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Vacancy or occupancy? A comparative analysis of methods for identifying short-term residential unit vacancy in multi-family housing

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ABSTRACT

In high-density urban areas, accurately identifying the vacancy status of multi-family residential buildings is crucial for forecasting urban energy consumption, mitigating vacant housing proliferation, preventing crime, and enhancing residents' experiences. However, vacancy research has mainly focused on single-family housing, neglecting multi-family housing. To address this gap, we examined 16 multi-family residential buildings (1020 residential units) in Inner Mongolia, China. We developed a vacancy identification framework involving data collection, housing identification and coding, multi-method vacancy identification, and validation. Building outlines and heights were determined using Digital Elevation Model (DEM) comparisons. Residential housing units were coded using daytime point cloud data, and their vacancy status analyzed using nighttime point cloud data, front-door images, and façade images. Analyses employed machine learning, multimodal large language models, and other advanced methods. Validation used electricity consumption data to assess accuracy. Findings show nighttime point cloud data offer superior accuracy and practicality due to ease of acquisition, while front-door images offer moderate accuracy, and façade images exhibit lower accuracy. The primary contribution of this study is the proposal and validation of scalable methods for identifying unit-level vacancy in multi-family housing, specifically focusing on units that have remained vacant for five consecutive days. As all data were independently collected, these methods demonstrate significant potential for transferability.

1. Introduction

Residential buildings can be broadly categorized into multi-family and single-family structures [1,2] (see Table 1). Multi-family housing consist of a single structure with multiple independent housing units [3]. These units, typically arranged across one or more floors, each feature dedicated living spaces—such as kitchens, bedrooms, and bathrooms—while sharing common areas like hallways, staircases, and elevators [4]. Common forms of multi-family housing include apartment buildings, townhouses, and duplexes/triplexes [4,5]. Given the high cost of land in urban areas, the vertical development of multi-family housing maximizes spatial efficiency [6], making it prevalent in densely populated and land-constrained regions such as city centers, commercial zones, transportation hubs, university towns, and industrial parks [7,8].

Multi-family buildings have become a dominant residential form in several countries, especially those with high urban densities. For instance, in 2019, the United States constructed 352,000 units of multi-family housing, exceeding the number built ten years ago (274,000) by more than 28 % [9]. In large U.S. cities like Chicago, apartment complexes and multi-family buildings are common [10]. Similarly, in metropolitan areas such as Tokyo and Osaka, apartments are the predominant form of housing [11,12]. In China, rapid urbanization in major cities like Beijing, Shanghai, Guangzhou, and Shenzhen has likewise rendered multi-family housing the mainstream residential choice. With accelerating urbanization and limited land in city centers, the proliferation of multi-family buildings is particularly notable in large urban areas [13].

Therefore, as the predominant architectural form in densely populated urban areas, multi-family housing is pivotal to urban resource management and energy efficiency [14,15], making the identification of

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Table 1
Difference between the multi-family housing and single-family housing.

Type	Multi-family Housing	Single-family Housing
Residential Density	High, multiple units per building	Low, one household per building
Privacy	Relatively low, shared common areas	High, standalone residences
Building Height	Multi-story, often high-rise	Single or low-rise
Management	Managed by property companies or landlords, primarily rented	Self-managed by owners, primarily owned
Maintenance	Centrally managed, usually by property or landlord	Individually managed by homeowners

vacant status within these units crucial for optimizing housing resource allocation and promoting sustainable urban development [16]. In terms of urban energy efficiency, occupied residential units generally consume more energy. Understanding vacancy patterns can improve the accuracy of building or regional energy demand evaluation, helping to mitigate urban heat island effects [17]. Additionally, knowledge of unit vacancy facilitates effective resource allocation, greatly assisting property management in equipment maintenance, waste disposal, and security. By reducing electricity, heating, and cooling in vacant units, it ensures the efficient and rational use of resources, thereby enhancing energy management efficiency [18].

From an urban management perspective, vacant units not only represent underutilized housing resources [19] but also negatively impact the real estate market, social welfare, and community environment. High vacancy rates often deter investment in affected areas, leading to declines in local property values and rental prices [20,21]. Furthermore, vacant properties, due to lack of supervision, may attract illegal activities, fostering crime and undermining residents' sense of security and well-being [22,23]. More critically, the presence of vacant housing can cause vacancy rates within the community to continue rising, as prolonged vacancies increase the risk of property abandonment or arson, creating a cycle of negative externalities [24]. Therefore, monitoring housing vacancy status is a crucial component of urban emergency management. In fires, earthquakes, and other emergencies, information on vacant units aids rapid rescue operations, reducing delays caused by information asymmetry [25]. From a broader perspective of urban planning and governance, real-time data on vacant residential fluctuations provides valuable insights for the spatial distribution of transportation networks, commercial facilities, and public services. This supports intelligent resource allocation and promotes sustainable urban development [26].

Unfortunately, driven by factors such as population outmigration [27], aging demographics [28], investment-driven purchases, and economic crises [29], housing vacancies have become widespread globally, which underscores the critical importance of monitoring vacancy status within multi-family housing units. In 2023, the housing vacancy rate in the United States was approximately 6.8 %, encompassing both vacant homes for sale and for rent [30]. In Japan, the vacancy rate reached 13.6 % in 2023, a figure that has been steadily increasing [31]. Major Canadian cities, including Vancouver and Toronto, are also facing rising vacancy rates [32]. Clearly, identifying residential vacancy status is of significant importance.

However, due to challenges in data collection and limitations in identification technology, determining housing vacancy status—particularly within multi-family residences—remains a global challenge (Table 2). While some countries and regions have obtained overall housing vacancy data through methods such as sample surveys and tax records—like the U.S. Housing Vacancy Survey [33], Japan's Residential Land Survey [31], and Canada's National Housing Census [34]—these data are typically published only at the administrative level, such as census tracts, lacking the detailed information necessary for building-level analysis. This limitation hinders the accuracy of vacancy rate identification in multi-family housing. In certain countries, such as China, there is a complete absence of official vacancy data, further complicating effective identification efforts.

