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An occupant-centric control case study based on internet of things and data mining for an office space

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A R T I C L E I N F O

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A B S T R A C T

Although research on Occupant Behavior (OB) and Occupant-Centric Control (OCC) is extensive, the actual application of OCC remains limited. This study addresses this gap by introducing a comprehensive OCC workflow and conducting a case study in an office building in Changsha, China. Firstly, three months of meteorological, indoor environmental, and energy interaction behavior data were collected by multiple IoT sensors from November 2023 to January 2024. In the second step, indoor comfort levels were analyzed according to ASHRAE standards, revealing that 15.3 % of the time during this period fell within uncomfortable intervals. Based on these findings, an OCC experiment was proposed to improve indoor comfort. A data-driven air-conditioning usage behavior model was developed. Subsequently, a two-week pre-heating experiment was conducted following the recommendations of the proposed model. For comparison, non-heating and pre-heating days were alternated. Finally, the experiment was evaluated using occupants' thermal comfort voting and energy consumption analysis. Participants' thermal comfort was recorded using five metrics and one behavioral metric via surveys. Five metrics include thermal sensation, comfort, preference and acceptance. The results indicated a significant improvement in occupant comfort levels, with acceptance ratings increasing from an average of 3.78–4.38. With pre-heating, the air conditioning energy consumption increased by 1.35 kWh per person per day, representing an increase of approximately 0.98 % overall energy usage. Additionally, a web-based platform named OBIoT was developed to integrate this workflow. These findings provide meaningful insights for improving indoor comfort and optimizing energy consumption.

1. Introduction

Occupant behavior (OB) is a key factor affecting building energy consumption [1]. Understanding OB and controlling building systems based on it constitutes occupant-centric control (OCC) [2], which is beneficial to city energy saving [3] and carbon emission [4]. Unlike traditional building automation systems, OCC monitors and responds in real-time to occupants' behaviors and interactions with the environment, enhancing energy use efficiency while significantly improving occupant comfort and satisfaction [5]. OCC

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finely tunes building systems by capturing and addressing the genuine needs of occupants [6]. Liu et al. [7] indicated that using OCC systems can significantly enhance building energy efficiency and comfort, achieving 15 %–25 % savings. Consequently, OCC offers the potential to enhance energy efficiency without compromising occupant comfort [8].

A deep understanding of OB is crucial for implementing OCC and is fundamental in designing effective building control strategies [9,10]. OB primarily encompasses two categories [11]: occupancy status and energy-related interaction behavior. The first category, occupant status, can be divided into several dimensions [12], including whether occupants are present, their number, their locations, and even their identities [13]. Natarajan et al. [14] conducted an exhaustive survey of various occupancy detection and localization schemes, evaluating them against many factors to determine their suitability for home energy management systems. Sithravel et al. [15] used various non-invasive sensors to detect the presence of occupants, including passive infrared (PIR), microwave, and optical sensors. They evaluated the effectiveness of various sensing technologies in real applications for enhancing energy efficiency and meeting user behavioral needs. Mutis et al. [16] employed a combination of deep-learning hardware and software components to build a deep-learning model that accurately predicted the movement and activities of individuals indoors. The second category involves energy-related interaction behaviors [17] and includes how occupants operate systems such as window opening, lighting, shading, HVAC, etc. Wu et al. [18] developed a data-driven approach to extract air conditioning usage behavior models. Dai et al. [19] utilized the k-means algorithm and statistical analysis to compare air conditioning usage OB between an extremely hot summer and a typical summer, according to a dataset supplied by an AC manufacturing company's big data monitoring platform. These studies demonstrated that monitoring and analyzing occupant behaviors enable building automation systems to adjust environments based on occupant needs, enhancing energy efficiency and comfort.

Current research on OCC systems primarily focuses on optimizing the operation of building systems such as lighting, HVAC, and shading systems through advanced algorithms, with some practical applications already demonstrated [20]. For instance, Jin et al. [21] proposed a lighting control system based on a temporal sequential-based artificial neural network. The results indicated that the proposed method achieved higher accuracy for MPC and was successfully applied in an office space. The findings demonstrate significant improvements in indoor thermal comfort duration by 24 % and a reduction in air conditioning usage by 24.7 % in sample rooms. However, the study was limited to lighting systems in controlled office environments, and its scalability to more complex settings, such as mixed-use buildings, remains uncertain. Similarly, Peng et al. [22] introduced an innovative OCC system for HVAC management based on o neural network-based algorithms, demonstrating potential energy savings of 4 %–25 % under real-world conditions. Moreover, the practical application of a deep reinforcement learning (DRL) framework named Branching Dueling Q-network (BDQ) was used to control a real office space [23]. The BDQ model yielded impressive results, including a 14 % decrease in cooling energy consumption and an 11 % improvement in overall thermal comfort. Nonetheless, its reliance on extensive training data and computational resources poses challenges for deployment in resource-constrained environments. In the rapidly advancing field of smart building management, the critical importance of data-driven methodologies in enhancing OCC systems is becoming increasingly evident [24]. However, effectively implementing these algorithms requires accurate and real-time data on occupant behavior and environmental conditions, which is often challenging in practice [25]. Existing studies often rely on idealized datasets or controlled environments, which may not fully capture the complexity of occupant behaviors in real-world scenarios [26]. This study addresses these limitations by incorporating diverse data streams from IoT sensors across different building types and conditions, enabling the development of robust OCC systems that account for real-world variability.

