Blue-Light Blocking Glasses Using Machine Learning

***Abstract*—The objective of short-wavelength ("blue") light-filtering lenses is to enhance physiological wellness and sleep. While UV filters are commonly used, there is limited information about their relative effectiveness in reducing exposure to blue light while preserving visibility. Five light sources were utilized to test fifty standard lenses: the sun, a fluorescent ceiling luminaire, an incandescent lamp, and a blue LED array. To calculate the percentage of transmission, absolute irradiance was measured at baseline and for each lens across the visible spectrum (380-780 nm). Additionally, transmission specificity was evaluated to determine whether light transmission was primarily non-proficient (380-454 nm and 561-780 nm) or circadian-proficient (455-560 nm). Lenses were grouped by tint, and metrics were compared between the groups. Red-tinted lenses transmitted the least amount of circadian-efficient light. In this paper, our focus was on studying the various properties of blue blockers across different lighting conditions and investigating patterns that could have potentially assisted future users of blue blockers effectively through different findings.**

***Index Terms*—SVM, KNN, LR, R2, MSE, RMSE, MAE**

I. Introduction

The characteristics of light absorption and transmission exhibited by materials are referred to as spectrophotometric qualities. These characteristics are crucial for the efficacy of blue blockers in blocking or filtering blue light. Blue light, emitted by electronics, LED lights, and sunlight, can be harmful to the eyes and can be mitigated using glasses or contact lenses known as blue blockers. [2] These blockers lower the activation of intrinsically photosensitive retinal ganglion cells (ipRGCs), which are most sensitive to blue light and are a significant input for circadian regulation, blue-blocking glasses improve sleep by triggering the onset of dim-light melatonin. Blue blockers, marketed for industrial use, selectively filter or block blue light while permitting other wavelengths of light to pass through. [3] The recognition of the blue lightsensitive retinal photoreceptor, which alerts the brain to daytime, raised the possibility that the circadian system may be blocked by wearing orange-tinted glasses with a blue-blocking coating. The effectiveness of blue blockers is influenced by the specific qualities of the lenses and the lighting conditions in which they are employed. Blue light is emitted in varying intensities and spectra across different lighting situations, encompassing artificial lighting, natural sunlight, and electronic device screens. Consequently, to comprehensively assess the performance of blue blockers, it becomes imperative to examine their spectrophotometric characteristics under diverse lighting scenarios. An essential characteristic of blue blockers is their transmittance spectrum, which illustrates the amount of light transmitted at distinct wavelengths. While exhibiting higher transmittance in other regions of the visible light spectrum, blue blockers typically demonstrate reduced transmittance in the blue light range (approximately 400–500 nanometers). [4] The experiment was designed to see if blocking out the blue part of the light spectrum with orange-lens glasses (blue blockers) would stop the light-induced melatonin suppression. This test is frequently used to evaluate the indirect sensitivity of the circadian clock. The incorporation of specific lens coatings or additives can significantly impact a blue blocker's ability to selectively filter blue light. For instance, certain blue-blocking materials may possess a yellow or amber tint to enhance blue light absorption. These tinted lenses, by diminishing transmission in the blue region and altering color perception, can influence the spectrophotometric properties.

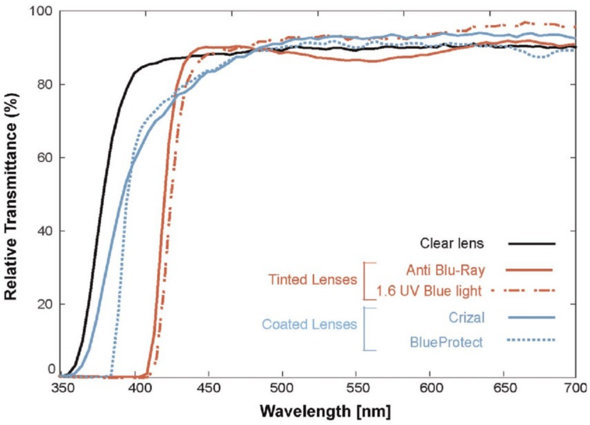

Fig. 1. Wavelength vs. Relative Transmittance Graph of Clear, Tinted, and Coated Lens

