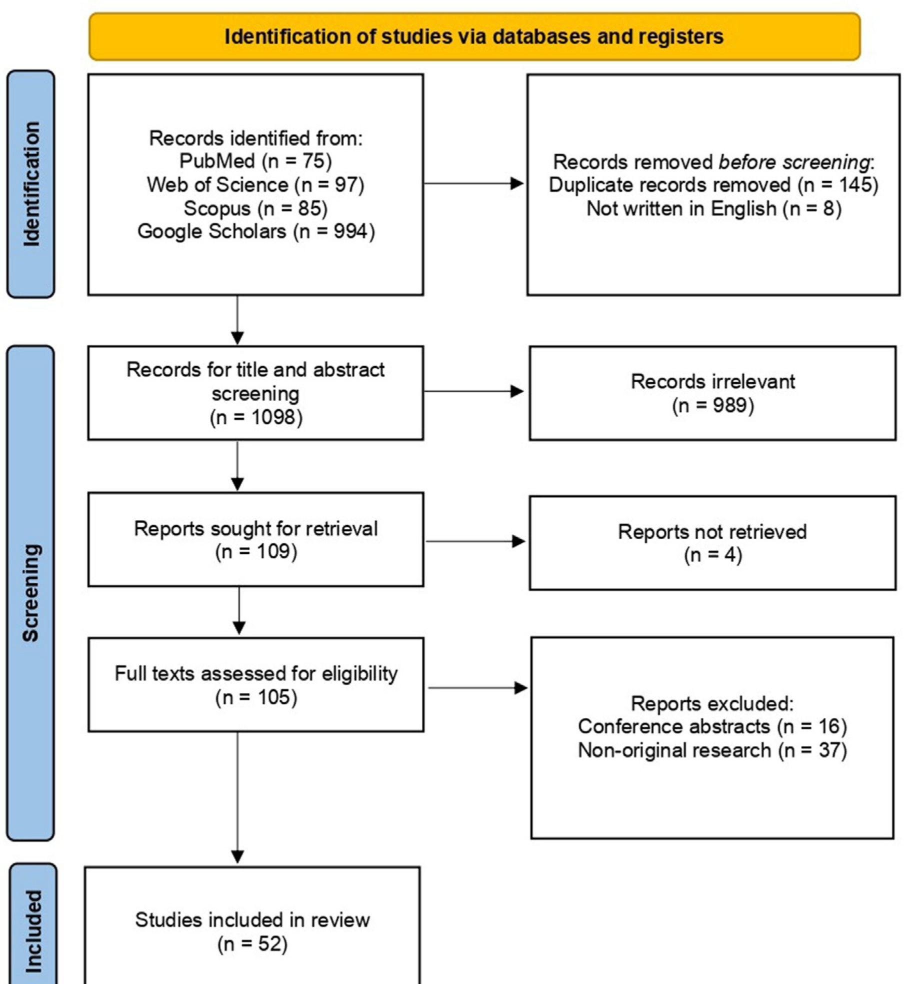

Fig. 1. PRISMA 2020 flow diagram for this systematic review.

(ophthalmology, eye diseases, ophthalmic disorders, ophthalmic diagnostics), AI-related terms (artificial intelligence, deep learning, machine learning) and smartphone-related terms (smartphone, smart phone, mobile phone). Finally, the following combined terms: ("Ophthalmology" OR "Eye Diseases" OR "Ophthalmic Disorders" OR "Ophthalmic Diagnostics") AND ("Artificial Intelligence" OR "Deep Learning" OR "Machine Learning") AND ("Smartphone" OR "Smart Phone" OR "Mobile Phone") were used to retrieve pertinent articles published from January 2018 to November 2023.

2.2. Article selection criteria

The specific inclusion criteria was established for selecting the article. Firstly, we chose the publication date spanning from January 2018 to November 2023 to ensure the inclusion of up-to-date findings. Initially, 1251 articles were acquired from databases. Inclusion criteria encompassed peer-reviewed articles, reviews, original research studies, and meta-analyses focusing on the integration of smartphone technology and AI in ophthalmic care. Studies discussing smartphone-based imaging modalities, AI algorithms in ophthalmology, tele-ophthalmology, and ocular disease management were considered.

Meanwhile, studies meeting the following criteria will be excluded: (1) not written in English; (2) duplicate records previously included in the review; (3) irrelevant topics, where the article is unrelated to ophthalmology or the application of AI and smartphone technology; (4) conference abstracts, and (5) non-original research, such as editorials, case reports or commentaries.

2.3. Data extraction

Relevant data including study objectives, methodology, smartphone-based imaging techniques utilized, AI algorithms employed, diagnostic accuracy, patient outcomes, and limitations were extracted from selected articles. Information pertaining to the efficacy, feasibility, and challenges of integrating smartphone technology and AI in ophthalmic care was collated.

2.4. Quality assessment

Quality assessment was performed to evaluate the rigor and reliability of included studies. Criteria included study design, sample size, methodology, validation of AI algorithms, and the reliability of smartphone-based imaging techniques. We focused on articles which utilized the integration of smartphone technology and AI to improve the diagnosis, treatment, accessibility, and personalized care in ophthalmology.

