

Bio-signals based occupant-centric lighting control for cognitive performance, visual fatigue and energy consumption

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ABSTRACT

While artificial lighting significantly impacts occupants' health and productivity in commercial buildings, current fixed lighting conditions lack the adaptability to real-time occupant status, highlighting the need for a more responsive and data-driven approach. This study presents the Cognitive Performance (CP), Visual Fatigue (VF), and Energy consumption Optimization (CVEO) model for occupant-centric lighting control. The CVEO model aims to search for correlated color temperature and illuminance that maximize CP while minimizing VF and energy consumption using non-dominated sorting genetic algorithm-II. In this study, the objective functions involve stacking ensemble models that predict CP and VF based on occupants' bio-signals (i.e., heart rate variability, brain waves, and ocular response) and tree-based machine learning algorithms. For model evaluation, experiments were conducted based on the collected data from 15 subjects. As a result of evaluating stacking ensemble models, personal models outperformed general models, with root mean squared errors averaging 0.023 and 0.012 for CP and VF predictions, respectively. Additionally, in 2,000 scenarios with randomly determined presence of the 15 occupants, the CVEO model showed better performance in objectives than fixed lighting conditions from previous studies. The CVEO model can dynamically reflect real-time occupant status through bio-signals, thereby optimizing lighting to enhance work productivity, alleviate eye-related symptoms, and achieve energy savings. This approach offers significant potential for improving indoor environmental quality and occupants' well-being.

1. Introduction

1.1. Research background

Artificial lighting in buildings has advanced beyond its initial purpose of providing visibility, contributing to sustainable building practices by enhancing occupants' health [1,2], productivity [3,4], and energy saving [5,6]. As lightings facilitate various tasks, demands for diverse lightings for different purposes have also emerged, a compound annual growth rate of the smart lighting market increasing to 22.1 % from 2023 to 2030 [7]. Meanwhile, artificial lighting energy consumption accounts for 16.5 % of the world's annual electricity production, indicating significant potential for energy savings [8]. Consequently, interest has increased in developing smart lighting controls that adjust lighting conditions based on occupancy or daylighting to improve occupants' well-being and reduce building energy consumption [9–12].

In addition to building energy consumption, lighting significantly

affects biological mechanisms and emotions [13–16], leading to a surge in demand for occupant-centric lighting control. Unlike existing lighting control focused on energy saving, occupant-centric lighting control adjusts the correlated color temperature (CCT) of lighting according to occupants' preference or controls lighting conditions based on occupants' behavior [17]. Particularly, occupant-centric lighting control has become an essential technology to be incorporated into the lighting design of commercial buildings such as classrooms and offices [18,19]. Introduction of occupant-centric lighting control in commercial buildings is driven by two major motivations. First, lighting control in commercial buildings targets occupants primarily performing visual tasks such as learning and working; therefore, the lighting environment must be designed to consider occupants' work productivity and learning efficiency. Thus, numerous studies have been conducted to observe and analyze occupants' physiological responses and cognitive test scores in relation to lighting conditions, making occupants' cognitive performance (CP) a crucial aspect of occupant-centric lighting control [20–23]. Consequently, lighting control technologies that not only minimize energy consumption but also enhance occupants' work

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Nomenclature		HR	Heart rate
BA	Blink amplitude	MAPE	Mean absolute percentage error
CBR	CatBoost regressor	NSGA-II	Non-dominated sorting genetic algorithm-II
CCT	Correlated color temperature	PCA	Principal correlation analysis
CP	Cognitive performance	PSD	Power spectral density
CVEO	Cognitive performance, visual fatigue, and energy consumption optimization	PUI	Pupillary unrest index
ECG	Electrocardiography	RFR	Random forest regressor
EEG	Electroencephalography	RMSE	Root mean squared error
EOG	Electrooculography	RMSSD	Root mean square of successive differences
GBM	Gradient boosting regressor	SDNN	Standard deviation of NN intervals
		VF	Visual fatigue
		XGR	XGboost regressor

productivity or learning efficiency have been developed [24]. Secondly, unlike the past when paper-based work was predominant, occupants in modern classrooms and offices mainly use visual display terminals, necessitating lighting conditions that also consider occupants' eye health [25]. Particularly, research has been conducted to create lighting environments that can reduce eye-related symptoms such as computer vision syndrome, addressing the issue of persistent visual fatigue (VF) and ensuring visual comfort [26].

Therefore, this study proposed an occupant-centric lighting control method that simultaneously considers occupants' CP, VF and energy consumption based on bio-signals. Firstly, a framework of a multi-objective optimization model for occupant-centric lighting control was proposed. Then, experiments were conducted to evaluate the performance of the stacking ensemble models and multi-objective optimization model using collected data. The CVEO model showed significant effects in maximizing occupants' CP and minimizing VF and energy consumption.

1.2. Related works

In previous studies, various research efforts have been conducted for occupant-centric lighting control in commercial buildings. Firstly, studies have proposed specific lighting conditions to enhance occupants' cognition-based work productivity or learning efficiency, and to prevent eye-related symptoms (refer to Table 1). These studies conducted experiments to analyze impact of lighting conditions on CP and VF. The aim of these studies was to narrow down the range or value of optimal lighting conditions for specific objectives (i.e., CP or VF).

As described in Table 1, the proposed lighting conditions for occupants' CP and VF lack consistency. The range of the proposed lighting conditions yielded by the previous studies is quite large, from 3,300K to 6,500K and from 200lx to 2,500lx. Some studies reported that medium illuminance such as 500 – 750lx is more effective than other illuminance levels [36,38], while several studies have demonstrated that increased illuminance can positively influence CP [47]. Yet there are studies that showed higher illuminance can result in reduced CP [28], including research suggesting that 200lx is more effective than 500lx when using visual display terminals [48]. Lan et al.(2021) measured creativity and

Table 1
Proposed lighting conditions suggested by previous studies.

Objective	Experimental set up		Proposed lighting condition		Measured indicators	Ref.
	Environment	Subject	CCT	Illuminance		
Cognitive performance	500lx and 2,500lx	15	None	2,500lx	Attention and concentration	[27]
	200lx and 500lx	30	None	200lx	Computing power, attention, and vigilance	[28]
	4,500K and 200-1500lx	33	None	1500lx	Attention, reaction time, executive ability	[29]
	4,000-6,500K and 500-750lx	20	4000K	700lx	Cognitive efficiency	[30]
	200-800lx	20	None	500-800lx	Reading comprehension	[31]
	2,700-6,500K and 100-2,500lx	24	4000K	None	Perception, memory, number calculation and executive function	[32]
	2,500-6,500K and 40lx	16	6500K	None	Sustained attention and executive function	[33]
	3,000-6,000K and 75-500lx	18	4000K	None	Work efficiency (e.g., reading efficiency)	[34]
	3,000-6,500K and 200-1,200lx	60	6,500K	None	Executive function, working memory, and emotional congruence	[35]
	2,000-6,500K and 200-750lx	36	4,000-6,500K	750lx	Task performance	[36]
	3,000-6,500K	32	5,100-5,800K	None	Attention	[37]
	75-1,200lx	28	None	500-750lx	Executive functions	[38]
Visual fatigue	4,000-6,000K	20	5,000K	None	Subjective visual discomfort	[39]
	3,000-5,700K and 650-1050lx	60	4,000K	None	Subjective lighting comfort and glare	[40]
	2,000-6,500K and 200-750lx	36	4,000K	None	Subjective visual perception	[36]
	3,000-6,000K and 75-500lx	18	None	300lx	Flash fusion frequency and subjective comfort	[34]
	2,700-5,500K and 100-900lx	16	5,005K	885lx	Subjective satisfaction	[41]
	50-500lx	12	None	500lx	Visual fatigue scale, blink rate, and pupil accommodation	[42]
	2,000-100,000K	12	6,236K	None	Subjective comfort	[43]
	2,700-6,300K	40	6,300K	None	Subjective satisfaction	[44]
	3,300-5,300K and 300-750lx	46	3,300K and 4,300K	300lx	Alpha wave and subjective comfort	[45]
	3,000-5,500K and 300-1,000lx	16	4,300K	500-1,000 lx	Critical flicker fusion frequency and subjective visual fatigue	[46]

Note: CCT stands for correlated color temperature and Ref. stands for reference

analytical ability under various combinations of CCT and illuminance, analyzing that the lighting conditions at which the highest levels of both abilities were observed differed [49]. Similarly, there were cases where the lighting conditions suggested by previous studies conflicted with each other. The inconsistency of the proposed lighting conditions for VF also exists as shown in Table 1.

Additionally, this approach makes it difficult to reflect trade-offs between different objectives such as energy consumption. Therefore, research has been conducted to consider energy consumption alongside other objectives through multi-objective optimization. Zhang et al. (2024) proposed a lighting control system that simultaneously considers visual and non-visual effects and energy consumption in enclosed spaces [50]. Similarly, there were a number of studies that attempted to optimize lighting conditions for non-visual effects such as circadian rhythm and energy consumption [51–53]. Other studies have suggested lighting controls that maintain a certain level of illuminance while minimizing energy consumption [54], or that consider visual discomfort alongside energy savings [55]. However, the objective functions of these multi-objective optimizations often rely on mathematical equations derived from past studies that analyzed the relationship between lighting conditions and occupants' CP or VF. Thus, while these optimizations reflect trade-offs between various objectives, they still fail to account for occupants' real-time status.

Studies proposing specific lighting conditions and those suggesting lighting control through multi-objective optimization share a common limitation: they do not consider the actual status of occupants in the space where the lighting conditions are applied. Occupants' CP and VF can change over time due to various factors, even interactions between them. Liu et al. (2021) observed work efficiency and ocular performance under different lighting conditions [16]. Since ocular performance must accompany the completion of CP tasks at a certain level, both variables increase together until VF gradually occurs, causing CP to initially rise and then decline. Based on these research results and the experiments of previous studies, the variability of proposed lighting conditions can be attributed to differences in subjects' characteristics, status, and the tasks assigned to them. Particularly, several previous studies indicate that personally controlled lighting conditions can bring greater benefits to CP and VF compared to fixed lighting conditions [56,57]. This suggests that deriving lighting conditions through a data-driven approach, which considers occupants' status and changes in status over time or activities, is more appropriate than establishing fixed lighting conditions.

Based on the implications derived from previous studies, a new approach is needed for controlling optimal lighting conditions for CP, VF, and energy consumption. Firstly, due to the inconsistency in results from previous studies on lighting conditions for CP and VF, a data-driven approach is more efficient than setting fixed values or specific ranges. Additionally, a data-driven approach benefits from reflecting occupants' real-time status. Numerous studies have confirmed that CP and VF have significant relationships with bio-signals such as heart rate variability,

brain waves, and ocular responses [16,58–61]. Therefore, predicting occupants' status (i.e., CP and VF) through bio-signals and applying this to multi-objective optimization could effectively derive optimal lighting conditions that reflect occupants' real-time status.

2. Proposed model for occupant-centric lighting control

This study proposes CP, VF and energy consumption optimization (CVEO) model for occupant-centric lighting control. Fig. 1 shows the overall framework of the CVEO model.

First, occupant data (i.e., subject-label and bio-signals) are loaded into the CVEO model. Then, lighting conditions and the loaded occupants' data are input into stacking ensemble models to predict occupants' CP and VF, and into an interpolation model to predict energy consumption. Based on predicted CP, VF, and energy consumption, an optimization algorithm searches for the lighting conditions that maximize CP and minimize VF and energy consumption. The CVEO model enables occupant-centric lighting control as the model optimizes CP and VF based on occupants' bio-signals while considering energy consumption simultaneously. This CVEO model was constructed in four stages: (i) defining the optimization problem; (ii) defining decision variables; (iii) developing stacking ensemble models to predict CP and VF and presenting an interpolation model to predict energy consumption; and (iv) solving the optimization problem using the non-dominated sorting genetic algorithm-II (NSGA-II).

2.1. Optimization problem statement

The aim of the CVEO model is to maximize CP and to minimize VF and energy consumption. The multi-objective optimization problem of CVEO model is defined as shown at Eq. (1).

$$\begin{cases} \text{Maximize } Z_1 = f_{cp}(L_{cct}, L_i, x_1, x_2, \dots, x_n) \\ \text{Minimize } Z_2 = f_{vf}(L_{cct}, L_i, x_1, x_2, \dots, x_n) \\ \text{Minimize } Z_3 = f_{energy}(L_{cct}, L_i) \end{cases} \quad (1)$$

$$L_{cct} \in [4000, 6500], L_i \in [200, 800], x_n \in [0, 1]$$

Where, f_{cp} stands for objective function of cognitive performance; f_{vf} stands for an objective function of visual fatigue; f_{energy} stands for an objective function of energy consumption; L_{cct} stands for correlated color temperature; L_i stands for illuminance; x stands for subject-label and bio-signals

The decision variables of the CVEO model are lighting conditions, specifically CCT and illuminance (refer to Section 2.2). The objective functions of the CVEO model are as follows: (i) maximizing CP, (ii) minimizing VF, and (iii) minimizing energy consumption (refer to Section 2.3). Specifically, the objective functions for CP and VF are stacking ensemble models that predict CP and VF based on occupant data (i.e., subject-labels and bio-signals). For energy consumption, the

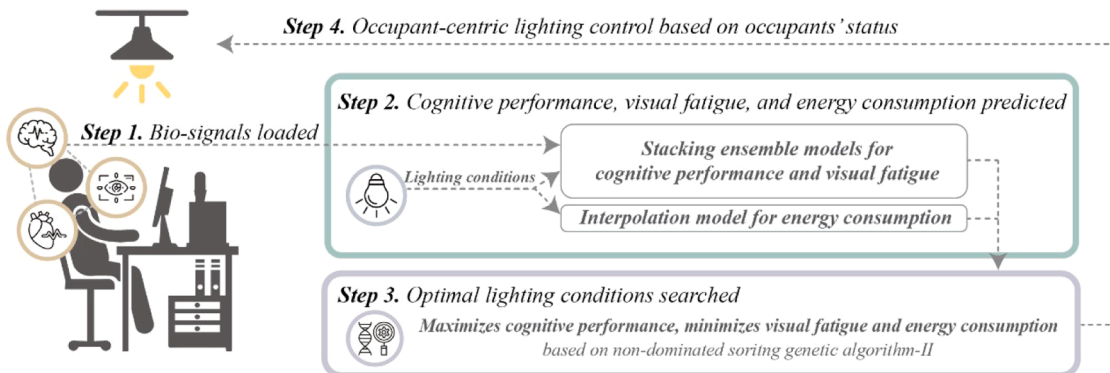


Fig. 1. Overall framework of the CVEO model.

interpolation model acts as the objective function. Lastly, NSGA-II was selected for the multi-objective optimization algorithm (refer to Section 2.4).