To address this issue, scholars have explored various data sources and methods to determine whether housing units are vacant or occupied. Some researchers utilize nighttime light data to analyze nighttime population distributions and estimate vacancy rates [35–38]. Although effective in certain contexts, the low resolution of nighttime light data limits accuracy at the housing unit or building level. Similarly, data from location-based services (LBS) and mobile phone signaling can typically only yield vacancy rates at a broader regional scale [38]. A few studies have employed high-resolution remote sensing data or street view image data combined with manual reviews, identifying vacant homes based on environmental characteristics such as overgrown vegetation and accumulated debris [39,40]. In recent years, some studies have begun using Wi-Fi probe detection to ascertain the presence of Wi-Fi connected devices within housing [41], as well as assessing lighting conditions to determine vacancy status [42]. However, these studies are primarily applicable to single-family housing and heavily rely on manual inspection methods. Some studies employ electricity consumption data to identify vacant housing [43,44]. Whether dealing with multi-family or single-family housing, electricity consumption data can determine occupancy status at the housing level. However, this data is typically controlled by government agencies or utility companies and involves extensive personal information, making it difficult for researchers to access. This challenge is amplified in major cities, where strict privacy protection measures, closed-off community management, centralized installation of meters in locked rooms, and encryption of smart meter data create significant barriers for external researchers. Consequently, its scalability is limited, highlighting the urgent need for alternative, independent methods. The limitations of these research approaches highlight a significant gap in effective technological methods for identifying vacancies in multi-family housing, ultimately restricting the rational management and utilization of this critical resource.

This study addresses this issue by proposing an innovative method for identifying vacancies within multi-family housing, aiming to overcome the limitations of current identification techniques in such

Table 2
Data utilized for identifying vacant housing.

Data Source		Results Obtained	Collection Cost	Scalability	Data Category	Processing Method	Reference
Government survey data		HVR	Low	High	Open data	Spatial analysis	[33]
Nighttime light data	DMSP/OLS	HVR	Low	High	Open data	Spatial analysis	[35]
	NPP/VIIRS	HVR	Low	High	Open data	Spatial analysis	[36]
	Luojia-01	HVR	Low	High	Open data	Spatial analysis	[37]
	Jilin-01	HVR	Moderate	Moderate	Purchased data	Spatial analysis	[38]
LBS data		HVR	Moderate	Moderate	Purchased data	Spatial analysis	[38]
Mobile signaling data		HVR	Moderate	Moderate	Purchased data	Spatial analysis	[38]
Street view image data		Vacant housing (single-family only)	Low	High	Open data	Deep learning	[39]
Remote sensing image data		Vacant housing (single-family only)	Low	High	Open data	Deep learning	[40]
Wi-Fi probe data		Vacant housing (single-family only)	High	Low	Self-collected data	Field survey & Spatial analysis	[41]
Nighttime image data		Vacant housing	High	Low	Self-collected data	Manual audit	[42]
Electricity consumption data		Vacant housing	High	Low	Sensitive data	Spatial analysis	[43,44]

settings. By leveraging a comparison of multiple novel data sources and efficient data-processing algorithms, this approach enables precise vacancy detection at the building level, which enhances its applicability and transferability in multi-family housing contexts. This innovative method not only applies broadly to multi-family residences across various cities and regions but also provides new technological support for optimizing urban housing resource management, alleviating housing market pressures, and enhancing community quality of life.

2. Method

2.1. Study design

This study is structured into five stages, following a sequential process of " data collection – housing identification and coding–multi-method vacancy identification–validation." Through the integration of field surveys and the comparison of various data sources, this approach aims to establish scalable methods for measuring vacant housing specifically within multi-family residential contexts. The detailed technical roadmap of the study is presented in Fig. 1.

2.2. Study area

This study selects a residential community in the Inner Mongolia Autonomous Region as the focus for methodological exploration. The area spans 49,051 m^2 and comprises 16 multi-family buildings (Fig. 2). Given the limited availability of open big data resources for this area and its alignment with the typical context of high-density, high-rise housing in China, this site offers substantial representativeness and research value as a pilot area for methodological testing.

2.3. Data collection

2.3.1. Data description

Open-source big data within the study area is extremely limited, posing challenges for subsequent identification of vacant housing. Therefore, from October 18 to October 24, 2023, this study conducted extensive self-collected data gathering across the research area (Table 3).

2.3.2. Data collection

(1) DOM imagery and DEM imagery

This study employed the DJI Phantom 4 RTK drone to autonomously collect digital orthophoto maps (DOM) and digital surface models (DSM). The DJI Phantom 4 RTK is a compact, multi-rotor UAV designed for high-precision aerial surveying, equipped with a D-RTK module that enables centimeter-level positioning accuracy. This advanced capability effectively addresses the limitations associated with traditional GPS, barometric altimeters, and compasses. During the survey, the drone captured a total of 196 aerial photographs of the study area, which were subsequently processed using Pix4D software. This processing yielded TIF-format DOM and DSM images, both characterized by a resolution of 0.99 m, with file sizes of 356 MB and 81 MB, respectively (Fig. 3a-b).

(2) Daytime point cloud data

The daytime point cloud data was acquired through oblique photogrammetry using the DJI P4 RTK drone in the study area. In this operation, the drone was flown at an altitude of 100 m, with a forward overlap of 70 % and a lateral overlap of 60 %. Photographs were