In accordance with the PRISMA guidelines, this review includes a comprehensive literature search, specific inclusion criteria, and thorough data extraction. A total of 52 articles were independently screened for eligibility by two reviewers (Kai Jin and Yingyu Li), including assessments of titles and abstracts, followed by full-text review. Any disagreements were solved through discussion with a third author (Juan Ye). Ultimately, 52 studies were included in the review.

2.5. Data synthesis and analysis

A narrative synthesis approach was employed to summarize findings from the included studies. Key themes regarding the integration of smartphone technology and AI in ophthalmology were identified, synthesized, and presented in a coherent manner to elucidate the current state of the field.

2.6. Risk of bias assessment

Any potential biases within the included studies were assessed and discussed. This encompassed biases related to study design, methodology, funding sources, and conflicts of interest.

2.7. Reporting standards

The reporting of this review adheres to the PRISMA guidelines to ensure transparency, accuracy, and completeness in reporting the findings related to the integration of smartphone technology and AI in ophthalmic care.

3. Results

We eventually included 52 studies. The results (Table 1) cover a wide range of studies in the field of ophthalmology, highlighting the enormous potential of integrating smartphone technology and AI for ophthalmic care. Subfields encompass retinal diseases (26 studies), glaucoma (9 studies), cataract (4 studies), visual impairment in children (4 studies), ocular surface diseases (6 studies) and other diseases (3 studies) (Fig. 2).

3.1. Retinal diseases

The retina is the site of various sight-threatening eye diseases including DR, diabetic macular edema (DME), AMD and retinopathy of prematurity (ROP), which makes it important in preventing serious eye disorders. In recent studies, AI-based smartphone technology has been employed for the detection of retinal diseases, showcasing significant potential for the future.

With the increasing prevalence of diabetes mellitus globally, DR has become a leading cause of blindness in adults worldwide.[9] To prevent permanent visual impairment, screening is pertinent to detect referable cases that need timely treatment.[10] The current screening strategy includes direct or indirect ophthalmoscopy and mydriatic or non-mydriatic color retinal photography, but there is still a requirement for a more low-cost, effective and convenient method to detect DR, especially in the lower and middle-income areas.[11] Therefore, the integration of AI and smartphone technology has garnered much attention due to its great performance in several studies. Rajalakshmi et al. evaluated the effect of an automated AI-based interpretation of smartphone-based fundus photography system for detecting DR and grading images to identify sight-threatening DR (STDR).[12] They used the EyeArt™ software to automatically analyze retinal images and provide DR severity and screening recommendation, showing that the screening system had 95.8% sensitivity and 80.2% specificity for detecting any DR and 99.1% sensitivity and 80.4% specificity in detecting STDR. In another study, Al-Karawi et al. proposed a framework utilizing edge computing on a mobile device and deep learning (DL) with three benchmark convolutional neural networks (CNNs) architectures (EfficientNetB7, ResNet50, and VGG19) to detect the severity level of DR, which achieved a high classification accuracy (96.0%) and reduction of the transmitted data amount and the response time.[13] At the same time, the application of the offline smartphone-based AI platforms makes the DR screening faster and more convenient without a network connection. Natarajan et al. conducted the first study assessing an offline AI algorithm named Medios AI (Remidio) on a smartphone-based, nonmydriatic retinal camera.[8] The performance of this offline system reached a sensitivity of 100.0% and specificity of 88.4% in diagnosing referable DR and a sensitivity of 85.2% and specificity of 92.0% in diagnosing any DR, compared with ophthalmologist grading using the same images. The similar results also be proved in the research by Sosale et al. to show the potential of the offline smartphone-based AI system in enhancing DR diagnosis, especially in remote areas or outlying islands.[14]

DME, the leading cause of vision loss and referrals associated with DR, can be accurately detected using a portable smartphone-based camera integrated with the AI algorithm as well. Conventionally, diagnosis requires both fundus examination and OCT imaging. Hwang et al. established a mobile application on Android system based on an offline smartphone-based AI (MobileNet) screening platform, which can analyze

Table 1
Summary of representative studies using the integration of smartphone technology and AI in ophthalmology.

