REVIEW

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Application of artificial intelligence in myopia prevention and control

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ABSTRACT
The global incidence of myopia is increasing, and high myopia increases the risk of pathological myopia, which can lead to irreversible visual impairment, posing a significant global health concern. Artificial intelligence (AI) may be a solution to the myopia pandemic, with potential applications in early identification, risk stratification, progression prediction, and timely intervention to address unmet needs. AI has been developed to detect, diagnose, and predict the progression of myopia in both children and adults. In this review, the current state of AI technology applications in the field of myopia has been comprehensively reviewed, and the challenges, current development status, and future directions of AI have also been discussed, which hold great significance for the further application of AI in myopia management.

KEYWORDS
Artificial intelligence, Deep learning, Machine learning, Myopia

INTRODUCTION

Myopia is currently a critical public health issue,[1] a global prevalence of approximately 28.3% (2 billion) of the world's population and 4.0% (277 million) suffering from high myopia. By 2050, the "myopia pandemic" is projected to affect 49.8% (4.758 billion) of the global population, with 9.8% (938 million) having high myopia (≤ -5.00 dioper [D]).[2] Any degree of myopia increases the risk of adverse changes in ocular tissues, while high myopia and pathological myopia significantly elevate the risk of irreversible vision damage, such as glaucoma, retinal detachment, myopic macular degeneration, and the formation of choroidal neovascularization, which can even lead to blindness.[3] This not only reduces patients' quality of life but also leads to a global medical and economic burden. Therefore, it is of great significance to comprehensively conduct myopia healthcare services, including detection, diagnosis, progression, prediction, and treatment of myopia, as well as the management and prevention of ocular complications and vision damage in patients with high myopia.[1]

The concept of artificial intelligence (AI) was initially proposed by John McCarthy in 1956, who defined AI as the simulation of human intelligence through machines.[4] With the continuous development of computer technology, big data acquisition, and imaging methods, the application of AI in the medical field is constantly expanding. The development of multi-modal imaging, fundus photography,

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and optical coherence tomography (OCT) has provided rich datasets for the development of AI models, making the vigorous development of AI in ophthalmology.[1] Machine learning (ML), a subset of AI, primarily uses computer system programming to perform tasks or predict outcomes.[5] ML can also identify biomarkers that are difficult even for human experts to identify, providing new opportunities to improve the accuracy and efficiency of refractive error detection and treatment.[6,7] The diagnosis of many ophthalmic diseases requires not only symptom assessment but also imaging information, a feature that has led to the widespread application of AI technology represented by deep learning (DL) in clinical ophthalmology.[8] AI models based on big medical data have the potential for individualized treatment and help achieve precise diagnosis and treatment of myopia.[9,10]

This paper reviews the clinical application and significance of AI in the field of myopia prevention and control, including the assessment of risk factors for myopia, myopia detection, myopia prediction models, myopia control methods, behavioral interventions, and monitoring devices. It also discusses the potential challenges and current development status of AI in myopia prevention and control and proposes future development directions.

ASSESSMENT OF RISK FACTORS FOR MYOPIA

In addition to the statistical analysis of myopia data, ML can identify more relevant factors, facilitating better predictions of myopia. Based on questionnaire surveys, Xiao et al.[11] analyzed the relationship between living environment, genetics, and living habits and myopia using the following three ML methods: support vector machine (SVM), logistic regression (LR), and XGBoost. They found that age was the most significant risk factor for myopia, while protective measures taken by children, such as choosing not to look at the blackboard or promptly reporting to teachers or parents when they could not see the blackboard clearly, had the strongest protective effect on vision compared with squinting to see the blackboard. An XGBoost-based model for myopia prediction is recommended.[11] Li et al.[12] applied ML to longitudinal, cycloplegic refractive data to explore risk factors for myopia progression in primary school children, and found that uncorrected distance visual acuity and spherical equivalent (SE) were good predictors of myopia progression in children during primary school. Parental myopia played a significant role in the early stages of myopia progression but diminished with increasing age. Therefore, further research on the impact of environmental factors on children with myopia is needed to evaluate their interaction and feasibility in different populations and individuals. Tu et al.[13] investigated key factors contributing to the prevalence of myopia among students by building ML models. They found that urban living, parental myopia, high body mass index, and engaging in intense near work were associated with a higher prevalence of myopia in children, while increased outdoor activities helped reduce the prevalence of myopia. Zhang et al.[14] used ML techniques to screen for risk factors associated with high myopia, including 74 factors related to demographics, physical examinations, nutrition and serology, immunology, and past medical history. They found that high levels of serum vitamin A appeared to be associated with an increased prevalence of high myopia. Tong et al.[15] analyzed the similarities and differences in influencing factors of myopia for students across different school stages (primary, middle, and high school) using a myopia classification model based on ML algorithms. They found that lower-grade students appeared to be more susceptible to genetic or parental behaviors, whereas eye health awareness and eye use behaviors may influence higher-grade students. These findings are beneficial for further guiding the prevention and control of myopia in children and adolescents.

