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AI-Driven Modeling of Window Opening Behavior in Kindergarten Classrooms: A Case Study during the Transitional Season in the Cold Region of China

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ABSTRACT

With increasing awareness of energy conservation and environmental protection, optimizing indoor air quality and energy consumption through rational control of window opening behavior (WOB) has become a crucial issue in building design and environmental management. However, existing research primarily focuses on buildings for adults, with relatively few studies on buildings for children, particularly those used by children aged 3–6. Moreover, previous studies often overlook the impact of functional differences between buildings on occupant behavior patterns. This study focuses on a kindergarten and proposes an event-based method for analyzing and modeling WOB. The results show that events such as arrival, class, and departure are associated with higher frequencies of window opening (exceeding 50%), whereas events such as dietary activity, indoor/outdoor activity, sleep, and tidying exhibit lower probabilities. WOB is more sensitive to indoor air quality during events with higher student activity (e.g., class, dietary activity, and indoor activity), resulting in more frequent ventilation. In terms of modeling, the Random Forest (RF) algorithm achieved higher prediction accuracy than Logistic Regression (LR) and Support Vector Machine (SVM). To reduce the complexity associated with multi-model integration, a stacking model was introduced, further enhancing predictive performance. Finally, the generalizability of the proposed method was validated using office building data from the ASHRAE occupant behavior database, achieving a maximum accuracy improvement of 3.87%. This study presents a novel approach for modeling WOB in functional buildings such as kindergartens and provides theoretical support for energy efficiency optimization and indoor air quality management.

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Abbreviations

WOB	Window Opening Behavior
AQI	Air Quality Index
IAQ	Indoor Air Quality
TVOC	Total Volatile Organic Compounds
RF	Random Forest
LR	Logistic Regression
SVM	Support Vector Machine

1 Introduction

Buildings have become a core focus in addressing the global challenge of reducing greenhouse gas emissions [1]. Research on building energy conservation typically emphasizes the design, layout, and material selection of the building envelope [2,3], while often neglecting the impact of human behavior on energy consumption during building operation. This results in energy-saving measures failing to achieve the desired outcomes. In recent years, China has actively advanced its dual-carbon goals [4], placing particular emphasis on energy conservation and environmental protection within the building sector. Energy consumption during a building's use phase accounts for a significant proportion of its full life-cycle carbon emissions. The energy consumed during operation is closely related to user behavior [5]. Therefore, optimizing user behavior is one of the most important ways to improve building energy efficiency and reduce carbon emissions [6]. Clevenger et al. [7] demonstrated that occupant behavior can significantly influence building performance, with potential impacts on annual energy consumption reaching approximately 75% in residential buildings and up to 150% in commercial buildings. Using real data from office buildings, Amasyali and El-Gohary [8] showed that optimizing occupant-behavior could reduce energy consumption by 11% to 22% while simultaneously improving occupant comfort. These findings indicate that accurately modeling occupant behavior is not only essential for improving the accuracy of energy consumption predictions but also a necessary approach for achieving energy savings. Among these behaviors, WOB is the most common and frequent type of occupant-building interaction, due to its significant impact on indoor air quality (IAQ) and thermal comfort [9]. Accurately understanding and modeling users' window-opening behavior (WOB), particularly its characteristics of uncertainty and randomness, is of great significance for achieving more refined building energy simulation and control strategies [10]. It will also play an active role in reducing carbon emission during the operation phase of a building and in implementing the goals of the "dual-carbon" policy. Pandey and Dong [11] reported that in university dormitories, window-opening behavior during the heating season could result in energy consumption as high as 16,349.98 kWh, which would be entirely overlooked if not accounted for in modeling. Similarly, Peng et al. [12] found that in primary school classrooms, window-opening behavior during winter could cause an additional daily energy consumption of 12.83 kWh. These findings highlight that understanding window-opening behavior patterns and developing accurate prediction models are critically important for achieving building energy savings. Scholars worldwide are conducting in-depth investigations into WOB from multiple perspectives, contributing to improvements in building performance [13,14], reductions in energy consumption [11,15], and enhancements in occupant comfort [16,17]. In the 20th century, scholars began studying WOB in office buildings [18], and the research was gradually extended to residential buildings [19–22]. Due to individual differences in thermal comfort [23], personal habits [24], and psychological conditions [25], occupants' WOB exhibits significant randomness. Accurately describing the characteristics of WOB requires accounting for multiple factors, including building type, environmental conditions, room function, and seasonal variations. However, because buildings with predominantly adult occupants make up the majority of the total, most existing research has focused on these buildings. In contrast, few studies have examined buildings used by minors. Nonetheless, there remains room for further optimization of existing studies on adults. This is illustrated in the following section through an analysis of buildings primarily occupied by adults and minors.

1.1 Adult-Occupied Buildings

Characteristics: Indoor and outdoor temperature and humidity are the environmental factors that have the greatest impact on window opening behavior [26,27]. However, Sansaniwal et al. [28] concluded that CO_2 concentration in office buildings is the primary driver, followed by indoor and outdoor temperatures. Notably, commuting time also had a significant effect on window opening. Additionally, commuting times to and from work have a strong impact on window opening. For residential buildings, indoor and outdoor temperatures, as well as humidity, remain the dominant drivers [21]. Moreover, indoor CO_2 concentration, indoor $PM_{2.5}$ concentration, and outdoor PM_{10} and $PM_{2.5}$ concentrations, which affect indoor air quality, also have a significant impact on WOB [29,30]. Interestingly, everyday practices, such as morning routines and daily activities, also affect WOB. The characteristics of WOB in the kitchen [29], bedroom [27], and living room [15] within the same type of residential building also differed. As this line of research became more comprehensive, scholarly attention gradually shifted toward analyzing WOB in various other building types, including general hospitals [24], and maternity and child hospitals [31]. The results showed that outdoor temperature, relative humidity, and $PM_{2.5}$ concentration were significantly correlated with WOB in general hospitals. Moreover, $PM_{2.5}$ concentration exhibited a strong correlation with environmental factors in both wards and doctors' offices in maternity and child hospitals.

It follows that indicators relevant to thermal comfort and air quality are essential considerations when studying window-opening behavior. Notably, as shown above, various factors also have a significant impact on window-opening behavior over time [32–34]. Due to differences in function and intended use, various types of buildings experience distinctly fixed events during specific periods (e.g., office buildings: meetings, business negotiations, working hours; academic buildings: classes, exams, lectures). These differences also fundamentally influence window-opening behavior patterns. However, most current approaches to incorporating time factors are similar to those used for environmental factors, focusing on analyzing the correlation between time and WOB, or the relationship between different times of day and WOB [19,22,31,35]. As shown in Table 1, existing studies generally quantify time as a continuous or graded variable and infer the events that may underlie window opening based on temporal trends. However, time is essentially a marker for the occurrence of events rather than a fundamental driver of behavior. Accurately modeling the driving mechanisms of WOB is challenging if the event attributes underlying time are overlooked. Therefore, factors corresponding to time should be extracted and categorized based on objective events, and an event-based analysis framework should be developed to provide a more accurate description of WOB. However, related research has not yet been conducted in this direction.

Model: Accurately establishing a model for WOB is essential for improving the precision of building energy consumption predictions. However, the high degree of randomness increases the complexity of predicting WOB. Currently, efforts to improve the predictive performance of WOB models focus primarily on three aspects. First, the selection of input parameters; environmental and non-environmental driving factors are typically considered essential inputs for the model. For the time factor in non-environmental variables, time is currently quantified as a categorical or continuous variable [19,36], and either directly incorporated into modeling or divided into different periods according to the daily time sequence, as shown in Table 1. However, once time is quantified, its interaction with WOB states and environmental factor values is often overlooked, leading to deviations in predicting WOB. The influence of time on WOB essentially stems from the dynamic changes associated with different events. Therefore, time-related information should be extracted based on objective events, and a WOB model should be constructed using events as the basic unit to improve modeling accuracy. However, no existing studies have yet explored this approach. Second, the performance of the algorithm: Logistic regression (LR) is the most frequently used algorithm for modeling WOB [37–40], and it is often used as a benchmark for comparsion with advanced algorithms due to its general applicability [39,41–43]. With the increasing need to predict WOB, algorithms such as neural networks and machine learning methods are being gradually employed [44–46]. The results indicate that different algorithms exhibit varying applicability to different sample data, highlighting the need to develop WOB models tailored to buildings of various types and climate zones. Third, refinement of the sample dataset, which leads to an increase in the number of models: To improve model performance, separate models are established for multiple types of rooms, seasons, scenarios, and numbers of windows within the same building [11,29,47,48]. However, this approach is cumbersome for subsequent application in actual building simulations, and the problem has not yet been resolved. Ensemble algorithms not only integrate multiple models but also enhance predictive performance. The stacking model, as one method of integrated modeling, has been investigated as a new approach to improve model performance in predicting precipitation, air quality index (AQI), and inverse heat transfer problems. The results show that the stacking model typically performs as well as, or better than any individual model and is an effective means of enhancing the generalizability of models [49,50]. However, the applicability of this method to the field of WOB has yet to be validated.

Table 1: Review of time factors in WOB analysis and modeling

Reference	Building type	Analyzing the time factor approach	Time factor modeling approach
[51]	Office	Quantify time into categorical variables	Time is divided into six sequential periods: (Early Morning, Morning, Noon, Afternoon, Evening, and Night) and is used in conjunction with environmental factors as input parameters.
[38]	Dormitory	Quantified into numerical values without specifying whether they are categorical or continuous variables.	Time is divided into four sequential periods: (Morning, Afternoon, Evening, and Night) and is used together with environmental factors as input parameters.
[52]	Residential	Quantify time into categorical variables	Time is divided into four sequential periods: (Morning, Afternoon, Evening, and Night) and is used together with environmental factors as input parameters.

(Continued)

Table 1 (continued)

Reference	Building type	Analyzing the time factor approach	Time factor modeling approach
[22]	Residential	Quantify time into continuous variables	/
[53]	Residential	Quantify time into categorical variables	/
[35]	Residential	Quantify time into categorical variables	Time is divided into four sequential periods: (Day and Night) and is used together with environmental factors as input parameters.
[54]	Residential	Quantify time into categorical variables	The bedroom is divided sequentially into five periods: morning, daytime, afternoon, night, early morning, while the living room is divided into four periods: morning, afternoon, night, early morning.
[55]	Residential	Quantify time into categorical variables	Time is not divided into periods but is used directly as an input parameter.
[56]	Office	Quantify time into categorical variables	Time is used directly as an input parameter without being divided into periods.
[57]	Office	Quantify time into categorical variables	/

1.2 Minor-Occupied Buildings

Research indicates that indoor air pollution has a notable impact on factors such as hypertension, systolic blood pressure, lung function, and academic performance in students under the age of 18 [58,59]. Estimates suggest that 52% of school-age children in developed countries are exposed to $PM_{2.5}$ levels exceeding the WHO's recommended limits [60]. Young children's respiratory systems are more vulnerable to the impacts of environmental pollution compared to those of older children and adults [61]. In children aged 4–6 years, excessive indoor air pollutants are strongly correlated with cough, runny nose, and nasal congestion [62,63]. Kindergarten children are the youngest and most sensitive of all school-age children, spending almost a third of their day in kindergarten.

Almost a third of the day is spent in kindergarten. However, in recent years, policies promoting energy conservation have been implemented, and emission-reduction measures have increased the air tightness of modern buildings. The widespread use of various decorative materials has raised the concentration of indoor pollutants, such as formaldehyde, benzene, and toluene, which degrade indoor air quality and pose specific health risks to children [64]. Therefore, research on WOB in spaces primarily occupied by minors is highly valuable. Unlike adults, minors have relatively uniform lifestyles, with schools serving as their primary environments. As shown in Fig. 1, existing studies on WOB for minors have primarily focused on two types of buildings: classrooms and dormitories.

