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Understanding Myopia in the Digital Age: The Role of Screen Time in Myopia Prevalence

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ABSTRACT

The prevalence of myopia in children is increasing globally, with heightened screen time identified as a potential contributing factor. This study aims to investigate the effect of more than 15 hours of screen time per week on the prevalence of myopia in children aged 6 to 8 years.

A logistic regression model was employed to analyze data from 681 children. Key variables included screen exposure (TV and computer hours per week), genetic factors, and eye metrics such as spherical equivalent and axial length. K-fold cross-validation (n=6) was used to evaluate model performance. Children with more than 15 hours of screen time per week had a 16% increased likelihood of developing myopia (mean odds ratio = 1.16). The findings suggest that excessive screen time is associated with a higher risk of myopia in young children. A multifactorial approach—including age, genetic, and eye metrics—provides a more accurate prediction of myopia. These findings highlight the importance of managing screen time and further research to better understand its role in myopia development.

Keywords: myopia, screen time, children, axial length, logistic regression, prevalence, eye health

Introduction

The prevalence of myopia or nearsightedness is increasing globally, according to Dr. Elise Kramer, myopia is "on the rise in younger generations" (para. 8) [1]. Recent data indicates that 41% of children aged 5-17 in the United States are affected. This trend is characterized by both a reduction in the age of onset and an acceleration in the rate of progression. Myopia is defined as a condition where near objects are seen clearly, while distant objects appear blurry. A potential driver of this increase in myopia is the heightened exposure to technological devices.

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Technological devices are used at a closer distance, and prolonged screen usage has been involved in eye strain, which contributes to the development of myopia.

Children typically view screens at closer distances, leading to increased eye strain, prolonged accommodation, reduced blinking, and exposure to blue light, all factors that significantly contribute to myopia. Accommodation is the process by which the ciliary muscles contract to change the shape of the lens, allowing the eye to focus light correctly on the retina. Prolonged close-up activities, such as reading or screen use, require sustained accommodation. Over time, the ciliary muscles may remain contracted even when focusing on distant objects, due to muscle strain. Continuous contraction of the ciliary muscles can induce structural changes in the eye, contributing to axial elongation (the measurement from the cornea to the back surface of the eye). Dr. Connie Gan and Dr. Kimberley Ngu highlight that "axial length change has the highest correlation with myopic progression" (para. 3) [2].

During near-sighted activities, reduced blinking rates lead to dry and irritated eyes. Additionally, blue light emitted from screens causes more strain than other wavelengths. Blue light scatters more easily, making it harder for the eye to focus and increasing eye strain.

Population-based studies have begun to show a connection between screen time and myopia, indicating that increased screen time is associated with a higher prevalence of myopia, greater myopic spherical equivalent, and longer axial length. However, other studies have not found such a link, highlighting the need for further research (Joshua Foreman et al., 2021) [3].

Literature Review

The increasing prevalence of myopia among children has raised significant concerns among healthcare professionals and researchers. Myopia has emerged as a global problem, mainly due to "exceptionally high myopia prevalence rates in school children in East Asia (73%)" (Grzybowski et al., 2020, para. 2) [4]. An extensive body of evidence suggests an association between increased screen time and higher rates of myopia. This literature review examines recent studies exploring this connection.

Association Between Screen Time and Myopia. Several studies have found an association between screen time and myopia. A study published in BMC Public health (Zong et al., 2024) [5] found a strong association between increased screen time and the prevalence of myopia. This study analyzed 19 studies involving 102,360 participants, and the analysis showed a significantly higher odds ratio of myopia in children with high screen time exposure compared to those with low screen time exposure. Similarly, another study published in the Lancet Digital Health (Joshua Foreman et al., 2021) [6] found a relationship between higher levels of screen time and higher risk of myopia. The analysis found that high levels of screen time were associated with

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nearly a 30% higher risk of myopia. When excessive computer screen time was included, this risk increased to nearly 80%. Research suggests multiple ways through which screen time may influence myopia development. Prolonged accommodation, where extended near work such as reading or using digital devices leads to increased eye strain, is one pathway through which screen time may influence myopia development. Additionally, decreased time spent outdoors, often replaced by screen time, has been linked to lower levels of ambient light exposure and higher levels of blue light exposure, contributing to the development of myopia.

