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*Research Article*

# Window Opening Behavior of Residential Buildings during the Transitional Season in China's Xi'an

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Window opening behavior in residential buildings has important theoretical significance and practical value for improving energy conservation, indoor thermal comfort, and indoor air quality. Climate and cultural differences may lead to different window opening behavior by residents. Currently, research on residential window opening behavior in northwest China has focused on indoor air quality, and few probabilistic models of residential window behaviors have been established. Therefore, in this study, we focused on an analysis of factors influencing window opening behavior and the establishment of a predictive model for window opening behavior. Four typical residential buildings in different locations and building types in Xi'an were selected. The indoor and outdoor environments and window opening states were measured. Subsequently, a multivariate analysis of variance was used to determine the factors that had a significant effect on window opening behavior. Single- and multiparameter logistic regression models for window opening behavior were established. Of all the measured factors, we found that indoor temperature and $CO_2$ concentration, outdoor temperature, and relative humidity had significant effects on window opening behavior, and indoor relative humidity and noise did not. Meanwhile, the temperature was positively correlated with the window opening probability, whereas indoor $CO_2$ concentration and outdoor relative humidity were negatively correlated. The prediction accuracy of the multiparameter model was promising, at almost 75%, and the model can provide theoretical support for modelling residential buildings in Xi'an.

## 1. Introduction

Energy consumption has become a primary worldwide concern as it has risen continuously over the past few decades. Past studies have found that simulated building energy consumption is very different from that generated by actual building operations. This difference is due to the influence of user behavior on building energy consumption, which is not normally considered in the research process [1, 2]. In recent decades, the impact of people's behavior on building energy consumption has been widely researched and accepted by academia [3, 4]. Indoor air quality and thermal comfort are particularly important, considering that residents spend over 80% of their time in the living room, the study, and the bedroom [5, 6].

Occupant behaviors are diverse and uncertain, which affect building energy performance and human comfort [7]. Generally, people in a building will take measures to meet their requirements for indoor environmental quality and comfort [8, 9]. Measures usually include adjusting the indoor facilities (such as air-conditioning temperature and lighting equipment) or building accessories (such as curtains, windows, and sunshade switches) and adjusting themselves (such as adding or removing clothing, etc.). Of these, window operation is one of the most common ways building users adjust indoor air quality and comfort. Meanwhile, window operation has an important impact on building energy consumption and improving simulation accuracy of consumption.

Personal window opening behavior is complex and has many influencing factors that are different across building types [10, 11]. In hospital buildings, indoor air temperature and relative humidity are the main factors affecting window opening behavior, and their effects also vary with the seasons [12]. In office buildings, however, most window state changes occur when people arrive at the office, and the percentage and frequency of window opening are highly correlated with the season [13].

Most studies on window opening behavior have focused on environmental factors [14, 15]. These include indoor and outdoor dry bulb temperature, relative humidity, wind speed, solar radiation, $CO_2$ concentration, rainfall, PM2.5, and so on. Many researchers have argued that indoor and outdoor temperatures are the main factors affecting window opening and closing [16, 17]. Jones and others [18] distinguished the driving factors of window operation. They found that both indoor and outdoor temperatures were closely correlated with changes in window status. Window opening behavior was positively related to indoor temperature but negatively related to outdoor temperature and outdoor relative humidity. Window closing behavior was positively related to outdoor temperature but negatively related to indoor temperature. In addition, the study also found that the percentage of window opening increases as indoor relative humidity increases and decreases as outdoor relative humidity increases.

In addition to indoor and outdoor temperatures, which have a strong influence on window opening behavior, scholars have identified other influencing environmental factors [19, 20]. Calì et al. [21] conducted a 10-year study on window opening behavior in 60 apartments to determine the driving factors of the corresponding mathematical model. The study found that different times of the day and indoor $CO_2$ concentration were the main driving factors for window opening behavior, and different times of day and outdoor temperature were the main driving factors for window closing behavior. Jones et al. [18] found that wind speed had a weak influence on and a negative correlation with window opening behavior.

Some studies have found that window opening behavior in residential buildings is likely to be affected by residents' living habits, gender, age, and other factors [22, 23]. Fabbri [24] considered residential window opening behavior using online questionnaires. Analysis of the results showed that residents' daily window opening frequency and times were due to differences in their living habits and the requirements to meet indoor comfort. Some researchers have found that age also affects window opening behavior to some extent. Guerra-Santin and Itard [25] found shorter window opening times in bedrooms and living rooms among elderly people than among other members of the study population. In families with children, the windows of children's rooms often remain closed. Moreover, personal and contextual aspects can be regarded as additional domains influencing occupants' perception and behavior [26]. Torresin et al. [27] found participants who viewed more vegetation from windows in Italy were more likely (odds ratio: 1.279) to keep windows open while working from home. Kumar et al. [28] administered questionnaires by recording building occupants' sensations and preferences for the air temperature to evaluate thermal comfort and study the methods of thermal adaptation, such as adjusting clothing, window opening, and the use of air circulation fans. They found that air velocity controls were a better method of thermal adaptation than adjusting clothing and opening windows, but the artificial regulation of wind speed was difficult. The interaction between gender and environmental perceptions has an effect on window opening behavior. Andersen and others [29] found that women open windows more frequently than men when they perceive ambient light.

Various window probabilistic models have been developed by scholars over the years [30, 31]. A probability distribution model for window opening behavior can be obtained by monitoring window state data and real-time environmental parameters. Sun [32] incorporated the outdoor environment into a grey prediction model for predicting window opening degree. The study found that 15%~30% of the window opening in office buildings occurred during the transitional season in the Hangzhou area. D'oca and Hong [33] proposed a probabilistic model based on prior window states and using indoor and outdoor temperatures as parameters. Also, they introduced different periods of the day as parameters into the random model. Meng et al. [34] used a BP (backpropagation) neural network classification method to predict window opening behavior. The results showed that when the amount of training data exceeded 15 days, the prediction result of the BP model was significantly better than the logistic regression result, with prediction accuracy rates between 4% and 6% higher in comparison.

Although few studies have used probabilistic models to study window behavior, building probabilistic models for window opening improves the accuracy of building energy consumption simulation as well as the indoor environment and thermal comfort. Rijal et al. [35] found that logistic regression analysis can be used to formulate an adaptive algorithm to predict the likelihood that windows are open. When embedded into simulation software, insight can be obtained that cannot be obtained using typical simulation methods and allows for quantification of the effect of building design on window opening behavior. Haldi and Robinson [36] applied logistic regression techniques to these results to predict the probability of occupants' actions to adapt both personal (clothing, activity, and drinking) and environmental (windows, doors, fans, and blinds) characteristics. Many factors affect window opening behavior, which also differs across regions. Studies of window opening behavior in the residential buildings of northwestern China have focused on indoor air quality, and a probability model for residential buildings has not been established. In addition, to ensure the integrity of the data across various regions, behavioral data from the cold regions of northwest China as represented by Xi'an are needed. To help fill this data gap, we conducted three months of residential window monitoring in Xi'an, Shaanxi, under a wide variety of conditions. This article describes the procedures used in this study, presents the results of a statistical analysis of the data, establishes a corresponding window probability model, and provides recommendations for follow-up studies.

## 2. Methodology

*2.1. Field Measurements*

*2.1.1. Recruited Residences.* Four residential buildings in Xi'an were selected to study the factors influencing occupants' window opening behavior. The locations of the selected residences are shown in Figure 1.

The four residential buildings were all multi-story apartment buildings with different surrounding environments. They were located in the southern suburbs of Xi'an, where all the building structures are reinforced concrete. Residence #1 was a high-rise building with a middle school to the north and high-rise residential buildings of the same type to the east. Residence #2 had 18 floors, with an industrial plant (about 15 m high) to the south and residential buildings of the same type surrounded by trees on other sides. The south and west sides of residence #3 contained the same types of residential buildings. Residence #4 was located on the top floor of a building, with high-rise office buildings to the east and north and residential buildings of the same type to the south. Detailed information about the four residential buildings are listed in Table 1.

China's general residential buildings are made up of 370 mm brick walls with thermal conductivity of 0.114 W/$m^2$.K. The selected residences have double-layer hollow glass windows with thermal conductivity of about 0.48 W/$m^2$ K.