MYOPIA DETECTION

A traditional refractive examination is not only time-consuming and labor-intensive but also relies on expensive machines, experienced doctors, and technicians.[1] People with expression difficulties (such as young children, the elderly, and patients with language communication barriers) have difficulty cooperating during the examination process.[16] In developing or impoverished countries, due to the lack of doctors and medical equipment, it is difficult to accurately assess refractive errors so patients are likely to miss the optimal treatment window, resulting in irreversible visual loss.[1] Therefore, it is necessary to provide timely and high-quality refractive examination services that are acceptable to the general population.[1] With the continuous update of AI technology, imaging-based ML or DL plays a supporting role in the clinical management of myopia, filling the gap in AI algorithms for myopia and providing a new direction for myopia detection.[9] Mechanisms of ML and DL in myopia application based on fundus images are shown in Figure 1. Moreover, attention should be paid to the related risks of myopia complications during ocular imaging assessment, which may help reduce the overall burden of myopia.[17]

A summary of the application of AI in myopia detection, based on different types of images, is presented in Table 1. Yang et al.[18] trained a DL system to automatically detect myopia from visual appearance images, which achieved an area under the receiver operating characteristic curve of 0.9270, providing a reference value for screening and monitoring refractive status in children with myopia in remote areas. Varadarajan et al.[19] were the first to estimate refractive errors with high accuracy based on retinal fundus

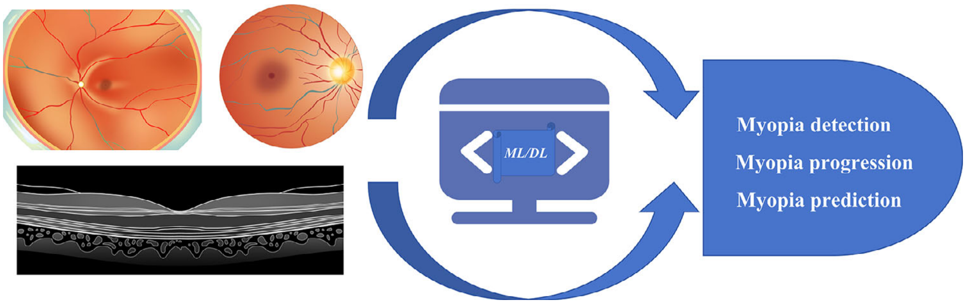

FIGURE 1 Mechanisms of machine learning and deep learning in myopia application based on fundus images. DL, deep learning; ML, machine learning.

TABLE 1 Summary of artificial intelligence in myopia detection

References	Modalities	AI model	Tasks	Performance
Yang et al., 2020[18]	Ocular appearance images	DL	Myopia detection and diagnosis	AUC: 0.9270
Varadarajan et al., 2018[19]	Fundus images	DL	SE assessment	MAE of 0.56 D in the UK Biobank data set and 0.91 D in the AREDS data set
Tan et al., 2019[20]	Fundus images	DL	Prediction of SE and detection of high myopia	MAE of 1.20 D for SE prediction; AUC of 0.942 for high myopia detection
Tan et al., 2021[21]	Fundus images	DL	Detection of myopic macular degeneration and high myopia	AUC: 0.913
Yoo et al., 2022[22]	OCT images	DL	Uncorrected refractive error assessment	AUC: 0.813; accuracy: 71.4%
Cao et al., 2023[23]	Fundus images	AI	Detection of 7 fundus conditions in a real-world setting with an AI-based fundus screening system	AUC greater than 0.8 for pathologic myopia