With the advancement of information and communication technologies, integrating Internet of Things (IoT) technology into OCC has become increasingly feasible [27]. IoT technology enables building systems to respond more precisely to occupant needs by providing real-time data sensing and controls [28]. Initially, IoT devices served as supplementary tools for real-time monitoring of OB, offering the capability to transmit data back to the central system promptly [29]. Researchers and practitioners can better understand energy usage patterns by utilizing IoT to gather and process real-time data on OB and environmental conditions [30]. As technology advances, the IoT is directly involved in actual control [31]. For instance, smart homes and buildings increasingly adopt IoT solutions to bolster energy efficiency, elevate occupant comfort, and improve operational performance [32]. Several frameworks demonstrate the potential of IoT-enabled OCC systems, but they also reveal certain limitations. Rafsanjani et al. [33] proposed an IoT-based energy assistant framework named iSEA, which achieved 34 % energy savings during the experimental period. This framework focused on individual user interactions within commercial buildings, using smartphones interfaced with building energy systems to promote energy-aware behaviors, providing real-time feedback and control options. While effective, the study's focus on commercial buildings and individual user interactions may limit its scalability to larger, more complex building environments where diverse occupant profiles coexist. Nweye et al. [34] introduced a framework capable of sensing occupancy profiles and delivering estimations of energy savings. This system, applied to multiple university buildings, utilized smart meters, CO2 sensors, PIR sensors, and image sensors to collect detailed data on occupancy and energy consumption, which was then analyzed to optimize HVAC system scheduling and operation. However, this framework's reliance on a wide range of sensors increases implementation costs and may pose challenges in retrofitting older buildings with limited infrastructure compatibility. Collectively, they offer persuasive evidence that IoT can substantially improve the accuracy and functionality of OCC systems. However, many existing frameworks are constrained by scalability and cost concerns, particularly in large, complex, or resource-constrained environments [35]. This study addresses these limitations by proposing an IoT-enabled OCC system that minimizes dependency on expensive sensor networks through the integration of advanced data fusion techniques.

While the research of OB and OCC both made significant progress over the past few years, real-world applications of OCC in buildings remain relatively rare. One major challenge is the lack of standardized experimental and evaluation procedures, which limits the scalability and generalizability of OCC systems. Zhang et al. [36] proposed an occupancy-based control protocol and comprehensively evaluated the case study. They tested four representative people-counting sensors using an eight-diversity testing protocol to compare sensor performance comprehensively. Despite the robustness of their approach, the study's reliance on controlled environments raises questions about the protocol's applicability to diverse real-world scenarios, where sensor performance may vary significantly. Kong et al. [37] conducted a side-by-side occupancy-based control experiment in commercial buildings, and the results indicated that occupancy-based control could maintain good thermal comfort and indoor air quality (IAQ) with a satisfaction ratio above 80 % while achieving weekly energy savings between 17 % and 24 %. Further advancements in OCC research have introduced adaptive and learning-based controls to improve energy efficiency and occupant comfort. For example, a self-tuned HVAC controller was designed to adapt to the thermal preferences of individual occupants while optimizing energy usage [38]. The experimental results showed a 20 % improvement in thermal comfort and a 15 % reduction in energy use compared to traditional baseline controllers. Park et al. introduced HVACLearn [39] and LightLearn [40]. Both reinforcement learning-based OCCs achieved significant energy savings, with results showing 10 % and 25 % reductions, respectively. Despite their effectiveness, these reinforcement learning-based systems are often limited by their reliance on extensive training data and computational resources, making them difficult to deploy in resource-constrained or older buildings. In addition, due to the limitations of experimental conditions, many OCC studies remain confined to simulation environments. Quintana et al. [41] proposed a simulation tool to apply OCC to building controls to improve occupant thermal comfort. Zhu et al. [42] developed an intelligent HVAC control system tailored to accommodate occupant thermal preferences. Ye et al. [43] evaluated two advanced OCC strategies for energy-saving potential for primary schools, and the energy-saving potentials vary from 1.79 % to 12.41 % for different climates and code versions. The lack of standardized experimental procedures limits the further development of OCC research and hinders its application in real building environments. To bridge this gap, future research must prioritize the development of standardized testing protocols that account for diverse building types, occupant behaviors, and environmental conditions.

Another bottleneck in OCC's practical application is the long-term data monitoring and integration [44]. While initial data collection can quickly establish an OCC system, maintaining its long-term operation requires continuous indoor environment monitoring. This ongoing data collection allows for model adjustments and evaluations, enabling the system to adapt to occupant behavior. Despite its importance, most current OCC experiments have relatively short durations. Hou et al. [45] conducted OCC experiments over time-driven optimal control (TDOC) from July 1 to July 7 for seven days and event-driven optimal control from August 1 to August 7 for seven days. The results indicated that event-driven optimal control is more robust in handling model errors and significantly reduces negative rewards. Li et al. [46] assessed the performance of the proposed control strategies in optimizing energy usage and maintaining indoor comfort. Experiments were conducted over one week from July 1 to July 7, with data collected at optimization

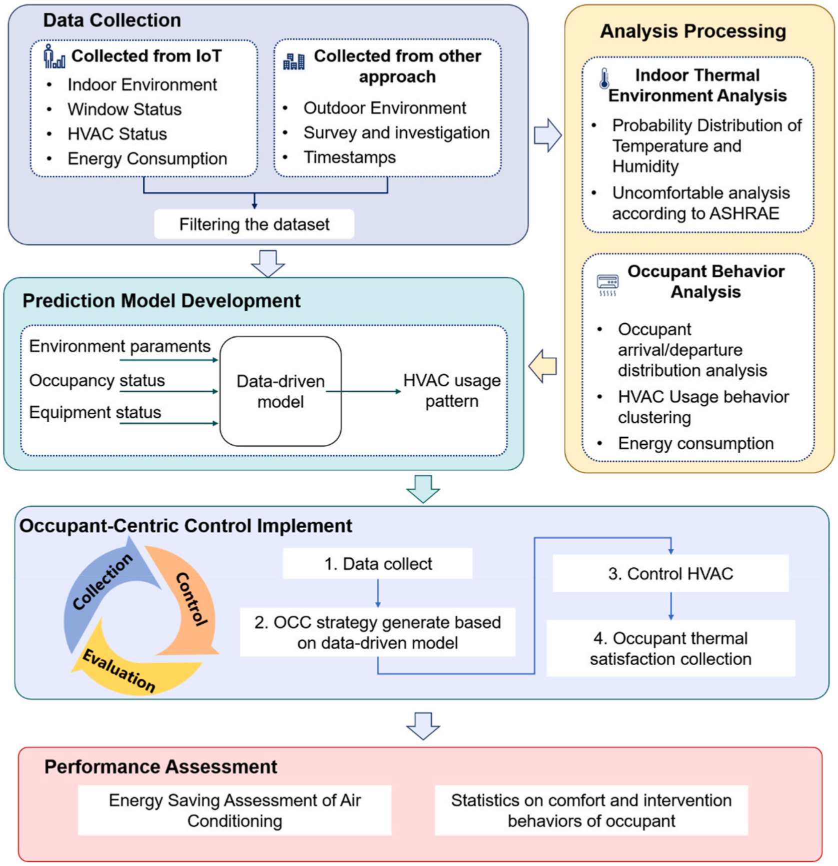


Fig. 1. The entire workflow of this paper.

frequencies of 15 min, 30 min, 60 min, and 120 min to evaluate the impact of model accuracy on TDOC. While the study provided valuable insights into model performance, the limited experimental timeframe raises concerns about its scalability and reliability in extended real-world applications. Jung et al. [47] presented Real-COMFORT, an occupant-centered real-time control system for optimizing indoor temperature using deep learning algorithms. The system was evaluated through climate chamber experiments conducted over 21 days from June 4 to June 25, 2021.