No Association Between Screen Time and Myopia. Other studies such as the one published in Ophthalmic & Physiological Optics (RO Staff, 2020) [7] suggest that the association between screen time and myopia is not consistent. The review analyzed 15 studies involving 49,789 children aged 3 to 19, with 7 studies reporting a link and 5 reporting no significant association. Researchers "found no clear association between screen time and myopia prevalence, incidence, or myopia progression" (RO Staff, 2020). Additionally, A study in the Lancet Digital Health (Joshua Foreman et al., 2021) [8] explores the link between screen time and myopia. This systematic review and meta-analysis of 33 studies yielded mixed results. 50-60% of studies found associations between screen exposure and prevalent/incident myopia, while the others did not find a significant association.

While the relationship between screen time and myopia is supported by various studies, there are challenges in establishing a directly correlated relationship. Differences in population demographics and hours spent on technological devices could potentially introduce variability in findings. Studies have employed a range of methodologies, including meta-analyses (Joshua Foreman et al., 2021) [9], systematic reviews (Lanca & Saw, 2020) [11], and others.

The reviewed literature suggests mixed opinions, with some articles suggesting clear association between increased screen time and higher rates of myopia and others suggesting no clear association between the two. Considering screen time as a risk factor could potentially play a crucial role in managing the global myopia epidemic, highlighting the importance of developing effective strategies to mitigate its impact on eye health.

Despite the abundance of evidence, there is a need for more studies to establish a stronger relationship between screen time exposure and myopia. Additionally, research focusing on interventions to reduce the impact of screen time on eye health is limited. Understanding how prolonged screen exposure leads to adaptive changes in the eye is crucial for addressing myopia development.

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Materials and Methods

Data Collection

Data from Kaggle article "Myopia Study" (Papachristou, 2023) [12] and Journal of the Chinese Medical Association article "Prevalence and risk factors for myopia in second-grade primary school children in Taipei: A population-based study" (Chih-Chien, 2016) [13] were extracted. Values were simulated for the last 12 columns of the Kaggle dataset (618) to eye 1 of the second dataset. The "sample" function in R was used to do uniform sampling. The combined dataset had 681 entries. Variables that were extracted included participants age, gender, year of study, myopia prevalence, eye metrics, screen exposure measures, genetic influences, and other potential risk factors. See table 3 for more detail about each variable.

Table 3: Table of Variables That Were Included in the Combined Dataset

Abbreviation	Full word	Meaning
ID	ID	Used for indexing, 1 is the first participant, 618 is the last.
STUDYYEAR	Year of study	The year the data of the participant was collected.
MYOPIC	Myopia Prevalence	1 if myopia present, 0 if not.
AGE	Age	Age of participant. (Range: 6-8)
GENDER	Gender	Gender of participant.
SPHEQ	Spherical Equivalent Refraction	A metric used to describe the refractive error of the eye.
AL	Axial Length	The distance from the front (cornea) to the back (retina) of the eye.
ACD	Anterior Chamber Depth	The distance between the cornea (the front of the eye) and the lens inside the eye.
LT	Lens Thickness	Measurement of the thickness of the eye's lens.
VCD	Vitreous Chamber Depth	Distance from the lens to the retina (back of the eye).
SPORTHR	Sport hours	Hours spent on sports per week.
READHR	Read hours	Hours spent reading per week
COMPHR	Computer hours	Hours spent on computer per week.
STUDYHR	Study hours	Hours spent studying per week.
TVHR	Tv hours	Hours spent on TV per week.
DIOPTERHR	Diopter hours	The cumulative exposure to near work activities.
MOMMY	Myopia prevalence in mom	1 if myopia present, 0 if not.
DADMY	Myopia prevalence in dad	1 if myopia present, 0 if not.

