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School-level prediction and management of myopia in children and adolescents

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Abstract

Background Previous Artificial Intelligence (AI) models are mainly based on hospital data to predict myopia progression in myopic children. However, school-level AI models for predicting myopia onset in non-myopic children are lacking. There is a need for more precise and comprehensive tools for full myopia management, from the onset of myopia to its progression.

Methods This study was conducted in 870 centers dispersed across seven cities in China from September 2019 to December 2021, with participants observed for two years. Machine learning models were trained and internally validated on datasets from Shenzhen, and then externally tested from the other six cities. Of 1,123,602 children and adolescents aged 4–18 years old, 1,105,271 individuals were confirmed eligible. After two-year follow-up, 915,991 individuals were included in analysis. Data were analyzed from June 2022 to July 2023. Main outcomes and measures are the occurrence of myopia, and the change of spherical equivalent refraction in 2 years.

Results Of 915,991 participants, 405,784 (44.3%) were identified as myopic at baseline. In two years, the occurrence of myopia was 45.5% and the overall myopic shift was − 0.97 ± 1.32D. The optimal machine learning models were established for predicting myopia occurrence in non-myopic individuals; and predicting progression of any amount (defined as an annual progression of < − 0.25D) in myopic individuals. The performance in predicting occurrence (AUC 0.962, 95% CI 0.956–0.968) and progression (AUC 0.923, 95% CI 0.912–0.934) were acceptable in the external test set. The interactions between age and other variables were revealed by the algorithms, and hence the final prediction models were established based on age segmentation. In the external test set, the performance of the models for both 4–11-years (occurrence prediction: AUC 0.978, 95% CI 0.972–0.984; progression prediction: AUC 0.957, 95% CI 0.951–0.963) and 11–18-years age groups (occurrence prediction: AUC 0.966, 95% CI 0.960–0.972; progression prediction: AUC 0.928, 95% CI 0.917–0.939) were improved. Finally, user-friendly software was developed, which makes this model accessible for school use.

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Conclusions The algorithm developed in the current study for predicting myopia occurrence and progression showed excellent performance in school settings using real-world data, indicating its potential application in school-level myopia management.

Trial registration chictr.org Identifier: ChiCTR2200057391.

Keywords Myopia, Children, Prediction model, Machine learning

Introduction

Myopia is a global widespread visual issue that commands broad concern [1, 2]. The management of myopia assumes paramount importance [3]. Researchers believed that the management of myopia should be as early as possible and therefore have established a series of means for early myopia intervention, achieving key progress [4–9].

Despite the significant benefits of early preventive intervention for myopia in children, this approach may not be necessary for all non-myopic children, as not everyone will eventually develop myopia [10]. Considering the potential adverse events of interventions and cost, it is unwise to take measures on all children indiscriminately [11, 12]; yet, if intervention is delayed, the effectiveness will be greatly reduced [9]. Some researchers have realized this paradox and established prediction models to identify which children will develop myopia or experience rapid myopia progression in the future [13–16]. The Wenzhou Medical University Essilor Progression and Onset of Myopia (WEPrOM) study proposed a prediction model for the onset of myopia, based on a combination of age, gender, parental myopia, refraction, axial length (AL), accommodative parameters, near work, and outdoor time, achieving a moderate performance with an AUC of 0.74 [17]. On the other hand, the Northern Ireland Childhood Errors of Refraction (NICER) study introduced the Predicting Myopia Onset and progression (PreMO) risk assessment model, which utilized age, parental history of myopia, cycloplegic refraction, and AL to predict future myopia onset and progression [18, 19]. Notably, recently, based on the Collaborative Longitudinal Evaluation of Ethnicity and Refractive Error (CLEERE) study, Mutti et al. established a model using cycloplegic refraction, astigmatism, age, sex, and race, achieving exceptional results with an AUC of 0.96 for predicting the onset of myopia in children aged 7–8 within one year [20]. In addition, based on the CLEERE study, the prior change was identified as having limited significance for predicting subsequent myopia progression, providing important guidance for in-depth research on myopia prediction models [21].

Artificial intelligence (AI) is an important tool for predicting various clinical outcomes of diseases and has gradually gained the attention of scholars. Lin et al. proposed an AI model to predict myopia progression from hospital-level data, achieving relatively superior performance compared to traditional models mentioned above [16]. However, data relying solely on hospital may pose challenges for forecasting myopia occurrence, as non-myopic individuals are rarely present in hospital settings for eye examinations. Afterward, some studies have used AI algorithms to predict occurrence based on school-based data [15, 22]. Despite the valuable insights, these studies included a relatively small population, suggesting that there may still be room for optimization of AI algorithms.

School is a place where students regularly attend, making it a potential setting for early detection and monitoring of myopia occurrence and progression [23]. If myopia can be regularly managed within school settings rather than hospitals, it represents an upstream containment measure [8, 9]. The escalating prevalence of myopia in China has prompted government attention, leading to financial support for myopia screening in local schools, which provides the basic conditions for school-level management [24]. Our preliminary investigations have yielded a predictive model specifically for high myopia, yet a more encompassing model that fully addresses the occurrence and progression of myopia is still absent [24].

To address this challenge, this study collected longitudinal data spanning 2 years from 870 centers dispersed across seven cities, covering 1,123,602 children and adolescents spanning a broad age range of 4–18 years. To create a comprehensive school-based myopia management strategy, this research bifurcated the cohort into non-myopic and myopic individuals, with the prediction for occurrence in non-myopic and the progression in myopic. In addition to external testing with data collected from other cities, it was also externally tested in a school-based randomized controlled trial (RCT) [5, 6]. By establishing and validating this prediction model based on large-scale and multi-center datasets, schools are expected to be activated and take a pivotal role in myopia management, providing possibilities for early management of myopia.

Materials and methods

Study design and participants

The current school-based, observational cohort study involved 1,123,602 Chinese children and adolescents from 870 centers located in seven cities (Fig. 1). The specific locations of the center were recorded in Additional file 1. The majority of schools (n = 841) in Shenzhen have participated, with the exception of a small number of private schools and vocational schools. In the other six cities, 29 schools were selected based on cluster sampling technique to serve as the validation set. The recruitment began in September 2019 and completed in December 2019. After the assessment, 1,105,271 individuals were included. After a two-year follow-up which concluded in December 2021, 915,991 individuals were included in the analysis (Fig. 1). Data collated from these annual evaluations is contemporaneously uploaded to a cloud-based repository. All students have a unique ID number to ensure the continuity of data during the transfer or advancement process. The study protocol can be found in Additional file 1.

The current observational cohort study was conducted in compliance with the ethical standards outlined in the Declaration of Helsinki. Approval for the study was granted by the Institutional Review Board (IRB) or Ethics Committee of Sun Yat-sen University, located in Guangzhou, China (2021KYPJ185). Additionally, the study was registered with the Chinese Clinical Trial Registry (ChiCTR; identifier: ChiCTR2200057391). Before the commencement of the study, a seminar was organized at the participating schools to elucidate the objectives and procedures of the research to the legal guardians of the children involved. Following a thorough briefing, written informed consent was obtained, ensuring their understanding and agreement.

Model development and internal validation

All records were deidentified before data analysis. A large-scale dataset (n = 897,902) collected from 841 centers in Shenzhen was used as the training set to develop the model (Fig. 1A). For personalized myopia management, separate predictive models for non-myopic and myopic individuals were established, forecasting occurrence in the former and progression in the latter (Fig. 1B). The inputs were age, refraction, grade, sex, and vision. The ten-fold cross-validation technique was utilized for internal validation [25].