Abbreviations: AI, artificial intelligence; AREDS, Age-Related Eye Disease Study; AUC, area under the curve; D, diopter; DL, deep learning; MAE, mean absolute error; OCT, optical coherence tomography; SE, spherical equivalent.

photographs, demonstrating that DL can be applied to make new predictions from medical images. This study showed that the foveal region is one of the most important areas for prediction, achieving a technological leap in accurately predicting refractive errors from retinal fundus images. Tan et al.[20] also reported that a system consisting of a convolutional neural network pre-trained with the XGBoost algorithm can evaluate refractive errors with high accuracy by using color fundus photographs. Tan et al.[21] developed a DL algorithm based on retinal photographs to detect high myopia. The DL algorithm is expected to become an effective tool for risk stratification and screening of myopia and high myopia in a large global population, to identify individuals with the highest risk of future complications, which may be important in addressing the global burden of myopia. In addition, existing studies have developed DL models to predict uncorrected refractive errors from OCT images, indicating that OCT can also be applied to refractive error detection.[22] Cao et al.[23] found that in the real world, AI-based fundus screening systems have better performance in detecting pathological myopia.

Self-monitoring equipment and applications enable continuous remote monitoring of diseases, providing new strategies for myopia detection.[17] SVOne is a portable Hartmann-Shack wavefront aberrometer that uses a wavefront sensor to measure eye aberrations. It can be connected to a smartphone to objectively measure refractive errors in the eye.[24,25] Studies have found no significant differences in refractive error measurements of normal young adults between the SVOne handheld aberrometer and other subjective and objective programs. Therefore, this instrument is valuable for vision screening and examinations conducted outside clinical settings and can serve as an auxiliary examination for standard optometry exams.[24] Studies have developed a Web-based test to measure visual acuity, as well as spherical and cylindrical refractive errors.

The results indicated that the web-based ophthalmic test is an effective and safe method for measuring visual acuity and refractive errors in healthy eyes, especially for low myopia. This tool can be used for screening purposes and is an easily accessible alternative to subjective optometry tests.[26] These applications can be built on a large database, providing personalized and frequent monitoring of patients' myopia status, while paving the way for precision medicine in myopia treatment.[17] Chi et al.[27] proposed a "self-service" intelligent vision screening system based on an embedded AI platform, where individuals can independently complete the task without any technical assistance. The deployment of this intelligent system has brought great convenience to large-scale and rapid vision screening, and its effectiveness has been proven.

MYOPIA PREDICTION MODEL

Considering the potential burden of irreversible diseases in adulthood, parents, clinicians, and policymakers are concerned about the potential progression rate and risk of developing myopia in children to high or even pathological myopia.[28] Therefore, predicting the progression of myopia can provide a basis for changing clinical practice, health decision-making, and precise individualized intervention measures for the practical control of myopia during school age.[1] In recent years, the development of AI technology has provided new possibilities for myopia prediction (Figure 1). The increase in the quantity and availability of biomedical data, including biometric data, refractive data, treatment responses, and ocular imaging data from different modes, has enabled multimodal AI solutions to capture the complexity of myopia, providing data support for the establishment of myopia prediction models.[17] This study summarized the myopia prediction models developed in recent years and their significance, as shown in Table 2.

