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Untangle the Effects of Classroom Environmental Features on Middle-School Students' Mood Perception with Machine Learning and XAI

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Abstract

Proper daylighting in educational buildings improves students' mood and health. However, daylighting can be affected by multiple environmental features, and comprehensive investigations remain limited. This study examined how various classroom environmental features affect students' mood perception in six classrooms of three middle schools in eastern China. Eighteen environmental features across six dimensions were assessed through field studies and software simulations, and 557 valid mood responses were collected from 243 students through questionnaires. Traditional machine learning and deep learning models were used to predict students' mood perception with the environmental features, with SHapley Additive exPlanations (SHAP) applied to interpret the contributions of different features. Results showed that Random Forest achieved a relatively high accuracy of 82% in the binary classification of mood perception prediction. Among all features, Exterior view evaluation (EVE) had the largest impact and showed a strong interaction with floor level. Higher floors and EVE ≥ 3 were associated with more positive moods. Beneficial conditions for mood perception also included horizontal desktop illuminance above 300 lx, frontal eye-level illuminance below 400 lx, left-side eye-level illuminance within 300–1000 lx, and proximity to windows below 2.5 m. These findings provide new insights and practical guidance for designing healthier classroom environments to promote adolescent mental health, thereby contributing to sustainable educational environments that integrate human well-being with energy-efficient daylighting design.

Keywords: daylight; classroom environmental features; middle-school students; mood perception; machine learning; explainable AI

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Received: 29 August 2025
Revised: 13 October 2025
Accepted: 21 October 2025
Published: 24 October 2025

Citation: Xu, H.; Zhang, L.; Zeng, Y.; Bergefurt, L.; Xu, J. Untangle the Effects of Classroom Environmental Features on Middle-School Students' Mood Perception with Machine Learning and XAI. *Sustainability* **2025**, *17*, 9459. https://doi.org/10.3390/su17219459

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1. Introduction

Under the current educational context in China, adolescents have been confronted with an increasing prevalence of mental health issues, such as depression, poor sleep quality, and other suboptimal health conditions [1]. These issues have prompted considerable concern across governments, society, and academia, underscoring the imperative for urgent

and multifaceted interventions. At the national level, a multitude of policies have been implemented to foster healthy campuses and promote adolescent health [2,3]. Improving the classroom environment is an important measure, as the indoor environments the adolescents experience every day are closely related to their health [4].

Classrooms serve as the primary environments for adolescents' daily living, with students typically spending over eight hours per day in these spaces. As a vital component of this environment, the impact of daylighting on adolescent health has long been a significant research topic. Traditional research on daylighting environment has primarily focused on visual comfort [5–7], glare evaluation [8,9], and energy efficiency [10]. Since the discovery of intrinsically photosensitive retinal ganglion cells (ipRGCs) in 2002 [11], there has been a deepening understanding of the non-visual effects of light in recent years, including its impacts on mood, cognition, sleep, etc. [12,13]. Therefore, researchers have shifted their attention from solely visual effects to also addressing non-visual effects.

To improve daylighting quality in educational buildings, scholars have conducted extensive controlled experiments to explore the impact of various lighting environments on adolescents' learning efficiency, mood, alertness, and other physiological and psychological indicators [14–17]. Previous studies have confirmed that a favourable daylighting environment improves mood and enhances cognitive performance [18–20]. Mood plays a crucial role in adolescents' mental health among various non-visual health indicators, particularly during the middle school years, spanning ages 12–15. Students at this stage frequently exhibit pronounced mood fluctuations and polarisation tendencies, increasing vulnerability to mood-related problems that may trigger psychological issues [21]. Although previous studies have pointed out that daylighting has a significant impact on students' mood, relying solely on daylighting parameters is insufficient for accurately assessing occupants' mood perceptions [22–25]. In fact, factors influencing the quality of classroom daylighting include daylighting parameters (e.g., horizontal illuminance, eye-level illuminance) [26], classroom characteristics (e.g., spatial dimensions, window size) [27], and exterior views [28]. These factors all interact in complex and multi-dimensional ways with students' mood perception. Therefore, it is necessary to identify the key classroom environmental features that influence mood in order to provide effective guidelines for the implementation of healthy campuses.

To achieve this purpose, traditional statistical methods, such as correlation analysis and linear regression, are among the most commonly used evaluation techniques for identifying the relationship between occupants' perception and environmental parameters. However, due to their overly stringent assumptions regarding the relationship between dependent and independent variables, they encounter difficulties in revealing the complex non-linear relationship between the daylighting environment and occupants' perception [29]. Particularly in real-world scenarios where multiple factors are intertwined, accurate predictions are often elusive. Therefore, it is necessary to explore new technical approaches, which could elucidate the relationships between multiple features in the real classroom spaces and students' mood perception.

In recent years, integrating artificial intelligence (AI) techniques, especially machine learning (ML) models, has provided new ideas and solutions for optimising classroom daylighting environments [30–34]. ML, with its automation capabilities, can process vast amounts of complex multidimensional data to reveal potential associations and patterns among multiple environmental features and students' perceptions within classroom daylighting environments. In the existing body of research, some scholars have used ML to predict the objective performance of buildings as a means of optimising building performance. For example, Han et al. [35] proposed a daylighting performance prediction model with high generalisation ability and high prediction accuracy based on an artificial neural

network agent model, which provides a favourable and fast prediction and evaluation tool for the early design stage of office buildings. Xuan et al. [36] achieved rapid prediction and multi-objective coupled optimisation of daylighting performance in reading spaces by introducing techniques such as random forest and genetic algorithm optimisation. Additionally, Lin et al. [37] proposed a daylight simulation agent model based on a convolutional neural network and a generative adversarial network, which is capable of predicting static and annual daylighting performance, as well as spatial illuminance distribution, respectively.

Collectively, these studies have provided new ways and established a more solid foundation for the prediction and optimisation of building daylighting performance. However, research applying ML to predict students' mood perception and exploring the relationship between classroom environmental features and mood perception remains relatively limited [38]. This is partly due to the inherent subjectivity and complexity of perception, as there is not just a straightforward causal relationship between objective features and subjective perceptions [39]. Hence, a more extensive collection of classroom environmental features and mood perceptions, along with in-depth research, is needed.

Considering the limitations of established research, this study selected typical classrooms in three middle schools located in Suzhou, Eastern China, as the research subjects. By employing ML models, students' mood perception was predicted based on various classroom environmental features, especially daylighting parameters. Furthermore, Explainable AI (XAI) was applied to interpret the prediction results. The objectives of this study are twofold: (1) To develop highly accurate ML classification models to predict students' mood perceptions; (2) To explore the key classroom environmental parameters that affect mood perceptions, as well as to analyse their underlying mechanisms and interactions. This study is expected to offer new approaches and technical references for research on the environmental designs of educational buildings. As an exploratory endeavour, our methodology and findings may hold significant practical implications and contribute to the optimal design of healthy classroom environments, thereby promoting adolescents' mental health. Moreover, this study supports sustainable architectural design by integrating human well-being with energy-efficient daylighting strategies.

2. Methodology

The research workflows can be summarised into data collection, data preprocessing, ML model construction, training and evaluation, and SHAP-based XAI analysis (Figure 1). Firstly, classroom characteristics and surrounding conditions were obtained in six typical classrooms through field investigations. Subsequently, classroom models were established, and daylighting simulations were conducted to derive quantitative daylighting parameters. Second, questionnaires were collected about students' mood perception, and contextual variables such as time and weather were also recorded along with the questionnaires. Third, the above-mentioned features and perception scores were organised into a standardised dataset suitable for ML analysis. ML was then applied to construct the prediction model for students' mood perception. Finally, statistical analysis methods, Confusion matrix, model evaluation index and XAI were used for data analysis.

2.1. Data Collection

The data collection gathered eighteen input features across six dimensions, and students' mood perception data. Features include daylighting parameters, classroom characteristics, spatial information of seats, exterior view evaluations (EVE), time, and weather parameters, which were obtained through field tests and software simulation. Students' mood perception data were obtained through questionnaires.

