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Research on the Energy Consumption Influence Mechanism and Prediction for the Early Design Stage of University Public Teaching Buildings in Beijing

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Abstract: The public teaching buildings of universities have a large flow of people, high lighting requirements, and large energy consumption, which present significant potential for energy saving. The greatest opportunity for integrating "green" architectural design strategies lies in the design phase, especially the early stage of architectural design. However, current designers often rely on experience or qualitative judgment for decision-making. Thus, there is a pressing need for rational and quantitative green architectural design theories and techniques to guide and support decision-making for the design parameters of teaching buildings. This study, based on field surveys of 40 teaching buildings, constructs building archetypes regarding energy consumption including 28 typical values. Based on the "Rectangle", "L", "U", and "Courtyard" archetypes, through batch energy consumption simulation and multiple regression methods, the influence mechanisms of nine energy consumption influencing factors on four types of building energy consumptions were explored, and energy consumption prediction models were derived. The findings of this research can serve as factor evaluation and selection in the early stage of architectural design for public teaching buildings at universities, and the prediction model can assist in the early estimation of energy consumption. This aims to enrich and supplement green architectural design methods by supporting the design of green public teaching buildings and providing reference and application for relevant engineering practices.

Keywords: teaching buildings at universities; energy consumption prediction; energy consumption influence mechanism; early architectural design stage

Citation: Wang, J.; Zhu, Z.; Zhao, J.; Li, X.; Liu, J.; Yang, Y. Research on the Energy Consumption Influence Mechanism and Prediction for the Early Design Stage of University Public Teaching Buildings in Beijing. *Buildings* **2024**, *14*, 1358. https://doi.org/10.3390/buildings14051358

Academic Editor: Pierfrancesco De Paola

Received: 7 March 2024
Revised: 19 April 2024
Accepted: 6 May 2024
Published: 10 May 2024

1. Introduction

Currently, humanity faces issues like energy crises, climate change, and environmental degradation, prompting countries worldwide to focus on energy-saving and emission-reduction research [1]. The International Energy Agency (IEA) reports that the construction industry accounts for approximately 30% to 40% of the world's total energy consumption [2–4]. In the U.K., school buildings are the third-largest energy consumers after commercial buildings and office buildings [5]. Among these, public teaching buildings at universities, with high foot traffic, frequent use, and demanding lighting requirements, have a significant share in campus energy consumption. Therefore, this study focuses on public teaching buildings at universities.

Many studies and practices show that there is over 40% energy-saving potential in the architectural design stage [6–8], which is the main stage for decision-making and determining various parameters. Research by the University of Cambridge also indicates that the greatest opportunity for integrating "green" architectural design strategies is in the architectural design stage [9].

However, in the early stage of architectural design, architects and engineers often rely on experience or qualitative judgment, which lacks scientific rigor. Additionally, detailed energy modeling and simulation in the early architectural design phase are constrained by the need for extensive building details (available only in later stages) and the time and specialized personnel required, limiting the application of energy consumption simulation software in the early architectural design stage [7,8,10,11]. The result of the above situation is a lack of synchronization between architectural design analysis and energy consumption analysis, causing uncertainties in low-energy teaching architectural design.

If we can explore the impact mechanism between significant design parameters and energy consumption, examine the sensitivity of design parameters to energy consumption, and construct a rapid prediction model for this relationship, many problems can be effectively addressed. The influence mechanism obtained from this research can theoretically assist architects and engineers in making more scientifically rational choices regarding design parameters. The energy consumption prediction model can provide simple and fast energy consumption forecasts and analysis for early design proposals, aiding in the scientific optimization of design schemes.

Firstly, this study summarizes the archetypes of public teaching buildings in Beijing's universities regarding energy consumption based on field research and data collection from 40 public teaching buildings. These archetypes include 28 typical values across factors like location and climate, typical architectural forms, building envelope structures, HVAC systems, and indoor loads. Then, 10 types of parameters were selected from 28 types of factors, including building shape, Orien, SHGC, U_{window}, $Insul_{d\text{-}wall}$ $Insul_{d\text{-}roof}$, WWR_{north}, WWR_{south}, WWR_{east}, and WWR_{west}. Based on the building shape factor (four typical public teaching building shapes including the "Rectangle" archetype, the "L" archetype, the "U" archetype, and the "Courtyard" archetype), the influence mechanism, sensitivity, and prediction of energy consumption of the other nine building factors were investigated. This research used multiple linear regression methods and standardized regression coefficients (SRCs) to analyze the relationship between these nine building input factors and four types of energy consumption output (heating, cooling, lighting, and comprehensive) in four building Archetypes. A predictive model for energy consumption is developed, aiming to assist in the early-stage decision-making of architectural design parameters, thus maximizing energy savings in teaching buildings.

Most previous studies [6,8–11] were carried out based on the rectangular shape of buildings, and most studied the influence of a single factor on energy consumption. However, there are few studies and discussions on the energy consumption of university teaching buildings in Beijing. The innovation of this research is as follows: First, university teaching buildings are selected as the building type to carry out research in Beijing. Second, the "Rectangle", "L", "U", and "Courtyard" archetypes are selected to carry out this research. Third, this research studies the influence of multiple factors on energy consumption, including Orien, U_{window}, SHGC, WWR_{south}, WWR_{north}, WWR_{west}, WWR_{east}, $Insul_{d\text{-}wall}$, $Insul_{d\text{-}roof}$, etc.

The aim of this study is to create teaching building archetypes, explore the influence mechanism of various factors on energy consumption, and develop models to predict energy consumption in order to support architectural design factor decision-making in the early design phase, so as to realize the green architectural design of public teaching buildings at universities.

2. Building Archetypes

A building archetype model database for public teaching buildings of universities in Beijing was established. This involved detailed field surveys of 40 public teaching buildings at universities across Beijing. The process integrated domestic industry standards and research findings, as well as internationally advanced technical parameters. The collected data were systematically organized and analyzed. This study identified and extracted 28 types of factors that characterize the energy consumption of Beijing's university public teaching buildings, covering aspects like geographic location and climate, architectural forms, building envelope structures, HVAC systems, and indoor loads. These factors were detailed in terms of their characteristic values, distribution, and range, providing foundational data for this research.

2.1. Location and Climate Parameters

This study focuses on Beijing because of its status as a representative city in China and the abundance of university teaching buildings in the region, providing numerous foundational cases and data.

During energy consumption simulations, the geographic location was set to Beijing. Meteorological parameters were derived from the Chinese Standard Weather Data (CSWD) database within EnergyPlus 9.0.1 software, specifically using Beijing's meteorological data, as shown in Table 1.

Table 1. A list of location and climate factors for creating an archetype simulation model of public teaching buildings in Beijing.

Factor Type	Variable Name and Unit	Value	Interval	Quantity (PCS)
Location and climate factors	Location	Beijing city	—	—
	Climate	CSWD (Chinese Standard Weather Data)	—	—

2.2. Typical Architectural Form Parameters

Field surveys and analyses revealed that the standard floor area of university public teaching buildings is typically around 2500 m^2, with a standard number of floors being five, and a typical floor height of 4.0 m.

Furthermore, four basic architectural shapes (archetypes) for these buildings were identified as follows: "Rectangle", "L", "U", and "Courtyard". It was observed that the "Rectangle" and "L" building archetypes commonly have a layout of a "central single corridor with classrooms on both sides," and the "U" and "Courtyard" archetypes often adopt a "single corridor with classrooms" format. To ensure that all four shapes maintain a floor area of 2500 m^2, typical dimensions were determined based on common architectural practices, as shown in Figure 1.

This study assumes that when a building faces due south, the Orien factor is denoted as 0°. This research found a variety of orientations for teaching buildings, including not only cardinal directions (south, north, east, and west) but also other angles. Therefore, to comprehensively understand the impact of the Orien factor on energy consumption, 19 typical orientation scenarios were extracted at 10° intervals, ranging from 0° to 180°, as detailed in Table 2. Based on the survey data from 40 cases, it was determined that the window-to-wall ratio (WWR) of teaching buildings generally ranges from 0.20 to 0.70. Consequently, this study set the variation range of these factors to 0.20–0.70, with intervals of 0.05, distributed uniformly, as shown in Table 2.