We can see in Table 1 that the construction years of the four measured residences ranged from 2000 to 2014. People resided from floors five to 23, from low-rise to multi-storey buildings, facilitating this study of the impacts of different building types on window opening behavior. Apartments consisted of two rooms and two halls or three rooms and two halls. Furthermore, the dimensions ranged from 94 $m^2$ to 125 $m^2$, and floor plans for the four residences are shown in Figure 2. The number of people in each apartment ranged from three to six with different living habits that affect the window opening behavior between families. In addition, the window types were all casement.

*2.1.2. Experimental Methods.* Because occupants had control over the indoor air temperature through thermostats available in each apartment, turning on or off mechanical ventilation, and manually operable windows, the resulting indoor air temperature was assumed to be directly influenced by occupants' actions and their initial indoor climate. Additionally, occupants were the main source of the indoor $CO_2$ in the monitored residences, so the measured $CO_2$ values reflected the occupants' activity and resulting metabolic rate.

For each apartment, parameters including window state and environmental factors were measured for six months. To avoid the potential deviation caused by seasonal differences in window opening behavior and taking into account the integrity of the data, measurement results from a total of 12 rooms of the four apartments during the transitional season (from September 1 to November 31) were selected in the study. According to a questionnaire, no one in the four households smoked. The influence of smoking on indoor window opening and closing was therefore ruled out.

Indoor air quality affects the health level of residents to some extent. On this basis, for people who need to work indoors for a long time, their health level will also affect the work efficiency of residents to a certain extent; this study used $CO_2$ concentrations as an indicator of indoor air quality. During the test process, according to the results of the questionnaire, the room was occupied almost all day long, which can exclude the situation of no one in the room, which is a necessary condition for us to study the window opening behavior of residents. Additionally, to exclude the influence of window orientation on opening behavior, only south-facing windows were selected for the study. During the transitional season, residents mainly opened windows for natural ventilation and did not turn on indoor air-conditioning equipment. Therefore, it was not necessary to consider the influence of air-conditioning equipment. Factors affecting indoor thermal comfort and air quality were considered in combination with the actual situation in and around the four apartments in this study. Accordingly, six factors that may have impacted window opening behavior were selected for measurement, that is, indoor temperature and humidity, outdoor temperature and humidity, indoor $CO_2$ concentration, and indoor noise.

The testing instruments included window state sensors and Netatmo intelligent weather stations for testing environmental factors. The Netatmo weather stations monitor temperature, humidity, air pressure, noise, air pollution index, carbon dioxide concentration, and so on and send the measured information to a mobile phone or a computer terminal almost instantly, as shown in Figure 3. In this study, two types of Netatmo intelligent weather stations were placed in each apartment for long-term monitoring, measuring indoor and outdoor environmental parameters separately. Equipment for measuring indoor parameters was placed in the rooms with studied windows, and equipment for measuring outdoor parameters was placed outside the living room windows. Outdoor environmental parameters were measured using the Netatmo intelligent weather stations, rather than weather stations in the urban areas. Therefore, the parameters better reflected the meteorological conditions of the local area and the accuracy was higher.

The tested windows were all sliding windows, and opening or closing was sensed by the proximity and separation of the sensor body and the magnet. When the gap between the main body and the magnet was greater than 0.22 cm, the window was open (recorded as "1"). Otherwise, it was closed (recorded as "0"). When the window switch state changed, the sensors automatically recorded the corresponding time and the state. Figures 2(c) and 2(d) show the window magnetic sensor setup. Installations in all four apartments were set up in this way.

The Netatmo intelligent weather stations measured indoor and outdoor temperatures, indoor and outdoor relative humidity, indoor $CO_2$ concentration, and other parameters. Parameters were recorded every 30 minutes. The recorded

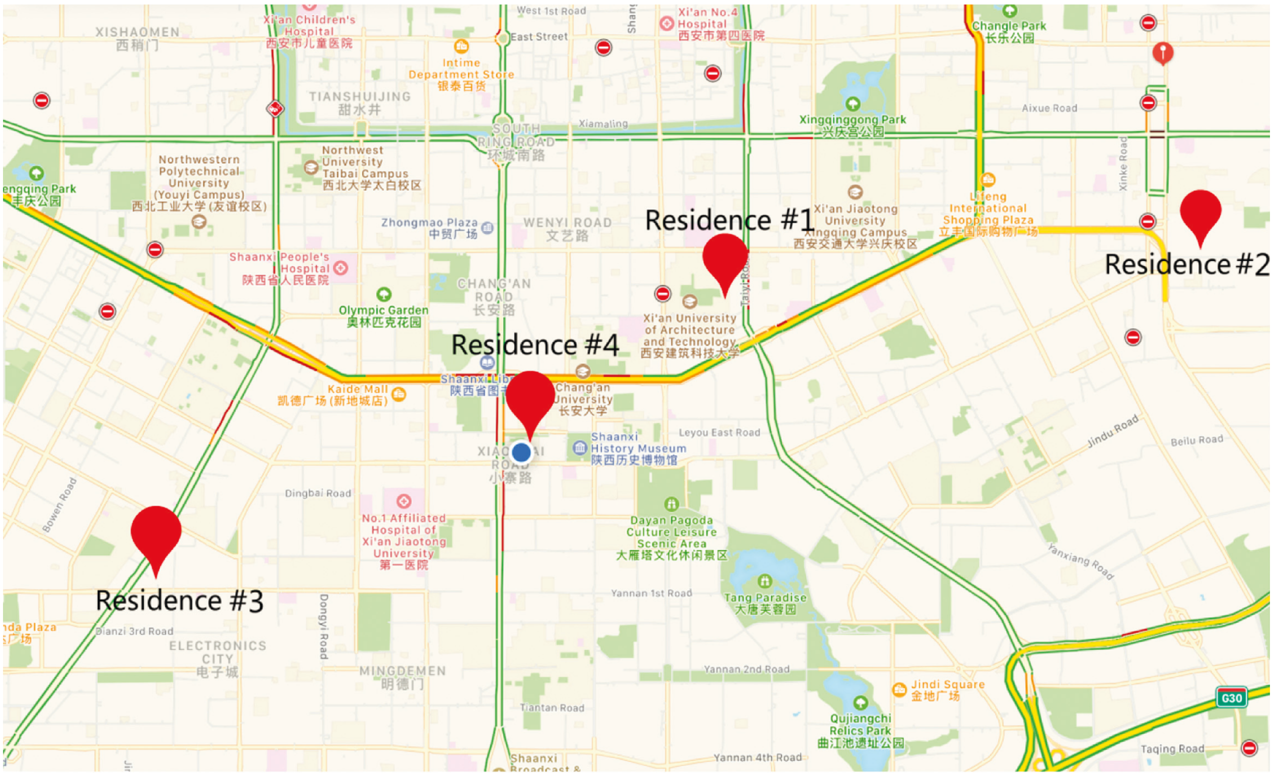


FIGURE 1: Locations of the four measured residences.

TABLE 1: Detailed information on the four recruited residences.

| Residence | #1 | #2 | #3 | #4 |
|---|---|---|---|---|
| Type of building | High-rise | High-rise | High-rise | Mid- and high-rise |
| Year of construction | 2014 | 2013 | 2013 | 2000 |
| Number of floors | 23/34 | 5/18 | 19/29 | 7/7 |
| Dimensions | 115 $m^2$ | 94 $m^2$ | 125 $m^2$ | 120 $m^2$ |
| Apartment composition | Three rooms and two halls | Two rooms and two halls | Two rooms and two halls | Three rooms and two halls |
| Window types | Casement | Casement | Casement | Casement |
| Window materials | Aluminum alloy double-layer hollow glass | Aluminum alloy double-layer hollow glass | Aluminum alloy double-layer hollow glass | Aluminum alloy double-layer hollow glass |
| Number of occupants | 4 | 5 | 4 | 3 |
| Room situation | All day | All day | All day | All day |
| Smoking habits | None | None | None | None |

window state and environmental parameters referred to the state at the time of logging. Table 2 shows the details of the tested indoor and outdoor environmental parameters.