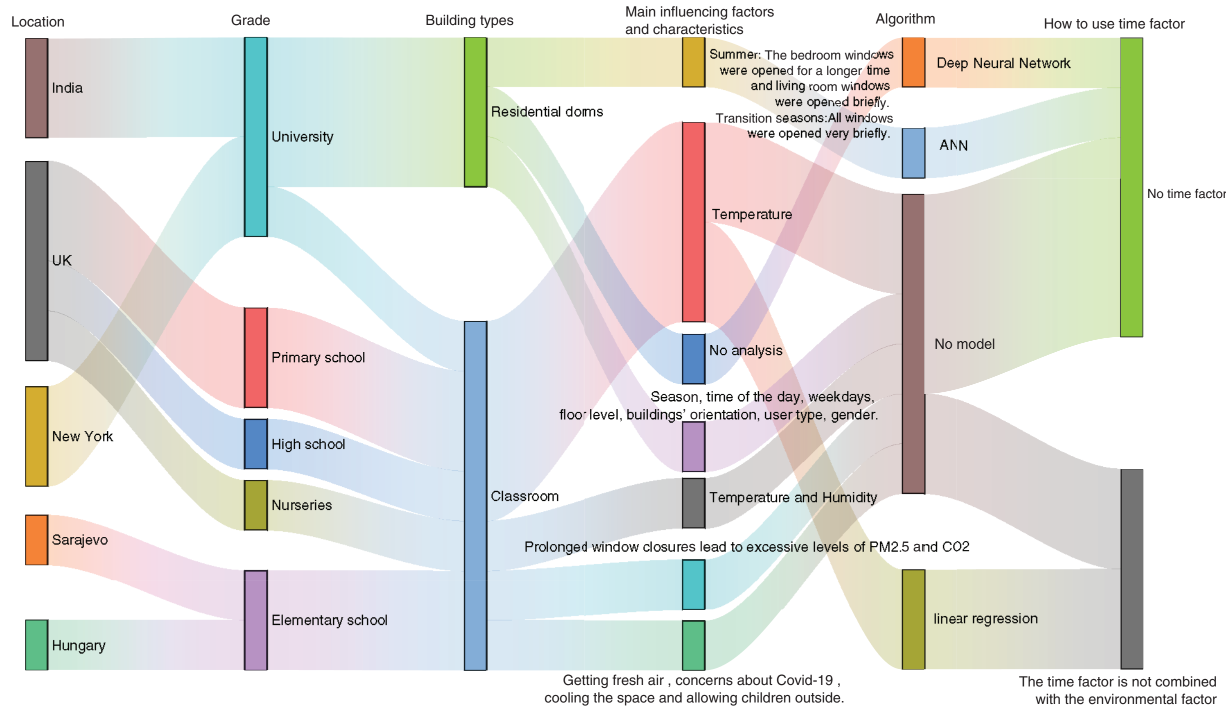


Figure 1: WOB in minors: influencing factors and methods across ages and building types

Characteristics: A literature search in the Web of Science (WOS) database using the query window opening behavi∗ (All Fields) and nursery (All Fields) or kindergarten (All Fields) yielded only one relevant study—Zhang et al. (2023). This study evaluated the impact of air purifiers and window operation on indoor air quality in multiple nurseries across the UK. The results indicated that during the non-heating season, at least one window was kept open for 77%–92% of the occupied time (average 85%), whereas this proportion dropped to 20%–90% (average 58%) during the heating season. Some classrooms exhibited distinct behavioral differences between the two seasons, which may be related to changes in COVID-19 control policies or individual teachers' preferences. Notably, when air purifiers were used to reduce indoor $PM_{2.5}$ concentrations, windows remained closed in 63% of cases and open in 46%, suggesting that mechanical ventilation devices cannot fully replace the ventilation and comfort benefits provided by window operation. This finding not only underscores the necessity of sustained WOB research in early childhood education buildings but also highlights the scarcity of work in this field, thereby reinforcing the practical significance and innovation potential of the present study [65]. In addition, previous studies have shown that the primary influencing WOB in university and high school classrooms is the combination of indoor and outdoor temperatures. Moreover, daily routines in high school classrooms significantly impact students' behavior, with windows typically opened during breaks, particularly in the morning [65]. Mohd Faheem et al. [38] found that season, time of day, weekday, floor, building orientation, user type, and gender of the occupants affected WOB in a university dormitory study in India. In addition, insect and animal threats (snakes, squirrels, lizards, mosquitoes) hindered WOB. The study focused on occupants in elementary school classrooms, specifically students aged 9–12 years, as they are considered to have a better perception of and ability to provide feedback on their surroundings compared to younger students.

Additionally, older children are taller, which allows them to operate indoor equipment more autonomously [66,67]. A study of WOB in elementary school classrooms revealed that indoor and outdoor temperature, as well as CO_2 concentration, were the primary influences during the heating season, whereas indoor and outdoor relative humidity were the main influences during the non-heating season. Furthermore, CO_2 was found to be negatively correlated with WOB [68]. In addition, the questionnaire revealed that opening windows due to "too hot" conditions was the most common complaint, while opening windows due to "dullness" was also frequently cited. More than 90% of teachers opened the windows at least once a day [69]. Shuo Zhang et al. [70] used a questionnaire to analyze the drivers of window openings in a UK kindergarten building during the outbreak. The findings indicated that WOB occurred more frequently during the outbreak period, with ventilation being the primary reason for window use. The main motivations for operating windows and external doors were obtaining fresh air (32%), concerns related to COVID-19 (28%), cooling the indoor space (24%), and providing children with outdoor access (16%). However, the study was somewhat biased toward identifying the habit of opening windows during the COVID-19 period, as suggested by the sample data.

Model: Due to limited attention on WOB in buildings occupied by minors, existing modeling studies in this area are scarce. Most linear regression methods used to describe the relationship with WOB report a model fit of $R^2 = 0.551$. for university dormitory buildings when indoor environmental factors are included. Bing Dong et al. [13] developed a deep neural network model for a university dormitory building in New York, achieving an accuracy of 96.71%.

The following gaps can be drawn from the above analysis:

1. Current research on WOB primarily focuses on environmental and non-environmental factors, but has not fully considered the unique effects of objective events associated with different building types.
2. Research on buildings primarily occupied by minors is limited, particularly in kindergartens, where children aged 3–6 spend extended periods, and for which no relevant studies are currently available.
3. The challenge of model overabundance, arising from efforts to enhance predictive accuracy, remains unresolved.

To address this issue, this study focuses on a kindergarten building in Beijing, where real-time monitoring of indoor environmental parameters and window status was conducted. Firstly, based on the daily schedule of the kindergarten building, the objective events are defined, and the WOB characteristics are described, taking into account the specificity of these events and the randomness of environmental factors. Secondly, three machine learning algorithms—RF, SVM, and the traditional LR—were used to establish prediction sub-models for different events, and the stacking model was employed for the first time to integrate multiple sub-models. Finally, the event-based segmentation method proposed in this study is validated and discussed using public data from the ASHRAE Occupant Behavior Database.

2 Methods

2.1 Research Route

This study is divided into three main parts. First, unlike traditional research on WOB, the data are categorized into eight event-based datasets according to objective events. Second, the characterization of WOB and the analysis of environmental factors are conducted from an event perspective. Finally, the event sub-model is developed using the algorithm most suitable for WOB data from kindergarten buildings and integrated through the stacking model, as shown in Fig. 2.

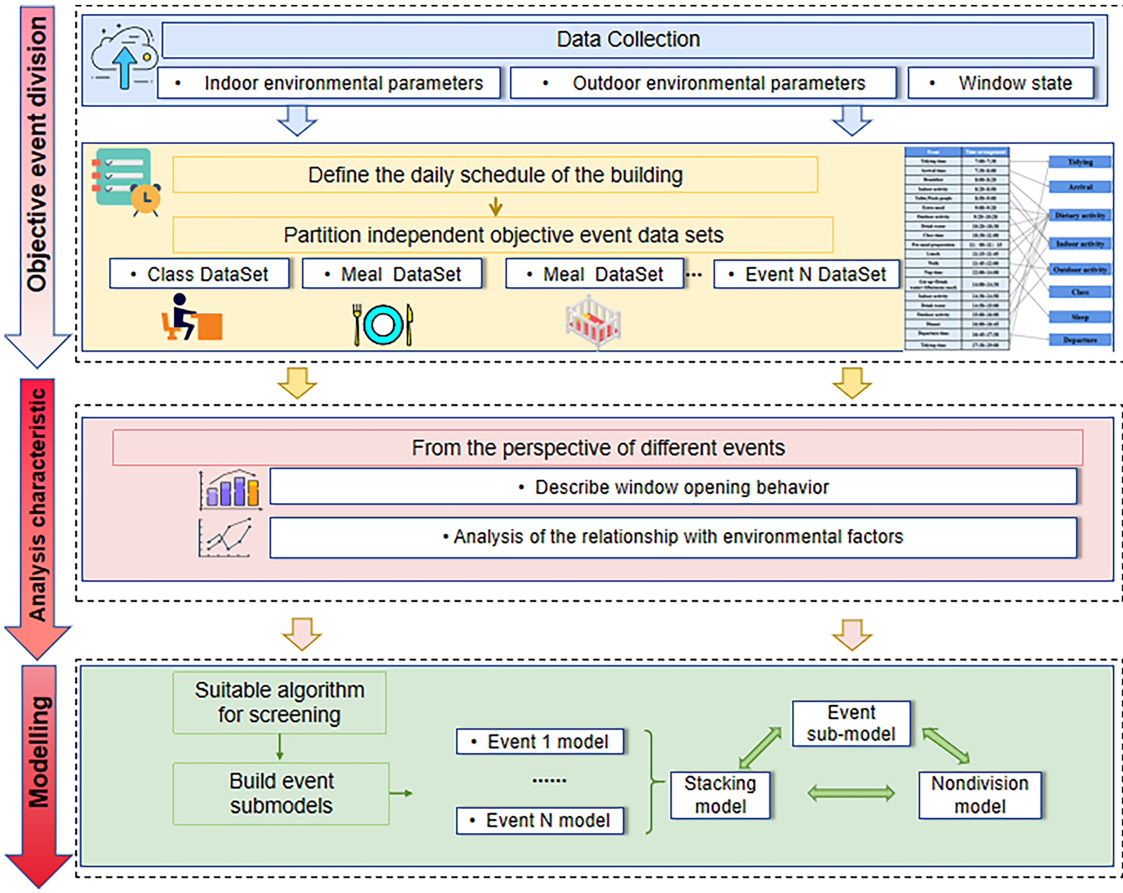


Figure 2: Research framework

2.2 Description of the Built Environment

2.2.1 Building Overview

In this study, six classrooms in a kindergarten in Beijing were selected for field tests. The building structure consists primarily of reinforced concrete with thermal insulation materials. The surrounding outdoor environment is relatively quiet, which mitigates the potential impact of external noise on window-opening operations. The external view of the building is shown in Fig. 3a. The classroom doors open onto corridors, with three classrooms equipped with sliding windows and three with casement windows, all connected to the outdoor environment. Spring in Beijing is a typical transitional season, characterized by moderate outdoor temperatures and relatively low demand for mechanical cooling or heating. Under these conditions, natural ventilation is the primary means of regulating the indoor thermal environment, enabling a more accurate observation of occupants' autonomous window-opening behavior. Moreover, the mild spring climate minimizes external interference from extreme weather conditions, such as high summer temperatures or severe winter cold, in window-opening decisions. In addition, spring coincides with the regular school term in kindergartens, avoiding the vacancy caused by student absence during summer or winter breaks and facilitating long-term on-site monitoring without disrupting normal teaching activities. During the monitoring period, classroom occupancy was assessed through field observations and consultations with kindergarten teachers. The classroom windows are controlled by the teacher, who adjusts ventilation based on personal judgment and the students' needs. The internal layout of the classroom is shown in Fig. 3b.