Reference	Year	Application	Performance measure	Data source	AI models	Mobile software
Rajalakshmi et al.[12]	2018	DR detection	DR (sensitivity = 95.8%, specificity = 80.2%) STDR (sensitivity = 99.1%, specificity = 80.4%)	Fundus photographs taken by the Remidio Fundus on Phone (Remidio Innovative Solutions Pvt. Ltd, Bangalore, India)	EyeArt	EyeArt™ software (version v2.1.0) (EyeNuk Inc., Los Angeles, CA)
Al-Karawi et al.[13]	2023	DR progression prediction	Accuracy = 96.0%	The fundus image dataset by Asia Pacific Tele-Ophthalmology Society	CNNs (EfficientNetB7, ResNet50, and VGG19)	An Android application
Natarajan et al.[8]	2019	DR detection	Referable DR (sensitivity = 100.0%, specificity = 88.4%) DR (sensitivity = 85.2%, specificity = 92.0%)	Fundus photographs taken by the Remidio NonMydriatic Fundus on Phone (Remidio Innovative Solutions Pvt Ltd)	MobileNet, InceptionV3	Medios AI (Remidio)
Malerbi et al.[16]	2021	DME detection in type 2 diabetes patients	/	Fundus photographs taken by a smartphone-based hand-held device (Eyer, Phelcom Technologies, São Carlos, Brazil)	PhelcomNet	/
Hwang et al.[15]	2020	DME evaluation and measurement	Accuracy = 90.02%	The OCT images collected from patients	MobileNet	An Android application (https://aicl.ddns.net/DME.apk)
Young et al.[19]	2023	ROP detection and grading	Referral-warranted ROP (sensitivity = 80.0%, specificity = 59.3%) Treatment-requiring ROP (sensitivity = 100.0%, specificity = 58.6%)	Fundus photographs taken by SBFI systems (the Make-In-India Retcam/ Keeler Monocular Indirect Ophthalmoscope devices)	ResNet18	/
Qidwai et al.[18]	2022	AMD prognosis prediction	Accuracy >92.0%	Measurements of baseline, changes in visual acuity and macular thickness after four months of treatment	Adaptive neuro-fuzzy inference system	Ophnosis^{AMD}
Nakahara et al.[21]	2022	Glaucoma detection	Glaucoma (AUC = 0.842) Advanced glaucoma (AUC = 0.900)	Fundus photographs taken by an iPhone 8 with the D-Eye lens (D-EYE S.r.l., Padova, Italy)	ResNet	/
Wu et al.[23]	2020	IOP measurements	The mean difference for GAT = +0.24 mm Hg The 95% limits of agreement for GAT = −4.35–4.83 mm Hg	IOP measured by a smartphone tonometer prototype	A machine learning method based on kmeans, colour filtering and geometry	/
Hu et al.[24]	2020	Cataract grading	F1-score = 0.923 AUC = 0.9198 Accuracy = 93.5%	Ocular images taken by the smartphone-based slit-lamp	YOLO v3, ShuffleNet, and SVM	/
Vasan et al.[25]	2023	Cataract detection and grading	Cataract detection (sensitivity = 96.0%, specificity = 25.0%) Immature cataracts (accuracy = 94.2%) Mature cataracts (accuracy = 22.0%) Posterior chamber intra-ocular lenses (accuracy = 29.3%) Clear lenses (accuracy = 2.0%)	Ocular images taken by a smartphone using e-Paarvai	E-Paarvai's network based on CNNs	E-Paarvai
Chen et al.[28]	2023	Visual impairment in children detection	Internal validation set (AUC = 0.940) External validation set (AUC = 0.843) Real-world test (AUC = 0.859)	3.5-min videos capturing phenotypic features and ocular movements recorded by the inbuilt front camera of the smartphone	DL models in the AIS system	The AIS app
Murali et al.[30]	2020	Amblyopia detection	Sensitivity = 88.2% Specificity = 75.6% F-score = 0.732 Accuracy = 79.6%	Ocular images taken by a smartphone	Kanna algorithm	An Android application
Liu et al.[31]	2023	Pterygium detection and grading	Sensitivity = 93.60% Specificity = 96.13% F1-score = 0.9313 AUC = 0.9426 Accuracy = 92.38%	The smartphone-based dataset collected from the Xiamen Eye Center of Xiamen University and Xiang'an Hospital of Xiamen University	RFRC, SRU-Net	/
Wang et al.[32]	2021	Infectious keratitis classification	Global images (AUC = 0.9588, QWK = 0.9130) Regional images (AUC = 0.9425, QWK =	5673 slit-lamp photographs and 400 smartphone photographs	A DL network based on the InceptionV3	/

(continued on next page)

Table 1 (*continued*)

Reference	Year	Application	Performance measure	Data source	AI models	Mobile software
			0.8872) Smartphone images (AUC = 0.5379, QWK = 0.8529)			
Chen et al.[34]	2021	Eyelid measurements prediction	Pearson correlation coefficient (MRD1 = 0.91, MRD2 = 0.88, LF = 0.73)	Bilateral orbital photographs taken by a smartphone (iPhone 11 Pro Max, with flash and a 1:1 ratio)	CNNs	MAIA software (Muen Biomedical and Optoelectronic Technologist Inc; Version1.2.0)
Tabuchi et al.[35]	2022	Ptosis detection	Sensitivity = 83.0% Specificity = 82.5% AUC = 0.900 Accuracy = 82.8%	Facial photographs taken by an iPad Mini 5	MobileNetV2	/

NA: AI, artificial intelligence; DL, deep learning; DR, diabetic retinopathy; STDR, sight-threatening DR; CNNs, convolutional neural networks; DME, diabetic macular edema; ROP, retinopathy of prematurity; AMD, age-related macular degeneration; OCT, optical coherence tomography; SBFI, smartphone-based fundus imaging; AUC, area under the curve; IOP, intraocular pressure; GAT, Goldmann applanation tonometry; SVM, support vector machine; AIS, Apollo Infant Sight; QWK, quadratic weighted kappa; MRD1, Margin reflex distance 1; MRD2, Margin reflex distance 2; LF, levator muscle function.