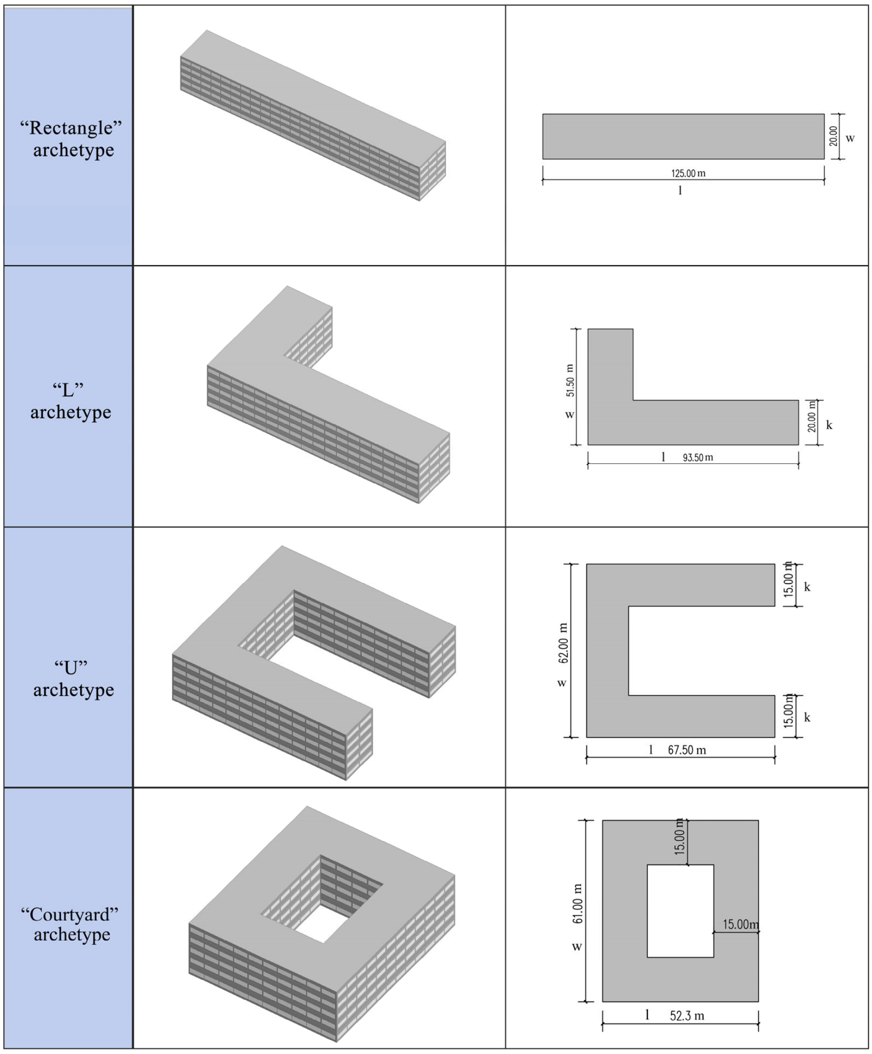

Figure 1. A schematic diagram of the "Rectangle", "L", "U", and "Courtyard" building archetypes.

Table 2. A list of architectural form factors for creating an archetype simulation model of public teaching buildings in Beijing.

Factor Type	Variable Name and Unit	Value	Interval	Quantity (PCS)
Architectural form factors	Standard floor area	2500 m^2	—	1
	Number of floors	5	—	1
	Building height per floor	4.0 m	—	1
	Building shape	"Rectangle" archetype "L" archetype "U" archetype "Courtyard" archetype	—	4
	Orien	0°/10°/20°/30° . . .340°/350°/360°	10°	19
	WWR_{east}	0.20/0.25/0.30/0.35 . . .0.60/0.65/0.70	0.05	11
	WWR_{west}	0.20/0.25/0.30/0.35 . . .0.60/0.65/0.70	0.05	11
	WWR_{north}	0.20/0.25/0.30/0.35 . . .0.60/0.65/0.70	0.05	11
	WWR_{south}	0.20/0.25/0.30/0.35 . . .0.60/0.65/0.70	0.05	11

2.3. Typical Building Envelope Structure Parameters

U_{wall} is a critical parameter that influences energy consumption. Typically, for a given wall insulation material, U_{wall} is primarily determined by the thickness d of the insulation material. Therefore, this study selected $Insul_{d\text{-}wall}$ as the factor for this research. The survey found that the insulation board material is mostly EPS board. In line with the survey results and relevant standards [12–14], the value of U_{wall} was determined to be in the range of 0.10 to 0.50 W/(m^2·K), where the minimum value represents the most advanced level of insulation internationally, and the maximum value meets the baseline requirements of energy-saving standards. Through conversion, the range of variation for $Insul_{d\text{-}wall}$ was approximately 0.06 to 0.30 m, with a step size of 0.01 m. The details are provided in Table 3.

Table 3. A list of building envelope structure factors for creating an archetype simulation model of public teaching buildings in Beijing.

Factor Type	Variable Name and Unit	Value	Interval	Quantity (PCS)
Building envelope structure factors	$Insul_{d\text{-}wall}$	0.06~0.30 m	0.01	25
	SHGC	0.30, 0.34, . . ., 0.90, 0.94	0.04	17
	U_{window}	1.0, 1.2, 1.4, 1.6, 1.8, . . ., 3.2, 3.4, 3.6, 3.8, 4.0 W/(m^2·K)	0.2	16
	$Insul_{d\text{-}roof}$	0.06~0.30 m	0.01	25
	Ground layer heat transfer coefficient U	0.45	—	1
	Floor heat transfer coefficient U	1.20	—	1

Compared with window frames, external window glass typically has a larger area and poorer insulation performance, which significantly influences the overall thermal performance of a window. Therefore, this study chose to analyze two key thermal parameters of external window glass including U_{window} and SHGC. Window frame factors are not considered in this research. Based on field surveys of university teaching buildings, reference to relevant Chinese standards, and drawing from advanced domestic and international engineering technologies, the range for U_{window} was set between 1.0 and 4.0 W/(m^2·K), with an interval of 0.02. The SHGC values ranged from 0.30 to 0.94, with an interval of 0.04, both uniformly distributed.

Similarly, integrating the results of field surveys and relevant standards [12–14], U_{roof} was determined to be in the range of 0.10 to 0.45 W/(m^2·K). Through conversion, $Insul_{d\text{-}roof}$ was established as 0.06 to 0.30 m, with a step size of 0.01 m.

After reviewing the relevant literature and conducting field surveys, the typical thermal transmittance coefficients for ground floors and building slabs were determined to be 0.45 and 1.20, respectively.

"In this study, 40 cases of public teaching buildings in Beijing were examined through actual investigation and construction drawing data. In addition, reference was also made to the Chinese standard atlas "External Wall Insulation Building Construction 10J121" and "Beijing Public Building Design Standard DB11/687-2011" [14]. The typical exterior wall construction hierarchy was finally determined, which is shown in Table 4. Similarly, combining the actual survey data and the flat roof construction with reference to the building standard design atlas, the typical building roof construction hierarchy of public teaching buildings in Beijing universities was obtained, as shown in Table 5".

Table 4. Typical exterior wall construction hierarchy.

Exterior Wall	Structural Levels and Materials		U_{wall} (W/(m^2·K))
Interior finishes	Plaster		
Base wall	Concrete hollow block walls (or aerated concrete)		
Exterior insulation system	Leveling and gluing layers	1:3 cement mortar	0.10~0.50
	Insulation layer	EPS insulation materials	
	Plastering layer	First anti-cracking mortar + one layer of alkali-resistant glass fiber mesh cloth + second anti-cracking mortar	
	Finishing layer	Paint or tile	

Table 5. Typical building roof structure hierarchy.

Building Roof Structure Hierarchy	Construction Materials	U_{roof} (W/(m^2·K))
Protective layer	40 thick C20 fine gravel concrete	0.10~0.45
Separation layer	10 thick low-strength mortars	
Waterproofing layer	Waterproofing membrane or coating layer	
Leveling layer	20 thick 1:3 cement mortars	
Insulation layer	EPS insulation board	
Slope-finding layer	2% of thinnest 30-thick LC5.0 lightweight aggregate concrete	
Structural layer	100 thick reinforced concrete roof slabs	

2.4. Typical HVAC System and Indoor Load Parameters

Referencing the GB 50189-2015 [13] and considering related research and field survey data, typical factors for HVAC systems and indoor load factors for the public teaching buildings at universities in Beijing were determined. Details of these factors are provided in Tables 6 and 7.

Table 6. A list of HVAC system factors for creating an archetype simulation model of public teaching buildings in Beijing.

Factor Type	Variable Name and Unit	Value	Interval	Quantity (PCS)
HVAC system factors	Heating system	Heat source: gas boiler Comprehensive efficiency of heating system: η_1 = 0.60	—	—
	Cooling system	Cold source: electric drive chiller Comprehensive performance coefficient of cooling system: $SCOP_T$ = 2.50	—	—
	Heating design temperature (°C)	20 °C Refrigeration design temperature (°C) Per capita fresh air volume (m^3/h-person)	—	—
	Heating preheating temperature (°C)	12 °C; 18 °C	—	—
	Heating duty temperature (°C)	5 °C	—	—
	Cooling design temperature (°C)	26 °C	—	—
	Cooling pre-cooling temperature (°C)	28 °C	—	—
	Fresh air volume per capita (m^3/h·person)	24	—	—

Table 7. A list of indoor load factors for creating an archetype simulation model of public teaching buildings in Beijing.

Factor Type	Variable Name and Unit	Value	Interval	Quantity (PCS)
Indoor load factors	Personnel density (m^2/person)	Teaching area: 1.39 Auxiliary area: 30.0	—	—
	Lighting power density (W/m^2)	Teaching area: 9.0 Auxiliary area: 5.0	—	—
	Electrical equipment power density (W/m^2)	Teaching area: 9.0 Auxiliary area: 5.0	—	—

After consulting relevant standards and performing statistics through field investigation, data such as the occupancy rate, lighting utilization rate, and electrical equipment utilization rate were obtained, as shown in Figures 2 and 3. In addition, this study assumed that classrooms were empty on weekends and during winter and summer vacations.