(a) (b) (c) (d)

Figure 3: Details of the case study building: (**a**) the surrounding environment, (**b**) main entrance and corridor area, (**c**) interior furnishings and classroom seating layout, (**d**) sleeping area and cabinets

2.2.2 Measured Situation

Field measurements were conducted during the spring season, from 7 March 2021, to 29 April 2021. During this period, neither heating nor air conditioning was used, and occupants frequently relied on natural ventilation. The real-time monitoring of physical environmental parameters included indoor ecological indicators (temperature, relative humidity, CO_2 concentration, $PM_{2.5}$ concentration, and TVOC) and outdoor indicators (temperature, relative humidity, $PM_{2.5}$ concentration, wind speed, and AQI). In addition, window status was monitored using a magnetic switch recorder. To ensure the accuracy of the test data, all instruments were calibrated before each test. Indoor environmental parameters were measured using self-recording devices for temperature, relative humidity, and carbon dioxide. Outdoor environmental parameters were obtained from a widely used meteorological website (https://www.aqistudy.cn), which is commonly referenced by researchers [54,71,72]. Window-opening and closing states were tracked using a magnetic switch recorder, with a window considered open if the opening exceeded 2 cm. A classroom was classified as having open windows if at least one window was open. Environmental parameters were measured at 15 min intervals, while window status was recorded every 5 min. To unify the data, linear interpolation was applied to adjust the environmental parameters to 5-min intervals. Fig. 4 illustrates the on-site installation of the instruments, and the details of data recording are provided in Table 2.

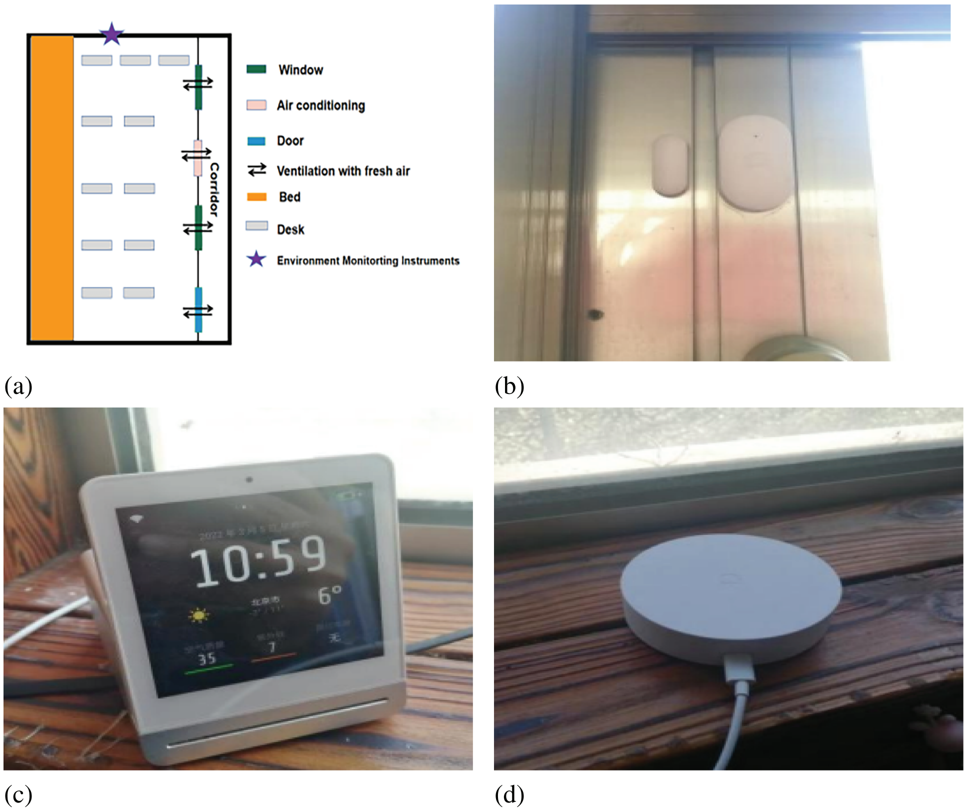


Figure 4: On-site installation condition, (**a**) layout of the monitored rooms, (**b**) window sensor, (**c**) indoor environmental sensor, (**d**) multifunctional wireless gateway

Table 2: Monitor data parameters

Monitoring instruments	Environmental parameters	Range	Error	Recording interval
Indoor environmental sensor	Temperature	10°C∼50°C	±0.5°C	5 min
	Relative humidity	0%–100% RH	±5%	
	Carbon dioxide concentration	400–9999 ppm	±15%	
	$PM_{2.5}$ concentration	0–999 µg/m^3	±10%	
	Total Volatile Organic Compounds (TVOC)	0.005–9.999 mg/m^3	±15%	
Meteorological station	$PM_{2.5}$ concentration Temperature Relative humidity Air Quality Index (AQI)	/	/	1 h
Magnetic field strength sensor	Window status	/	/	5 min

2.3 Event Division

The structured scheduling of daily routines is a key organizational feature in kindergartens and reflects the historical evolution of societal, educational, and parental expectations for children's upbringing [73,74]. The current daily schedule includes eating, indoor and outdoor activities, teaching, naps, and other events, all carried out in accordance with the kindergarten's designated timetable. Early childhood is a critical period for establishing positive routines and habits. A structured daily schedule enhances children's sense of security, trust, and independence, while also supporting their socio-emotional and cognitive development [75]. In designing daily routines, kindergartens typically arrange core events to align with the regular rhythms of family life and to meet the structured requirements of educational activities. Evidence suggests that consistent and predictable family routines—such as waking up, mealtimes, and bedtime—promote children's emotional stability and healthy development, and help ease adaptation stress during the transition to preschool [76]. Accordingly, kindergartens often integrate regular elements of home life (e.g., arrival, meals, nap time, departure) with key phases of the educational process (e.g., indoor and outdoor activities, group lessons, teacher preparation, cleanup) to form a relatively stable "routine event" framework. Such arrangements not only facilitate teachers' organization of instruction and caregiving at fixed times but also help children establish consistent rhythms between home and school, thereby reducing the disruptive impact of abrupt changes in daily life. This study incorporates both family routines and school teaching activities in 20 specific activities that constitute the kindergarten daily schedule. However, the 20 items are not entirely distinct, as some overlap remains. For example, the 'dietary activity' category includes breakfast, snacks, lunch, afternoon snacks, and dinner, all of which focus on nutritional intake and meal management, sharing common objectives and rhythmic characteristics. Similarly, although drinking water and pre-meal preparation are separated from main meals in timing, they serve the same functional purpose of supporting nutritional intake and the development of healthy habits. These are important components for developing healthy eating habits and raising dietary awareness in children [77]. Therefore, integrating these items into a unified dietary activity category is justified. Similarly, in consolidating indoor activities, inherent teaching and physical activities are combined with toilet use and handwashing, which are also categorized under indoor activity. This classification is based on their fixed spatial locations (within classrooms or restrooms), short time allocations, reliance on teacher guidance, and limited independent analytical value in relation to research objectives such as physical activity or social interaction. This integration approach is also reflected in research on daily structures in kindergartens. For example, comparative studies of daily activities in Slovenian and Belgian kindergartens show that activities such as personal hygiene and brief transitions are often incorporated into broader event categories [78]. Therefore, following this logic, the study categorizes and integrates recurring activities in the schedule into eight core event categories. We acknowledge certain limitations of this classification, for instance, it may not capture qualitative differences in content or children's engagement within the same category—such as indoor activities encompassing both free play and teacher-led academic tasks. Variations in the duration and frequency of these events may also influence children's physical activity levels and learning experiences [79]. Furthermore, cultural and policy contexts can shape the objectives and implementation of specific activities differently across regions. Therefore, this study divides the data into eight datasets corresponding to the eight event categories for analysis. Thus, the daily activities of the kindergartens examined in this study do not differ from those of regular kindergartens. As shown in Fig. 5, the kindergarten operates from 7:00 am. to 7:00 pm., with 20 events scheduled over 12 h, many of which are repetitions or similar activities. After classifying events with similar themes and content, the independent events identified in this kindergarten are as follows: arrival (7:30–8:00), dietary activity (8:00–8:20, 9:00–9:20, 10:20–10:30, 11:00–11:45, 14:00–14:30, 14:50–15:00, 16:00–16:45), indoor activity (8:20–8:50, 8:50–9:00, 14:30–14:50), outdoor activity (9:20–10:20, 11:45–12:00, 15:00–16:00), class (10:30–11:00), sleep (12:00–14:00), departure (16:45–17:30), and teacher's tidying (7:00–7:30, 17:30–19:00). In total, eight independent event categories are defined.

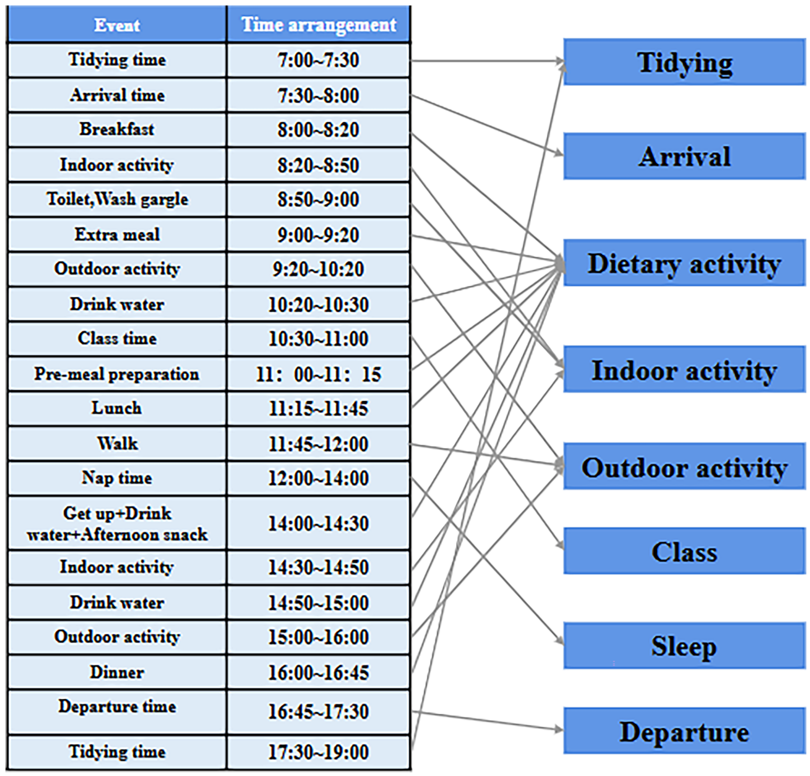


Figure 5: Daily schedule of kindergarten

2.4 Model Algorithms

Building on validations by scholars from various countries, numerous algorithms have been demonstrated as feasible in WOB research. Through in-depth analysis and comparison of the review papers in [80,81], this study selects three commonly used algorithms—LR, SVM, and RF—as the basis for establishing the WOB model of kindergarten buildings.

2.4.1 Logistic Regression

The binary logistic regression (LR) algorithm is a classification method used to predict binary or multiple outcomes based on a set of explanatory variables, it estimates the probability of a given outcome and determines whether the corresponding event is likely to occur. At present, owing to its relative simplicity, the LR algorithm offers fast computation and easily interpretable results. Consequently, it is one of the most frequently window-opening behavior. The regularization parameter (C) in the LR represents the penalty coefficient controlling error tolerance, with typical values ranging from 0.0001 and 10,000. A higher C value reduces the model's tolerance for error, allowing it to classify the data more accurately; however, excessively large values may lead to over-fitting. Conversely, very small C values may impose overly strong regularization, resulting in underfitting.

2.4.2 Support Vector Machine

Among machine learning classifiers, SVM is distinguished by its robustness, efficiency, and strong generalization ability. Comparable to multilayer perceptron and radial basis function networks, it can be applied to both pattern classification and nonlinear regression, with particular suitability for binary classification problems. SVM models can be optimized through parameter tuning to achieve an optimal structure. A kernel function is often employed to obtain the optimal solution efficiently, thereby avoiding unnecessarily computational complexity. Among the parameters, the choice of kernel function is the most critical: an inappropriate kernel may map the samples into an unsuitable feature space, resulting in poor model performance.

In addition to kernel selection, other key hyperparameters substantially influence the effectiveness of the algorithm. Commonly used kernel functions include the linear, polynomial, sigmoid, and radial basis function (RBF) kernels.

Key hyperparameters:

1. C (penalty parameter): A larger C increases model complexity and can improve prediction accuracy, but excessively high values may lead to overfitting.
2. Gamma (γ): A larger gamma assigns greater weight to nearby data points, making the model more sensitive to individual samples; however, if gamma value is too small, the model may underfit.