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Logistic Regression Model

A logistic regression classifier was selected for this study because it effectively handles binary outcomes, such as the presence or absence of myopia, and estimates the probability of myopia based on predictor variables like screen time. It also provides clear interpretations of the relationship between screen time and myopia prevalence through coefficients and odds ratios, making it well-suited for understanding the impact of screen time on myopia prevalence. The model was implemented using the scikit-learn Python library. A parameter for a max iteration of 10,000 was used in the logistic regression model. Before the model was used to train and test the dataset, the number of participants with myopia and without myopia was printed to understand the distribution of data.

K-Fold Cross Validation

To evaluate the model's generalization performance and ensure thorough assessment while reducing the risk of overfitting, a K-Fold Cross-Validation technique was employed with three splits (n_splits=3). This method involved partitioning the dataset into three equal-sized folds, ensuring a balanced representation of classes within each fold. The model was trained on two folds (combined) and evaluated on the remaining fold. This process was repeated three times, each time with a different fold serving as the test set. Empty arrays for performance metrics (accuracy scores, recall scores, f1 scores, and precision scores) were created. Predictions on the test set were made, and the corresponding y_test and y_pred labels were used to calculate performance metrics. The performance metrics were added to their corresponding array. The K-Fold cross-validation and performance metric calculations were implemented using scikit-learn version 1.5.3. To visualize the classification performance, confusion matrices were generated for each fold using the confusion_matrix function from sklearn.metrics and plotted with a heatmap representation. These matrices provided insights into the types of errors the model was making, such as misclassifications between specific classes (false positives and false negatives). Additionally, the accuracy score of each fold was printed.

After completing the cross-validation, summary statistics for each performance metric were calculated, including the minimum, maximum, mean, median, and standard deviation. This analysis, performed using standard statistical functions in Python, provided a detailed understanding of the model's performance consistency and reliability across different data splits.

Optimizing Model Performance

The model was tested while setting the X variable to various features (excluding myopia prevalence) and the Y variable remaining constant (myopia prevalence, 0 or 1). The X variable always included the ‘TVHR’ and ‘COMPHR’ features since those were the screen exposure

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variables, but additional features were added and removed. Each iteration was analyzed to see which set of features gave the best results. Performance metrics, feature names, and the number of true positive, true negative, false positive, and false negative were stored in a table. Redundant features were eliminated through this process. The selection process of non redundant features was done manually, until the best features were selected and the best results for each performance metric was achieved.

Performance Metrics + Data Visualization

A new column was created in the dataframe called 'TVHR_COMPHR_Sum.' The values in this column represented the total amount of screen time per week, by adding up the 'TVHR' and 'COMPHR' variables for each participant. Then, another column was created called 'TVHR_COMPHR_Binary' which assigned a 1 for each participant that had a total amount of screen time that was greater than 15 hours, and a 0 for each participant that had a total amount of screen time that was 15 hours or less. The K fold cross validation model was run again, but this time 'TVHR_COMPHR_Binary' was the feature (X) and 'MYOPIC' was the outcome (y). Additionally, the folds were increased to 6, for better utilization of data and less bias in training/testing subsets. For each fold, we recorded the model coefficients and calculated the odds ratios by exponentiating the coefficients. We also calculated the intercept odds by exponentiating the intercept. After performing the 6 fold cross-validation, we calculated the mean coefficients and intercept across the 6 folds. The mean odds ratios were then obtained by exponentiating the mean coefficients, and the mean intercept odds were obtained by exponentiating the mean intercept. This process provided a reliable estimate of the effect of combined screen time per week on myopia prevalence.

The two exposure variables for screen time were the number of hours spent on a computer per week (COMPHR) and number of hours spent on a TV per week (TVHR). To analyze the distribution of the variable COMPHR in the dataset, a statistical approach was employed to calculate its mean and standard deviation. The mean of the COMPHR variable was calculated using the .mean() function. The standard deviation was calculated using the .std() function. The number of samples in the COMPHR variable was calculated using the .count() function. To visualize the normal distribution, simulated data points were generated based on the calculated mean and standard deviation. This was achieved using the np.random.normal() function, which generates a sample of data points from a normal distribution defined by the mean and standard deviation. The number of generated samples matched the original dataset's sample size. A histogram of the simulated data was plotted with 30 bins specified to categorize the data points into intervals, and density=True so that the area under the histogram equals 1. The plt.xlim() function was used to capture the x-axis limits of the histogram for consistent plotting. The normal distribution's probability density function was calculated using the formula and it was

