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Identifying key determinants for building energy analysis from urban building datasets

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Abstract: Urban and building morphologies, usually determined at the design stage, have been proven as important determinants of energy usage at later operational stages. However, questions remain regarding the identification of the key determinants that influence urban building energy usage. To address this, in this study, an urban building dataset of 539 residential buildings and 153 public buildings was used to extract the building morphology factors as the determinants. A principal component analysis was performed to identify the key determinants for three buildings groups—residential buildings, residential blocks, and public buildings. The results show that the key determinants for residential buildings are their orientation, ratio of obstruction height to the canyon width from the south and west directions, shape coefficient, perimeter-to-area ratio, and building aspect ratio. The key determinants for public buildings are similar to those for residential buildings with the exception of the ratio of the obstruction height to the canyon width from the south direction. The key determinants for residential blocks are the ratio of the obstruction height to the canyon width from the south and west directions, mass space proportion, building aspect ratio, and floor area ratio. The findings of this study provide insights into the key drivers of urban

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building energy usage and the strategies that could be used to improve urban energy planning.

Keywords: Urban building dataset, residential buildings, public buildings, energy determinants, sustainable urban design

1. Introduction

With the acceleration of urbanization, especially in China, urban buildings are consuming more energy to meet the demand of the booming population and are thereby becoming the main energy consumer that affects global carbon emissions [1,2]; therefore, the sustainable development of urban building environments is necessary. The three main strategies for reducing building energy usage are sustainable design [3], building thermal improvements incorporated during the construction phase [4], and the use of energy-efficient controls and retrofitting during the operation phase [5]. As urban and building design are the prerequisite and would make a great effect on energy demand, great objectives have been pursued, from seeking urban morphologies having lower energy demand to the development of urban and building models with low energy usage and technologies for energy savings. Researchers have started to address the importance of energy-efficient urban and building design and the planning [6] and to encourage the consideration of urban morphologies and verify their effects on urban energy usage. Early studies usually started from constructing a relationship between the urban micro-climate and urban design to reveal how the urban morphology influences the urban micro-climate and, in turn, the energy usage [7,8]. Urban and building forms are the key factors that influence the urban micro-climate, such as solar radiation [9], wind environment [10], as well as the related energy demand [11,12]. Yuan et al. highlighted the effect of the urban morphologies on the urban heat island (UHI) effect and integrated a geographic information system and computational fluid dynamics for modeling the impact of urban morphology on the heat dispersion [13]. The wind field, speed, and shadow in the city have been proved to be highly influenced by the design parameters, e.g., open space and layout, of the urban morphology [14]. Solar radiation has been recognized as another important climate parameter that is significantly related to building energy demand and also potentially provides solar energy [15] while being highly dependent on the inter-building effect (IBE) (e.g., shading and roof design) in urban environments.

To reveal the inter-related effects of urban building design, climate, and energy usage and obtain potential information regarding energy-efficient designs, researchers have attempted to analyze urban and building design factors and how they are associated with energy usage [16,17]. In terms of the building level, the various building design parameters have different effects on energy consumption and can explain approximately 39% to 42% of the variability in domestic energy consumption [18]. Horvátha et al. evaluated the received solar radiation of different building form types and their roof area and the potential energy production and energy demand depending on the climatic conditions [19]. Ratti et al. studied the influence of courtyard buildings and centralized buildings of various scales on the microclimate in hot and dry areas and morphological design that is suitable for realizing energy savings [20]. Different building archetypes exhibit different ventilation and solar-radiation performances, e.g., the deep-enclosure archetype absorbs less solar radiation than other types but effectively resists the invasion of winter winds [21]. Quan et al. found that, in Portland, enclosed blocks demonstrated the best energy-consumption performance when the building density was less than 50% [22]. Salat found that the building shape factors and passive volume (for natural ventilation and daylighting) are functions of urban morphology and could influence the energy efficiency and CO_2 emissions in the various zones of Paris [23]. The orientation of buildings is also an essential factor affecting building energy usage [24,25]. Valladares-Rendón reviewed the energy saving potential that can be realized by using the optimal building orientation for solar control techniques and the strategic placement of facade shading systems [26]. Krüger et al. also proved that the orientation of buildings affects the angle of direct sunlight, which influences the urban thermal environment as well as the corresponding cooling and heating demands [27].

In addition to the association between building morphologies and energy demand, the correlations between the morphological factors and energy demand are also of significant importance at the urban scale [28,29]. Recent studies have shown that urban geometries, especially the morphologies of building stocks, directly help urban planners and designers to verify the physical forms affecting energy consumption, especially in urban canyons [30–32] and urban blocks [33]. Strømann-Andersen & Sattrup revealed that the geometry of urban canyons can have a significant impact on the total energy consumption of up to 30% in the case of offices and 19% in the case of housing in northern Europe [34]. Zhang studied 30 typical city blocks of six types in the tropical high-density city of Singapore to analyze the correlation between the urban block typology and building energy usage efficiency. The results indicated that under the same planning conditions and design premises, different urban block typologies could lead to up to 200% increase in solar energy, 12 times higher reduction of building cooling loads. [35]. Urban density determines the intensity of the development and the compactness of buildings in a certain area. Wong studied the influence of urban geometry on ambient temperature through the simulation of variations in urban density, building coverage ratio, and floor area ratio (FAR) and established an energy simulation to reveal the correlation between urban density and energy demand [36]. Urban density can be quantified using specific indicators such as the building coverage ratio, building FAR, and sky view factor (SVF), all of which are coupled to building energy consumption. The SVF can reveal how the building density and height change the urban environment through solar radiation attenuation and shading [37], thus affecting the heat island and energy consumption [38].

Energy usage can be determined primarily based on urban and building design factors, and researchers have thus attempted to identify the key energy determinants in such designs. Regression models, and especially the least squares method, have been widely used to analyze the correlation between the related variables and energy consumption [39]. Huebner et al. recognized the multi-collinearity problem among predictors and used Lasso regression to select the determinants, including building factors, socio-demographics, users' behaviors, and attitudes, and found that building factors accounted for 39% of the variability in energy consumption [40]. In a study on the relationship between urban multivariable geometries and energy consumption, Lee & Jeong used both the normal least squares method and the gamma regression model and found that the latter was more suitable for analysis. [41]. In [42], Oh & Kim simulated a building block's energy-usage dataset and identified the key urban geometry types while integrating regression and a clustering algorithm to determine the design directions for various urban energy groups. To obtain urban energy usage data, an energy simulation was primarily used in previous studies to identify the key determinants from urban and building morphologies, as it is difficult to acquire real energy data. However, some studies highlighted the gap between the modelled and actual energy consumptions [43]. Using a simulation, Quan et al. found that whether the neighborhood typology was taken into consideration in the simulation experiment resulted in completely different conclusions regarding the relationship between density and energy consumption [44].