2.2. Decision variables

The decision variables and their ranges of the CVEO model were set. Among various parameters representing lighting characteristics, CCT and illuminance, which are known to be relatively easy to measure and control, and significantly impact occupants' experience, were defined as the decision variables of the CVEO model. [14,35,36,62]. The range of CCT was constrained from 4,000K to 6,500K. Based on previous studies that revealed the impact of CCT on CP, general values of CCT in classrooms and offices range from warm white lighting to daylighting. Specifically, CCT values ranging from 4,000K to 6,500K were found to be most preferred by occupants or most effective for CP in related works. [37,63–65].

In addition, the range of illuminance was set from 200 to 800lx. According to the WELL standard, the illuminance at workstations or desks must exceed at least 215lx [66]. Also, the minimum illuminance threshold for classrooms and offices presented by the United States Services Administration is approximately 320lx [67]. The illuminance standard of South Korea [68] presents three illuminance standard categories for classrooms and offices, with the lowest illuminance category ranging from 150lx to 300lx, recommended for meeting rooms and auditoriums mainly using visual display terminals. Accordingly, the illuminance range of the CVEO model was set to a minimum of 200lx. Additionally, for spaces such as design areas in classrooms and offices that require detailed work, an illuminance range of 600lx or higher is recommended. Reflecting this, the maximum illuminance of the CVEO model was set to 800lx.

2.3. Objective function

The optimization problem of the CVEO model considers three objectives for lighting control in commercial buildings: (i) maximizing CP; (ii) minimizing VF; and (iii) minimizing energy consumption. Therefore, CP, VF, and energy consumption have to be defined. To solve the optimization problem, values of CP, VF, and energy consumption for all possible lighting conditions within the range of decision variables defined in the optimization problem are required. For CP and VF, values can be measured by occupants performing cognitive tests and surveys on VF. However, having occupants perform the test and survey in every environment is time-consuming and disrupts their daily lives and work. Hence, in this study, a machine learning approach was used to develop stacking ensemble models for predicting CP and VF based on occupants' data (i.e., subject-label and bio-signals). Meanwhile, energy consumption values can be measured using an electricity meter. However, like CP and VF, measuring energy consumption values for all lighting conditions is inefficient, so energy consumption was predicted via the interpolation model based on measured lighting conditions. As a result, the developed models were used as objective functions in the CVEO model. Once the preliminary data collection is conducted to measure CP and VF via tests and surveys, the predictive models for CP and VF allow for prediction of the real-time occupant status.

2.3.1. Definition of objectives

The objectives of the CVEO models are defined to be (i) CP, (ii) VF, and (iii) energy consumption and Table 2 shows the components of each objective.

The first objective of the CVEO model is CP, which an extensive body of research has shown to be influenced by lighting conditions, primarily due to intrinsically photosensitive retinal ganglion cells circuit mechanisms [69]. The CP in this study consists of basic and complex CP. The American Psychiatric Association has defined key cognitive functions into six domains [70] and previous studies have revealed the influence

Table 2
Components of objectives.

Objective	Components	
Cognitive performance	Basic cognitive performance	Complex attention
		Executive function Learning and memory Language Perceptual-motor function Social cognition Creativity
	Complex cognitive performance	Reasoning
Visual fatigue	Visual fatigue metrics	Eye fatigue Eye pain Eye dryness Eye itchiness Blurred vision Double vision Glare
Energy consumption	Lighting energy consumption	-

of lighting conditions on each domain based on biological mechanism: (i) complex attention [71,72], (ii) executive function [73,74], (iii) learning and memory [75,76], (iv) language [77], (v) perceptual-motor function [78], and (vi) social cognition [79,80]. Furthermore, occupants generally engage in high-level mental activities that require a combination of multiple basic CPs in commercial buildings. Therefore, creativity and reasoning were defined as complex CPs in this study. A number of studies has investigated the effective lighting conditions for creative [49,81] and reasoning tasks [49,82], and reported the significant impact of lighting conditions. Detailed definitions of each CP are presented in supplementary materials. The final CP value used in the CVEO model is the average value of both basic and complex CPs and its value is also normalized to range from 0 to 1. Eq. (2) shows how the measured CP (i.e., y_{cp}) is calculated.

$$\begin{cases} Z_1 = y_{cp} = \frac{CP - CP_{min}}{CP_{max} - CP_{min}} \\ CP = \frac{CP_{basic} + CP_{complex}}{8} \end{cases} \quad (2)$$

Where, CP stands for score of cognitive performance (CP); CP_{min} stands for minimum score of CP; CP_{max} stands for maximum score of CP; CP_{basic} stands for the score of basic CP; and $CP_{complex}$ stands for the score of complex CP.

The second objective of the CVEO model is VF, a primary symptom of computer vision syndrome, which frequently occurs in modern commercial buildings. Since VF encompasses a range of ocular symptoms and visual difficulties that arise during visual tasks, it is evaluated using multiple metrics rather than a single metric [28,42]. Consequently, VF includes self-reported (i) eye fatigue [83], (ii) eye pain [84], (iii) eye dryness [28], (iv) eye itchiness [85], (v) blurred vision [86], (vi) double vision [87], and (vii) glare [88]. Principal component analysis (PCA) can be used to effectively derive these metrics into VF. Since occupants' sensitivity to each metric can vary, PCA was used to derive VF by reflecting the variance of each metric, rather than simply defining VF as the average of all metric values. The loadings of the principal components derived from PCA can be used as the weights for each metric [89,90], as shown in Eq. (3). VF is the calculated value y_{vf} , which is derived from the seven metrics using Eq. (3) and then min-max normalized to a value between 0 and 1.

$$\begin{cases} Z_2 = y_{vf} = \frac{VF - VF_{min}}{VF_{max} - VF_{min}} \\ VF = \sum_{i=1}^k L_n \cdot X_n \end{cases} \quad (3)$$

Where, VF stands for degree of visual fatigue (VF); VF_{min} stands for minimum degree of VF ; VF_{max} stands for maximum degree of VF ; L stands for the loading of principal component; and X stands for VF metric.

The last objective of the CVEO model is energy consumption. In this study, energy consumption is limited to energy consumption by artificial lightings since the CVEO model derives optimal lighting conditions, and it is min-max normalized to a value between 0 and 1.

2.3.2. Bio-signal based stacking ensemble models for cognitive performance and visual fatigue prediction

Among the objective functions of the CVEO model, $f_{cp}(L_{ccb}, L_b, x_1, \dots, x_n)$ and $f_{vf}(L_{ccb}, L_b, x_1, \dots, x_n)$ are stacking ensemble models that can predict CP and VF respectively (refer to Fig. 2). Specifically, $f_{cp}(L_{ccb}, L_b, x_1, \dots, x_n)$ predicts y_{cp} and $f_{vf}(L_{ccb}, L_b, x_1, \dots, x_n)$ predicts y_{vf} based on lighting conditions and occupant data (i.e., subject-label and bio-signals). As described in Section 2.3.1, y_{cp} and y_{vf} are calculated values that can be directly measured by occupants performing CP tests and VF surveys. However, with pre-trained models like f_{cp} and f_{vf} , these measurements can be predicted solely based on occupant data without the need for repetitive tests and surveys.

Wu et al. (2023) proposed three different modeling approaches: benchmark, subject-label, and individual models [91]. Benchmark and individual models refer to general and personal models, respectively, in typical terms. Meanwhile, the subject-label model is a general model with features that can identify individual subjects such as subject identification number and gender. Their research noted that the subject-label approach can improve accuracy over general models while maintaining greater efficiency compared to personal models. Accordingly, general models with subject-labels and personal models were developed, and their performance was compared in this study.

Both models use predictor variables including lighting conditions (i.e., CCT and illuminance) and bio-signals (i.e., heart rate variability,

brain waves, and ocular response), and subject-labels (i.e., gender and eyewear) are additionally put into the general models. The target variables are CP and VF, respectively.

First of all, two kinds of subject-labels were selected.

- **Gender:** It was presented that gender difference exists in CP and VF under different lighting conditions [92–95]. In this model, males were defined as 0 and females as 1.
- **Eyewear:** Eyewear of occupants was also considered as subject-label in this model. There were three categories to identify the eyewear status; (i) no eyewear, represented as 0; (ii) contact lens, represented as 0.5; and (iii) glasses, represented as 1.

The following bio-signals were also selected as input parameters of CVEO model.

- **Heart rate variability:** Previous studies have revealed that changes in sympathetic and parasympathetic activity can indicate different CP [58,96]. Heart rate (HR) is highly associated with sympathetic and parasympathetic activity, indicating a stress or aroused state [97]. Specifically, standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) are also related to autonomic regulation and parasympathetic activity [98,99]. Yang et al. (2021) has revealed that short-term memory has a significant correlation with heart rate variability [100], and Chauhan et al. (2023) has used heart rate as predictor for CP in their prediction modeling [59].
- **Brain waves:** A great number of studies have investigated the lighting conditions impacts on CP using brain waves collected by electroencephalography (EEG) [101]. Specifically, there are delta, theta, alpha and beta waves according to the frequency. Delta waves that range from 0.5 to 4 Hz are generally observed in deep sleep and delta waves can increase in mental tasks that require attention [102]. Theta waves range from 4 to 8 Hz and previous studies have found out that they appear in humans' creative states or meditation states [103,104]. Alpha waves are in the middle frequency (i.e., 8 to 13 Hz) and they indicate relaxation, primarily observed when the eyes are closed [105]. Lastly, beta waves range from 13 Hz to 30 Hz which means they are one of the fastest brainwaves indicating active

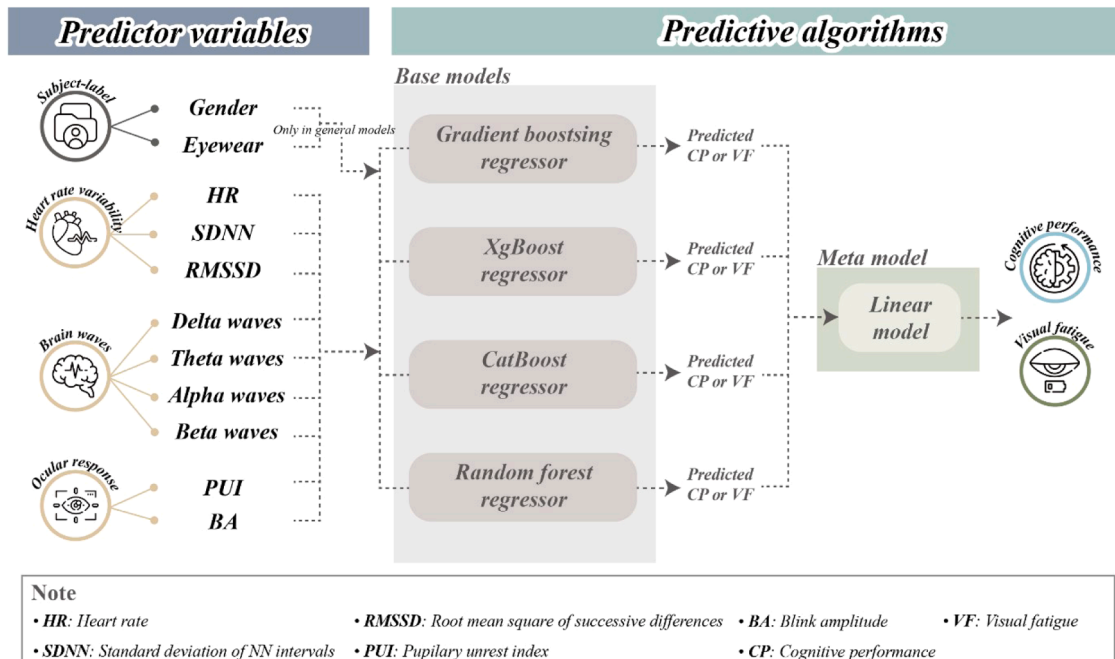


Fig. 2. Structure of stacking ensemble models to predict CP and VF.

thinking and mental activity [106]. Frequency domain, specifically relative power derived from power spectral density (PSD), were set as the predictors in this study [107,108]. Zhang et al. (2024) has reviewed 52 studies that explored lighting conditions and CP using EEG, and concluded that future lighting control should consider using EEG data for personalized lighting conditions [109].

- **Ocular responses:** Ocular responses such as the pupillary unrest index (PUI) and blink amplitude (BA) were collected. PUI refers to the cumulative variations in pupil diameter and BA indicates blinking frequency [16]. The pupil diameter varies depending on the lighting conditions and has been used as an indicator of visual perception and VF [110,111]. Also, BA has been investigated by a number of studies to measure VF and cognitive load [112,113].

As shown in Fig. 2, predictive models for VF and CP are trained using a stacking ensemble approach that combines various machine learning algorithms. The stacking ensemble approach enhances predictive performance by combining the predictions of different base models to make a final prediction [114–116]. In this study, predictive models for CP and VF were developed by combining four base models (i.e., gradient boosting regressor (GBR) [117], XGboost regressor (XGR) [118], CatBoost regressor (CBR), [119] and random forest regressor (RFR) [120]) and a meta model (i.e., linear regression). GBR, XGR, CBR, and RFR are all decision tree-based models and ensemble models that use boosting and bagging. These algorithms have strengths in preventing overfitting by employing various regularization techniques and hyperparameter tuning [121,122]. GBR, which can capture complex interactions in datasets, may perform poorly with imbalanced data, but this weakness can be compensated for by using XGR or CBR [123,124]. Additionally, CBR effectively handles categorical variables but has the disadvantage of long training times [119]. This weakness can be mitigated by combining CBR with XGR and RFR [125]. Thus, the stacking ensemble approach can improve the overall performance of the model by compensating for the weaknesses of each base model. When training each base model, Optuna is used for hyperparameter optimization [126]. Optuna is an automatic hyperparameter optimization framework that efficiently searches for the best hyperparameters within a defined range (refer to Table 3).

2.3.3. Interpolation model for energy consumption prediction

Unlike CP and VF, energy consumption can be predicted solely based on CCT and illuminance. Belany et al.(2024) reported that the relationship between lighting intensity and energy consumption is linear [127]. Also, maintaining particular CCTs requires voltage, which implies energy consumption varies depending on CCT [128]. Therefore, this study aimed to measure energy consumption according to CCT and

illuminance and develop a linear interpolation model based on the measured discrete values for use as an objective function. Specifically, energy consumption was measured under nine lighting conditions combining 4,000K, 5,000K, and 6,500K with 200lx, 500lx, and 800lx. The energy consumption of lighting bulbs was measured using an Arduino-based split core current sensor [129]. Based on the measured data, linear interpolation was conducted so that a continuous value of energy consumption could be predicted via CCT and illuminance (refer to Eq. (3)).

$$\begin{cases} f_{\text{energy}}(L_{\text{cct}}, L_i) = \sum_{i=1}^n w_i \cdot e_i \\ w_i = \frac{1}{d_i} \\ d_i = \sqrt{(L_{\text{cct}} - L_{\text{cct}'})^2 + (L_i - L_i')^2} \end{cases} \quad (4)$$

Where, f_{energy} stands for an objective function of energy consumption; L_{cct} stands for correlated color temperature (CCT); L_i stands for illuminance; w stands for weight; e stands for the energy consumption at corresponding CCT and illuminance; d stands for the distance between new lighting conditions and given lighting conditions; $L_{\text{cct}'}$ stands for new CCT; and L_i' stands for new illuminance.