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plotted over the histogram using plt.plot(), providing a visual comparison between the actual data distribution and the bell curve (normal distribution). The plot was titled "Bell Curve (Normal Distribution)" and labeled with the x-axis as 'Value' and the y-axis as 'Frequency'. This visualization was created using Matplotlib, and it allowed for the assessment of how closely the data approximated a normal distribution. This same process was repeated for the TVHR variable and TVHR_COMPHR_Sum.

Using matplotlib, a plot was created to compare TVHR_COMPHR_Sum and myopia prevalence. This plot was used to show the relationship between higher (15> hours per week) and lower values (<=15 hours per week) and myopia prevalence (0 or 1).

Results

The model was tested while setting the X variable to various features (excluding myopia prevalence) and the Y variable remaining the outcome variable (myopia prevalence, 0 or 1).

Using only TVHR and COMPHR as features resulted in a mean accuracy of 86.89 but a mean precision, recall, and F1 score of 0 indicates that the model predicted no myopia for all instances. The best performance was observed using the feature set 'AGE', 'SPHEQ', 'ACD', 'VCD', 'AL', 'DADMY', 'COMPHR', 'GENDER', and 'TVHR', which yielded notable results in accuracy, precision, recall, and F1 score (See Table 1 for details). This model also achieved the best results for false positives and false negatives.

The dataset contained 681 participants total. Class representation was uneven. (See figure 1).

A positive association was observed between screen time and myopia across all folds (See table 2). In fold 3 the odds ratio was 1.16, which indicates a 16% increase in the likelihood of myopia for participants with more than 15 hours of screen time per week. Fold 4 revealed the strongest positive association, the odds ratio of 1.48 indicates a 48% increase in the likelihood of myopia for participants exceeding 15 hours of screen time per week. Similarly in fold 6, the odds ratio of 1.27 indicates a 27% increase in the likelihood of myopia for participants with more than 15 hours of weekly screen time. The baseline odds of myopia in participants with 15 or less hours of screen time ranged from 0.13 - 0.157 across folds 3, 4, and 6.

The mean coefficient of 0.15 across all folds indicates a positive association between screen time and myopia prevalence, suggesting that increasing screen time to more than 15 hours per week is linked to higher odds of developing myopia. The mean odds ratio of 1.16 signifies a 16% increase in the likelihood of myopia for participants with more than 15 hours of screen time. The mean intercept odds of 0.15, or 15%, represent the baseline odds of myopia for participants with 15 or fewer hours of screen time, reflecting the lower prevalence of myopia in this group.

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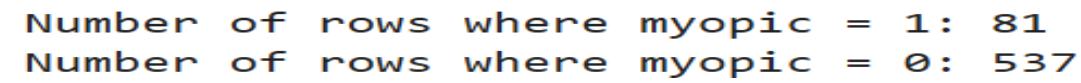
Table 1: Performance Metrics for Models Predicting Myopia (Myopic) Using Varying Feature Sets

	X (excluding myopia)	y	Mean Accuracy	Mean Precision	Mean Recall	Mean F1	true positive #	true negative #	false positive #	false negative #
Model A	all	MYOPIC	88.19	63.11	30	39	8	173.67	5.3	19
Model B	TVHR	MYOPIC	86.89	0	0	0	0	179	0	27
Model C	COMPHR,TVHR,MOMMY,DADMY	MYOPIC	86.89	0	0	0	0	179	0	27
Model D	STUDYYEAR, AGE, SPHEQ, AL, ACD, LT, VCD	MYOPIC	89.16	73	27	39	7.3	176.3	2.67	19.67
Model E	AGE, SPHEQ, ACD, VCD, AL, DADMY	MYOPIC	89.64	79.63	31.26	43.69	8.3	176.3	2.67	18.67
Model F	AGE, SPHEQ, ACD, VCD, AL, DADMY,COMPHR	MYOPIC	89.81	80	32.4	45.11	8.67	176.3	2.67	18.67
Model G	AGE, SPHEQ, ACD, VCD, AL, DADMY,COMPHR,GENDER,TVHR	MYOPIC	90.13	82.18	33.74	46.74	9	176.67	2.3	18
Model H	TVHR,COMPHR	MYOPIC	86.89	0	0	0	0	179	0	27
Model I	COMPHR	MYOPIC	86.89	0	0	0	0	179	0	27