Therefore, real energy-consumption data is particularly important in the extraction of the key factors of urban and building morphologies that affect energy usage. Furthermore, previous studies usually focused on several particular urban and building design parameters, and the investigation of determinants at the different levels and types of buildings was ignored. To address this issue, in this study, an urban building dataset was created using the real urban building energy usage of 539 residential buildings from 42 residential urban blocks and 153 public buildings from a count-level city. The urban and building design factors were calculated based on the basic geometries of buildings. Eight factors at the building level for the residential and public building and 10 factors at the urban block level for a residential block were extracted as indicators for analyzing the energy performance. A principal component analysis (PCA) method was selected to identify the key determinants among the building geometry factors for the three groups of buildings. The findings of this study can be used to provide insight for energy-efficient urban design and planning. The structure of this paper is as follows. The methodology of this study is presented in Section 3, the description of the urban building datasets is presented in Section 4, and the results and discussion are presented in Sections 5 and 6, respectively. The final section presents the conclusions of this work.

3. Methodology

3.1 Determinants from urban building dataset

In this study, urban and building morphological factors (including basic building information and the IBE dataset) that influence the building energy usage are identified. The IBE has been investigated in many studies, including those that reported the effects of neighboring buildings (such as shading), which is an important factor for target building energy analysis [45,46]. The identified urban building energy determinants are listed in Table 1 and include the building aspect ratio (BAR), shape coefficient (SC), FAR, perimeter-to-area ratio (PA), mass–space proportion (MSP), and ratio of obstruction height to canyon width (HW). The aspect ratio of a geometric shape is the ratio of its dimensions. The shape coefficient of a building denotes the ratio of its surface area ($S_{surface}$) that is exposed to the air divided to the building volume. These are the geometric elements that indirectly represent the solar radiation that a building receives. The FAR is the ratio of a building's total floor area (gross floor area) to the size of the piece of land upon which it is built. The FAR is often used as a regulation in city planning along with the building-to-land ratio [47] and as an important factor that architects take into consideration in their designs. The PA was applied in a previous study [42] to represent the influence of sunlight and ventilation from a façade, which has also been clarified in [48,49]. The MSP represents the ratio of open space to the total area of a block. Orientation represents the position of a building in relation to seasonal variations in the sun's path as well as prevailing wind patterns. A favorable orientation can increase the energy efficiency of a building as it influences the solar penetration into a building. The shading from neighborhood buildings can cause a variation in the solar gain in buildings and is considered a significant element in the determination of building energy consumption and solar potential [32]. To represent a street layout using a numerical value, the ratio of the building height to the street width is used as defined in [42]. In particular, the maximum value of HW is calculated to determine the effects of overshadowing due to neighboring buildings for a given urban space. Accordingly, the maximum value of HW is defined for 24 directions from a building's centroid at regularly spaced intervals of 15°.

Table 1 The urban building energy determinants and their equations applied in this study.

Determinants	Calculation Method	Index	Description
BAR	$AR_{building} = \frac{a}{b}$	(1)	a: length of the building b: width of the building
SC	$SC_{building} = \frac{S_{surface}}{S \times h} = \frac{1}{h} + \frac{2}{a} + \frac{2}{b}$	(2)	$S_{surface}$: area of the above surface S: floor area of the building
	$SC_{block} = \frac{\sum S_{surface}}{\sum S \times h}$	(3)	h: height of the building
FAR	$FAR_{block} = \frac{\sum\sum S}{A_{block}}$	(4)	A_{block}: total occupied area of the block
PA	$PA_{building} = \frac{P}{S}$	(5)	P: perimeter of the building
	$PA_{block} = \frac{\sum P}{\sum S}$	(6)	
MSP	$MSP_{block} = \frac{A_{block} - A_{openspace}}{A_{openspace}}$	(7)	$A_{openspace}$: area of open space in the block.
HW	$HW_i = \frac{\sum_{f=1}^{k}[max\{(H_{o,f} - H_f)/W}{k}$	(8)	HW_i: maximum ratio in the ith direction
	$HW\_North_{building}, HW\_East_{building}, HW\_South_{building}, HW\_West_{building} = \frac{\sum_{i=1}^{6} HW_i}{6}$	(9)	$H_{o,f}$: height of the obstructing building from the fth floor H_f: height of each floor of the target building k: number of stories of the large building W: width of the canyon

3.3 Identification of key determinants

After the factors that may affect urban-building energy usage were identified, a vector consisting of factors and the building energy usage dataset could be created. This dataset included the feature dataset identified from the urban datasets and target (energy usage intensity, i.e., EUI). The PCA method was then applied to identify the main components that influenced the EUI of the group of buildings. The PCA is a popular statistical procedure that reduces the dimensionality of a dataset to determine lower-dimensional representative components of the dataset with some penalties. The PCA is mostly used in exploratory data analyses and for developing predictive models. The following equations begin with *p*-dimensional $x = (X_1, X_2, \ldots, X_P)^T$ with *n* buildings $x_i = (x_{i1}, x_{i2}, \ldots, x_{iP})^T$ and where i = 1, 2, …, n. The first step is to normalize the dataset to create a dimensionless dataset, which can be calculated as follows:

$$Z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}, i = 1, 2, \ldots, n; j = 1, 2, \ldots, p \tag{10}$$

where $\bar{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}, s_j = \sqrt{\frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2}{n-1}}$, $\bar{x}_j$ is the mean value, and s_j is the standard deviation.

After the normalized matrix (*Z*) of the dataset is calculated, the matrix of the correlation coefficient *R* can be calculated as follows:

$$R = \frac{Z^T Z}{n - 1} \tag{11}$$

To solve the characteristic equation (Eq. 12) and figure out the principal components of the dataset features.

$$|R - \lambda I_p| = 0 \tag{12}$$

$$\frac{\sum_{j=1}^{m} \lambda_j}{\sum_{j=1}^{p} \lambda_j} \geq t \tag{13}$$

where λ and I_p are the eigenvalue and eigenvector, respectively. *t* is the threshold value of the proportion of solved principle components, which is usually 80%.

4. Description of urban building datasets

The selected case city is Jianhu City, a county-level city, in Jiangsu Province, China, that has a total area of approximately 1160 km^2 and a total population of approximately 0.8 million. The city is at an altitude of approximately 2 m, and its latitude and longitude are from 33°16′ to 33°41′ and from 119°33′ to 120°05′, respectively. It has a typical subtropical climate (Cwa) according to the Koppen–Geiger climate classification. The dataset in this study includes a total of 692 buildings, as shown in Fig. 1—539 residential buildings from 42 residential block communities and 153 public buildings.