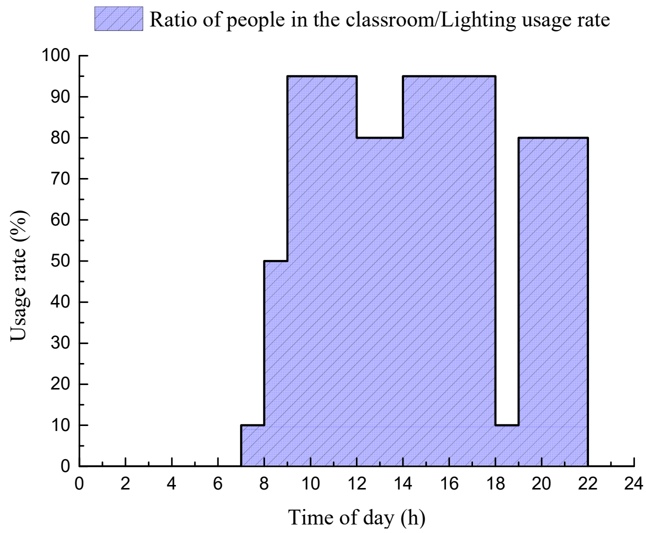

Figure 2. The occupancy rate of occupants and artificial lighting utilization rate on weekdays in public teaching buildings.

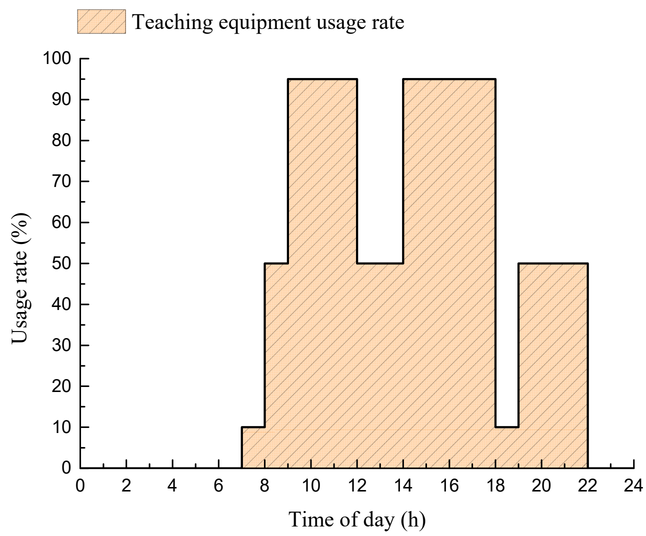

Figure 3. The utilization rate of electrical equipment on weekdays in public teaching buildings.

3. Methodology

3.1. Building Energy Consumption Prediction Methods

Building energy consumption prediction is a method of describing the complex process of building energy use through derived and generalized mathematical formulas or equations. It is vital for energy management and conservation in buildings [15,16].

Currently, there are four main methods for rapid energy consumption prediction in the early stage of architectural design including the following: simplified engineering calculations, statistical methods (multivariate regression models), artificial intelligence methods (artificial neural network models), and parallel computing methods [17]. Among these, regression models are straightforward, effective, and widely applied data-driven models. They use statistical analysis to estimate the relationship between factors and build mathematical models, thus providing a mathematical description of the entire building system [18–23]. When the outcome to be predicted is determined by multiple input factors, a multiple linear regression method can be applied for modeling and analysis. Therefore, this study employs a multiple linear regression approach to predict the four types of energy consumption in the public teaching buildings of universities in the Beijing area.

Regression analysis involves using statistical principles to process a large amount of data, determining the correlation between a dependent variable and one or more independent variables, and establishing a regression equation (functional expression) for predicting future changes in the dependent variable. It includes both univariate and multiple regression analyses, with the latter dealing with two or more independent variables.

There are n sets of actual data between the independent variables $x_1, x_2, \ldots, x_{k-1}$ and the dependent variable y. Here, y is an observable random variable influenced by k – 1 non-random parameters $x_1, x_2, \ldots, x_{k-1}$ and a random parameter ε.

A linear regression model with k − 1 variables can be expressed as shown in Equation (1) [24].

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_{k-1} x_{k-1} + \varepsilon \tag{1}$$

In the above linear regression model, ε represents the random error after accounting for the effects of the $k - 1$ independent variables on y. It is an unobservable random variable with a mean of zero and a variance $\sigma^2 > 0$, typically assumed to follow a normal distribution, $\varepsilon \sim N(0, \sigma^2)$. When the experimental or model system undergoes n ($n \geq p$) independent observations, a dataset of n groups is obtained. The relationships and data points can be expressed as shown in Equations (2)–(4).

$$\left\{ \begin{array}{l} y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{12} + \ldots + \beta_{k-1} x_{1k-1} + \varepsilon_1 \\ y_2 = \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \ldots + \beta_{k-1} x_{2k-1} + \varepsilon_2 \\ y_3 = \beta_0 + \beta_1 x_{31} + \beta_2 x_{32} + \ldots + \beta_{k-1} x_{3k-1} + \varepsilon_3 \\ \ldots \\ y_n = \beta_0 + \beta_1 x_{n1} + \beta_2 x_{n2} + \ldots + \beta_{k-1} x_{nk-1} + \varepsilon_n \end{array} \right\} \tag{2}$$

$$Y = \begin{Bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{Bmatrix}_{n\times 1}, \ X = \begin{Bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k-1} \\ 1 & x_{21} & x_{22} & \vdots & x_{2k-1} \\ 1 & x_{31} & x_{32} & \vdots & x_{3k-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \ldots & x_{nk-1} \end{Bmatrix}_{n\times k} \tag{3}$$

$$\beta = \begin{Bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{k-1} \end{Bmatrix}_{k\times 1}, \ \varepsilon = \begin{Bmatrix} \varepsilon_0 \\ \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{n-1} \end{Bmatrix}_{n\times 1} \tag{4}$$

In the above equations, y is the dependent variable (model output); x_{k-1} is the (k-1)th model input factor; $k-1$ is the number of independent variables (input factors); β_{k-1} is the regression coefficient for the $(k-1)$th input factor in the multivariate linear regression equation; and β_0 is the constant term.

In multivariate linear regression, the regression coefficients of different variables may have different dimensions because of varying units and ranges of the independent variables. These coefficients indicate the numerical relationship between the dependent and independent variables but do not reflect the sensitivity of the independent variables in the regression equation. To compare the relative importance of each input factor, the regression coefficients are normalized to SRCs [25], meaning each variable is adjusted by subtracting its mean and dividing by its standard deviation. The absolute value of the SRC reflects the sensitivity of a parameter; a larger absolute value indicates higher sensitivity. The sign of the SRC determines the direction of the relationship between independent and dependent variables: a positive SRC suggests a positive correlation, while a negative SRC indicates a negative correlation [26].

3.2. Research Process

3.2.1. Selection of 9 Input Energy Consumption Influencing Factors and 4 Output Energy Consumption Variables

Numerous studies have demonstrated that building orientation significantly affects energy consumption [27,28]. The major components of a building's envelope, such as external walls, windows, and roofs, are critical factors influencing energy consumption [29–32]. However, less research has been performed on ranking the influence of these factors on energy consumption.

Based on the building shape factor ("Rectangle" archetype, "L" archetype, "U" archetype, and "Courtyard" archetype). The influence mechanism, sensitivity, and prediction of energy consumption of the other nine building factors were investigated. The selected nine architectural energy consumption influencing factors are Orien, U_{window}, SHGC, WWR_{south}, WWR_{north}, WWR_{west}, WWR_{east}, $Insul_{d\text{-}wall}$, and $Insul_{d\text{-}roof}$, as detailed in Table 8. The four types of output energy consumption variables are heating, cooling, lighting, and total energy, as specified in Table 9.

Table 8. A table of multiple linear regression input variables.

Input Variable Name	Variable Meaning	Input Variable Value and Unit	Interval	Quantity (PCS)
x_1	Orien	0.0°~180.0°	10°	19
x_2	SHGC	0.30~0.94	0.04	17
x_3	U_{window}	1.00~4.00	0.20	16
x_4	$Insul_{d\text{-}roof}$	0.06~0.30 (m)	0.01	25
x_5	$Insul_{d\text{-}wall}$	0.06~0.30 (m)	0.01	25
x_6	WWR_{south}	0.20~0.70	0.05	11
x_7	WWR_{north}	0.20~0.70	0.05	11
x_8	WWR_{west}	0.20~0.70	0.05	11
x_9	WWR_{east}	0.20~0.70	0.05	11

Table 9. A table of multiple linear regression output variables.

Output Variable Name	Variable Meaning	Variable Value and Unit
y_1	Annual building heating energy consumption	kWh/a
y_2	Annual building cooling energy consumption	kWh/a
y_3	Annual building lighting energy consumption	kWh/a
y_4	Annual building total energy consumption	kWh/a

3.2.2. Calculating the Standard Regression Coefficient SRC and Deriving the Energy Consumption Prediction Model

Applying a multiple regression approach, this study focuses on the public teaching buildings of universities in Beijing. The relationship between each input factor and the building's output energy consumption variables is analyzed using standardized regression coefficients (SRCs). On this basis, predictive models for heating, cooling, lighting, and total energy consumption were constructed. The entire research process is illustrated in Figure 4.

