Is artificial intelligence a solution to the myopia pandemic?

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Artificial intelligence (AI) has been billed as a key component of the Fourth Industrial Revolution. Currently, we are witnessing the growing shift of AI from theoretical ideations to practical applications in healthcare.[1 2] Ophthalmology has emerged as one of the focal points of AI research.[3–5] Current AI platforms are highly successful in screening for diabetic retinopathy, age-related macular degeneration and glaucoma.[6–11] Other fields including cataract screening are similarly producing promising results.[12 13]

The WHO has identified that least 1 billion suffer from vision impairment that is preventable or treatable—of which myopia is a significant factor. With its growing prevalence in East Asia and many parts of the world, the 'myopia pandemic' is estimated to affect 50% (4.7 billion) of the world's population by 2050, with 10% (1 billion) having high myopia (≤ -5.00 D).[14–16] This could lead to a staggering number of myopic individuals at risk of developing blinding conditions including myopic macular degeneration (MMD) and macular neovascularisation (MNV).[17] However, AI research efforts in the field of refractive errors,[18] particularly myopia[19] are still relatively underdeveloped (table 1).

The global attention towards myopia has led to a renewed focus on prediction, prevention, prognostication, early control as well as diagnostic accuracy.[20] Early identification of high-risk individuals and unhindered access to appropriate healthcare will be critical in stemming the myopic tide. This has led to greater emphasis to develop dedicated AI models to address these unmet needs, especially for different phenotypes of myopia—childhood and adult myopia (high and pathological myopia). Relevant considerations include age, population size of each segment and measurable dataset, resource allocation, potential social burden, complication risks, access to quality myopia treatment, impact of universal health coverage,[21] stakeholder (patients, parents, clinicians and policy makers) concerns and treatment aims. Overall, the interventional aims of AI in myopia are dependent on the phenotype of myopia, comprising (1) diagnostic; (2) individualised disease prediction and prognostication; (3) individualised treatment planning; (4) rapid accessible risk-assessment platforms for national screening programmes or primary ophthalmic healthcare providers.

CHILDHOOD MYOPIA

Due to the potential irreversible disease burden during adulthood, it is imperative that childhood myopia is detected early and combined with effective therapy to retard progression. The implementation of AI platforms would require a holistic approach, in order to achieve all interventional aims as stated. Diagnostic AI models calibrated for rapid national screening programmes would aid in early identification of otherwise undetected childhood myopia. Complementing this approach would involve AI algorithms developed to predict disease progression in order to achieve precision therapy.

Recently, deep learning and computer vision technology applied to large-scale myopia screening using ocular appearance images yielded promising results.[22] In a study by Lin *et al*,[23] random forest machine learning was trained and validated with real world clinical refraction data to predict development of high myopia over a period of 10 years and by the age of 18. They achieved a high area under the receiver operating characteristic curves (AUC) in all scenarios with clinically acceptable prediction of actual refraction in future time points. This demonstrates that development of clinically viable AI prediction models for childhood myopia could be nearing maturity. Further research would still be required for interpopulation validation in order for these models to be generalised.

As AI evolves, more advanced predictive models are being developed. In childhood myopia, parental concern would be the potential progression rate and risk of developing high or even pathological myopia in their child. It is thus clinically important that high risk individuals are appropriately identified for early intervention. Current myopia preventive strategies include pharmacotherapies and various optical myopia control modalities.[24–30] Anticipating each individual's response to various modalities, either as mono or combination therapy could be a differentiating factor between treatment success and failure. Therefore, the development of AI treatment models could possibly bridge this gap and optimise patient outcomes. Possible models could use serial refraction data, axial length changes as well as optical coherence tomography (OCT) choroidal thickness or vascularity changes to derive treatment protocols.[31] Currently, there are no published models for treatment individualisation in myopia. However, future improvements of predictive AI models coupled with prospective data collation could potentially lay the foundations of individualised treatment models.

ADULT MYOPIA

The structural composition of myopia presents a life-long susceptibility to complications such as retinal detachment and glaucoma. These concerns are particularly pressing in myopic adults. The indications of AI-based management in this population would need to be narrowed down to (1) diagnostic challenges; (2) population screening for pathological myopia; (3) predictive prognostication for sight threatening complications.

Myopic diagnostic challenges in adulthood include accurate assessment of glaucomatous damage in highly tilted myopic disc.[32 33] Generalisable AI models would hence be a valuable tool to discern suspicious discs for the concerned glaucomatologist. Separately, the scalability of AI models can potentially enable large-scale automated rapid screening modalities, particularly in countries with high prevalence of the disease.

Current developments involve convoluted neural network (CNN) models developed to identify vision-threatening conditions in highly myopic adults using OCT macular images for retinoschisis, macular hole, retinal detachment and MNV,[34] with good sensitivities and AUC.[35]

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Table 1 Summary of current Artificial Intelligence research in myopia