Lin et al.[29] used a random forest ML model to predict the onset and progression of myopia in children and adolescents over the next 10 years based on age, SE, and annual myopia progression rate. The prediction performance was good. This work provided evidence for changing clinical practice, health policy development, and precise personalized interventions for practical control of myopia in school-age children. Yang et al.[30] developed a prediction model for myopia in adolescents based on the integrated data including gender, measurement data (axial length and corneal curvature), behavioral data (outdoor and indoor exercise time, close visual work habits), dietary habits, and family history data (number of parents wearing glasses). They inferred a relationship between myopia and different factors. The model achieved reasonable performance and accuracy, which is beneficial for formulating policies to help prevent myopia. Tang et al.[31] studied the optimal model for predicting axial elongation based on integrated data including demographics (gender and age), SE, corneal metrology (average K value), corneal diameter (WTW), and central corneal thickness, demonstrating that in the absence of clinical data, ML algorithms can provide practitioners with a reasonable model for estimating increases in axial length, which is especially useful when monitoring the myopia progression in orthokeratology lens wearers. Li et al.[12] established an ML-based prediction model for myopia progression in primary school students based on uncorrected distance visual acuity, SE, axial length, flat corneal curvature, gender, and parental myopia. The model has good accuracy in predicting myopia progression. Foo et al.[32] developed models to predict the risk of high myopia (SE ≤ -6.00D) 5 years later during teenage years (aged 11–17) using clinical data (age, gender, ethnicity, parental myopia, and baseline SE), fundus image data, and a combination of the two based on a DL system. The DL system in this study can predict the development of high myopia in primary school students during adolescence, which has the potential to serve as a clinical decision-support tool to identify "high-risk" children for early intervention. The performance of the fundus image model has the potential to be translated and implemented as a community or school project to identify high-risk children for further assessment and intervention when needed. Huang et al.[33] used a time-aware long short-term memory method based on historical visual records, including uncorrected visual acuity, spherical power, astigmatism degree, astigmatism axis, corneal curvature, and axial length, to quantitatively predict SE of children and adolescents over 2.5 years, facilitating the early identification of myopia progression and allowing for targeted interventions and proactive preventive measures. Wang et al.[34] developed different ML models to predict the best corrected visual acuity of patients with high myopia over the next 3 and 5 years, as well as the risk of visual impairment over the next 5 years. The data included general information, basic ophthalmic information, and 34 variables such as the category of myopic maculopathy based on fundus and OCT images. The results showed that it is feasible to develop accurate models for predicting long-term visual acuity in patients with high myopia based on clinical and imaging information, which can be used for clinical assessment of future visual acuity. Barraza-Bernal et al.[35] developed ML-based models to predict the onset and progression of myopia based on age, gender, biometrics, and refractive parameters, which will help generate a high-quality algorithm for predicting the development of refractive errors. Zhu et al.[36] predicted SE and axial length in students from grades 1–6 based on ML and predicted children's future SE and axial length using ML, thereby assisting doctors in making diagnoses and taking timely preventive measures based on the prediction results, which is significant for the prevention and control of myopia in children. Some

TABLE 2 Summary of artificial intelligence in myopia prediction

References	Modalities	AI model	Tasks	Performance
Lin et al, 2018[29]	Integrated data	ML	Prediction of SE and high myopia onset	AUC: 0.801–0.837
Yang et al., 2020[30]	Integrated data	ML	Prediction of myopia at 6th grade	AUC: 0.87–0.98
Tang et al., 2020[31]	Integrated data	ML	Prediction of AL elongation	Best model: Robust linear regression R^2: 0.87
Li et al., 2022[12]	Integrated data	ML	Prediction of myopia progression for all 5 years	Combined weight of 77% and prediction accuracy of over 80%
Foo et al., 2023[32]	Integrated data	DL	Prediction of 5-year high myopia risk	Image models AUC: 0.91–0.93; clinical models AUC: 0.93–0.94; mixed models AUC: 0.97–0.98
Huang et al., 2023[33]	Variable-length historical vision records	DL	Prediction of the children's and adolescents' SE within two and a half years	Overall error 0.103 D
Wang et al., 2023[34]	Integrated data	ML	Prediction of BCVA at 3 and 5 years and the risk of developing VI at 5 years	Support vector machines for BCVA at 3 years. R^2: 0.682; random forest for BCVA at 5 years, R^2: 0.660; logistic regression for VI at 5 years, AUC: 0.870
Barraza-Bernal et al., 2023[35]	Integrated data	ML	Prediction of refractive error and its progression	The Pearson correlation coefficient between prediction and measured data was 0.77, the bias was −0.05 D and the limits of agreement were 0.85 D
Zhu et al., 2023[36]	SE and AL	ML	Prediction of SE and AL	OMP model for SE: R^2 up to 0.8997; KR and MLP models for AL: R^2 up to 0.9072
Oh et al., 2023[37]	UWF images	DL	Prediction of SE and AL	R^2: 0.815
Wang et al., 2024[38]	UWF images	DL	Prediction of AL of moderate to high myopic patients	R^2, MSE, and MAE were 0.579, 1.419, and 0.9043, respectively
Li et al., 2024[39]	Integrated data	ML	Prediction of myopia progression and high myopia risk in children	AUC: 0.80–0.96
Qi et al., 2024[40]	Integrated data	DL	Prediction of myopia onset	AUC: 0.769–0.908
Zhao et al., 2024[41]	Age at baseline and SE	ML	Prediction of SE and onset of myopia and high myopia in a specific year	R^2 exceeding 0.729 for SE prediction, AUC of myopia onset: 0.845–0.953 over 15 years, AUC of high myopia onset prediction: 0.807–0.997 over 13 years, with the 14th year at 0.765