2.4.3 Random Forest

The Random Forest (RF) ensemble learning algorithm uses decision trees as base learners, improving both the accuracy and stability of the model by aggregating predictions from multiple decision trees [82]. Initially, k samples were randomly drawn from the original dataset using bootstrap sampling, with each sample containing n data points selected at random from the training set. Next, k decision tree models were constructed, each corresponding to one of the k samples, generating k distinct classification outcomes. Finally, the prediction receiving the highest number of votes was chosen as the final result [83].

The following hyperparameters have a significant influence on the fit of the RF model:

1. n estimators: Increasing the number of trees reduces the risk of overfitting. As the number of trees increases, the predictions of the RF model become more stable, since averaging across multiple trees helps to reduce random error.
2. max depth: Increasing the maximum depth of a tree may lead to overfitting. Deeper trees can fit the training data more closely but are also more prone to overfitting. By limiting the maximum depth, the complexity of the model can be controlled, thereby reducing the risk of overfitting.
3. max features: In RF models, only a subset of features is considered at each node. Increasing the value of the maximum features increases the randomness of each tree, thereby reducing the risk of over-fitting.
4. min_samples_split: Refers to the minimum number of samples required for a node to split, thereby controlling the growth of the tree. Smaller values can lead to overfitting, as nodes attempt to split based on very small subsets of the data. Larger values help prevent overfitting and make the decision tree more generalized.
5. min_samples_leaf: Refers to the minimum number of samples required to form a leaf node. Similar to min samples split, this parameter regulates the minimum sample size at the leaf

node level. It prevents the decision tree from being overly subdivided with very few samples per leaf node, helping to generate a simpler model with better generalization capabilities.

2.4.4 Stacking Model

This study first evaluated three commonly used algorithms—Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF)—as candidate models. Each algorithm was applied for modelling and prediction, and the best-performing model was identified based on prediction accuracy and goodness of fit. On this basis, event-specific sub-models were further developed for eight routine events (arrival, dietary activity, indoor activity, outdoor activity, class, sleep, departure, and tidying). To simplify the application process while ensuring predictive accuracy, the study adopted an ensemble learning approach. There are three general approaches to ensemble learning. The first is the Boosting architecture [84], which uses a serial approach between base learners to construct models with strong fusion. The second is the Bagging architecture [85], which builds strong learners by creating multiple independent models, and then combining them through voting or weighting. The third method is Stacking, which combines the two ensemble techniques. Stacking typically consists of two layers. The first layer comprises base models that demonstrate outstanding performance. Level 1: Basic models for excellent performance. The second layer, also known as the "meta-model", takes the outputs of the first layer models as a training set, builds the model, and produces the final predictions. Thus, if a first-level learner makes an error in a specific region of the feature space, the second-level learner can effectively correct it by integrating the learning behaviors of other first-level learners. For a single model, fitting complex data is challenging, and the model is less resilient to interference. Therefore, integrating multiple models can leverage the strengths of different models to enhance the model's generalization ability [86,87]. As illustrated in Fig. 6, the stacking framework adopted in this study consists of two layers. In the first layer, eight event-specific sub-models are constructed, each corresponding to a routine event (arrival, dietary activity, indoor activity, outdoor activity, class, sleep, departure, and tidying). These sub-models are trained using 5-fold cross-validation to generate out-of-fold (OOF) predictions—each model is trained on 80% of the data and predicts the remaining 20%, ensuring that every sample is predicted by a model that has not seen it during training. The resulting OOF predictions are concatenated in their original order to form a new feature matrix, which serves as the input for the second-layer meta-model.

In traditional stacking methods, each base learner is typically trained on the same dataset and generates predictions for all samples. These predictions are then concatenated into a multi-dimensional input matrix to train the second-layer meta-model. By contrast, this study introduces an event-driven framework. The eight event-specific sub-models are trained on their respective data subsets, and their out-of-fold (OOF) prediction results are aggregated to form a prediction vector consisting of eight elements. This vector serves as the input to the meta-model, which further calibrates and integrates the outputs of the sub-models. Although this structure does not fully conform to the strictest definition of stacking, its advantage lies in significantly simplifying the deployment process by avoiding the need for frequent model switching within building energy simulation platforms. At the application stage, simulation tools such as Energy Plus only need to invoke this integrated model to generate predictions across multiple event types, thereby improving the practical value of the model.

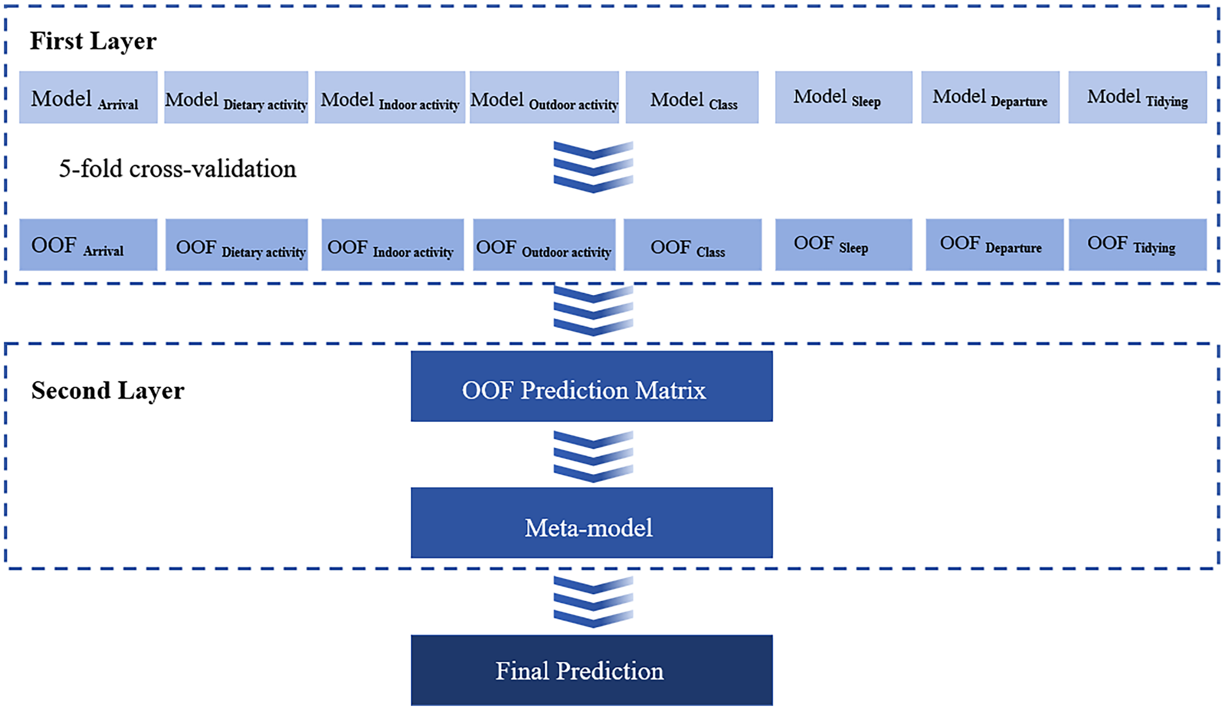


Figure 6: Stacking model flow

2.5 Evaluation Indicators

In framing window-switching as a binary classification task, instances can be assigned to either a positive or a negative class. This results in four possible outcomes in the classification process: (1) an instance belongs to the positive class and is correctly identified as positive, termed True Positive (TP); (2) an instance belongs to the positive class but is mistakenly classified as negative, known as a False Negative (FN); (3) an instance belongs to the negative class but is incorrectly classified as positive, called a False Positive (FP); and (4) an instance belongs to the negative class and is correctly classified as negative, referred to as a True Negative (TN).

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

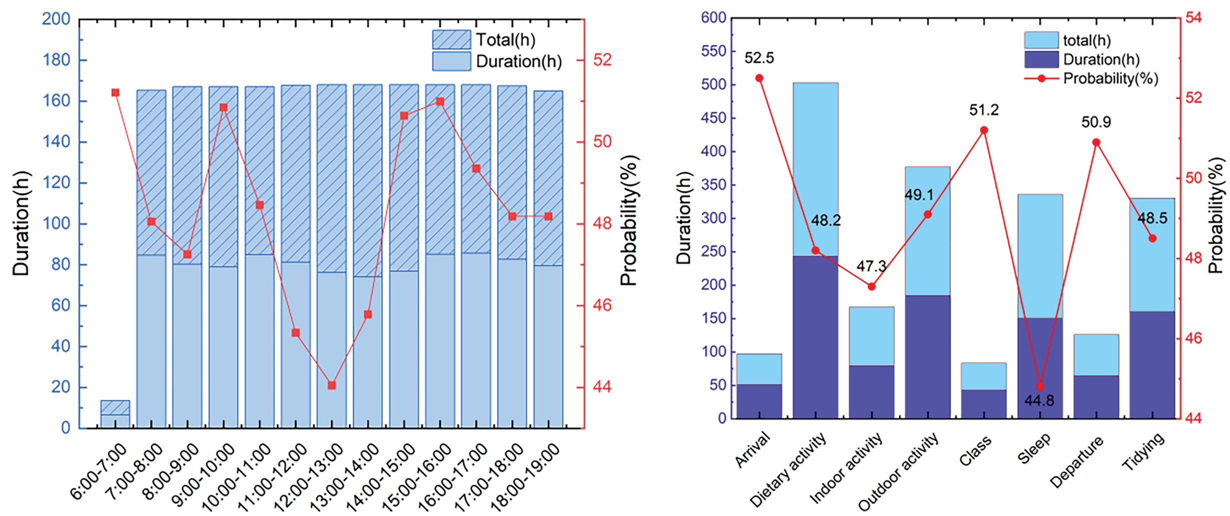
$$F1score = \frac{2TP}{2TP + FP + FN} \tag{2}$$

For unbalanced data, the AUC index offers greater advantages and can better reflect the model's performance [88]. Therefore, in this paper, AUC, F1 score, and accuracy are used to evaluate the optimal model.

3 Results

3.1 Analysis of the Impact of Events on WOB

By analyzing the measured data from 7 March 2021, to 29 April 2021, it can be observed that the period from 6:00 to 7:00 is characterized by a high volume of people entering, and the power is turned on irregularly, resulting in fewer total operating hours. The remaining periods have more consistently recorded hours. As shown in Fig. 7a, in the traditional method of analyzing window-opening behavior based on time, the time divisions are not flexible, resulting in two issues. The first is the mixing of multiple activities within the same period. For example, between 8:00 and 9:00, activities such as breakfast, indoor activity, toilet use, and washing or gargling occur, and none of these events alone characterizes window-opening behavior (WOB). The second issue arises when different periods involve the same event but display similar window-opening characteristics, resulting in repeated representation. For instance, the two time slots, 12:00–13:00 and 13:00–14:00, correspond to nap time, with window-opening probabilities of 44% and 45.8%, respectively, which can be combined and analyzed.



(a) (b)

Figure 7: WOB duration and proportion with and without event-based division: (**a**) window-opening probability at different times of day, (**b**) window opening probability for different events

From a relative perspective, the method of dividing events is more reasonable. As shown in Fig. 7b, the eight events have different window-opening durations, allowing for a comprehensive analysis of the variability in WOB characteristics due to the diversity of events. In kindergarten buildings during the spring season, arrival, class, and departure events exhibit relatively proactive WOB, with window-opening probabilities exceeding 50% for all three events. Notably, the arrival event has the shortest duration and cumulative window-opening duration, yet it exhibits the highest window-opening probability. The corresponding probability for the departure event is also high at 50.9%, indicating a preference for opening windows upon leaving the premises to improve indoor air quality for the following day.

Furthermore, WOBs during dietary activity, indoor activity, outdoor activity, and sleep events are relatively passive. In particular, during sleep, with a total duration of 336 h, the window-opening probability is the lowest at only 44.8%, suggesting that teachers consider the sensitivity of children's bodies and reduce WOB during sleep.