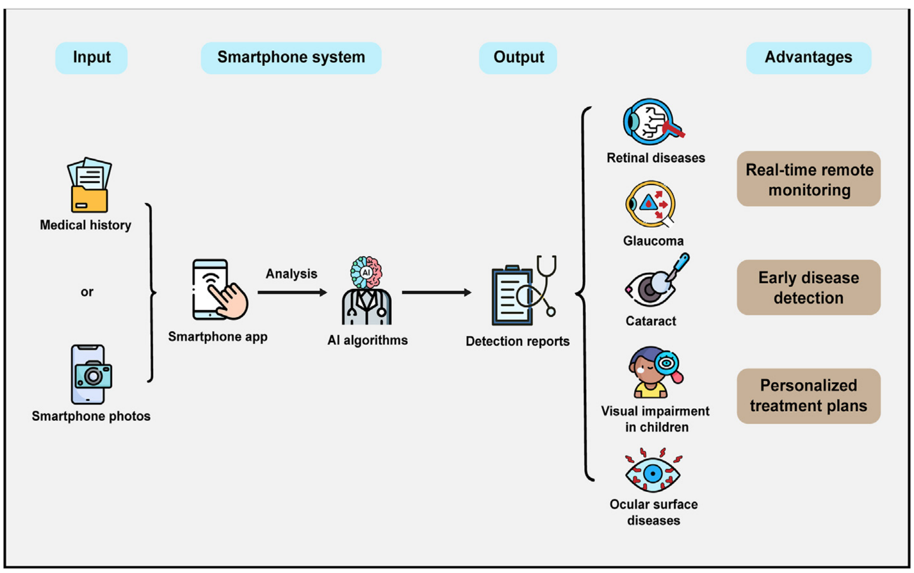

Fig. 2. Workflow of the integration of smartphone technology and AI for advanced ophthalmic care. The medical history including previous examination reports or ocular images taken by the smartphone-based camera are input into a smartphone with a special screening system. Then, the system analyzes these data with AI algorithms to detect the ocular diseases and send a report back, which has the potential to provide patients with real-time remote monitoring, early disease detection and personalized treatment plans.

optical coherence tomography (OCT) images from patients with a diagnostic accuracy of 90.02% for DME.[15] In another study, Malerbi et al. adopted an AI algorithm to improve screening in color fundus photographs obtained with a low-cost smartphone-based handheld retinal camera.[16] Considering its portability and affordability, smartphone-based handheld fundus camera played a crucial role in monitoring various diabetic retinal diseases.[17] Meanwhile, the integration with AI has the potential to further improve the low quality of this handheld fundus camera compared to the traditional tabletop fundus camera and achieve automatic grade ability with handheld images which may provide DME patients with a more effective and convenient screening strategy.

Furthermore, the integration of AI and smartphone technology has significant impact on other retinal diseases. To better predict the outcomes of the treatment for AMD early, Qidwai et al. explored a smart AI-based App based on adaptive neuro-fuzzy inference system to aid the clinician to visualize the progression of the patient and make better decisions related to the treatment.[18] The model had ultimately shown to have a high accuracy (92%) and works in near-real-time scenarios. Another study aimed to acquire a cost-effective alternative in the ROP telemedicine screening program by smartphone-based fundus imaging (SBFI) systems with AI and finally revealed that the two SBFI systems used in the ROP screening program were highly sensitive for treatment requiring-ROP.[19]

3.2. Glaucoma

Glaucoma, characterized by progressive, irreversible optic neuropathy and visual-field damage, stands as the primary cause of irreversible blindness worldwide. Early detection is crucial for treating and slowing the progression of glaucoma.[20] Meanwhile, considering the growing glaucoma population, the fundus cameras available at medical facilities are not sufficient to complete early detection of all the patients. Therefore, Nakahara et al. developed a DL-assisted program for screening glaucoma and applied it to a smartphone-based fundus camera compared with a normal fundus camera.[21] Although its area under the curve (AUC) value (0.842) was lower than that with the normal fundus camera (0.989), the smartphone-based fundus camera showed favourable diagnostic ability and reached a higher AUC value (0.900) in eyes with advanced glaucoma. Besides, apart from fundus photography, measurements of visual field (VF) and intraocular pressure (IOP) can become strategies to develop the detecting device. Li et al. developed a smartphone application-based DL system called iGlaucoma in detecting glaucomatous VF changes.[22] The iGlaucoma performed an accuracy of 99.0%, AUC of 0.966, the sensitivity of 95.4% and specificity of 87.3% in recognizing different patterns in pattern deviation probability plots region. In Wu et al. study, a prototype smartphone tonometer was compared with other tonometers to measure IOP in clinical practice and eventually the result was grossly equivalent.[23]

3.3. Cataract

Cataract patients usually experience clouding of the lens which can significantly reduce visual acuity and quality of life. Even though a relatively simple surgery can restore vision by installing an artificial lens, effective early detection is critical to ensure that the patient receive the best treatment before vision is severely impaired. Some researchers have applied smartphones to capture the ocular images and analyzed them with AI for early detection and management of cataract. In 2020, Hu et al. employed an AI algorithm to automatically classify cataract of varying severity according to the photometric appearance of the nuclear region of the crystalline lens of the eyes.[24] The results came to a high accuracy of 93.5% and speed in evaluating a cataract severity (29 ms) and the entire classification process (less than 1s). Another research conducted by Vasan et al. assessed the accuracy of an AI-based smartphone application (e-Paarvai) when detecting and grading cataracts compared with slit-lamp based diagnoses based on slit-lamp by ophthalmologists and found there is still room for improvement with a relatively poor specificity in detecting cataracts and unsatisfying accuracy in grading several types of cataracts.[25]

