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Comprehensive System Framework for Visual Fatigue and Cognitive Performance Management based on Predictive Models

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Abstract: With the modern workplace's increasing dependence on computer-based tasks, traditional lighting standards have been identified as insufficient for optimal occupant comfort and productivity. Therefore, this paper presents a comprehensive system framework designed to manage visual fatigue and cognitive performance within office environments. Classification and regression models using gradient boosting machine and random forest to predict visual fatigue and cognitive performance were developed based on data collected from 16 subjects in experiments. To this end, the proposed system consists of two modules: the first module predicts visual fatigue and cognitive performance levels using classification models, offering immediate feedback to occupants. The second module, targeted at facility managers, uses regression models and a genetic algorithm to identify optimal lighting settings, aiming to minimize visual fatigue and enhance cognitive performance. This system can help to manage visual fatigue and cognitive performance simultaneously, contributing to improvement of eye health and productivity.

Keywords: visual fatigue, cognitive performance, predictive model, lighting, multi-objective optimization

1. INTRODUCTION

In the modern workplace, the significance of lighting in built environments has surpassed its basic functionality, which is visibility, to encompass aspects of health, well-being, and productivity. Particularly, with the rise of computer-based tasks, recent studies have reported that traditional indoor lighting standards may not be optimal for some occupants due to the luminous screens that are stimulating to the eyes [1-2]. Occupants in the modern workplace are also easily exposed to visual fatigue symptoms such as computer vision syndrome which severely affects eye health [3]. While thermal environments can be uniformly maintained for most occupants by setting the appropriate temperature through heating or cooling systems, the lighting environment can create varying levels of visual fatigue for each occupant due to factors not only from artificial lighting but also from factors like daylight and luminous screens. However, recent studies are still focusing on investigating certain illuminance or correlated color temperature that is optimal for occupants' visual fatigue [4-5]. Accordingly, the traditional approach of uniformly controlling indoor environments to minimize visual fatigue caused by office lighting environments may not be effective. Insights into resolving this issue can be found by looking at the latest research on indoor environments, especially on those related to thermal environment. Recent studies on thermal environments have predominantly focused on creating hyper-personalized environments by predicting occupants' individual thermal comfort based on actual data from occupants [6-7]. However, research into lighting environments has yet to be conducted in this direction. Also, minimizing visual fatigue for eye health enhancement is critical, yet maintaining productivity above a certain level is equally important, as the primary purpose of spaces like offices is generating profits. However, visual tasks are integral to work productivity and minimizing visual fatigue without considering these issues could impact productivity. Thus, there is a need for an intelligent system that comprehensively manages both aspects.

Previous studies have investigated visual fatigue under lighting environments and sought to identify lighting environments that could satisfy visual comfort. Notably, with the development of eye-tracking technology that can measure pupil size and detect blinks, research in this area has become more active. Additionally, studies have continuously been conducted up to the present measuring learning effects or work productivity that require cognitive abilities. Liu et al. (2021) investigated the impact of luminance contrast on occupants' visual fatigue and visual tasks through experiments [8]. Another study applied eye blink frequency as an objective measure of visual fatigue and surveys as a subjective measure, examining changes when using display screens under different illuminance levels [9]. Despite previous efforts including these studies, studies developing models to predict visual fatigue have been rare. Most models predicting visual fatigue focused on visual fatigue induced by displays rather than lighting environments, not considering occupants' physiological responses or lighting environments as predictive variables but concentrating on the video's pixels or frames. Most of the studies that aimed to predict visual fatigue primarily focused on the development stage of technologies for detecting eye blinks [10]. Compared to the active development of machine learning-based models for predicting occupants' indoor environmental evaluations like thermal comfort or satisfaction, research on developing visual fatigue prediction models based on various physiological responses is clearly lacking. Models predicting cognitive performance have been conducted more frequently than those for visual fatigue. However, research on developing systems or modules that manage both visual fatigue and cognitive performance simultaneously has been almost nonexistent.