To address these challenges, recent advancements in IoT technology have opened new possibilities for conducting OCC experiments through long-term monitoring of OB data and real-time occupant feedback. This study proposes a workflow for implementing and evaluating OCC experiments in practical settings. The workflow includes five key steps: data acquisition from IoT devices, analytical processing of environmental and OB data, development of predictive models for occupant behavior, implementation of intelligent control strategies for building systems, and extensive performance assessment. To validate this workflow, a case study was conducted in an office space, where a two-week pre-heating experiment was performed to evaluate its effectiveness in terms of comfort and energy efficiency. Moreover, a web-based platform called OBIoT was created to facilitate the integration of this workflow, enabling continuous data collection, analysis, and system optimization. By addressing the limitations of short-duration experiments and leveraging IoT technologies for real-world applications, this study provides a scalable and practical solution for advancing OCC research and implementation.

2. Methodology

The workflow of this study is illustrated in Fig. 1, comprising a five-step process: (1) Data Collection, (2) Analysis, (3) OB Prediction model, (4) Occupant-Centric Control, and (5) Performance Estimation. In the first step, data is collected across three dimensions, including indoor and outdoor environmental parameters, occupant behavior-related parameters, and energy consumption data. The raw data undergoes a rigorous preprocessing procedure to ensure quality and consistency. This stage involves noise reduction, imputation of missing values, outlier correction, and data normalization, setting the stage for comprehensive analysis. In the second stage, the preprocessed data is analyzed to extract key features that reflect capture OB and environmental conditions, including the times of occupants leaving and arriving, indoor comfort levels, and indoor energy consumption levels. The third step uses machine learning models to develop behavioral patterns for air conditioning usage. The input variables include environmental parameters and occupant status, while the output parameter is the number of air conditioning units turned on and off. We conducted a pre-heating experiment in the fourth step to validate our proposed OB model. This two-week experiment aimed to improve indoor comfort by pre-heating spaces anticipating occupant needs. Finally, in the fifth step, the system's performance was evaluated through questionnaires and comparing energy consumption metrics through occupant feedback.

2.1. Data collection

2.1.1. Basic information of case study office room

The case study room used for testing was in a two-story educational building designed for research activities. The room had a total floor area of 40 m^2, with dimensions of 7.6 m × 5.6 m and a ceiling height of 4.3 m. It was equipped with eight student workstations and one teacher workstation. The building envelope consisted of a brick-concrete structure with a wall thickness of 28 cm and a window-to-wall ratio of 10.9 %. The roof was equipped with a layer of insulation. The calculated thermal conductivity of the walls is approximately 1.8 W/m·K. Among the students occupying the eight student workstations, there were three males and five females. The

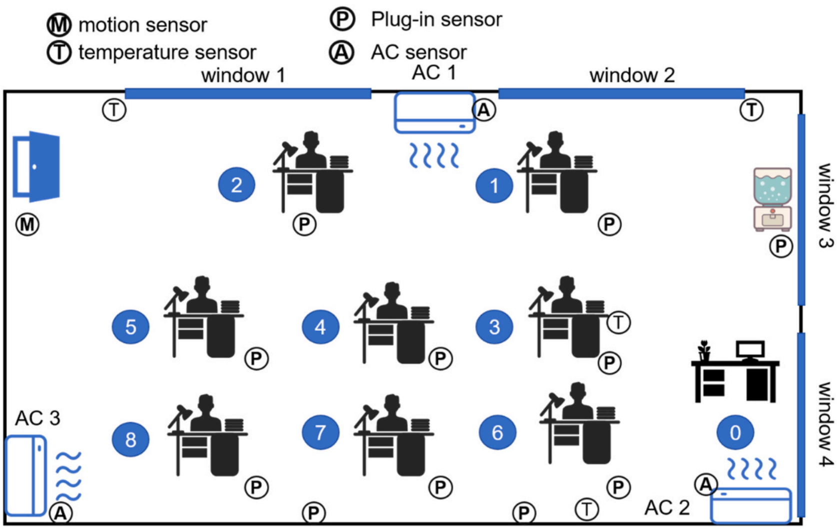


Fig. 2. Layout of the case study office and the sensors.

experiment was conducted mainly on the eight student workstations. As shown in Fig. 2, the room contained three split air conditioners, each paired with an air conditioning companion to enable precise monitoring and control.

Additionally, intelligent sockets were installed beneath each workstation to monitor real-time electricity consumption. In addition, this room also featured four windows, as depicted in Fig. 2, with door and window sensors installed on each window to track their open/close status. Door and window sensors are installed on each window to monitor its opening. Finally, this room has four temperature and humidity sensors and one motion sensor, which are arranged as shown in Fig. 2.

2.1.2. Data collection of case study office room

Table 1 summarizes the number of IoT devices in the case study room, the types and the quantity they include and the parameters they collect. Through IoT communication devices, we send an API request every 5 min to collect indoor environmental parameters, while outdoor devices are set to record data at a fixed interval of 5 min. In addition to the four devices mentioned earlier, such as temperature and humidity sensors, there are also ten plug-in devices and five-door and window sensors in this study. The temperature and humidity sensors are installed in locations that avoid direct sunlight to ensure measurement reliability.

2.2. Indoor environment analysis

This study used door and window sensor data to categorize each day into 'Occupied' and 'Unoccupied' periods. This categorization allowed for a focused thermal comfort analysis when occupants were in the room. By analyzing conditions specifically during these occupied periods, the study offers insights into how the indoor environment responds to and meets the needs of its occupants. Unlike approaches that solely analyze indoor environmental conditions, this case study uniquely integrates OB into its analysis of the indoor environment. This integration provides a more holistic understanding of how the space is utilized and the impact of OB on energy consumption and comfort levels.

Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) [48] are two commonly used indices for assessing indoor thermal comfort. These indices are based on Fanger's thermal comfort theory and incorporate various factors, including air temperature, humidity, air velocity, radiant temperature, clothing insulation, and metabolic rate, all of which are key factors influencing an individual's thermal comfort perception in a given environment. Although the PMV and PPD models theoretically provide a comprehensive framework for evaluating thermal comfort, practical application may have limitations. For instance, individuals' perceptions of indoor comfort can vary [49]. Therefore, this paper draws on [50], adopting indoor temperature as a simplified method for quickly assessing indoor thermal comfort. While not as comprehensive as the PMV and PPD models, this approach is particularly suited for situations where comprehensive assessment is not feasible or where quick adjustments are necessary, based on the 80 % and 90 % acceptability thresholds provided by ANSI/ASHRAE Standard 55 [51] in some instances.

2.3. AC usage pattern clustering and prediction

This study's air conditioning control based on the occupant preference model is constructed using a data-driven approach. The Random Forest algorithm is employed to build the preference model. Fig. 3 outlines the sequential methodology the OBIoT platform employs for intelligent HVAC management, emphasizing an occupant-centric approach. The first step is data collection, which is bifurcated into gathering environmental and occupational parameters. Environment Parameters include the indoor temperature (T_{in}), relative humidity (Rh_{in}), and illumination, as well as outdoor temperature (T_{out}) and relative humidity (RH_{out}). Occupant Parameters focus on detecting the absence or presence of individuals, tracking HVAC system interactions, and recording timestamps for each event. The second step, Environment Clustering, involves sophisticated data processing and analytics that feed into black-box modeling. This results in the prediction of environmental conditions, providing a nuanced understanding of the indoor climate. In the third step, HVAC Control Preference, a similar data analytics process is applied to the OB data to deduce black-box models that predict occupant preferences regarding HVAC settings. Finally, the fourth step is OCC, where the system actuates HVAC controls based on data-informed predictions. It includes turning on the HVAC system and pre-heating the space, tailored to the predicted

Table 1
Collection approach for different data in case study office room.

Data Type	Features	Sensor Type	Measure range and accuracy	Collection approach
Outdoor climate data	Outdoor temperature	RS-WS-N01-6*-*	40 °C–85 °C, ±0.3 °C	Local Weather
	outdoor relative humidity	RS-WS-N01-6*-*	0 %–100 % RH, ±2 %	
	wind speed	RS-FSJT-*	0–60 m/s, ±0.3 m/s	
	wind direction	RS-FXJT-*-*	0–360°, 3°	
	solar irradiance		0–2000W/m^2, 1W/m^2	Web site
Indoor environment data	indoor temperature,	WSDCGQ12LM	10~50 °C, ±0.3 °C	Temperature Sensor
	indoor relative humidity,		0~95 % RH, ±0.3 %	
	atmospheric pressure		30 kPã110 kPa, ±120 Pa	
	indoor light intensity	RTCGO15LM		Motion sensor
Occupant related data	Door and window switch	MCCGQ14LM	0; 1	Door sensor
	air conditioning operation and power consumption	KTBL12LM	max 4000 W	AC sensor
	socket power consumption	QBCZ11LM	max 2500 W	Plug-in sensor
	personnel movement at the door	RTCGO15LM	0; 1	Motion sensor

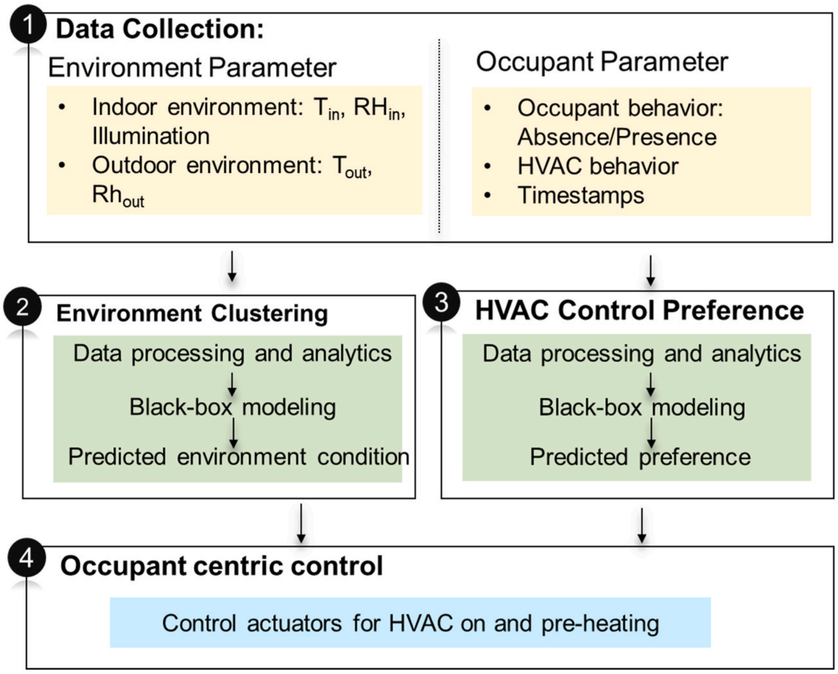


Fig. 3. The Occupant-Centric control logic in this paper.

environmental conditions and the occupants' preferences.

This study employed the data-driven model for cluster analysis and predictive modeling of AC usage patterns. Five widely adopted algorithms are used for the cluster analysis and predictive modeling of AC usage patterns. These algorithms include Xgboost [52], RF [53], gboost [54], LDA, and BPNN [55]. These algorithms have been extensively validated in prior studies for their effectiveness in clustering and predictive modeling, particularly in energy and occupant behavior applications [56]. As illustrated in Fig. 3, the data processing steps of this model are as follows: merging indoor and outdoor environmental parameters to construct the input model and then using a personnel model to trim the dataset, selecting only the data from the first hour of daily occupancy. The AC operation modes are categorized into eight different modes. This modeling approach represents a critical advancement in augmenting the predictive accuracy of the OCC system within the OBIoT platform. The model's primary objective is to forecast the required adjustments in air conditioning systems, ensuring optimal comfort levels are promptly achieved as occupants enter the space. This proactive adjustment strategy is vital for maintaining a balance between energy efficiency and occupant comfort, showcasing the potential of smart building systems in adapting to real-time environmental and occupancy changes.