The dataset was obtained from the official Department of Power Supply in Jianhu City. The information of these buildings comprises their address, year built, footprints, geometry (area, length, width, and height), and energy usage for the year 2018. The public buildings include public service buildings (e.g., government building or service buildings provided by the government), educational buildings (e.g., primary, junior, or high schools), and commercial buildings (e.g., industries, hotels, retail stores, restaurants, and hospitals). In this study, these buildings were grouped together as public buildings. Fig. 2 presents an example of a block among the residential communities, and the basic parameters for extracting and calculating the determinants are listed in Table 1.

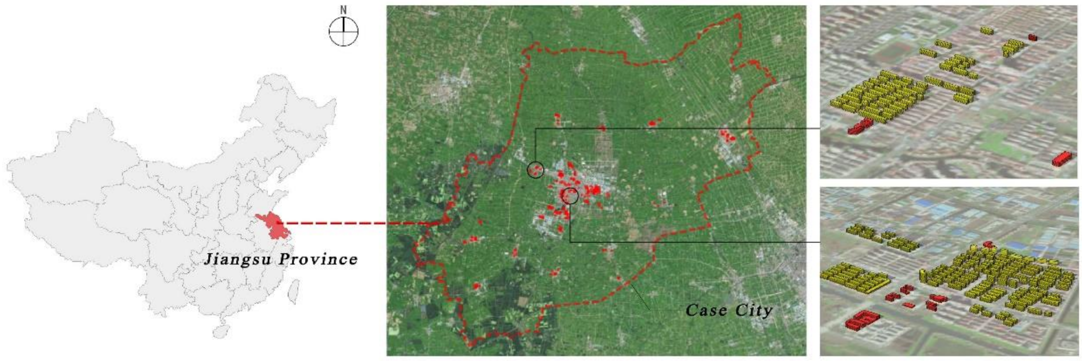


Fig. 1. The location and layout of Jianhu City and distribution of the available buildings in this study (red: public building; yellow: residential building).

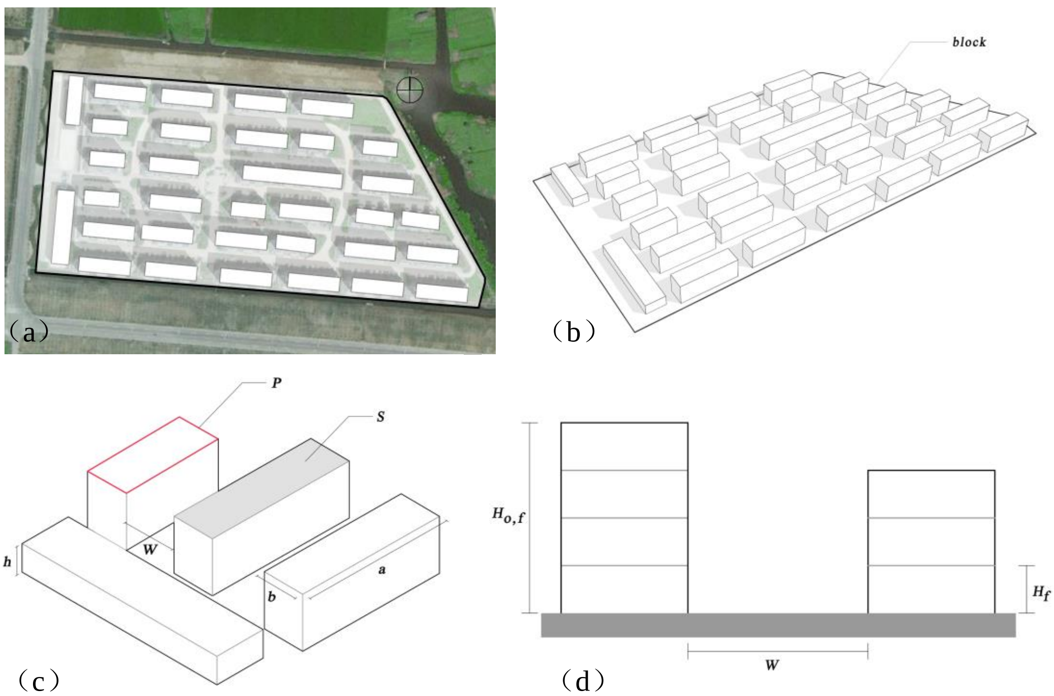


Fig. 2. An example of one residential building block for extracting energy determinants: (a) origin block; (b) 3D view of the block; (c) basic physical parameters of block; (d) basic parameters for calculating the HW.

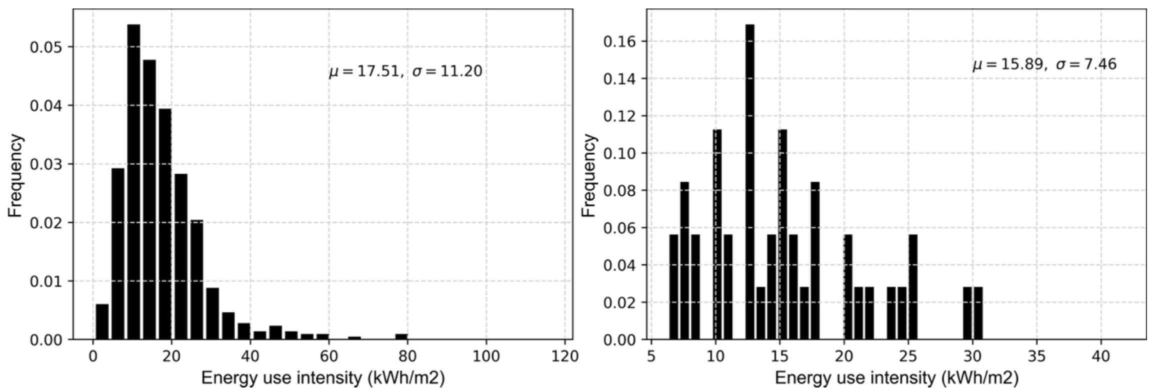
To quantify the target, the EUI (per area and per year) was selected in this study, and it is usually calculated using the total energy usage and building floor area (S) as follows:

$$EUI_{building,S} = \frac{E_{building}}{\sum S} \tag{14}$$

$$EUI_{block,S} = \frac{\sum E_{building}}{\sum \sum S} \tag{15}$$

where $EUI_{building,S}$ and $EUI_{block,S}$ are the EUIs at the building level and block level (per area, kWh/m^2). $E_{building}$ is the energy usage (electricity in this study), and S is the building floor area.