Therefore, this study aims to develop classification and regression models for predicting visual fatigue and cognitive performance and to propose a system framework that can comprehensively manage visual fatigue and cognitive performance based on these models. Firstly, physiological response and cognitive performance data were collected from 16 healthy subjects and preprocessed. Secondly, classification and regression models were developed, and their predictive performances were assessed. Lastly, framework of the visual fatigue and cognitive performance management system was proposed. To this end, comprehensive system that consists of two modules was suggested: (i) Module 1 to predict visual fatigue and cognitive performance based on classification model; and (ii) Module 2 to derive optimal lighting environment for visual fatigue and cognitive performance.

2. MATERIALS AND METHODS

In this study, classification and regression models to predict visual fatigue and cognitive performance were developed based on data collected from 16 subjects, and the system framework was proposed.

2.1. Data collection and preprocessing

To develop models for predicting visual fatigue level and cognitive performance, human subject experiments were conducted for data collection. 16 healthy adults who are in their 20s and 30s and had no history of chronic diseases including oscular issues were recruited as subjects of the experiments. In the experiments, nine different office lighting types were tested to evoke various visual fatigue levels and cognitive abilities. Nine office lighting types were combinations of three levels of illuminance (i.e., 200lx, 500lx and 800lx) and three types of correlated color temperature (i.e., 4,000K, 5,000K, and

6,500K) that are generally used in office environments. Subjects conducted primary and complex cognitive ability tests on the computer for 15 minutes and responded to a survey related to visual fatigue after the cognitive ability tests. This procedure was repeated for nine times where different office lighting types were formed in random order. During the experiment, three major measurements were conducted: (i) cognitive abilities, (ii) subjective visual fatigue levels, and (iii) physiological responses.

Firstly, complex cognitive ability tests measured creativity, reasoning, and comprehension ability that are commonly used in office. To measure creativity quantitatively, alternative uses task (AUT) test, in which subjects are asked to think of as many uses as possible for a common object within a set period of time, was conducted [11]. Reasoning was measured by number pattern tests in which subjects have to infer the pattern of the sequence of numbers presented and identify the number that fits in a missing space [12]. Also, three passages were given to subjects to answer multiple-choice comprehension questions [13]. Primary cognitive ability tests were conducted to activate cognitive ability and engagement of subjects as the experiment was conducted for nine times. So, only complex cognitive ability test results were used to develop prediction models, and the test scores were calculated using Eq (1) and standardized using T-score.

$$Cognitive\ performance = \left[(Accuracy)^{0.5} \times \frac{1}{(Response\ time)^{0.5}}\right]^2 \tag{1}$$

Secondly, subjective visual fatigue level was measured by survey that is designed to evaluate various visual fatigue symptoms perceived by the subjects on a seven-point Likert scale. The specific questions used to evaluate visual fatigue include: (i) eye fatigue, (ii) eye pain, (iii) eye dryness, (iv) eye itchiness, (v) blurred vision, (vi) double vision and (vii) glare. Lastly, various physiological responses were measured by electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG) and eye-tracking glasses. EEG, EOG and ECG data were collected by Biopac Systems, and raw data was preprocess by AcqKnowledge software that Biopac Systems provide [14]. EEG data in the time domain were transformed into four distinct frequency bands (i.e., delta wave, theta wave, alpha wave, and beta wave) across the frontal, temporal, parietal, and occipital lobes, respectively, using power spectral density (PSD) method. From raw ECG data, mean heart rate (MHR), standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) were extracted. Eye-tracking glasses was Tobii Glasses 3 manufactured by Tobii Technology, and the raw data was preprocessed to extract eye validity and pupil diameter by Tobii Pro Lab software. Consequently, the pupillary unrest index (PUI) and blink amplitude (BA) were calculated based on the preprocessed data.

2.2. Predictive model development

The system proposed in this study is mainly based on classification and regression models to predict visual fatigue level and cognitive performance (i.e., creativity, reasoning, and comprehension ability). These predictive models were developed by supervised machine learning algorithms, specifically gradient boosting machine (GBM) and random forest (RF). Both algorithms offer strong predictive performance, prevent overfitting through their unique learning processes, allow for the identification of feature importance, and are versatile, applicable to multi-class classification, and regression problems. In this study, both classification and regression models were developed as the distinct characteristics of each were essential for the system. Specifically, classification models offer the advantage of producing more intuitive results compared to regression models, making them easier for end-users, such as occupants, to understand. On the other hand, regression models, which yield outcomes in continuous numerical values, are more advantageous for solving problems like multi-objective optimization. Fig 1 shows the process of predictive model development.