### 2.2. Methods

*2.2.1. Multivariate Analysis of Variance.* Multivariate analysis of variance can analyze not only the influence of each individual factor on the predictor but also whether it affects the predictor when multiple factors interact. In this study, we selected six factors to test their influence on window opening behavior. However, it was not clear which factors would influence behavior, the magnitude of the impact, and whether there were interactions between these factors. Therefore, a multivariate analysis of variance was used to determine the significant influencing factors.

In multivariate analysis of variance, the $F$ test is a key step. We obtained the ratio of the variance between and within groups and then consulted the $F$ value distribution table to obtain the predicted probability $P$ value. After obtaining the $P$ value, the significance level $\alpha$ (usually 0.05) was given according to the actual situation, and the two were compared. If the $P$ value was less than or equal to $\alpha$, it meant that the factor had a significant effect on window opening behavior; otherwise, it meant that the factor had no significant effect.

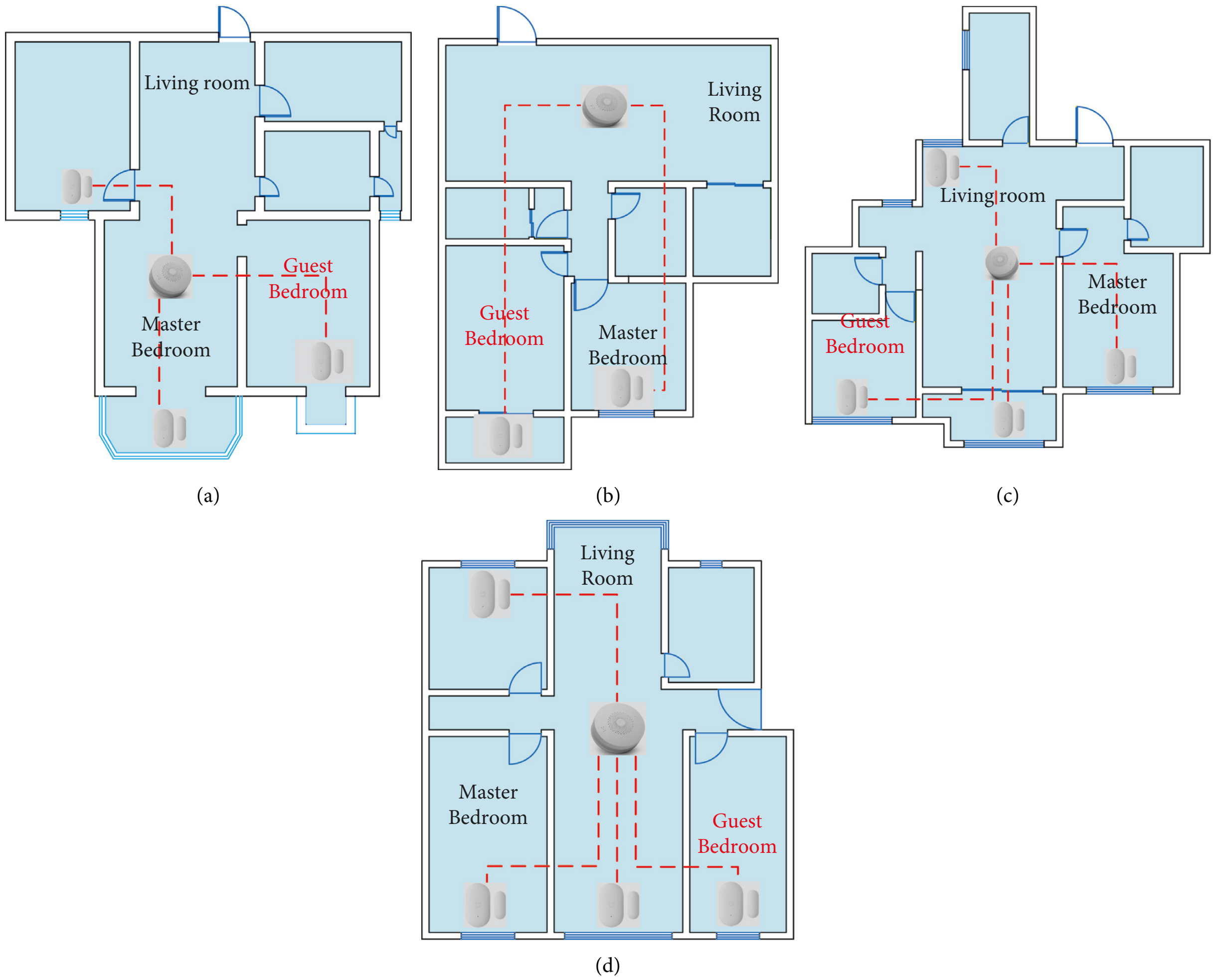


FIGURE 2: Floor plans for the selected four apartments: (a) residence #1, (b) residence #2, (c) residence #3, and (d) residence #4.

(a) (b) (c)

FIGURE 3: Continued.

(d)

Figure 3: Test instruments: (a) window sensors, (b) Netatmo intelligent meteorological station, (c) open window state, and (d) closed window state.

Table 2: Netatmo intelligent instrument environmental parameters.

| Parameter | Range | Accuracy |
|---|---|---|
| Indoor temperature (°C) | 0~50 | ±0.3 |
| Indoor relative humidity (%) | 0~100 | ±3.0 |
| Outdoor temperature (°C) | −40~65 | ±0.3 |
| Outdoor relative humidity (%) | 0~100 | ±3.0 |
| Indoor $CO_2$ concentration (ppm) | 0~5,000 | ±50.0 |
| Indoor noise (dB) | 35~120 | |

Because the measured factors were continuous variables, they were divided into ordered multi-categorical variables. We divided all factors into five levels according to the data range of each factor obtained from testing, as shown in Table 3.

*2.2.2. Logistic Regression.* The logistic regression model can be used to predict a variable with two types of values or multiple categorical values. The predictor in this study was window opening and closing behavior, which had only two outcomes: open (recorded as "1") and closed (recorded as "0"), so window behavior was a binary classification problem. Then we used a logistic regression model to predict the probability of window opening behavior and obtain the regression equation between the influencing factors and window opening behavior.

Before the logistic regression model was established, it was necessary to test whether there was collinearity among various factors. We used the variance inflation factor (VIF) and tolerance (TOL) indices in SPSS for multi-collinearity tests. We found that there was multi-collinearity among factors when VIF was greater than 5 or TOL was less than 0.2. A single-parameter logistic regression model between the factors and window opening behavior was established after the multi-collinearity tests. Because many factors influenced window opening behavior, a multiparameter logistic regression model with all factors acting together was established.

The parameter logistic regression model of window opening behaviors can be expressed as follows:

$$P_i = \frac{1}{1 + e^{-(\alpha+\beta x_i)}} = \frac{e^{(\alpha+\beta x_i)}}{1 + e^{(\alpha+\beta x_i)}}, \tag{1}$$

where $P_i$ is a nonlinear function of $x_i$, indicating the probability of window opening in the $i$-th event, $\alpha$ is the intercept of the function, $\beta$ is the coefficient of the function, and $x_i$ is the control variable. In this formula, $x_i$ includes the indoor temperature ($T_{\text{in}}$), outdoor temperature ($T_{\text{out}}$), outdoor relative humidity ($RH_{\text{out}}$), and indoor $CO_2$ concentration ($FCO_2$).

For the establishment of the multiparameter model, each factor was screened to gradually move the likelihood ratio forward (forward:LR) on the model between the factors, and the window opening behavior was greater than 0.05. The ratio of the conditional probability of an event occurring versus not occurring is

$$\text{In}\frac{\text{P}}{1 - P} = \alpha + \beta_i x_i, \tag{2}$$

where $x_i$ represents the control variable; $P$ is a linear function of $x_i$, which represents the probability of an event occurring when the values of multiple control variables $x_i$ are given; $\alpha$ indicates the influence of factors unrelated to the control variable $x_i$; and $\beta_i$ is the regression coefficient of the control variable $x_i$, the size of which is determined by the factor $x_i$.