To select the model with the best performance, seven venerable machine learning algorithms were executed and compared, including Random Forest (RF), Support Vector Machines (SVM), eXtreme Gradient Boosting (XGB), CatBoost (CB), Gradient Boosting Decision Tree (GBDT), Light Gradient Boosting Machine (LGBM), and k-Nearest Neighbor (KNN) [26–28]. After this selection, oversampling techniques, including Adaptive Synthetic Sampling (ADASYN), Synthetic Minority Over-sampling

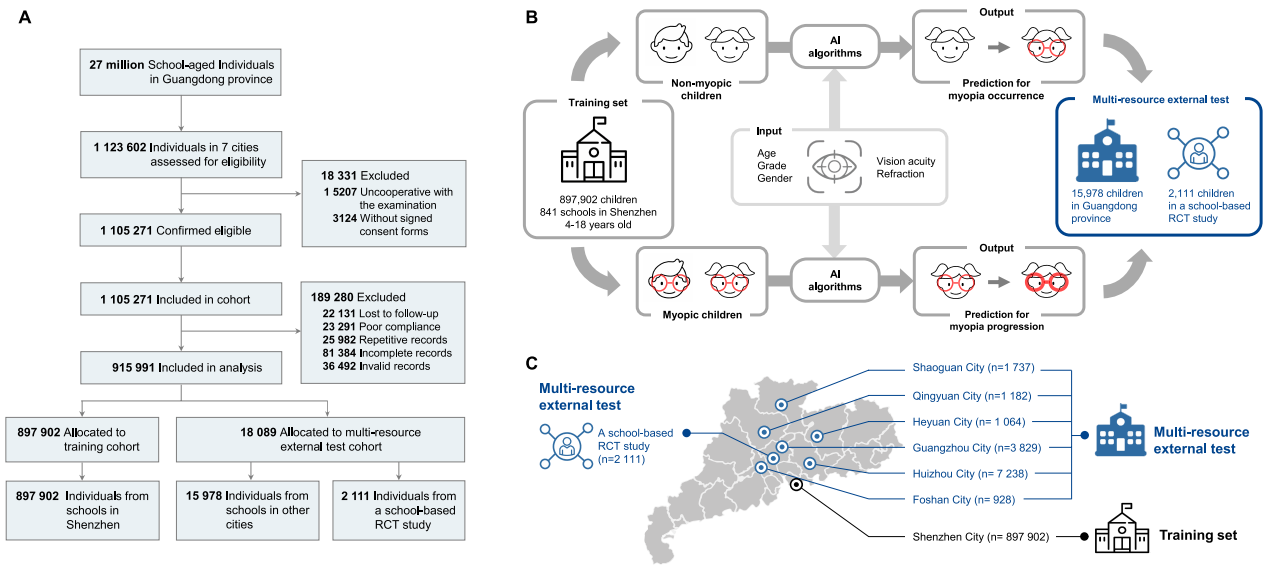


Fig. 1 Study design and data sources. Flow diagram of participants according to STROBE Statement (**A**). Design of the prediction model including the categorization of myopic and non-myopic children and adolescents' groups and the input variables (**B**). Geographical distribution of the real-world settings used in the model training and testing (**C**). *RF* random forest, *SVM* support vector machines, *XGB* eXtreme gradient boosting, *CB* CatBoost, *GBDT* gradient boosting decision tree, *LGBM* light gradient boosting machine, *KNN* k-nearest neighbor, *RCT* randomized controlled trial

Technique (SMOTE), and Random Over Sampling (ROS), were employed to further enhance model performance [29–31]. The technical details were provided in Additional file 1.

Multi-resource external test

To assess the model's applicability in real-world scenarios, the external test was conducted using school screening datasets from 29 real-world school settings (Fig. 1C). These settings, which featured no duplication with the training set locales, spanned across seven cities, including Guangzhou, Huizhou, Foshan, Heyuan, Qingyuan, and Shaoguan, where the model would be applied (Additional file 2: Table S1). The multi-resource external test also included a dataset derived from a school-based RCT [5, 6]. Owing to reduced input variable demands, a marginally larger sample size than published RCT from this dataset was incorporated (n = 2111) [5, 6].

Algorithm performance evaluation

Model efficacy was appraised using a suite of metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC). Precision is defined as the proportion of true positive predictions out of all positive predictions made, reflecting the reliability of positive class predictions. Conversely, recall quantifies the proportion of true positive predictions out of all actual positive cases, gauging the model's capacity to identify all relevant instances [24, 25]. The model that exhibited superior performance in the validation phase was earmarked for extended examination.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}},$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$

In this context, a true positive (TP) denotes the instances accurately identified as positive, whereas a false positive (FP) signifies instances erroneously labelled as positive when they are, in fact, negative. A false negative (FN) represents instances mistakenly classified as negative when they are positive in reality. Precision is the proportion of positive predictions that are actually correct, while recall is the proportion of actual positives that are correctly identified. The F1 score is the harmonic mean of precision and recall. An F1 score closer to 1 indicates a balanced and high precision and recall, with a good performance in predicting positive instances. Conversely, a low F1 score suggests the model may be imbalanced in its precision or recall. The Shapley Additive exPlanations (SHAP) methodology was used to evaluate the importance of features [32, 33]; details were provided in Additional file 1. The SHAP values were then graphically represented to demonstrate the interactive effects between input variables.

Measurements

Uncorrected Distance Visual Acuity (UDVA) was measured using a standardized Chinese logarithmic visual acuity (VA) chart (GB11533-2011) situated within an illuminated cabinet (WSVC-100; Qingda Vision Co., Wenzhou, China). The resulting LogMAR VA scores were documented. The autorefractor (SW-800; Suoer Co., Tianjin, China) was employed to evaluate the refraction. The technical details were provided in Additional file 1.

Definitions

Refraction was determined as the spherical equivalent refraction (SER), which was calculated by adding the spherical diopters to half the cylindrical diopters from autorefractor data [34]. Myopia is defined as an SER of − 0.50 diopters (D) or more [34]. Myopia progression is defined as an annual SER progression < − 0.25D [35–37]. Hence, in this study, "myopia occurrence" is defined as non-myopic individuals developing myopia at any follow-up point within 2 years (either in the first or second year). Meanwhile, "myopia progression" is defined as myopic individuals having a progression of more than − 0.25D per year over the 2-year period (i.e., a total progression of more than − 0.5D).

Considering the real-world, large participant base and the associated adverse events with cycloplegia in Asian populations, cycloplegic autorefraction was calculated using a validated formula rather than directly collected [38, 39]. The formula used to calculate cycloplegic refraction was developed and demonstrated strong accuracy, within the demographic of children aged 4 to 15 years in the Shanghai region ($R^2 > 0.90$) [40, 41]. Subsequently, this formula was also applied in another epidemiological survey on myopia [42]. Calculated SER was used as the input for the model, and it was also employed for the outcome, i.e., in the definition of myopia mentioned above.

$$Y = 0.831 + \left(0.954 \times \textit{refraction}\right) + \left(-0.065 \times \textit{age}\right) + (0.539 \times \textit{UCVA}).$$

Statistical analysis

Owing to the pronounced interocular correlation observed within individuals ($R^2 > 0.98$), analysis was confined to data derived exclusively from the right eye. The distribution of participant characteristics was quantitatively summarized using means and standard deviations (SD) or medians and interquartile ranges (IQR) for the continuous variables and by frequencies and percentages for the categorical variables. We evaluated baseline disparities among the different cohorts through analysis of variance (ANOVA) for the continuous variables and the Chi-squared test for the categorical data. All hypotheses tested were two-sided, and p-values less than 0.05 were considered statistically significant. The computational analysis was conducted employing R and Python 3.8 [43, 44].