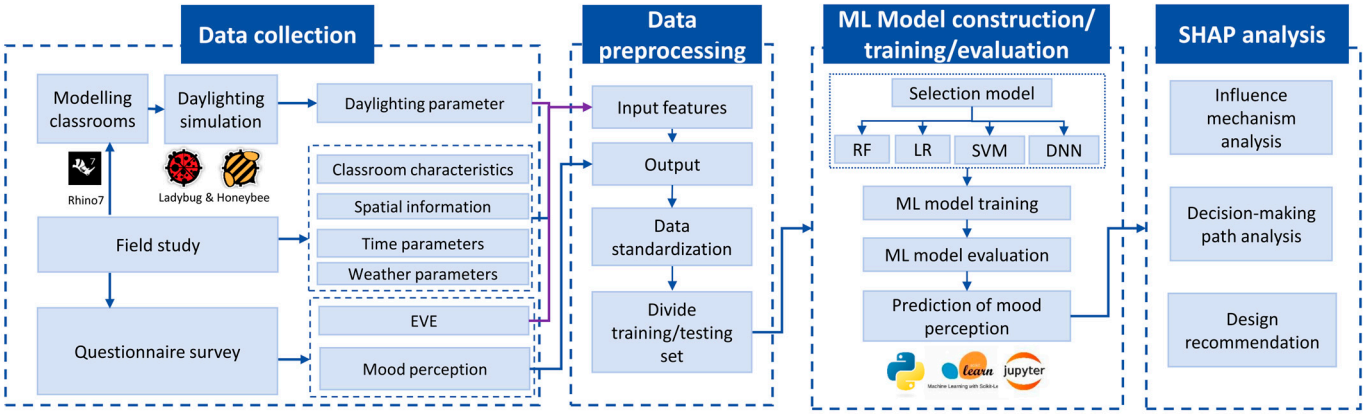


Figure 1. The workflow of the study.

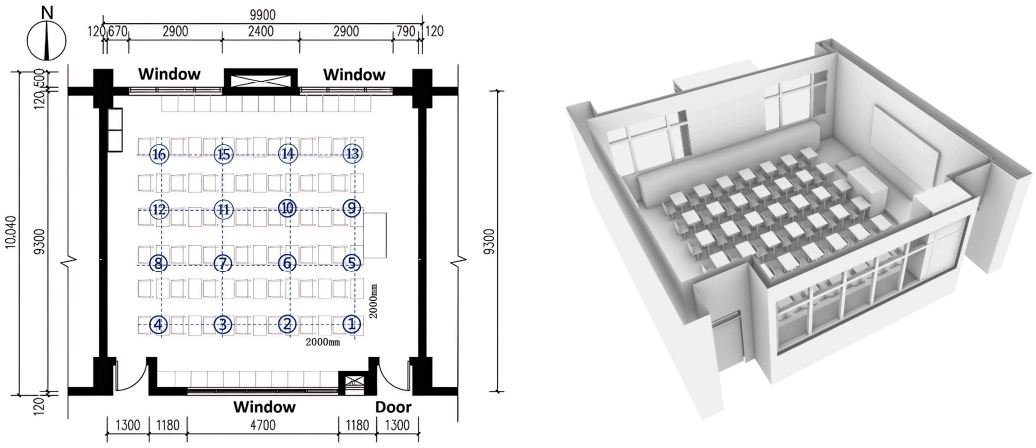
2.1.1. Classroom Environmental Features Collection

Typical classroom environmental features in Suzhou (latitude 31°30′ N, longitude 120°59′ E) in eastern China have been summarised in the previous field studies, which investigated 26 classrooms across seven primary and middle schools [19,40]: Educational buildings are generally characterised by a north–south orientation and consist of 4 to 5 floors. The campus landscapes are primarily composed of roadways, courtyard greenery, and rooftop gardens. Classrooms exhibit typical characteristics in terms of orientation and spatial layout, although they differ in classroom size, window-to-wall ratio (WWR), exterior views, and other aspects. They adopt a double-sided daylighting design with corridors on the south side, featuring primary daylighting from north-facing windows and supplementary daylighting from south-facing windows. Additionally, all the classrooms adopt a single-person desk layout.

Based on the above typical characteristics, this study selected six representative classrooms from three middle schools for in-depth analysis, namely Wujiang School Affiliated to Soochow University (S1), Xinghai Experimental Junior High School in Suzhou Industrial Park (S2), and the Experimental School of Soochow University (S3), during the period from March to May 2024.

Using S1 as an example, field measurements were taken to obtain data on classroom dimensions (depth, width, and height), corridor dimensions, and window dimensions. Daylighting conditions in the classrooms, reflectance of major material surfaces, and light transmittance of windows were measured using an illuminance meter (Konica Minolta T-10A). The measurement process was carried out strictly following local standards [41,42]. In each classroom, we created a grid of 16 measurement points (①–⑯) across the classroom with a spacing of 2.0 m, as shown in Figure 2a. The peripheral measurement points were positioned 1–2 m away from the surrounding walls. Horizontal desktop illuminance (E_h) on the working plane was measured at each grid point at desk level (0.75 m above the floor) every hour from 09:00 to 16:00. During the measurement, daylight served as the sole source of illumination in the classroom; all curtains were fully open, and all the electric lights were switched off.

Next, Rhino7 software was used to build the classroom model (Figure 2b) and the Honeybee plug-in was applied for daylight simulation [43,44]. Specifically, historical meteorological data, the sky model, material reflectance (including blackboard, wall, table, chair, floor level), and window transmittance, among other parameters, were input to obtain simulated values of E_h at each measurement point. Then, the relative root-mean-square error (RMSE) was controlled to within 10% through time-by-time validation of the simulated and field-measured values at the measurement points to ensure the accuracy of the model.



(**a**) (**b**)

Figure 2. (**a**) Locations of measurement points in classroom (placed on desks); (**b**) S1 School Classroom Interior Model.

After verification, the simulation obtained the E_h and eye-level illuminance values at each seat in the classroom at the time when the questionnaires were distributed. Considering the possibility that the direction of a student's gaze changes frequently in the classroom, the eye-level illuminance from three main gaze directions (45°, 90°, and 135°) was simulated [45]. These directions were represented as left ($E_{v\ left}$), front ($E_{v\ front}$), and right ($E_{v\ right}$) eye-level illuminance, respectively. Additionally, it was assumed that the students in this study were mainly facing the blackboard, i.e., $E_{v\ front}$.

2.1.2. Questionnaire for Mood Perception

The questionnaires used in this study were derived from a large-scale longitudinal field survey investigating the impact of classroom daylighting environments on visual and non-visual health perceptions among middle school students [40]. This study specifically focuses on the various classroom environmental features, utilising ML techniques to analyse their impact mechanisms on students' mood perception. The questionnaire included basic demographic information about the students (class, age, gender, etc.) and indicators of their mood perception. Mood perceptions were measured using a 7-point Likert scale, with the question 'What is the impact of daylight quality in the classroom on your mood perception?' [40]. The mood perception rating scale ranged from 1 (very unpleasant) to 7 (very pleasant).

An increasing number of studies have taken into account the influence of exterior views on the evaluation of mood perception, but have not delved into the differences in the level of quality of exterior views on students' moods [46,47]. Therefore, a question specifically about the quality of the view was added to the questionnaire, 'How do you evaluate the typical view through the exterior windows?' [48] The rating scales for this question ranged from 1 (very uninteresting) to 5 (very interesting), aiming to explore the influence of exterior views on students' mood perception.

The questionnaire was distributed between April and May 2024 with three distinct weather conditions: sunny, cloudy and overcast [49]. Researchers distributed questionnaires to students with instructions to complete them at approximately 9:00, 11:00, and 15:00. During all sessions of the questionnaires, the classroom curtains remained fully open, the electric lighting was switched off, and outdoor illuminance was concurrently recorded. A total of 243 first-year middle-school students (13.6 ± 0.7 years old) participated in the experiment. All students were in good health, had normal vision or corrected vision, and had no emotional type or other chronic health problems. A total of 653 questionnaires were

returned. After excluding invalid questionnaires (incomplete responses, identical answers for all questions, redundant selections, etc.), 557 valid questionnaires were obtained.

2.2. Data Preprocessing

After data collection, one dataset was created, consisting of 18 input features and one label, the students' mood perception as output [31,32,50–52]. Specifically, the 18 input features included daylighting parameters such as E_h, $E_{v\ front}$, $E_{v\ left}$, $E_{v\ right}$, and outdoor illuminance; classroom characteristics, namely width, depth, window-to-floor ratio (WFR), window-to-wall ratio of the south windows (WWR_S), window-to-wall ratio of the north windows (WWR_N), south window transmittance (SWT), north window transmittance (NWT), and floor level; spatial information of seats in the classroom namely distance from the seat to the nearest window (DNW); EVE; time parameters like time of day, morning/afternoon, and weather parameter. Then, categorical data, such as time and weather parameters, were coded with continuous integers. Next, the data was randomly divided into a training dataset (70%) and a test dataset (30%) for ML. Given the large variation in the value ranges of different features within the dataset, data normalisation of these features was applied to enhance the efficiency and accuracy of the training process.