2.4. Non-dominated sorting genetic algorithm-II

Based on the developed stacking ensemble models, occupants' CP and VF can be predicted using occupant data. These predictive models were used as objective functions for optimization, aiming to maximize CP while minimizing VF and energy consumption, forming a multi-objective optimization problem. The NSGA-II algorithm was chosen to identify the optimal lighting conditions (i.e., CCT and illuminance), as it effectively handles the non-linear and complex relationships between CP, VF and lighting conditions by exploring Pareto front solutions [130, 131].

The NSGA-II is an evolutionary algorithm designed to solve multi-objective optimization problems by searching for a set of Pareto-optimal solutions [132]. The algorithm initializes a random population of solutions, which are then evaluated based on the objective and fitness functions. NSGA-II performs non-dominated sorting to rank the solutions, dividing them into different fronts or layers based on dominance. To maintain diversity among solutions within the same front, NSGA-II calculates a crowding distance, which measures how close a solution is to its neighbors. Selection is performed using a tournament selection method that considers both front and crowding distance. Solutions with lower ranks and higher crowding distances are preferred, ensuring both convergence towards the Pareto front and diversity.

The selected solutions undergo crossover and mutation operations to generate offspring, introducing variability and exploring new areas of the solution space. These offspring are then combined with the parent population to form a new population. Environmental selection follows, and the best solutions are chosen to form the next generation, ensuring that the population evolves toward better solutions over successive generations. The NSGA-II algorithm repeats these steps until a pre-defined termination condition is met.

Table 3
Defined range of hyperparameters.

Algorithm	Hyperparameter	Defined range
Gradient boosting regressor	Number of estimators	[100, 500]
	Learning rate	[0.01, 0.1]
	Maximum depth	[3, 10]
	Minimum samples split	[2, 10]
	Subsample	[0.5, 1.0]
XGboost regressor	Number of estimators	[100, 500]
	Learning rate	[0.01, 0.1]
	Maximum depth	[3, 10]
	Subsample	[0.5, 1.0]
	Minimum split loss	[0.001, 1.0]
CatBoost regressor	Iterations	[100, 500]
	Learning rate	[0.01, 0.1]
	Depth	[3, 10]
Random forest regressor	Number of estimators	[100, 500]
	Maximum depth	[3, 30]
	Minimum samples split	[2, 10]

3. Experiment

Experiments were conducted to evaluate the performance of the CVEO model. Specifically, data was collected from 15 subjects under nine different lighting conditions and preprocessed. The stacking ensemble models to predict CP and VF were trained using the collected data. Lastly, multi-objective optimizations were performed using the developed stacking ensemble models.

3.1. Data collection

3.1.1. Environmental setting and subjects

Nine different lighting conditions (i.e., 4,000K and 200lx, 4,000K and 500lx, 4,000K and 800lx, 5,000K and 200lx, 5,000K and 500lx, 5,000K and 800lx, 6,500K and 200lx, 6,500K and 500lx, and 6,500K and 800lx) were set in the data collection. Lighting conditions were controlled by smart lighting emitting diodes installed in the artificial climate chamber. As the data was collected in the artificial climate chamber, other indoor environmental factors such as temperature, relative humidity, acoustics and indoor air quality were maintained at the same level throughout data collection. Specifically, the thermal environment was consistently kept at 26 °C with a relative humidity of 50 %. The climate chamber was closed to minimize external noises and ventilation system of the climate chamber enabled to control air quality.

Fifteen healthy adults (i.e., 8 males and 7 females) were recruited as the subjects of the data collection. The subjects' average age was 24.4 ± 2.36 years, and all were in their 20 s with relatively stable physical conditions, including vision. Their body mass index was 22.0 ± 2.76 kg/m², and they confirmed that they were free of chronic diseases (e.g., neurological disorders, diabetes, hypertension, etc.), including ocular issues. All subjects had no difficulty in conducting computer-based CP tests as college and graduate students. Subjects with poor vision wore their usual corrective lenses, and those wearing glasses had additional corrective lenses inserted into eye-tracking glasses to conduct the CP tests. On the day of the data collection, caffeine intake was restricted to prevent any influence on brain arousal states, and subjects were specifically requested to avoid alcohol for 24 h prior to the data collection. Lastly, subjects' clothing was set to 0.7 clo.

3.1.2. Process of data collection

Fig. 3 shows the overall data collecting process. Data collection was conducted under nine different lighting conditions. A total of 15 participants completed data collection across all nine lighting conditions, and every data collection was conducted involving one subject at a time. Before the data collection, the research team explained the procedures to the subjects and obtained their consent for participation. Subjects were given about 30 min to learn about CP tests and to train for basic CP tests to minimize learning effects. After confirming that the scores of the basic CP tests converged within a certain range, subjects were fitted with electrocardiography (ECG), EEG, and eye-tracking glasses under the

direction of the research team. The equipment for collecting bio-signals is described in supplementary materials.

Before the start of each data collection, subjects waited with their eyes closed while the research team set the lighting conditions. Based on previous studies indicating that the average adaptation time for the human eye to different lighting conditions is a few seconds [133], subjects were instructed to open their eyes and adapt to the lighting condition for about 1 min after it was set. Then, the research team started recording the subjects' bio-signals, and subjects were instructed to begin the CP tests. The total duration for the CP tests was 15 min: 6 min for basic CP tests and 9 min for complex CP tests. After conducting the CP tests, the research team stopped recording the bio-signals and instructed subjects to complete the VF surveys. At the end of each data collection, subjects took a break for 5 to 10 min, during which they were instructed to look at a distant point and then close their eyes to rest. This process was repeated nine times, and the types of lighting conditions were in a randomized order for each subject during the data collection process. The process of data collection was reviewed and approved for safety and ethics by the institutional review board (IRB no. 7001988-202311-HR-2089-02).

3.2. Stacking ensemble model

3.2.1. Data preprocess and feature selection

To develop stacking ensemble models for CP and VF predictions, collected data was preprocessed. Firstly, bio-signals collected by ECG, EEG, and eye-tracking glasses were preprocessed to derive predictor variables. As ECG and EEG data were collected by Biopac Systems, the raw data was preprocessed by AcqKnowledge software and predictor variables (i.e., HR, SDNN, RMSSD, and brain waves from four lobes) were extracted using the software with HeartPy and signal library in Python [134,135]. The noises of data were removed by comb band-pass filters, and artifact removal from EEG signals was also conducted using EOG data [136]. PUI and BA were extracted after preprocessing the pupil and eye validity data using Tobii Prolab [137]. All the collected bio-signals were averaged into 1-minute intervals and subsequently used as predictors in the model.

To derive CP as a target variable, accuracy and response time were measured in each task and each CP was calculated using Eq. (4) [135, 138]. Six basic CPs and two complex CPs were then integrated and normalized using Eq. (2). The process to derive accuracy and response

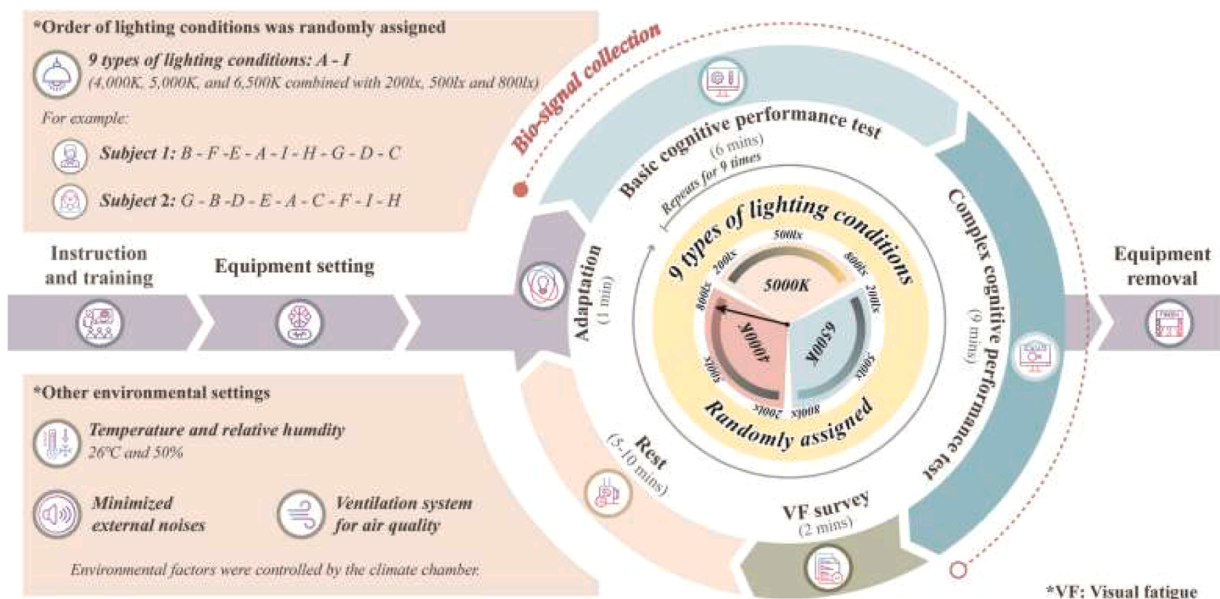


Fig. 3. Data collection process.

time in each task are shown in SM Table 1. VF, another target variable, was measured through 7-point Likert scale surveys for seven VF metrics. These responses were integrated into VF using PCA and Eq. (3) (refer to Section 2.3.1). The definitions of accuracy and response time for each CP and detailed process of calculating VF are illustrated in supplementary materials.

$$CP_n = \left(Accuracy^{0.5} \times \frac{1}{Response\ time^{0.5}} \right)^2 \quad (5)$$

Where, CP_n stands for each type of CP

Lastly, a preliminary experiment was conducted for feature selection. Although the base models are primarily boosting and ensemble-based, which generally perform well with correlated variables, the strong correlations between bio-signals could still negatively impact predictive performance. Therefore, PCA was used to transform the correlated variables into new independent principal components, removing the correlation while preserving as much variance as possible [139,140]. Seven principal components were derived that could explain variance over 70 % and the seven components were used as predictors. Consequently, it was revealed that all the base models showed higher performance when all the predictors were used rather than using principal components to reduce correlations. Specifically, the average root mean squared error (RMSE) of base models using principal components recorded 0.11 and 0.15 for CP and VF, respectively, while that of models using all the predictors recorded 0.08 and 0.10. Also, average coefficient of determination (R^2) of base models using principal components showed 0.67 and 0.62 for CP and VF, respectively, which were much lower than that of models using all the predictors (i.e., 0.81 and 0.85 for CP and VF, respectively). Therefore, it was decided to use all the predictors in this study.

3.2.2. Model training and evaluation

Datasets consisted of 2025 data points (i.e., 15 min of 15 subjects under 9 lighting conditions) and were split in an 8:2 ratio for the training and test datasets, respectively. The architecture of the stacking ensemble model, along with the hyperparameters and optimization method, was set as described in Section 2.3.2. To evaluate the performance of each base model and the stacking ensemble model, three types of evaluation metrics were used [141,142]: (i) RMSE, (ii) mean absolute percentage error (MAPE), and (iii) R^2 . RMSE indicates the difference between values predicted by a model and the actual values, while MAPE refers to the error as a percentage of the actual values. R^2 is a statistical measure that indicates how well the predictor variables in a model explain the variability of the target variable.

3.3. Multi-objective optimization

3.3.1. Pareto front analysis of multi-objective optimization

Using the bio-signals collected from 15 subjects in this study, Pareto front solutions for the CVEO model were derived. Firstly, a multi-objective optimization was performed based on the bio-signals of all subjects to determine the optimal lighting conditions (i.e., Pareto front solutions) for a situation where multiple occupants are present simultaneously. CP and VF were predicted using each subject's bio-signals and personal stacking ensemble models. The multi-objective optimization considered the CP, VF, and energy consumption of all subjects simultaneously.

Secondly, multi-objective optimization was performed based on the bio-signals of each individual subject to determine the optimal lighting conditions for each occupant. For this, all data collected from the subjects, excluding the portion used as the training dataset, were used to maximize the representation of the characteristics of all 15 subjects for multiple occupants and each individual subject for individual occupants. Accordingly, during each generation of the NSGA-II, samples were randomly selected from the dataset to predict CP and VF, and the

average values of the results were used in the fitness evaluation, ensuring that all collected bio-signals were reflected in the optimization.

The population size was set at 46 for each occupant, following a previous study suggesting that the population size should be 2-4 times the number of optimization variables (i.e., two lighting variables and 21 bio-signals making 23 optimization variables altogether). The iteration process was stopped if the relative change rate between the average of the optimal solutions and the average of the previous generation's optimal solutions was less than 1 %. All optimizations converged before 110 iterations.

3.3.2. Comparative analysis using scenarios

To evaluate the performance of the CVEO model, a comparative analysis was conducted to assess the effects of the fixed lighting conditions proposed in previous studies and the Pareto front solutions derived from the CVEO on enhancing occupants' CP and reducing VF and energy consumption. Two types of fixed lighting conditions were selected. The first fixed lighting condition, aimed at improving CP, was selected based on the results of experiments conducted on the largest number of subjects (refer to Section 1.2) and was 6,500K and 750lx [35,36]. The second fixed lighting condition, aimed at reducing VF, was selected based on the same criteria and was 4,300K and 300lx [40,45]. To simulate real-world implementation, 2,000 scenarios were generated, with the occupancy status of 15 subjects randomly set for each scenario. Each scenario featured a different combination of occupants, and the bio-signals of each subject were also randomly assigned. The CVEO model was applied based on the subjects' bio-signals in each scenario. Additionally, using the two fixed lighting conditions and the subjects' bio-signals for each scenario, the stacking ensemble models, and the interpolation model were employed to derive each occupant's CP, VF, and energy consumption.

4. Experimental results

4.1. Performance evaluation of stacking ensemble models

Fig. 4 shows the actual and predicted values of the stacking ensemble models that predict CP and VF based on occupants' bio-signals, and their predictive performance was evaluated and compared as follows.

4.1.1. Cognitive performance predictive models

To operate as an objective function for CP, two stacking ensemble models to predict CP were developed and compared: (i) a general CP predictive model, and (ii) a personal CP predictive model. The general CP predictive model's predictors consist of subject-label and bio-signals, and it was trained on data from all subjects. In contrast, the personal CP predictive model's predictors are bio-signals, and each model was built for individual subjects using only data from each subject. The stacking ensemble models consist of GBR, XGR, CBR, RFR models, and a linear meta-model. Table 4 shows the performance of general and personal CP predictive models, specifically their base models and stacking ensemble models.