Note. The table presents the performance metrics for models predicting 'MYOPIC' as the outcome with varying feature sets. Performance metrics include mean accuracy, mean precision, mean recall, and mean f1 as well as true/false positives and true/false negatives to measure each model's predictive ability.

Figure 1: Number of Participants With or Without Myopia



Note. 1 represents participants with Myopia and 0 represents participants without Myopia.

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Table 2: 6-Fold Cross-Validation Results: Association Between Screen Time and Myopia Prevalence

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Mean of All Folds
Coefficients	-0.08	0.08	0.15	0.40	0.11	0.24	0.15
Intercept	-1.87	-1.92	-1.85	-2.04	-1.98	-1.92	-1.93
Odds Ratios	0.92	1.08	1.16	1.48	1.11	1.27	1.16
Intercept Odds	0.15	0.15	0.16	0.13	0.14	0.15	0.15

Note. The table displays the results of the 6-fold cross validation, showing the association between weekly screen time and the prevalence of myopia. The coefficients, intercept, odds ratios, and intercept odds are presented, as well as the mean across all folds.

Computer usage hours, TV viewing hours, and their combined screen time among participants all follow a normal distribution (See figure 2). The bell-shaped curves indicate that the data is representative of a population's typical usage patterns, making the findings generalizable. These distributions provide a reliable basis for examining the effect of screen time on myopia prevalence.

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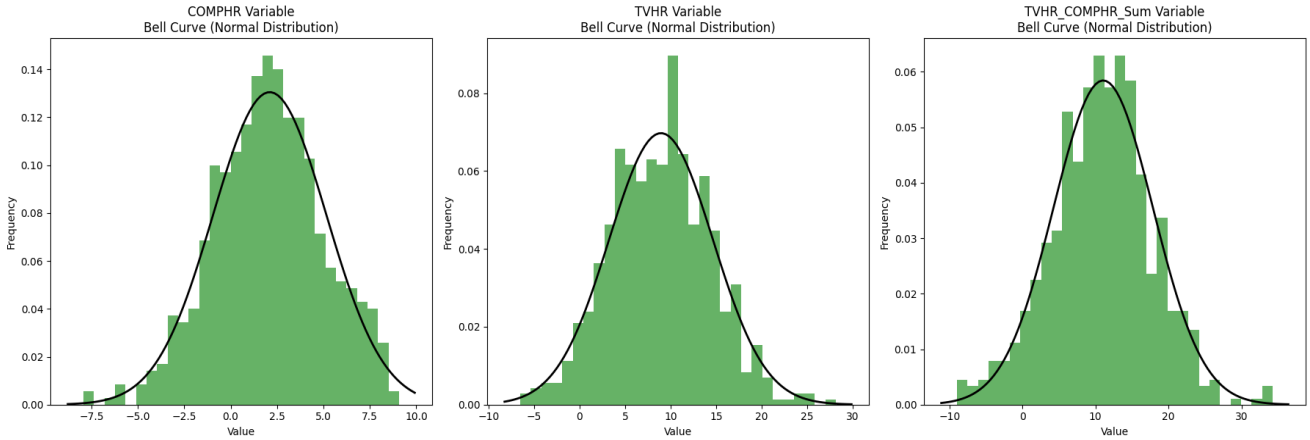
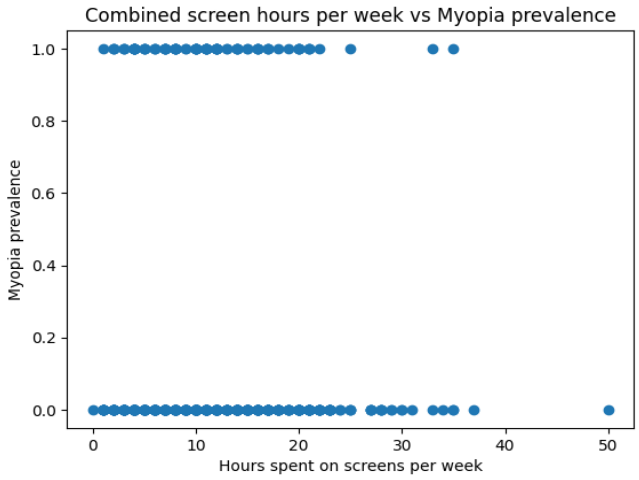
Figure 2: Distribution of Screen Time Variables (COMPHR, TVHR, and TVHR_COMPHR_Sum) and Comparison with Simulated Normal Distribution.