2.3. ML Model Training and Evaluation

After data collection and preprocessing, we used traditional ML and deep learning (DL) for the prediction model that takes classroom environmental features as input and the mood perception as output. In this study, we chose three classical ML models, i.e., Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF). In addition, we constructed a Deep Neural Network (DNN) model, which has one input layer, seven hidden layers, and one output layer, with the number of nodes in the hidden layers being 512, 256, 128, 128, 64, 32, and 16, respectively. All hidden layers use the ReLU activation function, and the output layer adopts softmax to predict the probabilities of each score. To overcome the limitations induced by the small sample size and the imbalanced data, we adopted L2 regularisation and the Adam optimiser in the DNN model [53–55]. For the LR, SVM, and RF models, we employed grid search with 5-fold cross-validation to determine the optimal hyperparameters. regularisation strategies were applied to mitigate overfitting, where LR and SVM used L2 regularisation with the penalty parameter (C) tuned over ({0.001, 0.01, 0.1, 1}), and SVM additionally optimised the kernel type (Radial Basis Function kernel) and kernel coefficient (gamma). For RF, the number of trees (n_estimators) was searched from 50 to 200, and the maximum tree depth (max_depth) ranged from 1 to 20. This unified optimisation framework ensured robust model performance while addressing the challenges of small sample size and class imbalance. These four models range from classical simple ML linear models (LR) to non-linear ML ones (SVM, RF), to complex deep neural networks (DNN). Specifically, while LR serves as a simple baseline and SVM/RF capture different types of non-linear patterns, the DNN was included to investigate whether deep architectures could automatically learn meaningful, complex feature representations that might be missed by the simpler models. Through comparative analysis, the aim was to select the classification model most suitable for this research task and to explore the complex associations between classroom environmental features and students' mood perception.

Model evaluation metrics were used to measure the performance of the constructed model after the model training was completed. Accuracy, precision, recall and F1-score were adopted as evaluation metrics. Accuracy serves as a global metric that measures the overall effectiveness of the classifier in correctly classifying samples. Precision refers to the proportion of true positive predictions among all instances that the model predicted

as positive. Recall refers to the proportion of true positive predictions among all actual positive instances. F1-score combines the model's performance in terms of precision and recall to provide a comprehensive evaluation. The definition and equation to calculate each metric are shown in Table 1:

Table 1. Model evaluation metrics.

Metric	Definition	Equation
Accuracy	The proportion of correct predictions in the total sample.	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
Precision	The proportion of true positive predictions among all positive predictions made by the model.	$Precision = \frac{TP}{TP+FP}$
Recall	The probability of being predicted as a positive sample in a true positive sample.	$Recall = \frac{TP}{TP+FN}$
F1-score	The summed average of Precision and Recall.	$F1 = \frac{2 \times Precision \times Recall}{Precision+Recall}$

TP: True positive is the correctly predicted positive class outcome of the model; TN: True negative is the correctly predicted negative class outcome of the model; FP: False positive is the incorrectly predicted positive class outcome of the model; FN: False negative is the incorrectly predicted negative class outcome of the model.

2.4. Model Interpretability Analysis: SHAP Method

AI is becoming increasingly popular in various applications due to its highly accurate classification and prediction power. However, researchers often find it difficult to fully take advantage of ML since the AI models are "black boxes" and thus cannot be used to interpret and explain the relationship between the input features and the results. In this paper, we adopted SHAP (SHapley Additive exPlanations) to tackle this issue. By calculating the SHAP values, the impact of each feature on the prediction of mood perception for all students, as well as individual differences, can be quantified. This approach enhances the interpretability of the predictive model and improves the transparency of its decision-making process, enabling researchers to better understand how these features affect the students' mood perception. This interpretability not only supports further academic research but also provides actionable recommendations for architects and school administrators aimed at improving the quality of daylight in educational buildings and improving the mental health of students.

This study involved the following SHAP analyses: SHAP bar plots and beeswarm plots were used to explain the feature importance ranking of the mood perception prediction model; dependence plots were applied to demonstrate the interaction effects of different features; and SHAP force plots were used to explain the model's decision-making process for specific samples. These global and local interpretation methods provided a clear visualisation of how exactly each feature affects the mood perception prediction model and shed light on the insights of how different feature interactions affect the decision process. Moreover, by analysing specific samples, the individual differences between students' mood perception, caused by the classroom environmental features, could be explored.

3. Results

3.1. Descriptive and Inferential Statistics

As shown in Table 2, the collected features were divided into six dimensions, namely daylighting parameters, classroom characteristics, spatial information of seats, EVE, time, and weather parameters. The total number of valid responses was 557, with no missing values or outliers.

For the daylighting parameters, E_h had a mean value of 766.81 lx and a standard deviation of 865.61 lx, reflecting significant differences in the daylighting environment within the classroom. In contrast, the $E_{v\ front}$ had a mean value of 388.56 lx and a standard

deviation of 386.93 lx, with a more concentrated data distribution. The mean and standard deviation of $E_{v\ left}$ and $E_{v\ right}$ were 779.30 lx ± 906.25 lx and 444.77 lx ± 388.67 lx, respectively, indicating that there is a greater difference in daylight between the left and right sides of the classroom. This is because these classrooms' left side faces north and typically has larger windows. As a result, the mean and standard deviation of the daylight from the left side were significantly higher than the right side during the questionnaire collection period.

Table 2. Descriptive statistics of 18 input features.

Input Features		Mean	Standard Deviation	Minimum	Median	Maximum
Daylighting parameters	E_h (lx)	766.81	865.61	26.18	487.83	6751.75
	$E_{v\ front}$ (lx)	388.56	386.93	14.27	283.12	3011.16
	$E_{v\ left}$ (lx)	779.30	906.25	36.75	448.81	7062.40
	$E_{v\ right}$ (lx)	444.77	388.67	7.19	350.47	3189.96
	Outdoor illuminance (lx)	34,425	15,962	10,000	30,000	60,000
Classroom characteristics	Width (m)	9.27	0.29	9.00	9.30	9.80
	Depth (m)	8.78	1.01	7.60	8.70	9.90
	Floor level	2.38	0.93	1.00	3.00	3.00
	WWR_N	0.36	0.03	0.33	0.37	0.40
	WWR_S	0.24	0.04	0.20	0.23	0.29
	WFR	0.26	0.05	0.21	0.25	0.33
	NWT	0.64	0.18	0.36	0.72	0.90
	SWT	0.67	0.17	0.36	0.72	0.81
Spatial information of seats	DNW (m)	2.31	1.23	0.40	2.50	4.40
Exterior view evaluations	EVE	3.69	1.00	1.00	4.00	5.00
Time	Time of day	11.65	2.41	9.00	11.00	15.00
	Morning/Afternoon	1.31	0.46	1	1	2
Weather parameters	Weather	2.20	0.80	1.00	2.00	3.00

The classroom characteristics had widths ranging from 9.0 to 9.8 m and depths ranging from 7.6 to 9.9 m, and all classrooms were located on the 1st and 3rd floors. The WWR of the classrooms showed a small range of variation. Specifically, the WWR_N ranged from 0.33 to 0.40, and the WWR_S ranged from 0.20 to 0.29. The north side was the primary daylighting facade and had a slightly larger window area than the south side. The mean value of EVE was 3.69, with a minimum value of 1 and a maximum value of 5, indicating that there was a wide variation in students' feedback on EVE.

As for the time and weather parameters, the weather was coded by integers 1, 2, and 3 for sunny, cloudy, and overcast weather conditions, respectively. The three types of weather conditions occur with roughly the same frequency. Similarly, we coded morning and afternoon as 1 and 2, respectively.

Figure 3 shows the distribution of the mood perception ratings. The x-axis marks the exact evaluation scores from 1 to 7, and the y-axis shows the count of questionnaires for each score. It can be seen that students' mood perception evaluations are unevenly distributed, i.e., imbalanced data, with significant bipolar differences. There are 14.54% more students who considered the indoor daylighting environment to be very pleasant (7 points) than those who considered it to be very unpleasant (1 point). Only 18.67% of the students perceived the effect of indoor daylight quality on their mood perceptions as unpleasant (1–3 points), 28% perceived their mood perceptions as neutral (4 points), while 53.32% of the students perceived the effect of indoor daylight quality on their mood perceptions as pleasant (5–7 points). This indicated that the majority of the students perceived the indoor daylighting environment as more conducive to a pleasant mood.