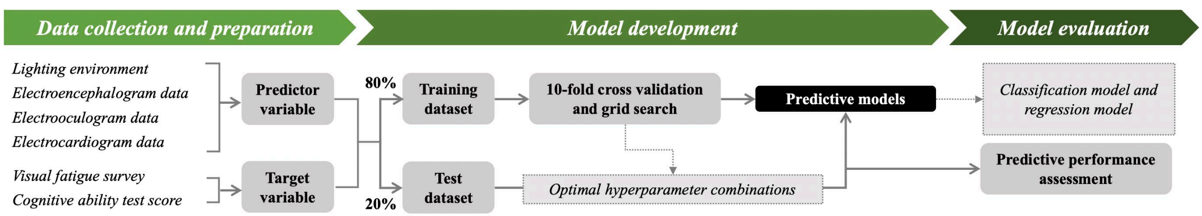

Fig 1. Procedure of predictive model development

Both the classification and the regression model used to predict visual fatigue level and cognitive performance share the same predictor variables. Predictor variables consist of lighting environment (i.e., illuminance and correlated color temperature) and physiological responses. The physiological responses used as predictor variables include delta, theta, alpha, and beta waves from four brain regions (i.e., frontal, temporal, parietal and occipital lobes) with a 1-minute time window applied, along with MHR, SDNN, RMSSD, PUI, and BA. Also, all predictor variables were normalized by min-max normalization. The target variable for visual fatigue level was derived from survey results. Principal component analysis (PCA) was used to derive a single target variable for visual fatigue from the results of seven survey questions (refer to Eq (2)). Using PCA enabled the identification and extraction of a principal component that captures the maximum variance within the dataset, which in this context, represents the underlying factor of visual fatigue as perceived by the occupants. This approach ensures that the derived target variable for visual fatigue embodies the most critical aspects of the condition as reported across the seven survey questions. The T-scores of cognitive ability tests were also applied as target variables. Consequently, four target variables (i.e., visual fatigue, creativity, reasoning, and comprehension) were prepared and for classification models, they were classified into three levels: (i) high (i.e., 1), (ii) neutral (i.e., 0) and (iii) low (i.e., -1).

$$Integrated\ index = \sum_{i=1}^{k} L_1 \cdot X_1 + L_2 \cdot X_2 + \cdots + L_k \cdot X_k \qquad (2)$$

Where, L stands for the loading of principal component; X stands for survey response value.

The datasets were divided into training datasets for model training and test sets for performance evaluation. The split ratio was decided based on previous research that reported the ideal split ratio between the training set and test set is the $\sqrt{p}$:1, where p represents number of predictor variables [15]. 10-fold cross-validation and grid search were conducted using training dataset to derive optimal hyperparameter combinations and to train the model. Lastly, the performance of models was assessed with various indices. For classification models, accuracy, precision, recall, F1 score and area under the receiver operating characteristics curve (AUC-ROC) were used for performance indices. Also, mean square error (MSE), root mean squared error (RMSE), mean absolute error (MAE), R^2 and adjusted R^2 were used for performance indices of regression models.

2.3. Proposal of visual fatigue and cognitive performance management system

A comprehensive system framework for visual fatigue and cognitive performance based on predictive models was proposed as Fig 2.