Fig. 3 presents the EUI distribution of the individual residential buildings group, residential block group, and public buildings group. It is found that the annual EUI of the residential buildings is much lower than that of the public buildings group. The average EUIs of the residential buildings group and total residential building block group are approximately 17.51 and 15.89 kWh/ m^2, respectively, and that of the public buildings group is approximately 39.35 kWh/ m^2. The cause for this discrepancy may be related to the heating, ventilation, and air-conditioning demands of public buildings, which are higher than those of residential buildings. Tables 2–4 detail the minimum, maximum, average, and standard variations of the characteristics of the basic information of the buildings and the determinants for the three groups considered. The area of the public buildings is usually greater than that of the residential buildings group, while the residential buildings are usually built taller than the public buildings. According to an analysis of building orientations, all the main façades of the buildings were built such that they faced south or approximately in the southern direction. In this study, the value of 270° is set as the southern direction (the value of the eastern direction is 0°, and all the values of the directions between 0° and 360° are positive). An analysis of the average direction shows that the direction of the residential buildings varies slightly from south to west, while that of the public buildings varies slightly from south to southeast. In terms of HW, the residential buildings exhibit higher values than the public buildings for all four directions, and thus, the impact of shading from the surrounding buildings on the residential buildings is much greater. The SCs, PARs, and BARs of both the groups were very close.



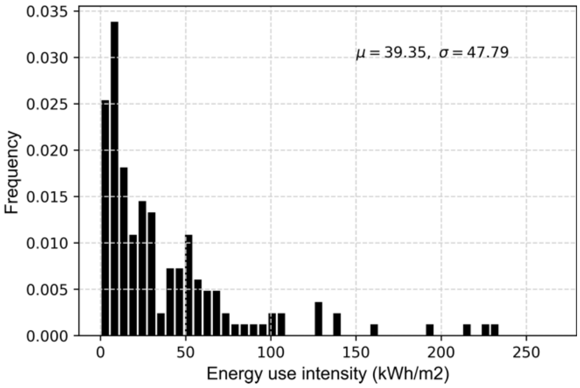


Fig. 3. Energy usage intensity distribution of individual residential buildings (upper left), residential block buildings (upper right), and public buildings (bottom left).

Table 2. The characteristics of the individual residential buildings group.

	Minimum	Maximum	Average	Standard Deviation
Year built	1996	2017	2011.3	3.98
Total area (m^2)	1104	35640	4151.89	2811.72
Number of floors	2	33	6.92	3.38
Orientation	246.9	272.74	258.06	9.50
HW_South	0	7.98	1.75	2.19
HW_West	0	19.08	1.81	5.83
HW_North	0	12.77	1.83	1.54
HW_East	0	25.24	1.56	1.61
SC	0.08	0.84	0.27	0.09
PAR	0.04	1.05	0.20	0.06
BAR	1.2	13.77	3.92	1.55
EUI (kWh/ m^2)	0.34	120.6	17.51	11.20

Table 3. The characteristics of the residential block buildings group.

	Minimum	Maximum	Average	Standard Deviation
Orientation	247.3	272.79	259.00	8.94
Average HW_South	0	4.56	1.52	0.90
Average HW_West	0	10.2	1.65	1.84
Average HW_North	0	6.61	1.58	1.15
Average HW_East	0	16.54	1.77	2.55
SC	0.12	0.34	0.26	0.04
PAR	0.04	0.48	0.20	0.06
FAR	0.3	2.48	1.32	0.47
BAR	1.66	8.83	3.96	1.37

MSP	0.01	0.43	0.20	0.10
EUI	6.33	42.71	15.89	7.54

Table 4. The characteristics of the public buildings group.

	Minimum	Maximum	Average	Standard Deviation
Year built	1963	2018	2004.50	11.70
Total area	158.27	190299.6	6400.30	17828.78
Number of floors	1	20	4.36	3.34
Orientation	170	385	281.72	36.00
HW_South	0	4.2	0.38	0.62
HW_West	0	2.05	0.32	0.50
HW_North	0	2.47	0.41	0.60
HW_East	0	2.62	0.34	0.55
SC	0.11	1.47	0.33	0.15
PAR	0.03	1.13	0.22	0.10
BAR	1	32.66	5.78	5.24
EUI	0.05	272.28	38.41	47.39

5. Results

5.1 Key determinants for residential buildings

The analysis of residential buildings has been divided into two sub-groups in this study: the individual residential buildings group and the total residential block group. Fig. 4 presents a histogram of the basic information of all the residential buildings, including the year built, total area, number of floors, and BAR. The majority of the residential buildings were built between the years 2006 and 2014, the number of which peaked in 2010, which accounts for nearly 25% of the residential buildings. This means that the majority of residential buildings are quite new. According to the total area, the majority of residential buildings—which accounts for approximately 62.55% of the buildings—take up between 3,000 and 9,000 m^2. The average total area of the residential buildings is 4151.89 m^2. The number of floors of those residential buildings is usually between four and seven, which accounts for 87.01% of the buildings, which are low-rise buildings. The BAR, which is calculated using the building length and width using Eq. 1, is normally distributed and its range with the highest proportion (41.74%) is between 3 and 4, with an average of 3.92. The orientation plot was drawn with different-level percentages of the number of different buildings within the resolution of 5º. As shown in Fig. 5, all the residential buildings face south to southwest, and their orientation range varies from 246.9° to 272.74°, which allows the buildings to receive more solar energy and adapt to natural daylight.