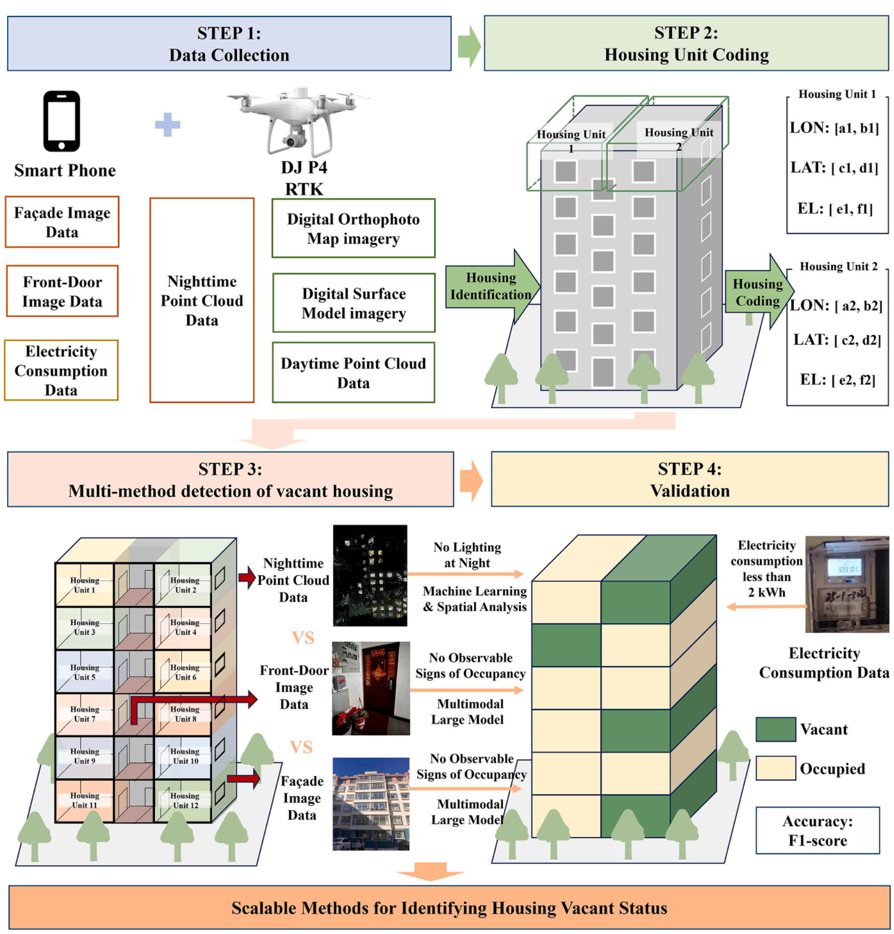


Fig. 1. Methodology flowchart.

Fig. 2. Study area.

Table 3
Data used in this study.

Purpose	Data	Collection equipment	Collection date/time	Data volume
Housing unit coding	Digital Orthophoto Map (DOM) imagery	DJ P4 RTK	October 19, 2023	356 M
	Digital Surface Model (DSM) imagery	DJ P4 RTK	October 19, 2023	81 M
	Daytime Point Cloud Data	DJ P4 RTK	October 19, 2023	209 M
Multi-method detection of vacant housing units	Nighttime Point Cloud Data	DJ P4 RTK	October 20–24, 2023, 20:00–22:00	4.80 G
	Façade Image Data	Smartphone	October 20–21, 2023	2.94 G
	Front-Door Image Data	Smartphone	October 21–24, 2023	1.60 G
Validation	Electricity Consumption Data	Smartphone	October 19 and 25, 2023	906.42 M

captured under sunny conditions, employing a 3:2 aspect ratio, with the camera angle set at −45 degrees. Following these configurations, the mission was saved and executed, resulting in data collection that lasted approximately 20 min. The collected 332 images were processed using Pix4D software, ultimately yielding a comprehensive daytime three-dimensional point cloud dataset (see Fig. 3c), with a total data size of 209 MB. In the aerial triangulation point cloud data, each point contains coordinates, elevation, and RGB information (Fig. 3c).

(3) Nighttime point cloud data

Between October 20 and 24, 2023, the study conducted oblique photogrammetry of the study area every 30 min from 20:00 to 22:30 to collect nighttime point cloud data. Given the low-light conditions at night, three preliminary trials with varying camera parameters were conducted to ensure data reliability. The final camera settings differed from those used for daytime point cloud data, with flight paths set perpendicular to buildings, a gimbal angle of −45 degrees, overcast mode enabled, ISO maximized to 12,800, aperture minimized to 2.8, and a shutter speed of 80 (Fig. 3d). Each data collection session required approximately 25 min. Additionally, the absence of sufficient ambient lighting at night disables the drone’s sensing system, resulting in stricter flying conditions that are highly weather-dependent. Data collection was ultimately conducted under stable weather conditions, yielding 22 rounds of nighttime imagery, totaling 8319 images. These images were imported into Pix4D software, where parameters for image coordinates, geolocation, orientation, and camera model were set. The 3D model template was selected to initialize processing, generate the point cloud, and produce textures, with data formatted in LAS. This process generated 22 sets of nighttime point cloud data covering various periods on weekdays and weekends, with a total data volume of 4.80 GB.

(4) Front-door image data

Data collection personnel, upon entry to a residential building, photographed items within a two-meter range in front of each dwelling’s entrance to obtain doorstep image data, naming and storing each image according to the resident coding scheme outlined in Section 4.3.2. This data collection process required a total of 17 h, resulting in 1028 front-door images with a total data volume of 1.60 GB (Fig. 3e).

(5) Façade image data

Data collection personnel conducted internal community surveys to capture facade images of each unit, ensuring all households within the unit were represented. This resulted in a total of 334 facade images collected over six hours, named and categorized by housing code, with a total data volume of 2.94 GB (Fig. 3f).

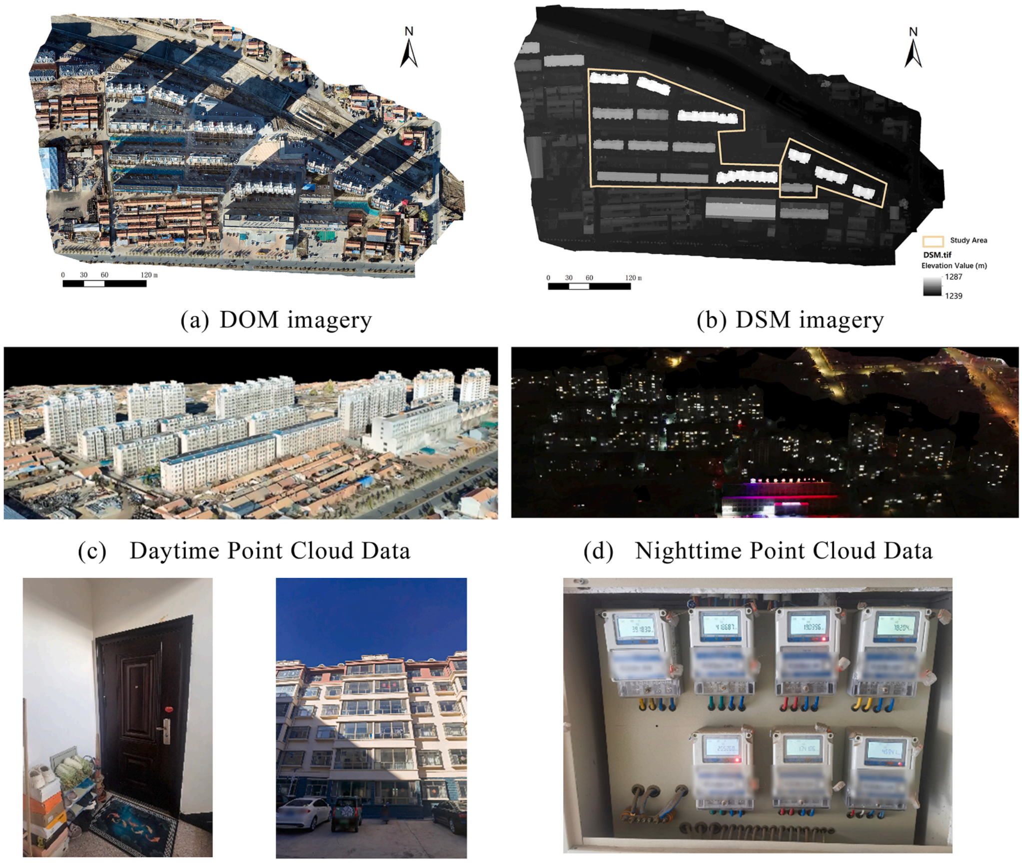
(6) Electricity consumption data

Within two residential communities, 526 housing units are equipped with smart meters. On October 18 and October 24, images of each unit’s electric meter were taken, with corresponding consumption data recorded in an Excel file (Fig. 3g).