3.4. Visual impairment in children

Children are vulnerable to various visual disorders including amblyopia, strabismus, refractive error, etc., which can impact their learning abilities and lead to irreversible lifelong visual loss. Early detection of visual impairment in children is crucial, but parents frequently miss it due to children's disability to complain of visual difficulties in time and unwillingness to cooperate with standard vision tests.[26,27] This condition arouses a growing clinical need that could benefit from the rapid development of AI and smartphone technology in early identifying and monitoring the progress of visual impairment in children. A smartphone-based system, the Apollo Infant Sight (AIS), has been presented by Chen et al. to identify visually impaired children in real-world settings.[28] In AIS, the cartoon-like stimuli were released firstly to maintain a steady gaze in children and then the inbuilt front camera of the smartphone captured their gazing behaviors and facial features in 3.5-min videos which were used to detecting visual impairment by DL models. Through the validation, this system achieved an AUC of 0.940 and 0.843 in the internal and external testing dataset respectively and performed well in a further test for at-home implementation by untrained users with an AUC of 0.859, proved to be a promising tool that can be applied in real-world settings. Besides, Ma et al. evaluated a new photo screening solution with a smartphone-based automated Hirschberg test and photorefraction powered by DL and image-processing algorithms and it showed that the sensitivity and specificity were both high in strabismus, myopia and anisometropia detection.[29] Combining principles of mobile screening and DL, Murali et al. built a simple photography-based system (Kanna) to help detect amblyopia based on the amblyogenic risk factors (ARF).[30] Five ARF (Anisometropia, Isoametropia, Strabismus, Ptosis, Media Opacities) were included in the risk prediction system and their prescribed thresholds were built according to the 2003 the American Association for Pediatric Ophthalmology and Strabismus referral criteria. To predict the presence of ARF, photographs acquired from a smartphone were analyzed with DL models which reached an F-score of 0.732 with an accuracy of 79.5%, a sensitivity of 88.2% and a specificity of 75.6%.

3.5. Ocular surface diseases

The integration of AI and smartphone technology in ophthalmology initially focus on diagnosing and managing fundus diseases. In most cases, the specialized portable retinal camera connected to the mobile device is used to take fundus images of patients which are uploaded to AI platforms for automatic diagnosis of diseases. However, recent research shows that this screening system has the potential for automatically detecting lesions of ocular surface and other areas such as the eyelid. Liu et al. compared their fusion training model (trained by smartphone and slit-lamp images) in smartphone-based images(F1-score of 0.9313, sensitivity of 93.60%, specificity of 96.13%, AUC of 0.9426 and accuracy of 92.38%) for pterygium screening with the model (trained by slit-lamp images) in slit-lamp images (F1-score of 0.9448, sensitivity of 91.65%, specificity of 96.89%, AUC of 0.9569 and accuracy of 94.29%), showing comparable performance.[31] Similarly, Wang et al. utilized a DL network trained by slit-lamp and smartphone photographs and investigated the potential in classifying infectious keratitis based on smartphone images.[32] Another study conducted by Zhang et al. to validate a corneal epithelium (CE) evaluation pipeline using a custom smartphone attachment and CNNs.[33] The results showed that the smartphone-based CE evaluation tool in calculating areas of CE disruption had qualitative concordance with those revealed by fluorescein staining slit-lamp photos graded by two clinicians. Apart from AI models, it should be noted that specialized equipment like slit-lamp is still necessary for smartphone-based anterior segment imaging and the smartphone camera is in need of a short focus distance to scan the ocular surface and high resolutions to capture the images.

Using mobile system with AI algorithms to evaluate ptosis has been proven feasible recently. Chen et al. were the first to propose a smartphone-based AI-assisted image processing algorithm for ptosis evaluation and management.[34] This algorithm was based on the relevant eyelid measurements including margin reflex distance 1, margin reflex distance 2 and levator muscle function which is defined as the distance between the upper eyelid margin and the center of the pupillary light reflex, the lower eyelid margin and the center of the pupillary light reflex and the upper eyelid margin moving from down-gaze to up-gaze without any eyebrow movement, respectively. Moreover, Tabuchi et al. developed an iOS application using machine learning for the automated diagnosis of blepharoptosis, which had a sensitivity of 83.0%, specificity of 82.5%, accuracy of 82.8% and AUC of 0.900 for classifying blepharoptosis and normal eyelids images taken by an iPad.[35]

4. Discussion

The integration of smartphone technology and AI in ophthalmic care presents a transformative path for the future, along with some challenges still need to be concerned (Fig. 3).

Progress in AI algorithms shows potential for more refined, accurate and automatic diagnosis in ocular diseases.[36] Meanwhile, the ongoing evolution of smartphone capabilities, including improved imaging modalities and connectivity, is positioned to facilitate remote patient monitoring and enhance accessibility to eye care services, particularly in resource-limited regions and underserved communities.[37] Looking forward, the integration of AI with smartphone-based diagnostics is anticipated to streamline disease detection with timely, efficient and cost-effective screening for ocular pathologies.[38] It also demonstrates the potential to promote self-monitoring, thus enabling better triaging to tertiary eye institutes and alleviating the burden on the health care system.[39] Moreover, tailored interventions based on individual patient data, gleaned from smartphone-enabled assessments and AI-driven analytics, could provide personalized treatment plans, optimizing outcomes and mitigating vision loss.