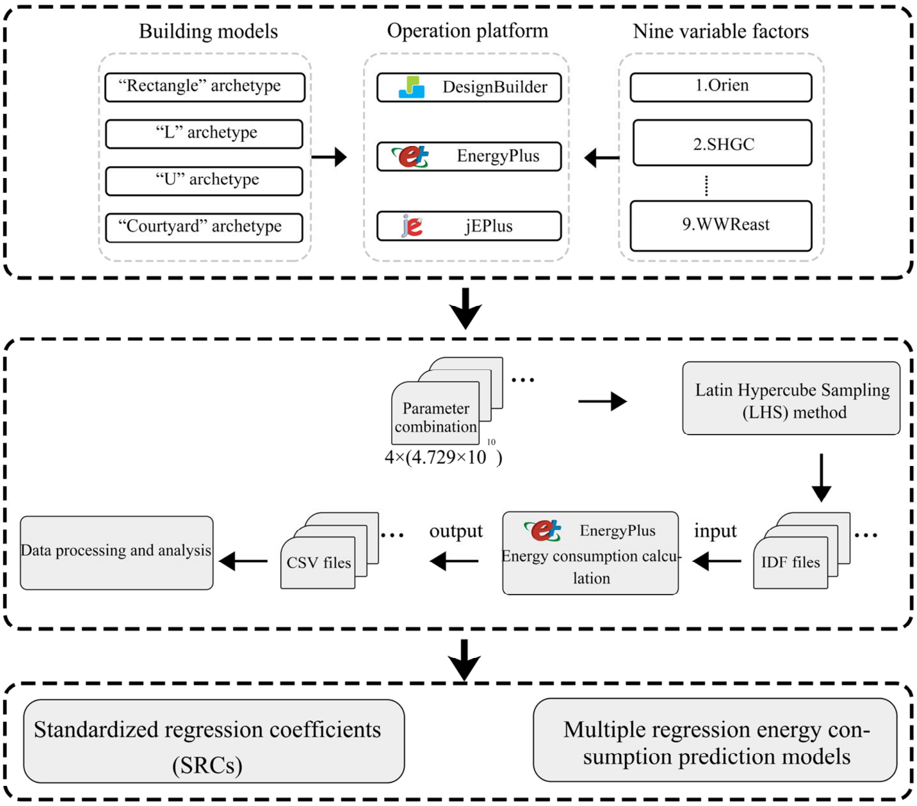

Figure 4. A flowchart of building energy consumption prediction models.

Initially, the building archetype model of public teaching buildings at universities was conducted using DesignBuilder, including the "Rectangular", "L", "U", and "Courtyard" archetypes. According to Table 2, values for 9 input energy consumption influencing factors and 19 other parameters were set. The EnergyPlus and jEPlus collaborative computing platforms were utilized to automate the value selection and variation in these nine input variables. For each architectural shape (each archetype), this process could generate $19 \times 17 \times 16 \times 25 \times 25 \times 11 \times 11 \times 11 \times 11 = 4.729 \times 10^{10}$ combinations of virtual building assemblies. For the four architectural archetypes combined, this amounted to $4 \times 4.729 \times 10^{10}$ building combinations.

Building upon the aforementioned framework, the Latin Hypercube Sampling (LHS) method was used to uniformly extract 5000 building combinations (IDF files) from each category of the 4.729×10^{10} groups, corresponding to each architectural shape. This resulted in a total of 20,000 combinations (5000×4), forming a sample set for specific energy consumption computations. LHS is a technique for stratified sampling from a multivariate parameter distribution, often used in computer experiments or Monte Carlo integrals. First, by using stratified sampling, the original sample extracted is more uniform, which will not produce an obvious aggregation phenomenon. Second, samples are forcibly extracted to each layer to ensure the comprehensiveness of the sample results. The 20,000 IDF files were input into EnergyPlus for batch energy consumption computation, subsequently yielding energy consumption results (CSV files).

Finally, based on the energy consumption simulation results of these 20,000 groups, a multiple linear regression method was used to calculate the standardized regression coefficients (SRCs). With nine building factors (x_1~x_9) as input variables and the annual energy consumption for heating, cooling, lighting, and total energy (y_1~y_4) as output variables, as detailed in Tables 3 and 4, simplified and intuitive building energy consumption regression equations were constructed. This involved deriving predictive estimation models for annual heating, cooling, lighting, and total energy consumption for the "Rectangular", "L", "U", and "Courtyard" archetype buildings. The predictive models were then subjected to verification and evaluation.

4. Results and Discussion

4.1. Influence Mechanism Analysis Based on SRC Values

4.1.1. Influence of Input Factors on Heating Energy Consumption

Figure 5 presents the size and polarity of SRCs for the nine types of energy consumption influencing factors in the four architectural archetypes including "Rectangle", "L", "U", and "Courtyard". It illustrates the intensity and direction of the effect of these nine factors on heating energy consumption. The larger the absolute value of the SRC, the greater the influence, although this absolute value does not represent the specific contribution rate. A positive SRC coefficient indicates a positive correlation between the input factor and output energy consumption, while a negative SRC implies the opposite.

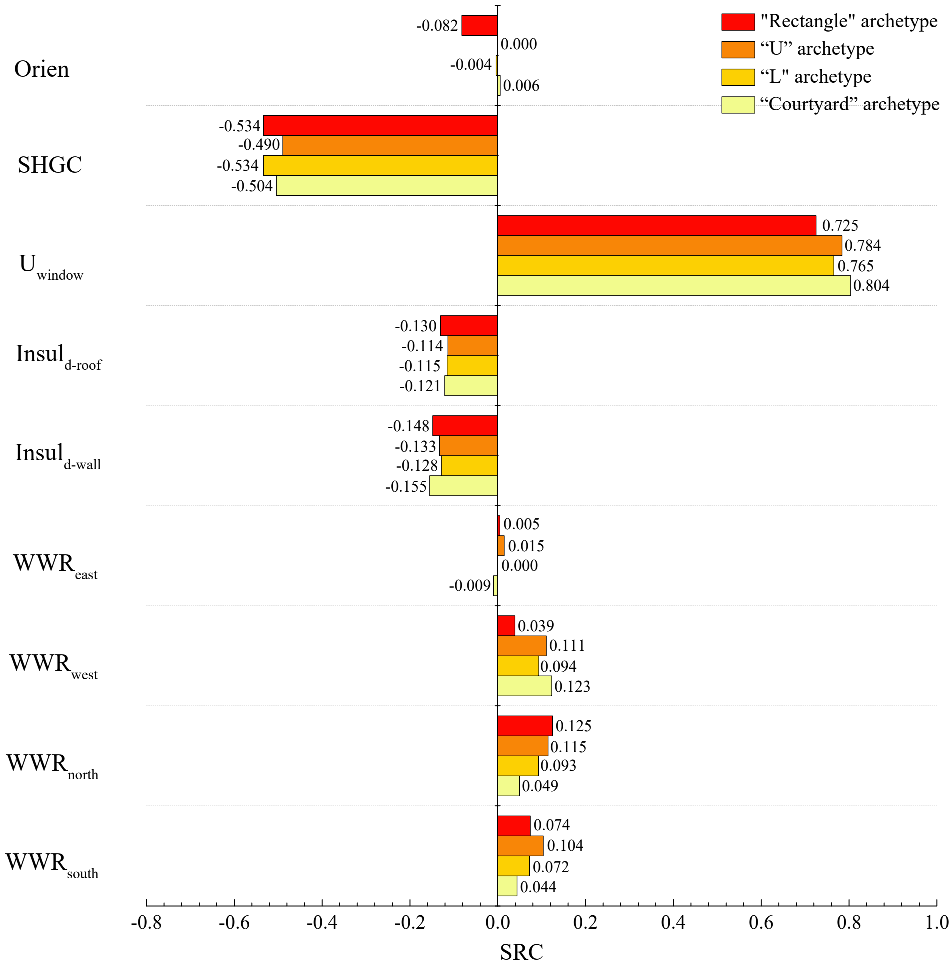

Figure 5. Analysis of the impact of energy consumption influencing factors on heating energy consumption for the four studied archetypes.

The analysis shows that among the nine influencing factors, the one with the most significant impact on heating energy consumption in all four architectural archetypes is U_{window} (SRCs of 0.725, 0.784, 0.765, and 0.804 for each archetype, respectively). The positive SRCs indicate a positive correlation between U_{window} and heating energy consumption in all four archetypes. The second most influential factor for heating energy consumption is SHGC, with SRC values of −0.534, −0.490, −0.534, and −0.504 for the four archetypes, respectively. The negative SRC values for SHGC suggest that heating energy consumption decreases as SHGC increases. Regarding the intensity of influence, factors such as $Insul_{d\text{-}wall}$, $Insul_{d\text{-}roof}$, WWR_{north}, WWR_{south}, WWR_{west}, and Orien are of moderate influence. However, the ranking of the influence of these factors varies among the "Rectangle", "L", "U", and "Courtyard" archetypes. For example, in the "Rectangle" archetype, the Orien factor has a stronger influence on heating energy consumption compared with the other forms. Regardless of the architectural shape, $Insul_{d\text{-}wall}$ generally has a stronger influence on heating energy consumption than $Insul_{d\text{-}roof}$. For instance, in the "Rectangle" archetype, $Insul_{d\text{-}wall}$'s influence is stronger than that of $Insul_{d\text{-}roof}$ ($|-0.148| > |-0.130|$), and similar trends are observed in the "U" archetype ($|-0.133| > |-0.114|$), "L" archetype ($|-0.128| > |-0.115|$), and "Courtyard" archetype ($|-0.155| > |-0.121|$). Overall, across all four building archetypes, WWR_{east} has the smallest SRC, indicating it has the least influence on heating energy consumption.

4.1.2. Influence of Input Factors on Cooling Energy Consumption

Figure 6 shows the SRCs of cooling energy consumption for four architectural archetypes and the analysis of the influence mechanism between nine types of energy consumption influencing factors and cooling energy consumption.