Title (year)	Population (age group)	Modalities	AI model	Aims	Use	Findings
Deep learning for predicting refractive error from retinal fundus images (2018)[18]	General population (adults)	Fundal imaging	DL—CNN	Refractive error prediction	Diagnostic/ detection	Mean absolute error (MAE) of 0.56–0.91 D
Prediction of myopia development among Chinese school-aged children using refraction data from electronic medical records: a retrospective, multicentre machine learning study (2018)[23]	General population (children)	Age, SE, annual progression rate	ML—random forest, mixed model, generalised estimating equation	High myopia over 10 years and by age 18	Prediction	High myopia over up to 10 years AUC: 3 years 0.874–0.976 5 years0.847–0.921 8 years 0.802–0.886 High myopia by 18 years old AUC: 3 years 0.940–0.985 5 years 0.856–0.901 8 years 0.801–0.837
A deep learning system for identifying lattice degeneration and retinal breaks using ultra-widefield fundus images (2019)[43]	General population (adolescent to adults)	Ultrawide fundal images	DL—CNN	Notable peripheral retinal lesions (lattice or breaks)	Diagnostic/ detection	AUC 0.999 Sensitivity 98.7% Specificity 99.2%
A machine learning-based algorithm used to estimate the physiological elongation of ocular axial length in myopic children (2020)[44]	0 to −8D myopia (children)	Demographics, SE, K, WTW, CCT	ML—linear regression vs SVM vs Bagged Trees	AL elongation prediction	Prediction	Best model: robust linear regression R^2 0.87, 0.003 to 0.116 mm/year
Accuracy of a deep convolutional neural network in the detection of myopic macular diseases using swept-source optical coherence tomography (2020)[45]	Myopia vs high myopia (adults)	Swept source-OCT (SS-OCT)	DL—CNN	Detection of myopic macular diseases (schisis, MNV)	Diagnostic/ detection	Detection of macular lesions: AUC 0.970 Sensitivity 90.6% Specificity 94.2% Accuracy of high myopia vs MNV vs schisis: 96.5% vs 77.9% vs 67.6%
Automatic identification of myopia based on ocular appearance images using deep learning (2020)[22]	All myopia (children)	Facial/ocular photos	DL—CNN	Myopia detection	Diagnostic/ detection	AUC 0.9270 Sensitivity 81.13% Specificity 86.42%
Development and validation of a deep learning system to screen vision-threatening conditions in high myopia using optical coherence tomography images (2020)[35]	High myopia (adults)	OCT	DL—CNN	Screening of vision-threatening conditions (schisis, macular hole, retinal detachment, MNV)	Diagnostic/ detection	AUC 0.961–0.999 Sensitivity and specificity >90%
Pathological myopia classification with simultaneous lesion segmentation using deep learning (2020)[36]	PALM dataset	Fundal images	DL—CNN	Detection of pathological myopia, foveal localisation, segmentation of retinal atrophy or retinal detachment	Diagnostic/ detection	Pathological myopia AUC 0.9867 Foveal localisation 58.27 pixels
Prediction of Myopia in adolescents through machine learning methods (2020)[46]	General population (children)	Family history, gender, indoor and outdoor activities, axial length, keratometry	ML—SVM	Myopia prediction at 6th grade	Prediction	AUC 0.98 Accuracy 93% Sensitivity 94% Specificity 94%
Using artificial intelligence and novel polynomials to predict subjective refraction (2020)[47]	General population (adults)	Wavefront aberrometry, LD/ HD polynomial	ML—XGBoost	Subjective refraction prediction	Diagnostic	Mean absolute error of power vectors between 0.094 and 0.301 D

AUC, area under receiver operating characteristic curve; CCT, central corneal thickness; CNN, convoluted neural network; DL, deep learning; K, keratometry; LD/HD, low degree/ high degree; MNV, myopic neovascularisation; OCT, optical coherence tomography; SE, spherical equivalent; WTW, white to white.

CNN models have also been developed to detect pathological myopia and semantic segmentation of myopia-induced lesions.[36] AI researches targeting the optic nerve head have also yielded encouraging results. The combination of disc photos with structural and functional inputs, such as automated perimetry and OCT, have achieved excellent results in identifying early glaucomatous injury.[37 38]

It is still possible that the diagnostic performance of AI in myopia will reach clinical acceptance in the future. However, the main barriers such as complicated disease-phenotype identification, unsatisfactory image acquisition as well as network and logistical difficulties in low-income and middle-income countries could impede final clinical implementation.

Unlike childhood myopia, predictive and prognosticative value of AI for adult myopic patients presents a different conundrum. Questions abound such as whether predictive prognostication by AI for post-surgical outcomes in patients who suffered complications such as foveoschisis is achievable. In addition, it is unknown whether AI can be harnessed to predict the trajectory of visual deterioration in the presence of sight-threatening complications as well. These pertinent doubts arise due to the lack of effective treatment in conditions such as MMD, relatively good overall prognosis for conditions like MNV[39] and rarity of surgical treatment for foveoschisis. Hence, technical deficiencies and questionable use-case in the face of constraint resources could limit the use of AI predictive models in adults.

CHALLENGES AND FUTURE DIRECTIONS

The application of AI into clinical practice for myopia face several challenges. First, it has been recognised that a successful myopia prevention programme requires a coordinated effort between all stakeholders, including governments, schools, parents or care-givers, primary eye care practitioners and ophthalmologists.[40] Thus, a successful AI programme that could benefit myopia prevention in children, would require the agreement and close collaboration among these key players. Second, in order for the benefits of AI to be easily accessible, it would require sustainable and cost-effective implementation into clinical practice.[41] The AI algorithms needs to undergo accurate training and validation across multi-ethnic datasets.[42] Furthermore, the inherent difficulty in image-capturing for highly myopic eyes needs to be overcome for efficient uninterrupted clinical implementation. Third, the implementation of AI solution in myopia needs to impact the change in clinical practice. It is important to ensure the consistency of AI algorithm performance in the clinical setting with generalisability across multi-ethnicity, particularly in heterogenous populations.

In conclusion, myopia is a growing pandemic that requires prompt attention. There is a need to transform clinical practice and healthcare policies to support the implementation of individualised treatment in myopia management. It is still an open debate about the role and impact AI will have in the field of myopia. Critical technical and clinical challenges have to be surmounted prior to the mass adoption of AI healthcare in myopia.

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