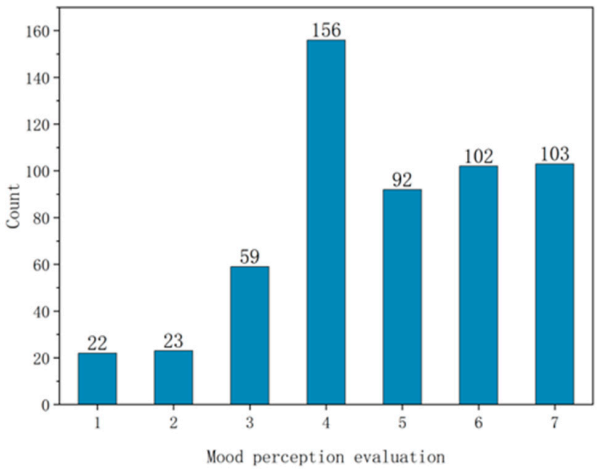


Figure 3. Histogram of the distribution of mood perception score.

Correlation analysis was used to evaluate the correlation between different features and mood perception. The results of the Kolmogorov–Smirnov test showed that the *p*-value for all variables was less than 0.05, indicating that none of the study variables followed a normal distribution. Therefore, we used Spearman's correlation coefficient and presented the detailed results in Figure 4. The results showed that the students' mood perception was most significantly correlated with EVE ($p < 0.001$), with a positive correlation coefficient of 0.57. It was also significantly correlated with E_h, WWR_S, and SWT, with a correlation coefficient of 0.21 ($p < 0.001$). It also showed significant correlations with $E_{v\ front}$, $E_{v\ left}$ and $E_{v\ right}$, outdoor illuminance, WFR and WWR_N ($p < 0.001$), with correlation coefficients greater than 0.15. Of the 18 input features selected, mood perception only showed a significant negative correlation with room depth ($p < 0.001$), with a correlation coefficient of −0.15. No correlations were found between the mood perception and weather conditions, time parameters, DNW, and floor level. These results suggested that classroom characteristics and daylighting parameters play a key role in shaping students' mood perception, with EVE emerging as the most influential feature.

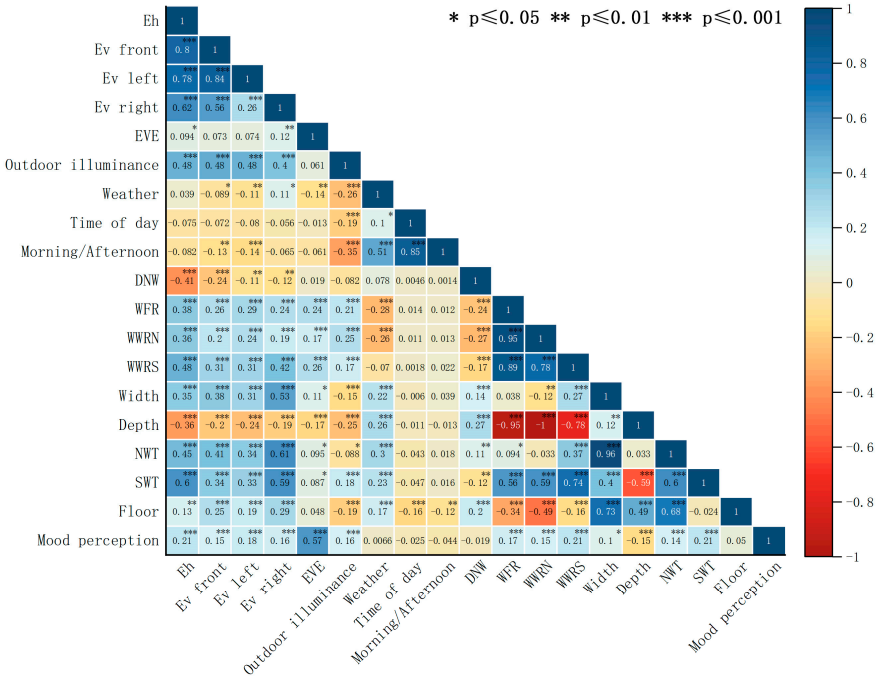


Figure 4. Spearman's correlation coefficient.

3.2. Classification Model Training and Validation

This study compared the performance of three classical ML models and a DNN on predicting students' mood perception based on classroom environmental features. The four commonly used metrics—accuracy, precision, recall, and F1 score—were selected as the model performance evaluation indicators. In this study, this prediction problem was modelled as multiclass and binary classifications.

3.2.1. Multiclass Classification for Mood Perception Prediction

Based on the mood perception scores level (Likert 7-point scale), a seven-class classification model was used for prediction. Results showed that the LR, RF, SVM, and DNN models achieved accuracies of 42.0%, 34.8%, 36.9%, and 40.5%, respectively. To further understand this inferior performance, the confusion matrices were plotted, as shown in Figure 5. The X-axis presents the predicted classes, while the Y-axis denotes the actual classes. The values within the grid indicate classification outcomes, where the upper-side numbers represent the sample count, and the percentages provide the proportion of each category. Additionally, recall was displayed in the rightmost column for each row. Precision was shown in the bottom row of each column. The overall accuracy of the model was highlighted in black at the bottom-right corner, summarising the model's overall classification performance.

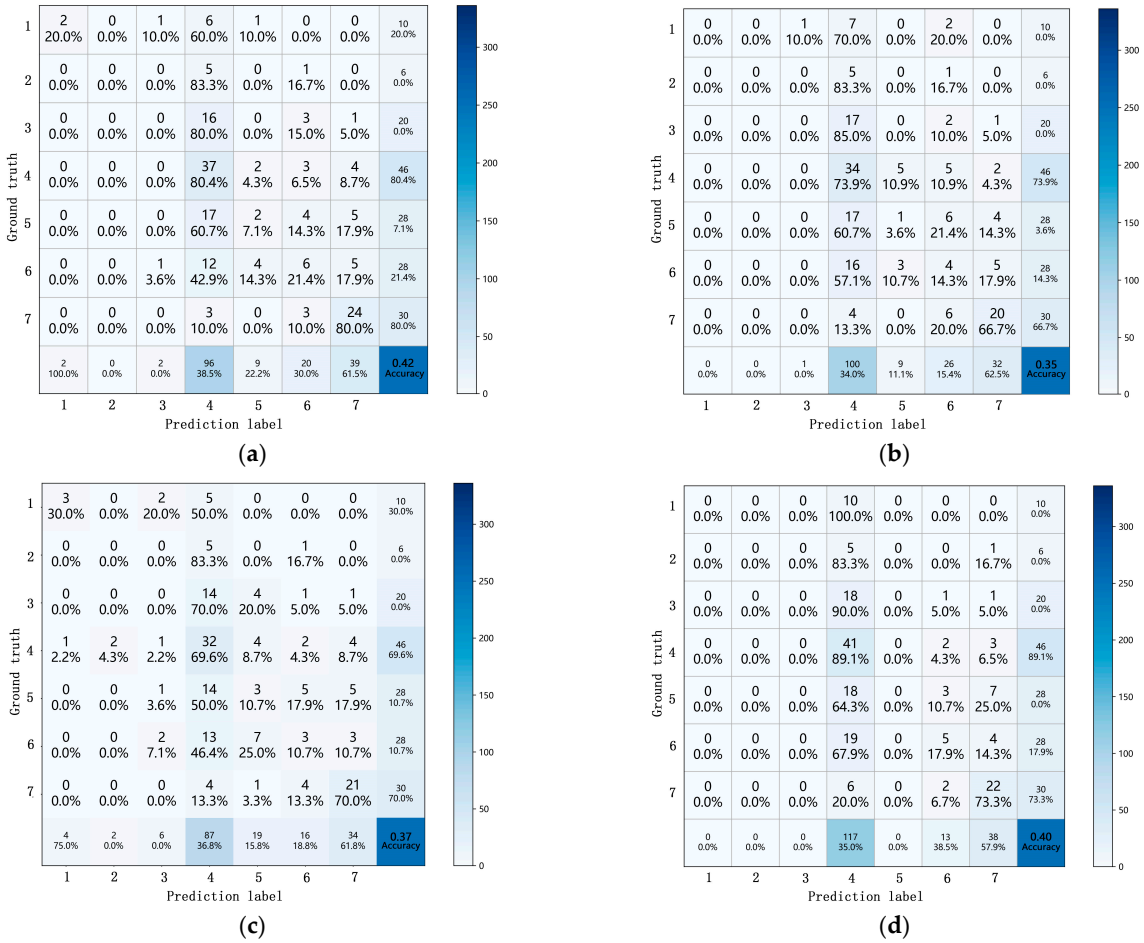


Figure 5. Confusion matrix. (**a**) LR; (**b**) RF; (**c**) SVM; (**d**) DNN. The X-axis presents the predicted classes, while the Y-axis denotes the actual classes. The values within the grid indicate classification outcomes, where the upper-side numbers represent the sample count, and the percentages provide the proportion of each category. The overall accuracy of the model was highlighted in black at the bottom-right corner.