Result

After the assessments, a total of 2,747,973 valid records of 915,991 participants were included in the current analysis (Fig. 1A). The demographic information and a comparison between individuals with myopia and non-myopia were presented (Additional file 2: Table S2). Among the 915,991 participants aged 4–18 years old, 405,784 (44.3%) were identified as myopic at baseline. The subsequent myopic shift was -0.97 ± 1.32D. Myopic individuals showed a slightly greater myopic shift than non-myopic, both at 1-year visit (− 0.72 ± 0.91D vs. − 0.65 ± 0.93D) and two-year visit (− 0.99 ± 1.38D vs. − 0.96 ± 1.28D) (all $P < 0.001$; Additional file 2: Table S2). To establish and validate machine learning algorithms, these data were divided according to their origin into a training set (n = 897,902) from Shenzhen and a multi-source external

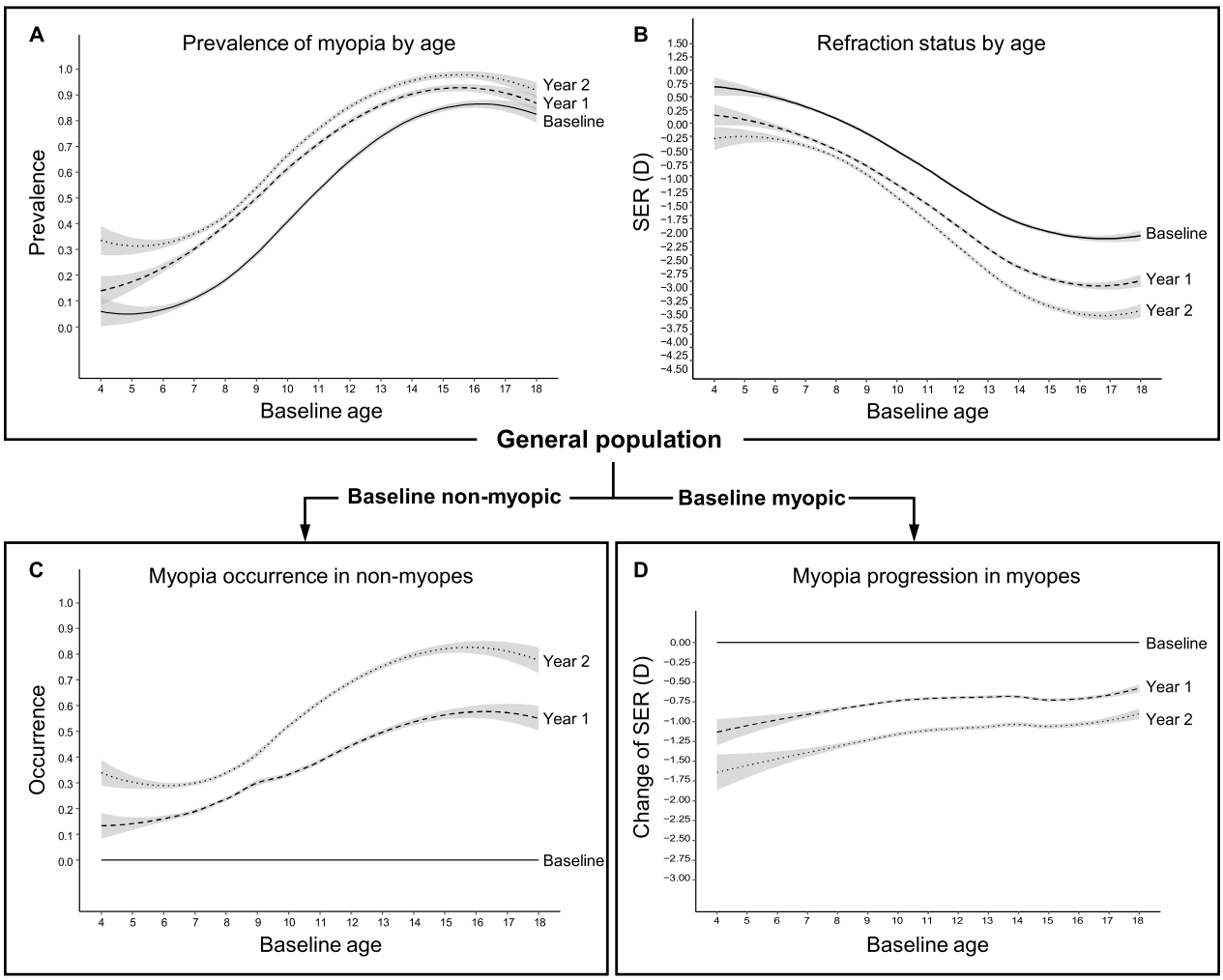


Fig. 2 Prevalence, severity, and subsequent progression of myopia in the overall dataset. The distribution of myopia prevalence (**A**) and refraction (**B**) across different age stages in baseline, 1-year, and 2-year follow-up. The distribution of myopia occurrence in non-myopic individuals (**C**) and the distribution of myopia progression in myopic individuals (**D**) across different age stages. Abbreviation: SER = spherical equivalent refraction

test set (n = 18,089) from other cities. The characteristics of the training and validation sets are summarized (Additional file 2: Table S3).

Pattern of myopia occurrence and progression across 2 years in children and adolescents aged 4–18 years

Figure 2A depicted the distribution of myopia prevalence by age over the first and second years. The overall distribution of refraction also presented this distribution (Fig. 2B). Then the general population was divided into baseline non-myopic and myopic cohorts. Figure 2C showed the pattern of myopia occurrence in initially non-myopic individuals. Figure 2D showed the pattern of myopia progression in initially myopic individuals, which also demonstrated an age-dependent tendency.

Establishment and optimization of machine learning algorithms for predicting myopia occurrence and progression

The performance of seven machine learning algorithms was evaluated and compared across multiple dimensions (Additional file 2: Table S4 and S5). As visualized in the ROC curves, for predicting myopia occurrence in non-myopic individuals, the RF algorithm demonstrated the best performance, in both internal validation and external testing results; for predicting myopia progression in myopic individuals, the XGB algorithm showed the optimal performance (Additional file 2: Fig. S1). Compared to the conventional logistic regression model, all seven machine learning algorithms shown significant improvement (Additional file 2: Table S4 and S5).