To evaluate the model's performance and accuracy, we employ a confusion matrix, a powerful tool for assessing classification models. This matrix allows us to visualize the algorithm's performance by displaying the actual versus predicted classifications [57]. The critical components of the confusion matrix include:

$$\text{precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FP + FN} \tag{2}$$

$$\text{recall} = \frac{TP}{TP + FN} \tag{3}$$

True Positives (TP): Instances where the model correctly predicts the need for air conditioning adjustments.
True Negatives (TN): Instances where the model correctly identifies no need for adjustments.
False Positives (FP): Instances where the model incorrectly predicts a need for adjustments.
False Negatives (FN): Instances where the model fails to identify the need for adjustments.

2.4. Model-based pre-heating experiment

After data analysis, a two-week pre-heating experiment was conducted in the case study room. Based on the proposed method, the experiment aimed to achieve partial energy savings while satisfying the occupants' needs as much as possible. To ensure the collection of as much data as possible, the laboratory requested that occupants enter the office at 9:00 a.m. every day. Thermal perceptions, thermal preferences, thermal acceptability, and behaviors were recorded at different time intervals after occupants entered the room, including upon entry, 15 min after entry, 30 min after entry, and 1 h after entry.

In the case study, we discussed the above mentioned scenarios, which can be categorized into six conditions based on the number of air conditioners turned on and whether pre-heating was applied. The six conditions include: (1) no air conditioning, (2) one air conditioner running, (3) two air conditioners running, (4) three air conditioners running, (5) pre-heating with a 15-min advance start, and (6) combinations of the above, as detailed in Table 2. It is important to note that the six conditions describe the broader situational context of air conditioning usage, whereas the "modes" listed in Table 2 represent specific control strategies implemented within these conditions. Based on preliminary research, it was found that after individuals enter an indoor space, the air conditioning takes approximately 15 min to reach a comfortable level. Therefore, the duration for air conditioning pre-heating is set to 15 min.

To assess the impact of the workflow on occupants' satisfaction, we employed an RF model to predict the air conditioning operation modes. These modes were then compared with the baseline scenario of no pre-heating (Mode 0). By comparing with the no-preheating scenario, we aimed to evaluate how much the OBIoT platform improves user satisfaction. Due to practical constraints, conducting a fully parallel controlled experiment was not feasible. Instead, the experiment was conducted in an alternating manner. On January 2 and every alternate day, the operation mode was used Mode 0. On other dates, the operation mode was determined using the proposed model. The air conditioning operation modes observed during the experiment were limited to Mode 0, Mode 4, Mode 5, and Mode 6. This was primarily due to weather conditions during the experiment, which did not meet the requirements for other modes. For instance, the outdoor temperature and humidity during the experiment did not necessitate the activation of individual air conditioners or the simultaneous operation of all three air conditioners. All participants were instructed to enter the office at 9:00 a.m. on the experiment dates to ensure consistent management. The control mode records during the experiment are shown in Table 3.

2.5. Experiment performance evaluation

The subjective responses and scale divisions were designed based on the studies conducted by He et al. [58], as shown in Table 4. To evaluate participants' thermal perceptions over time, their responses were recorded at four specific time points: immediately upon entering the room, 15 min after entry, 30 min after entry, and 1 h after entry. All participants were instructed to remain seated during the recording periods to minimize external influences, and the indoor environmental conditions (e.g., temperature, relative humidity) were logged simultaneously to correlate subjective sensations with objective data.

2.6. Platform development

There are many web-based platforms for urban buildings [59]. The interface display of OBIoT is shown in the diagram below. Currently, OBIoT consists of three pages: Home page, Device Management page, and User interface Page. The Home page provides an overview of OBIoT's basic information, including a brief description and relevant information about the development team. The Device Management page allows users to view the online status of all IoT devices, their associated gateways, and the rooms in which they are located. This information is presented in tabular form. The User Interface page is a data overview page designed to access and view relevant data for registered users. The platform's user interface page is intuitively designed for optimal user engagement and functionality, as shown in Fig. 4. The interface is segmented into distinct sections; the left navigation bar is dedicated to selecting different locations, enhancing user interaction by allowing easy access to various geographical data points. At the top, a separate navigation bar is available to select diverse parameters, facilitating a tailored data analysis experience according to the user's specific needs. The centerpiece of the interface is a dynamic 3D visualization area, offering users the flexibility to change viewpoints and interact with the data in a spatial context, thereby enriching the analytical process. On the right side of the interface, data visualization charts are displayed, correlating with the selected parameters and providing a comprehensive and immediate representation of the data trends and insights. This layout streamlines the navigation process and significantly enhances the platform's data exploration and analysis capabilities.

3. Result

3.1. Indoor environment analysis

This paper used data from November 1, 2023, to January 15, 2024, for analysis and illustration. And the monitoring period consisted of two distinct phases: an unobtrusive monitoring phase lasted two months, from November to December, followed by an OCC experiment conducted on weekdays between January 2 and January 12, 2024.

Table 2
Control mode in the case study.

Mode	Control	Mode	Control
0	No pre-heating	4	Turn on AC#1 and AC#2
1	Turn on AC#1	5	Turn on AC#1 and AC#3
2	Turn on AC#2	6	Turn on AC#2 and AC#3
3	Turn on AC#3	7	Turn on AC#1, AC#2 and AC#3

Table 3
The control mode in the experiment.

Date	Control Mode	Date	Control Mode	Date	Control Mode	Date	Control Mode
24-01-02	Mode 0	24-01-03	Mode 4	24-01-04	Mode 0	24-01-05	Mode 4
24-01-08	Mode 5	24-01-09	Mode 0	24-01-10	Mode 6	24-01-11	Mode 0

Table 4
The subjective responses and scale divisions of thermal comfort and behavior.