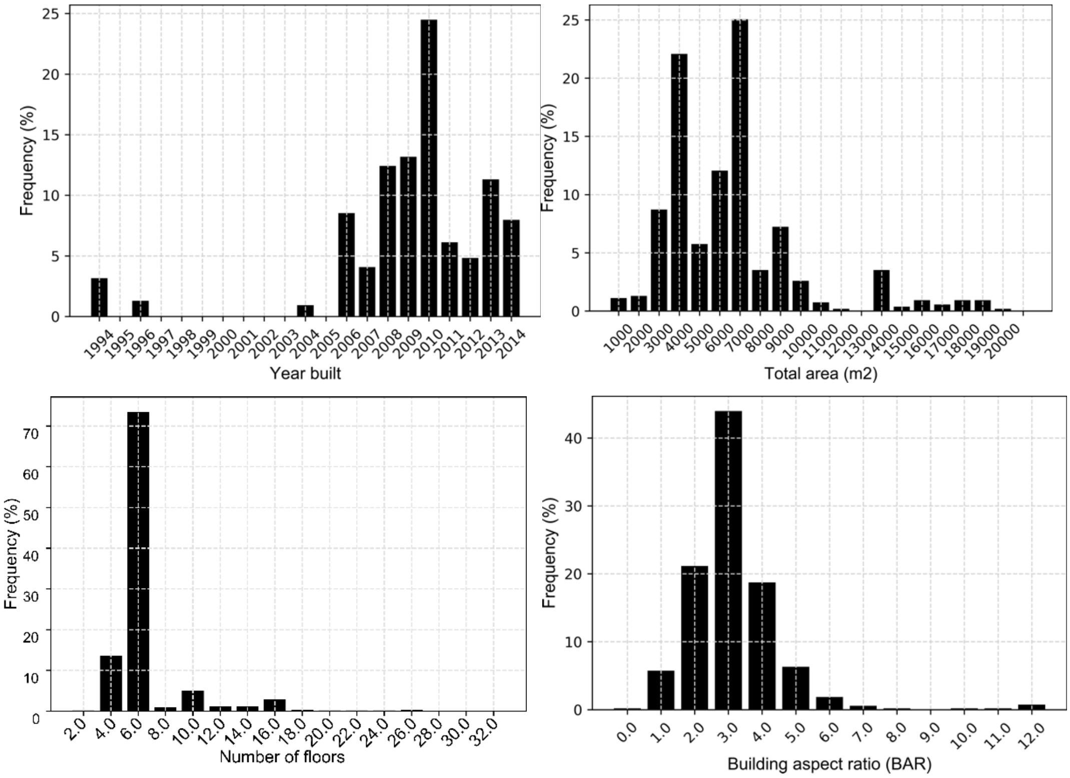


Fig. 4 The distribution of the year built, total floor area, number of floors, and BAR for residential buildings group.

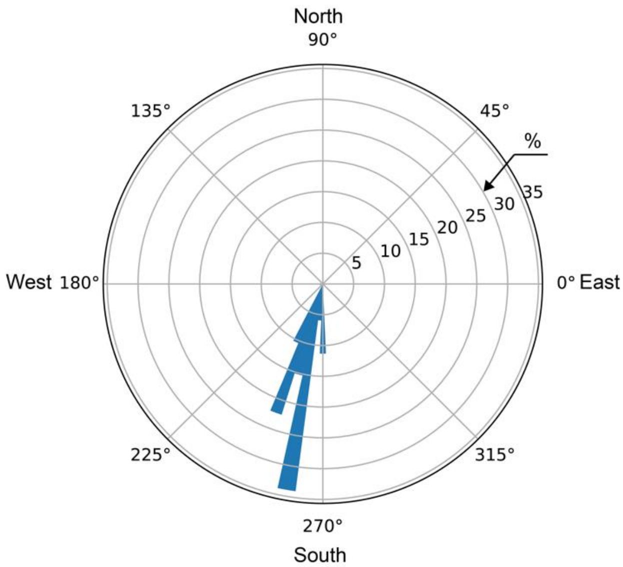


Fig. 5. The orientation distribution of the residential buildings group.

The results of HW in the four directions are presented in Fig. 6. The higher the HW, the greater the shadows that may be caused in neighborhood buildings. As shown in Fig. 6, the values of HW seem similar in the four directions, which indicates a similar urban neighborhood environment for the target residential buildings. The residential buildings' shape factors, which can influence the heat transfer between the buildings' indoor and outdoor environments, is distributed between 0.2 and 0.4 for the majority of the residential buildings, as shown in Fig. 6, and its average is 0.27, while the average PAR is approximately 0.2.

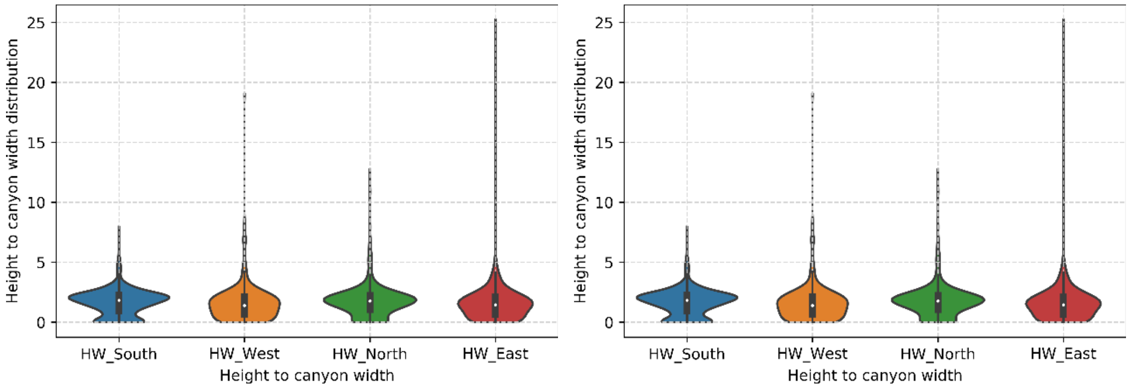


Fig. 6. The results of HW, SC, and PAR.

Table 5 lists the contribution of each determinant as determined on applying the PCA method. It was found that the orientation has the greatest contribution; its contribution was 20.78%. In the case of residential buildings, the orientation design is one of most important factors contributing to energy usage. The second most important factor is the ratio of the obstruction height to the canyon width from the south, which indicates that shading from the south can also influence the energy usage of residential buildings, and is followed by the ratio of the obstruction height to the canyon width from the west. The solar heat gains from the south and west directions are significant, while the minimum contributions are those of the ratios of the obstruction height to the canyon width from the north and east, which can be ignored. The contributions are listed in Table 5, and the results are presented in Fig. 7: when the threshold (t in Eq. 13) is 80%, the main components are the orientation, obstruction height to canyon width from the south and west, PAR, and BAR.

Table 5. The contributions of each determinant to the EUI for the residential buildings group.