Each control variable in the logistic regression model uses different measurement scales, so their relative effects cannot be directly compared. Therefore, the coefficients of each control variable need to be standardized for regression. The formula is as follows:

$$\beta_i = \frac{\beta S_X}{\pi/\sqrt{3}} = \frac{\beta S_X}{1.8138}, \tag{3}$$

where $\beta_i$ is the standardized regression coefficient, $\beta$ is the nonstandardized regression coefficient, $S_X$ is the standard deviation of the $x$-th control variable, and $\pi/\sqrt{3}$ is the

Table 3: Division of factors influencing window opening behavior.

| Factor | *L*1 | *L*2 | *L*3 | *L*4 | *L*5 |
|---|---|---|---|---|---|
| Indoor temperature (°C) | <15 | 15~20 | 20~25 | 25~30 | >30 |
| Indoor relative humidity (%) | <40 | 40~50 | 50~60 | 60~70 | >70 |
| Indoor $CO_2$ concentration (ppm) | <400 | 400~800 | 800~1,000 | 1,000~1,400 | >1,400 |
| Indoor noise (dB) | <40 | 40~45 | 45~50 | 50~60 | >60 |
| Outdoor temperature (°C) | <15 | 15~20 | 20~25 | 25~30 | >30 |
| Outdoor relative humidity (%) | <40 | 40~50 | 50~60 | 60~70 | >70 |

standard deviation of the distribution function of logistic random variables.

In this paper, the model coefficients, goodness of fit, and prediction accuracy of each single- and multiparameter model were examined after the model was established.

## 3. Results and Discussion

*3.1. Analysis of Measured Environmental Parameters.* Field data in terms of both occupant window behavior and relevant influential factors were collected from the four apartments during transitional seasons. Figure 4 is a wind rose diagram for Xi'an from September 1 to November 30. From the wind rose diagram, we can see that the main wind direction was northwest and wind speeds ranged from 0.4 to 1.2 m/s during data collection. Data from the residential buildings were collected to analyze the impact of environmental and nonenvironmental factors on window opening behavior.

*3.2. Observed Window Opening Behavior*

*3.2.1. Effect of Environmental Factors on Window Opening Behavior.* In this section, the main environmental factors were indoor temperature, indoor relative humidity, outdoor temperature, and indoor $CO_2$ concentration. The effects of these four factors on window opening behavior were analyzed. The influence of various environmental factors on indoor window opening probability was analyzed by a curve.

Figure 5(a) shows the probability of a window opening with a change in room temperature. When the indoor temperature was less than 16°C, the probability of window opening was very low, and the window was hardly opened. This may have been because residents closed the window to maintain the indoor temperatures. When the indoor temperatures were between 16°C and 28°C, the probability increased as the temperature increased and the slope of the curve was high, indicating that people were more sensitive to changes in indoor temperatures within this temperature range. The probability also varied greatly. When the indoor temperature was greater than 28°C, the probability still increased but at a slower rate. When the temperature exceeded 30°C, the probability was maintained above 0.85, meaning the windows remained open. Natural ventilation when temperatures are high can alleviate high indoor temperatures and maintain indoor thermal comfort.

The probability of a window opening with a change in the outdoor temperature is shown in Figure 5(b). When the outdoor temperatures were low (less than 8°C), the probability was low, which effectively prevented outdoor cold air from entering the room; when the outdoor temperatures increased from 8°C to 28°C, the probability was low. It increased at a higher rate when temperatures were greater than 28 °C, and the window opening probability was around 0.7.

There was a negative correlation between outdoor relative humidity and the probability of window opening, which gradually decreased with increasing outdoor relative humidity, as shown in Figure 5(c). When the outdoor relative humidity was low, the probability was high, and when the outdoor relative humidity was high, the probability was low. This is because when the humidity was high, it prevented people from evaporating and dissipating heat, making them feel hot and humid, and affecting indoor comfort. Reducing the frequency of window opening can alleviate this phenomenon. To ensure the experimental results were consistent with actual conditions when analyzing the influence of a single factor on window opening, factor analysis was used to analyze the measured factors in combination with other nonmeasured factors.

An analysis of indoor $CO_2$ concentration related to the probability of window opening is shown in Figure 5(d). A lower probability of window opening was associated with higher indoor $CO_2$ concentrations, which may be because high indoor $CO_2$ concentrations were caused by people closing windows when they slept at night. People tended to open windows to reduce indoor $CO_2$ concentrations when they were high and kept windows open when the $CO_2$ concentrations dropped to a lower level. This meant that window opening probability was high when $CO_2$ concentrations were low, which explained why the probability of window opening was high when the indoor $CO_2$ concentration was below about 1,000 ppm.

There was also a relationship between environmental factors and the length of time that windows were kept in a given state. Figure 6 shows the curves for indoor and outdoor temperatures and window opening time in the master bedrooms of the four households. Changes in the relationship between indoor and outdoor temperatures and window opening times were approximately the same. As outdoor temperatures decreased, the window opening time also decreased, and indoor temperatures were affected by the drop in outdoor temperatures. After November 15, the indoor temperatures suddenly increased, and the window opening time was longer. The above phenomenon was caused by municipal central heating during this period that led to an increase in indoor temperatures and the continuous opening time of windows. Most of them were still less than the opening times before heating.

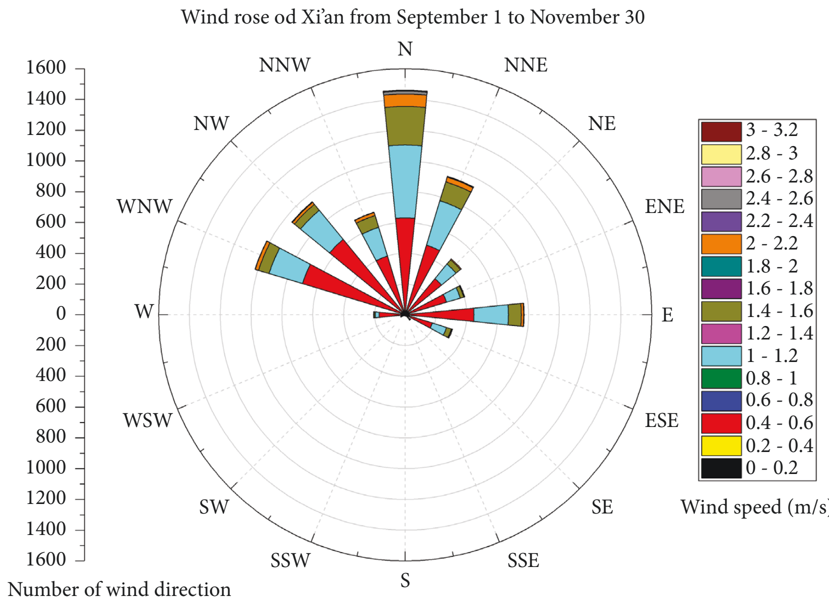


Figure 4: Analysis of wind direction and speed.