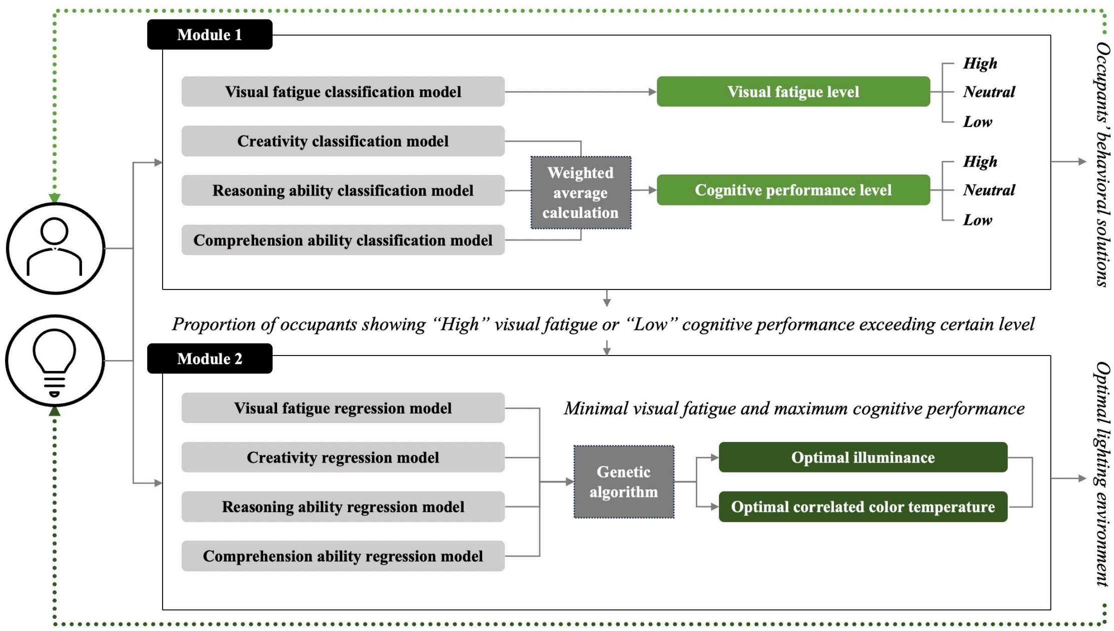

Fig 2. Framework of the system for visual fatigue and cognitive performance management

Module 1 is mainly for individual occupants to perceive their visual fatigue and cognitive performance level directly and manage them with behavioral solutions. Therefore, Module 1 consists of four classification models to respectively predict visual fatigue, creativity, reasoning. and comprehension ability. However, if prediction results are derived for three different cognitive abilities, maintaining a balance between visual fatigue and cognitive performance might become challenging due to an excessive number of considerations, making it difficult to comprehend the situation. Therefore, the results of classification models for predicting three cognitive abilities can be calculated by weighted average method and classified into three classes again.

Module 2 is designed for building or facility manager as this module decides optimal lighting environment for occupants based on actual data of occupants. This module activates if the proportion of occupants showing high visual fatigue level or low cognitive abilities, based on the results of Module 1, exceeds a certain level. Module 2 consists of regression models and genetic algorithm for multi-object optimization. Genetic algorithms are methods that solve optimization problems by mimicking the principles of natural selection and genetics. In this study, the multi-objective optimization defined the objective function using actual data, which is not formulated through equations or mathematical models. Moreover, the decision variables for optimization were defined as the elements of the lighting environment, namely correlated color temperature and illuminance. Consequently, performing multi-objective optimization based on real data can derive the lighting that minimize visual fatigue and maximize cognitive performance for the occupants. Correlated color temperature and illuminance are continuous values, with correlated color temperature set within the range typically used in office lighting, 4,000-6,500K, and illuminance constrained between 0-1,000 lux. The optimization carried out in this study is a form of multi-objective optimization, using the weighted Euclidean distance to define the fitness function. The weights can be determined based on the importance of each objective function, with the goal of minimizing visual fatigue, meaning solutions closer to 0 are optimal. Conversely, for the three cognitive task abilities, the goal is maximization, thus solutions closer to 1 are considered optimal. The fitness function defined in this manner is expressed as Eq (3), and the optimal lighting environment is defined by the values of the decision variables when the fitness score, derived using this fitness function, achieves the minimum value closest to the origin on the coordinate plane.

$$Fitness\ function = \sqrt{w_1 \times (S_1 - 0)^2 + w_2 \times (1 - S_2)^2 + w_3 \times (1 - S_3)^2 + w_4 \times (1 - S_4)^2} \quad (3)$$

Where, w stands for the weights of each objective function; S_1 stands for visual fatigue; S_2 stands for creativity; S_3 stands for reasoning ability; and S_4 stands for comprehension ability.