In all evaluation metrics, the stacking ensemble model demonstrated superior performance compared to each base model, indicating the benefit of using a stacking ensemble approach over individual algorithms. The effect was more pronounced in the general model, with RMSE and MAPE decreasing by 0.02 and 0.041, respectively. Although the difference was smaller, the personal model also showed reductions in RMSE and MAPE for the stacking ensemble model, and R^2 increased to similar levels for both the general and personal models. Notably, when comparing the performance of the general and personal models, the personal model outperformed the general model in all evaluation metrics. This trend was observed not only in the stacking ensemble model but also across all base models. Among all the CP predictive models, the personal model based on the stacking ensemble approach showed the highest performance: (i) RMSE at 0.023 ± 0.016 ; (ii) MAPE at $0.054 \pm$

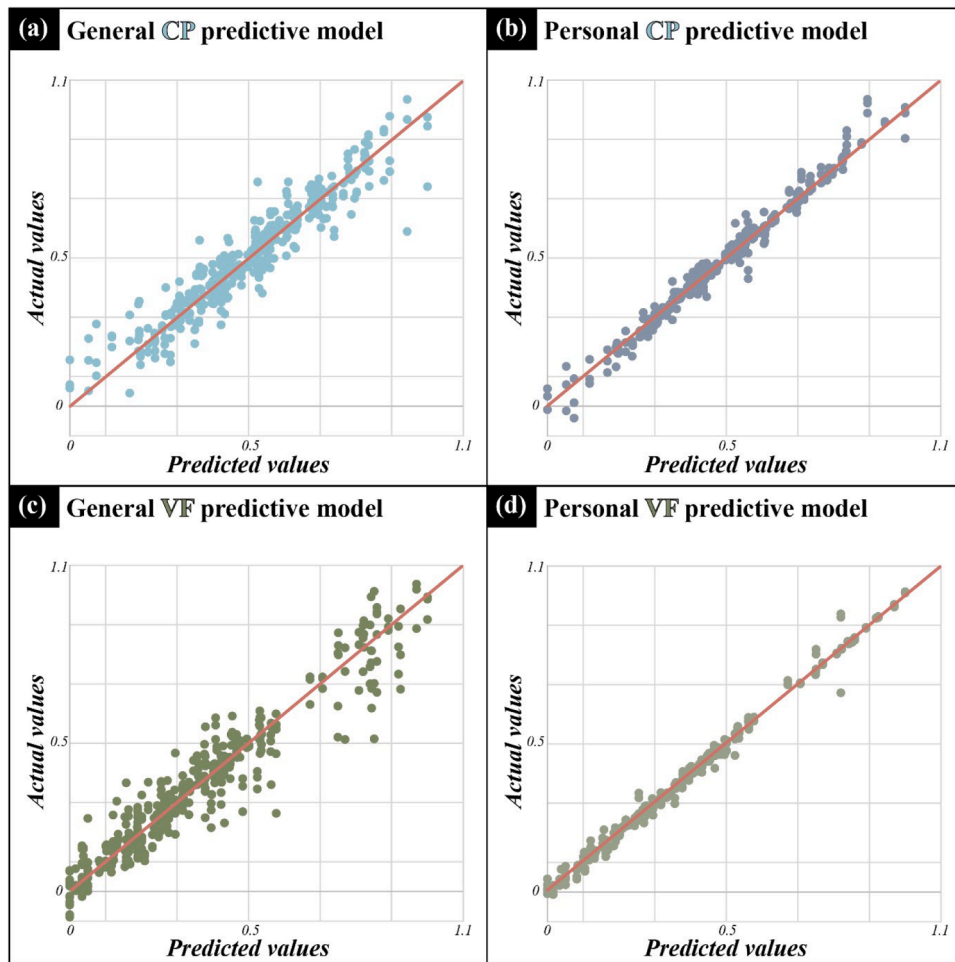


Fig. 4. Actual values and predicted values of general and personal predictive models.

Table 4
Performance of general and personal cognitive performance predictive models.

Models	Evaluation metric	Base models					Stacking ensemble model
		GBM	XGR	CBR	RFR	Average	
General model	RMSE	0.087	0.084	0.065	0.092	0.082	0.062
	MAPE	0.167	0.168	0.137	0.186	0.165	0.124
	R ²	0.790	0.806	0.883	0.767	0.812	0.895
Personal model	RMSE	0.029 (±0.024)	0.028 (±0.018)	0.027 (±0.012)	0.040 (±0.022)	0.031 (±0.020)	0.023 (±0.016)
	MAPE	0.062 (±0.083)	0.065 (±0.078)	0.062 (±0.073)	0.082 (±0.085)	0.068 (±0.080)	0.054 (±0.062)
	R ²	0.878 (±0.136)	0.907 (±0.096)	0.927 (±0.053)	0.814 (±0.159)	0.882 (±0.126)	0.942 (±0.056)

Note: GBR for gradient boosting regressor; XGR for XGboost regressor; CBR for CatBoost regressor; RFR for random forest regressor; RMSE for root mean squared error; MAPE for mean absolute percentage error; and R² for coefficient of determination

0.062; and (iii) R² at 0.942 ± 0.056 . Consequently, for the construction of the CVEO model, it is more appropriate to use the personal model, which predicts CP based on the bio-signals of individual occupants, as the objective function for CP, rather than the general model trained on data from all occupants.

4.1.2. Visual fatigue predictive models

Stacking ensemble models to predict VF were developed, and their performances were evaluated and compared: (i) general VF predictive model, and (ii) personal VF predictive model. The components and evaluation metrics of the stacking ensemble models were the same as

those used for the CP predictive models. Table 5 presents the performance of the general and personal VF predictive models.

Similar to the CP predictive models, the VF predictive models also showed higher performance with the stacking ensemble model compared to all base models. By using the stacking ensemble approach, RMSE decreased by approximately 0.01 to 0.02, and MAPE decreased by about 0.015 to 0.1. For the general model, R² improved by around 0.065, while the personal model showed a smaller increase of 0.051. The performance difference between the general and personal stacking ensemble models was more significant for the VF predictive models compared to the CP predictive models. When evaluated based on RMSE

Table 5

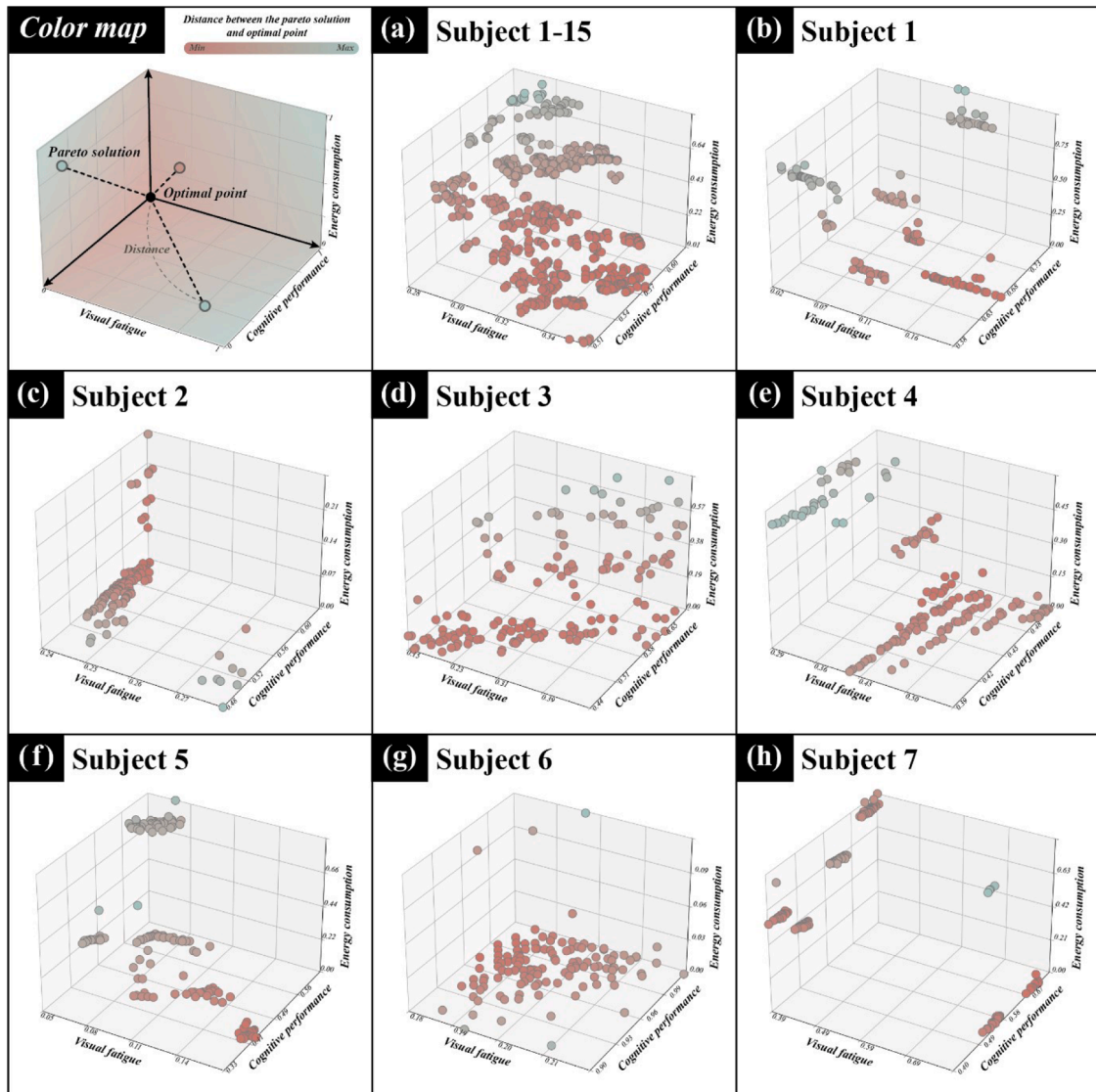
Performance of general and personal visual fatigue predictive models.

Models	Evaluation metric	Base models					Stacking ensemble model
		GBM	XGR	CBR	RFR	Average	
General model	RMSE	0.095	0.096	0.080	0.109	0.095	0.073
	MAPE	0.330	0.345	0.309	0.401	0.346	0.247
	R ²	0.849	0.845	0.893	0.801	0.847	0.912
Personal model	RMSE	0.014	0.014	0.019	0.032	0.025	0.012
		(±0.011)	(±0.008)	(±0.010)	(±0.016)	(±0.025)	(±0.007)
	MAPE	0.034	0.055	0.070	0.102	0.070	0.055
		(±0.044)	(±0.064)	(±0.083)	(±0.119)	(±0.085)	(±0.078)
	R ²	0.965	0.961	0.958	0.858	0.925	0.976
		(±0.042)	(±0.042)	(±0.038)	(±0.131)	(±0.095)	(±0.023)

Note: GBR for gradient boosting regressor; XGR for XGboost regressor; CBR for CatBoost regressor; RFR for random forest regressor; RMSE for root mean squared error; MAPE for mean absolute percentage error; and R² for coefficient of determination

and MAPE, the general model's VF predictive models had higher errors compared to the CP predictive models. However, in the personal model, the RMSE for the VF predictive models was lower, and MAPE was at a similar level. Notably, the personal VF predictive model achieved a very high R² of 0.976 and a low MAPE of about 0.055, demonstrating that it can predict individual VF with high accuracy using bio-signals. In

conclusion, it was determined that using the personal stacking ensemble model as the objective function for VF in the CVEO model is more appropriate than using the general model.

**Fig. 5.** Pareto front solutions for multiple and individual occupants (Subject 1-7).

4.2. Results of multi-objective optimization and performance evaluation

4.2.1. Pareto solutions for multiple and individual occupants

Figs. 5 and 6 show the Pareto front solutions for all the subjects together and the 15 individual subjects.

The analysis of the optimization results for multiple occupants is shown in Fig. 5 (a) revealed trade-off relationships among the three objectives, with energy consumption having the most significant impact on the distance between Pareto front solutions and the optimal point.

Additionally, as demonstrated in Figs. 5 and 6, the distribution of Pareto front solutions for individual occupants exhibited considerable variation. This indicates significant individual differences in CP and perceived VF, suggesting that each subject's dynamic relationship among CP, VF, and energy consumption can vary. Therefore, for occupant-centric lighting, a data-driven approach that reflects these individual differences in real-time may be more appropriate than a fixed lighting condition. Fig. 7 presents the distribution of each objective function for initial solutions and Pareto front solutions, illustrating the extent of improvement achieved through optimization. In most cases, the Pareto front solutions showed higher CP and lower VF and energy consumption compared to the initial solutions. It was also observed that even if other objectives remained at similar levels, one objective could

be significantly improved. Specifically, a significant increase in the median value of Pareto front solutions compared to initial solutions was observed only for energy consumption in Subjects 7 and 15, while in all other cases, it remained similar or decreased. In these two cases of increased energy consumption, VF and CP were significantly reduced compared to initial solutions.

As a result of the CVEO, the optimal CCT and illuminance values for maximizing CP and minimizing VF and energy consumption were derived (refer to Table 6). Ideal solutions for each individual objective (i. e., CP, VF, and energy consumption) were presented among the Pareto front solutions. Additionally, by assigning equal weights to each objective function and calculating the weighted Euclidean distance, the solution with the smallest distance among the Pareto front solutions was defined as the best solution. For multiple subjects, the ideal solution for CP and energy consumption were 5,019.20K and 200.80lx, while the ideal solution for VF was 4,821.80K and 495.04lx, showing differences in both CCT and illuminance. When all objective functions were equally weighted for fitness evaluation, 4,640.02K and 206.49lx emerged as the best solution. For individual subjects, there were some differences compared to the solutions for multiple subjects, but the ideal solutions for energy consumption generally converged to 4,000K and 200lx. The ideal solutions for CP ranged between 4,000K to 5,900K and 200lx to