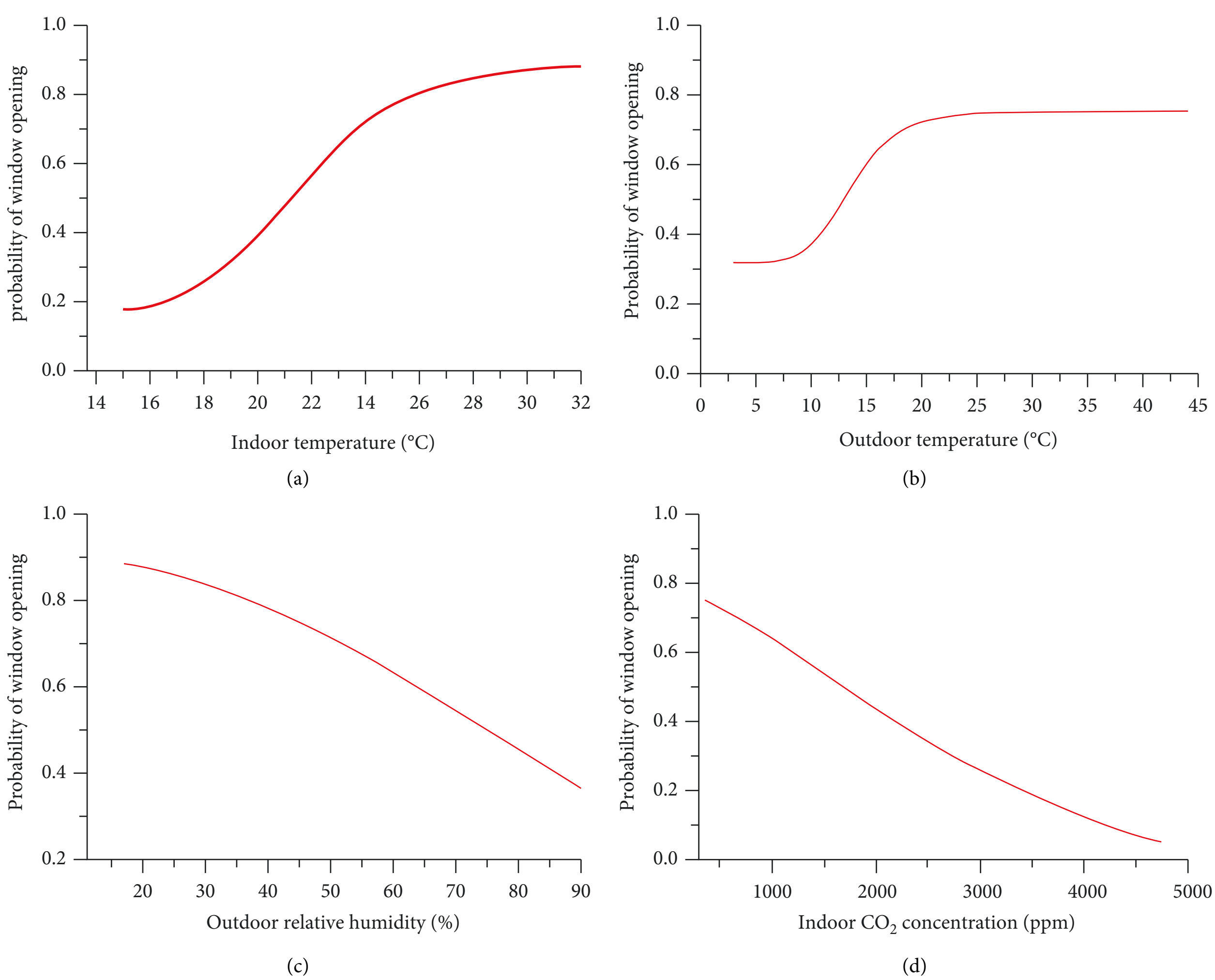


Figure 5: Relationship between environmental factors and window opening behavior: (a) the curve for indoor temperature and probability, (b) the curve for the outdoor temperature and of window opening probability of window opening, (c) the curve for outdoor RH and probability, and (d) the curve for indoor $CO_2$ concentration and of window opening probability of window opening.

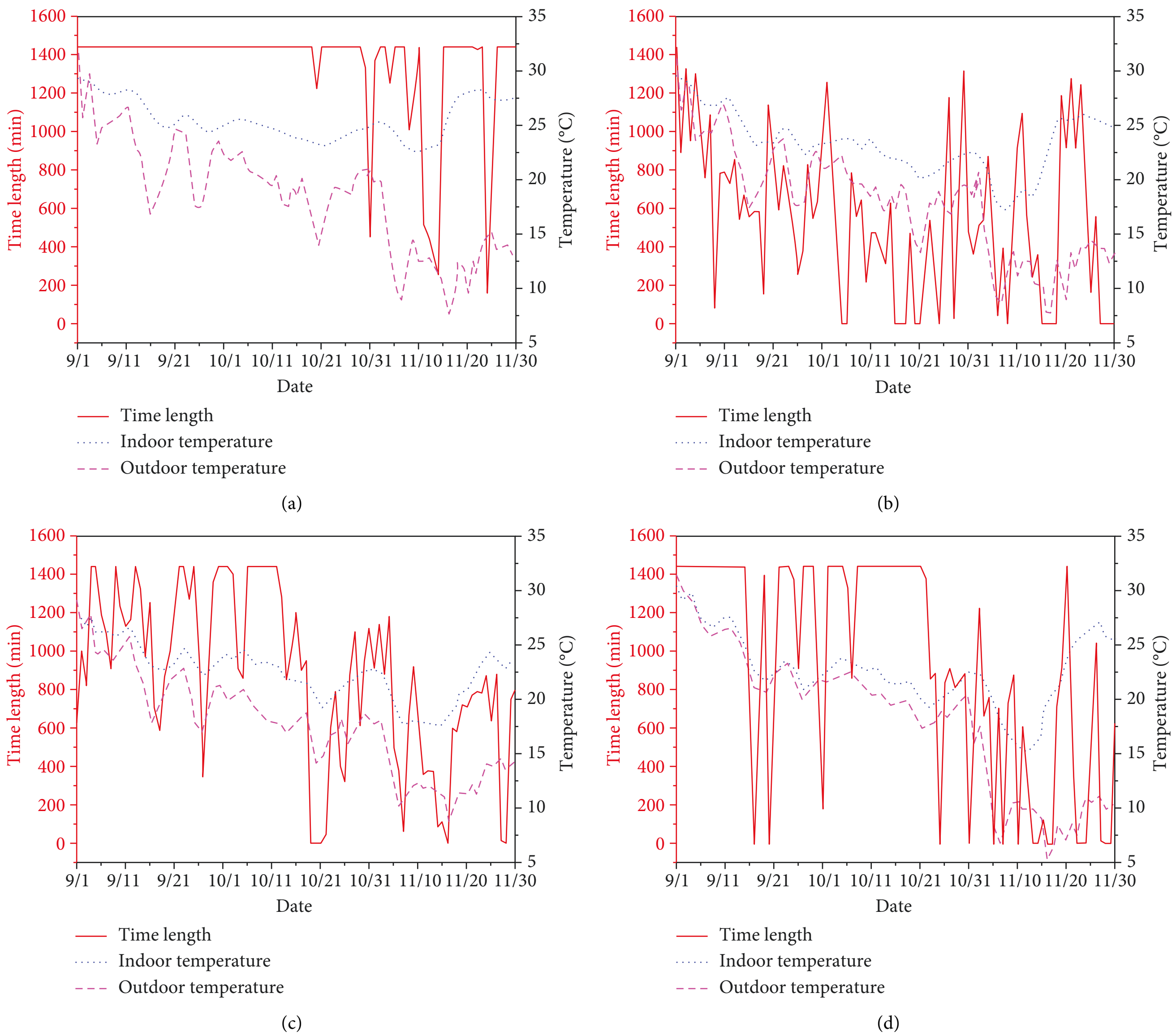


Figure 6: Window opening times and indoor and outdoor temperatures for the four residences: (a) residence #1, (b) residence #2, (c) residence #3, and (d) residence #4.

Figure 7 shows that the change in window opening times was consistent with outdoor relative humidity and indoor $CO_2$ concentrations in residence #2. On the contrary, no such relationship was observed in residence #1. This shows that residents of residence #2 were more sensitive to changes in outdoor relative humidity and indoor $CO_2$ concentrations. Also, there was a negative correlation between indoor $CO_2$ concentration and window opening time for all apartments. When the indoor $CO_2$ concentrations were high, the window opening duration at that corresponding time was short. However, when the indoor $CO_2$ concentrations were low, the opposite was true.

*3.2.2. The Effect of Different Periods on Window Opening Behavior.* Window operation at different times of the day was not consistent during the transitional season. People tended to open windows for natural ventilation when they got up and closed them to maintain the indoor temperatures when they slept at night. See Figures 8(a) and 8(b) for the probability of opening and closing windows at different times of the day.

Figure 8 describes the probabilities of the window opening or closing for four residential bedrooms in different periods during the transitional season. Figure 8(a) shows that the period with the highest probability of window opening was between 7 a.m. and 9 a.m., indicating that bedroom windows were opened for natural ventilation to improve the indoor environment when residents got up or left the house.

In Figure 8(b), the four households had a high probability of window closing between 8 p.m. and 12 p.m., which indicated that although the bedtimes of each household were different, they all had the habit of closing windows while sleeping.