Abbreviations: AL, axial length; AUC, area under the curve; BCVA, best corrected visual acuity; DL, deep learning; KR, kernel ridge; MAE, mean absolute error; ML, machine learning; MLP, multilayer perceptron; MSE, mean square error; OMP, orthogonal matching pursuit; PM, pathological myopia; SE, spherical equivalent; UWF, ultra-widefield; VI, visual impairment.

studies have developed DL-based models to predict AL through Ultra-widefield images. These findings may aid in better understanding the relationship between eye length and retinal changes.[37,38] Li et al.[39] established models to predict the progression of myopia and the risk of developing high myopia in children using various ML methods, such as the K-nearest neighbor, XGBoost, decision tree model, logistic regression model, and Gaussian NB model, based on students' basic information, parental myopia, and their education level, and eye usage habits. These models achieved good performance. Qi et al.[40] developed a DL algorithm called DeepMyopia, which can predict the occurrence of myopia in the next 3 years and accurately identify high-risk individuals by analyzing retinal fundus images, axial length, gender, age, and other information of children and adolescents, providing a reliable and efficient tool for early detection of myopia in children and possessing tremendous potential in large-scale public health screenings. Zhao et al.[41] predicted the SE and onset of myopia, and high myopia in specific years using random forest and XGBoost. They found that the XGBoost prediction model exhibited high accuracy in predicting SE and the onset of myopia and high myopia in children and adolescents aged 3–18 years. Their study emphasized the importance of early and regular examinations to predict high myopia, thus providing valuable insights for clinical practice.

Genetic factors are also a non-negligible contributor to myopia.[3] In myopia prediction, the key advantage of genetic data over refractive error lies in the fact that genotypes are fixed. Genetic data can be combined with age, sex, and other risk factors (such as parental SE) to predict the risk of myopia at a very young age. However, existing studies have shown that the added value of genetic data in myopia prediction is very limited, and research results are inconsistent.[42] Wei et al.[43] identified potential biomarkers for myopia using ML algorithms and determined four key biomarkers (NR1D1, PPP1R18, PGBD2, and PPP1R3D) for myopia, providing a foundation for future clinical and experimental validation studies and enhancing the diagnosis and prognostic prediction of myopia. Studies have found that the areas under the receiver operating characteristic curve (AUROCs) for predicting myopia using polygenic risk scores (PRS) were 0.67 (SE ≤ -0.75D), 0.75 (SE ≤ -3.00D), and 0.73 (SE ≤ -5.00D), respectively. Including PRS in the level of education slightly improved the AUROC for myopia, but had no effect on moderate and high myopia.[44] Chen et al.[45] evaluated the effect of adding genetic information to predict future myopia risk based on cycloplegic data from 1063 pairs of first-born twins from the Guangzhou Twins Eye Study. The results showed that adding genetic risk score (GRS) data did not significantly improve model performance. However, other studies have found that GRS improved model fit compared to using the number of myopic parents alone in predicting the incidence rate of myopia.[46] Therefore, further research is needed on the application of genetic data in the field of myopia.