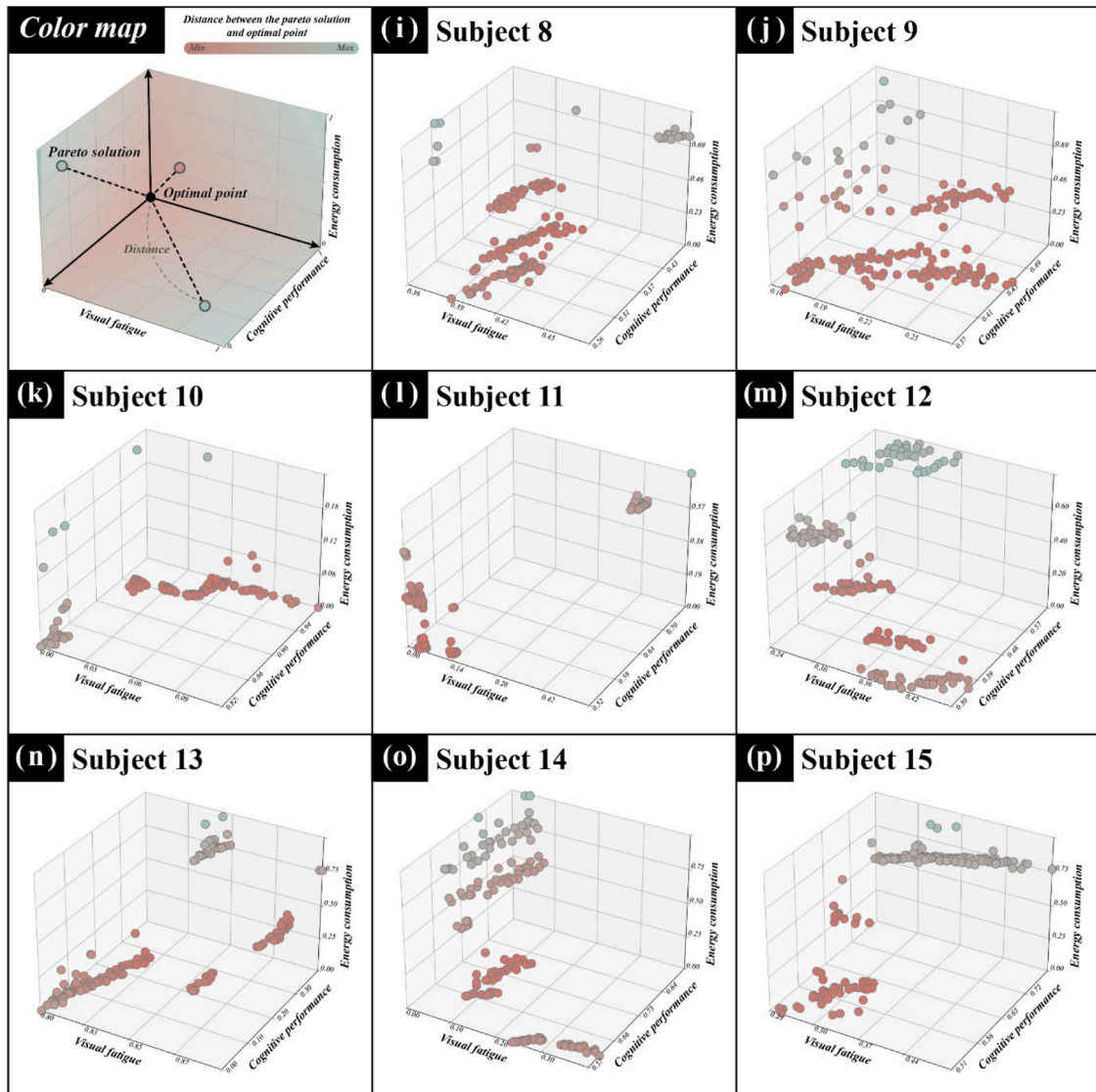


Fig. 6. Pareto front solutions for individual occupants (Subject 8-15).

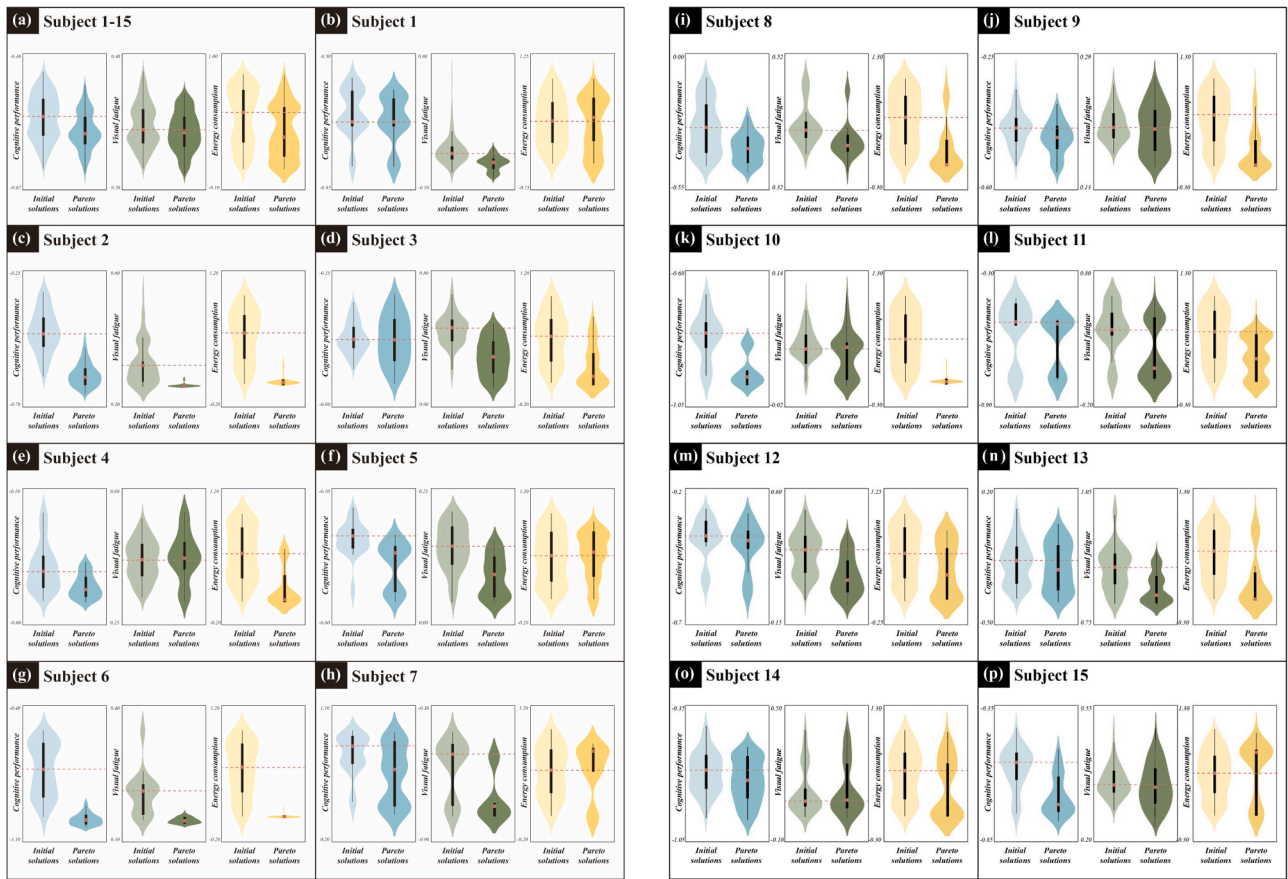


Fig. 7. Distribution of initial solutions and Pareto front solutions.

500lx, while the ideal solutions for VF ranged between 4,000K to 6,400K and 200lx to 760lx. The most significant difference among the ideal solutions for the three objective functions was observed for VF, and CCT exhibited greater variation than illuminance across all objective functions. This is likely because the impact of illuminance on energy consumption is dominant compared to that of CCT, resulting in a more constrained range of illuminance.

4.2.2. Comparison by scenarios

Fig. 8 presents the CP, VF, and energy consumption for occupants under the lighting conditions across the 2,000 scenarios.

Firstly, a comparison was made between the fixed lighting condition for CP and the Pareto front solutions. The best solution among the Pareto front solutions, with equal weights assigned to all objectives, showed a 7.1 % decrease in CP but a 3.11 % reduction in VF and approximately 90.54 % savings in energy consumption compared to the fixed lighting condition for CP. When comparing the fixed lighting condition with the ideal solutions for CP from the Pareto front solutions, VF decreased by 1.55 %, CP increased by 17.48 %, and energy consumption was reduced by 31.24 %. While the energy savings were less compared to the best solution, the ideal solutions for CP outperformed the fixed lighting condition in all objective aspects. Secondly, the comparison between the fixed lighting condition for VF and the Pareto front solutions yielded the following results. The best solution among the Pareto solutions showed a 10.58 % decrease in CP, a 7.6 % reduction in VF, and a 51.88 % savings in energy consumption compared to the fixed lighting condition for VF. The ideal solutions for VF, compared to the fixed lighting condition for VF, resulted in a 3.24 % decrease in CP and approximately a 1.5-fold increase in energy consumption, but a 22.04 % reduction in VF.

In the comparison of CP, VF, and energy consumption across 2,000 scenarios between the fixed lighting conditions and the Pareto front

solutions, the CVEO model demonstrated superior performance, particularly in reducing VF and energy consumption. The ideal solutions for CP showed the best performance for CP and also resulted in reductions in both VF and energy consumption, showcasing superior performance in all objectives.

5. Discussions

5.1. Practical implications of the proposed model

5.1.1. Real-time occupant status-based lighting control

The CVEO model can contribute to creating an occupant-centric lighting environment based on occupants' real-time CP and VF, particularly in commercial buildings such as offices and educational spaces. For example, a specific lighting condition might generally be effective for CP or VF, but the occupants' CP can temporarily decrease depending on the type and duration of the task even under the same lighting conditions, or some occupants might exhibit high VF due to excessive visual tasks. The CVEO model addresses this issue by including stacking ensemble models to predict CP and VF in real-time through bio-signals. The stacking ensemble models showed high predictive performance, with average RMSEs of 0.032 and 0.012 for CP and VF, respectively. Particularly, the results of predictive performance evaluation indicated that personal predictive models are more appropriate for occupant-centric control with higher predictive performance. The tendency for personal predictive models to outperform general predictive models in predicting occupant status using bio-signals has also been observed in previous studies. Wu et al. (2023) reported that accuracy of personal model ranged from 0.74 to 0.76 while that of general model ranged from 0.69 to 0.70 [91]. Chauhan et al. (2023) developed a model to predict CP based on individual bio-signals, achieving a high level of consistency

Table 6

Ideal and best solutions for multiple and individual subjects.

Subject		Lighting condition	Ideal solutions			Best solutions
			CP	VF	Energy	
Multiple	Subject 1-15	CCT (K) Illum. (lx)	5019.20 200.80	4821.80 495.04	5019.20 200.80	4640.02 206.49
Individual	Subject 1	CCT (K) Illum. (lx)	4020.56 352.08	4216.12 654.39	4000.00 200.00	4423.82 200.00
	Subject 2	CCT (K) Illum. (lx)	4000.00 200.00	4001.51 200.01	4000.00 200.00	4000.00 200.00
	Subject 3	CCT (K) Illum. (lx)	5605.10 240.69	5605.10 240.69	4000.00 200.00	4781.48 200.04
	Subject 4	CCT (K) Illum. (lx)	5035.55 500.00	6390.98 527.73	4000.09 200.00	4001.08 200.00
	Subject 5	CCT (K) Illum. (lx)	4499.08 500.05	6177.17 660.37	4003.44 200.00	4126.38 200.02
	Subject 6	CCT (K) Illum. (lx)	4000.00 200.00	4295.97 249.93	4000.00 200.00	4000.00 200.00
	Subject 7	CCT (K) Illum. (lx)	5892.38 500.40	5818.65 656.90	4000.55 200.00	4507.46 200.00
	Subject 8	CCT (K) Illum. (lx)	4000.04 200.00	5774.64 758.40	4000.03 200.00	4000.04 200.00
	Subject 9	CCT (K) Illum. (lx)	4006.76 200.00	4034.15 616.24	4000.00 200.00	4006.76 200.00
	Subject 10	CCT (K) Illum. (lx)	5000.29 200.00	5000.29 200.00	4000.00 200.00	5000.29 200.00
	Subject 11	CCT (K) Illum. (lx)	4826.63 350.02	4088.10 355.84	4000.46 200.00	4583.88 200.12
	Subject 12	CCT (K) Illum. (lx)	4000.01 200.00	5424.77 517.71	4000.00 200.00	4305.56 200.03
	Subject 13	CCT (K) Illum. (lx)	5002.41 200.00	5002.49 200.01	4000.15 200.00	5002.41 200.00
	Subject 14	CCT (K) Illum. (lx)	4971.83 200.01	5953.27 653.87	4008.41 200.00	5743.70 200.00
	Subject 15	CCT (K) Illum. (lx)	5187.94 202.57	6207.35 413.92	4000.00 200.00	5187.94 202.57

Note: CP for cognitive performance; VF stands for visual fatigue; CCT for correlated color temperature; and Illum. for illuminance.

between predicted and actual values (i.e., average R^2 at 0.63) and emphasized that individual variations could only be captured using a personal predictive model [59]. Moreover, state-of-the-art studies on occupant-centric control have also demonstrated a tendency to develop personal models over general models [143–145].

5.1.2. Lighting solutions for dynamic and personalized occupant scenarios

The CVEO model can effectively create personalized lighting environments that reflect the characteristics of the occupants present in the room. As shown in Section 4.2, occupants' status and preferences due to lighting vary greatly among individuals. These results align with previous studies showing that the optimal lighting environment for achieving maximum CP varies among individuals [59]. Deng et al (2021) also reported that there is individual difference in work engagement under the same lighting conditions [146]. Also, Hamedani et al (2020) revealed that individuals that are more sensitive to lighting perceive glare (i.e., one of the VF factors) more frequently, which insists that there is a possibility of individual difference in VF [61]. The ideal solution for CP was derived as 5019.20K and 200.80lx for 15 subjects in this study. This result aligns with some of the previous studies such as [37] and [28] that revealed 5,100–5,800K and 200lx are optimal for CP, but conflicts with results of greater number of studies that suggest different lighting conditions for maximizing CP [29,32,36]. Similarly, the ideal solution for VF in this study (i.e., 4,821.80K and 495.04lx) does not align with studies by [40,34,43] and etc. This implies that fixed lighting conditions are unlikely to consistently achieve optimal outcomes across all situations. Also, the CVEO model has shown superior performance for suggesting optimal lighting conditions for specific occupant combinations in 2,000 scenarios. Particularly, the CVEO model can significantly contribute to providing a personalized lighting environment for occupants who use personal office or offices shared by a specific group of occupants. Also, even in spaces such as classrooms

where random students frequently enter and exit, customized lighting can be provided to the students currently present as the CVEO model is a data-driven approach.

5.1.3. Balancing cognitive performance, visual fatigue and energy

The CVEO model can simultaneously optimize CP, VF, and energy consumption, which are the three key factors that must be considered in commercial building lighting control. Most of the previous studies explored optimal lighting conditions focusing on a single factor among CP, VF, and energy consumption. However, according to previous studies as illustrated in Section 1.2, lighting conditions for CP and VF showed different tendencies. Also, since indoor environmental quality for occupants and energy consumption generally have a trade-off relationship, the necessity of considering all three factors simultaneously in lighting control has been emphasized. This approach enables achieving three goals at the same time: (i) enhancing office workers' work productivity and students' learning efficiency, (ii) reducing eye-related symptoms, particularly benefiting occupants who predominantly use visual display terminals, and (iii) saving energy from artificial lighting in commercial buildings.