3.2 Analysis of Influencing Factors

3.2.1 Outdoor Environment

The WOB of the eight events varied according to the characteristics of each outdoor environmental factor. As shown in Fig. 8a, the probability of WOB for the arrival event increased gradually with rising outdoor temperature, indicating that in spring, teachers tend to actively open windows as students arrive in response to the warming conditions. In contrast, the WOB during the tidying and departure events appears to be more random under the influence of outdoor temperature. The other six events exhibited similar changes in WOB, all occurring at an outdoor temperature of 9°C. When the outdoor temperature was below 9°C, the WOB was not significantly affected by the low temperature, and the probability of window opening was around 70% for most events, even when the outdoor temperature was below zero, indicating that WOB at temperatures below 9°C was more random. When the outdoor temperature exceeded 9°C, the WOB exhibited a gradual increasing trend with rising temperature, indicating that higher outdoor temperatures have a facilitating effect on WOB.

As shown in Fig. 8b, the WOB of the eight events fluctuated between 40% and 60% with changes in outdoor relative humidity in most cases. This suggests that there is no strong correlation between outdoor relative humidity and the WOB of different events in the data. Regarding the grading of AQI indicators, each country has different classification standards. The China GB 3095-2012 Ambient Air Quality Standard specifies the following: 0–50 indicates non-pollution; 51–100 indicates an environment in which a minimal number of abnormally sensitive people should reduce outdoor activities; 101–150 indicates mild pollution; 151–200 indicates heavy pollution, for which it is recommended that children reduce long-term, high-intensity outdoor exercise.

As shown in Fig. 8c, the critical AQI value at which indoor occupants in kindergarten buildings become more sensitive to outdoor air quality is approximately 165. At AQI levels below 165, WOB is more random and unaffected by changes in AQI. When AQI is $\geq$165, the probability of WOB decreases rapidly for all five events except for arrival, tidying, and departure events. GB 3095-2012 specifies that $PM_{2.5}$ levels exceeding 50 μg/m^3 constitute an unhealthy environment.

The probability of WOB events changes when the outdoor $PM_{2.5}$ concentration reaches 90 μg/m^3, as shown in Fig. 8d. When the concentration exceeds 90 μg/m^3, the WOB probability for the three events—arrival, departure, and tidying—still shows an increasing trend, whereas the other five events exhibit a gradual decline. This suggests that while low outdoor $PM_{2.5}$ concentrations have no obvious driving effect, excessively high concentrations exert an inhibitory effect on occupants' WOB.

When the wind speed exceeds 6 m/s, the WOB of indoor events—including sleep, class, dietary activity, and indoor activity—decreases, especially during sleep, which is the most sensitive to wind speed among these four events, as shown in Fig. 8e. However, for the events of arrival, departure, tidying and outdoor activity, there are fewer children indoors. Therefore, even if the wind speed exceeds 8 m/s, WOB for these events still exhibits an upward trend.

It is worth noting that outdoor environmental factors are more reflected in the WOB of the three events—arrival, departure, and tidying—which almost differ from the trend observed in the other five events, corresponding to situations where student attendance is incomplete. It is evident that for events with fewer students present, WOB exhibits lower dependency on the outdoor environment and is relatively more random compared to other events.

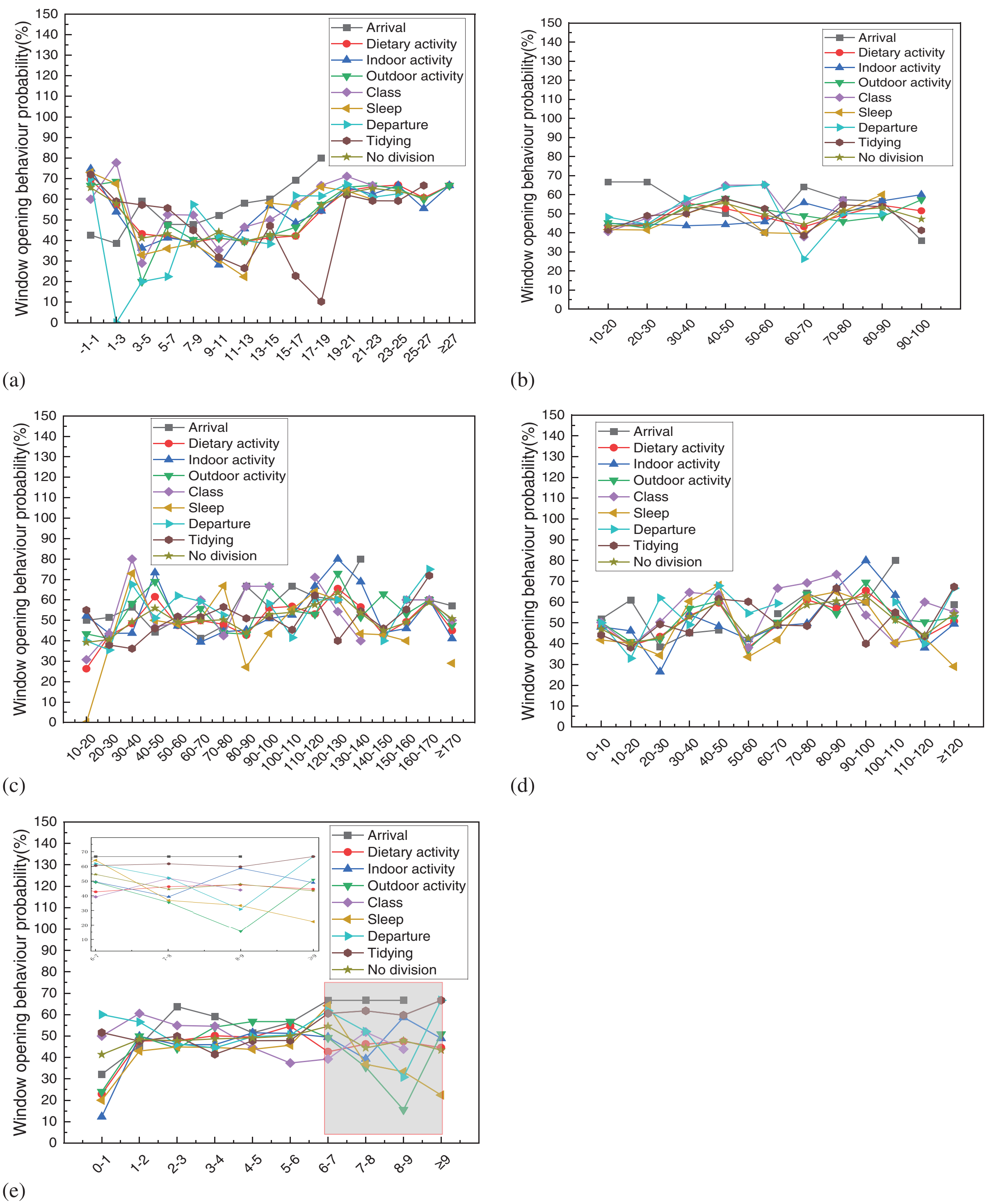


Figure 8: Relationship between outdoor environmental factors and WOB: (**a**) outdoor temperature (°C), (**b**) outdoor relative humidity (%), (**c**) outdoor AQI, (**d**) Outdoor $PM_{2.5}$ (μg/m^3), (**e**) outdoor wind speed (m/s)

Furthermore, it is evident that by differentiating events, the trends in the curves more accurately reflect the dynamic impact of each event on WOB at different stages. In contrast, when events are not differentiated, the overall curve presents only a singular trend, lacking the necessary detail and precision.

3.2.2 Indoor Environmental

Indoor environmental factors are categorized into two main groups: those affecting indoor air quality (indoor TVOC, indoor $PM_{2.5}$ concentration, and indoor CO_2 concentration), and those impacting thermal comfort (indoor temperature and relative humidity). The Indoor Air Quality Standard requires an indoor TVOC limit of 0.6 mg/m^3, as shown in Fig. 9a. When this limit exceeds 0.6 mg/m^3, occupants do not immediately open windows to improve the environment; notable changes in WOB begin at 2–2.5 mg/m^3. Specifically, class, indoor activity, and dietary activity are three events where the indoor TVOC concentration exceeds 2.5 mg/m^3, resulting in a significant increase in WOB probability. Indoor CO_2 is currently a focal point in the study of drivers of WOB. Most studies have shown that WOB exhibits a negative correlation with increasing indoor CO_2 concentration, especially in residential buildings, where high concentrations exceeding 1000 ppm generally occur during night time sleep and are therefore not considered a driver [67].

However, this study is divided by events. It is considered that the influence of indoor CO_2 on WOB differs across events as shown in Fig. 9b. When CO_2 is below 1200 ppm, indoor air quality is less affected by CO_2 concentration, so occupants do not open windows in response to CO_2. Within this range, all event window-opening behaviors were negatively correlated with CO_2. This suggests that indoor CO_2 concentration is at a healthy level when the probability of window opening is high, despite other factors. When the CO_2 concentration reached 1200 ppm or higher, the window-opening behavior during class, indoor activities, and meals exhibited a significant upward trend. Additionally, after the concentration exceeded 1500 ppm, the departure event also became more proactive in opening windows. This suggests that high CO_2 concentrations have a driving effect on these four events. The overall indoor CO_2 concentration during the arrival event did not exceed 1300 ppm, so there was essentially no driving condition for window opening. The window opening probabilities of the remaining three events all showed a decreasing trend with increasing CO_2 concentration, indicating that, on the one hand, occupants do not ventilate before leaving due to high CO_2 levels, and on the other hand, the sleeping event remains unaffected as a driver of WOB.

As shown in Fig. 9c, there is little difference between the trends of divided and non-divided events for <50 µg/m^3, and for ≥ 50 µg/m^3, the trends of events vary, but in general, WOB is positively correlated with indoor $PM_{2.5.}$

For the factors affecting human thermal comfort, the pattern of WOB for each event is more obvious, as shown in Fig. 9d. Except for the sharp drop of class in the range of 25°C–26°C, the WOB of other events increases with rising indoor temperature, indicating that the temperature rise has a strong driving effect on window-opening. On the contrary, after the indoor relative humidity reaches the range of 25%–30%, the WOB of all events is negatively correlated with indoor relative humidity, as shown in Fig. 9e. This indicates that in kindergarten buildings, where teachers serve as the primary regulators of the indoor environment, they pay close attention to children's thermal comfort and tend to actively adjust it by opening windows during the spring season.