2.4. Housing identification and unit coding method

In ArcMap software, the research team performed binarization and vectorization of DEM images to extract building outlines, utilizing elevation information from the DEM to determine the height and number of stories of buildings. By integrating DOM data, manual validation was conducted to ensure the accuracy of the three-dimensional building data.

Field survey observations revealed that all residential buildings employ a “one stairwell per two units” layout. Based on this, the study identified entrance locations from the daytime point cloud data, segmenting buildings into individual housing units. Each housing unit was assigned a unique ID, and with a standard floor height of 3 m, the 3D spatial boundaries of units were calculated. This process allowed for the association of point cloud data with housing unit IDs, assigning each point cloud a corresponding unit label.



(a) DOM imagery (b) DSM imagery

(c) Daytime Point Cloud Data (d) Nighttime Point Cloud Data

(e) Front-Door Image Data (f) Façade Image Data (g) Electricity Consumption Data

Fig. 3. Data presentation.

2.5. Multi methods for identifying vacant housing units

2.5.1. Identifying vacant housing units using nighttime point cloud data

This study observes whether residents keep their lights off over multiple nights to infer vacant status. The research is divided into two steps: first, the extraction of window, and second, the determination of nighttime lighting conditions.

(1) Window point cloud extraction

The study extracted the windows extents for each residence from daytime point cloud data, aiming to avoid biases caused by street lighting that could inflate wall brightness. To achieve this, the research team processed the daytime point cloud data through down-sampling and denoising techniques. Four residential buildings of varying heights and positions were selected for labeling, where window point clouds were marked as 1 and non-window point clouds as 0. This process generated a dataset containing 79,654 points, of which 70,687 were identified as window points. Multiple machine learning models were trained using the RGB values of the points as independent variables and the classification of window point clouds as the dependent variable. The model with the highest accuracy was then applied to the entire point cloud dataset to identify all window point clouds of the buildings.

(2) Determination of nighttime lighting conditions

For the nighttime point cloud data, luminance values for each point were calculated [45]. Manual random sampling was conducted on window point clouds with lights on at night, and after removing outliers, the minimum brightness threshold was found to be 118. Consequently, points with luminance values exceeding 118 were classified as illuminated. For each round of nighttime point cloud data, the study extracted luminance values of points within a 0.5-meter buffer around each identified window and counted the number of points exceeding the threshold of 118. Households with over 300 illuminated points (the minimum number of points for a single window) were classified as occupied, while those below this threshold were considered vacant.

$$Luminance = 0.2126 \times R + 0.7152 \times G + 0.0722 \times B \tag{1}$$

In this equation, *Luminance* represents the brightness value of the point cloud, while R, G, and B denote the RGB values of the point cloud data.

2.5.2. Methodology for identifying vacant housing units using front-door image data

By analyzing front-door image data, the vacant statuses of residences can be effectively assessed. This study utilizes the multimodal model "Tongyi Qianwen" to extract features corresponding to vacant and occupied statuses from the images. Features indicative of vacancy include unremoved door packaging films, obstacles that prevent the door from opening due to clutter, property notices about fee payments, and posted advertisements. Conversely, features indicating occupancy include the presence of garbage in front of the door, shoe racks, doormats, shoes, and items such as plants or vegetables. To ensure the model's accuracy, we randomly selected 100 front-door images and conducted manual audits to assess the model's precision.

2.5.3. Methodology for identifying vacant housing units using facade image data

By analyzing façade image data, we can observe the balcony usage of each household, which aids in identifying whether a residence is vacant. This study also employed Alibaba's multimodal large language model "Tongyi Qianwen" to extract relevant features from the images. Features indicative of vacancy include fully closed curtains and balconies devoid of any furniture. Conversely, features representing occupancy include drying clothes, visible potted plants, and open windows. To ensure the model's accuracy, we randomly selected 10 façade images containing information on 140 households and conducted manual audits to assess the model's precision.

2.6. Validation

The variation in electricity consumption between the two readings was calculated, with households consuming below a specified threshold classified as vacant. This study employs vacant households identified through electric meter data as the ground truth, comparing these results with vacancy information extracted from nighttime point cloud data, facade images, and doorstep image data. The objective is to perform a multi-method comparative analysis to identify the most accurate and scalable method for vacant housing detection.

3. Results

3.1. Housing identification

The study ultimately yielded data for 16 residential buildings, comprising 9 buildings with 6 stories or fewer, which include 448 residential units, and 7 buildings with 11 stories, containing 572 residential units. The footprint area of the buildings is 14,641 m^2, with a total area of 121,138 m^2.

3.2. Identifying vacant housing units using nighttime point cloud data

3.2.1. Results of window point cloud recognition

The performance of various models exhibited minor differences, with the XGBoost model achieving the highest performance, reflected in an F1 score of 0.93. In contrast, the Decision Tree model demonstrated the lowest performance, with an F1 score of 0.88. Among the different models, the variable B had a more significant weight. Consequently, the study employed XGBoost to process the entire point cloud dataset, resulting in a total of 284,589 point cloud data entries.

3.2.2. Results of identification of vacant housing units

Data from 22 rounds of nighttime point cloud measurements recorded the frequency of each housing unit being illuminated at night. Among these, a total of 149 housing units consistently showed no lighting and were thus classified as vacant units (Fig. 4). A total of 871 housing units were lighted at least once; among these occupied units, the average number of times they were illuminated was 11.2. On average, each data collection captured 565 housing units with lights on. The distribution of illuminated housing units across different dates and times is shown in Fig. 5, indicating that the number of lighting housing units is significantly higher on weekends than on weekdays. Additionally, the number of lit housing units decreases as night progresses, consistent with traditional household activity patterns.