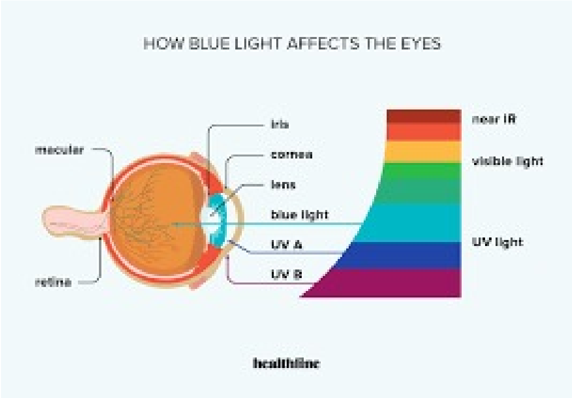

Fig. 2. Affects of Blue light in eyes

II. Literature Review

Due to its potential effects on human health and well-being, blue light has garnered significant research attention. [10]Blue light emitted by electronic devices, LED lights, and sunlight can be mitigated through the use of commercially available blue-blocking eyewear and lenses. The efficacy of blue blockers in blocking or filtering blue light is heavily reliant on their spectrophotometric characteristics. This literature review aims to provide an overview of recent studies on the spectrophotometric attributes of commercially available blue blockers across varying illumination conditions. [7]A pivotal spectrophotometric feature of blue blockers is the transmittance spectrum, which signifies the extent of light transmission at diverse wavelengths. Research indicates that blue light blockers tend to exhibit lower transmittance within the 400–500 nm range of blue light, while maintaining higher transmittance in other regions of the visible light spectrum. The transmittance spectra of blue blockers can be influenced by various manufacturing processes and materials employed in their construction, thereby impacting their blue light filtering efficacy. To enhance their blue light filtering capabilities, blue blockers often incorporate lens coatings, also referred to as tints. [6]These coatings or tints alter the spectrophotometric attributes of the lenses, resulting in heightened attenuation of blue light. For instance, lenses with a yellow or amber tint have been demonstrated to effectively block blue light and provide a more accurate perception of colors. Studies have investigated the effects of different coatings and tinting methods on the spectrophotometric qualities of blue blockers, [8]underscoring the importance of these elements in blue light filtration. The effectiveness of blue blockers can vary based on the lighting conditions they are employed in, owing to variations in the quantity and spectrum of blue light emitted by diverse light sources. Research has analyzed the spectrophotometric attributes of blue blockers under various lighting scenarios, encompassing artificial lighting, natural light, and screen illumination. [4] Blue blockers represent an elegant means to prevent the light-induced melatonin suppression. According to these studies, blue blockers may exhibit varying degrees of blue light filtration and alterations in color perception contingent upon the specific lighting context. [5]Researchers have employed a range of measurement strategies and evaluation techniques to assess the spectrophotometric properties of blue blockers. Spectrophotometers and colorimeters have been used to quantify transmittance spectra, color distortions, and overall spectral characteristics of blue blockers. These measurements enable a comprehensive comprehension of the spectrophotometric traits and performance of blue blockers under diverse lighting conditions. [3] It has been shown that abnormal light circumstances can alter mood and cognition directly through the ipRGC circuits' fast-acting direct routes as well as inadvertently through effects on circadian cycles and sleep. Additionally, while evaluating spectrophotometric characteristics, it is vital to consider user experience and visual comfort. Some research has focused on individuals utilizing blue blockers in different lighting environments to understand their subjective experiences. [2]Blue-blocking goggles are a valid intervention to suggest individuals with insomnia or an extended sleep phase because of the biological reason behind their effectiveness for inducing sleep, which has been solidified, and clinical evidence that supports this claim. Beyond their spectrophotometric attributes, assessments of visual comfort, color perception, and [7]visual performance have revealed further practical benefits associated with blue blockers.