Previous studies have also conducted objective optimizations to consider trade-offs. Zhang et al. (2024) conducted multi-objective optimization for visual and non-visual effects and energy consumption, and revealed 388lx and 493lx are optimal for general and fine work, respectively [50]. Zeng et al. (2021) also considered similar objectives, and derived 4,000K and 5,500K for general situations and specifically for non-visual effects, respectively [51]. In contrast, this study defines CP and VF as objectives, resulting in the best solution of 4,640K and 206.49lx. However, the key distinction from previous studies lies in the data-driven approach adopted in this research, which suggests that the optimal lighting condition may vary depending on the subject. Additionally, previous approaches required experiments with every

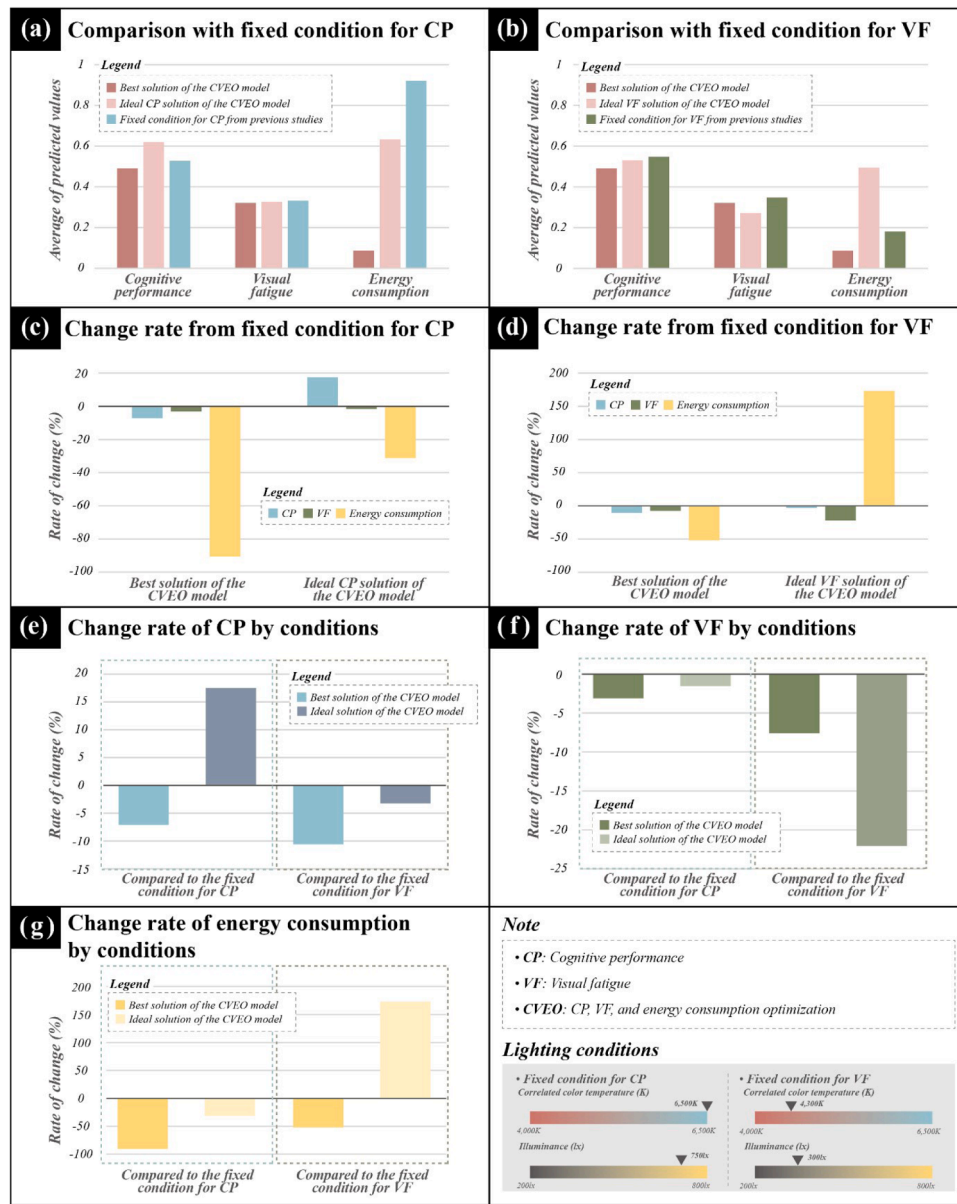


Fig. 8. Performance of the CVEO model.

combination of CCT and illuminance to find lighting conditions optimal for CP and VF. However, since both CCT and illuminance are continuous variables with extensive ranges, it is impossible to collect data with all combinations of CCT and illuminance. In contrast, this study adopts a data-driven approach, allowing the exploration of CCT and illuminance combinations across all ranges after collecting data from a few data collections.

5.2. Limitations and future directions

Despite the practical implications and contributions of the CVEO model, several limitations need to be addressed for its implementation in actual commercial buildings. Firstly, it is necessary to reduce the number of bio-signals required for the CVEO model or replace them with more accessible bio-signals. Although the CVEO model developed in this study targets bio-signals measurable by wearable devices, the accessibility of wearable devices for brain waves and ocular response is still low in terms of cost and usability. To improve the practicality of the CVEO model, it is necessary to develop stacking ensemble models focusing on

variables with high feature importance among the bio-signals.

Secondly, to enhance the effectiveness of the CVEO model implementation, more variables and objectives need to be additionally considered. For example, in actual commercial buildings, changes in CP, VF, and energy consumption due to daylighting should be considered along with artificial lighting. Zeng et al. (2021) reported that considering non-visual effect of lighting can increase the energy consumption up to 57 % [51]. Additionally, including non-visual effects such as circadian rhythm as an objective function or constraint can facilitate occupant-centric lighting control that more actively utilizes the biological effects of lighting [52].

Lastly, the CVEO model needs to be further specified and refined to show significant effects on CP. Ru et al. (2019) reported that non-visual effect of lighting can be varied by difficulty levels and types of the tasks [147]. This implies that the effect of lighting on CP may not be significant when performing certain difficulty levels and types of tasks. Although the CVEO model attempted to address these issues by enhancing flexibility with a data-driven approach and including multiple types of CPs to represent integrated CP, it still may not significantly

improve CP in specific situations, particularly where certain types of CPs are predominantly used. Therefore, a more refined method that considers complex mechanism of CP should be applied to the future CVEO model.

6. Conclusion

This study proposed the Cognitive performance (CP), Visual fatigue (VF), and Energy consumption Optimization (CVEO) model to advance occupant-centric lighting control. The CVEO model uses stacking ensemble models to predict occupants' real-time CP and VF based on bio-signals, and an interpolation model to predict energy consumption as the objective functions. The NSGA-II algorithm searches for the optimal correlated color temperature and illuminance that maximizes CP while minimizing VF and energy consumption.

To evaluate the model's performance, data from 15 subjects were collected under nine different lighting conditions. The results showed that personal models significantly outperformed general models, achieving low root mean squared errors of 0.023 and 0.012 for CP and VF predictions, respectively. Pareto front solutions for individual and multiple occupants demonstrated improved CP, reduced VF, and lower energy consumption compared to initial solutions. Additionally, in 2,000 simulated scenarios, the CVEO model consistently outperformed fixed lighting conditions proposed in prior studies.

The CVEO model represents a significant contribution to occupant-centric building systems. If the model is applied to future commercial buildings, it will be able to provide an optimal lighting environment depending on the occupants' real-time CP and VF. Its application in commercial buildings could improve office productivity, enhance learning outcomes for students, alleviate eye-related symptoms, and achieve substantial energy savings.

CRedit authorship contribution statement

Dahyun Jung: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Seunghoon Jung:** Writing – original draft, Visualization, Validation, Resources, Methodology, Conceptualization. **Jong-baek An:** Writing – original draft, Visualization, Validation, Resources, Methodology. **Taehoon Hong:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.buildenv.2024.112424](https://doi.org/10.1016/j.buildenv.2024.112424).

Data availability

Data will be made available on request.

References

- [1] K.K. Benke, K.E. Benke, Uncertainty in health risks from artificial lighting due to disruption of circadian rhythm and melatonin secretion: a review, *Hum. Ecol. Risk Assess.* (2013), <https://doi.org/10.1080/10807039.2012.702608>.
- [2] Y.M. Cho, S.H. Ryu, B.R. Lee, K.H. Kim, E. Lee, J. Choi, Effects of artificial light at night on human health: a literature review of observational and experimental studies applied to exposure assessment, *Chronobiol. Int.* (2015), <https://doi.org/10.3109/07420528.2015.1073158>.
- [3] I. Konstantzos, S.A. Sadeghi, M. Kim, J. Xiong, A. Tzempelikos, The effect of lighting environment on task performance in buildings – a review, *Energy Build.* (2020), <https://doi.org/10.1016/j.enbuild.2020.110394>.
- [4] J. Mogas-Recalde, R. Palau, Classroom lighting and its effect on student learning and performance: towards smarter conditions, in: *Smart Innov. Syst. Technol.*, 2021, https://doi.org/10.1007/978-981-15-7383-5_1.
- [5] A.M. Al-Ghaili, H. Kasim, N.M. Al-Hada, M. Othman, M.A. Saleh, A review: buildings energy savings - lighting systems performance, *IEEE Access* (2020), <https://doi.org/10.1109/ACCESS.2020.2989237>.
- [6] N. Gentile, Improving lighting energy efficiency through user response, *Energy Build.* (2022), <https://doi.org/10.1016/j.enbuild.2022.112022>.
- [7] Smart lighting market size, share & trends report, 2030, (n.d.), <https://www.grandviewresearch.com/industry-analysis/global-smart-lighting-market> (accessed March 12, 2024).
- [8] G. Zissis, P. Bertoldi, T. Serrenho, European Commission. Joint Research Centre., Update on the status of LED-lighting world market since 2018., (n.d.).
- [9] C. De Bakker, T. Van De Voort, A. Rosemann, The energy saving potential of occupancy-based lighting control strategies in open-plan offices: the influence of occupancy patterns, *Energies* (2018), <https://doi.org/10.3390/en11010002>.
- [10] C. de Bakker, M. Aries, H. Kort, A. Rosemann, Occupancy-based lighting control in open-plan office spaces: a state-of-the-art review, *Build. Environ.* (2017), <https://doi.org/10.1016/j.buildenv.2016.11.042>.
- [11] D. Caicedo, A. Pandharipande, Daylight and occupancy adaptive lighting control system: an iterative optimization approach, *Light. Res. Technol.* (2016), <https://doi.org/10.1177/1477153515587148>.
- [12] N.T. Al-Ashwal, A.S. Hassan, The integration of daylighting with artificial lighting to enhance building energy performance, in: *AIP Conf. Proc.*, 2017, <https://doi.org/10.1063/1.5005777>.
- [13] M.S. Rea, M.G. Figueiro, Light as a circadian stimulus for architectural lighting, *Light. Res. Technol.* (2018), <https://doi.org/10.1177/1477153516682368>.
- [14] Y. Li, T. Ru, Q. Chen, L. Qian, X. Luo, G. Zhou, Effects of illuminance and correlated color temperature of indoor light on emotion perception, *Sci. Rep.* (2021), <https://doi.org/10.1038/s41598-021-93523-y>.
- [15] X. Zhang, Y. Qiao, H. Wang, J. Wang, D. Chen, Lighting environmental assessment in enclosed spaces based on emotional model, *Sci. Total Environ.* (2023), <https://doi.org/10.1016/j.scitotenv.2023.161933>.
- [16] Y. Liu, S. Zhang, Y. Wu, D. Yang, Studies on visual health features of luminous environment in college classrooms, *Build. Environ.* (2021), <https://doi.org/10.1016/j.buildenv.2021.108184>.
- [17] A. Zarindast, A. Sharma, J. Wood, Application of text mining in smart lighting literature - an analysis of existing literature and a research agenda, *Int. J. Inf. Manag. Data Insights* (2021), <https://doi.org/10.1016/j.jjimei.2021.100032>.
- [18] E.J. Gago, T. Muneer, M. Knez, H. Köster, Natural light controls and guides in buildings. Energy saving for electrical lighting, reduction of cooling load, *Renew. Sustain. Energy Rev.* (2015), <https://doi.org/10.1016/j.rser.2014.08.002>.
- [19] E. Mills, The \$230-billion global lighting energy bill, in: *Proc. 5th Int. Conf. Energy-Efficient Light*, 2002.
- [20] O. Stefani, M. Freyburger, S. Veitz, T. Basishvili, M. Meyer, J. Weibel, C. Cajochen, Changing color and intensity of LED lighting across the day impacts on circadian melatonin rhythms and sleep in healthy men, *J. Pineal Res.* 70 (3) (2021) e12714.
- [21] S. Pradhan, Y. Jang, H. Chauhan, Investigating effects of indoor temperature and lighting on university students' learning performance considering sensation, comfort, and physiological responses, *Build. Environ.* (2024), <https://doi.org/10.1016/j.buildenv.2024.111346>.
- [22] W. Yang, J.Y. Jeon, Effects of lighting and sound factors on environmental sensation, perception, and cognitive performance in a classroom, *J. Build. Eng.* (2023), <https://doi.org/10.1016/j.jobe.2023.107063>.
- [23] J. Bao, X. Song, Y. Li, Y. Bai, Q. Zhou, Effect of lighting illuminance and colour temperature on mental workload in an office setting, *Sci. Rep.* (2021), <https://doi.org/10.1038/s41598-021-94795-0>.
- [24] H. Kim, H. Kang, H. Choi, D. Jung, T. Hong, Human-building interaction for indoor environmental control: evolution of technology and future prospects, *Autom. Constr.* 152 (2023) 104938, <https://doi.org/10.1016/j.autcon.2023.104938>.
- [25] S. Munshi, A. Varghese, S. Dhar-Munshi, Computer vision syndrome—A common cause of unexplained visual symptoms in the modern era, *Int. J. Clin. Pract.* (2017), <https://doi.org/10.1111/ijcp.12962>.
- [26] S.A. Randolph, Computer vision syndrome, *Work Heal. Saf.* (2017), <https://doi.org/10.1177/2165079917712727>.
- [27] J. Grünberger, L. Linzmayer, M. Dietzel, B. Saletu, The effect of biologically-active light on the neo- and thymopsychic and on psychophysiological variables in healthy volunteers, *Int. J. Psychophysiol.* (1993), [https://doi.org/10.1016/0167-8760\(93\)90092-4](https://doi.org/10.1016/0167-8760(93)90092-4).
- [28] K.S. Liu, C.M. Chiang, Y.S. Lin, Influences of visual fatigue on the productivity of subjects using visual display terminals in a light-emitting diode lighting environment, *Archit. Sci. Rev.* (2010), <https://doi.org/10.3763/asre.2009.0083>.