However, significant data gaps persist in critical areas within these advancements. The absence of comprehensive cost-effectiveness studies hampers understanding. Equally, the medicolegal implications arising from potential missed pathologies pose unresolved concerns, demanding robust ethical and legal frameworks. Furthermore, while current technologies primarily focus on singular diseases like DR, the absence of methodologies capable of simultaneously screening multiple ocular pathologies raises concern, particularly considering the likelihood of age-related multiple pathology coexistence within the same eye.[40]

Additionally, the collaborative efforts of clinicians, technologists, and regulatory bodies are pivotal in establishing robust frameworks for the

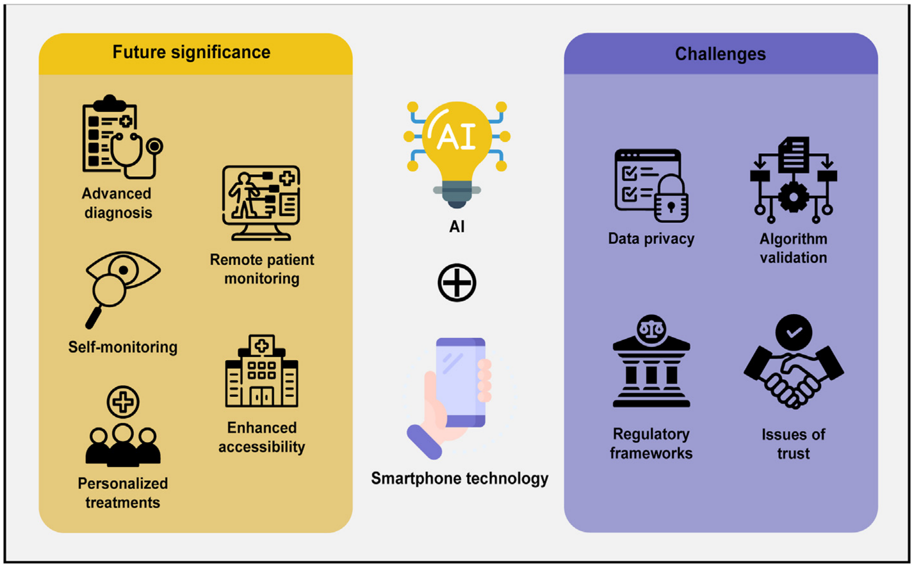

Fig. 3. Future significance and challenges of the integration of AI and smartphone technology.

ethical implementation and validation of AI algorithms within smartphone applications, while attention should be paid on the actual deployment and interdisciplinary cooperation to tackle ethical concerns.[41] Striking a balance between innovation and ethical considerations is imperative to ensure patient privacy, data security, and algorithmic reliability.[42] Besides, issues of trust between patients and this technology are need to be addressed, which requires a better accuracy, interpretability and privacy.[43] In order to make this technology employed in real ophthalmic care, more specific and systematic evaluation on real-world implementation is imperative as well, which is still lacked in the present study.

5. Conclusions

This review provides an overview of the integration between smartphone technology and AI on a few ocular diseases, highlighting the transformative possibilities in diagnosis, treatment, accessibility, and personalized care. While challenges such as ethical considerations, data security and issues of trust are still need to be addressed. The future landscape of ophthalmic care envisions seamless integration among smartphones, AI, and telemedicine, fostering a global network of interconnected platforms that enables real-time consultations and remote monitoring, ushering in an era of personalized, data-driven interventions tailored to individual patient needs.

Study approval

Not Applicable.

Author contributions

KJ led conceptualization, formal analysis, investigation, and drafted the original manuscript. YL contributed to methodology, validation, formal analysis, and initial drafting. HW contributed in methodology, validation, and formal analysis. YCT, VK, YZ, RK, and AG were crucial in manuscript review and editing. JY played a key role in conceptualization, supervision, manuscript refinement, and funding acquisition. All authors reviewed the results and approved the final version of the manuscript.

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Declaration of competing interest

The authors affirm that there are no apparent financial interests or personal relationships that might have influenced the reported work in this paper.

Abbreviations

AI	artificial intelligence
WHO	World Health Organization
DR	diabetic retinopathy
AMD	age-related macular degeneration
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyzes
DME	diabetic macular edema
ROP	retinopathy of prematurity
STDR	sight-threatening DR
DL	deep learning
CNN	convolutional neural networks
OCT	optical coherence tomography
SBFI	smartphone-based fundus imaging
VF	visual field
IOP	intraocular pressure
AUC	area under the curve
ARF	amblyogenic risk factors
CE	corneal epithelium

References

1. Vilela MAP, Arrigo A, Parodi MB, et al. Smartphone eye examination: artificial intelligence and telemedicine. *Telemedicine and e-Health.* Aug 16 2023. https://doi.org/10.1089/tmj.2023.0041.