To further optimize the models, three oversampling techniques were employed and compared. For predicting myopia occurrence, the SMOTE method was most effective at improving model performance (AUC 0.962, 95% CI 0.957–0.967; Fig. 3A); for predicting progression, ADASYN showed the best improvement (AUC 0.923,

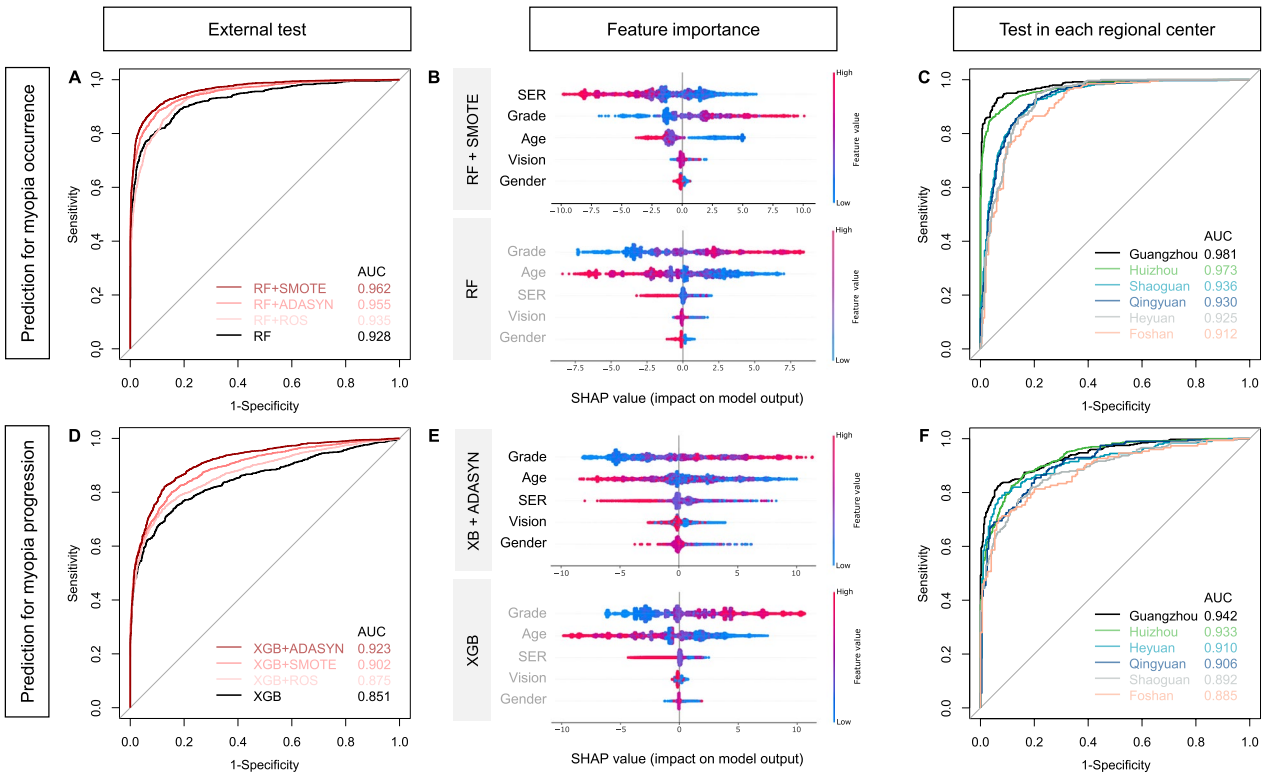


Fig. 3 Optimization of prediction models using oversampling techniques. The performance of prediction models before and after the optimization using oversampling techniques for predicting the myopia occurrence in non-myopic individuals (**A**), and the myopia progression in myopic individuals (**D**). Feature importance in models demonstrated by SHAP value before and after the optimization for predicting the myopia occurrence (**B**) and progression (**E**). The performance of final models with optimization in each region centers for predicting the myopia occurrence (**C**) and progression (**F**). *RF* Random Forest, *XGB* eXtreme Gradient Boosting, *ADASYN* adaptive synthetic sampling, *SMOTE* Synthetic Minority Over-sampling Technique, *ROS* Random Over Sampling, *SER* spherical equivalent refraction, *AUC* area under the receiver operating characteristic curve, *SHAP* shapley additive explanations

95% CI 0.913–0.933; Fig. 3D). Hence, the final models were confirmed, and their feature importance was also calculated via SHAP values and visualized for both the occurrence (Fig. 3B) and progression (Fig. 3E). Based on these two final models, the validation results from each center in the external test set were evaluated (Additional file 2: Table S6) and visualized separately for the occurrence (Fig. 3C) and progression (Fig. 3F).

Associations among features in the myopia occurrence and progression model

The relationships between features were examined based on the SHAP value. For the model predicting myopia occurrence, the interactions between grade, age, and SER were found to hold significant importance (Additional file 2: Fig. S2A–C). Scatter plots visualized a noticeable change of distribution around the age of 11 (Additional file 2: Fig. S2D–F). Similarly, the interactions were also significant (Additional file 2: Fig. S2H–J) in the progression prediction model. A significant change is also found in the grade and SER around the age of 11(Additional file 2: Fig. S2K–M). A three-dimensional distribution diagram illustrated the direct effects of different ages and grades on occurrence (eFig. 2G) and progression (Additional file 2: Fig. S2N). These findings presented that when students were in a grade higher than their age, there existed a heightened risk of both the occurrence and progression of myopia. Through individual case analysis, this connection was confirmed (Additional file 2: Fig. S3).

Hence, to mitigate this age-related interaction on the prediction model, the dataset was split into two groups: individuals aged 4–11 years and those aged 11–18 years. Comparative analysis revealed a substantial reduction in interaction effects following age segmentation (Additional file 2: Table S7 and S8), indicating the necessity of the age segment.