Fig. 3. Blue light & Eye health

III. Research Methodology

To develop a machine learning model for "Blue light emission glasses" using the k-nearest neighbors algorithm, the following methodology is employed:

A. Data Collection

Two distinct datasets [1] are meticulously gathered to encompass a wide range of information concerning various types of glasses and their corresponding blue light emission levels. These datasets serve as the foundational source of information for the subsequent stages of model development.

B. Data Preparation

The collected raw data undergoes a rigorous preprocessing phase to ensure its quality and suitability for the training of the k-nearest neighbors algorithm. This process includes a thorough cleansing procedure to rectify any inconsistencies or inaccuracies. Furthermore, the treatment of missing values is undertaken to mitigate their potential impact on the model's performance. To facilitate seamless training, categorical variables are meticulously transformed into numerical representations, and numerical features are standardized or normalized.

C. Feature Selection/Extraction

The dataset is subjected to an intensive analysis to discern the most pertinent features that significantly contribute to predicting blue light emission levels accurately. In this critical phase, considerations extend to factors such as the inherent characteristics of the glass material, the intricacies of the manufacturing process, the presence of coatings, and other relevant attributes. [9]The culmination of this process entails identifying a subset of features that holds the utmost predictive power.

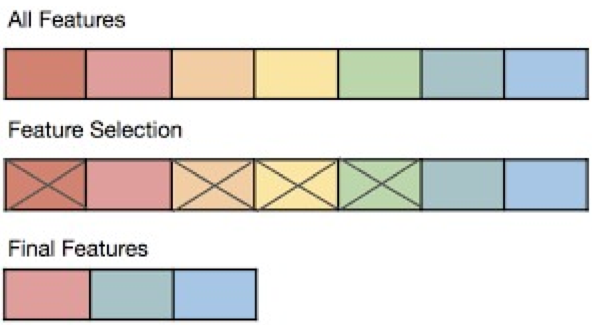

Fig. 4. Selecting features from given data

D. Dataset Splitting

With a primed dataset in hand, it is judiciously partitioned into distinct subsets: a training set and a test set. The training set, constituting around 70-80% of the dataset, serves as the cornerstone for model construction. Conversely, the test set is earmarked for robustly evaluating the model's generalization capabilities. This separation ensures that the model is evaluated on unseen data, a crucial element in assessing its real-world performance.

E. Optimal K Selection

A paramount decision pertains to determining the optimal value for the k in the k-nearest neighbors algorithm. A comprehensive exploration of various k values is undertaken, encompassing experimentation and evaluation. Techniques like cross-validation and grid search are employed to systematically identify the k value that maximizes the model's predictive accuracy and overall performance.

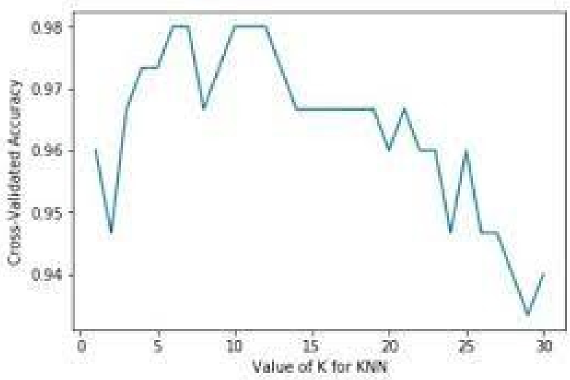

Fig. 5. Value of K vs. Cross-Validated Accuracy

F. Model Training

The core part of the methodology lies in the training phase of the k-nearest neighbors algorithm. This algorithm is rigorously applied to the training set, wherein it orchestrates the identification of the k-nearest neighbors for each data instance. The chosen distance metric governs this process, enabling the algorithm to iteratively refine its predictive capabilities based on the proximity of data points.