Scale	Thermal sensation	Thermal comfort	Thermal preference	Scale	Thermal acceptation	Behavior
3	Hot	Very comfortable	Much warmer	6	Totally acceptable	Turn on AC
2	Warm	Comfortable	Warmer	5	Acceptable	Adjust set point
1	Slightly warm	Slightly comfortable	Slightly warmer	4	Slightly acceptable	Add auxiliary heat
0	Neutral	No feeling	No change	3	Slightly unacceptable	No change
−1	Slightly cool	Slightly uncomfortable	Slightly cooler	2	Unacceptable	Open window
−2	Cool	Uncomfortable	Cooler	1	Totally unacceptable	Add cloth
−3	Cold	Very uncomfortable	Much cooler			Turn down AC

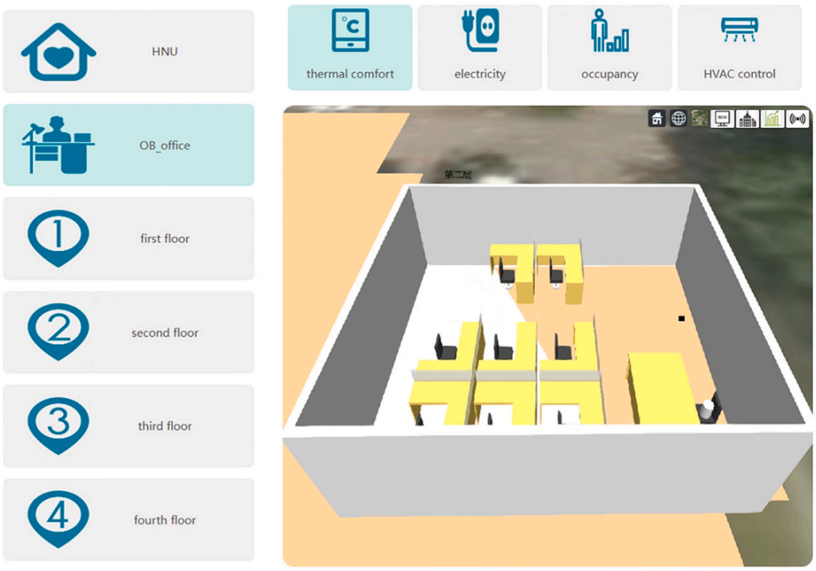


Fig. 4. User interface Page display.

3.1.1. *Indoor environment with occupied*

During the indoor environment analysis, the daily timeframes when occupants were present in the office were extracted, capturing their initial arrival times and final departure times. The thermal and humidity levels within this timeframe were then examined. Additionally, the proposed platform's algorithm was employed to estimate the ratio of indoor thermal comfort zones, providing insight into their perceived comfort.

In the environment shown in Fig. 5, during the observation period, the outdoor temperature ranged from −4.5 °C to 24.5 °C, with an average temperature of 8.45 °C (std = 5.76). The outdoor relative humidity ranged from 25.6 % to 95.9 %, averaging 69.5 % (std = 15.1). These fluctuations in outdoor conditions directly influenced the indoor environment, emphasizing the importance of efficient control strategies. The indoor temperature ranged from 8.69 °C to 28.1 °C, with an average temperature of 19.2 °C (std = 2.57). The indoor relative humidity ranged from 18.5 % to 74.2 %, averaging 44.5 % (std = 10.4). These values demonstrate that the proposed platform effectively maintained indoor conditions within a relatively stable range compared to outdoor fluctuations. However, the variability in indoor conditions still highlights the challenges of achieving consistent thermal comfort, particularly during significant outdoor temperature changes.

In this experiment, the defined occupant arrival time was set at 9:00 a.m., with a fixed working schedule from 9:00 a.m. to 6:00 p.m. However, the last person typically left the indoor space around 11:00 p.m. Fig. 6 below presents the occupancy schedule statistics during the experimental period.

Furthermore, the thermal comfort acceptability during the occupied period was analyzed, as shown in Fig. 7. The "Occupied period" of the room was defined as the time interval between the first arrival of an occupant and the last departure, based on data

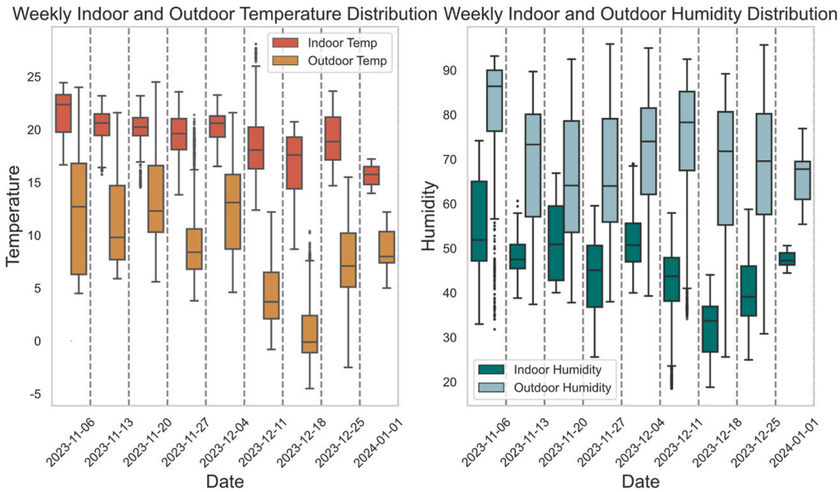


Fig. 5. The temperature and humidity distribution.

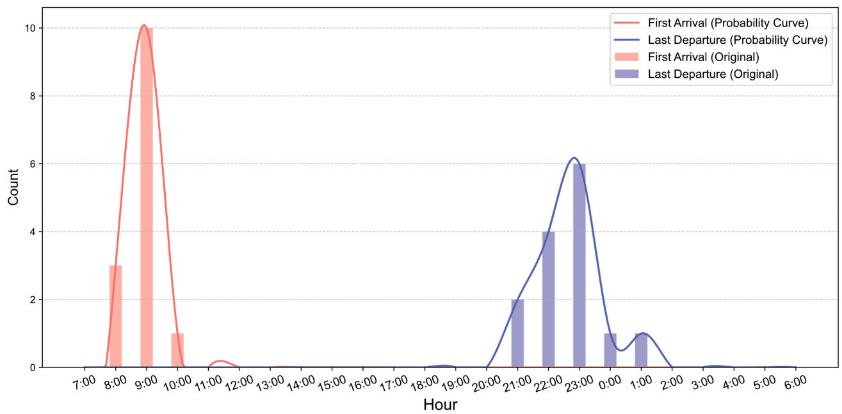


Fig. 6. Actual occupancy schedule with probability curve.

extracted from door and occupancy sensors. During these occupied periods, the indoor thermal comfort situation was analyzed. The results revealed that, among all measured data points, 28.6 % were located outside the thermal comfort range of 90 %, and 15.3 % were outside the 80 % range, highlighting instances where the indoor environment deviated from optimal comfort levels.