2. Bhavnani SP, Narula J, Sengupta PP. Mobile technology and the digitization of healthcare. *Eur Heart J*. May 7 2016;37(18):1428–1438. https://doi.org/10.1093/eurheartj/ehv770.
3. Jin K, Ye J. Artificial intelligence and deep learning in ophthalmology: current status and future perspectives. *Advances in Ophthalmology Practice and Research*. Aug 24 2022;2(3):100078. https://doi.org/10.1016/j.aopr.2022.100078.
4. *Blindness and Vision Impairment*; Aug 10 2023. https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment.
5. Kumari R, Pratap Singh K, Dubey G, et al. Chronic impediment in utilization of eye-care services. *Journal of Ophthalmology and Research*. 2020;3(2). https://doi.org/10.26502/fjor.2644-00240020.
6. Baskaran M, Foo RC, Cheng CY, et al. The prevalence and types of glaucoma in an urban Chinese population: the Singapore Chinese eye study. *JAMA Ophthalmol*. Aug 2015;133(8):874–880. https://doi.org/10.1001/jamaophthalmol.2015.1110.
7. Li R, Chen W, Li M, et al. LensAge index as a deep learning-based biological age for self-monitoring the risks of age-related diseases and mortality. *Nat Commun*. Nov 6 2023;14(1):7126. https://doi.org/10.1038/s41467-023-42934-8.
8. Natarajan S, Jain A, Krishnan R, et al. Diagnostic accuracy of community-based diabetic retinopathy screening with an offline artificial intelligence system on a smartphone. *JAMA ophthalmology*. Oct 2019;137(10):1182–1188. https://doi.org/10.1001/jamaophthalmol.2019.2923.
9. Cheung N, Mitchell P, Wong TY. Diabetic retinopathy. *Lancet (London, England)*. Jul 10 2010;376(9735):124–136. https://doi.org/10.1016/S0140-6736(09)62124-3.
10. Vujosevic S, Aldington SJ, Silva P, et al. Screening for diabetic retinopathy: new perspectives and challenges. *Lancet Diabetes Endocrinol*. Apr 2020;8(4):337–347. https://doi.org/10.1016/S2213-8587(19)30411-5.
11. Ryan ME, Rajalakshmi R, Prathiba V, et al. Comparison among methods of retinopathy assessment (CAMRA) study: smartphone, nonmydriatic, and mydriatic photography. *Ophthalmology*. Oct 2015;122(10):2038–2043. https://doi.org/10.1016/j.ophtha.2015.06.011.
12. Rajalakshmi R, Subashini R, Anjana RM, et al. Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. *Eye*. Jun 2018;32(6):1138–1144. https://doi.org/10.1038/s41433-018-0064-9.
13. Al-Karawi A, Avşar E. A deep learning framework with edge computing for severity level detection of diabetic retinopathy. *Multimed Tool Appl*. Mar 22 2023:1–22. https://doi.org/10.1007/s11042-023-15131-4.
14. Sosale B, Sosale AR, Murthy H, et al. Medios–An offline, smartphone-based artificial intelligence algorithm for the diagnosis of diabetic retinopathy. *Indian J. Ophthalmol.* Feb 2020;68(2):391. https://doi.org/10.4103/ijo.IJO_1203_19.
15. Hwang DK, Yu WK, Lin TC, et al. Smartphone-based diabetic macula edema screening with an offline artificial intelligence. *J Chin Med Assoc*. Dec 2020;83(12):1102–1106. https://doi.org/10.1097/JCMA.0000000000000355.
16. Malerbi FK, Mendes G, Barboza N, et al. Diabetic macular edema screened by handheld smartphone-based retinal camera and artificial intelligence. *J. Med. Syst.* Dec 11 2021;46(1):8. https://doi.org/10.1007/s10916-021-01795-8.
17. Naz H, Nijhawan R, Ahuja NJ. Clinical utility of handheld fundus and smartphone-based camera for monitoring diabetic retinal diseases: a review study. *Int Ophthalmol*. Feb 9 2024;44(1):41. https://doi.org/10.1007/s10792-024-02975-4.
18. Qidwai U, Qidwai U, Raja M, et al. Smart AMD prognosis through cellphone: an innovative localized AI-based prediction system for anti-VEGF treatment prognosis in nonagenarians and centenarians. *Int. Ophthalmol.* Jun 2022;42(6):1749–1762. https://doi.org/10.1007/s10792-021-02171-8.
19. Young BK, Cole ED, Shah PK, et al. Efficacy of smartphone-based telescreening for retinopathy of prematurity with and without artificial intelligence in India. *JAMA ophthalmology*. Jun 1 2023;141(6):582–588. https://doi.org/10.1001/jamaophthalmol.2023.1466.
20. Jonas JB, Aung T, Bourne RR, et al. Glaucoma. *Lancet (London, England)*. Nov 11 2017;390(10108):2183–2193. https://doi.org/10.1016/S0140-6736(17)31469-1.
21. Nakahara K, Asaoka R, Tanito M, et al. Deep learning-assisted (automatic) diagnosis of glaucoma using a smartphone. *Br J Ophthalmol*. Apr 2022;106(4):587–592. https://doi.org/10.1136/bjophthalmol-2020-318107.
22. Li F, Song D, Chen H, et al. Development and clinical deployment of a smartphone-based visual field deep learning system for glaucoma detection. *NPJ digital medicine*. 2020;3:123. https://doi.org/10.1038/s41746-020-00329-9.
23. Wu Y, Luttrell I, Feng S, et al. Development and validation of a machine learning, smartphone-based tonometer. *Br J Ophthalmol*. Oct 2020;104(10):1394–1398. https://doi.org/10.1136/bjophthalmol-2019-315446.