AI AND MYOPIA TREATMENT

The use of corneal parameters and AI models based on corneal topography provides more accurate lens-wearing and personalized treatment plans for children wearing orthokeratology lenses. Fang et al.[47] employed ML to predict the treatment effects of orthokeratology based on ocular parameters and clinical features. The C-statistic of the prediction model was 0.821, indicating that this auxiliary model can assist ophthalmologists in making clinical decisions for patients, improving myopia control, and predicting the clinical effect of orthokeratology treatment through retrospective non-interventional trials. Fan et al.[48] constructed an ML-based model for estimating the alignment curve of orthokeratology lens fitting. This model can minimize the number of lens trials, enhance efficiency while maintaining accuracy, and represent an improvement over previous calculation methods. It can also provide clinicians with an effective approach to estimate the alignment curve of visual reshaping treatment lenses and reduce the probability of cross-infection caused by trial lenses. Zhang et al.[49] developed a DL-based automated model using corneal topography to determine the treatment zone and peripheral steep zone after orthokeratology treatment. This system reduced the manpower, effort, and time required for treatment effect assessment and follow-up, providing a reliable detection tool for clinical research. Additionally, some studies have identified the optimal intraocular pressure monitoring module based on ML and established an accurate baseline intraocular pressure as a clinical safety reference for atropine treatment in patients with myopia.[50]

5G and 6G will support virtual reality (VR) technology, where simulated presence is generated by computer graphics, allowing users to interact with simulated elements in a seemingly realistic way.[51] Currently, the application prospects of VR and augmented reality technology in ophthalmology are still in their infancy. For myopia, VR technology can simulate outdoor environments relatively well, adjust the light intensity and spectral composition, and maintain peripheral defocus in a VR environment. Based on these principles, some have suggested that VR devices may be a possible method for controlling myopia.[52] Recently, researchers have designed a new optical system based on augmented reality that enables sustained and long-term reduction of axial length and refractive endpoints under specific myopic defocus stimuli, which is beneficial for controlling myopia progression in adults.[53] Some studies have found that the choroidal thickness of young people increased significantly after wearing the VR headset.[54] However, further research is needed to determine whether this change affects myopia progression in young people and its role in controlling myopia in children.

AI AND MONITORING DEVICES IN BEHAVIORAL INTERVENTION

Effective behavioral interventions and early detection are equally important for preventing myopia and limiting its progression. Self-monitoring devices and applications such as mobile health apps and web-based tools enable continuous remote monitoring of the disease, potentially serving as new methods for myopia prevention and control. To understand the behaviors associated with the onset and progression of myopia, a study developed the Vivior monitor (Vivior AG) using ML algorithms to investigate visual behaviors related to myopia in children aged 6–16. This wearable device can identify types of visual activity, such as viewing handheld media, desktop work, and computer work. The study found that older children spend less time on distant vision and physical activities, and more time on computers.[55] Another research institute has developed a novel wearable fitness tracker that can record the wearer's time spent outdoors and send feedback to parents and children.[56] Clouclip (Grasen Technology Co., Ltd.) is a cloud-based sensor device attached to both sides of eyeglasses, which can objectively and dynamically monitor the wearer's near vision distance, duration, and light intensity exposure levels. When the device detects myopia-related risky behaviors such as excessively close vision or sustained near vision activities, it can provide vibration alerts and significantly encourage changes in unhealthy near vision behaviors among school-aged children. These effects can persist for a period of time, making it a potential strategy for managing myopia.[17,57,58] Additionally, relying on Clouclip to assess differences in daily behaviors between myopic and non-myopic participants can explore protective factors for myopia, including longer exposure to higher light intensities and engagement in visual activities at greater distances.[57,58] Researchers have studied the effectiveness of AI-based alerts in modifying screen time practices, demonstrating that AI alerts are effective in prompting users to timely correct screen-related behaviors.[59] A recent study developed a DL-based AI system called DeepMyopia, which has been proven to be a reliable and effective AI-based decision support system for intervention guidance in children at high risk of myopia. Moreover, the intervention guidance provided by DeepMyopia can be flexibly adjusted based on individual risk profiles and clinician assessments.[40]

CHALLENGES AND FUTURE DIRECTIONS OF ARTIFICIAL INTELLIGENCE APPLICATIONS

Despite the great success achieved in the clinical application of AI in the field of myopia, challenges and obstacles still exist. In the face of challenges, clarifying future developmental directions and updating coping strategies in time are conducive to promoting the application of AI in the field of myopia prevention and control.