Determinants	Orientation	HW_South	HW_West	PAR

Contributions	20.78%	17.82%	16.55%	11.61%
Determinants	BAR	SC	HW_North	HW_East
Contributions	11.42%	8.54%	6.69%	6.60%

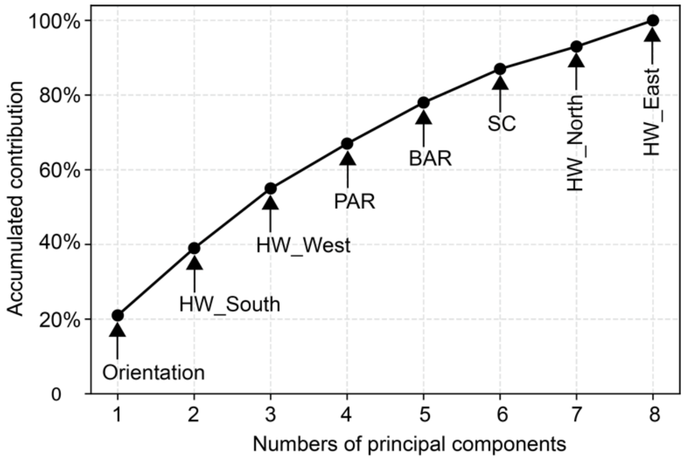


Fig. 7. The results of the PCA for the residential buildings group (Note: Each arrow indicates that one component is added to the previous components).

Fig. 8 presents the orientation distribution of the residential block buildings group. The orientation of one residential block is averaged by the orientation results of all the residential buildings in this block, and HW is the same from all four directions. At the block level, in this study, two important determinants were added: the FAR and MSP. The FAR is an important factor that architects must take into consideration in the design process, and it determines the living comfort of residents; it is usually less than 5 for a high-rise residential block and 3 for a multi-story residential block. In this study, the maximum FAR is approximately 2.48. Fig. 9 shows that the FAR is distributed very evenly, and in Table 3, the average FAR is approximately 1.32. The overall FAR is quite small and satisfies the maximum suggested design parameters. The MSP can reflect the proportion of open space area. The greater the MSP, the smaller the open space area; however, open space area has been recognized as having an important influence on the block-level microclimate and energy usage. Fig. 9 shows that the MSP is mostly less than 0.5, which indicates that the open space is greater than 0.5.

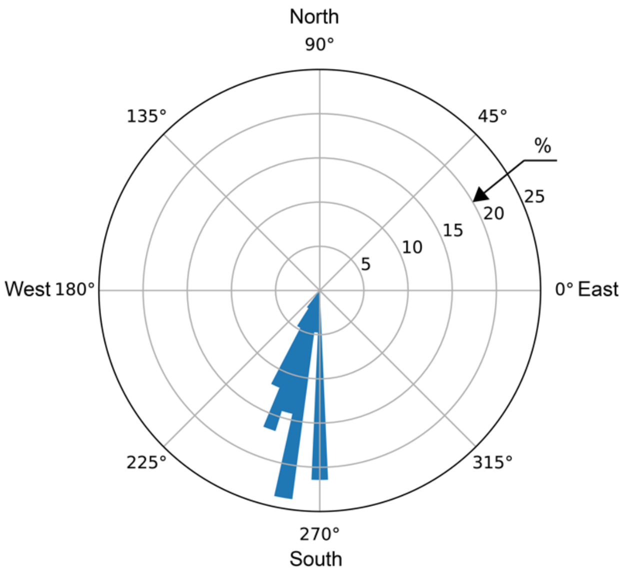


Fig. 8. The orientation distribution of the residential block buildings group.

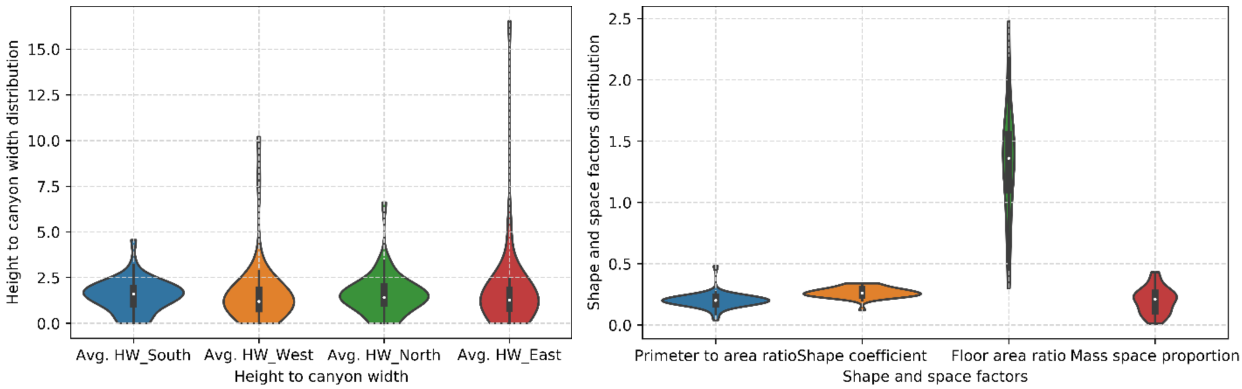


Fig. 9. The results of the average HW, PAR, SC, FAR, and MSP.

Table 6 presents the contributions of each determinant. As compared with the individual residential buildings group, the orientation is not a key determinant as its contribution is only 2.9%, while the HW values for the south and west are still the two most important determinants. The next determinant is the MSP, which contributes 13.59%. The minimum contributions are those of the HW from the north and east, which can be ignored while analyzing the urban energy at the individual building and block levels. As shown in Fig. 10, the main components are the HW from the south and west, MSP, BAR, and FAR when the threshold is 80%.

Table 6. The contributions of each determinant to the EUI for the residential block buildings group.

Determinant	Average HW_South	Average HW_West	MSP	BAR	FAR
Contributions	27.1%	23.58%	13.59%	10.99%	9.87%
Determinant	SC	PAR	Orientation	Average HW_East	Average HW_North
Contributions	5.57%	3.66%	2.9%	1.47%	1.28%

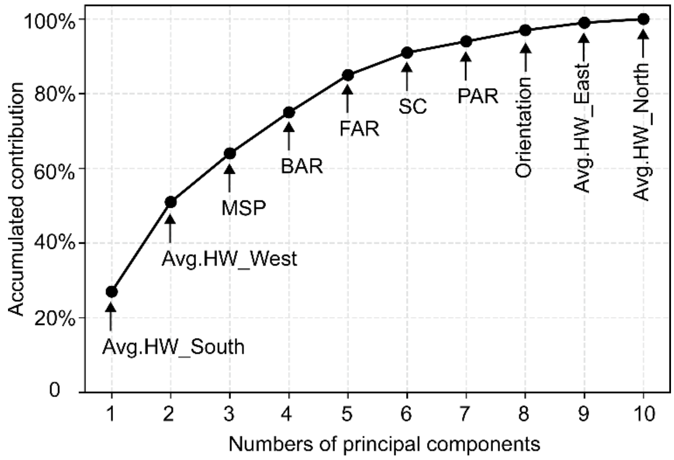


Fig. 10. The results of the PCA for the residential buildings group (Note: Each arrow indicates that one component is added to the previous components).