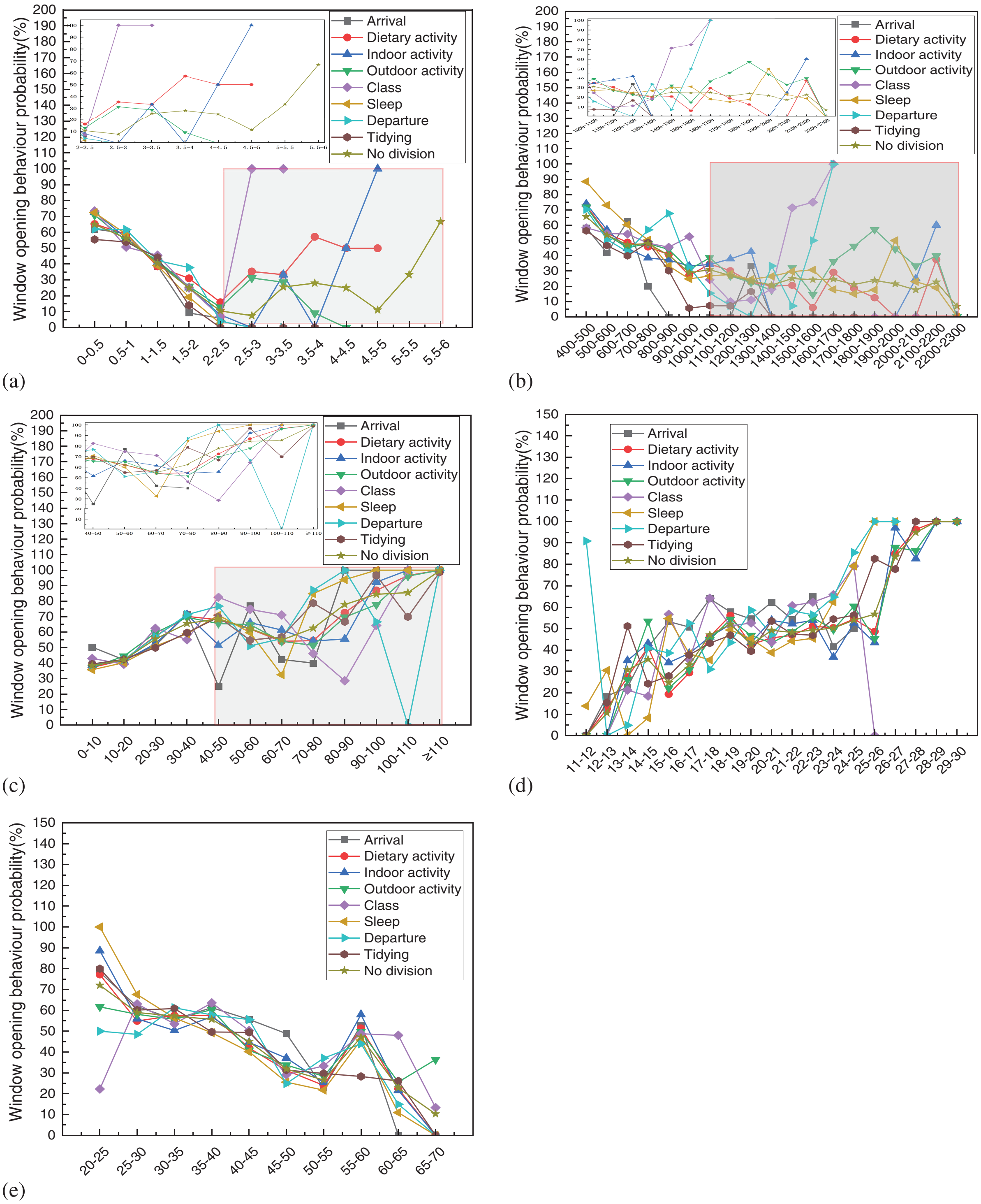


Figure 9: Relationship between indoor environmental factors and WOB: (**a**) indoor TVOC (mg/m³), (**b**) indoor CO_2 (ppm), (**c**) indoor $PM_{2.5}$ (μg/m³), (**d**) indoor temperature (°C), (**e**) indoor relative humidity (%)

It is worth noting that the events class, indoor activity, and dietary activity are more sensitive to indoor air quality factors. The probability of window opening for these events increases as indoor TVOC and CO_2 concentrations rise. These events typically occur during times when students and teachers are cognitively active, suggesting that during mentally engaging indoor activities, both children and teachers are more inclined to open windows to improve indoor air quality.

3.3 Modeling and Prediction

Firstly, this section models and predicts WOB using four algorithms on data without event differentiation, selecting the algorithm that most accurately describes WOB in kindergarten buildings and identifying the optimal hyperparameter combination. In the event-free model, the time factor is quantified both as a continuous variable and a categorical variable and is used as one of the input parameters. Secondly, the optimal algorithm is applied to establish eight event-specific sub-models, and their performance is compared with that of the undifferentiated model (to highlight the impact of event differentiation, the algorithm parameters remain unchanged). Finally, a stacking model is used to integrate the event sub-models.

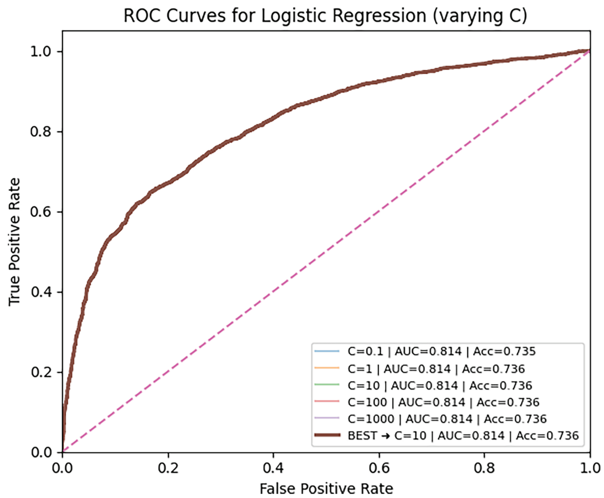
3.3.1 Logistic Regression

The variation of the C value from 0.1 to 1000 can essentially explain the performance of the logistic regression model. Traditional modeling methods without event division typically quantify time factors as either continuous or categorical variables. As shown in Table 3, the prediction accuracy corresponding to C values from small to large demonstrates that, regardless of whether time factors are quantified as continuous or categorical variables, the prediction accuracy of the logistic regression algorithm for WOB data in kindergarten buildings remains below 80%.

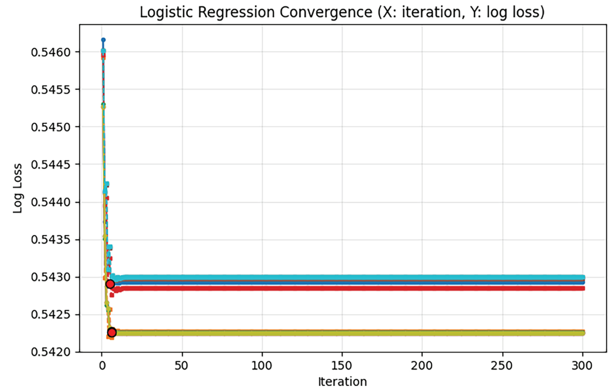
Table 3: LR model results

C	Non-division (Time: Continuous variable)		Non-division (Time: Hierarchical variable)	
	Train	Test	Train	Test
0.1	73.39	73.52	73.37	73.48
1	73.41	73.61	73.39	73.46
10	73.36	73.6	73.39	73.46
100	73.42	73.59	73.37	73.49
1000	73.4	73.61	73.39	73.42

As shown in Fig. 10a, the AUC value under the ROC curve remains consistently at 0.814, indicating that the logistic regression model has moderate discriminative capacity but falls far short of high accuracy requirements. Meanwhile, the curves across different C values almost entirely overlap, and the prediction accuracy consistently hovers around 0.735–0.736, further underscoring the performance bottleneck of the model. The learning curves in Fig. 10b show that for all C values, the log loss of both the training and validation sets decreases rapidly within the first 2–3 iterations and stabilizes around the third iteration, reflecting the model's fast convergence and good stability. Overall, although the logistic regression model exhibits good convergence, its predictive power remains insufficient and cannot meet the requirements for high-precision modelling of WOB.



(a)



(b)

Figure 10: Performance of the logistic regression model, (**a**) ROC curve, (**b**) learning curve

3.3.2 Support Vector Machine

For the SVM algorithm, the use of different kernel functions can lead to significant differences in the model's effectiveness. To explore a more applicable model for kindergarten buildings, this paper uses four kernel functions for SVM, which are modeled and predicted for all the spring data from the kindergarten buildings. As shown in Fig. 11a, the linear kernel function has an accuracy of less than 73.5% when the C value is <0.01. The accuracy ranges between 73.5% and 74% when the C value is between 0.01 and 10. When the C value exceeds 10, the process takes longer than 24 h. Therefore, the C value is measured up to 10, considering the algorithm's implementability. In Fig. 11b, for the polynomial kernel, C was set to 0.01, 0.1, 1, and 10, and γ to 0.01, 0.1, 1, and 10. Across these combinations, the graded variables produced by the two models do not differ significantly, and the maximum accuracy is approximately 88%.

For the RBF kernel function, C was set to 0.01, 0.1, 1, and 10, and γ to 0.01, 0.1, 1, 10, and 100. Across these combinations, as shown in Fig. 11c, when $C < 1$, both training and test accuracy stay around 51%, indicating persistent under-fitting. When $C > 1$, training accuracy approaches 100% while test accuracy is more than 10% lower, evidencing over-fitting. Thus, tuning C—whether small, moderate, or large—does not yield a configuration that meets the study's performance criteria; generalization remains unsatisfactory.

As shown in Fig. 11d, the change in the C value for the Sigmoid kernel function has a significant impact on whether the time factor is treated as a continuous or graded variable. When the C value exceeds 0.1, the accuracy of the model in which time is a graded variable is higher than that of the model in which it is continuous by 20%. However, regardless of the C value, the maximum accuracy does not exceed 60%.

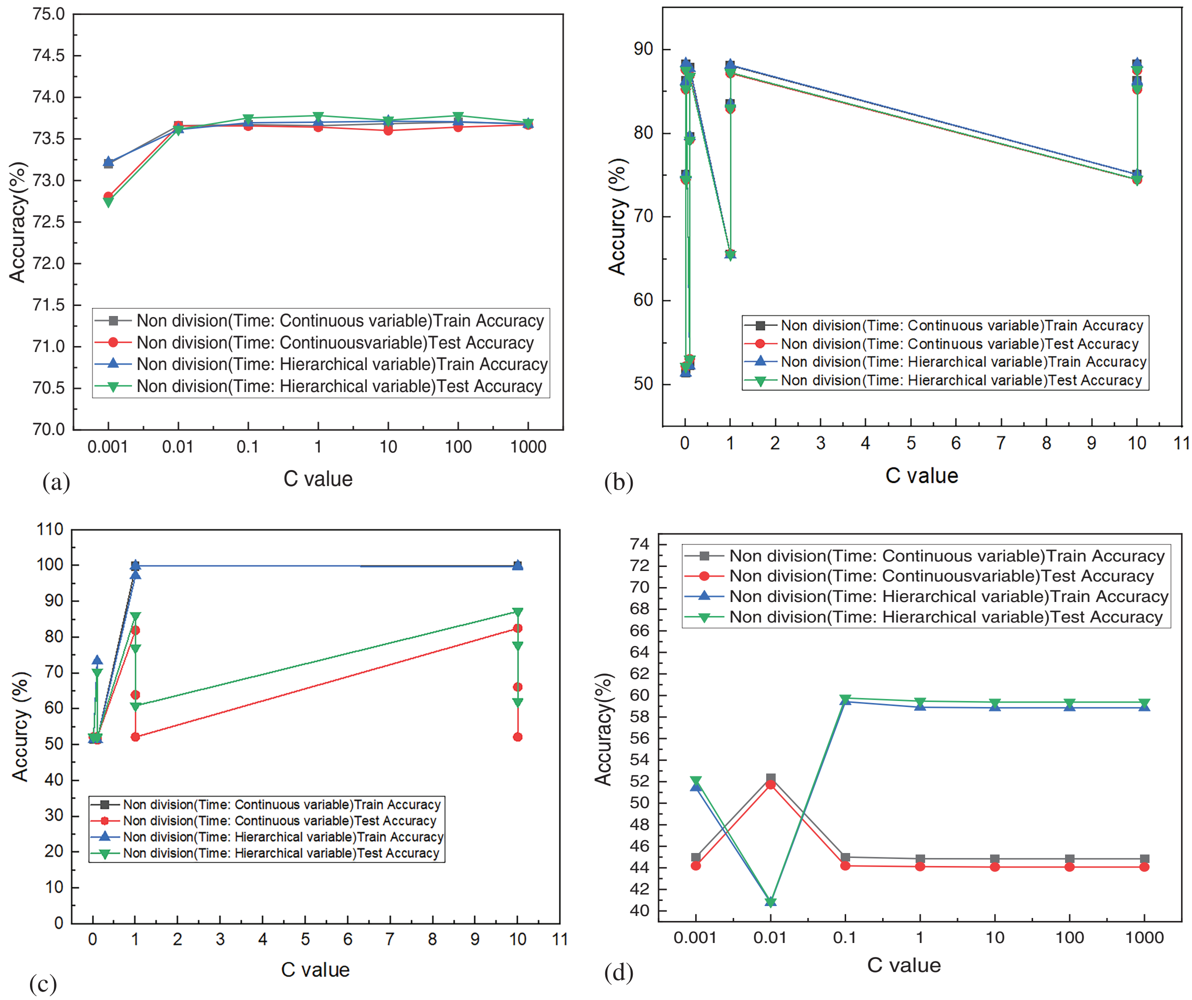
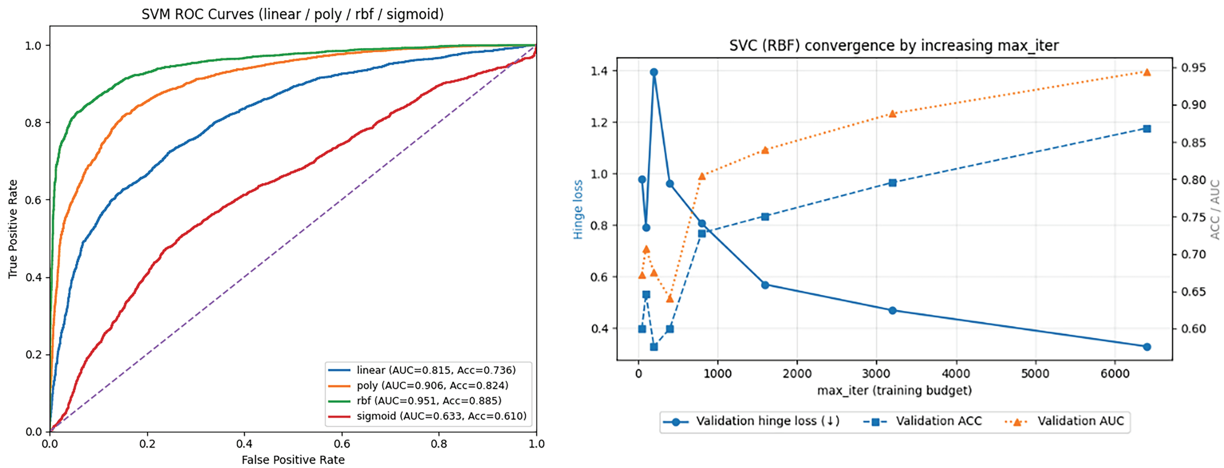