3.3. Identifying vacant housing units using front-door image data

3.3.1. Performance of multimodal large model

To assess the performance of the multimodal large model, a random sample of 100 front-door images was audited. The findings indicate that the multimodal large model performed well in identifying various features, achieving an average F1-score of 0.86. The model excelled particularly in recognizing the couplets feature, attaining an F1-score of 0.98, while its performance was weakest in the overdue payment notices affixed by property management feature, with an F1-score of 0.70. Consequently, the multimodal large model was applied to the entire set of front-door images.

3.3.2. Results of identification of vacant housing units

Using the multimodal large model, the study initially identified 93 housing units exhibiting clear signs of vacancy. Further analysis uncovered 90 housing units with no indicators of occupancy (Fig. 6). In total, the study classified 183 housing units as vacant and 837 as occupied.

3.4. Identifying vacant housing using façade image data

3.4.1. Performance of multimodal large model

To validate the performance of the multimodal large model, the study randomly selected 40 facade images, covering a total of 140 households, for auditing. The results revealed that the multimodal large model still maintained a relatively strong level of accuracy, with an average F1-score of 0.77. Specifically, the model performed best in recognizing the "Clothes Hanging" feature, achieving an F1 score of 0.88. In contrast, it performed worst in detecting the "Complete Absence of Life Traces" feature, with an F1 score of 0.69. Given the model's overall solid performance, it was subsequently applied to process all facade images in the study.

3.4.2. Results of identification of vacant housing units

Using the multimodal large model, the study initially identified 623 housing units with evident signs of occupancy. Further analysis revealed 3 housing units with no features of vacancy (Fig. 7). Ultimately, the study classified 368 housing units as vacant and 626 as occupied.

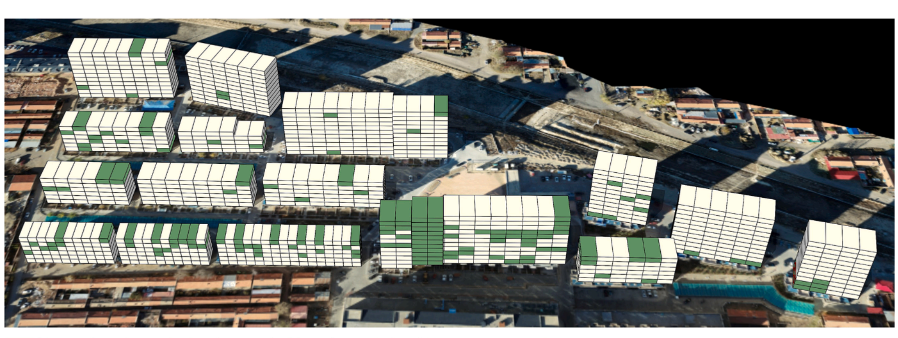


Fig. 4. Distribution of vacant and occupied housing unit identified by nighttime point cloud data.

	20:00	20:30	21:00	21:30	22:00	22:30	Avg
Oct 20th (Friday)	525			621	443		532
Oct 21st (Saturday)	648	569	725	520			520
Oct 22nd (Sunday)	726	602	565	507	405	288	400
Oct 23th (Monday)	537	596	609	548	451	350	450
Oct 24th (Tuesday)	615	592	532	448			448
Avg	610	590	608	529	433	319	

726
288

Fig. 5. The number of housing units illuminated at different times.

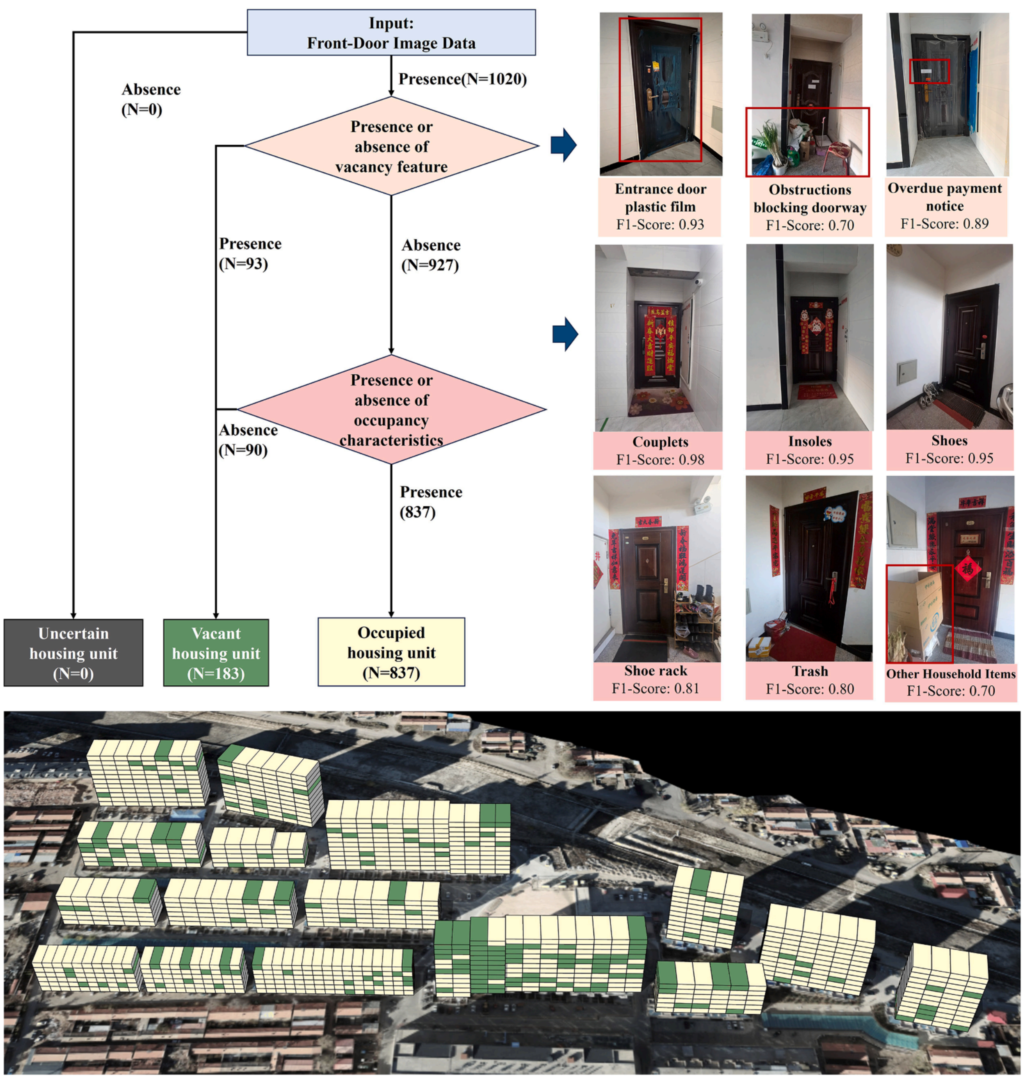


Fig. 6. Workflow for determining housing vacancy status using front-door image data.