G. Model Evaluation

The performance evaluation of the trained k-nearest neighbors model is a pivotal step to gauge its efficacy in predicting blue light emission levels. The test set serves as the crucible for this assessment, wherein the model's predictions are contrasted with the actual values. Essential evaluation metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2), are meticulously computed to provide a comprehensive understanding of the model's predictive accuracy and potential areas for improvement.

H. Parameter Tuning

An iterative process, building upon the findings from the preceding steps, involves fine-tuning the model's parameters. Steps "D to G" are revisited to explore different values of the k and to experiment with various distance metrics. This meticulous process aims to unlock the optimal configuration that fine-tunes the model's predictive prowess, ensuring that it attains the pinnacle of performance.

I. Model Deployment

Upon achieving a level of satisfaction with the model's performance, the final iteration is primed for deployment. This entails integrating the model into practical applications to enable predictions on new instances of glasses. The versatility of deployment extends to integration within broader applications or standalone usage, thereby harnessing the model's predictive capabilities for real-world scenarios.

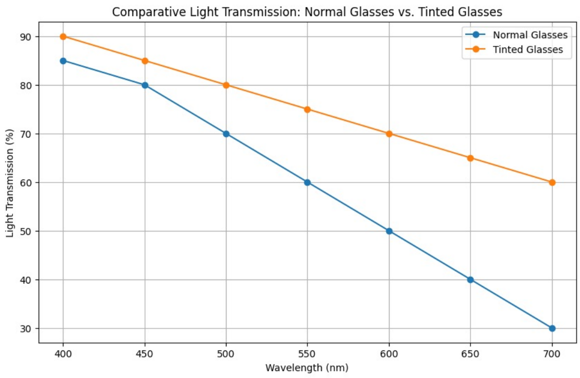

Fig. 6. Comparative Light Transmission: Normal glasses vs. Tinted glasses

IV. Data Analysis

A. Commercially available lenses and circadian rhythm

Commercially available lenses designed to block short-wavelength ("blue") light are marketed to improve circadian rhythm health and sleep. Despite their widespread use, limited information exists about their relative effectiveness in reducing sensitivity to blue light while maintaining visibility. Fifty commercial lenses were tested using a blue LED array, a computer tablet display, an incandescent lamp, a fluorescent overhead luminaire, and natural sunlight. The maximal irradiance across the visual spectrum (380–780 nm) was measured at baseline and for each lens, allowing for the calculation of percentage transmission.

B. Data Requirements

Fifty blue blocker glasses were selected based on their prior use in studies exploring the non-visual effects of light, current marketing claims related to blocking circadian-proficient or "blue" light, and the extent to which the lenses were tinted or filtered (and thus expected to reduce light exposure). Lenses requiring a prescription, unavailable in the American market, or featuring magnification or distortion were excluded.

C. Data Cleaning

The collected raw data from the Blue Blocker glasses was presented in tabular form. This presentation contained both essential and extraneous information for this specific study. The use of OpenRefine facilitated the organization of rows and columns for data examination and cleansing purposes. Missing and null data values were excluded, and columns and rows were merged to align with the study's criteria and software analysis.

D. Data Processing

To discern whether light transmission was predominantly circadian-proficient (455–560 nm) or non-proficient (380–454 nm and 561–780 nm), transmission specificity was evaluated. Measurements were compared among groups of lenses after categorizing them by tint. The transmission of circadian-proficient illumination was least pronounced in red-tinted glasses and most pronounced in reflective blue lenses. While orange-tinted lenses and red-tinted lenses transmitted similar amounts of circadian-proficient light, the former also transmitted more non-circadian-proficient light, leading to increased transmission specificity. In normal daylight conditions, orange-tinted glasses exhibited the highest transmission specificity while restricting exposure to physiologically active light. Currently, glasses equipped with these lenses hold significant potential to regulate circadian sleep-wake rhythms.