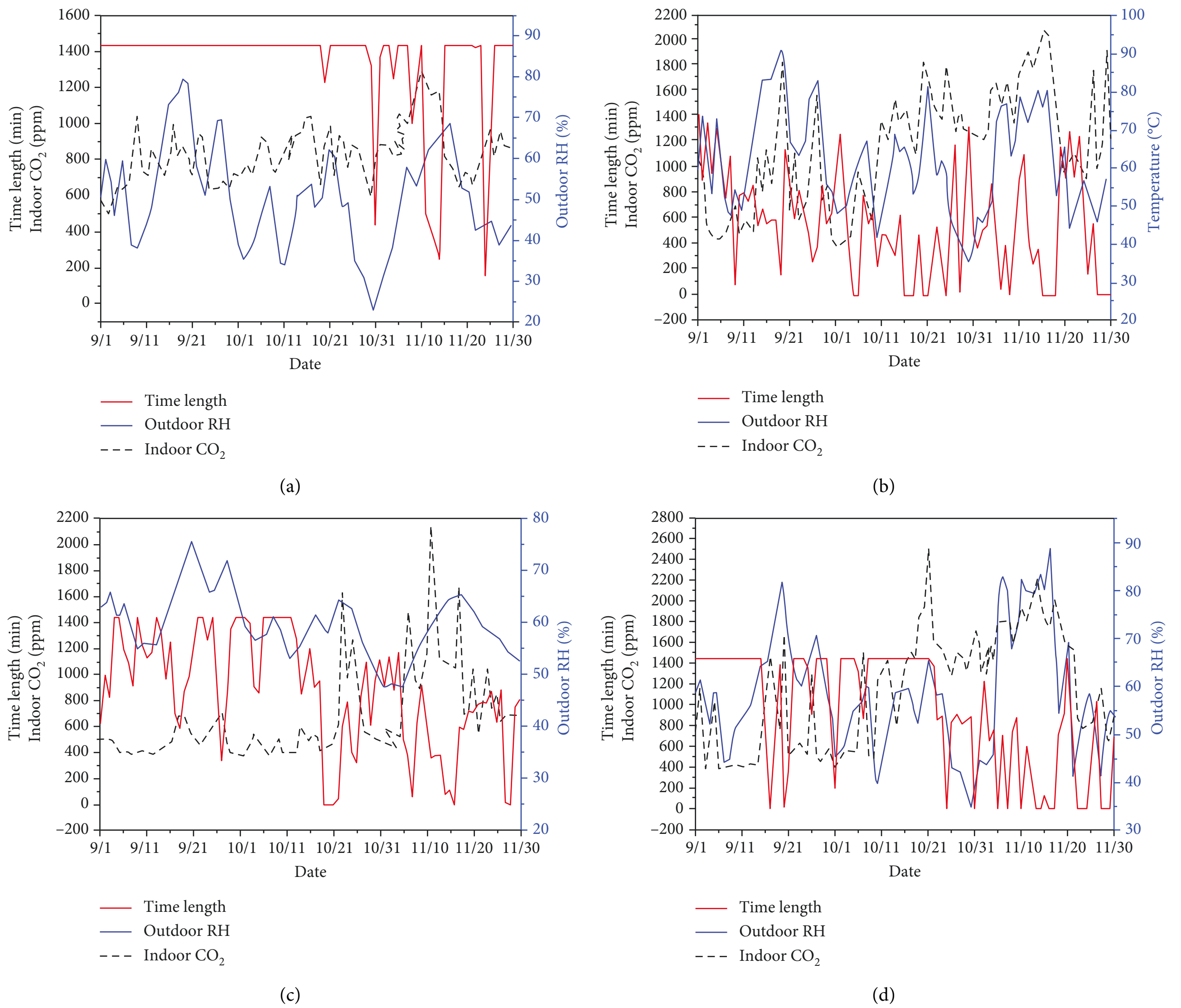


FIGURE 7: Window opening times and outdoor RH and indoor $CO_2$ concentration for the four residences: (a) residence #1, (b) residence #2, (c) residence #3, and (d) residence #4.

*3.2.3. The Influence of Building Type on Window Opening Behavior.* Here, the effects of household features on window opening probability were analyzed. The results for the transitional season are shown in Figure 9.

The probabilities of window opening for multi-story and mid-rise buildings were higher than in high-rise buildings, and probabilities were similar within the same type of high-rise buildings. This was because high-rise buildings were less affected by surrounding buildings than lower floors, and the high floors usually had higher outdoor wind speed, which may have affected the window opening probability. In addition, high-rise buildings were exposed to strong solar radiation, and closing windows can reduce radiation-generated heat indoors. However, because of the influence of surrounding buildings and trees, multi-story buildings and mid-rise buildings reduced indoor radiant heat and wind speeds. People tended to open windows for ventilation to improve the indoor thermal environment compared with high-rise buildings.

*3.2.4. The Influence of Personal Habits on Window Opening Behavior.* The influence of residents' personal habits on window opening behavior was obtained by analyzing the length of window opening times and the number of windows opened in the bedrooms each day. Windows opening times for each house are shown in Figure 10, and the numbers of windows opened and closed are presented in Figure 11.

The findings presented in Figure 10(a) show that the average daily window opening time for residence #1 was 1,347 min and the longest of the four measured residences. The average window opening time for residence #2 was 528 min and the shortest, and the average window opening times for residences #3 and #4 were similar, 879 min and 932 min, respectively. Figure 10(b) shows that the average window opening times for the four measured residences gradually decreased over the months studied. According to Figure 11(a), the average number of window openings in residence #1 was 0.14 times/day; the mean number of

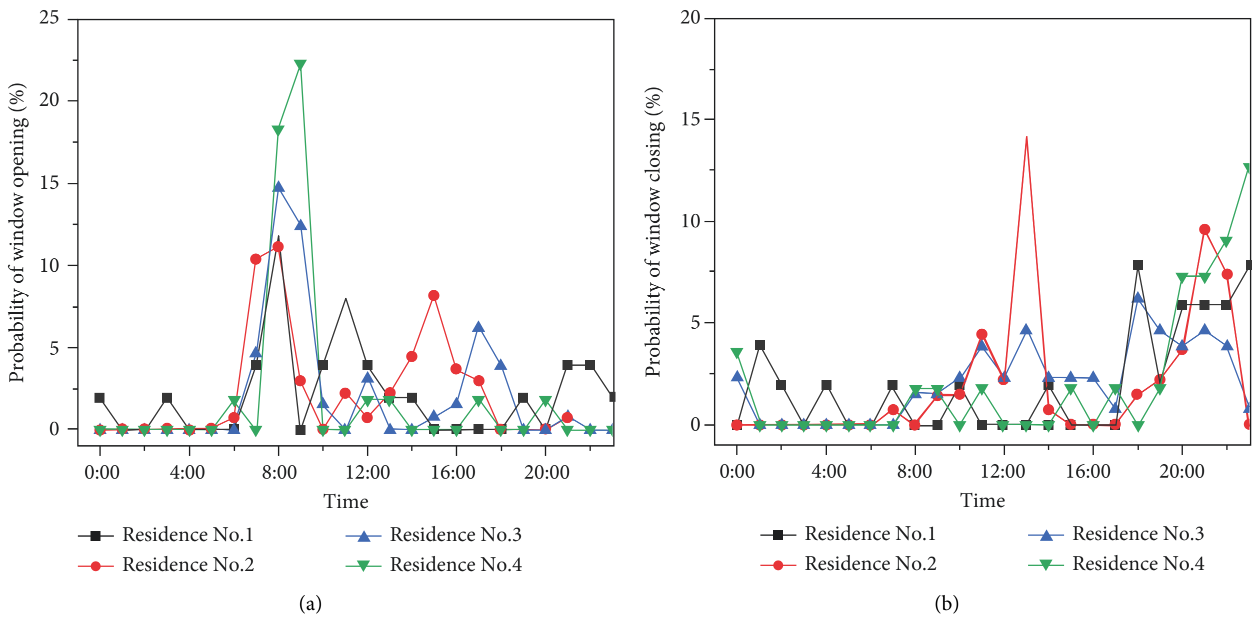


Figure 8: Window opening probabilities at different times of the day: (a) window opening and (b) window closing.