Through the confusion matrices of the four models, it was observed that all the models' precision on category 7 (very pleasant) is relatively higher (57.9–61.8%) than that of most other categories. According to Figure 5, classifiers like Logistic Regression, RF, and DNN mislabelled a few samples of Category 7 to Category 4 (3–6 samples) and Category 6 (2–6 samples). SVM also mislabelled one sample from Category 7 to Category 5. This result suggests that the difference between Category 7 (very pleasant) and the other categories is relatively large, indicating that when students rated 7, the classroom environments differed more significantly from those present when they gave lower ratings. Moreover, almost all models achieved the highest recall in predicting Category 4 (69.6–89.1%). This is because Category 4 has the largest sample size (156/557) among all categories. Hence, the ML models have more training samples to learn about the uniqueness of the samples in this category, and they tend to label all samples as Category 4 for higher recall. This can be observed from the prediction results of samples in Categories 1 and 6, which are all labelled as Category 4, thus resulting in the lowest precision and recall of 0%. It was also noticed that the classifiers can mislabel samples of Category 4 as Category 5, 6, 7, and, seldomly, as 1, 2, and 3 (only SVM). Such bias stems from imbalanced training data distribution, causing ML models to be apt to recognise neutral mood perception as positive. For Categories 5 and 6, most samples were mislabelled as belonging to Category 4, and some were mislabelled as in Category 6 or 5. Overall, the multiclass classifiers were dominated by the imbalance data and thus performed poorly in labelling negative samples, but could almost always label positive samples correctly as positive.

The precision of the above results is relatively low, which may be attributed to the number of classification categories. As suggested by Fathy et al. [56], in studies of human perception and behaviour, an excessive number of categories can result in a small perceptual difference among the intermediate values. This makes it difficult for people to clearly and accurately differentiate between the levels. As a result, the model is unable to accurately predict these intermediate categories, thereby impacting the overall prediction accuracy of the model. Given the suboptimal prediction accuracy of the multiclass model, binary classification was adopted as an alternative approach.

3.2.2. Binary Classification for Mood Perception Prediction

Based on our follow-up survey, students indicated during interviews that a score of 4 reflected a more positive attitude toward mood pleasantness. Therefore, we grouped scores of 1–3 as Category 0 (unpleasant) and scores of 4–7 as Category 1 (pleasant). The following binary classification analysis is based on this evaluation classification method.

To address the issue of class imbalance, evaluation metrics (e.g., precision, recall, and F1-score) reported in Table 3 are weighted averages. Specifically, each metric was calculated as the sum of class-specific metric values weighted by their respective class supports (i.e., number of true samples), normalised by the total number of samples. This approach ensures that the performance on each class is accounted for proportionally to its frequency in the dataset, thereby reducing evaluation bias caused by imbalanced class distributions.

Table 3. Prediction results of RF, DNN, LR, and SVM models on students' mood perception.

	Accuracy	**Precision (Weighted)**	**Recall (Weighted)**	**F1-Score (Weighted)**
RF	0.82 ± 0.03	0.84 ± 0.02	0.96 ± 0.01	0.89 ± 0.01
DNN	0.82 ± 0.02	0.80 ± 0.03	0.82 ± 0.02	0.80 ± 0.03
LR	0.81 ± 0.01	0.81 ± 0.01	1.00 ± 0.00	0.89 ± 0.01
SVM	0.81 ± 0.01	0.73 ± 0.05	0.81 ± 0.01	0.75 ± 0.02

As described in Table 3, the RF demonstrates the most balanced performance across both classes. Its precision (0.84 ± 0.02) and recall (0.96 ± 0.01) are well-aligned, resulting in a high F1-score (0.89 ± 0.01). This indicates that the model maintains a consistent trade-off between false positives and false negatives, suggesting it generalises well to both categories. In comparison, the LR exhibits comparable overall performance, achieving a similar F1-score (0.89 ± 0.01). Despite its slightly lower precision (0.81 ± 0.01), its recall (1.00 ± 0.00) is the highest among all models, implying that it successfully captures nearly all positive samples but at the cost of generating more false positives. This result suggests that while LR effectively models the relationships within the feature space, it may slightly overestimate the performance of one category. The DNN shows moderate performance, with precision (0.80 ± 0.03) and recall (0.82 ± 0.02). However, its relatively low F1-score (0.80 ± 0.03) suggests a trade-off in recall, particularly for the minority class (i.e., Category 0). This outcome may reflect two factors: (1) the underlying non-linear relationships are not sufficiently complex to benefit from a deep architecture, or (2) the dataset may be too small to effectively train a deep neural network, resulting in suboptimal generalisation. The SVM model yields the lowest performance across all evaluation metrics. Its low precision (0.73 ± 0.05) and F1-score (0.75 ± 0.02) indicate a tendency to generate a high number of false positives, and an overall poorer balance between the two classes. This may stem from SVM's sensitivity to class imbalance, which is common for subjective datasets. Therefore, RF was used as the classification model for the SHAP analysis in Section 3.3, because it demonstrates an overall superior performance for binary classification.

3.3. SHAP Interpretability Analysis

3.3.1. Influence Mechanism Analysis

SHAP is a technique for interpreting ML predictions by attributing the contribution of each input variable to the final output. It breaks down a prediction into the summed influences of individual features [57]. The feature importance is indicated by absolute mean SHAP values, which explain the extent and direction to which different environmental features influence the prediction of students' mood perception. As shown in Figure 6a, the SHAP bar plot ranks all the features by their importance when making the classification decisions. The x-axis of the bar plot is the mean absolute SHAP value of the features, with higher values representing greater impact on the model output; the y-axis lists the features in descending order of impact. In comparison, the SHAP beeswarm plot further demonstrates the impact of the features on classifying each sample in the dataset as the target category (Category 1), as shown in Figure 6b. For each feature, every dot represents one sample in the dataset, with the x-axis value being determined by the magnitude and the direction of the SHAP value. If two samples possess the same SHAP value for one feature, the two dots in the beeswarm plot stack vertically, thus resulting in spindle-shaped distributions. The raw values of the feature are indicated by the colour of the dots (red for high values and blue for low values).

In Figure 6a, it can be observed that the five most influential features on the classifier are EVE, $E_{v\ front}$, $E_{v\ left}$, E_h, and DNW. It can be seen in Figure 6b that higher EVE scores have a more positive impact on students' mood perception (stacked red dots correspond to positive SHAP values). On the other hand, it can also be observed that, for EVE, almost all blue dots have negative SHAP values. Moreover, the range of these blue dots' absolute SHAP values can be up to four times higher than that of the red dots with positive SHAP values, which suggests that for a few students, the negative effect of a lower EVE on mood perception is significantly stronger. In contrast, for DNW, a spindle-shaped cluster of blue dots can be seen (students who sat closer to the windows), with small but positive SHAP values, whereas some red dots (students who sat further away from the windows) have

larger but negative SHAP values. This suggests that sitting close to the window has a relatively small but positive impact on the students' pleasant mood perception (Category 1), while sitting away from the window tends to affect the students' mood perception detrimentally, and this negative impact increases with a larger distance. Furthermore, for the $E_{v\ front}$, most red dots were concentrated on the left side of the baseline, suggesting that a higher $E_{v\ front}$ leads to negative mood perception, whereas a lower E_h leads to negative mood perception. A beeswarm plot is informative as it provides a broad overview of SHAP values for many features at once. However, both plots can only demonstrate the impact of single features. Therefore, the SHAP feature dependence plots were created to understand the non-linear relationship between features and model outputs, the feature interaction effects, and the influence of features in different value intervals. In the SHAP feature dependence plot, each dot represents a sample. The x-axis represents the raw value of the target feature, and the y-axis gives the SHAP value, i.e., the impact of the target feature on the classification decision. The colour coding of each dot (red–blue) represents the raw value of the feature that interacts with the target feature.