4. Method validation

4.1. Identifying vacant housing units using electricity consumption data

Recognizing that some vacant properties may contain appliances such as refrigerators, which could remain connected to prevent malfunction even if the property is unoccupied, this study estimates a baseline electricity consumption for a vacant household. The weekly electricity consumption of a refrigerator was calculated to set a minimum expected energy use in a vacant state.

First, the refrigerator's power rating (W), which can typically be found on its manual or energy efficiency label, was determined. For this study, a refrigerator power rating of 150 W was assumed. Second, it was considered that refrigerators do not run continuously; instead, they cycle on and off based on internal temperature and external conditions. Assuming the compressor operates for approximately 15 min per hour, the estimated daily runtime is 8 h. Thus, daily electricity consumption (kWh) can be calculated as power (kW) multiplied by time (h), yielding

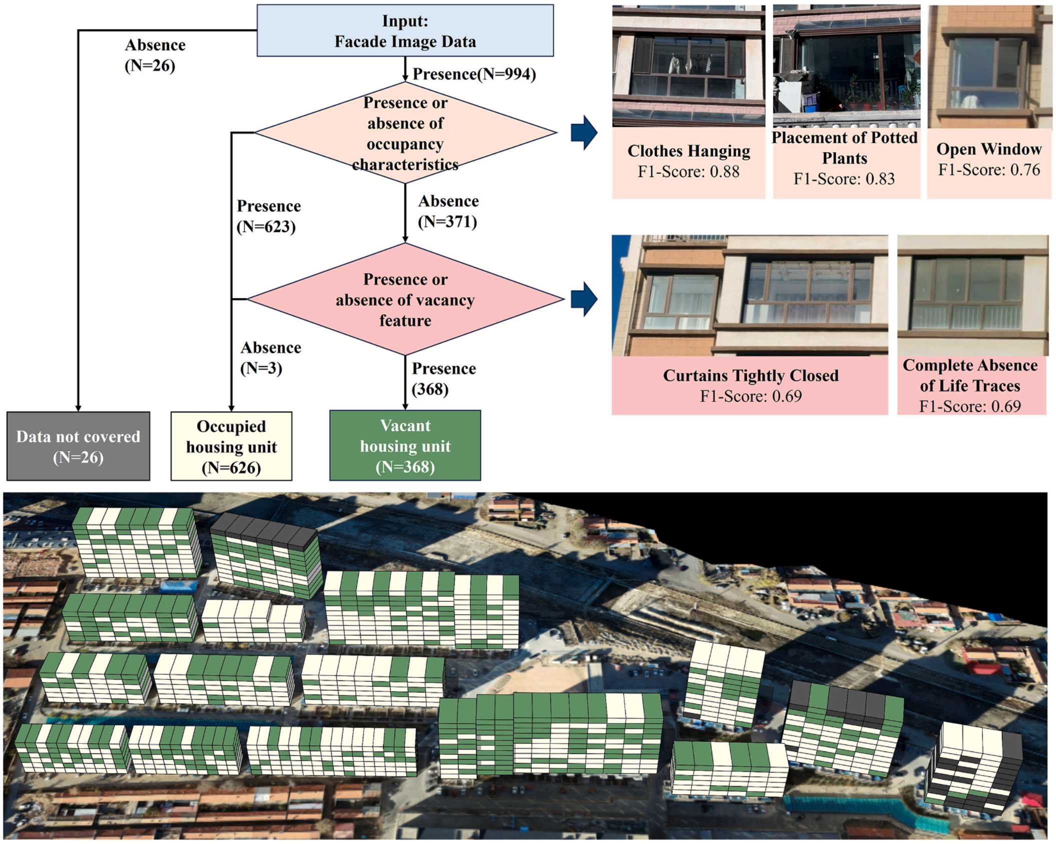


Fig. 7. Workflow for determining housing vacancy status using facade image data.

a weekly consumption of 2 kWh. This threshold aligns with previous studies that utilized electricity consumption data to identify vacant properties (Jiang et al., 2020). Based on this calculation, 56 housing units exhibited electricity consumption changes of less than 2 kWh during the observation period, leading to their classification as vacant.

4.2. Accuracy comparison of different data

In this study, each housing unit was treated as an observational unit, using electricity consumption data as the ground truth for identifying vacant households. A direct comparison was conducted between the vacancy data derived from nighttime point cloud data, front-door images and facade images on a household-by-household basis. Considering the variable coverage of households by each data source, only households that were covered in both electricity consumption data and other self-collected datasets were included in this analysis.

The confusion matrix (Fig. 8) reveals that nighttime point cloud data exhibited minor errors, with some vacant housing incorrectly identified as occupied and vice versa. However, both front-door and facade image data showed greater discrepancies, particularly in misidentifying vacant housing as occupied.

The study employed precision, recall, and F1-score as performance metrics to evaluate the accuracy of each method. Precision and recall, commonly used in information retrieval and classification, provide a balanced assessment of predictive accuracy and coverage. Results (Fig. 8) indicate that nighttime point cloud data outperformed other methods, achieving the highest recall and F1 score in vacant housing detection. In contrast, facade data had a lower precision, suggesting a

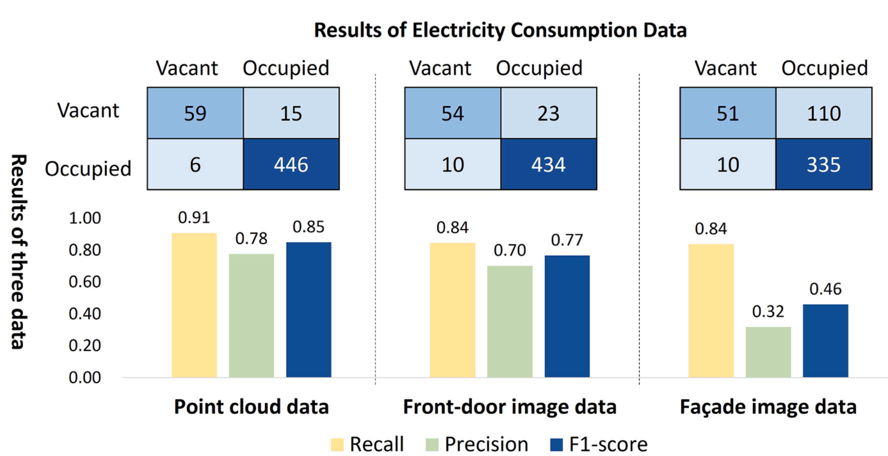


Fig. 8. Accuracy comparison of different data.

higher tendency to mislabel occupied housing as vacant.