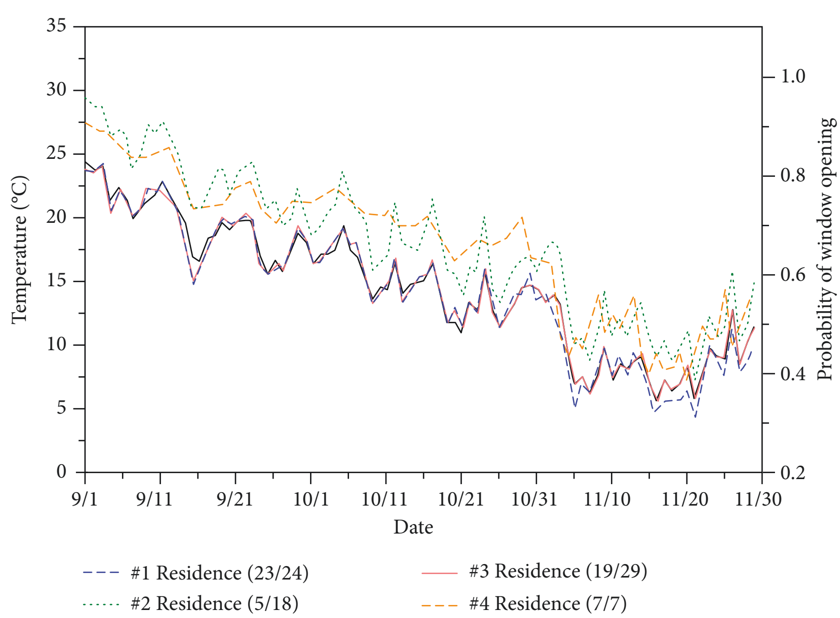


Figure 9: Probability change chart of window opening for different building types.

window openings in residence #2 was 0.93 times/day; the mean number of window openings in residence #3 was 0.71 times/day; and the mean number of window openings in residence #4 was 0.23 times/day.

From Figures 10 and 11, it was found that the window opening time for residence #1 was the longest but with the fewest number of windows, indicating that the occupants in residence #1 did not operate the windows frequently but kept them in the same position for a long time after each window was opened. On the contrary, the window opening time for residence #2 was the shortest but with the most windows, indicating that residents operated the windows more frequently but kept them close for a long time. Although the window opening time for residence #3 was similar to residence #4, the windows of residence #3 remain open for a shorter time, indicating that residents of residence #3 preferred to operate the window.

*3.3. Logistic Regression Models of Window Opening Behaviors.* Indoor air temperatures, outdoor air temperatures, indoor $CO_2$ concentrations, and noise were considered using correlation tests and multi-collinearity diagnosis before developing logistic regression models. Firstly, a single-

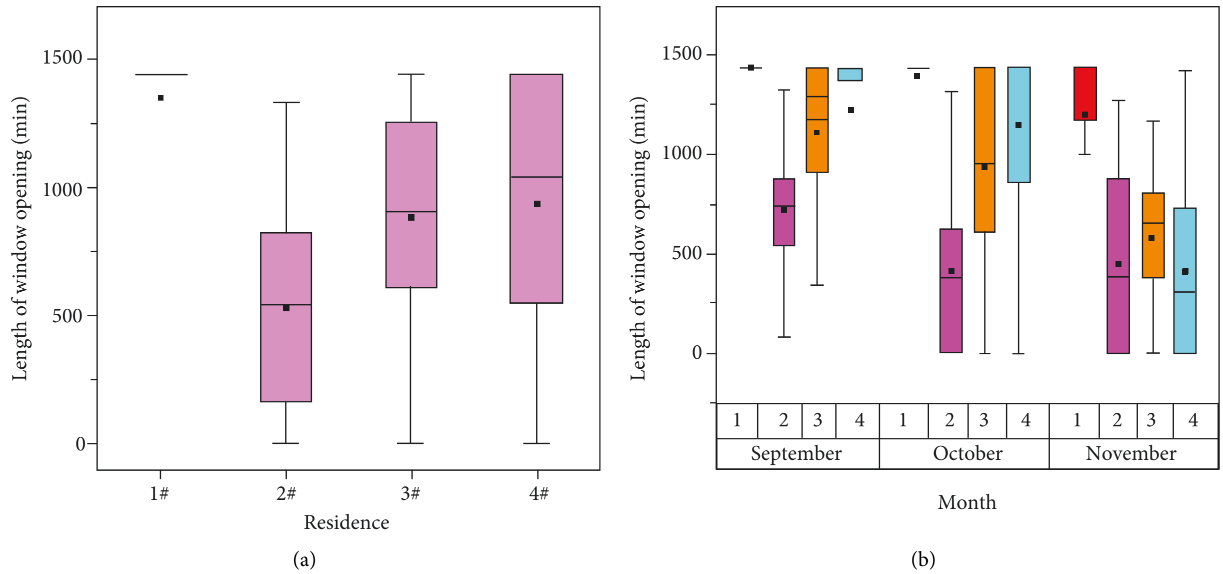


Figure 10: Box plot of the length of the window opening for each residence: (a) total length of window opening and (b) total length of window opening per month.

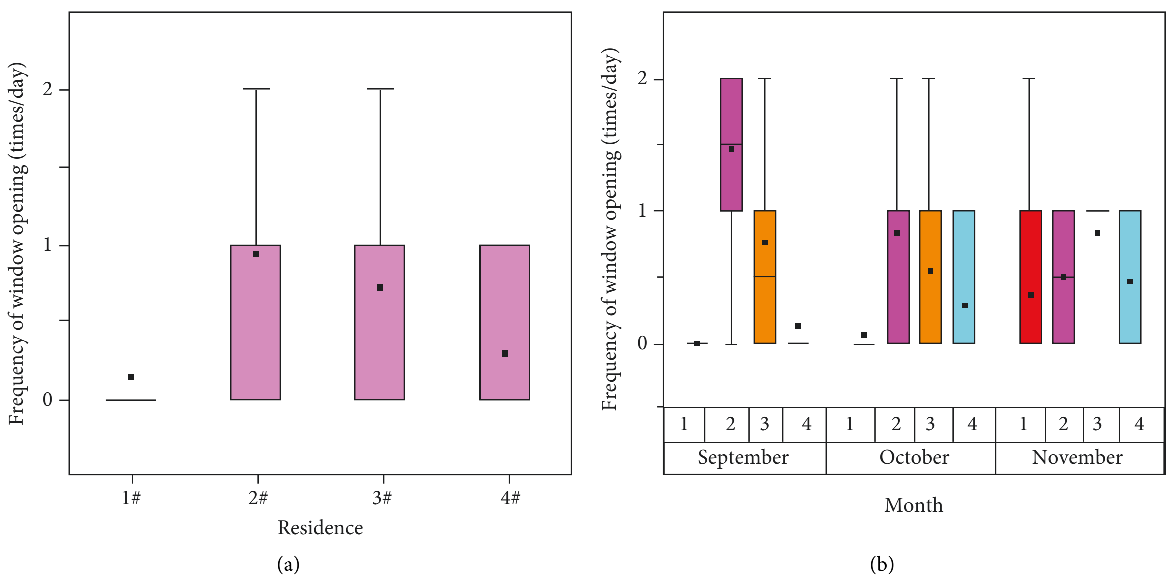


Figure 11: Box plot of window opening times for each residence: (a) total frequency of window opening and (b) frequency of window opening per month.

Table 4: Model coefficient test results.

| Model | Parameter | Chi-square | $d_f$ | Sig. |
|---|---|---|---|---|
| Single-parameter model 1 | Indoor temperature | 2,389.691 | 1 | 0.000 |
| Single-parameter model 2 | Outdoor temperature | 2,068.266 | 1 | 0.000 |
| Single-parameter model 3 | Outdoor relative humidity | 856.791 | 1 | 0.028 |
| Single-parameter model 4 | Indoor relative humidity | 171.126 | 1 | 0.005 |
| Single-parameter model 5 | Indoor $CO_2$ concentration | 1,651.369 | 1 | 0.000 |
| Single-parameter model 6 | Indoor noise | 603.501 | 1 | 0.000 |
| Multiparameter model | | 3,963.964 | 6 | 0.000 |

Table 5: Coefficient tests with single and multiple parameters.

| Model | Parameter | Chi-square | $d_f$ | Sig. |
|---|---|---|---|---|
| Single-parameter model 1 | Indoor temperature | 2,389.691 | 1 | 0.000 |
| Single-parameter model 2 | Outdoor temperature | 2,068.266 | 1 | 0.000 |
| Single-parameter model 3 | Outdoor relative humidity | 856.791 | 1 | 0.028 |
| Single-parameter model 4 | Indoor $CO_2$ concentration | 171.126 | 1 | 0.005 |
| Single-parameter model 5 | Outdoor relative humidity | 1,651.369 | 1 | 0.000 |
| Single-parameter model 6 | Indoor noise | 603.501 | 1 | 0.000 |
| Multiparameter model | | 3,963.964 | 6 | 0.000 |