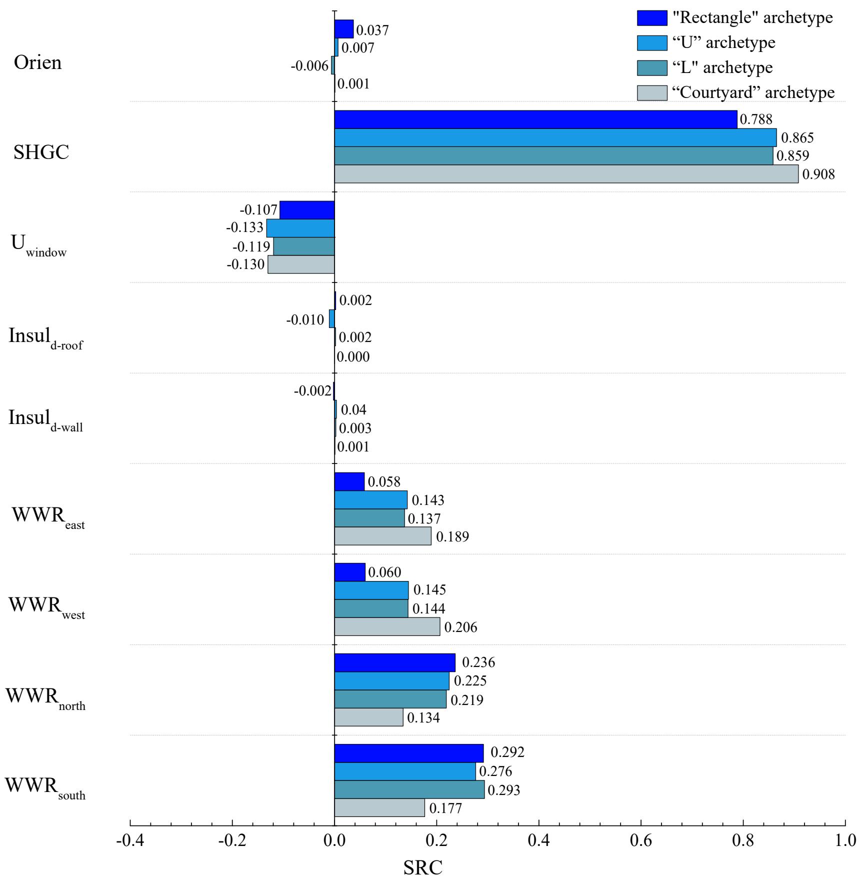

Figure 6. Analysis of the impact of energy consumption influencing factors on cooling energy consumption for the four studied archetypes.

A comprehensive analysis of the four architectural shapes reveals that their influencing factor SHGC corresponds to SRCs of 0.788, 0.865, 0.859, and 0.908, respectively. As Figure 4 visually indicates, this factor has the most significant impact on cooling energy consumption, proving that SHGC plays a decisive role in the variation in cooling energy consumption. Adjusting this parameter is an essential means of controlling building cooling energy consumption. A positive SRC value suggests that an increase in SHGC leads to increased cooling energy consumption.

Subsequently, the factors that moderately influence cooling energy consumption are WWR_{south}, WWR_{north}, WWR_{east}, WWR_{west}, and U_{window}. The SRCs for WWR_{south} in the four shapes are 0.292, 0.276, 0.293, and 0.177; for WWR_{north}, they are 0.236, 0.225, 0.219, and 0.134, respectively. Compared with WWR_{south} and WWR_{north}, WWR_{east}, WWR_{west}, and U_{window} have a weaker influence on cooling energy consumption. Notably, U_{window}, which has the most significant impact on heating energy consumption, shows only a moderate influence on cooling energy consumption. The SRCs for WWR_{south}, WWR_{north}, WWR_{east}, and WWR_{west} are all positive, indicating a positive correlation with the building's cooling energy consumption. The SRCs for U_{window} are negative, showing a negative influence on cooling energy consumption.

The next factors are Orien, $Insul_{d\text{-}wall}$, and $Insul_{d\text{-}roof}$. The SRCs for the Orien factor in the four archetypes are 0.037, 0.007, −0.006, and 0.001, with both positive and negative values, indicating uncertainty in the direction of Orien's influence on cooling energy consumption. The SRCs for $Insul_{d\text{-}wall}$ are −0.002, 0.04, 0.003, and 0.001, and for $Insul_{d\text{-}roof}$, they are 0.002, −0.010, 0.002, and 0.000, respectively, all of which are nearly zero. This indicates that $Insul_{d\text{-}wall}$ and $Insul_{d\text{-}roof}$ have a minimal impact on cooling energy consumption in buildings.

4.1.3. Influence of Input Factors on Lighting Energy Consumption

Figure 7 shows the SRCs for lighting energy consumption in the four archetypes. The analysis of the interaction between nine types of energy consumption influencing factors and lighting energy consumption is as follows. Overall, the results for the "Rectangle", "L", and "U" archetypes are similar, whereas the "Courtyard" archetype shows some differences.

(1) For the "Rectangle", "L", and "U" archetypes:

The top two influencing factors for lighting energy consumption are WWR_{south} and WWR_{north}. In these three archetypes, the SRCs for WWR_{south} are −0.697, −0.720, and −0.696, respectively; for WWR_{north}, they are −0.567, −0.476, and −0.535. Factors with moderate influence on lighting energy consumption include WWR_{east}, WWR_{west}, Orien, and SHGC. The SRC coefficients for WWR_{east} are −0.109, −0.183, and −0.202; for WWR_{west}, they are −0.071, −0.192, and −0.185; for Orien, they are −0.097, 0.187, and −0.004; and for SHGC, they are −0.125, −0.107, and −0.097. The varying SRCs for Orien, some positive and some negative, suggest a potential non-linear relationship with lighting energy consumption. Factors such as U_{window}, $Insul_{d\text{-}roof}$, and $Insul_{d\text{-}wall}$ have no impact on lighting energy consumption, consistent with natural laws and indirectly confirming the accuracy of this study's energy consumption simulation and regression analysis.

(2) For the "Courtyard" archetype:

The top two influencing factors are WWR_{north} and WWR_{east}, with SRCs of −0.711 and −0.421, respectively. Factors with moderate influence include Orien, WWR_{west}, WWR_{south}, and SHGC. The SRC for Orien is −0.280, for WWR_{west}, it is −0.244, for WWR_{south}, it is −0.241, and for SHGC, it is −0.094. Similar to the other three shapes, factors like U_{window}, $Insul_{d\text{-}roof}$, and $Insul_{d\text{-}wall}$ have almost no impact on the lighting energy consumption of the "Courtyard" archetype.

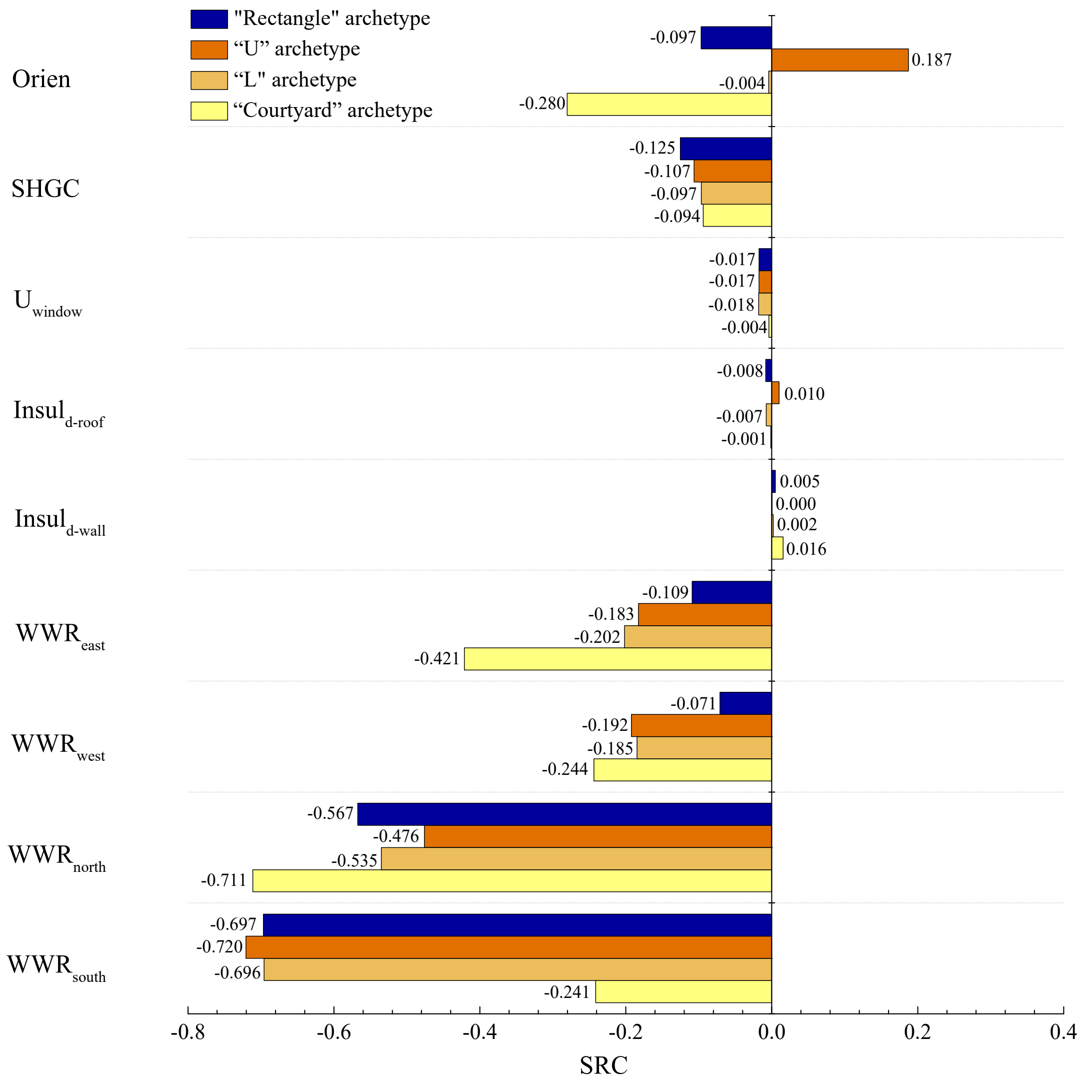

Figure 7. Analysis of the impact of energy consumption influencing factors on lighting energy consumption for the four studied archetypes.