V. Prototype Implementation

A. Data Preprocessing

The prototype implementation of the research involves a crucial phase of data preprocessing to lay the groundwork for subsequent stages. This section provides an insightful overview of the process, model initialization, training, prediction, evaluation, visualization and metric interpretation employed to ensure the dataset's suitability for model development and evaluation. The implementation commences by meticulously importing requisite libraries, including numpy, pandas, scikit-learn (sklearn), and matplotlib. These libraries form the bedrock of the implementation, enabling seamless data manipulation, robust machine learning modeling, and effective visualization of outcomes. The cornerstone of the data preprocessing phase resides in the dataset itself, encompassing both the relevant features and the pivotal target variable, i.e., spectrometric values. The dataset, housed within a CSV file, serves as the bedrock of the implementation process. The pivotal pd.read_csv() function, a cornerstone of the pandas library, is harnessed to efficiently load the dataset into a structured DataFrame christened as *data*. This DataFrame acts as a malleable container, affording researchers a dynamic platform to interact with the data at every step. To pave the way for effective modeling and evaluation, the dataset is thoughtfully divided into two core components: the input features (x) and the target variable (y). A pivotal step involves the utilization of the train_test_split() function, seamlessly integrated from the sklearn library. This fundamental procedure partitions the dataset into discrete subsets designated for training and testing, a practice paramount in machine learning endeavors to rigorously evaluate the model's predictive performance. The resultant dataset, primed for subsequent stages, bears testimony to the careful curation and thoughtful handling of data, setting the stage for the ensuing stages of model development and evaluation.

B. Model Initialization and Training

Three regression models are initialized: Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), and Linear Regression. These models are initialized using their respective classes from the sklearn library. Each model is then trained using the training data (input features and target variable) using the .fit() method.

C. Prediction and Evaluation

After training, the models are used to make predictions on the testing set (x_test). The predicted values are stored in svm_pred, knn_pred, and linear_pred for each respective model. Several evaluation metrics are calculated for each model, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2). These metrics are used to assess the performance of each model.

D. Visualization

A scatter plot is created to visually compare the actual spectrometric values (y_test) against the predicted values (knn_pred) from the K-NN model. This plot helps to visualize how well the model's predictions align with the actual values.

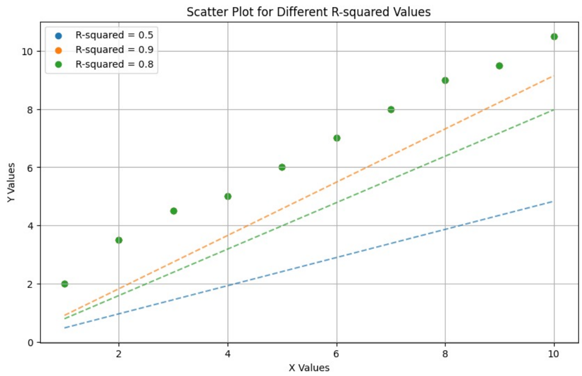

Fig. 7. Scatter plot for different R-squared values

E. Metric Interpretation

The code provides an interpretation of the evaluation metrics for each model. It explains how to interpret higher and lower values of MSE, RMSE, and MAE, and how R2 indicates the variance explained by the models.

F. Conclusion

Based on the evaluation results and interpretation, the K-NN model performs the best among the three models for predicting the spectrometric characteristics of blue-light-blocking eyewear. It recommends using the K-NN model due to its accuracy and strong R2 score.