Table 6: Hosmer and Lemeshow tests with single and multiple parameters.

| Model | Parameter | Chi-square | $d_f$ | Sig. |
|---|---|---|---|---|
| Single-parameter model 1 | Indoor temperature | 239.003 | 1 | 0.064 |
| Single-parameter model 2 | Outdoor temperature | 112.459 | 1 | 0.082 |
| Single-parameter model 3 | Outdoor relative humidity | 179.386 | 1 | 0.060 |
| Single-parameter model 4 | Indoor $CO_2$ concentration | 396.371 | 1 | 0.000 |
| Single-parameter model 5 | Outdoor relative humidity | 233.872 | 1 | 0.061 |
| Single-parameter model 6 | Indoor noise | 475.574 | 1 | 0.038 |
| Multiparameter model | | 180.435 | 8 | 0.113 |

Table 7: Logistic regression equations with single and multiple parameters.

| Model | Parameter | Logistic regression |
|---|---|---|
| Single-parameter model 1 | Indoor temperature | $p = e^{(0.283T_{\text{in}}-5.961)}/1 + e^{(0.283T_{\text{in}}-5.961)}$ |
| Single-parameter model 2 | Outdoor temperature | $p = e^{(0.128T_{\text{out}}-1.616)}/1 + e^{(0.128T_{\text{out}}-1.616)}$ |
| Single-parameter model 3 | Outdoor relative humidity | $p = e^{(-0.036RH_{\text{out}}+2.732)}/1 + e^{(-0.036RH_{\text{out}}+2.732)}$ |
| Single-parameter model 5 | Indoor $CO_2$ concentration | $p = e^{(-0.001F_{CO_2}+1.400)}/1 + e^{(-0.001F_{CO_2}+1.400)}$ |
| Multiparameter model | | $P = e^{(0.237T_{\text{in}}+0.019T_{\text{out}}-0.034RH_{\text{out}}+}$ $0.042RH_{\text{in}} - 0.804F_{CO_2} - 0.029F_{\text{noise}}-$ $1.210)/1 +$ $e^{(0.237T_{\text{in}}+0.019T_{\text{out}}-0.034RH_{\text{out}}+0.042RH_{\text{in}}-0.804F_{CO_2}-0.029F_{\text{noise}}-1.210)}$ |

Table 8: Model prediction accuracy.

| Model | Parameter | Prediction accuracy of window closing model (%) | Prediction accuracy of window opening model (%) | Accuracy of comprehensive forecast (%) |
|---|---|---|---|---|
| Single-parameter model 1 | Indoor temperature | 33.9 | 90.9 | 70.8 |
| Single-parameter model 2 | Outdoor temperature | 38.8 | 87.0 | 70.1 |
| Single-parameter model 3 | Outdoor relative humidity | 18.5 | 94.9 | 68 |
| Single-parameter model 5 | Indoor $CO_2$ concentration | 23.1 | 95.0 | 69.7 |
| Multiparameter model | | 47.5 | 89.6 | 74.8 |

Table 9: Standardized regression coefficients for the control variables.

| Parameter | Nonstandardized coefficient, $\beta$ | Standard deviation, $S_x$ | Standardized regression coefficient, $\beta_i$ |
|---|---|---|---|
| Room temperature | 0.237 | 2.992 | 0.39094 |
| Outdoor temperature | 0.019 | 6.188 | 0.06482 |
| Outdoor relative humidity | −0.034 | 13.338 | −0.25000 |
| Indoor relative humidity | 0.042 | 10.136 | 0.23471 |
| Indoor $CO_2$ concentration | −0.804 | 0.632 | −0.28015 |
| Indoor noise | −0.029 | 8.585 | −0.13726 |

parameter logistic regression model was built to describe the relationship between the probability of window opening and a single environmental factor. Secondly, factors were screened based on the stepwise forward approach of the likelihood ratio chi-square. Many factors affect window opening behavior, so a multiparameter logistic regression model with six major factors improving window opening behavior was built.

Model coefficients were tested using the likelihood ratio chi-square when establishing single- and multiparameter models. When the sig-value was less than 0.05, the factor introduced in the model had a significant relationship with window opening behavior, a dependent variable, and the model was meaningful. The results of the coefficient tests for the single- and multiparameter models are shown in Table 4.

The control variables passed the test except for indoor noise and relative humidity under the coefficient test, Hosmer–Lemeshow test, and ROC curve test for each single and multiparameter model. The Sig. values for the single-parameter model and the multiparameter model are shown in Table 5. Both were less than 0.05, indicating that these models explained the window opening behavior of people in Xi'an residential buildings. Table 6 contains the Sig. values of the two single-parameter models for indoor noise and indoor relative humidity, which were less than 0.05. The Sig. values of other single- and multiparameter models were all greater than the significance level of 0.05. Therefore, except for single-parameter models 4 and 6, other models had a good fit to the data. The ROC curve was used to analyze and evaluate the effect of binary classification. The fitting effect was judged by comparing the calculated area under the ROC curve (area under curve (AUC)). The closer AUC is to 1, the better the diagnostic effect. AUC values of the ROC curve for the six models were between 0.63 and 0.77, indicating good accuracy. The logistic regression equations of each parameter are described in Table 7.

When $P$ (i.e., the probability of window opening or closing) was greater than the classification cutoff value (generally 0.5), the prediction of the logistic regression model for window opening behavior was judged to be accurate, and a higher the $P$ value indicated higher model prediction accuracy. The accuracy of the model was calculated by comparing the measured values with the predicted values. The prediction accuracies of the single- and multiparameter models are shown in Table 8.

As shown in Table 8, the prediction accuracy of the model for window opening was almost 90%, much higher than the window closing state. The prediction accuracy was greater than 68%, which indicated good overall prediction. The prediction accuracy of the multiparameter model was greater than the single-parameter model, which indicated that the multiparameter model was better at predicting window opening behavior in Xi'an residences. The value of $\beta$ was given in the multivariate model, and $S_X$ was obtained by descriptive statistics for the control variables.

By comparing the absolute values of the standardized regression coefficients for the control variables in Table 9, it can be found that indoor temperature had the greatest influence on the window opening behavior in Xi'an residences, followed by indoor $CO_2$ concentration. Indoor noise and the outdoor temperature had the least impact. In this study, the effects of outdoor and indoor relative humidity on window opening behavior were similar, but the relationship between them and window opening behavior was the opposite.

## 4. Conclusions

Field measurements from four residential buildings in Xi'an were used to model and analyze window opening behavior during the transitional season (September 1–November 30 2018). In this study, multi-variate analysis of variance showed that the effects of indoor and outdoor temperatures, outdoor relative humidity, and indoor $CO_2$ concentration had different effects on window opening behaviors. Meanwhile, we also summarized and analyzed the influence degree of various factors on fenestration behavior below. Indoor temperature was the most significant, whereas indoor relative humidity had no significant effect on window opening behavior. The probability of window opening increased as indoor or outdoor temperature increased but decreased as outdoor relative humidity or indoor $CO_2$ concentration increased during the transitional season. The highest probability of window opening occurred between 7 a.m. and 9 a.m., while the highest probability of window closing occurred between 8 p.m. and 12 p.m.

This paper established single- and multiparameter models according to environmental factors. The indoor temperature had the greatest effect on indoor window opening behavior in Xi'an residential buildings in the transitional season, as seen in the analysis of the standardized regression coefficients of the control variables. We also found that the prediction accuracy of the multiparameter model was promisingly adaptable with an accuracy of almost 75%. The prediction accuracy of the single-parameter model was promisingly adaptable with accuracy greater than 68%.

Many factors affect window opening behavior. In addition to indoor and outdoor temperatures, indoor and outdoor relative humidity, indoor $CO_2$ concentration, and indoor noise tested in this article, outdoor PM2.5, VOC, noise, and formaldehyde will be added to future tests. Moreover, this article did not consider energy consumption and the number of residential buildings in the sample was small. In the future, window opening behavior impacts on air-conditioning and heating will be analyzed based on the increase of experimental samples.

## Data Availability

There are no data to share.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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