4.1.4. Influence of Input Factors on Total Energy Consumption

Observing Figures 5–8, it is evident that the relationship between total energy consumption and the nine input factors is primarily determined by heating and cooling energy consumption, with an influence mechanism closer to that of heating energy consumption.

U_{window} positively correlates with heating energy consumption (as detailed in Figure 5) and negatively with cooling energy consumption (as detailed in Figure 6). Regarding total energy consumption (as shown in Figure 8), the SRC for U_{window} is positive, indicating that as U_{window} increases, the change in heating energy consumption far exceeds that of cooling energy consumption, suggesting that total energy consumption is more significantly influenced by heating energy consumption. SHGC is negatively correlated with heating energy consumption but positively influences cooling energy consumption, being the most significant factor for the latter. The opposing effects cancel each other out, significantly weakening SHGC's influence on total energy consumption. In this study, a positive SRC indicates that the increase in heating energy consumption caused by the increase in SHGC is slightly less than the increase in cooling energy consumption. Similarly, the influence of the factor Orien on total energy consumption is uncertain, indicating a non-linear relationship.

Regarding the total energy consumption of buildings, the sensitivity of the influencing factor U_{window} is the highest, with SRCs of 0.669, 0.789, 0.788, and 0.866 for the "Rectangle", "L", "U", and "Courtyard" archetypes, respectively. The following factors are WWR_{south}, WWR_{north}, and WWR_{west}; then $Insul_{d\text{-}wall}$, $Insul_{d\text{-}roof}$, and WWR_{east}; and lastly, SHGC and Orien. Overall, the ranking of the influence of various factors on total energy consumption is more similar to that of heating energy consumption. Therefore, it can be concluded that heating energy consumption is the dominant energy consumption in the public teaching buildings of universities in Beijing.

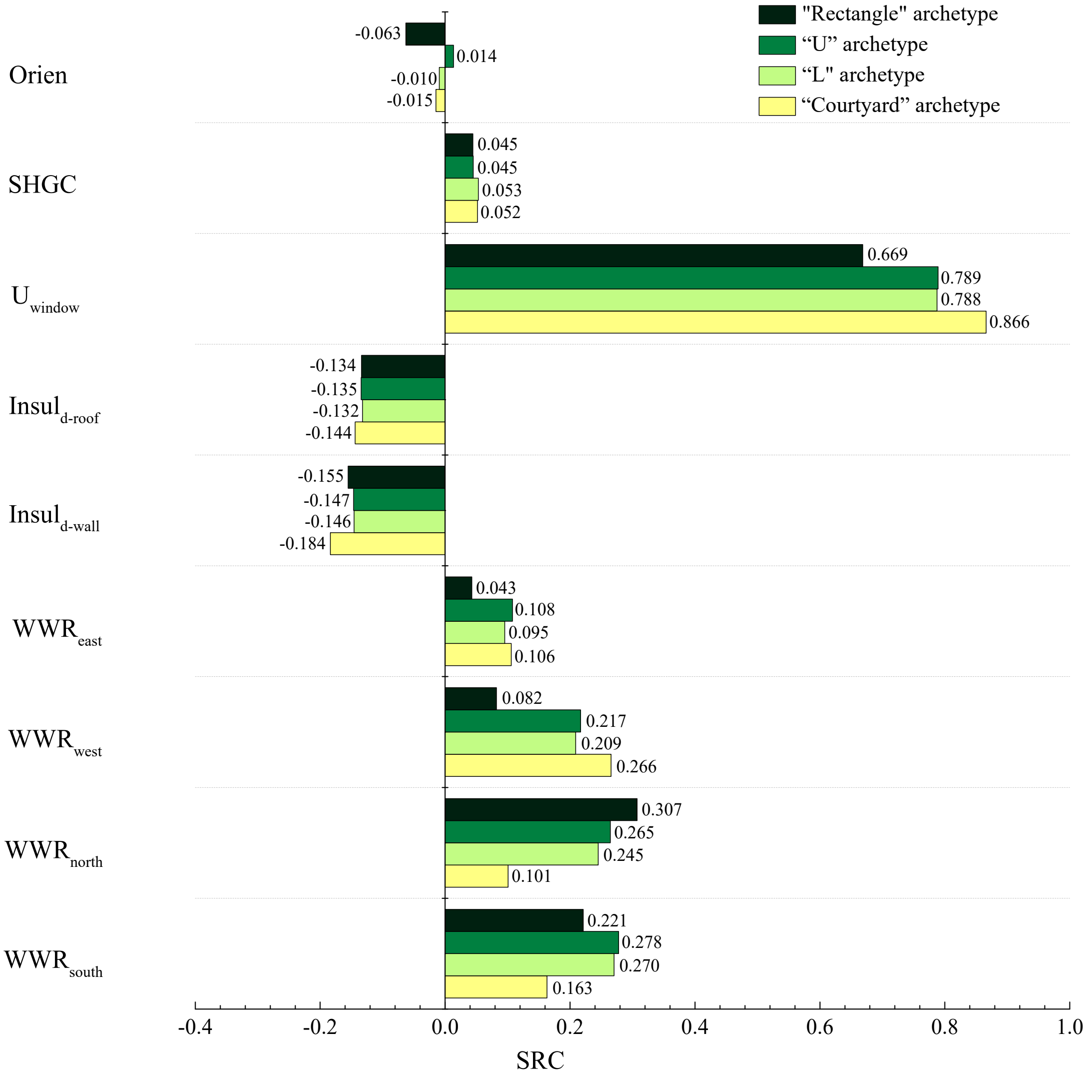

Figure 8. Analysis of the impact of energy consumption influencing factors on total energy consumption for the four studied archetypes.

4.2. Derivation and Evaluation of Prediction Models

4.2.1. Building Energy Consumption Prediction Models for the "Rectangle" Archetype

Through multivariate linear regression analysis, as shown in Table 10, the regression coefficients and fitting degree indexes for the annual heating, cooling, lighting, and comprehensive energy consumption of the "Rectangle" archetype public teaching buildings at universities in Beijing were obtained. The calculated prediction models are as follows:

$$y_1 = 117{,}000.0 - 44.7x_1 - 81{,}350.0x_2 + 23{,}490.0x_3 - 53{,}990.0x_4 - 61{,}420.0x_5 + 925.8x_6 + 7414.0x_7 + 23{,}670.0x_8 + 22{,}220.0x_9 \quad (5)$$

$$y_2 = 146{,}900.0 + 15.0x_1 + 89{,}120.0x_2 - 2573.0x_3 + 750.5x_4 - 714.2x_5 + 8203.0x_6 + 8418.0x_7 + 40{,}960.0x_8 + 52{,}530.0x_9 \quad (6)$$

$$y_3 = 153{,}600.0 - 3.4x_1 - 1226.0x_2 - 36.3x_3 - 223.7x_4 + 129.6x_5 \\ -1326.0x_6 - 862.2x_7 - 8480.0x_8 - 10{,}920.0x_9 \tag{7}$$

$$y_4 = 552{,}000.0 - 33.1x_1 + 6552.0x_2 + 20{,}880.0x_3 - 53{,}460.0x_4 - 62{,}000.0x_5 \\ +7804.0x_6 + 14{,}970.0x_7 + 56{,}150.0x_8 + 63{,}830.0x_9 \tag{8}$$

where:

y_1 represents the annual heating energy consumption of the "Rectangle" archetype, kWh/a;
y_2 is the annual cooling energy consumption, kWh/a;
y_3 is the annual lighting energy consumption, kWh/a;
y_4 is the annual total energy consumption, kWh/a;
x_1 is Orien, °; x_2 is SHGC; and x_3 is U_{window}, W/(m^2·K);
x_4 is $Insul_{d\text{-}roof}$, m; x_5 is $Insul_{d\text{-}wall}$, m;
x_6 is WWR_{east}; x_7 is WWR_{west};
x_8 is WWR_{north}; x_9 is WWR_{south}.

Table 10. Multivariate regression coefficients and fitting degree indexes of the annual energy consumption prediction models for the "Rectangle" archetype.

Prediction Models for the "Rectangle" Archetype		y_1 (kWh/a)	y_2 (kWh/a)	y_3 (kWh/a)	y_4 (kWh/a)
Regression coefficients	β_0	117,000.0	146,900.0	153,600.0	552,000.0
	β_1	−44.7	15.0	−3.4	−33.1
	β_2	−81,350.0	89,120.0	−1226.0	6552.0
	β_3	23,490.0	−2573.0	−36.3	20,880.0
	β_4	−53,990.0	750.5	−223.7	−53,460.0
	β_5	−61,420.0	−714.2	129.6	−62,000.0
	β_6	925.8	8203.0	−1326.0	7804.0
	β_7	7414.0	8418.0	−862.2	14,970.0
	β_8	23,670.0	40,960.0	−8480.0	56,150.0
	β_9	22,220.0	52,530.0	−10,920.0	63,830.0
Fitting degree indexes	R_2	87.2%	79.7%	87.2%	65.0%

Note: The prediction model is for the annual heating, cooling, lighting, and total energy consumption of the building archetypes. Corresponding monthly, daily, and per unit area energy consumption can be obtained through relevant conversion calculations.