Challenges faced by AI

First, the quality control of datasets poses a challenge to the application of AI owing to the diversity of data obtained through various inspection methods. Recall bias in questionnaire-based data collection poses a significant challenge to both the quality and quantity of data, especially regarding environmental and lifestyle risk factors.[9] Image-based AI requires large volumes of standardized and labeled data. However, the currently available ophthalmology datasets are relatively small,[60] and some publicly available datasets used in some studies contain numerous images of poor quality.[61,62] Therefore, the acquisition of large-scale and high-quality data represents a significant challenge. Second, the reference value of the currently researched models in clinical settings is limited. Because most AI systems trained in tertiary hospitals have not undergone large-sample testing in primary health-care environments, there may be discrepancies in disease types and conditions between real-world and training populations.[63] Hence, further validation of these models is necessary before their practical clinical application. Third, AI, as a subdomain of computer science, lacks the ability to explain test results and provide an accurate basis for judgment of test results, leading to the so-called "black box phenomenon".[1,61] This may reduce the acceptance of test results by ophthalmologists and patients.[64] Fourth, with the increasing use of AI, concerns about safety and privacy have arisen.[65] Due to the potential for AI models to cause medical-legal issues,[66] there is currently a lack of legal protection and regulatory systems related to AI technology.[61,67] In case of errors, who will be responsible for the legal consequences of adverse outcomes resulting from misjudgments made by AI algorithms?[68] These issues contribute to difficulties in implementing AI in real-world clinical practice. Lastly, the lack of infrastructure and resource constraints, especially in developing and less-developed regions, affect the implementation of new technologies.[9,17] The direct and indirect costs associated with the development, implementation, and maintenance of AI-related equipment and technologies may also pose significant obstacles in less-developed regions.[69]

Future directions

Accurate identification of children at risk for myopia is crucial for myopia management, allowing the formulation of appropriate prevention strategies. Future AI research should focus not only on the improvement of myopia-related models, but also on their implementation, and finally promote the establishment of a personalized myopic management model.

First, the optimization and implementation of myopia-related models are crucial. In terms of model optimization, combining AI technology with multi-dimensional models of genetic, environmental, and socio-economic factors is a good way to improve the prediction accuracy of myopia identification. In addition, the various currently established models require further research to be validated for widespread implementation. When the models need to be refined, it is also necessary to solve the "black-box phenomenon" of AI to improve the acceptance of test results by ophthalmologists and patients. The emergence of explainable AI (XAI) technology has the potential to address the obstacle of explainability in AI.[70,71] An XAI framework for diagnosing macular diseases based on OCT images has already been studied.[72] This provides a reference for the application in the field of myopia because there is no research using XAI in the field of myopia. Secondly, the development of relevant standards or guidelines is quite essential. Therefore, it is necessary to utilize multi-ethnic genetic samples for research to advance new insights into myopia management, due to the diversity of myopia across different environments, geographies, and cultures.[9,73] The combination of AI and blockchain technology is a new development direction, which can achieve data collection and sharing across regions or platforms on the basis of maintaining data integrity.[74] Thirdly, individualized management of myopia is also a new model of myopia management. The development of AI technology and 5G networks has made telemedicine new insights for myopia management, especially in remote areas.[75] Researching the application of AI-integrated remote platforms in the prevention and control of myopia will promote personalized management models and may also help to solve eye care problems in remote and underdeveloped areas.[75,76] At last, before implementing AI, it is necessary to establish standards and norms, improve confidentiality agreements and data safety, and strengthen legal supervision. The emergence of federated learning provides new possibilities for data privacy protection and has not been applied to the field of myopia.[77] The combination of AI and blockchain technology enables international data collection and sharing across various platforms with accountability and transparency, which is expected to provide technical support for improving the relevant liability system.[74]

CONCLUSION

Our review shows that significant progress has been made in the clinical application of AI in myopia, especially in facilitating personalized management of risk assessment, treatment, behavioral intervention, and monitoring. However, attention still needs to be paid to unresolved technological challenges, such as building high-quality datasets, improving the processing capability of multimodal inputs, designing new algorithms, and exploring new application scenarios. In addition, the explainability, human-computer interaction capabilities, generalization, and robustness of AI models should be optimized, clinical standards should be established, large-scale datasets should be integrated, and evaluation frameworks should be developed to promote their widespread clinical application.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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