24. Hu S, Wang X, Wu H, et al. Unified diagnosis framework for automated nuclear cataract grading based on smartphone slit-lamp images. *IEEE Access*. 2020;8:174169–174178. https://doi.org/10.1109/ACCESS.2020.3025346.
25. Vasan CS, Gupta S, Shekhar M, et al. Accuracy of an artificial intelligence-based mobile application for detecting cataracts: results from a field study. *Indian J Ophthalmol*. Aug 2023;71(8):2984–2989. https://doi.org/10.4103/IJO.IJO_3372_22.
26. Keil S, Fielder A, Sargent J. Management of children and young people with vision impairment: diagnosis, developmental challenges and outcomes. *Arch Dis Child*. Jun 2017;102(6):566–571. https://doi.org/10.1136/archdischild-2016-311775.
27. Lagrèze WA. Vision screening in preschool children: do the data support universal screening? *Deutsches Arzteblatt International*. Jul 2010;107(28-29):495–499. https://doi.org/10.3238/arztebl.2010.0495.
28. Chen W, Li R, Yu Q, et al. Early detection of visual impairment in young children using a smartphone-based deep learning system. *Nat Med*. Feb 2023;29(2):493–503. https://doi.org/10.1038/s41591-022-02180-9.
29. Ma S, Guan Y, Yuan Y, et al. A one-step, streamlined children's vision screening solution based on smartphone imaging for resource-limited areas: design and preliminary field evaluation. *JMIR mHealth and uHealth*. Jul 13 2020;8(7):e18226. https://doi.org/10.2196/18226.
30. Murali K, Krishna V, Krishna V, et al. Application of deep learning and image processing analysis of photographs for amblyopia screening. *Indian J. Ophthalmol.* Jun 25 2020;68(7):1407. https://doi.org/10.4103/ijo.IJO_1399_19.
31. Liu Y, Xu C, Wang S, et al. Accurate detection and grading of pterygium through smartphone by a fusion training model. *Br J Ophthalmol*. Mar 1 2023. https://doi.org/10.1136/bjo-2022-322552. bjo-2022-322552.
32. Wang L, Chen K, Wen H, et al. Feasibility assessment of infectious keratitis depicted on slit-lamp and smartphone photographs using deep learning. *Int J Med Inf*. Nov 2021;155:104583. https://doi.org/10.1016/j.ijmedinf.2021.104583.
33. Zhang A, Pratap JS, Young JR, et al. Pilot clinical validation of a machine learning platform for noninvasive smartphone-based assessment of corneal epithelial integrity. *medRxiv*. Aug 2023. https://doi.org/10.1101/2023.08.29.23293788v1.
34. Chen H-C, Tzeng S-S, Hsiao Y-C, et al. Smartphone-based artificial intelligence–assisted prediction for eyelid measurements: algorithm development and observational validation study. *JMIR mHealth and uHealth*. Oct 2021;9(10):e32444. https://doi.org/10.2196/32444.
35. Tabuchi H, Nagasato D, Masumoto H, et al. *Developing an iOS Application that Uses Machine Learning for the Automated Diagnosis of Blepharoptosis*. Graefe's Archive for Clinical and Experimental Ophthalmology; Apr 2022:1–7. https://doi.org/10.1007/s00417-021-05475-8.
36. Schmidt-Erfurth U, Sadeghipour A, Gerendas BS, et al. Artificial intelligence in retina. *Prog. Retin. Eye Res.* Nov 2018;67:1–29. https://doi.org/10.1016/j.preteyeres.2018.07.004.
37. Hogarty DT, Hogarty JP, Hewitt AW. Smartphone use in ophthalmology: what is their place in clinical practice? *Surv Ophthalmol*. 2020;65(2):250–262. https://doi.org/10.1016/j.survophthal.2019.09.001.
38. Wasmann J-W, Pragt L, Eikelboom R, et al. Digital approaches to automated and machine learning assessments of hearing: scoping review. *J. Med. Internet Res.* Feb 2 2022;24(2):e32581. https://doi.org/10.2196/32581.
39. He J, Baxter SL, Xu J, et al. The practical implementation of artificial intelligence technologies in medicine. *Nat Med*. Jan 2019;25(1):30–36. https://doi.org/10.1038/s41591-018-0307-0.
40. Gomez Rossi J, Rojas-Perilla N, Krois J, Schwendicke F. Cost-effectiveness of artificial intelligence as a decision-support system applied to the detection and grading of melanoma, dental caries, and diabetic retinopathy. *JAMA Netw Open*. Mar 1 2022;5(3):e220269. https://doi.org/10.1001/jamanetworkopen.2022.0269.
41. Dow ER, Keenan TDL, Lad EM, et al. From data to deployment: the collaborative community on ophthalmic imaging roadmap for artificial intelligence in age-related macular degeneration. *Ophthalmology*. May 2022;129(5):e43–e59. https://doi.org/10.1016/j.ophtha.2022.01.002.
42. Gooding P, Kariotis T. Ethics and law in research on algorithmic and data-driven technology in mental health care: scoping review. *JMIR mental health*. Jun 10 2021;8(6):e24668. https://doi.org/10.2196/24668.
43. Tseng RMWW, Gunasekeran DV, Tan SSH, et al. Considerations for artificial intelligence real-world implementation in ophthalmology: providers' and patients' perspectives. *Asia-Pacific Journal of Ophthalmology*. May 2021;10(3):299–306. https://doi.org/10.1097/APO.0000000000000400.