4.2.2. Building Energy Consumption Prediction Models for the "L" Archetype

Through multivariate linear regression analysis, as detailed in Table 11, the regression coefficients and the fitting degree indexes for the annual heating, cooling, lighting, and comprehensive energy consumption of the "L" archetype public teaching buildings at universities were obtained. Additionally, the derived prediction models are represented by Formulas (9)–(12).

$$y_1 = 110{,}700.0 - 2.2x_1 - 87{,}050.0x_2 + 26{,}590.0x_3 - 51{,}220.0x_4 - 57{,}020.0x_5 \\ +58.2x_6 + 18{,}910.0x_7 + 18{,}750.0x_8 + 14{,}690.0x_9 \tag{9}$$

$$y_2 = 144{,}300.0 - 2.4x_1 + 95{,}410.0x_2 - 2828.0x_3 + 586.5x_4 + 805.0x_5 \\ +18{,}900.0x_6 + 19{,}800.0x_7 + 30{,}170.0x_8 + 40{,}490.0x_9 \tag{10}$$

$$y_3 = 151{,}900.0 - 0.1x_1 - 858.3x_2 - 34.2x_3 - 181.1x_4 + 50.1x_5 \\ -2222.0x_6 - 2033.0x_7 - 5898.0x_8 - 7672.0x_9 \tag{11}$$

$$y_4 = 541{,}400.0 - 4.8x_1 + 7505.0x_2 + 23{,}730.0x_3 - 50{,}820.0x_4 - 56{,}160.0x_5 \\ +16{,}740.0x_6 + 36{,}670.0x_7 + 43{,}020.0x_8 + 47{,}500.0x_9 \tag{12}$$

Table 11. Multivariate regression coefficients and fitting degree indexes of the annual energy consumption prediction models for the "L" archetype.

Prediction Models for the "L" Archetype		y_1 **(kWh/a)**	y_2 **(kWh/a)**	y_3 **(kWh/a)**	y_4 **(kWh/a)**
Regression coefficients	β_0	110,700.0	144,300.0	151,900.0	541,400.0
	β_1	−2.2	−2.4	−0.1	−4.8
	β_2	−87,050.0	95,410.0	−858.3	7505.0
	β_3	26,590.0	−2828.0	−34.2	23,730.0
	β_4	−51,220.0	586.5	−181.1	−50,820.0
	β_5	−57,020.0	805.0	50.1	−56,160.0
	β_6	58.2	18,900.0	−2222.0	16,740.0
	β_7	18,910.0	19,800.0	−2033.0	36,670.0
	β_8	18,750.0	30,170.0	−5898.0	43,020.0
	β_9	14,690.0	40,490.0	−7672.0	47,500.0
Fitting degree indexes	R_2	92.5%	91.6%	85.0%	84.2%

In Equations (9)–(12), y_1, y_2, y_3, and y_4 represent the annual heating energy consumption, cooling energy consumption, lighting energy consumption, and comprehensive energy consumption of the "L" archetype buildings, respectively, measured in kWh/a. The other variables are the same as those in Equations (5)–(8).

4.2.3. Building Energy Consumption Prediction Models for the "U" Archetype

Table 12 presents the fitting degree indexes and multiple regression coefficients calculated through multivariate linear regression fitting analysis for the annual heating, cooling, lighting, and comprehensive energy consumption of the "U" archetype public teaching buildings at universities. The corresponding prediction models are represented, respectively, by Formulas (13)–(16).

$$\begin{aligned} y_1 = {} & 102{,}400.0 + 0.2x_1 - 99{,}050.0x_2 + 33{,}750.0x_3 - 62{,}420.0x_4 - 72{,}820.0x_5 \\ & +3725.0x_6 + 27{,}740.0x_7 + 28{,}740.0x_8 + 25{,}950.0x_9 \end{aligned} \tag{13}$$

$$\begin{aligned} y_2 = {} & 140{,}900.0 + 3.1x_1 + 108{,}000.0x_2 - 3532.0x_3 - 3525.0x_4 + 1213.0x_5 \\ & +22{,}030.0x_6 + 22{,}370.0x_7 + 34{,}760.0x_8 + 42{,}670.0x_9 \end{aligned} \tag{14}$$

$$\begin{aligned} y_3 = {} & 147{,}100.0 + 5.4x_1 - 816.2x_2 - 28.3x_3 + 208.6x_4 + 7.6x_5 - 1731.0x_6 \\ & -1822.0x_7 - 4515.0x_8 - 6818.0x_9 \end{aligned} \tag{15}$$

$$\begin{aligned} y_4 = {} & 523{,}900.0 + 8.7x_1 + 8100.0x_2 + 30{,}190.0x_3 - 65{,}730.0x_4 - 71{,}600.0x_5 \\ & +24{,}030.0x_6 + 48{,}290.0x_7 + 58{,}990.0x_8 + 61{,}810.0x_9 \end{aligned} \tag{16}$$

Table 12. Multivariate regression coefficients and fitting degree indexes of the annual energy consumption prediction models for the "U" archetype.

Prediction Models for the "U" Archetype		y_1 **(kWh/a)**	y_2 **(kWh/a)**	y_3 **(kWh/a)**	y_4 **(kWh/a)**
Regression coefficients	β_0	102,400.0	140,900.0	147,100.0	523,900.0
	β_1	0.2	3.1	5.4	8.7
	β_2	−99,050.0	108,000.0	−816.2	8100.0
	β_3	33,750.0	−3532.0	−28.3	30,190.0
	β_4	−62,420.0	−3525.0	208.6	−65,730.0
	β_5	−72,820.0	1213.0	7.6	−71,600.0
	β_6	3725.0	22,030.0	−1731.0	24,030.0
	β_7	27,740.0	22,370.0	−1822.0	48,290.0
	β_8	28,740.0	34,760.0	−4515.0	58,990.0
	β_9	25,950.0	42,670.0	−6818.0	61,810.0
Fitting degree indexes	R_2	92.7%	91.9%	84.5%	86.5%

In Equations (13)–(16), y_1, y_2, y_3, and y_4 represent the annual heating energy consumption, cooling energy consumption, lighting energy consumption, and comprehensive energy consumption of the "U" archetype building, respectively, measured in kWh/a. The other variables are the same as those in Equations (5)–(8).

4.2.4. Building Energy Consumption Prediction Models for the "Courtyard" Archetype

Similarly, through multivariate linear regression analysis, the prediction models for the annual heating, cooling, lighting, and comprehensive energy consumption of the "Courtyard" archetype public teaching buildings at universities in Beijing were obtained, as shown in Formulas (17)–(20). The corresponding regression coefficients and fitting indexes are presented in Table 13.

$$\begin{aligned} y_1 = {} & 119{,}100.0 + 3.3x_1 - 84{,}550.0x_2 + 28{,}580.0x_3 - 54{,}970.0x_4 - 70{,}680.0x_5 \\ & -1968.0x_6 + 25{,}520.0x_7 + 10{,}220.0x_8 + 9093.0x_9 \end{aligned} \tag{17}$$

$$\begin{aligned} y_2 = {} & 152{,}900.0 + 0.4x_1 + 92{,}860.0x_2 - 2827.0x_3 + 128.6x_4 + 236.7x_5 \\ & +23{,}940.0x_6 + 26{,}110.0x_7 + 16{,}980.0x_8 + 22{,}320.0x_9 \end{aligned} \tag{18}$$

$$\begin{aligned} y_3 = {} & 155{,}200.0 - 11.1x_1 - 1038.0x_2 - 9.3x_3 - 42.0x_4 + 468.9x_5 \\ & -5760.0x_6 - 3336.0x_7 - 9728.0x_8 - 3297.0x_9 \end{aligned} \tag{19}$$

$$\begin{aligned} y_4 = {} & 560{,}900.0 - 7.4x_1 + 7266.0x_2 + 25{,}740.0x_3 - 54{,}890.0x_4 - 69{,}970.0x_5 \\ & +18{,}380.0x_6 + 46{,}120.0x_7 + 17{,}480.0x_8 + 28{,}120.0x_9 \end{aligned} \tag{20}$$

Table 13. Multivariate regression coefficients and fitting degree indexes of the annual energy consumption prediction models for the "Courtyard" archetype.

Prediction Models for the "Courtyard" Archetype		y_1 (kWh/a)	y_2 (kWh/a)	y_3 (kWh/a)	y_4 (kWh/a)
Regression coefficients	β_0	119,100.0	152,900.0	155,200.0	560,900.0
	β_1	3.3	0.4	−11.1	−7.4
	β_2	−84,550.0	92,860.0	−1038.0	7266.0
	β_3	28,580.0	−2827.0	−9.3	25,740.0
	β_4	−54,970.0	128.6	−42.0	−54,890.0
	β_5	−70,680.0	236.7	468.9	−69,970.0
	β_6	−1968.0	23,940.0	−5760.0	18,380.0
	β_7	25,520.0	26,110.0	−3336.0	46,120.0
	β_8	10,220.0	16,980.0	−9728.0	17,480.0
	β_9	9093.0	22,320.0	−3297.0	61,810.0
Fitting degree indexes	R_2	95.6%	96.6%	89.0%	92.9%

In Equations (17)–(20), y_1, y_2, y_3, and y_4 represent the annual heating energy consumption, cooling energy consumption, lighting energy consumption, and comprehensive energy consumption of the "Courtyard" archetype building, respectively, measured in kWh/a. The other variables are the same as those in Equations (5)–(8).