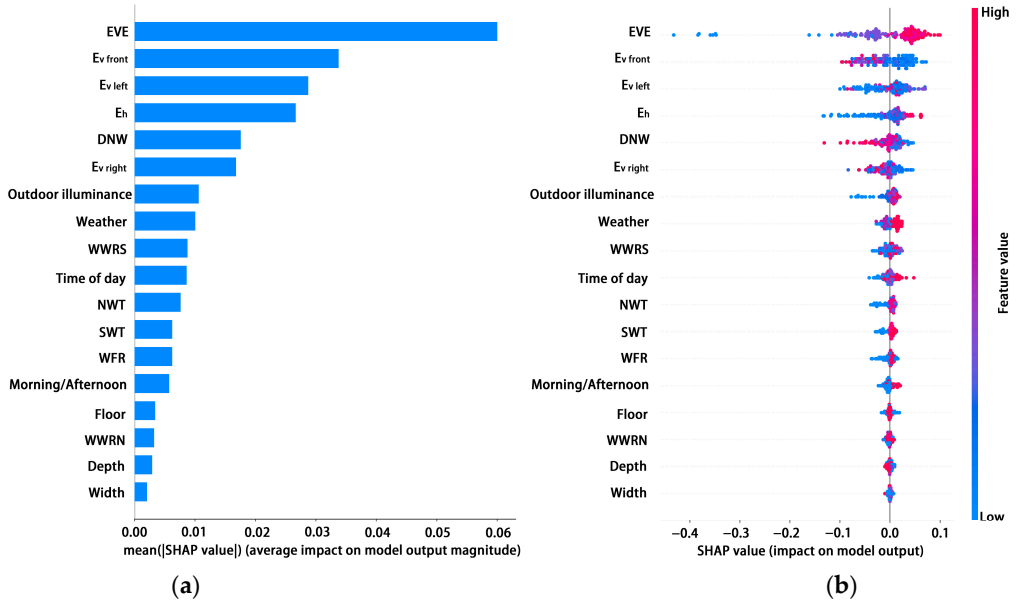


Figure 6. (**a**) SHAP bar plot: The average feature contributes to predicting mood perception. (**b**) SHAP beeswarm plot: Scatter diagram of the SHAP values of each feature in mood perception. Each point represents a SHAP value for a feature and a subject. The vertical axis represents the features, and the horizontal axis represents the SHAP values. Redder colour indicates higher feature values.

In Figure 7a, it can be observed that the effect of EVE on mood perception is almost decisive: when the EVE value equals or is lower than 3, the samples almost always have negative SHAP values, which suggests that when students consider EVE to be poorer, their mood perception tends to be negatively affected; whereas when EVE is higher, e.g., 4 or 5 point, it tends to have a positive effect on their mood perception. Moreover, "Floor level" had a strong interaction with EVE. With the same x-axis value, i.e., the same EVE, the y-axis value, i.e., the SHAP value, changed when the feature "Floor level" varied. For example, for students who rated EVE 4 or 5, the red dots are almost always distributed on top of the blue dots, which suggests that for students with higher scores on EVE, those on the 3rd floor were more apt to feel pleasant than those on the 1st floor.

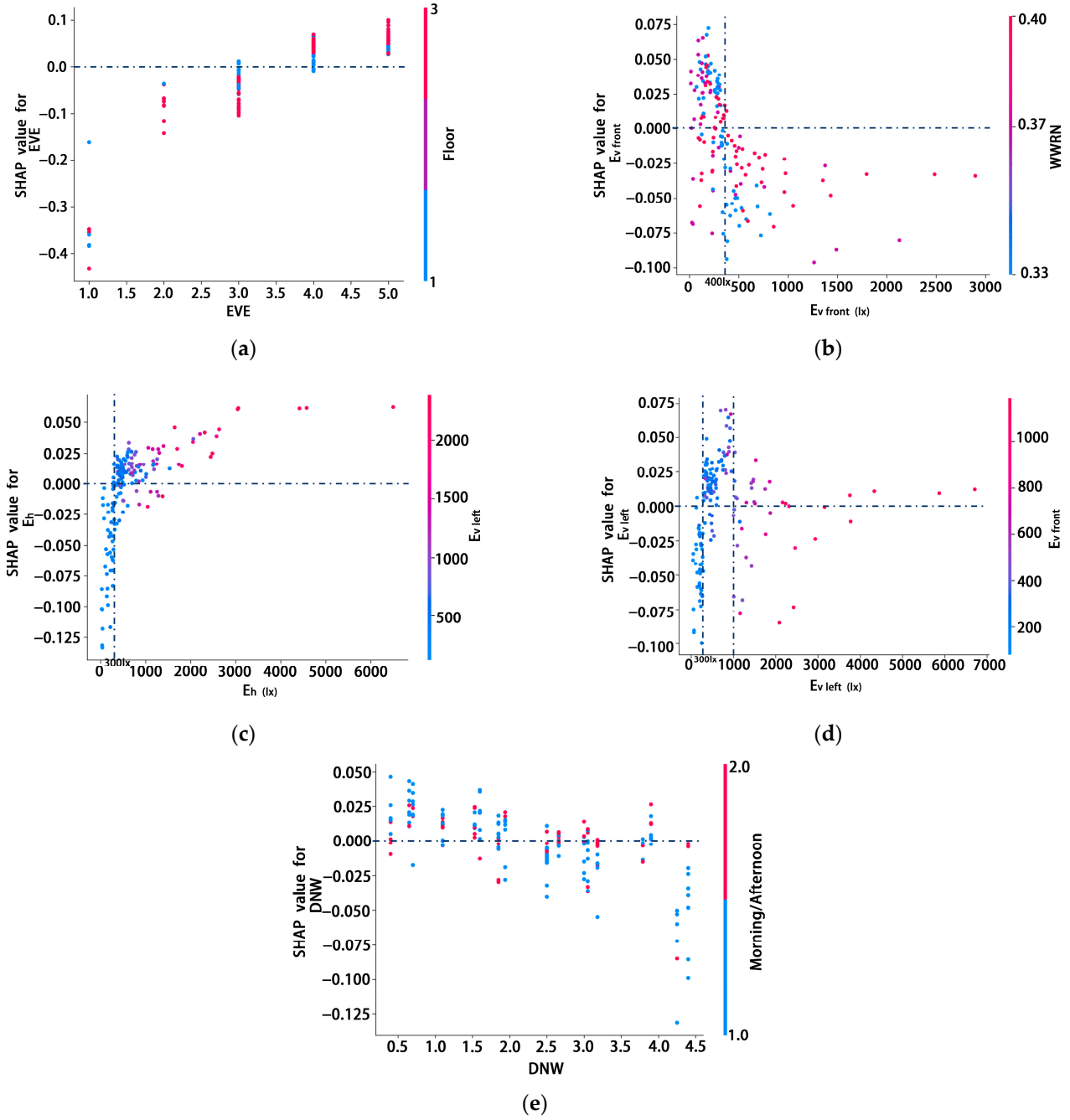


Figure 7. SHAP feature dependence plots. (**a**) Effects of EVE and Floor Interaction on Mood Perception; (**b**) Effects of Ev left and WWRN interaction on mood perception; (**c**) Effects of Eh and Ev left interaction on mood perception; (**d**) Effects of Ev left and Ev front interaction on mood perception; (**e**) Effects of DNW and Morning/Afternoon interaction on mood perception.

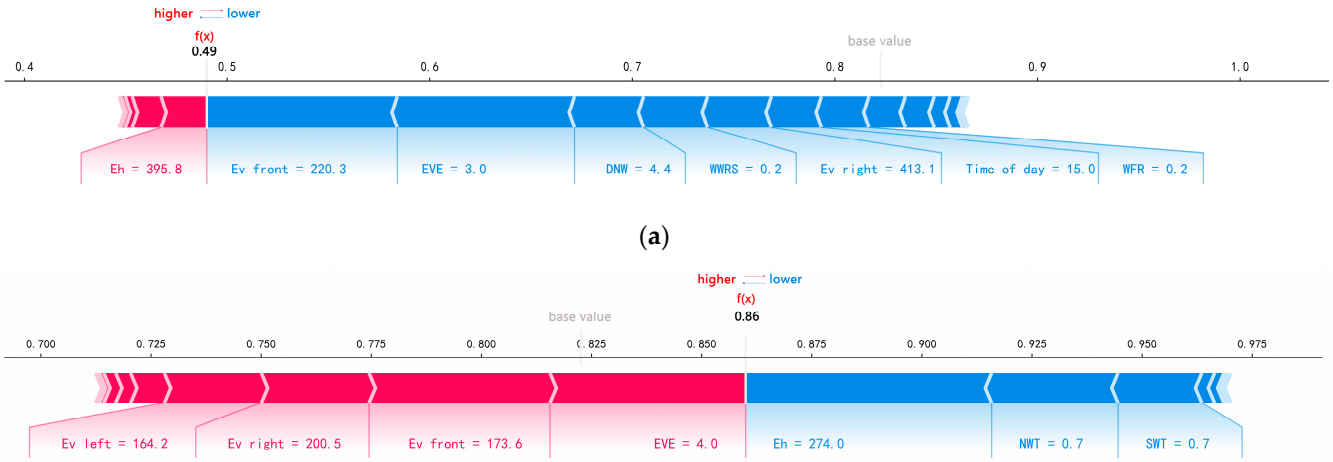
Figure 7b shows that with increasing $E_{v\ front}$, the SHAP value decreases, indicating that the impact on students' mood perception gradually shifts from positive to negative. In addition, when $E_{v\ front}$ was approximately greater than 400 lx, the SHAP values of all samples were below 0, suggesting that when the vertical illuminance of the students' eyes looking towards the blackboard is greater than 400 lx, the daylight may cause visual discomfort, and thus negatively affect students' mood perception. E_h, on the other hand, showed the opposite trend to $E_{v\ front}$ (Figure 7c). In general, as E_h increases, its impact on students' mood perception gradually shifts from negative to positive. We found that when E_h exceeded 300 lx, it almost always had a positive effect on students' mood perception.