- [29] Z. Mohebian, S. Farhang Dehghan, H. Dehghan, Evaluation of the combined effects of heat and lighting on the level of attention and reaction time: climate chamber experiments in Iran, *Sci. World J.* (2018), <https://doi.org/10.1155/2018/5171582>.
- [30] Z. Hu, C. Yi, J. Hao, X. Qiao, X. Guo, Comparative study on the effects of lighting on cognitive ergonomics in single and multi-working modes, *Neuroquantology* (2018), <https://doi.org/10.14704/nq.2018.16.5.1290>.
- [31] C.C. Lin, Effect of noise intensity and illumination intensity on visual performance, *Percept. Mot. Skills* (2014), <https://doi.org/10.2466/26.24.PMS.119c2021>.
- [32] C. Sun, Z. Lian, L. Lan, Work performance in relation to lighting environment in office buildings, *Indoor Built Environ.* (2019), <https://doi.org/10.1177/1420326x18820089>.
- [33] S.L. Chellappa, R. Steiner, P. Blattner, P. Oelhafen, T. Götz, C. Cajochen, Non-visual effects of light on melatonin, alertness and cognitive performance: can blue-enriched light keep us alert? *PLoS One* (2011) <https://doi.org/10.1371/journal.pone.0016429>.
- [34] M. Lu, S. Hu, Z. Mao, P. Liang, S. Xin, H. Guan, Research on work efficiency and light comfort based on EEG evaluation method, *Build. Environ.* (2020), <https://doi.org/10.1016/j.buildenv.2020.107122>.
- [35] Y. Zhu, M. Yang, Y. Yao, X. Xiong, X. Li, G. Zhou, N. Ma, Effects of illuminance and correlated color temperature on daytime cognitive performance, subjective mood, and alertness in healthy adults, *Environ. Behav.* (2019), <https://doi.org/10.1177/0013916517738077>.
- [36] J.H. Ma, J.K. Lee, S.H. Cha, Effects of lighting CCT and illuminance on visual perception and task performance in immersive virtual environments, *Build. Environ.* (2022), <https://doi.org/10.1016/j.buildenv.2021.108678>.
- [37] C. Liu, L. Sun, X. Jing, Y. Zhang, X. Meng, C. Jia, W. Gao, How correlated color temperature (CCT) affects undergraduates: a psychological and physiological evaluation, *J. Build. Eng.* (2022), <https://doi.org/10.1016/j.jobe.2021.103573>.
- [38] L. Tong, N. Liu, S. Hu, M. Lu, Y. Zheng, X. Ma, Research on the preferred illuminance in office environments based on EEG, *Buildings* (2023), <https://doi.org/10.3390/buildings13020467>.
- [39] J. Cai, W. Hao, Y. Guo, P. Du, R. Wen, X. Yang, Influence of LED Correlated Color Temperature on Ocular Physiological Function and Subjective Perception of Discomfort, *IEEE Access*, 2017, <https://doi.org/10.1109/ACCESS.2017.2780276>.
- [40] W. Yang, J.Y. Jeon, Effects of correlated colour temperature of LED light on visual sensation, perception, and cognitive performance in a classroom lighting environment, *Sustainability* (2020), <https://doi.org/10.3390/SU12104051>.
- [41] J. Shen, Z. Lian, Multivariate analysis of subjective evaluation of indoor lighting environment, *Front. Archit. Res.* (2021), <https://doi.org/10.1016/j.foar.2021.02.006>.
- [42] X. Xie, F. Song, Y. Liu, S. Wang, D. Yu, Study on the effects of display color mode and luminance contrast on visual fatigue, *IEEE Access* (2021), <https://doi.org/10.1109/ACCESS.2021.3061770>.
- [43] Q. Wang, H. Xu, F. Zhang, Z. Wang, Influence of color temperature on comfort and preference for LED indoor lighting, *Optik (Stuttg)* (2017), <https://doi.org/10.1016/j.jileo.2016.10.049>.
- [44] A. Jiang, X. Yao, S. Westland, C. Hemingray, B. Foing, J. Lin, The effect of correlated colour temperature on physiological, emotional and subjective satisfaction in the hygiene area of a space station, *Int. J. Environ. Res. Public Health* (2022), <https://doi.org/10.3390/ijerph19159090>.
- [45] X. Fu, D. Feng, X. Jiang, T. Wu, The effect of correlated color temperature and illumination level of LED lighting on visual comfort during sustained attention activities, *Sustainability* (2023), <https://doi.org/10.3390/su15043826>.
- [46] R. Dang, Y. Liu, S. Chang, The impact patterns of classroom lighting parameters on visual fatigue and a mathematical model, *Build. Environ.* 234 (2023) 110193, <https://doi.org/10.1016/j.buildenv.2023.110193>.
- [47] C. Liu, J. Li, X. Wang, Q. Zang, W. Wang, W. Gao, A review of subjective evaluation, physiological indicators and cognitive performance in indoor light environment: the role of illuminance and correlated color temperature, *J. Build. Eng.* 95 (2024) 110224, <https://doi.org/10.1016/j.jobe.2024.110224>.
- [48] Z. Hamedani, E. Solgi, T. Hine, H. Skates, Revealing the relationships between luminous environment characteristics and physiological, ocular and performance measures: an experimental study, *Build. Environ.* (2020), <https://doi.org/10.1016/j.buildenv.2020.106702>.
- [49] L. Lan, S. Hadji, L. Xia, Z. Lian, The effects of light illuminance and correlated color temperature on mood and creativity, *Build. Simul.* (2021), <https://doi.org/10.1007/s12273-020-0652-z>.
- [50] X. Zhang, J. Wang, Y. Zhou, H. Wang, N. Xie, D. Chen, A multi-objective optimization method for enclosed-space lighting design based on MOPSO, *Build. Environ.* (2024), <https://doi.org/10.1016/j.buildenv.2024.111185>.
- [51] Y. Zeng, H. Sun, B. Lin, Optimized lighting energy consumption for non-visual effects: a case study in office spaces based on field test and simulation, *Build. Environ.* (2021), <https://doi.org/10.1016/j.buildenv.2021.108238>.
- [52] H. Cai, Q. Lin, H. Liu, X. Li, H. Xiao, A multi-objective optimisation mathematical model with constraints conducive to the healthy rhythm for lighting control strategy, *Mathematics* (2022), <https://doi.org/10.3390/math10193471>.
- [53] L. Bellia, U. Błaszczak, F. Diglio, F. Fragiasso, Light-environment interactions and integrative lighting design: connecting visual, non-visual and energy requirements in a case study experiment, *Build. Environ.* (2024), <https://doi.org/10.1016/j.buildenv.2024.111323>.
- [54] E.N.D. Madias, P.A. Kontaxis, F.V. Topalis, Application of multi-objective genetic algorithms to interior lighting optimization, *Energy Build.* (2016), <https://doi.org/10.1016/j.enbuild.2016.04.078>.
- [55] S. Carlucci, G. Cattarin, F. Causone, L. Pagliano, Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II), *Energy Build.* (2015), <https://doi.org/10.1016/j.enbuild.2015.06.064>.
- [56] W. Luo, R. Kramer, M. Kompier, K. Smolders, Y. de Kort, W. van Marken Lichtenbelt, Personal control of correlated color temperature of light: effects on thermal comfort, visual comfort, and cognitive performance, *Build. Environ.* (2023), <https://doi.org/10.1016/j.buildenv.2023.110380>.
- [57] M. Dick, W. Pohl, H.K. Lackner, E.M. Weiss, M. Canazei, Effects of personalized lighting on subjective ratings, cognitive performance, and physiological stress response in a simulated office environment, *LEUKOS - J. Illum. Eng. Soc. North Am.* (2024), <https://doi.org/10.1080/15502724.2023.2292960>.
- [58] A. Luque-Casado, M. Zabala, E. Morales, M. Mateo-March, D. Sanabria, Cognitive performance and heart rate variability: the influence of fitness level, *PLoS One* (2013), <https://doi.org/10.1371/journal.pone.0056935>.
- [59] H. Chauhan, Y. Jang, S. Pradhan, H. Moon, Personalized optimal room temperature and illuminance for maximizing occupant's mental task performance using physiological data, *J. Build. Eng.* (2023), <https://doi.org/10.1016/j.jobe.2023.107757>.
- [60] Y. Tyukhova, C.E. Waters, Subjective and pupil responses to discomfort glare from small, high-luminance light sources, *Light. Res. Technol.* (2019), <https://doi.org/10.1177/1477153518772000>.
- [61] Z. Hamedani, E. Solgi, T. Hine, H. Skates, G. Isoardi, R. Fernando, Lighting for work: a study of the relationships among discomfort glare, physiological responses and visual performance, *Build. Environ.* (2020), <https://doi.org/10.1016/j.buildenv.2019.106478>.
- [62] I. Golasi, F. Salata, E. de L. Vollaro, A. Peña-García, Influence of lighting colour temperature on indoor thermal perception: a strategy to save energy from the HVAC installations, *Energy Build.* (2019), <https://doi.org/10.1016/j.enbuild.2018.12.026>.
- [63] S.H.A. Begemann, G.J. Van Den Beld, A.D. Tenner, Daylight, artificial light and people in an office environment, overview of visual and biological responses, *Int. J. Ind. Ergon.* (1997), [https://doi.org/10.1016/S0169-8141\(96\)00053-4](https://doi.org/10.1016/S0169-8141(96)00053-4).
- [64] R.R. Baniya, E. Tetri, L. Halonen, A study of preferred illuminance and correlated colour temperature for LED office lighting, *Light Eng.* (2015).
- [65] L. Shi, T. Katsuura, Y. Shimomura, K. Iwanaga, Effects of different light source color temperatures during physical exercise on human EEG and subjective evaluation, *J. Human-Environ. Syst.* (2009), <https://doi.org/10.1618/jhes.12.27>.
- [66] Visual lighting design | WELL Standard, (n.d.). <https://standard.wellcertified.com/light/visual-lighting-design> (accessed July 18, 2024).
- [67] P-100 Facilities standards for the public buildings service, 2018.
- [68] K.S. A 3011, Illuminance standards, 1998.
- [69] H.L. Mahoney, T.M. Schmidt, The cognitive impact of light: illuminating ipRGC circuit mechanisms, *Nat. Rev. Neurosci.* (2024), <https://doi.org/10.1038/s41583-023-00788-5>.
- [70] P.S. Sachdev, D. Blacker, D.G. Blazer, M. Ganguli, D.V. Jeste, J.S. Paulsen, R. C. Petersen, Classifying neurocognitive disorders: the DSM-5 approach, *Nat. Rev. Neurol.* (2014), <https://doi.org/10.1038/nrneuro.2014.181>.
- [71] B.K. Min, Y.C. Jung, E. Kim, J.Y. Park, Bright illumination reduces parietal EEG alpha activity during a sustained attention task, *Brain Res.* (2013), <https://doi.org/10.1016/j.brainres.2013.09.031>.
- [72] T. Åkerstedt, D. Hallvig, G. Kecklund, Normative data on the diurnal pattern of the Karolinska sleepiness scale ratings and its relation to age, sex, work, stress, sleep quality and sickness absence/illness in a large sample of daytime workers, *J. Sleep Res.* (2017), <https://doi.org/10.1111/jsr.12528>.
- [73] H.H. Lee, Y.C. Tu, S.L. Yeh, In search of blue-light effects on cognitive control, *Sci. Rep.* (2021), <https://doi.org/10.1038/s41598-021-94989-6>.
- [74] F. Ferlazzo, L. Piccardi, C. Burattini, M. Barbalace, A.M. Giannini, F. Bisegna, Effects of new light sources on task switching and mental rotation performance, *J. Environ. Psychol.* (2014), <https://doi.org/10.1016/j.jenvp.2014.03.005>.
- [75] A. Alkozei, R. Smith, N.S. Dailey, S. Bajaj, W.D.S. Killgore, Acute exposure to blue wavelength light during memory consolidation improves verbal memory performance, *PLoS One* (2017), <https://doi.org/10.1371/journal.pone.0184884>.
- [76] H.C. Jung, J.H. Kim, C.W. Lee, The effect of the illuminance of light emitting diode (LED) lamps on long-term memory, *Displays* (2017), <https://doi.org/10.1016/j.displa.2017.05.001>.
- [77] H. Zohdi, R. Egli, D. Guthruf, F. Scholkmann, U. Wolf, Color-dependent changes in humans during a verbal fluency task under colored light exposure assessed by SPA-fNIRS, *Sci. Rep.* (2021), <https://doi.org/10.1038/s41598-021-88059-0>.
- [78] J. Arede, M. Carvalho, P. Esteves, B. de las Heras, N. Leite, Exploring the effects of LED lighting training program on motor performance among young athletes, *Creat. Res. J.* (2021), <https://doi.org/10.1080/10400419.2020.1817693>.
- [79] S. Sabbah, M.S. Worden, D.D. Laniado, D.M. Berson, J.N. Sanes, Luxotonic signals in human prefrontal cortex as a possible substrate for effects of light on mood and cognition, *Proc. Natl. Acad. Sci. U. S. A.* (2022), <https://doi.org/10.1073/pnas.2118192119>.
- [80] G. Vandewalle, S. Schwartz, D. Grandjean, C. Vuilleumier, E. Baeteau, C. Degueldre, M. Schabus, C. Phillips, A. Luxen, D.J. Dijk, P. Maquet, Spectral quality of light modulates emotional brain responses in humans, *Proc. Natl. Acad. Sci. U. S. A.* (2010), <https://doi.org/10.1073/pnas.1010180107>.
- [81] W. Weitbrecht, H. Bärwolf, A. Lischke, S. Jünger, Effect of light color temperature on human concentration and creativity, *Fortschritte Der Neurol. Psychiatr.* (2015).
- [82] M.S. Mott, D.H. Robinson, A. Walden, J. Burnette, A.S. Rutherford, Illuminating the effects of dynamic lighting on student learning, *SAGE Open* (2012), <https://doi.org/10.1177/2158244012445585>.