4.2.5. Evaluation of Prediction Models

In order to evaluate the goodness of fit of the multivariate regression equation obtained for building energy consumption, the model's fit adequacy is further illustrated using the coefficient of determination (R^2). R^2 represents the proportion of the original model's output that is explained by the linear regression model's output [22].

$$R^2 = \frac{S_{regression}}{S_{total}} = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \overline{y})^2} = 1 - \frac{S_{residual}}{S_{total}} \tag{21}$$

where S_{total} represents the total sum of squares of variation, which indicates the differences among all data points. It is the sum of squared differences between each observed value and the sample mean. $S_{regression}$ is the part of the total variation that is explained by the regression equation. $S_{residual}$ is the portion of the total variation that is not explained by the regression equation.

If the regression equation explains and fits all the sample values, then:

$$S_{residual} = \sum (y_i - \hat{y}_i)^2 = 0 \tag{22}$$

$$R^2 = 1 \tag{23}$$

Therefore, when R^2 equals 1, the model system is linear, and the regression model can explain all the model system outputs caused by the parameters. If R^2 is closer to 1, it indicates that the multivariate regression equation has a better degree of fit.

According to Tables 5–8, the R^2 values for the four types of energy consumption (heating, cooling, lighting, and comprehensive) in the "Rectangle" archetype buildings are 87.2%, 79.7%, 87.2%, and 65.0%, respectively. Among these, two R^2 values are greater than 85%, and one is close to 80%, indicating that the regression models are relatively reasonable. It should be noted that the fitting degree for comprehensive energy consumption is relatively lower, suggesting that there are stronger nonlinear effects among the parameters in comprehensive energy consumption. The R^2 values for the four types of energy consumption regression models in the "L" archetype buildings are 92.5%, 91.6%, 85.0%, and 84.2%,with two values over 90% and two close to 85%. This indicates a high degree of explanation for all sample simulation values by the regression models, suggesting the models are reasonable and relatively precise. The R^2 values for the four types of energy consumption in the "U" archetype buildings are 92.7%, 91.9%, 84.5%, and 86.5%, which also indicates that the four regression equations for the "U" archetype are reasonable and relatively precise. The R^2 values for the four types of energy consumption regression models in the "Courtyard" archetype buildings are 95.6%, 96.6%, 89.0%, and 92.9%, with three values over 90% and one close to 90%, indicating a high degree of fit and suggesting that the regression models are quite precise.

5. Conclusions

In this study, based on field research and relevant standard references, 28 types of factors characterizing the energy consumption features of public teaching buildings at universities in Beijing, including their values and distribution, were summarized and extracted. Subsequently, ten more critical energy consumption factors were selected for research, which were building shape, Orien, SHGC, $U_{window,}$ $Insul_{d\text{-}wall}$ $Insul_{d\text{-}roof}$, WWR_{north}, WWR_{south}, WWR_{east}, and WWR_{west}. Based on the building shape factor (four archetypes including "Rectangle", "L", "U", and "Courtyard"), the influence mechanism, sensitivity, and prediction of energy consumption of the other nine building factors were explored.

By coordinating EnergyPlus, DesignBuilder, and jEPlus, a comprehensive dataset of these nine energy consumption influencing factors was constructed for four architectural archetypes including "Rectangle", "L", "U", and "Courtyard". Using the Latin Hypercube Sampling (LHS) method, a total of 20,000 datasets were extracted to form samples for computational analysis. Finally, the energy consumption data were processed using multivariate linear regression, with the obtained SRCs used to further determine the direction and intensity of the impact of the nine energy consumption influencing factors on output energy consumption. Additionally, prediction models for the nine energy consumption influencing factors aimed at the output energy consumption of the four types of buildings were derived and evaluated.

(1) The influence mechanism among the nine energy consumption factors and four types of output energy consumption

(I) Heating energy consumption:
Among the four architectural archetypes, the most significant influencing factor on heating energy consumption is U_{window}. The second most influential factor for heating energy consumption is SHGC. The factors that exhibit a moderate impact include $Insul_{d\text{-}wall}$, $Insul_{d\text{-}roof}$, WWR_{north}, WWR_{south}, WWR_{west}, and Orien. It is important to note that for the four different architectural archetypes, the ranking of these six influencing factors varies. WWR_{east} has the least impact on heating energy consumption.

(II) Cooling energy consumption:
This influencing factor has the greatest impact on cooling energy consumption, indicating that SHGC plays a decisive role in the changes in cooling energy consumption. The factors showing a moderate impact on cooling energy consumption include WWR_{south}, WWR_{north}, WWR_{east}, WWR_{west}, and U_{window}. Next in influence are Orien, $Insul_{d\text{-}wall}$, and $Insul_{d\text{-}roof}$. The SRCs for the Orien factor in the four archetypes include both positive and negative numbers, indicating an uncertain direction of impact between Orien and cooling energy consumption and suggesting that this factor may have strong interactive effects. $Insul_{d\text{-}wall}$ and $Insul_{d\text{-}roof}$ have the weakest impact on the cooling energy consumption of buildings.

(III) Lighting energy consumption:
Regarding the relationship between the nine types of energy consumption influencing factors and energy consumption, overall, it was found that the results for the "Rectangle", "L", and "U" archetypes are quite similar, while the "Courtyard" archetype exhibits some differences. In the "Rectangle", "L", and "U" archetypes, the two most significant factors affecting lighting energy consumption are WWR_{south} and WWR_{north}. Factors with a moderate impact include WWR_{east}, WWR_{west}, Orien, and SHGC, whereas factors such as U_{window}, $Insul_{d\text{-}wall}$, and $Insul_{d\text{-}roof}$ have almost no impact on lighting energy consumption. For the "Courtyard" archetype, the factors showing significant influence are WWR_{north} and WWR_{east}, with Orien, WWR_{west}, WWR_{south}, and SHGC displaying moderate influence. The other factors are consistent with the first three architectural archetypes.

(IV) Total energy consumption:
The ranking of the influence of various factors on comprehensive energy consumption is more similar to that of heating energy consumption. Comprehensive energy consumption is primarily determined by both heating and cooling energy consumption, with a somewhat greater influence from heating energy consumption.

(2) Energy consumption prediction models

The goodness of fit R^2 values for the prediction models of the four archetypes of energy consumption in the "Rectangle" archetype are 87.2%, 79.7%, 87.2%, and 65.0%, respectively; for the "L" archetype, they are 92.5%, 91.6%, 85.0%, and 84.2%; for the "U" archetype, they are 92.7%, 91.9%, 84.5%, and 86.5%; and for the "Courtyard" archetype, the R^2 values are 95.6%, 96.6%, 89.0%, and 92.9%. Except for the slightly weaker performance in comprehensive energy consumption for the "Rectangle" archetype, the obtained prediction models can accurately forecast the annual heating, cooling, lighting, and comprehensive energy consumption of the buildings.

The influence mechanisms and prediction models between the energy consumption influencing factors and energy consumption obtained in this study can assist in parameter analysis, balancing, and decision-making during the early stage of the architectural design of public teaching buildings at universities in Beijing. They can help to optimize the pre-construction design scheme and then improve the energy-saving level of the teaching building. The aim is to enrich and supplement green architectural design methods, contributing to the design of green public teaching buildings at universities and providing a reference for relevant engineering practices and applications. The overall method of this study has a certain universality and can be used to study other building types and other building energy consumption parameters. It should be added that thermal comfort-related content is indeed an important goal and function of university teaching buildings [33]. In a follow-up study on the premise of ensuring the thermal comfort of buildings, we will continue to explore the energy-saving design strategy of the teaching building. There are some limitations in this study, such as the occupation and use schedule, the function and use of the building depending on the influence of academic courses, etc. These limitations will be studied and analyzed in detail in our future research.

Author Contributions: Conceptualization, J.W.; methodology, J.W., Z.Z. and Y.Y.; software, J.W. and J.Z.; validation, J.W. and Z.Z.; investigation, J.W. and J.Z.; writing—original draft preparation, J.W.; writing—review and editing, J.W.; visualization, X.L. and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Natural Science Foundation of Shannxi Province (No. 2024JC-YBQN-0488), Basic Scientific Research Projects of National Universities (No. D5000230151), and the Fellowship of China Postdoctoral Science Foundation (No. 2021M70261).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: Author Jiacheng Zhao is employed by the China Construction Integrated Science & Technology Co., Ltd. Author Xinqi Li is employed by the China Coal Tianjin Design Engineering Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

Nomenclature	Abbreviation	Unit
Chinese Standard Weather Data	CSDW	—
heating, ventilation, and air conditioning	HVAC	—
solar heat gain coefficient	SHGC	—
thickness of roof insulation layer	$Insul_{d\text{-}roof}$	mm
thickness of external wall insulation	$Insul_{d\text{-}wall}$	mm
heat transfer coefficient of roof	U_{roof}	$W/(m^2 \cdot K)$
heat transfer coefficient of exterior wall	U_{wall}	$W/(m^2 \cdot K)$
heat transfer coefficient of exterior window	U_{window}	$W/(m^2 \cdot K)$
orientation	Orien	°
east-facing window-to-wall ratio of the building	WWR_{east}	%
north-facing window-to-wall ratio of the building	WWR_{north}	%
south-facing window-to-wall ratio of the building	WWR_{south}	%
west-facing window-to-wall ratio of the building	WWR_{west}	%
standardized regression coefficients	SRCs	—

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