Moreover, almost all of the samples with E_h lower than 300 lx also have $E_{v\ left}$ values less than 300 lx. Considering that the left side of the classroom is the primary daylighting side, the low E_h and $E_{v\ left}$ indicate that these students were sitting further away from the north windows (e.g., in the middle or south side of the classroom), and therefore their moods were negatively affected by an insufficient amount of daylight gained. This is also supported by Figure 7d, showing that the samples with positive SHAP values almost all have $E_{v\ left}$ values between 300 and 1000 lx. This was consistent with our conclusions from Figure 7c. In addition, Figure 7e shows that when the DNW was less than 2.5 m, it generally had a positive effect on most students' mood perception. However, when the DNW was between 2.5 and 4.5 m (i.e., in the middle of the classroom), it tended to have a negative impact on the majority of students' mood perception.

3.3.2. Decision Analysis

With the above global analyses, the relative influence of each feature on mood perception classification could be determined. However, it remains difficult to interpret the contribution of each sample to the results. The SHAP force plot presents the decision-making process for each sample based on an additive feature attribution approach. This allows for a more comprehensive understanding of the underlying patterns and relationships in the data, facilitating a more detailed examination of specific samples or comparisons between different samples, and enabling the drawing of more reliable conclusions about the relevance of various features in influencing mood perception.

The SHAP value for each feature in the SHAP force plot was represented by length, and the effect was represented by direction, with positive effects shown in red and negative effects shown in blue. Figure 8 illustrates a typical SHAP force plot for two random samples from the dataset: sample (a) and sample (b).



(**a**)

(**b**)

Figure 8. Decision analysis process. (**a**) SHAP force plot for a negative mood sample; (**b**) SHAP force plot for a positive mood sample.

In sample (a), the predicted value of the assessment result was 0.49, with only the E_h (395.8 lx) making a positive contribution and causing a positive effect on mood perception; the top three negative contributions were $E_{v\ front}$ (220.3 lx), EVE (3 points) and DNW (4.4 m), suggesting that the sample was in the far window area and did not perceive a good view of nature, causing a negative effect on mood perception. In sample (b), the predicted value of the assessment result was 0.86, with a significant increase in positive contributing features, EVE (4 points) and $E_{v\ front}$ (173.6 lx) had the highest positive contribution to the

predicted result, while E_h (274 lx) had the most significant negative impact on the predicted result. These results indicate that different combinations of classroom environmental features contribute to mood perception in different individual samples. However, some high-frequency features, such as EVE, E_h, and $E_{v\ front}$, consistently appear across samples. This provides useful insights for identifying key feature combinations and threshold ranges that should be prioritised in specific spatial zones, thereby enabling targeted optimisation of classroom design.

4. Discussion

4.1. Performance of Predictive Models for Mood Perception

This study aimed to develop an ML classification model to predict students' mood perception and explore the environmental parameters that affect this perception. Furthermore, the performance of different predictive models on a seven-classification and a binary classification task was compared.

The models showed better performance on the binary classification task. We used a seven-point Likert scale for questionnaire collection, which is a widely employed measurement tool in psychological and social science research to refine human perceptions and to distinguish subtle differences in certain perceptions. However, this approach introduces a significant degree of difficulty in actual perception prediction. Due to individual differences, human perceptual evaluations exhibit a high degree of uncertainty and instability, particularly around the neutral score. Therefore, it is more reasonable to predict whether an environment will be perceived as positive or negative, and to treat the perception prediction as a binary classification task [58].

The optimised RF model performed well, achieving an accuracy of 83% on the binary classification task. While some studies have shown that ML models can predict the objective performance, such as daylight and energy performance of buildings, with an accuracy higher than 90% [37,59,60], there are still many challenges in predicting occupants' perceptions due to high uncertainty and individual differences. For example, Zhang et al. [58] used a DL model to predict human perceptions of street images in large cities such as Beijing and Shanghai, including six human perception indicators: safe, lively, beautiful, rich, depressing, and boring. The results showed that the prediction accuracy ranged from 65% to 87%. Liu et al. [61] trained ML models for heat sensation prediction, classifying heat sensation into three binary classification models for hot, neutral, and cold sensations. They compared SVM, ANN, and the three tree models, and the results showed that the three tree models performed significantly better, with an accuracy between 66% and 85%. The accuracy of occupants' daylight satisfaction evaluation and daylight complexity evaluation prediction models constructed using XGBoost in the study by Sun et al. [26] was 74% and 76%, respectively. By comparing these past studies, it can be concluded that the current optimised prediction model of students' mood perception in classroom environments achieved a relatively high level of accuracy.

4.2. The Effect of Classroom Environmental Features on Students' Mood Perception

The consistency of the results from the SHAP analyses was compared with several existing studies. In this study, we found that the most influential feature for students' mood perception is the EVE. It has been extensively shown that natural views impact human physiology and psychology [29,62–65]. Since Ulrich proposed the "Biophilia Hypothesis" [66], an increasing number of studies have demonstrated that natural views have therapeutic effects on psychological cognition and emotional well-being, effectively alleviating negative reactions and regulating mood [28,67,68]. In studies related to educational buildings, Sepideh et al. [69] showed that natural landscapes outside windows

in Iranian classrooms provide a pleasant and relaxing visual experience, which can help reduce students' stress and anxiety, thereby improving their mental health and mood states. A previous longitudinal study conducted by Xu et al. [40] revealed that students' mood perception ratings increased with the perceived "interest level of the exterior landscape". The present study further identified a strong interaction between EVE and floor level, specifically finding that students in classrooms on the third floor were more likely to experience positive mood perception than those on the first floor when the quality of the EVE was high. This finding shows that the exterior views play an important role in students' mood perception in educational buildings. In traditional school designs, greenery landscapes are predominantly located on 1st floor. Based on the results of this study, the landscape design of educational buildings should not only be considered on the ground floor, but also at various vertical heights, such as rooftop gardens and vertical greening. This insight may provide architects with a more refined design strategy for school landscape design, ensuring that students on all floors have access to high-quality natural views.

Moreover, through SHAP dependence plots, a significant difference between E_h and $E_{v\ front}$ regarding students' mood perception was found. The plots showed opposite data distribution trends, indicating that students' mood perception ratings increased with an increasing E_h and decreased with increasing $E_{v\ front}$. Moreover, mood perception increased rapidly as E_h increased and then levelled off gradually. In previous studies, most researchers have focused on the effects of the presence or absence of daylight or the duration of daylight exposure on occupants' perceptions [70–72]. However, less attention has been paid to the effect of different illuminance ranges on occupants' mood perception. GB50034-2024 requires that the E_h of desktops in classrooms should be no less than 300 lx [73], and WELL Building Standard [74] requires that the illuminance of work surfaces in classrooms should be no less than 323 lx. While all these standards prescribe the minimum illuminance requirement to meet visual tasks, this study showed that when the E_h exceeded 300 lx, students' mood perception tended to be more favourable, which enriched the implications of the current standards. However, the range of E_h levels that are conducive to positive moods in adolescents under daylight conditions still requires in-depth exploration.

Many standards have taken into account circadian lighting. For example, the WELL Building Standards proposed a minimum threshold of 120 EML (1 point) and 180 EML (3 points) for projects with enhanced daylight. The 'Ranking evaluation for classroom lighting quality in primary and middle schools' [75] specifically provides recommendations for classroom lighting regarding Circadian Lighting, requiring a minimum threshold of 150 EML (AAAA). In addition, based on the CIE Position Statement on Integrative Lighting [76], the illuminance during the day should not be less than 250 lx. In summary, there is no uniform provision for the threshold range of the vertical illuminance yet.