Figure 11: Performance of SVM with different kernel functions: (**a**) Linear, (**b**) Poly, (**c**) RBF, (**d**) Sigmoid

As shown in Fig. 12a, the performance of SVM varied significantly across different kernel functions. The RBF kernel performed best (AUC = 0.951, Acc = 0.885), effectively capturing the nonlinear features of WOB data, followed by the poly kernel (AUC = 0.906, Acc = 0.824). The linear kernel showed only moderate performance (AUC = 0.815, Acc = 0.736). In contrast, the sigmoid kernel performed considerably worse (AUC = 0.633, Acc = 0.610), approaching random classification, indicating its predictive capability is limited in this context. As illustrated in Fig. 12b, when SVM is applied with the RBF kernel, the validation hinge loss converges rapidly after around 200 iterations. It stabilizes at approximately 2000 iterations, while further increases in the number of iterations provide only limited improvement and even introduce fluctuations. Meanwhile, the validation accuracy and AUC gradually increased with the number of iterations, with the AUC rising from about 0.6 to nearly 0.9, indicating a substantial enhancement in the model's discriminative capability. Overall, the RBF kernel effectively captures the nonlinear characteristics of WOB data, achieving optimal predictive performance and convergence within the range of 2000–4000 iterations.



(a) (b)

Figure 12: Performance of the SVM model, (**a**) ROC curve, (**b**) learning curve

3.3.3 Random Forest

As with the modeling approach described above, the RF model hyperparameters were tuned using undivided event data. The results of the hyperparameters tuning are as follows:

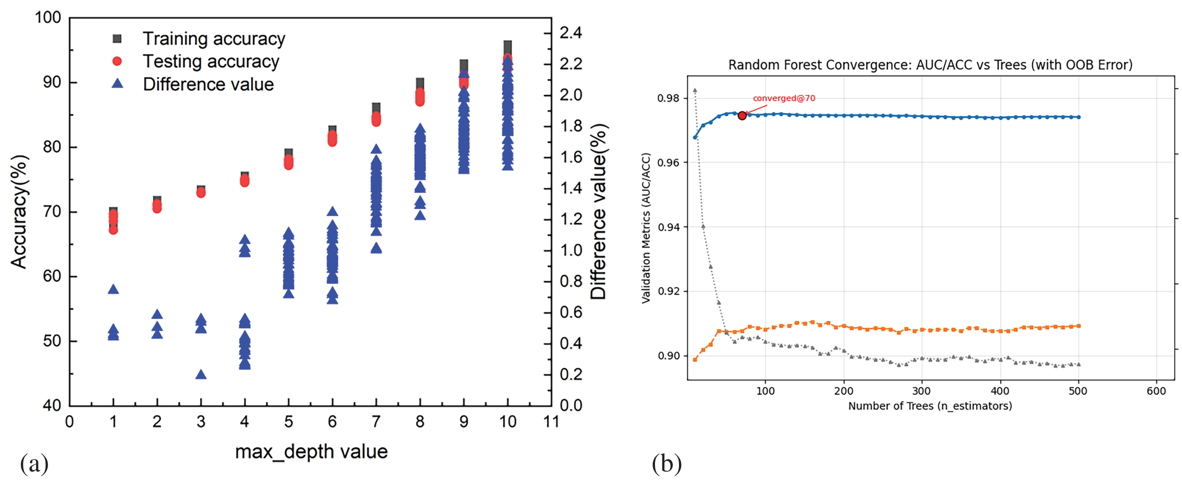
As shown in Table 4, in range (1), models generated from the hyperparameters displayed training set accuracy consistently higher than that of the test set. Additionally, instances occurred where the training set accuracy reached 100% for every value within the range of max depth. Moreover, as the maximum depth increased, the accuracy of the test set also rose. Hence, it can be inferred that the models generated from the hyperparameters within range (1) were over-fitting, with max depth being the most influential hyperparameter affecting model prediction accuracy.

Table 4: RF Modeling Results

Hyperparameters	n_estimators	max_features	max_depth	min_samples_leaf	min_samples_split
Range (1)	50, 100, 200, 300	sqrt, log2	10, 20, 30, 40, 50	1, 2, 4, 8	2, 5, 10, 20
Range (2)	50, 100, 200, 300	sqrt, log2	1∼10	1, 2, 4, 8	2, 5, 10, 20
optimum	300	log2	10	1	2

In range (2), with all other parameters held constant, max_depth was set between 1 and 10, resulting in 1280 hyperparameter combinations. As depicted in the graph, as max_depth increased, both training and testing set accuracy, as well as the difference (difference = training set − test set), gradually increased. The difference did not exceed 5%, and the accuracy reached 90%. Furthermore, there were no instances in which the training set accuracy reached 100%. Therefore, it can be considered that RF is the most accurate model for classifying the WOB state among the three models. The combination of max_depth = 10, max_features = sqrt, min_samples_leaf = 1, min_samples_split = 2, and n_estimators = 300 represents the optimal case.

As shown in Fig. 13a, the accuracy of the random forest model on both the training and testing sets increases with the maximum depth of the decision trees. Shallow models exhibit clear underfitting, whereas when the depth reaches 7–9, the testing accuracy stabilizes at around 85%–90%, with the difference between training and testing accuracy remaining below 2%, indicating strong generalization ability. At a max_depth of 10, the training accuracy approaches 100% and the testing accuracy reaches about 95%, although the slightly larger gap suggests a potential risk of overfitting. Random forests are not trained via gradient descent and thus do not generate a global loss curve that decreases monotonically with iterations. Instead, each tree is independently constructed based on bootstrap sampling and split-purity criteria, and the convergence of the ensemble is evaluated through the stability of performance metrics such as validation AUC, validation accuracy, or out-of-bag (OOB) error as the number of trees increases. As shown in Fig. 13b, the validation AUC rises sharply and peaks at approximately 0.97 around 60 trees, after which it remains essentially stable; the validation accuracy fluctuates slightly between 0.90 and 0.91. Meanwhile, the OOB error drops rapidly at first and levels off near 0.10 after about 100 trees, suggesting that further increases in the number of trees yield diminishing returns. In practice, selecting around 120–200 trees provides an appropriate balance between computational cost and performance.



(a) (b)

Figure 13: The performance of the random forest model: (**a**) relationship between RF max depth hyperparameter value and prediction accuracy, (**b**) learning curve

In summary, considering the influence of hyperparameters and the algorithm's implementability, the accuracy rate of the LR algorithm is approximately 73%. The poly kernel function is the most effective in SVM, achieving an accuracy of roughly 88%. RF reaches approximately 93%, making it the most suitable algorithm for predicting WOB in kindergarten buildings among the three.

3.3.4 Event Sub-Model and Stacking Model

As shown in Fig. 14, the non-division models achieved the lowest predictive accuracy, at 93.55% when time was treated as a continuous variable and 93.57% when treated as a hierarchical variable. In contrast, the event-specific models consistently outperformed the traditional non-division approach, with accuracy ranging from 92.48% to 98.26%. Notably, the Sleep event achieved the highest predictive accuracy (98.26%), approximately 4.4% higher than the non-division model, followed closely by Tidying (97.98% for direct prediction and 97.49% for OOF prediction) and Class (96.84% and 94.35%). These results demonstrate that modeling based on distinct events provides a clear advantage in accurately predicting WOB. Moreover, the differences between OOF predictions generated by 5-fold cross-validation and direct predictions were consistently within 1%, indicating strong stability of the event-based framework. Considering that managing multiple event-specific models may increase the workload in practical applications, a stacking model was used to integrate the eight event sub-models. The stacking model achieved an overall accuracy of 96.68%, comparable to the best-performing single-event models, while requiring computational resources similar to those of a single sub-model. These findings highlight the advantages of event-based modeling in enhancing predictive performance and further demonstrate that stacking learning can streamline the workflow without compromising accuracy.

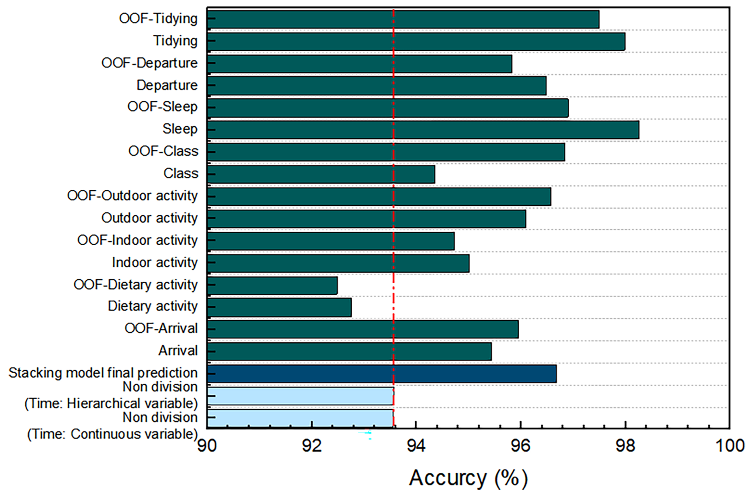


Figure 14: Comparison of results for the division sub-model, stacking model, and non-division model

4 Discussion

4.1 Analysis of Window Opening Behavior Differences across Seasons and Building Types

The impact of seasonal changes on window opening behavior across different building types cannot be overlooked, and is particularly significant in regions with distinct climatic variations. Even within the same spring season, different building types exhibit notable differences in window operation. In residential buildings, springtime window opening during the day is primarily driven by "thermal comfort needs" and "fresh air needs," with behavior concentrated in daytime hours, especially in the morning. This is likely related to residents' habits of airing their homes after waking up or before leaving for work. In summer, however, high daytime temperatures suppress the willingness to open windows, and nighttime (21:00–04:00) becomes the main period for window operation [22,53]. In office buildings, multiple studies have shown that changes in window states often occur when occupants arrive or leave the office. After employees begin work, windows are frequently opened to alleviate stuffiness and reduce poor air quality, while behavior associated with "lunch break" and "work sessions" also occurs [26]. In maternal and child hospitals, where the main occupants are postpartum women, ward behavior shows certain similarities to residential buildings. The probability of window opening increases by 5%–10% in the morning but gradually decreases after 21:00, consistent with the "morning opening, bedtime closing" pattern observed in residences [89]. However, "consideration for maternal comfort" (67.35%) was identified as the main reason for window closing, while some motivations for opening or closing windows were influenced by cultural traditions such as "avoiding drafts," suggesting that environmental comfort was not always the primary factor [90].