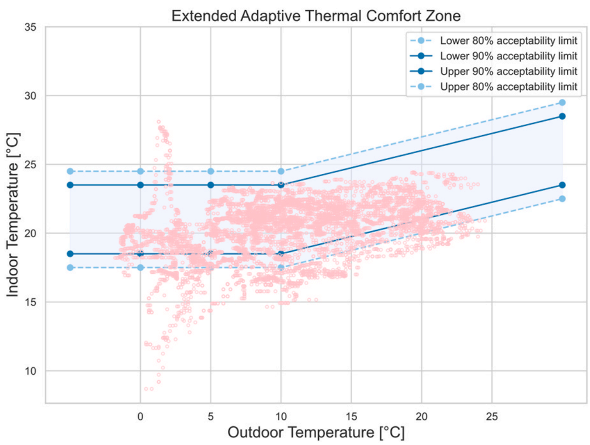


Fig. 7. Thermal comfort distribution when the case study room is occupied.

Further analysis revealed that among the points falling outside the 80 % thermal comfort range, 62.6 % were recorded before 12 p.m. Additionally, 87.2 % of the points with temperatures below the 80 % interval were identified during the morning hours. Specifically, the probability of encountering temperatures below the 80 % comfort range was 2.2 % around 8 a.m., 14.6 % at 9 a.m., 22.5 % at 10 a.m., and 15.5 % at 11 a.m., coinciding with the times people typically enter the building. Therefore, increasing the temperature at these entry moments can effectively enhance the comfort of occupants indoors.

3.1.2. Energy consumption analysis

In the case study room, this research installed ten plug-in devices, nine of which were located at individual workstations and one dedicated to monitoring the electricity consumption of a water dispenser. Monitoring eight student workstations revealed significant individual differences in energy usage due to device use patterns and occupant behavior. For instance, the average power consumption at seat #7 was 146.8 W due to the use of a high-power supplementary heating device. In contrast, Seat #2 was only 6.09 W, likely reflecting minimal device usage. Based on the statistics, the total plug-in energy consumption in the case study room was 151.25 kWh in November and 240 kWh in December, reflecting a seasonal increase in energy usage. These findings provide a valuable reference for developing a prototype building simulation model, particularly by incorporating occupant behavior and individual device usage into the analysis.

Fig. 8 provides a visual representation of the energy usage patterns at individual workstations over a specified period, highlighting the variations in power consumption. In particular, the graph illustrates a notable variance in energy consumption across the different seats. From the data gathered during the initial weeks, it was observed that the users at seats #6 and #7 exhibited behavior of not powering down their computers after work hours, which resulted in a persistent energy load throughout the night. Such patterns are vividly depicted in the graph, where a sustained level of energy usage is visible for these particular seats during off-hours, as opposed to the baseline energy consumption of other seats. Moreover, a significant spike in energy usage at seat #7 is observable during the seventh and eighth weeks. This surge corresponds to when the occupant utilized a high-power supplementary heating device, markedly elevating the energy consumption beyond the usual levels experienced at other workstations. This deviation from the norm is particularly prominent in the graph and aligns with the quantitative findings. The graph and associated data underscore the importance of addressing the energy wastage resulting from behaviors such as leaving computers on when not in use and operating high-energy-consuming devices without regulation. Implementing automated systems for shutting down or switching devices to energy-saving modes during unoccupied hours presents a tangible opportunity for energy conservation (see Fig. 9).

Additionally, monitoring and managing the use of high-power appliances can further enhance energy efficiency within the workspace. The insights drawn from the individual energy consumption profiles, as visualized in the graph, are integral to developing effective energy management strategies. They inform the design of intelligent building models that can dynamically respond to collective and individual energy use trends, ensuring a balance between operational efficiency and occupant comfort.

3.2. HVAC usage model assessment

Table 5 provides the results of the analysis and predictive modeling of air conditioning usage patterns. Table 5 emphasizes Xgboost as a robust classification algorithm with outstanding performance in this study and the highest precision, at 0.96, making it suitable for analyzing and predicting air conditioning usage patterns. These results provide valuable insights into the performance of different algorithms, helping researchers select the best one for their specific tasks.

Models with commendable predictive strength, such as Xgboost and RF, have prediction accuracies in Tables 6 and 7. Table 6 performs well in classifying labels 0# and 6#, with most predictions being correct, but it shows a relatively higher number of misclassifications for label 1#. Particularly for label 6#, despite mostly accurate predictions, there is noticeable confusion with labels 0# and 2#. Table 7 accurately predicts labels 0# and 4#, demonstrating good classification performance. However, labels 2#, 3#, and 7# exhibit some misclassification, especially label 2#, which is significantly confused with label 0#. These analytical results reveal the strengths and weaknesses of each model on specific labels, providing a basis for improving the models and adjusting classification strategies.

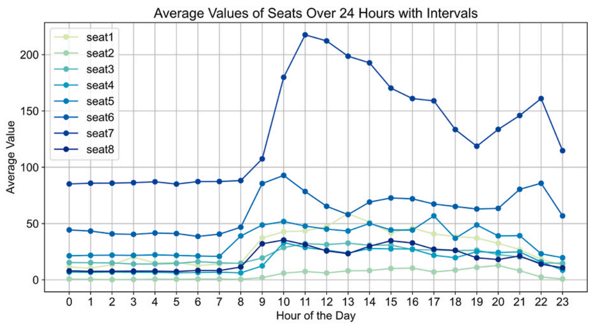


Fig. 8. Plug-in Energy consumption during the monitoring.

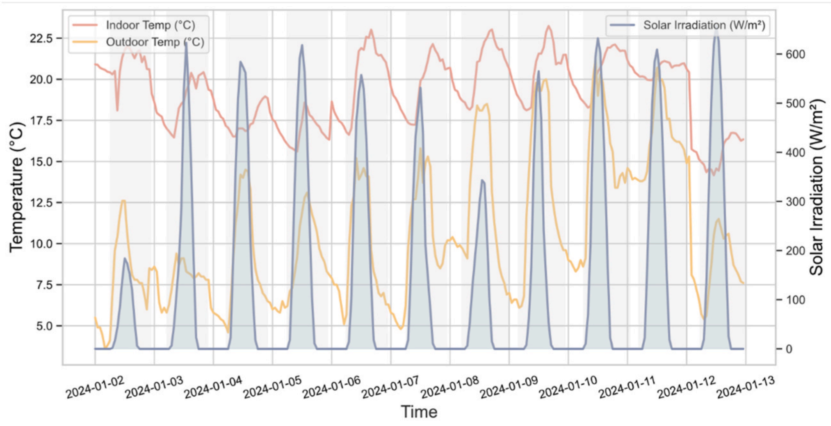


Fig. 9. Indoor and Outdoor Temperature with Solar Irradiation during the experiment.