In this study, we found that $E_{v\ front}$ greater than 400 lx can negatively impact students' mood perception. Combining these criteria and the current study results, considering students' emotional well-being, we recommend that $E_{v\ front}$ in classroom spaces should be less than 400 lx as much as possible. In addition, our results showed that $E_{v\ left}$ range from 300 to 1000 lx is beneficial to students' mood perception. This may be attributed to the fact that the north side is the primary daylighting side of all the classrooms in this study, resulting in significantly higher illuminance for the $E_{v\ left}$ than for the $E_{v\ front}$. It is well known that adolescents are generally more sensitive to light than adults. Nevertheless, the lowest boundary of $E_{v\ front}$, which positively affects middle-school students' mood perception, as well as the interactions among $E_{v\ front}$, $E_{v\ left}$, and $E_{v\ right}$, still require thorough investigation through more detailed controlled experiments.

Our findings also show that students seated in the middle of the classroom, away from the window, tend to have more negative mood perceptions, while those closer to

the window exhibit more positive mood perceptions. This can be caused by better views out of the window and increased access to daylight. Yildirim et al. [77] also noted in a study on office spaces that employees close to windows have more positive subjective evaluations. Other studies [78–80] have observed that hospital patients closer to windows in healthcare buildings experience more beneficial effects. In addition, some other studies proved that participants showed negative emotions in the near-window area, as direct sunlight during screen-based cognitive tasks caused discomfort and negative states [81–83]. Therefore, exterior views through windows should be carefully designed to reduce glare while promoting students' positive mood perception.

It is worth noting that middle school classrooms in eastern China have a typical spatial layout, with windows on both the north and south sides for daylighting, primarily on the north side. Our results showed that most students experience positive mood perception within 2.5 m from the windows, and the depth of the classroom is significantly negatively correlated with mood perception. Thus, it is recommended that classroom depths should be minimised while still meeting the standard. In terms of classroom space layout, desks and chairs can be arranged in the window area as much as possible, or the students' seats can be rotated periodically to ensure that each student has more access to the exterior view. Previous studies have predominantly discussed the effect of classroom window size on daylighting [84–86], but the impact of classroom size (depth and width) on students' perceptions has been less addressed, which could be a key factor to consider in future research.

4.3. Decision Routes Within the Mood Perception ML Models

In this study, the individual decision-making of two students using SHAP force plots was visualised to find typical decision routes. In this process, it was found that the influence of features on mood perception often occurred as a result of multiple classroom environmental features. For example, EVE, E_h and $E_{v\ front}$, which are crucial features, usually appeared in combination. Based on the decision analyses, it is evident that different features may have different effects on each student. Exploring the decision routes in the model is significant because it can guide the construction of buildings with healthy daylighting environments to develop more refined and personalised design strategies.

Some researchers have explored the characteristics and the effects of daylight on mood perception. For example, the study by Zhang et al. [71] showed that the amount of daylight accumulated before arousal in summer was significantly associated with mood. Yang et al. [87] showed that insufficient daylight in autumn and winter can affect college students' mood and reduce their learning efficiency. Although these studies confirmed the impact of daylight on health, they only consider features such as daylight-related metrics. However, in real spaces, the influence of daylighting on occupants' perceptions of health is often far more complex than daylight metrics alone can capture. It results from a more intricate interplay of factors and is continually evolving.

Therefore, the optimisation of daylighting environments extends beyond merely adjusting the parameter range of a single feature. It encompasses the dynamic interplay of multiple features in various combinations. In designing healthy daylighting environments, the focus should not simply be on achieving a static 'ideal' light range. Rather, greater emphasis should be placed on creating a flexible space that can adapt to different circumstances and individual requirements through the comprehensive adjustment of multiple environmental features. This is crucial to the design and optimisation of architectural daylighting environment strategies.

4.4. Limitations and Suggestions for Future Research

This study also inevitably has some limitations. Firstly, in terms of feature selection, this study examined 18 classroom environmental features, including daylighting parameters, classroom characteristics, spatial information of seats, EVE, time and weather parameters, and demonstrated the synergistic effects of these features on middle-school students' mood perception. However, it did not account for features such as daylight spectrum and seasons that could impact students' mood perception. More comprehensive features should be considered in future studies. Secondly, although this study collected 557 valid questionnaires from 243 students, the dataset size is considered insufficient for ML, especially DL models. Moreover, the imbalanced data distribution further undermined the power of these models. Therefore, future studies will further expand the dataset size to improve the performance of mood perception prediction models. Finally, it should be acknowledged that predicting occupants' subjective perceptions is a challenging task, fraught with numerous uncertain and uncontrollable factors. Consequently, future research may adopt more multi-source and more objective data collection methods, such as physiological data collection, to minimise the potential biases of subjective factors and achieve the goal of improving the accuracy of prediction models.

5. Conclusions

This study examined the complex relationship between middle-school students' mood perception and classroom environmental features, such as daylighting parameters and classroom characteristics in educational buildings. The research is significant for designing a healthy classroom environment that can have a positive impact on middle-school students' mood and potentially their mental health. Apart from the educational buildings in Suzhou, the research findings can also be applied to other areas in eastern China with similar climatic characteristics and educational building typologies. Specifically, this study proposed a workflow for collecting field data and constructing an ML predictive model of middle-school students' mood perception in the classroom environment. Firstly, classroom characteristics and daylighting parameters were obtained through field measurements and software simulations, while perception data were collected from middle-school students via questionnaires. Subsequently, three ML models and a DNN model were developed and evaluated to predict middle-school students' mood perception, with the most suitable prediction model being identified. Finally, an interpretability analysis of the model prediction results was conducted using the SHAP method. The main findings were summarised as follows:

(1) In predicting human perceptions, ML models demonstrated superior performance when using binary classification rather than a seven-point classification. The RF model, in particular, showed higher accuracy and efficiency, with accuracy improving from 34.8% in seven-point classification to 82% in the binary classification.

(2) Exterior view evaluation (EVE) was identified as the most influential factor affecting students' mood perception. Specifically, higher EVE scores were associated with more positive mood perception. In addition, the floor level was the most important feature interacting with EVE. Students located on the higher floors with attractive views tend to exhibit more positive mood perception.

(3) There was an opposite trend in the effects of E_h and $E_{v\ front}$ on students' mood perception. Specifically, as E_h increased, students' mood perception gradually shifted from negative to positive, while as $E_{v\ front}$ increased above 400 lx, the mood perception shifted from positive to negative. The results of the SHAP analysis indicated that the E_h of the desktop should be no less than 300 lx, while the $E_{v\ front}$ should be maintained below 400 lx. Additionally, the $E_{v\ left}$ should be kept in the range of 300–1000 lx.

(4) As for the spatial layout, the typical layout of the middle school classroom in Suzhou was characterised by windows on the north and south sides for daylighting. Our findings indicated that students seated near the centre of the classroom—farther from the windows on both sides—tend to report more negative mood perceptions. Consequently, excessive classroom depth is not recommended in design. Additionally, school administrators can periodically reassign students' seats to ensure that each student has access to more exterior views.

Author Contributions: Methodology, L.Z., Y.Z. and J.X.; software, H.X. and L.Z.; validation, H.X. and L.Z.; formal analysis, H.X., L.Z. and J.X.; investigation, H.X. and J.X.; resources, J.X.; data curation, H.X.; writing—original draft preparation, H.X.; writing—review and editing, H.X., L.Z., Y.Z., L.B. and J.X.; visualisation, H.X.; supervision, J.X.; funding acquisition, J.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Programme of China (Grant No. 2021YFE0200100), the China Scholarship Council (Grant No. 202106920031), and the Major Project of Philosophy and Social Sciences Research in Jiangsu Universities (Grant No. 2025SJZD149).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Soochow University (protocol code SUDA20240119H03 and date of approval 19 January 2024).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to ethical restrictions aimed at protecting the privacy of the underage participants, in accordance with requirements from the schools.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ML	Machine learning
E_h	Horizontal desktop illuminance (lx)
$E_{v\ front}$	Frontal eye-level illuminance (lx)
$E_{v\ left}$	Left-side eye-level illuminance (lx), oriented 45° to the left of the forward-facing direction
$E_{v\ right}$	Right-side eye-level illuminance (lx), oriented 45° to the right of the forward-facing direction
WFR	Window-to-floor ratio
WWR_S	Window-to-wall ratio of the south windows
WWR_N	Window-to-wall ratio of the north windows
DNW	Distance from the seat to the nearest window
EVE	Exterior view evaluations
SWT	South window transmittance
NWT	North window transmittance
RF	Random forest
LR	Logistic regression
SVM	Support vector machine
DNN	Deep-learning neural network
SHAP	SHapley Additive exPlanations

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