- [83] M. Divjak, H. Bischof, Eye blink based fatigue detection for prevention of computer vision syndrome, in: *Proc. 11th IAPR Conf. Mach. Vis. Appl. MVA*, 2009, p. 2009.
- [84] M. Khalaj, M. Ebrahimi, P. Shojai, R. Bagherzadeh, T. Sadeghi, M. Ghalenoei, Computer vision syndrome in eleven to eighteen-year-old students in Qazvin, *Biotechnol. Heal. Sci.* (2015), <https://doi.org/10.17795/bhs-28234>.
- [85] W.A.E.W.A. Ghani, I. Zahari, N.W. Shafee, M.R. Hilmi, F.Y. Alias, M.A.S. A. Rahim, An investigation of computer vision syndrome in optometry students during the covid-19 outbreak, *Int. J. Allied Heal. Sci.* 7 (2023) 259–267, <https://doi.org/10.31436/IJAHS.V7I5.856>.
- [86] F. Zheng, F. Hou, R. Chen, J. Mei, P. Huang, B. Chen, Y. Wang, Investigation of the relationship between subjective symptoms of visual fatigue and visual functions, *Front. Neurosci.* (2021), <https://doi.org/10.3389/fnins.2021.686740>.
- [87] J. Kuze, K. Ukai, Subjective evaluation of visual fatigue caused by motion images, *Displays* (2008), <https://doi.org/10.1016/j.displa.2007.09.007>.
- [88] S. Glinne, R. Brautaset, C. Österman, Visual fatigue during control room work in process industries, *Work* (2020), <https://doi.org/10.3233/WOR-203141>.
- [89] I. Primpas, G. Tsirtsis, M. Karydis, G.D. Kokkoris, Principal component analysis: development of a multivariate index for assessing eutrophication according to the European water framework directive, *Ecol. Indic.* (2010), <https://doi.org/10.1016/j.ecolind.2009.04.007>.
- [90] X. Peng, T. Zhang, O.W. Fraunfeld, K. Wang, C. Mu, An integrated index of cryospheric change in the Northern Hemisphere, *Glob. Planet. Change* (2022), <https://doi.org/10.1016/j.gloplacha.2022.103984>.
- [91] Y. Wu, J. Fan, B. Cao, Comparison among different modeling approaches for personalized thermal comfort prediction when using personal comfort systems, *Energy Build.* (2023), <https://doi.org/10.1016/j.enbuild.2023.112873>.
- [92] L.E. Hartstein, M.T. Durniak, R.F. Karlicek, N.E. Berthier, A comparison of the effects of correlated colour temperature and gender on cognitive task performance, *Light. Res. Technol.* (2018), <https://doi.org/10.1177/1477153517721728>.
- [93] R.H. Huang, L. Lee, Y.A. Chiu, Y. Sun, Effects of correlated color temperature on focused and sustained attention under white LED desk lighting, *Color Res. Appl.* (2015), <https://doi.org/10.1002/col.21885>.
- [94] D. Jung, J. An, T. Hong, M. Lee, Visual fatigue prediction using classification model based on physiological responses of occupants under office lightings, *J. Build. Eng.* 98 (2024) 111146, <https://doi.org/10.1016/j.jobe.2024.111146>.
- [95] I. Knez, Effects of indoor lighting on mood and cognition, *J. Environ. Psychol.* (1995), [https://doi.org/10.1016/0272-4944\(95\)90013-6](https://doi.org/10.1016/0272-4944(95)90013-6).
- [96] G. Forte, F. Favieri, M. Casagrande, Heart rate variability and cognitive function: a systematic review, *Front. Neurosci.* (2019), <https://doi.org/10.3389/fnins.2019.00710>.
- [97] P.C. De Looft, L.J.M. Cornet, P.J.C.M. Embregts, H.L.I. Nijman, H.C.M. Didden, Associations of sympathetic and parasympathetic activity in job stress and burnout: a systematic review, *PLoS One* (2018), <https://doi.org/10.1371/journal.pone.0205741>.
- [98] H.A. Abhishekh, P. Nisarga, R. Kisan, A. Meghana, S. Chandran, T. Raju, T. N. Sathyaprabha, Influence of age and gender on autonomic regulation of heart, *J. Clin. Monit. Comput.* (2013), <https://doi.org/10.1007/s10877-012-9424-3>.
- [99] C.U.D. Stenfor, L.M. Hanson, T. Theorell, W.S. Osika, Executive cognitive functioning and cardiovascular autonomic regulation in a population-based sample of working adults, *Front. Psychol.* (2016), <https://doi.org/10.3389/fpsyg.2016.01536>.
- [100] Y. Yang, L. Hu, R. Zhang, X. Zhu, M. Wang, Investigation of students' short-term memory performance and thermal sensation with heart rate variability under different environments in summer, *Build. Environ.* (2021), <https://doi.org/10.1016/j.buildenv.2021.107765>.
- [101] N. Zhang, C. Liu, J. Li, K. Hou, J. Shi, W. Gao, A comprehensive review of research on indoor cognitive performance using electroencephalogram technology, *Build. Environ.* 257 (2024) 111555, <https://doi.org/10.1016/j.buildenv.2024.111555>.
- [102] T. Harmony, T. Fernández, J. Silva, J. Bernal, L. Díaz-Comas, A. Reyes, E. Marosi, M. Rodríguez, M. Rodríguez, EEG delta activity: an indicator of attention to internal processing during performance of mental tasks, *Int. J. Psychophysiol.* (1996), [https://doi.org/10.1016/S0167-8760\(96\)00053-0](https://doi.org/10.1016/S0167-8760(96)00053-0).
- [103] C.E. Stevens, D.L. Zabelina, Creativity comes in waves: an EEG-focused exploration of the creative brain, *Curr. Opin. Behav. Sci.* (2019), <https://doi.org/10.1016/j.cobeha.2019.02.003>.
- [104] J. Lagopoulos, J. Xu, I. Rasmussen, A. Vik, G.S. Malhi, C.F. Eliassen, I.E. Arntsen, J.G. Sæther, S. Hollup, A. Holen, S. Davanger, Ø. Ellingsen, Increased theta and alpha EEG activity during nondirective meditation, *J. Altern. Complement. Med.* (2009), <https://doi.org/10.1089/acm.2009.0113>.
- [105] A.A. Benasich, Z. Gou, N. Choudhury, K.D. Harris, Early cognitive and language skills are linked to resting frontal gamma power across the first 3 years, *Behav. Brain Res.* (2008), <https://doi.org/10.1016/j.bbr.2008.08.049>.
- [106] T. Womelsdorf, P. Fries, The role of neuronal synchronization in selective attention, *Curr. Opin. Neurobiol.* (2007), <https://doi.org/10.1016/j.conb.2007.02.002>.
- [107] J. Lin, S. Westland, V. Cheung, Effect of intensity of short-wavelength light on electroencephalogram and subjective alertness, *Light. Res. Technol.* (2020), <https://doi.org/10.1177/1477153519872801>.
- [108] T. Kim, G. Lee, M. Park, H.M. Lee, J.W. Park, H.J. Suk, User responses to dynamic light in automobiles with EEG and self-assessments, *IEEE Access* (2022), <https://doi.org/10.1109/ACCESS.2022.3223665>.
- [109] N. Zhang, C. Liu, C. Hou, Z. Wang, X. He, W. Gao, The application in electroencephalogram technology for investigating indoor lighting environments: a review, *J. Build. Eng.* 94 (2024) 110020, <https://doi.org/10.1016/j.jobe.2024.110020>.
- [110] S. Mathôt, Tuning the senses: how the pupil shapes vision at the earliest stage, *Annu. Rev. Vis. Sci.* (2020), <https://doi.org/10.1146/annurev-vision-030320-062352>.
- [111] W. Nowak, A. Zarowska, E. Szul-Pietrzak, M. Misiuk-Hojło, System and measurement method for binocular pupillometry to study pupil size variability, *Biomed. Eng. Online* (2014), <https://doi.org/10.1186/1475-925X-13-69>.
- [112] S. Karar, T. Kanumuri, Assessment of driver fatigue and drowsiness based on eye blink rate, in: *Lect. Notes Networks Syst.*, 2023. https://doi.org/10.1007/978-9-81-99-6550-2_24.
- [113] S. Schwerd, A. Schulte, Evaluating blink rate as a dynamic indicator of mental workload in a flight simulator, in: *Proc. Int. Jt. Conf. Comput. Vision, Imaging Comput. Graph. Theory Appl* 1, 2024, pp. 362–368, <https://doi.org/10.5220/0012319100003660>.
- [114] M.H.D.M. Ribeiro, L. dos Santos Coelho, Ensemble approach based on bagging, boosting and stacking for short-term prediction in agribusiness time series, *Appl. Soft Comput. J.* (2020), <https://doi.org/10.1016/j.asoc.2019.105837>.
- [115] A. Daza, C.F. Ponce Sánchez, G. Apaza-Perez, J. Pinto, K.Z. Ramos, Stacking ensemble approach to diagnosing the disease of diabetes, *Informatics Med. Unlocked* (2024), <https://doi.org/10.1016/j.imu.2023.101427>.
- [116] J. Moon, S. Jung, J. Rew, S. Rho, E. Hwang, Combination of short-term load forecasting models based on a stacking ensemble approach, *Energy Build.* (2020), <https://doi.org/10.1016/j.enbuild.2020.109921>.
- [117] J.H. Friedman, Greedy function approximation: a gradient boosting machine, *Ann. Stat.* (2001), <https://doi.org/10.1214/aos/1013203451>.
- [118] T. Chen, C. Guestrin, Xgboost: a scalable tree boosting system, in: *Proc. 22nd Acm Sigkdd Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 785–794.
- [119] L. Prokhorenkova, G. Gusev, A. Vorobev, A.V. Dorogush, A. Gulin, Catboost: unbiased boosting with categorical features, *Adv. Neural Inf. Process. Syst.* (2018).
- [120] L. Breiman, Random forests, *Mach. Learn.* (2001), <https://doi.org/10.1023/A:1010933404324>.
- [121] G. Biau, B. Cadre, Optimization by gradient boosting, in: *Adv. Contemp. Stat. Econom. Festschrift Honor Christine Thomas-Agnan*, 2021. https://doi.org/10.1007/978-3-030-73249-3_2.
- [122] D. Boldini, F. Grisoni, D. Kuhn, L. Friedrich, S.A. Sieber, Practical guidelines for the use of gradient boosting for molecular property prediction, *J. Cheminform.* (2023), <https://doi.org/10.1186/s13321-023-00743-7>.
- [123] J. Tanha, Y. Abdi, N. Samadi, N. Razzaghi, M. Asadpour, Boosting methods for multi-class imbalanced data classification: an experimental review, *J. Big Data* (2020), <https://doi.org/10.1186/s40537-020-00349-y>.
- [124] C.V. Priscilla, D.P. Prabha, Influence of optimizing xgboost to handle class imbalance in credit card fraud detection, in: *Proc. 3rd Int. Conf. Smart Syst. Inven. Technol. ICSSIT 2020*, 2020, <https://doi.org/10.1109/ICSSIT48917.2020.9214206>.
- [125] A.V. Dorogush, V. Ershov, A.G. Yandex, CatBoost: gradient boosting with categorical features support, (2018). <https://arxiv.org/abs/1810.11363v1> (accessed July 18, 2024).
- [126] T. Akiba, S. Sano, T. Yanase, T. Ohta, M. Koyama, Optuna: a Next-generation Hyperparameter Optimization Framework, in: *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2019, <https://doi.org/10.1145/3292500.3330701>.
- [127] P. Belany, P. Hrabovsky, S. Sedivy, N. Cajova Kantova, Z. Florkova, A comparative analysis of polynomial regression and artificial neural networks for prediction of lighting consumption, *Buildings* 14 (2024) 1712, <https://doi.org/10.3390/buildings14061712>.
- [128] H. Chen, R. Zhu, Y.-H. Lee, S.-T. Wu, Correlated color temperature tunable white LED with a dynamic color filter, *Opt. Express* (2016), <https://doi.org/10.1364/oe.24.00a731>.
- [129] J. An, S. Yeom, T. Hong, K. Jeong, J. Lee, S. Eardley, J. Choi, Analysis of the impact of energy consumption data visualization using augmented reality on energy consumption and indoor environment quality, *Build. Environ.* (2024), <https://doi.org/10.1016/j.buildenv.2024.111177>.
- [130] D.F. Pires, C.H. Antunes, A.G. Martins, NSGA-II with local search for a multi-objective reactive power compensation problem, *Int. J. Electr. Power Energy Syst.* (2012), <https://doi.org/10.1016/j.ijepes.2012.05.024>.
- [131] H. Ma, Y. Zhang, S. Sun, T. Liu, Y. Shan, A comprehensive survey on NSGA-II for multi-objective optimization and applications, *Artif. Intell. Rev.* (2023), <https://doi.org/10.1007/s10462-023-10526-z>.
- [132] K. Deb, S. Agrawal, A. Pratap, T. Meyarivan, A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II, *Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* (2000), https://doi.org/10.1007/3-540-45356-3_83.
- [133] J. Zhang, K. Lv, X. Zhang, M. Ma, J. Zhang, Study of human visual comfort based on sudden vertical illuminance changes, *Buildings* (2022), <https://doi.org/10.3390/buildings12081127>.
- [134] T.T.K. Munia, A. Islam, M.M. Islam, S.S. Mostafa, M. Ahmad, Mental states estimation with the variation of physiological signals, in: *2012 Int. Conf. Informatics, Electron. Vision, ICIEV 2012*, 2012, <https://doi.org/10.1109/ICIEV.2012.6317333>.
- [135] D. Jung, J. An, T. Hong, Exploring the relationship between office lighting, cognitive performance, and psychophysiological responses: a multidimensional approach, *Build. Environ.* (2024).
- [136] R.J. Croft, R.J. Barry, Removal of ocular artifact from the EEG: a review, *Neurophysiol. Clin.* (2000), [https://doi.org/10.1016/S0987-7053\(00\)00055-1](https://doi.org/10.1016/S0987-7053(00)00055-1).

- [137] D.C. Niehorster, R.S. Hessels, J.S. Benjamins, GlassesViewer: open-source software for viewing and analyzing data from the Tobii Pro Glasses 2 eye tracker, *Behav. Res. Methods* 52 (2020) 1244–1253, <https://doi.org/10.3758/s13428-019-01314-1>.
- [138] H. Kim, T. Hong, Determining the optimal set-point temperature considering both labor productivity and energy saving in an office building, *Appl. Energy* (2020), <https://doi.org/10.1016/j.apenergy.2020.115429>.
- [139] S. Ibrahim, S. Nazir, S.A. Velastin, Feature selection using correlation analysis and principal component analysis for accurate breast cancer diagnosis, *J. Imaging* (2021), <https://doi.org/10.3390/jimaging7110225>.
- [140] Y. Lu, I. Cohen, X.S. Zhou, Q. Tian, Feature selection using principal feature analysis, in: *Proc. ACM Int. Multimed. Conf. Exhib.*, 2007, <https://doi.org/10.1145/1291233.1291297>.
- [141] N.K. Rai, D. Saravanan, L. Kumar, P. Shukla, R.N. Shaw, RMSE and MAPE analysis for short-term solar irradiance, solar energy, and load forecasting using a recurrent artificial neural network, *Appl. AI IOT Renew. Energy* (2022), <https://doi.org/10.1016/B978-0-323-91699-8.00010-3>.
- [142] D. Chicco, M.J. Warrens, G. Jurman, The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation, *PeerJ Comput. Sci.* (2021), <https://doi.org/10.7717/PEERJ-CS.623>.
- [143] Y. Bai, L. Liu, K. Liu, S. Yu, Y. Shen, D. Sun, Non-intrusive personal thermal comfort modeling: a machine learning approach using infrared face recognition, *Build. Environ.* (2024), <https://doi.org/10.1016/j.buildenv.2023.111033>.
- [144] C. Yang, R. Zhang, H. Kanayama, D. Sato, K. Taniguchi, Hybrid personalized thermal comfort model based on wrist skin temperature, *Build. Environ.* 268 (2025) 112321, <https://doi.org/10.1016/j.buildenv.2024.112321>.
- [145] N. Alam, S.A. Zaki, S.A. Ahmad, M.K. Singh, A. Azizan, N. Othman, Machine learning approach for predicting personal thermal comfort in air conditioning offices in Malaysia, *Build. Environ.* 266 (2024) 112083, <https://doi.org/10.1016/j.buildenv.2024.112083>.
- [146] M. Deng, X. Wang, C.C. Menassa, Measurement and prediction of work engagement under different indoor lighting conditions using physiological sensing, *Build. Environ.* 203 (2021) 108098, <https://doi.org/10.1016/j.buildenv.2021.108098>.
- [147] T. Ru, K.C.H.J. Smolders, Q. Chen, G. Zhou, Y.A.W. de Kort, Diurnal effects of illuminance on performance: exploring the moderating role of cognitive domain and task difficulty, *Light. Res. Technol.* (2021), <https://doi.org/10.1177/1477153521990645>.