5. Discussion and conclusions

5.1. Academic contribution compared to previous studies

As a critical component of urban environments, multi-unit residential buildings are increasingly defining the spatial structure of cities [7,8]. Vacant housing within these areas not only leads to energy waste but may also trigger further vacancy rates [14,24]. Thus, accurately identifying the distribution of vacant housing is crucial for urban governance, facilitating the effective reuse of existing housing resources, minimizing unnecessary energy consumption, and preventing vacancy escalation. However, due to the high-rise nature of multi-unit buildings, accurately mapping vacant units presents substantial challenges. This study proposes a methodological framework to systematically identify vacant units within multi-unit residential buildings on a large scale.

In this study, we propose an innovative framework for identifying vacant housing units in multi-unit residential buildings, presenting several significant contributions in terms of novelty and practicality:

(1) High granularity: achieving vacancy identification at the unit level in multi-unit residences

This study introduces a multi-innovative framework that leverages nighttime point cloud data, front-door image data, and façade image data to identify vacant units within multi-unit residential buildings. Unlike previous studies, which either focused on vacancy identification in single-family buildings or assessed housing vacancy rates at the parcel level in multi-family buildings, our approach extends the analysis to the individual residential unit level, which enables a much deeper understanding of vacancy distribution within multi-unit residential complexes. Specifically, traditional methods, such as using street-view imagery [39] or remote sensing imagery [40] to identify poorly maintained housing, often fail to address the complexity of multi-unit residential buildings, because visual similarities across units and buildings in fixed areas can obscure vacancy patterns. By focusing on the unit level, our method provides a more accurate and detailed vacancy analysis specifically suited for multi-unit residential buildings, offering critical insights for optimizing urban spatial resource management and improving vacancy mitigation strategies.

(2) Strong transferability **– a self-sufficient data ecosystem**

Unlike previous studies that rely on third-party data, this research utilizes self-collected data such as daytime and nighttime point cloud data obtained through consumer-grade drones and front-door image data and façade image data obtained through smartphones. The key merits of this methodology lie in its non-invasive data collection, comprehensive spatial coverage, high spatial resolution, high data availability and low subjective bias. Specifically, this approach overcomes the limitations of third-party data, such as incomplete regional coverage and insufficient resolution in sources like street-view imagery [39] or remote sensing imagery [40]. Additionally, it addresses accessibility issues associated with electricity consumption data and location-based services (LBS) data, which often incur privacy concerns and costs [38]. In contrast to conventional methods like questionnaires, interviews, and on-site household surveys, our approach is non-invasive and does not depend on resident cooperation [46]. Additionally, these traditional methods are typically sample-based, necessitating multiple rounds to mitigate chance-related biases and remaining susceptible to the introduction of subjective biases from both residents and enumerators.

Furthermore, while the data collection process involves investments in equipment, operator training and the time required for data gathering, the method proves to be relatively efficient. The complete data acquisition for 1020 housing units required 12.5 h for nighttime point clouds, 17 h for front-door images, and 6 h for façade images. This equates to an average data collection time of less than one minute per housing unit. Such a relatively low temporal investment demonstrates the practicality and cost-effectiveness of our research method, thereby enhancing the transferability and applicability of the proposed framework.

(3) **High automation – saving time and reducing costs in manual review and virtual auditing**

The methods employed in this study are highly automated, significantly improving data processing efficiency. Machine learning and spatial analysis techniques are used to automatically process nighttime point cloud data, enabling fast and accurate assessments of unit vacancy. In the realm of image analysis, this research utilizes advanced multimodal large model to interpret front-door and façade image data. The efficacy of such models in extracting salient information from images is well-established in prior literature [47,48], and in our own validation, the multimodal large models achieved F1-scores ranging from 0.69 to 0.98, underscoring their reliability. This automated workflow not only increases processing efficiency but also enhances the scalability and operability of the framework, making it suitable for broad implementation.

5.2. Performance of different datasets

This study validates the use of electricity consumption data against nighttime point cloud data, front-door image data, and facade image data to assess their relative accuracy in vacancy detection, revealing that point cloud data performs best, followed by front-door image data, with façade image data showing the lowest accuracy.

(1) Electricity **consumption data**

Electricity consumption data, while highly accurate, presents significant challenges for large-scale acquisition due to privacy concerns. First, data accessibility presents a formidable obstacle. Despite low time costs for onsite collection, data gatherers must enter each building to access meters, which are often concealed in non-visible areas, complicating collection. The data is processed through manual structuring, incurring high processing costs. However, in many Chinese cities, residential compounds are gated communities where electricity meters are centrally located in locked rooms, rendering them physically inaccessible to external researchers. Furthermore, with increasingly stringent privacy regulations, smart meter data are often encrypted, making it difficult even for property management to share raw data with third parties. Consequently, obtaining such data necessitates protracted coordination with utility companies or government agencies—a process characterized by low success rates.

Second, the incomplete coverage of smart meters further contains this method. In our own study area, for instance, only 51.57 % of residential units had corresponding smart meters, a proportion that is likely lower in older districts or less-developed cities. Previous research also indicates that electricity meter data can only measure vacant housing that has been sold but remains vacant, as unsold vacant units lack meter data [49]. These factors underscore the poor scalability of this data source.