5.2 Key determinants for public buildings

This section provides the results for 153 public buildings, and Fig. 11 presents the basic information with the distribution of all the public buildings. The majority of public buildings were built between 2005 and 2014, with the highest concentration in 2011. According to the total area characteristics, the obtained results suggest that many public buildings have larger total floor areas than residential buildings, as presented in Fig. 11 and Table 4. Of public buildings, 79.74% have a total floor area of less than 6,000 m^2. Furthermore, public buildings consume more energy per square meter than residential buildings. 95.5% of the public buildings has less than six stories as they are low-rise buildings. The range of the BAR with the highest proportion (49.67%) is less than 4, and the average is approximately 5.78. As shown in Fig. 12, the majority of the public buildings face south although the proportion of those facing southwest and east is greater in the case of public buildings as compared to that of residential buildings.

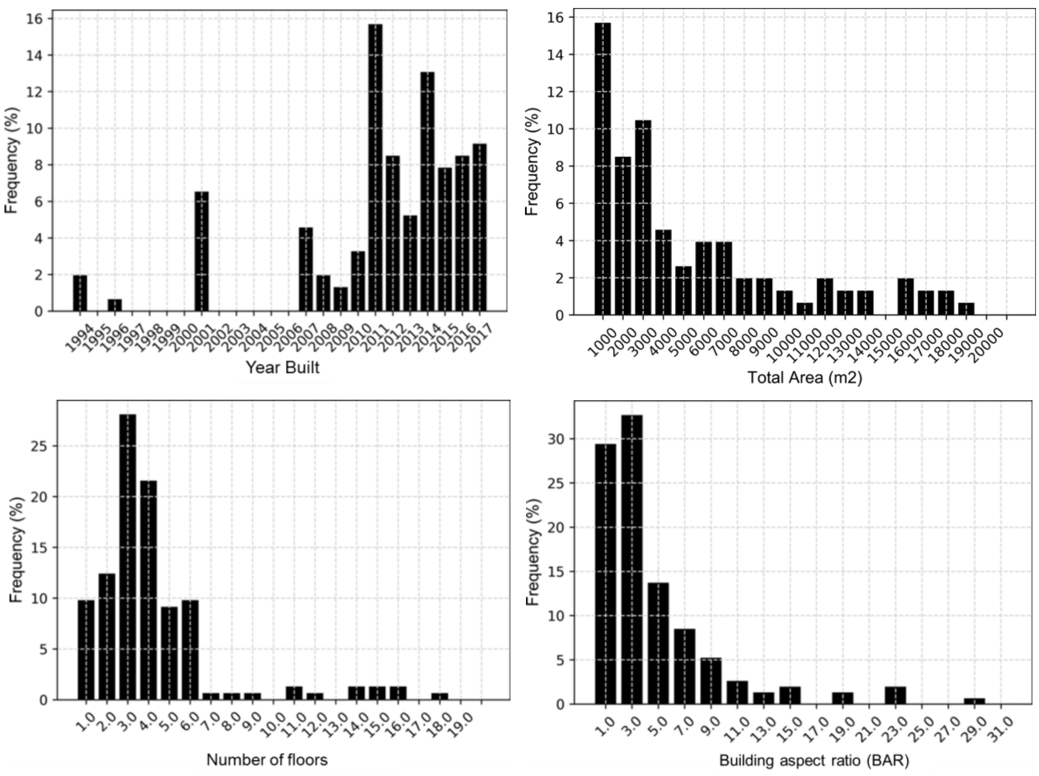


Fig. 11. The distribution of the year built, total floor area, number of floors, and BAR for the public buildings group.

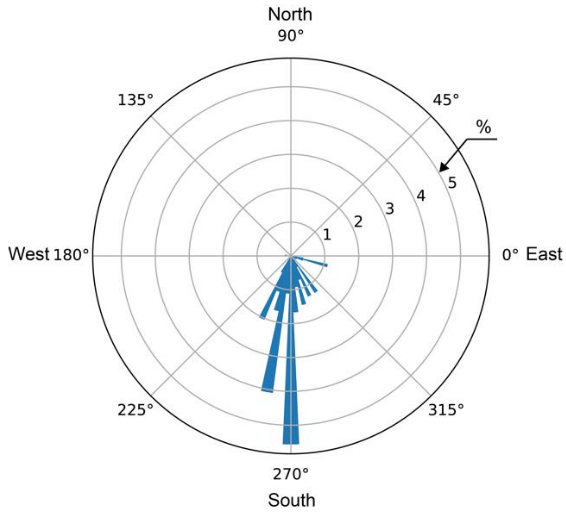


Fig. 12. The orientation distribution of the public buildings group.

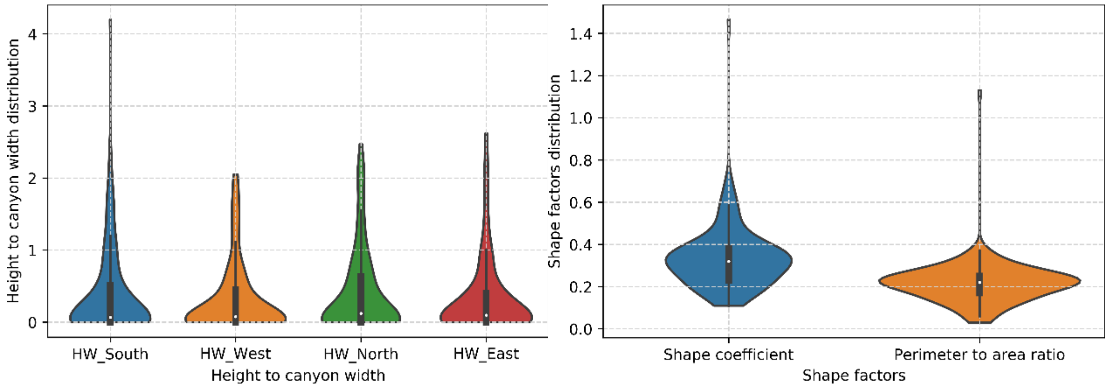


Fig. 13. The results of the HW, SC, and PAR of the public buildings group.

As shown in Fig. 13, the distributions of HW are close; however, the ratios are quite small, and their average value is only approximately 0.3 to 0.4, which is smaller than that of residential buildings and indicates that public buildings receive less shading from neighborhood buildings. In the case of the shape factors of public buildings, this value for the majority of residential buildings is distributes between 0.2 and 0.4, as listed in Table 6, and its average is 0.33, which is very close to the corresponding value of residential buildings. The PAR is also similar to that of residential buildings.