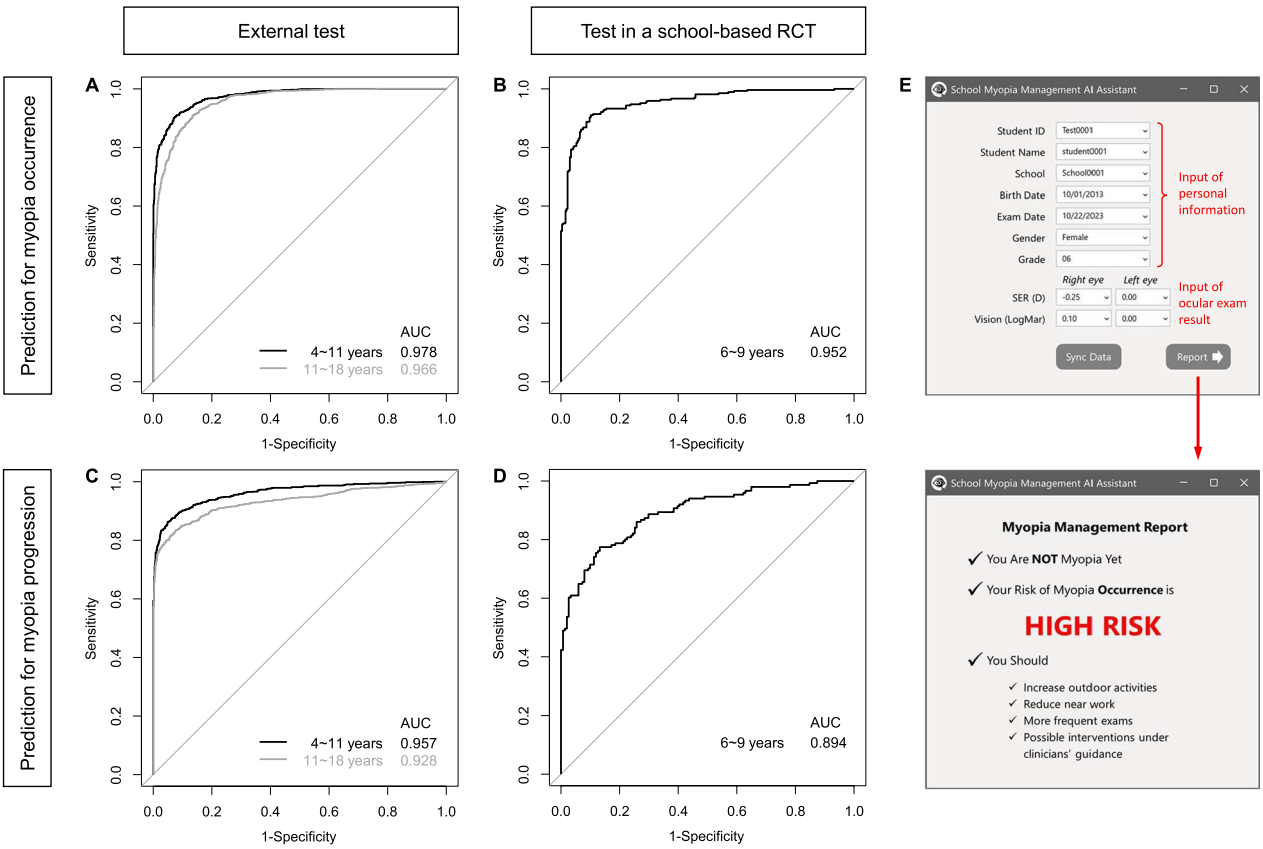


Fig. 4 Performance of age-specific myopia occurrence and progression prediction models and development of user-friendly software. The performance of the prediction model after age segment for predicting the myopia occurrence in non-myopic individuals (**A**) and myopia progression in myopic individuals (**H**) in the overall external test. The performance of the prediction model after age segment for predicting the myopia occurrence in non-myopic individuals (**B**) and myopia progression in myopic individuals (**D**) in an RCT. A user-friendly software interface, comprising an input interface for entering personal information and ocular examination results, as well as a report interface providing prompt notifications for low or high risk of myopia (**E**). *AUC* area under the receiver operating characteristic curve, *RCT* randomized controlled trial

Establishment of age-specific myopia occurrence and progression prediction models and development of software

After the age segmentation, initial internal validation results indicated an enhancement in performance. This improvement was observed in the 4–11 years group (occurrence prediction: AUC 0.991, 95% CI 0.989–0.993; progression prediction: AUC 0.984, 95% CI 0.980–0.988) as well as the 11–18 years group (occurrence prediction: AUC 0.949, 95% CI 0.941–0.957; progression prediction: AUC 0.927, 95% CI 0.915–0.939) (Additional file 2: Table S9).

Then, the age-specific prediction models for myopia occurrence and progression were subsequently evaluated using the external test set. As illustrated in Fig. 4, after segmentation by age, the performance of the models for both 4–11-years (occurrence prediction: AUC 0.978, 95% CI 0.972–0.984; progression prediction: AUC 0.957, 95% CI 0.951–0.963) and 11–18-years age groups (occurrence prediction: AUC 0.966, 95% CI 0.960–0.972; progression prediction: AUC 0.928, 95% CI 0.917–0.939) showed improvement compared to the models without age segmentation (occurrence prediction: AUC 0.962, 95% CI 0.957–0.967; progression prediction: AUC 0.923, 95% CI 0.913–0.933) (Fig. 4A, C).

A school-based RCT was also used for the test set, where cycloplegic refraction was employed, and SER examinations were performed using more precise equipment (KR-8800; Topcon). External tests in this school-based RCT also achieved an acceptable performance (occurrence prediction: AUC 0.952, 95% CI 0.940–0.964; progression prediction: AUC 0.894, 95% CI 0.878–0.910) (Fig. 4B, D). Additionally, after age segmentation, the performance was enhanced at various sub-centers (Table 1).

Finally, to maximize the potential of these algorithms for myopia management, user-friendly software was developed (Fig. 4E). Upon launching the software, school staff can input information under clear guidance. By clicking the "Sync Data" button, the software automatically stores the necessary data; by clicking the "Report" button, a corresponding report is generated to guide the next steps in myopia prevention and control, thereby facilitating myopia management at the school level. The software is currently in use at all participating schools. Due to the dataset embedded in the software being regulated by the Institutional Review Board (IRB), it cannot be made publicly available online. However, the source code has been shared on GitHub (https://github.com/Shengsong-Xu/Shenzhen-Myopia-prediction-model) and Gitee (https://gitee.com/Shengsong-Xu/Shenzhen-Myopia-prediction-model).

Table 1 Performance of the individualized models (according to age) in external test across regional centers

	Prediction for myopia occurrence					Prediction for myopia progression				
	AUC	Accuracy	Precision	Recall	F_1-score	AUC	Accuracy	Precision	Recall	F_1-score
Guangzhou										
4–11 years old	0.985	0.939	0.942	0.975	0.958	0.976	0.934	0.919	0.947	0.933
11–18 years old	0.983	0.967	0.955	0.938	0.947	0.958	0.946	0.909	0.931	0.920
Huizhou										
4–11 years old	0.981	0.957	0.956	0.949	0.952	0.960	0.936	0.935	0.911	0.923
11–18 years old	0.974	0.926	0.937	0.913	0.925	0.957	0.924	0.911	0.939	0.925
Foshan										
9–11 years old	0.905	0.877	0.892	0.862	0.877	0.889	0.865	0.848	0.865	0.857
11–16 years old	0.932	0.915	0.872	0.910	0.891	0.897	0.875	0.821	0.882	0.850
Heyuan										
5–11 years old	0.957	0.914	0.941	0.911	0.926	0.938	0.926	0.919	0.891	0.904
11–13 years old	0.912	0.890	0.888	0.886	0.887	0.917	0.877	0.848	0.887	0.867
Qingyuan										
4–11 years old	0.951	0.927	0.904	0.910	0.907	0.934	0.893	0.901	0.863	0.882
11–14 years old	0.938	0.913	0.903	0.881	0.892	0.915	0.878	0.932	0.896	0.914
Shaoguan										
5–11 years old	0.963	0.931	0.924	0.938	0.931	0.944	0.897	0.923	0.894	0.909
11–13 years old	0.939	0.920	0.918	0.906	0.912	0.917	0.874	0.854	0.895	0.874
School-based RCT										
6–9 years old	0.952	0.903	0.874	0.927	0.900	0.894	0.879	0.840	0.876	0.857

AUC area under the receiver operating characteristic curve

Discussion

A prediction model forecasting myopia at the school level can provide early warnings of myopia, which is crucial for myopia management. The current study gathered two-year large-scale longitudinal data from 870 centers in seven cities, encompassing over a million children and adolescents aged 4–18. Within the final comprehensive school-based myopia management model, personalized prediction models for non-myopic and myopic groups were conducted, tailored to the distinct developmental stages of myopia, and further refined by age segmentation for more precise and individualized predictions.