Note. The histograms show the distribution of screen time variables: COMPHR (hours spent on a computer per week), TVHR (hours spent on TV per week), and the combined sum of both (TVHR_COMPHR_Sum). The plots compare the actual data distribution with a simulated normal distribution. The x-axis represents the values of screen time (in hours), while the y-axis shows the frequency or density of the data points. All histograms are displayed with 30 bins and density scaling for comparison with the normal distribution curve.

Figure 3: Combined Screen Time Hours per Week vs. Myopia Prevalence



Note. The combined screen time for each participant (tv hours + computer hours) is plotted on the x axis and the myopia prevalence is plotted on the y axis.

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Participants with and without myopia are scattered across the entire range of screen hours, from low to high (See figure 3). The data shows no clear trend between screen time and myopia, with both myopic and non-myopic participants appearing at various screen time levels. Model performance metrics such as accuracy, precision, recall, and F1 score improved when additional features were included in the cross-validation. This suggests that the inclusion of additional features contributed to a better model performance, compared to screen time alone.

Discussion

The primary focus of this research was to investigate the relationship between screen time and the prevalence of myopia, with a specific emphasis on the impact of having more than 15 hours of screen time per week. Our findings provide substantial evidence supporting the hypothesis that increased screen time is associated with an increased risk of developing myopia. Additionally this study provides a comprehensive examination of the factors influencing myopia prevalence, while including other contributing variables. Our findings indicate that while screen usage hours per week is a significant factor, it is not the sole determinant of myopia.

The Model yielded an accuracy of 86.89% when using computer hours per week as the feature and when using TV hours per week as the feature. Both variables independently provide similar predictive power, reflecting the contribution of screen time to myopia prevalence. The model's accuracy improved to 90.13% when additional features were included. This improvement indicates that myopia is influenced by a combination of factors beyond just screen time, and that screen time is not the sole determinant of whether a participant has Myopia or not. These findings highlight the importance of considering a combination of demographic, genetic, and eye metric variables to achieve a more comprehensive and accurate prediction of myopia prevalence.

Additionally, while the high accuracy suggests that the model performs well in terms of overall correctness, this metric can be misleading, especially in imbalanced datasets where one class dominates. In this case there is a much larger number of participants without myopia (537 participants) in comparison to participants with myopia (81 participants). Due to this, the model could be achieving high accuracy by predominantly predicting the majority class. This claim is backed up by the model predicting no myopia for an average of 194.67 (number of true negatives + number of false negatives in model with highest accuracy) participants each fold , and the model predicting myopia for an average of 11.3 (number of true positives + number of false positives in model with highest accuracy) participants each fold. Since the dataset contained more participants without myopia and the model was predicting no myopia for most participants, the testing accuracy of the model was this high. The model is biased towards the majority class.

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The 6-fold cross-validation logistic regression analysis using a binary screen time variable for whether the participant was exposed to higher or lower hours of screen time per week provided clear evidence supporting the hypothesis that more than 15 hours of screen time per week increases the likelihood of developing myopia. The mean coefficient of 0.15 and mean odds ratio of 1.16 indicate that participants with greater than 15 hours of screen time per week have approximately 16% greater odds of having myopia compared to those with lesser screen time hours. This finding was consistent across all folds (excluding fold 1), where the odds ratios ranged from 1.08 to 1.48, reinforcing the significance of screen time as a risk factor for myopia.