On applying the PCA method, in this study, it was concluded that the contribution of each determinant in Table 7 and the principal components aligned with numbers of components and accumulated contributions presented in Fig. 14. From Table 7, it can also be observed that the orientation has the greatest contribution. Its contribution reached 27.35%. The public buildings group primarily comprises government office buildings and educational buildings. These buildings are usually built to face south, and their orientation is also an important determinant. The second most important determinant is the HW from the west, which means the shading from the south can also influence the energy usage of residential buildings, followed by the SC. The results presented Fig. 14 show that when the threshold is 80%, the main components are the orientation, the HW from the west, SC, PAR, and BAR.

Table 7. The contributions of each determinant to the EUI for the public buildings group.

Determinants	Orientation	HW_West	SC	PAR
Contributions	27.35%	18.31%	13.64%	12.64%
Determinants	BAR	HW_East	HW_North	HW_South
Contributions	10.21%	8.38%	7.7%	1.78%

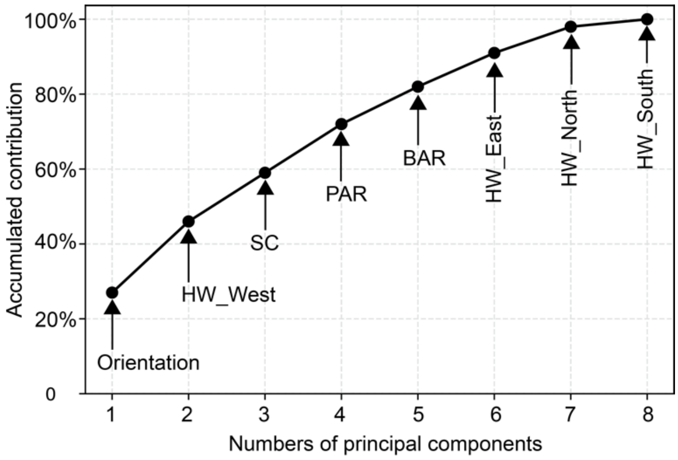


Fig. 14. The results of the PCA for the public buildings group (Note: Each arrow indicates that one component is added to the previous components).

6. Discussion

In this study, the key determinants of building EUI are investigated. These determinants are identified from a building's physical characteristics and surroundings. For the residential buildings group, the key determinants comprise the orientation, the HW from the south and west directions, PAR, BAR, and SC, while the HW from the north and east directions are unimportant. For the residential buildings block, the key determinants are the HW from the south and west directions, MSP, BAR, and FAR, while others are not included. Compared with the case of the individual residential buildings, the orientation is unimportant at the block level, and the FAR and MSP were added as key determinants. The FAR usually corresponds with the building density (in this study, the MSP), and these two factors can influence a building's outdoor environment and energy usage. A high floor area ratio and building density can cause the formation of UHIs [50]; however, the FAR is usually controlled by the government planning policy. In the case of public buildings, the orientation, HW from the west direction, SC, PAR, and BAR are the key determinants, along with obstruction the HW from the east, north, and south directions. The majority of the public buildings comprise municipal office buildings and multi-level educational buildings. For these buildings, the orientation is usually a key determinant, which has also been proved in this study. Among the results, the HW from the west direction is a common determinant of the energy usage. This factor denotes the shadow from the western-neighborhood buildings, and its high value indicates more shading from the west and the protection of buildings from solar heat gain during afternoons, which can reduce the energy usage, especially in summer [51].

This study provides insights regarding urban energy analysis, sustainable urban design, and urban energy planning. First, urban energy analysis usually includes three main branches [52]—big data mining that supports urban building energy policy-making [53,54], data-driven urban building energy modeling (classification, clustering, and prediction) [55–57], and urban-scale building energy simulation [58]. Recent studies have been focused more on the building energy usage dataset or building physical dataset for the simulation. This study suggests the addition of the determinants to such researches to obtain a more detailed urban energy analysis. In this study, several design parameters that should be considered in urban design were investigated, and the key determinants for the EUI of various building groups were revealed. Being important physical parameters, the urban and building morphologies are important in the study of energy simulation [59–61] and prediction [62,63]. Second, these key determinants should be considered during the architectural and urban design. As building and urban operations comprise the post-design process, realizing the optimal physical parameters of the building geometries is important for achieving sustainability in building design. For example, the HW or BAR should be optimally designed to reduce the energy usage of the buildings group. Finally, the findings of this study can help improve urban energy planning. Moreover, urban-scale energy usage corresponds highly to the urban design, especially in the building neighborhood level [64]. According to the basis of urban energy analysis and design, optimal key determinants can reduce the building energy demand as well as increase the renewable energy supply from the solar and wind energy sources to reduce the energy distribution cost. Although the dataset used in this study comprises existing buildings, the obtained results can be used to supplement new urban block and building design as well as improve the urban energy system design to balance the energy demand.

This study has some limitations. First, as this study focused on the key determinants during the building design stage that do not change over the years, this study did not analyze the urban energy variation with occupant-related energy behavior or the weather change, which are usually difficult to predict and are thus not considered in the design stage. Several studies have taken into consideration the influence of occupant behavior on urban energy consumption [65] as well as weather conditions [66]; therefore, these works can be extended in future to determine the key energy determinants of the operation stage at the urban level. Second, this study only used the PCA method to identify the key determinants. In the literature, other methods are also used, e.g., regression methods and machine learning techniques. Another limitation is that this study only covered the key determinants that influence the energy usage for three building groups. However, the influence of those key determinants on the energy usage was not quantified and an optimal combination of determinants was not determined to reduce the energy usage in buildings. Such questions can be solved by, for example, using machine learning techniques to optimize the design parameters or using parametric simulation techniques to find the best energy-efficient design combination, which is a good topic to study in future.

7. Conclusions

Energy-efficient urban design is becoming an increasingly significant urban topic for realizing energy savings during the design stage. To identify the key determinants that influence urban building energy usage, 12 determinants were extracted from buildings and their surroundings in this study. The buildings dataset used includes 539 residential buildings from 42 residential blocks and 153 public buildings, and the energy dataset includes the total energy usage for the year 2018 for all the 539 buildings. The results showed that for both the residential and public buildings, the orientation, HW from the west direction, SC, PAR, and BAR are the key determinants. Specifically, the HW from the south direction is an important determinant for public buildings, while for the residential block buildings, the key determinants are the HW from the south and west directions, MSP, BAR, and FAR. The results can be applied to future research comprising urban building energy analyses, sustainable urban design, and urban energy planning.

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