In this study, we initially outlined the pattern of myopia onset and progression, revealing the profound impact of age on the occurrence and progression of myopia (Fig. 2). This pattern aligned with recent research from mainland China, which exhibited a similar age-dependent distribution of myopia [45, 46]. Interestingly, the myopia progression was similar between baseline non-myopic and myopic individuals (1-year visit: − 0.72 ± 0.91D vs. − 0.65 ± 0.93D; 2-year visit: − 0.99 ± 1.38D vs. − 0.96 ± 1.28D). This is contrary to general expectations, suggesting that most of the baseline non-myopic individuals in this study were already in the pre-myopia stage, during which myopia progression would significantly accelerate [47]. However, merely summarizing the overall distribution of myopia was quite limited for individual prediction. To realize individualized prediction, seven sophisticated machine learning algorithms and three oversampling techniques were utilized to construct and enhance the optimal prediction model. In the final model, the combination of RF + SMOTE was considered the best for predicting the occurrence of myopia, while the combination of XGB + ADASYN was found to be the most effective for predicting the progression (Fig. 3). For the prediction of progression, it should be noted that this study employed a cut-off value of − 0.25D per year, which yields a relatively high proportion of positive outcomes [35–37]. Should the cut-off be raised to − 0.5D or − 0.75D, a reduction in the proportion of positive results is anticipated, concomitant with a decline in the performance of the model. Furthermore, attempting to predict the specific values of myopic progression will result in even poorer performance. The final models demonstrated that the most suitable AI algorithms for predicting the occurrence and progression are different. This may be related to the inherent characteristics of the algorithms. The RF algorithm is an ensemble learning algorithm based on decision trees, adept at constructing multiple decision trees to analyze the relationships between features and to output results stably, which may confer an advantage in predicting whether myopia will occur or not [28]. On the other hand, XGB excels at focusing on a limited number of features and iteratively optimizing the best model; it is better at capturing subtle changes, which may give it an advantage in predicting the progression [28]. However, the deeper reasons require further development and explanation by the computer science community. In addition to the disparities in algorithmic efficacy, variations are also observed across different test sets. These differences may be ascribed to the demographic distinctions between these sets. Guangzhou, with its economic development and policy formulation closely resembling that of Shenzhen (training cohort), achieved the most favorable validation results. Qingyuan and Heyuan, being more isolated regions, exhibited substantial disparities from Shenzhen, leading to slightly poorer validation outcomes. Notably, the validation results within the school-based RCT were relatively poor, potentially attributable to differences in SER measurements. This school-based RCT specifically employed cycloplegic refraction, leveraging more precise equipment (KR-8800; Topcon) [5, 6]. This observation suggested that the predictive model of this study may encounter limitations when applied to cycloplegic data. It is important to note that this does not imply that non-cycloplegic data should be intentionally prioritized over cycloplegic data, as cycloplegic refraction is generally considered to have a higher degree of validity. However, since the model of this study was built using non-cycloplegic data, it is naturally more suited to these data types, especially in scenarios where cycloplegic data may not be accessible.

Previous research on AI for myopia prediction has achieved advancements. Lin et al. constructed an AI model predicting myopia progression based on hospital-level data, along with successful external validation [16]. This focus, however, primarily on individuals already diagnosed with myopia in hospital settings, who are seeking treatment due to vision impairment caused by myopia [16]. It's evident that schools, not hospitals, serve as more suitable venues for observing and predicting the myopia. Research on AI models for myopia prediction at the school level is relatively scarce and limited in scope with a narrow age range [15, 22]. A recent investigation has led to the development of a school-based model for predicting the onset of myopia (AUC 0.891) with no external test [15]. Based on a multi-source external test, our machine learning models developed promising outcomes (Fig. 3). To delve deeper into the feature importance and their interplay within the prediction models, we visualized the interaction effects based on SHAP value (Additional file 1: Fig. S2). Notably, significant interactions between age and other variables were identified, which suggested that 11 years might represent a significant threshold. These age-related interactions suggested that the effects of other variables, including SER

and grade, may vary across different ages, and therefore it may be necessary to establish separate models for different age stages.

In the realm of myopia studies, the age of 11 has been consistently highlighted as a pivotal point, as affirmed in numerous preceding studies [41, 48–51]. Recent research, incorporating a wide age range of children and examining their long-term changes of myopia progression, similarly found considerable variances before and after the age of 11 [48]. Moreover, studies concerning myopia intervention have indicated that the difference before and after the ages of 10–11, given the distinct sensitivity to various interventions across these age brackets [49–51]. Incorporating the algorithmic discoveries of our study and the insights from previous studies, we ultimately developed age-segmented model for prediciton. Across the multi-source external test set, the prediction models for the age groups 4–11 and 11–18 all showed improved performance compared to the non-age-segmented model (Fig. 4). For predictive models within specific age segments, the predictive efficacy for younger children is also stronger than for older children. Subsequent testing of each sub-center within the external test set also indicated improvements following age segmentation (Table 1).

Historically, significant efforts in early school-level myopia prediction research were made. Zadnik et al. screened multiple variables, including demographic and accommodative factors, ultimately deducing that cycloplegic refraction data alone could reliably forecast myopia onset (AUC 0.87 to 0.93) [52]. Recent model based on school data, acknowledged the importance of accommodative parameters, though the age range remained limited [14]. However, these investigations predominantly utilized traditional predictive models. In this study, the performance of the logistic regression model was only 0.752 (for myopia occurrence) and 0.703 (for myopia progression), while the optimized AI model could achieve 0.962 and 0.923, respectively. Benefiting from the application of AI, the current study showed an improvement and covered a more comprehensive age range (4–18 years old), thus enhancing its applicability in real-world school settings. Finally, our user-friendly software can empower school-level myopia management (Fig. 4).

Limitations

This study utilized non-cycloplegic refraction to better align with practical needs at the school level. This approach inevitably introduced deviations, because cycloplegic refraction is currently the gold standard recognized [53, 54]. However, due to the imbalance in regional and national development, cycloplegia, which requires certain medical investment, is impractical in routine school-level management of myopia, especially in remote or medically underserved areas [38, 55]. To solve this issue, we applied a formula to calculate cycloplegic refraction [40, 41, 56]. It should be noted that the Suoer SW-800 used in this study has an accuracy of ± 0.50 D, which may also introduce bias in the measurement of refractive error. Another limitation was the geographical scope of our external test set, confined to Guangdong Province, an economically advanced region in China. This could limit the representativeness. During the inclusion of the training set, some private schools and vocational schools did not participate, which may bias the prevalence of myopia. In addition, the high prevalence of myopia in these sets may lead to a potential imbalance between myopic and non-myopic groups, which may affect the accuracy and generalizability of the model. Subsequent data from more diverse sources are necessary to clarify this issue.

Conclusion

In conclusion, this study, grounded in two-year longitudinal data from schools and experimenting with various machine learning algorithms and optimization techniques, successfully established a comprehensive predictive system featuring age-segmented designs. This system encompassed predictions for both the myopia occurrence in non-myopic individuals and the myopia progression in myopic. Building on this, user-friendly software was developed, facilitating school-level myopia management. Since earlier interventions yield superior outcomes, targeting the school stage may hold promise for shifting myopia management upstream. However, further refinement and external testing remain warranted.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12967-025-06855-y.

Additional file 1: Study protocol. Longitudinal Collection of School Children's Refractive Data for the Development and Validation of a Prediction System for Myopia Onset and Progression.

Additional file 2: Figure S1. Selection of the optimal machine learning algorithm based on the training and external test sets. Figure S2. Distribution of feature importance and the interaction effects between features on the myopia occurrence and progression model. Figure S3. Individual case analysis of the prediction results for the myopia occurrence prediction model and the myopia progression model. Table S1. Distribution of population in training and test set. Table S2. Demographic characteristics of the individuals with myopia and non-myopia. Table S3. Baseline Characteristics of training and external test sets. Table S4. Performance of applied machine learning models in internal validation (tenfold cross-validation). Table S5. Performance of applied machine learning models in external test set. Table S6. Performance of the optimized models in external test across regional centers. Table S7. Multivariable regression model showing the impact of interacting factors. Table S8. Multivariate regression model showing the impact of interacting factors after age stratification. Table S9. Performance of the optimized models in internal validation (tenfold cross-validation).

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Author contributions
SX and XY had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis. SX and LL are co-first authors. Concept and design: SX, YH, XY, GZ, MF and YL. Acquisition, analysis, or interpretation of data: LL, YZ, ZR, YQ, ZZ, YH, ZL, FH, XZ, XH, YL, ZW, SD and YZ. Drafting of the manuscript: SX, LL and YH. Critical review of the manuscript for important intellectual content: LL, YZ, ZR, YQ, ZZ, YH, ZL, FH, XZ, XH, YL, ZW, SD, YZ, GZ, MF and XY. Statistical analysis: SX, YH, FH and ZW. Obtained funding: YZ and XY. Administrative, technical, or material support: LL, YZ, ZR, YQ, ZZ, YH, ZL, FH, XZ, YL, XH, YL, ZW, SD, YZ, GZ, MF and XY. Study supervision: YH, XZ, GZ, MF and XY.