VI. Result Analysis

This analysis is aimed at comparing the performance of three regression models for predicting the spectrometric characteristics of blue-light-blocking eyewear: Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), and Linear Regression. The goal is to comprehend how well these models predict the spectral properties of the glasses based on input parameters. We implement the following evaluation indicators to rate the performance of the models:

Mean Squared Error (MSE): Mean squared error (MSE) measures the average squared difference between the predicted and actual spectrometric values. A lower MSE suggests more accurate prediction. Mathematically, it is calculated from the formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

Root Mean Squared Error (RMSE): Root Mean Squared Error (RMSE) measures error in the same unit as spectrometric data and is the square root of Mean Squared Error (MSE). Mathematically calculated as:

$$RMSE = \sqrt{MSE} \tag{2}$$

Mean Absolute Error (MAE): Mean Absolute Error (MAE) represents the average absolute difference between the expected and actual values. Mathematically calculated as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

R-squared (R2): R-squared (R2) denotes the percentage of the variance in the spectrometric data that the models are able to account for. The better the fit, the greater the R2. Mathematically calculated as:

$$R2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

A. *Model Evaluation Results*

Support Vector Machine (SVM):
In this study, we employed the Support Vector Machine (SVM) method to analyze a dataset of blue light blocking glasses. Our dataset encompassed various features related to the glasses' characteristics, such as lens type, Circadian transmission, non-circadian transmission and specificity. Through a supervised learning approach, we labeled glasses as "effective" or "ineffective" in blocking blue light based on predefined criteria. Following data preprocessing and splitting, we trained the SVM model to classify the glasses. The SVM model's performance was evaluated using performance evaluation metrics, revealing valuable insights into the glasses' effectiveness in mitigating blue light. By leveraging SVM's classification capabilities, we gained a nuanced understanding of how different attributes contribute to the glasses' performance, shedding light on their potential benefits and informing future design considerations.

K-Nearest Neighbors (K-NN):
In this study, we used the K-nearest neighbors (KNN) method to examine a dataset pertaining to blue light-blocking eyewear. Based on predetermined criteria, we classified glasses as "effective" or "ineffective" at reducing blue light using a supervised technique. We used the KNN method to forecast the effectiveness of the glasses after preprocessing and splitting the data. The performance of the glasses in reducing blue light was evaluated using pertinent measures, which produced insightful results. We were able to get a thorough grasp of the various features that affect the performance of the glasses by utilizing KNN's proximity-based categorization, which has important implications for their design and usefulness.

Linear Regression:
Finally, to analyze our dataset, we used linear regression analysis. Our dataset included a variety of parameters, including specificity, lens kinds, non-circadian transmission, and circadian transmission features. We sought to find relationships between these characteristics and how well the glasses minimized blue light using a regression approach. To calculate the effect of different features on blue light reduction, we built a linear regression model using data preprocessing and division. The practicality of the model was evaluated using pertinent measures, which provided insightful information about the connections between features and efficacy. We were able to get important insights into the aspects that contributed to the performance of the glasses by utilizing the interpretability of linear regression, which has important ramifications for design optimization and reasoned decision-making.

TABLE I
MODEL EVALUATION RESULTS IN TABULAR FORMAT

	Mean Squared Error (MSE)	**Root Mean Squared Error (RMSE)**	**Mean Absolute Error (MAE)**	**R-Squared**
Support Vector Machine (SVM)	211.039	14.527	10.365	0.483
K-Nearest Neighbor (K-NN)	35.059	5.921	3.844	0.914
Linear Regression (LR)	82.907	9.105	1.399	0.797

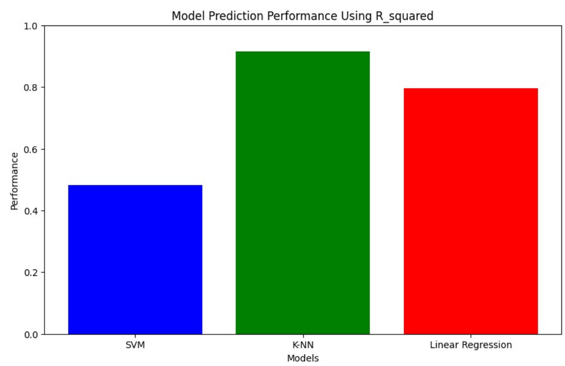

Fig. 8. Model Prediction Performance using R-Squared

B. *Metric Interpretation*

- Higher MSE, RMSE, and MAE values in the SVM model point to more prediction errors and a weaker fit.