These findings indicate that the temporal distribution of WOB is only a surface manifestation. Even within the same season, different building types exhibit fundamentally different temporal demands for window operation, which are essentially driven by events. Therefore, WOB should be analyzed from an event-based perspective, tailored to building type. The kindergarten buildings investigated in this study differ fundamentally from the types mentioned above. Their main occupants are young children, whose daily schedules include not only life routines but also structured educational activities. Consequently, aside from higher window-opening probabilities during arrival (52.5%) and departure (50.9%), there is also a high probability observed during "class" events (51.2%).

Moreover, differences exist among classrooms across age groups. Existing research has focused more on older students with better cognitive expression and self-regulation abilities. For example, in high school classrooms during the heating season, window opening is more frequent in the first half of the morning, particularly during breaks (10:50–11:10), upon arrival (08:00–08:10), and between classes. During lessons, even when indoor conditions deteriorate, students rarely open windows proactively, reflecting low sensitivity to the environment [65]. In primary school classrooms during winter, window opening is more frequent at arrival times, while windows are more often closed at departure, with little interaction at other times [91]. Some studies recommend that teachers guide students to open windows during class breaks [92].

The focus of this study is kindergartens, primarily occupied by children aged 3–5, which differ from the educational buildings mentioned above. Young children cannot operate windows independently; teachers act as the actual operators, adjusting window behavior based on their understanding of children's needs, which introduces marked differences. Research has shown that in spring, during events with active child participation (e.g., class, meals, and indoor activity), window operation is more sensitive to indoor air quality, with teachers more likely to open windows to improve the environment—a behavior that contrasts with that in high school classrooms. Therefore, even among educational buildings, window-opening behavior requires age-specific and season-specific analysis.

4.2 Characteristic Analysis

In current research, the time factor has been widely regarded as the main influence on WOB. However, the effect of each time period on WOB varies. Office buildings show a higher proportion of window openings during working hours [93], especially when occupancy is higher, as the probability of window openings increases [94]. On weekdays, in ordinary homes, people frequently open windows in the morning before going to work [53,55]. However, the baby house differs from typical adult homes, showing a "twin peaks" pattern of window opening at 9:00–10:00 and 19:00–20:00. These correspond to the times when parents care for infants in the morning and spend time with their children in the bedroom after work [54]. It is evident that data quantified by the time factor does not fully capture its effect on WOB. The passage of time brings about changes in events, which are the main factors influencing people's behavior.

To demonstrate that the event classification method is not only applicable to the sample data from the kindergarten building in this study but also generalizable to other WOB studies, this paper extracts WOB data from an open office building in Italy in the global ASHRAE Occupant Behavior Database (https://ashraeobdatabase.com) as the validation sample data [95]. These office schedules are divided into three categories: off-duty (7 p.m. to 9 a.m. the next day), lunch break (1 to 3 p.m.), and on-duty (9 a.m. to 1 p.m. and 3 to 7 p.m.) [34]. Since the original data recorded window status and indoor temperature every five minutes, each window-opening was recorded consecutively five times. The outdoor environmental parameters (including temperature, humidity, wind speed, wind direction, and solar radiation) were recorded every ten minutes. The data were then processed, and linear interpolation was used to calculate the values for these parameters. All data were subsequently recorded at uniform five-minute intervals.

As shown in Fig. 15, there are two peaks in WOB across the 24 periods. From the perspective of the traditional "daily time-period" analysis, significant differences exist between kindergarten and office buildings in the distribution of window-opening peaks and troughs. In kindergartens, the peaks occur mainly from 8:00 to 10:00 in the morning and 14:00 to 16:00, closely associated with ventilation practices after children's arrival and after nap time. The trough, in contrast, is concentrated between 12:00 and 14:00, when ventilation is reduced to avoid disturbing children during their midday rest. In comparison, office buildings (based on ASHRAE data) exhibit peaks from 9:00–12:00 in the morning and 13:00–18:00 in the afternoon, corresponding to regular working hours. The trough occurs between 12:00 and 15:00, during lunch breaks when occupant activity decreases, leading to lower window-opening rates. These differences highlight the essential distinctions in occupant routines and event-driven mechanisms between the two building types.

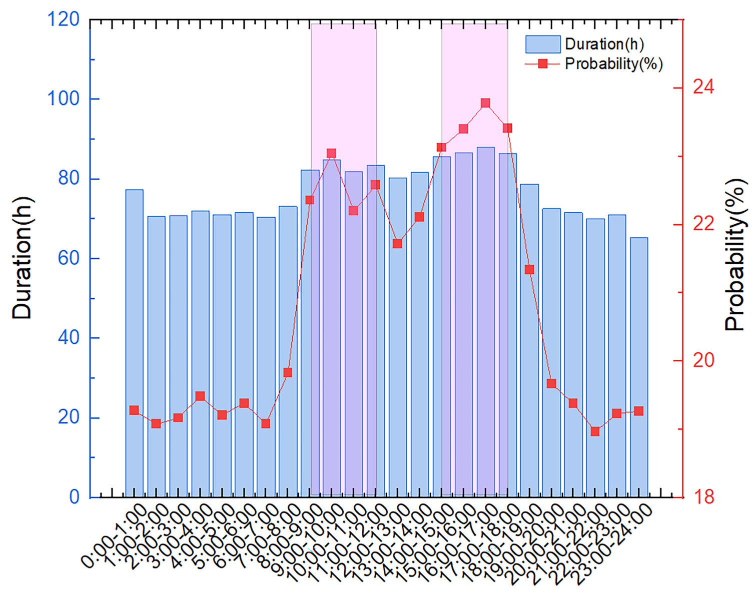


Figure 15: Correlation between the time of day and WOB in ASHRAE data samples

4.3 Modeling and Verification

The selection of input parameters plays a crucial role in model development, with the quantification of temporal factors as input data having been extensively applied in related studies. The first is a categorical variable. It has been demonstrated that month, day of the week, and hour of the day, as hierarchical variables, are significant input parameters for the model [36,53]. The day of the year ($R^2 = 0.967$) is more suitable as a WOB model parameter than the minute of the day ($R^2 = 0.438$) [96]. However, based on the analysis presented in this paper, the sub-model that divides events outperforms the traditional model, which uses time as the input parameter. As shown in Fig. 16, the non-division models achieved the lowest predictive accuracy, with only about 84% when time was quantified as either a continuous or hierarchical variable, indicating that solely relying on time quantification provides limited improvement to model performance. In contrast, event-based sub-models all achieved higher accuracy, with the Closing Time event performing best at approximately 89%, while Working Hours and Lunch Break also outperformed the traditional models. This demonstrates that event division can more effectively capture variations in occupant behavior patterns across different periods. Furthermore, by integrating multiple event-specific sub-models, the stacking model achieved an overall accuracy of over 96%, significantly surpassing both individual event models and non-division models, thereby confirming the advantages of event-based modeling and ensemble learning in enhancing WOB prediction performance.

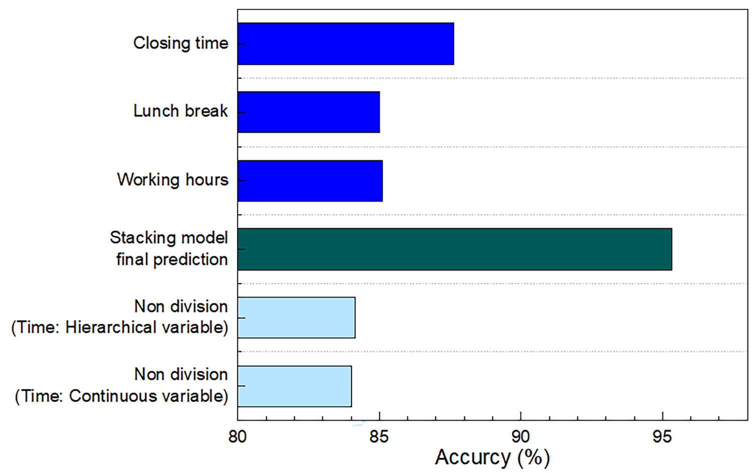


Figure 16: Verification result

The event-based research framework proposed in this study exhibits strong generalizability within kindergarten buildings located in cold regions of China. It is not only applicable to the case building analyzed but also holds promise for broader application across other kindergartens in regions with similar climatic conditions.

For kindergarten buildings in other climatic regions that follow similarly structured daily routines—such as regular activities including teaching, napping, and meals—the framework can be moderately adapted while maintaining its core modeling logic, and also offers methodological reference and reproducibility.

However, when applying this framework to buildings with significantly different climatic characteristics or functional types (e.g., office buildings or residential dwellings), it is necessary to carefully adapt the event definitions, occupant behavior modeling strategies, and algorithmic configurations to ensure the accuracy and applicability of window-opening behavior analysis and prediction.

5 Limitations

This study adopts an event-based approach to investigate window opening behavior, using field data collected from kindergarten buildings in a severe cold region. However, the limited sample size and focus on a single building type restrict the broader applicability of the findings. Although partial validation was performed using office building data from the ASHRAE public database, the current scope lacks sufficient diversity in building functions and climatic contexts. Given that behavioral patterns and event characteristics can vary significantly across different building types and user groups, the effectiveness of the proposed method in other contexts remains uncertain. Future studies should expand the research scope to include a wider variety of buildings and climate zones, thereby further testing the generalizability of the approach. Additionally, teachers are the primary decision-makers for window operations in kindergarten buildings. WOB is shaped not only by teachers' interpretations of students' needs but also by their individual preferences. In future research, teacher interviews and surveys should be conducted across different events to systematically collect information on their personal perceptions, environmental demands, and judgments of students' needs. These data should then be quantified and incorporated into the modelling inputs to more comprehensively reveal the decision-making mechanisms underlying window operations.

6 Conclusion

A direct relationship exists between the functional characteristics of buildings and the types of events that occur within them. Due to the essential difference in daily activities, kindergarten buildings exhibit unique window opening behave* (WOB) patterns compared with other building types. This paper analyzes the behavioral characteristics and prediction model of kindergarten building window opening from the perspective of event division.

(1) The events of arrival, class, and departure are associated with more frequent window opening, with probabilities exceeding 50%. In contrast, events such as dietary activity, indoor activity, outdoor activity, sleep, and tidying exhibit relatively lower probabilities of window opening. Notably, during events with fewer students present (such as arrival, departure, and tidying), window opening shows a reduced dependence on outdoor environmental factors and exhibits greater randomness. In contrast, events involving active student engagement (class, dietary activity, and indoor activity) show heightened sensitivity to indoor air quality, with windows being opened more frequently to improve air quality. Additionally, during the spring season, teachers generally pay closer attention to children's thermal comfort. As indoor temperature rises, window-opening behavior becomes more proactive, aiming to enhance the thermal environment within the classroom.

(2) Compared with LR and SVM, RF is more suitable for predicting the WOB of kindergarten buildings with extensive sample data, achieving an accuracy of about 93%. Additionally, there is almost no difference in the influence of how the time factor is quantified on the model's accuracy when it is treated as either a continuous or hierarchical variable.

(3) The divided event sub-model is generally more accurate than the traditional undivided model, with a maximum improvement of 4.4%. This is the first time the stacking model has been applied in WOB research, simplifying the complexity of multiple models and increasing accuracy by 0.99%.

(4) This paper demonstrates that analyzing WOB from the perspective of event division is more accurate, using the ASHRAE public database and Italian office building validation sample data. Furthermore, the event sub-model consistently achieves higher predictive accuracy compared to traditional models, with a maximum observed improvement of 3.63%.

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Pan and Jinshun Wu were responsible for data collection and organization. Mingyuan Qin and Lim Yin Cheng conducted the literature review and contributed to writing the review section. Feng Wang reviewed the manuscript's structure and logic and provided key suggestions for improvement. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Ethics Approval: Not applicable.

Informed Consent: Data collection in this study was conducted with the consent of the kindergarten's authorized personnel. The measurements were limited to environmental parameters (e.g., indoor air quality) and window operation states, and no personally identifiable information—such as children's names, gender, or other private details—was collected. Furthermore, no interventions were introduced that could affect the children's daily routines or well-being.

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