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Data availability
The data and materials utilized in this study are currently not accessible to the public due to institutional ethics requirements. However, interested parties may request access from the corresponding author, Prof. Xiao Yang, through reasonable inquiries.

Declarations

Ethics approval and consent to participate
Approval for the study was granted by the Institutional Review Board (IRB) or Ethics Committee of Sun Yat-sen University, located in Guangzhou, China (2021KYPJ185). Additionally, the study was registered with the Chinese Clinical Trial Registry (ChiCTR; identifier: ChiCTR2200057391).

Consent for publication
Not applicable.

Competing interests
The authors declared that there are no competing interests.

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References

1. Morgan IG, Ohno-Matsui K, Saw SM. Myopia. The Lancet. 2012;379(9827):1739–48. https://doi.org/10.1016/S0140-6736(12)60272-4.
2. Dolgin E. The myopia boom. Nature. 2015;519(7543):276–8. https://doi.org/10.1038/519276a.
3. Li R, Zhang K, Li SM, et al. Implementing a digital comprehensive myopia prevention and control strategy for children and adolescents in China: a cost-effectiveness analysis. Lancet Reg Health Western Pac. 2023;38:100837. https://doi.org/10.1016/j.lanwpc.2023.100837.
4. Yam JC, Zhang XJ, Zhang Y, et al. Effect of low-concentration atropine eyedrops vs placebo on myopia incidence in children: the LAMP2 randomized clinical trial. JAMA. 2023;329(6):472. https://doi.org/10.1001/jama.2022.24162.
5. Hu Y, Zhao F, Ding X, et al. Rates of myopia development in young chinese schoolchildren during the outbreak of COVID-19. JAMA Ophthalmol. 2021;139(10):1115. https://doi.org/10.1001/jamaophthalmol.2021.3563.
6. Li Q, Guo L, Zhang J, et al. Effect of school-based family health education via social media on children's myopia and parents' awareness: a randomized clinical trial. JAMA Ophthalmol. 2021;139(11):1165. https://doi.org/10.1001/jamaophthalmol.2021.3695.
7. He X, Wang J, Zhu Z, et al. Effect of repeated low-level red light on myopia prevention among children in china with premyopia: a randomized clinical trial. JAMA Netw Open. 2023;6(4): e239612. https://doi.org/10.1001/jamanetworkopen.2023.9612.
8. Li SM, Ran AR, Kang MT, et al. Effect of text messaging parents of school-aged children on outdoor time to control myopia: a randomized clinical trial. JAMA Pediatr. 2022;176(11):1077. https://doi.org/10.1001/jamapediatrics.2022.3542.
9. He M, Xiang F, Zeng Y, et al. Effect of time spent outdoors at school on the development of myopia among children in china: a randomized clinical trial. JAMA. 2015;314(11):1142–8. https://doi.org/10.1001/jama.2015.10803.
10. Jonas JB, Jonas RA, Bikbov MM, Wang YX, Panda-Jonas S. Myopia: histology, clinical features, and potential implications for the etiology of axial elongation. Prog Retin Eye Res. 2023;96: 101156. https://doi.org/10.1016/j.preteyeres.2022.101156.
11. Liu H, Yang Y, Guo J, Peng J, Zhao P. Retinal damage after repeated low-level red-light laser exposure. JAMA Ophthalmol. 2023;141(7):693–5. https://doi.org/10.1001/jamaophthalmol.2023.1548.
12. Yam JC, Zhang XJ, Zhang Y, et al. Three-year clinical trial of low-concentration atropine for myopia progression (LAMP) study: continued versus washout: phase 3 report. Ophthalmology. 2022;129(3):308–21. https://doi.org/10.1016/j.ophtha.2021.10.002.
13. Chen Y, Tan C, Foo LL, et al. Development and validation of a model to predict who will develop myopia in the following year as a criterion to define premyopia. Asia-Pac J Ophthalmol. 2023;12(1):38–43. https://doi.org/10.1097/APO.0000000000000591.
14. Guo C, Ye Y, Yuan Y, et al. Development and validation of a novel nomogram for predicting the occurrence of myopia in schoolchildren: a prospective cohort study. Am J Ophthalmol. 2022;242:96–106. https://doi.org/10.1016/j.ajo.2022.05.027.
15. Peng W, Wang F, Sun S, Sun Y, Chen J, Wang M. Does multidimensional daily information predict the onset of myopia? A 1-year prospective cohort study. BioMed Eng OnLine. 2023;22(1):45. https://doi.org/10.1186/s12938-023-01109-8.
16. Lin H, Long E, Ding X, et al. Prediction of myopia development among Chinese school-aged children using refraction data from electronic medical records: a retrospective, multicentre machine learning study. PLoS Med. 2018;15(11): e1002674. https://doi.org/10.1371/journal.pmed.1002674.
17. Wong YL, Yuan Y, Su B, et al. Prediction of myopia onset with refractive error measured using non-cycloplegic subjective refraction: the WEPrOM Study. BMJ Open Ophth. 2021;6(1): e000628. https://doi.org/10.1136/bmjophth-2020-000628.
18. Fulton JM, Leung TW, McCullough SJ, et al. Cross-population validation of the PreMO risk indicator for predicting myopia onset in children. Ophthalmic Physiol Opt. 2025;45(1):89–99. https://doi.org/10.1111/opo.13416.
19. O'Donoghue L, Kapetanankis VV, McClelland JF, et al. Risk factors for childhood myopia: findings from the NICER study. Invest Ophthalmol Vis Sci. 2015;56(3):1524–30. https://doi.org/10.1167/iovs.14-15549.
20. Mutti DO, Sinnott LT, Cotter SA, et al. Predicting the onset of myopia in children by age, sex, and ethnicity: results from the CLEERE study. Optom Vis Sci. 2024;101(4):179. https://doi.org/10.1097/OPX.0000000000002127.