(2) Nighttime point cloud data

By contrast, point cloud data requires lower labor costs for collection and processing, as it can be gathered without the collector entering the residential compound. This method achieves high accuracy, with an F1 score reaching 0.85, and covers all residential units within the study scope. These attributes contribute to its superior transferability and applicability. Observed inaccuracies in vacancy detection using point cloud data fell into two categories: a few vacant residences were erroneously identified as occupied due to reflected street lighting on lower floors, and 15 occupied residences were not detected as such due to unlit conditions during data capture. Although point cloud data collection took 12.5 h, findings indicate that after 7 collection rounds, the F1 score approximated 0.7, surpassing 0.75 by the 13th round, and exceeding 0.80 by the 15th round (Fig. 9). These findings suggest that the accuracy of nighttime point cloud data can be optimized with additional rounds of collection, and the efficiency of data acquisition improves with fewer

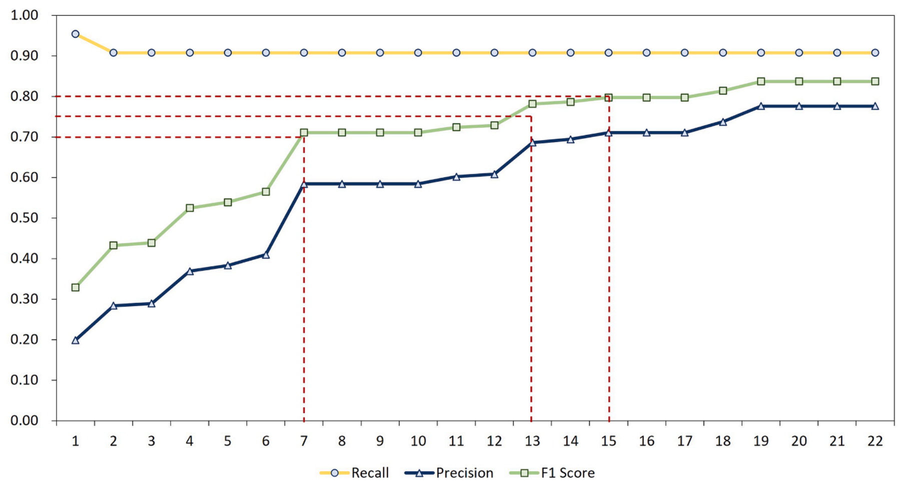


Fig. 9. The impact of point cloud collection frequency on the accuracy of vacant housing identification.

rounds while maintaining a high level of accuracy. Nevertheless, the limitations of point cloud data must be considered, such as the extensive approval processes required for strictly regulated areas, degraded drone positioning and stability within urban canyons, and its sensitivity to weather conditions.

(3) Front-door image data

Front-door image data offers low collection costs, requiring no specialized equipment and providing full residential coverage within the study area. Although less accurate than point cloud data, it still achieved an F1 score above 0.70. However, collection is labor-intensive, necessitating that collectors walk through buildings to capture images at each housing units. Indicators of occupancy—such as shoe racks or refuse at the doorstep—often reflect unregulated resident behavior, which introduces variability based on the level of residential building management and individual behavior.

For example, in this study, there were 23 occupied housing units where no visible signs of habitation, such as garbage disposal or other typical indicators, were observed in front of the residences. Furthermore, culturally specific features, such as Chinese couplets at doorways, suggest that occupancy indicators should be tailored to the region studied. Notably, the study's multimodal model automates feature recognition, eliminating the need for manual dataset annotation or model training, thus enhancing the approach's scalability.

(4) Façade image data

Lastly, facade image data is the least labor- and time-intensive to collect, requiring entry to the residential area but not to individual buildings. However, this study found that facade imagery provided low coverage and accuracy, with an F1 score of only 0.46. This limitation stems from the reliance on balcony features to infer occupancy status, which proves problematic. Because, unlike the open balconies used in previous studies employing commercial street view data [50], the balconies in the buildings of this study are glass-enclosed, often leading to reflective surfaces that obscure interior details or cause misinterpretations. This further confirms the universality of this research framework.

In summary, the labor and time costs associated with different data collection and processing methods, as well as their coverage and sensitivity to weather conditions, are presented in Table 4.

5.3. Limitations

We acknowledge several limitations in this study. First, the identification of housing units still relies on manual processes; for larger-scale studies, automation of unit segmentation could be achieved by applying deep learning models, as suggested by previous research [51].

Second, our point cloud data, generated via photogrammetry (reconstruction from images), is less effective on low-reflectivity surfaces compared to LiDAR data. While this limitation did not significantly impact our study's focus on nighttime lights, it would become a technical impediment for applications requiring precise identification of building materials or architectural details. Future work could employ LiDAR-equipped drones to improve data precision and broaden application scope, albeit at a substantially higher equipment cost.

Third, the framework's generalizability requires validation in more diverse urban contexts. While this study was conducted in low- and mid-rise areas representative of many Chinese cities, its direct applicability to megacities with super-high-rise buildings presents challenges [52] . For instance, acquiring nighttime point cloud data is hindered by high-altitude winds and GPS obstruction in "urban canyons," which can degrade drone stability and data accuracy [53,54]. These issues could be mitigated with drones that have superior wind resistance and positioning, or through optimized vertical flight paths [55]. Similarly, clutter in high-density common areas can visually occlude front-door imagery [38], and facade reflections on tall buildings can increase uncertainty. Therefore, future research must adapt and validate this framework in challenging high-density, high-rise environments to enhance its robustness and universality.

Furthermore, this study primarily provides occupancy or vacancy status of residential units within a short-term period. To obtain long-term vacancy results, additional data collection over multiple batches

Table 4
Performance of different datasets.

Data type	Equipment	Manual cost	Time cost	Processing method	Coverage	Accuracy
Electricity consumption data	Mobile Phone	High	8 h	Manual	51.57 %	High
Nighttime point cloud data	DJI P4RTK	Moderate	12.5 h	Automatic	100 %	High (F1-score: 0.85)
Front-door image data	Mobile Phone	High	17 h	Multimodal model	100 %	Moderate (F1-score: 0.77)
Façade image data	Mobile Phone	Moderate	6 h	Multimodal model	80.29 %	Low (F1-score: 0.46)

would be necessary.

6. Conclusions

This study addresses the identification of vacant housing units in multi-family residential buildings using an innovative framework and advanced data analysis techniques. The key conclusions are as follows:

(1) **Framework development:** A scalable, multi-step framework was developed for vacancy detection, comparing nighttime point cloud data, front-door image data, and façade image data, validated against electricity consumption as ground truth.
(2) **Effectiveness of nighttime point cloud data:** Among the three methods, nighttime point cloud data demonstrated the highest accuracy (F1 Score = 0.85) and scalability. Its automated processing offers a straightforward, time-efficient solution with relatively low data acquisition difficulty, thereby ensuring superior transferability and applicability.
(3) **Moderate performance of image data:** Front-door image data provided moderate accuracy (F1 Score = 0.77), with multimodal models effectively identifying features indicative of vacancy. Façade image data showed lower accuracy (F1 Score = 0.46) due to challenges like reflective surfaces and limited coverage in complex housing layouts.

CRediT authorship contribution statement

Huimin Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yitong Li:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Qiyuan Hong:** Writing – review & editing, Visualization, Investigation, Data curation. **Nanxi Su:** Writing – review & editing, Investigation, Data curation. **Lihua Rong:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation. **Ying Long:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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