All three histograms indicate a normal distribution centered around the mean, suggesting that the sample data is representative of typical screen time habits. This reinforces the reliability of the data and supports the generalizability of our findings. The inclusion of these features in predictive models seems to be appropriate since they represent common screen time habits within the population.

The scatter plot showed that myopia prevalence doesn't exhibit a clear trend across different levels of combined screen time (tv hours + computer hours) per week. This pattern aligns with our regression analysis, demonstrating that while screen time is a significant factor, its influence on myopia is best understood in concurrence with other variables.

These findings have important implications for public health, suggesting that reducing screen time and encouraging outdoor activities could be effective strategies for managing myopia progression in children. This research will give Ophthalmologists and Optometrists an early indicator of myopia progression in a child aged 6-8 years, which will allow these doctors to provide the right treatments/advice and make the necessary changes. Such treatments include atropine eye drops and peripheral defocus contact lenses. Additionally, educators should consider these findings when developing guidelines for screen use among children as students are exposed to screens for the majority of their school day. Interventions designed to reduce screen time and increase outdoor activities should be tested for their effectiveness in preventing myopia progression.

Limitations

A notable limitation of this study is the uneven distribution of participants, with 81 individuals classified as myopic and 537 as non-myopic. This significant imbalance could lead to biases in the model, making it more likely to predict cases of no myopia. The overrepresentation of non-myopic participants may cause the model to favor non-myopic predictions, potentially reducing its ability to accurately identify cases of myopia. As a result, the model's performance might be skewed, by reflecting an increased likelihood of predicting no myopia even in instances where it

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is present. This bias was present during the collection of data, when we were testing the model with different features. In all instances there were a higher number of false negatives in comparison to the number of false positives since due to the biased dataset, the model was incorrectly identifying the minority class (myopia prevalence).

Another limitation of this study is the small sample size of 681 participants, which may not be sufficient to fully validate the findings. A sample of this size may limit the statistical power of the analysis, leading to less reliable/generalizable results. With a smaller sample, the model may not capture the full variability of the population, increasing the risk of false positive and false negative errors. Future research should aim to include a larger sample size to enhance the validity and reliability of the conclusions drawn.

Another limitation of this study is the potential presence of unexplored variables that may influence myopia but were not included in our analysis. While the study focused on key factors such as screen time, age, genetic factors, and eye metrics, there may be other relevant variables such as lifestyle factors, environmental exposures, dietary habits, and other forms of screen exposure that were not accounted for. Future research should include a wider range of factors to better understand what contributes to myopia. Considering these unexplored variables could improve the model's accuracy and make the conclusions more reliable and relevant to different populations.

Another limitation of this study is the narrow age range of the participants, who were all between 6 and 8 years old. This age group restricts the generalizability of the findings to other age groups, such as older children, adolescents, and adults, who may exhibit different patterns of myopia prevalence. The prevalence of myopia can vary significantly with age, and the factors contributing to its occurrence may differ across different life stages. Therefore, the conclusions regarding myopia prevalence drawn from this study may not be fully applicable to a broader population. Future research should include a wider age range to better understand how myopia prevalence differs across different age groups, enhancing the reliability of the findings.

While this study contributes to the understanding of the impact of screen exposure on myopia prevalence, the limitations outlined above indicate the need for further research. Addressing these limitations in future studies will help to build a more accurate and comprehensive model of myopia prevalence, leading to more reliable and applicable findings.

Overall, our research confirms that screen time exceeding 15 hours per week in children aged 6-8 years is associated with a 16% higher risk of developing myopia. These findings are consistent with previous studies (Althnayan et al., 2022; Zong et al., 2024) [14] [15], and they underline the importance of considering screen time as a critical factor in myopia prevalence. The results

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suggest that an approach taking into account various influencing factors is essential for accurately predicting the prevalence of myopia.

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