21. Mutti DO, Sinnott LT, Brennan NA, Cheng X, Zadnik K, Group for the CLE of E and RE (CLEERE) S. The limited value of prior change in predicting future progression of juvenile-onset myopia. Optometry Vis Sci. 2022;99(5):424. https://doi.org/10.1097/OPX.0000000000001883.
22. Liu L, Li R, Huang D, et al. Prediction of premyopia and myopia in Chinese preschool children: a longitudinal cohort. BMC Ophthalmol. 2021;21(1):283. https://doi.org/10.1186/s12886-021-02045-8.
23. He X, Sankaridurg P, Wang J, et al. Time outdoors in reducing myopia: a school-based cluster randomized trial with objective monitoring of outdoor time and light intensity. Ophthalmology. 2022;129(11):1245–54. https://doi.org/10.1016/j.ophtha.2022.06.024.
24. Guan J, Zhu Y, Hu Q, et al. Prevalence patterns and onset prediction of high myopia for children and adolescents in southern China via real-world screening data: retrospective school-based study. J Med Internet Res. 2023;25: e39507.
25. van der Gaag M, Hoffman T, Remijsen M, et al. The five-factor model of the positive and negative syndrome scale II: a ten-fold cross-validation of a revised model. Schizophr Res. 2006;85(1):280–7. https://doi.org/10.1016/j.schres.2006.03.021.
26. Chauhan VK, Dahiya K, Sharma A. Problem formulations and solvers in linear SVM: a review. Artif Intell Rev. 2019;52(2):803–55. https://doi.org/10.1007/s10462-018-9614-6.
27. Hancock JT, Khoshgoftaar TM. CatBoost for big data: an interdisciplinary review. J Big Data. 2020;7(1):94. https://doi.org/10.1186/s40537-020-00369-8.
28. Ke G, Meng Q, Finley T, et al. LightGBM: a highly efficient gradient boosting decision tree. In: Advances in Neural Information Processing Systems. Vol 30. 1. Curran Associates, Inc.; 2017:1. Accessed 27 Jul 2023. https://proceedings.neurips.cc/paper/2017/hash/6449f44a102fde848669bdd9eb6b76fa-Abstract.html.
29. He H, Bai Y, Garcia EA, Li S. ADASYN: adaptive synthetic sampling approach for imbalanced learning. In: 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence). 2008; pp. 1322–1328. https://doi.org/10.1109/IJCNN.2008.4633969.
30. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: synthetic minority over-sampling technique. J Artif Intell Res. 2002;16:321–57. https://doi.org/10.1613/jair.953.
31. Van Hulse J, Khoshgoftaar TM, Napolitano A. Experimental perspectives on learning from imbalanced data. In: Proceedings of the 24th International Conference on Machine Learning. ICML '07. Association for Computing Machinery; 2007. pp. 935–942. https://doi.org/10.1145/1273496.1273614.
32. Nohara Y, Matsumoto K, Soejima H, Nakashima N. Explanation of machine learning models using shapley additive explanation and application for real data in hospital. Comput Methods Progr Biomed. 2022;214: 106584. https://doi.org/10.1016/j.cmpb.2021.106584.
33. Kim Y, Kim Y. Explainable heat-related mortality with random forest and SHapley Additive exPlanations (SHAP) models. Sustain Cities Soc. 2022;79: 103677. https://doi.org/10.1016/j.scs.2022.103677.
34. Flitcroft DI, He M, Jonas JB, et al. IMI-defining and classifying myopia: a proposed set of standards for clinical and epidemiologic studies. Invest Ophthalmol Vis Sci. 2019;60(3):M20. https://doi.org/10.1167/iovs.18-25957.
35. Chen J, Liu S, Zhu Z, et al. Axial length changes in progressive and non-progressive myopic children in China. Graefes Arch Clin Exp Ophthalmol. 2023;261(5):1493–501. https://doi.org/10.1007/s00417-022-05901-5.
36. Chamberlain P, Peixoto-de-Matos SC, Logan NS, Ngo C, Jones D, Young G. A 3-year randomized clinical trial of MiSight lenses for myopia control. Optom Vis Sci. 2019;96(8):556. https://doi.org/10.1097/OPX.0000000000001410.
37. Tang T, Yu Z, Xu Q, et al. A machine learning-based algorithm used to estimate the physiological elongation of ocular axial length in myopic children. Eye Vis. 2020;7(1):50. https://doi.org/10.1186/s40662-020-00214-2.
38. Mirshahi A, Kohnen T. Acute psychotic reaction caused by topical cyclopentolate use for cycloplegic refraction before refractive surgery: case report and review of the literature. J Cataract Refract Surg. 2003;29(5):1026–30. https://doi.org/10.1016/S0886-3350(02)01651-6.
39. Contreras-Salinas H, Orozco-Ceja V, Romero-López MS, Barajas-Virgen MY, Baiza-Durán LM, Rodríguez-Herrera LY. Ocular cyclopentolate: a mini review concerning its benefits and risks. Clin Ophthalmol. 2022;16:3753–62. https://doi.org/10.2147/OPTH.S388982.
40. Sankaridurg P, He X, Naduvilath T, et al. Comparison of noncycloplegic and cycloplegic autorefraction in categorizing refractive error data in children. Acta Ophthalmol. 2017;95(7):e633–40. https://doi.org/10.1111/aos.13569.
41. Sankaridurg P, Berntsen DA, Bullimore MA, et al. IMI 2023 digest. Invest Ophthalmol Vis Sci. 2023;64(6):7. https://doi.org/10.1167/iovs.64.6.7.
42. He X, Sankaridurg P, Xiong S, et al. Prevalence of myopia and high myopia, and the association with education: Shanghai Child and Adolescent Large-scale Eye Study (SCALE): a cross-sectional study. BMJ Open. 2021;11(12): e048450. https://doi.org/10.1136/bmjopen-2020-048450.
43. Team RC. The R project for statistical computing. The R Foundation. R-project org. Published online 2019.
44. Vallat R. Pingouin: statistics in Python. JOSS. 2018;3(31):1026. https://doi.org/10.21105/joss.01026.
45. Chang P, Zhang B, Lin L, et al. Comparison of myopic progression before, during, and after COVID-19 lockdown. Ophthalmology. 2021;128(11):1655–7. https://doi.org/10.1016/j.ophtha.2021.03.029.
46. Wang J, Li Y, Musch DC, et al. Progression of myopia in school-aged children after COVID-19 home confinement. JAMA Ophthalmol. 2021;139(3):293. https://doi.org/10.1001/jamaophthalmol.2020.6239.
47. Mutti DO, Hayes JR, Mitchell GL, et al. Refractive error, axial length, and relative peripheral refractive error before and after the onset of myopia. Invest Ophthalmol Vis Sci. 2007;48(6):2510. https://doi.org/10.1167/iovs.06-0562.
48. Jiang F, Wang D, Yin Q, He M, Li Z. Longitudinal changes in axial length and spherical equivalent in children and adolescents with high myopia. Invest Ophthalmol Vis Sci. 2023;64(12):6. https://doi.org/10.1167/iovs.64.12.6.
49. Xu S, Li Z, Zhao W, et al. Effect of atropine, orthokeratology and combined treatments for myopia control: a 2-year stratified randomised clinical trial. Br J Ophthalmol. 2023;107(12):1812–7. https://doi.org/10.1136/bjo-2022-321272.
50. Xu S, Li Z, Hu Y, et al. Development and validation of a prediction model for axial length elongation in myopic children treated with overnight orthokeratology. Acta Ophthalmol. 2021. https://doi.org/10.1111/aos.14658.
51. Cho P, Cheung SW. Retardation of myopia in orthokeratology (ROMIO) study: a 2-year randomized clinical trial. Invest Ophthalmol Vis Sci. 2012;53(11):7077–85. https://doi.org/10.1167/iovs.12-10565.
52. Zadnik K, Sinnott LT, Cotter SA, et al. Prediction of Juvenile-Onset myopia. JAMA Ophthalmol. 2015;133(6):683–9. https://doi.org/10.1001/jamaophthalmol.2015.0471.
53. Morgan IG, Wu PC, Ostrin LA, et al. IMI risk factors for myopia. Invest Ophthalmol Vis Sci. 2021;62(5):3. https://doi.org/10.1167/iovs.62.5.3.
54. Morgan IG, Iribarren R, Fotouhi A, Grzybowski A. Cycloplegic refraction is the gold standard for epidemiological studies. Acta Ophthalmol. 2015;93(6):581–5. https://doi.org/10.1111/aos.12642.
55. Fitzgerald DA, Hanson RM, West C, Martin F, Brown J, Kilham HA. Seizures associated with 1% cyclopentolate eyedrops. J Paediatr Child Health. 1990;26(2):106–7. https://doi.org/10.1111/j.1440-1754.1990.tb02399.x.
56. Du B, Wang Q, Luo Y, et al. Prediction of spherical equivalent difference before and after cycloplegia in school-age children with machine learning algorithms. Front Public Health. 2023;11(11):1096330.

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