3. RESULTS AND DISCUSSIONS

In this study, classification and regression models are developed and the rest of the system is suggested as framework. In this section, predictive performances are assessed, and implications along with limitations of each module are also suggested.

3.1. Performance assessment of predictive model

Classification models were developed to predict visual fatigue level, creativity, reasoning, and comprehension abilities (refer to Table 1). As GBM showed better performance for all classification models than RF in this study, models based on GBM are selected for optimal classification models for the visual fatigue and cognitive performance management system. Firstly, classification models to predict visual fatigue showed a relatively high performance with an average performance of 88.27% and accuracy of 86.11%. Also, the optimal hyperparameter combination for the visual fatigue model was as follows: the number of estimators is 100; maximum depth is 7; and subsample is 1.0. Secondly, the average predictive performance of the cognitive performance classification model was consistently between 85% and 87%. Classification model to predict creativity showed accuracy of 83.33% while the optimal hyperparameter combination was as follows: the number of estimators is 200; maximum depth is 7; and subsample is 1.0. The accuracy of classification model to predict reasoning ability was 84.29%, the optimal hyperparameter combination matched those for creativity, with the exception that the number of estimators was 300. Classification model to predict comprehension ability showed accuracy of 83.80% and the optimal hyperparameter combination was as follows: the number of estimators is 200; maximum depth is 7; and subsample is 0.8.

Table 1. Predictive performance of classification models (Unit: %)

Target variable	Algorithm	Accuracy	Precision	Recall	F1	AUC-ROC	Average
Visual fatigue	GBM	86.11	86.12	86.11	86.05	96.96	88.27
	RF	80.56	80.63	80.56	80.50	94.41	83.33
Creativity	GBM	83.33	83.48	83.33	83.27	95.03	85.69
	RF	73.15	73.62	73.15	73.03	89.70	76.53
Reasoning	GBM	84.26	84.46	84.26	84.24	95.95	86.63
	RF	80.09	80.46	80.09	80.06	92.41	82.62
Comprehension	GBM	83.80	84.05	83.80	83.76	95.40	86.16
	RF	78.47	79.10	78.47	78.33	92.29	81.33

Regression models were developed to predict visual fatigue level, creativity, reasoning, and comprehension abilities (refer to Table 2). Optimal regression models for the visual fatigue and cognitive performance management system were selected based on adjusted R^2. Consequently, the model for predicting visual fatigue was determined to be optimal using GBM, while the models for predicting cognitive performance were identified as optimal when using RF as the regression model. Firstly, regression model to predict visual fatigue showed RMSE of 0.19 and also showed the highest adjusted R^2 among the regression models, specifically 0.71. The optimal hyperparameter combination for the visual fatigue model was as follows: number of estimators is 300; maximum depth is 7; and subsample is 0.8. Also, regression model to predict creativity showed RMSE of 0.21 and showed highest adjusted R^2 among models to predict cognitive abilities. The result of grid search showed that the optimal hyperparameter combination was as follows: number of estimators is 400; maximum depth is 30; minimum samples split was 2; and the maximum features is 'sqrt'. RMSE of regression model to predict reasoning ability was 0.14 which was the lowest among the regression models, but adjusted R^2 was also the lowest. The optimal hyperparameter combinations were same with those for creativity with the exception that maximum features were 'log2'. Lastly, the regression model to predict comprehension ability showed similar performance to those of reasoning, with RMSE of 0.15.

Table 2. Predictive performance of regression models

Target variable	Algorithm	MSE	RMSE	MAE	R^2	Adjusted R^2
Visual fatigue	GBM	0.04	0.19	0.13	0.71	0.71
	RF	0.04	0.21	0.16	0.64	0.64
Creativity	GBM	0.01	0.12	0.09	0.58	0.58
	RF	0.04	0.21	0.16	0.65	0.64
Reasoning	GBM	0.02	0.13	0.09	0.50	0.49
	RF	0.02	0.14	0.11	0.51	0.50
Comprehension	GBM	0.02	0.13	0.09	0.62	0.61
	RF	0.02	0.15	0.11	0.50	0.50