- Lower MSE, RMSE, and MAE values for K-NN indicate superior performance with higher predicted accuracy, as well as a better R2.
- By balancing fit and accuracy, linear regression delivers a decent R2 score and reasonable error metrics.

C. Conclusion

The K-NN model stands out as the best performance when evaluation criteria and visualizations are taken into account. The highest R2 score and the lowest error metrics indicate accurate and well-fitted predictions. While the SVM model trails behind due to larger prediction errors and lesser explanatory power, linear regression also demonstrates promise.

In conclusion, it is advised to use the K-NN model to forecast the spectrometric characteristics of blue-light-blocking eyewear. Its remarkable accuracy and strong R2 score show that it is capable of accurately estimating spectral characteristics. This analysis offers suggestions for choosing a reliable regression model to forecast spectrometric characteristics in the context of blue-light-blocking eyewear.

REFERENCES

[1] B. J. Mason, A. S. Tubbs, F.-X. Fernandez, and M. A. Grandner, "Spectrophotometric properties of commercially available blue blockers across multiple lighting conditions," figshare, 2022. [Online].

[2] D. Dange, C. J. Barker, M. Heath, S. Mesiya, T. Tienabeso and K. Watson, "Evening wear of blue-blocking glasses for sleep and mood disorders: a systematic review", 2021. [online]. https://doi.org/10.1080/07420528.2021.1930029

[3] S. Skrede, O. B. Fasmer, H. Schoeyen, L. Leva, B. B. Jeanette, J. Assmus, B. Hamre, G. Janne, A. Lund, "Blue-blocking glasses as additive treatment for mania: a randomized placebo-controlled trial ". 2016 [2016]. https://doi.org/10.1111/bdi.12390

[4] A. Sasseville, N. Paquet, J. Sévigny, M. Hébert, "Blue blocker glasses impede the capacity of bright light to suppress melatonin production", 2016. https://doi.org/10.1111/j.1600-079X.2006.00332.x

[5] H. S. Alzahrani, S. K. Khuu, M. Roy, "Modelling the effect of commercially available blue-blocking lenses on visual and non-visual functions", 2021. https://doi.org/10.1111/cxo.12959

[6] J. G. Lawrenson, C. C. Hull, L. E. Downie, "The effect of blue-light blocking spectacle lenses on visual performance, macular health and the sleep-wake cycle: a systematic review of the literature", 2017. https://doi.org/10.1111/opo.12406

[7] J. A. Bigalke, I. M. Greenlund, J. R. Nicevski, J. R. Carter. "Effect of evening blue light blocking glasses on subjective and objective sleep in healthy adults: A randomized control trial", Volume 7, Issue 4, August 2021, Pages 485-490. https://doi/S2352721821000127

[8] G. Hockstein, C. MD. Dunaief, J. L. MD, "Could Blue Light–Blocking Lenses Decrease the Risk of Age-Related Macular Degeneration?". 2016 https:doi/2006/01000/.1.aspx

[9] Y. Esaki, T. Kitajima, Y. Ito, S. koike, Y. Nakao, T. Akiko, M. Hirose, "Wearing blue light-blocking glasses in the evening advances circadian rhythms in the patients with delayed sleep phase disorder: An open-label trial". 2016, https://doi.org/10.1080/07420528.2016.1194289

[10] A. C. Gregoire, B. M. J. Merle, T. Aslam, J. M. Seddon, I. Aknin, C. C. W. Klaver, Gerhard Garhöfer, Alfredo G. Layana, A. M. Minnella, R. Silva and C. Delcourt, "Blue Light Exposure: Ocular Hazards and Prevention—A Narrative Review", 2023. https://doi/10.1007/s40123-023-00675-3