3.2. Module 1: Visual fatigue and cognitive performance level prediction

Module 1 of the visual fatigue and cognitive performance management system consists of four classification models to predict visual fatigue and cognitive performance. This module is mainly designed for individual occupants as the results of this model are intuitive classes that display visual fatigue and cognitive performance levels based on individual occupants' physiological responses. Also, to help occupants understanding the current status and making better decision, cognitive performances of creativity, reasoning and comprehension are yielded as a single class calculated by weighted average method. Thus, occupants can refer to the predictions of classification models and make decisions to manage their visual fatigue and cognitive performance with behavioral solutions. For example, occupants can perceive that their visual fatigue is relatively high and adjust monitor brightness or task lighting to reduce their visual fatigue. This module can be helpful for occupants that are insensitive about visual fatigue, as this module can make occupants perceive their status based on physiological responses. Also, this module can help occupants manage their visual fatigue while considering their cognitive performance simultaneously to maintain or enhance their work productivity.

However, this module also has some limitations and challenges for the future study. Firstly, this module does not provide specific solutions to the occupants but to make them aware of their current status. Therefore, the behavioral measures taken by the occupants may not always result in an improvement of the status. For the future study, if the module can be developed to recommend specific solutions based on the predictions of visual fatigue and cognitive performance, it could enhance practical implications. Moreover, by providing personalized recommendations through individual data and reinforcement learning, along with task lighting or appropriate adjustment of monitor brightness, more precise management would be achievable. Also, the weight of each cognitive ability has not been determined in this study. Thus, the method of deriving the prediction results to a single class should be further studied.

3.3. Module 2: Derivation of lighting environment for visual fatigue and cognitive performance optimization

Module 2 of the visual fatigue and cognitive performance management system consists of four regression models and genetic algorithm to derive optimal lighting environment based on prediction of visual fatigue and cognitive performance. In this study, regression models to predict visual fatigue and cognitive performance in continuous values were developed and their predictive performances were assessed. Also, optimization by genetic algorithm were suggested as framework. It appears theoretically possible to derive correlated color temperature and illuminance that minimize visual fatigue and maximize three cognitive abilities through genetic algorithms [16]. However, since the objective function is based on actual data rather than a mathematical model, convergence to specific values was challenging in this study due to the limited diversity of the data. While Module 1 was designed for individual occupants, Module 2 is intended for facility managers who need to manage the overall indoor environment. Module 2 overcomes the limitation that the behavioral measures taken by individual occupants through Module 1 are not always appropriate, by deriving the optimal lighting environment based on the actual data of occupants. Also, this module is designed to operate only when the proportion of occupants with high visual fatigue or low cognitive performance exceeds a certain level, due to the potential for continuous changes in the lighting environment to induce visual fatigue.

This module also has several limitations. First, as identified in this study, a sufficient diversity of data is required for the module to function correctly. The module has been developed with only a regression model, and the remaining aspects are proposed as a framework, necessitating further research for validation. Additionally, future studies are needed to determine the criteria for Module 2's activation and to set the weights for the fitness function. Secondly, the predictive performance of the regression model may be somewhat lower compared to the classification model. Due to different performance indices, objective comparison might be challenging, yet the regression model has room for improvement in terms of overall performance enhancement.

4. CONCLUSION

This research proposes a comprehensive system to manage visual fatigue and cognitive performance within office environments based on classification and regression models for prediction and optimization. Data was collected from experiments involving 16 adults under nine different office lightings. Based on machine learning algorithms, specifically gradient boosting machine (GBM) and random forest (RF), classification and regression models to predict visual fatigue and cognitive performance were developed. These models showed promising results, with classification models achieving an accuracy of 73.15-86.11% and regression models showing mean square error of 0.01-0.04. The research introduced two modules based on these predictive models and genetic algorithm: Module 1 for individual occupants, providing intuitive feedback on their status, and Module 2 for facility managers, suggesting an optimal lighting environment based on actual occupants' data.

This study has significant implications, specifically that models to predict visual fatigue has been developed and that system to enhance eye health and productivity in office environments where most tasks are conducted on computers has been newly proposed. The classification and regression models developed in this study form the foundation for a management system that can offer both immediate, intuitive feedback to occupants and strategic, data-driven environmental adjustments by facility managers. However, the study recognizes its limitations, notably the challenge of reducing number of predictor variables and validation of the system framework.

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