Table 5
The classification result from different algorithms.

	Xgboost	RF	Gboost	LDA	BPNN
Accuracy	**0.95**	0.85	0.88	0.55	0.61
Precision	**0.96**	0.86	0.88	0.58	0.58
recall	**0.96**	0.85	0.88	0.48	0.61

Table 6
Confusion matrix of the Xgboost model for AC usage pattern classification.

		Predicted type							
		label 0#	label 1#	label 2#	label 3#	label 4#	label 5#	label 6#	label 7#
Observed type	label 0#	848	2	8	0	0	0	4	0
	label 1#	6	91	0	0	0	0	0	2
	label 2#	4	0	99	0	0	1	3	1
	label 3#	1	0	1	31	0	0	0	0
	label 4#	0	0	0	0	16	0	0	0
	label 5#	1	0	1	0	0	7	1	0
	label 6#	17	0	2	0	0	0	271	3
	label 7#	1	0	0	0	0	0	5	69

Table 7
Confusion matrix of the RF model for AC usage pattern classification.

		Predicted type							
		label 0#	label 1#	label 2#	label 3#	label 4#	label 5#	label 6#	label 7#
Observed type	label 0#	853	0	5	0	3	0	0	1
	label 1#	13	3	0	0	0	0	0	0
	label 2#	51	0	51	2	3	0	0	1
	label 3#	15	0	1	76	1	0	2	4
	label 4#	69	0	0	2	218	0	0	4
	label 5#	9	0	0	0	1	0	0	0
	label 6#	3	0	1	0	0	0	29	0
	label 7#	23	0	0	1	7	0	0	44

3.3. *The pre-heating experiment result evaluation*

3.3.1. *Thermal comfort evaluation*

The meteorological conditions during the experimental period are illustrated in Fig. 8, showing the trends of indoor temperature (red line), outdoor temperature (yellow line), and solar irradiation (blue shaded area) from January 2, 2024, to January 13, 2024. The gray-shaded areas indicate periods of indoor occupancy. Ideally, parallel experiments should be conducted under similar conditions to eliminate the influence of environmental variable differences across days. However, due to practical limitations, such as the physical constraints of the building and equipment, running the control and experimental groups simultaneously during the study was not feasible. We extended the experimental period and recorded detailed environmental parameters for each day to mitigate the impact of single-variable differences. Except for January 2 and January 8, the solar irradiation levels remained relatively consistent across the experimental days. Additionally, adjacent days were selected for comparison to further minimize variability.

Figs. 10 and 11 present a detailed comparison of average indoor temperature, indoor humidity, outdoor temperature, and outdoor humidity across different hours of the day under pre-heating and non-preheating conditions. The analysis reveals that pre-heating effectively increased the indoor temperature during the early morning hours, providing a more comfortable environment for occupants upon arrival. For example, at 9:00, the indoor temperature with pre-heating reached 15.9 °C, compared to only 14.2 °C without pre-heating. However, the temperature and humidity trends during the rest of the day remained relatively similar between the two conditions. The outdoor parameters show consistent patterns across both scenarios, indicating that the external environment was controlled and did not significantly impact the results. The Pearson correlation coefficient between the outdoor temperatures under pre-heating and non-preheating conditions is 0.948, while that for outdoor humidity is 0.95. This indicates a strong positive correlation between the two, suggesting that the external environmental conditions were consistent across both scenarios, providing reliability for the experimental comparisons. Indoor humidity levels were slightly lower with pre-heating during the early morning hours, potentially due to the operational characteristics of the air conditioning system. This comparison highlights the targeted impact of pre-heating on early morning comfort while maintaining similar environmental conditions during the rest of the day.

Then, in Fig. 12, we analyzed the comfort levels of occupants during different periods using the method described in Section 2.2.2. During the 8:00–10:00 period, satisfaction increased from 55.30 % to 65.40 %, indicating that the pre-heating strategy significantly improved comfort during the initial arrival phase. During the 12:00–20:00 time, satisfaction levels under both conditions were similar, suggesting that the indoor environment was relatively stable, and the impact of pre-heating on comfort was limited. During the 20:00–00:00 period, satisfaction under the pre-heating condition was slightly lower than that under the non-preheating condition, which may be related to the sustainability of pre-heating and environmental changes during the evening hours.

Table 8 provides data on various thermal comfort metrics measured at different time intervals after occupants enter a room, comparing conditions with and without pre-heating. Notably, under the pre-heating scenario, there is a significant improvement in the average thermal perception experienced by occupants as soon as they enter the room. Specifically, the average thermal perception at the time of entry increases from −0.91 in the no-preheating scenario to 0.19 with pre-heating, indicating a shift from a cooler to a more neutral and comfortable sensation. Furthermore, 30 min after entering the room, the thermal sensation improves in the pre-heating scenario, rising from an initial neutral value of −0.06 (without pre-heating) to a more comfortable value of 0.47 (with pre-heating). With pre-heating measures, the average thermal acceptance significantly improved at the moment of entry, rising from 3.78 to 4.44. This data clearly illustrates the benefits of pre-heating in enhancing the immediate and short-term thermal comfort of occupants, providing a more welcoming and pleasant indoor environment from the moment of entry and sustaining this enhanced comfort level as time progresses.

The graphical representations in Figs. 13 and 14 illustrate the distribution of various thermal comfort indices among occupants within the case study office room, both with and without the application of pre-heating. From the stacked bar charts, it is evident that pre-heating has a significant positive impact on occupant comfort. When comparing the 'Entering' data points from both scenarios, there is a clear shift towards more favorable thermal sensation and comfort levels in the presence of pre-heating. This shift is marked by an increased percentage of higher comfort and acceptance ratings immediately upon entering the room and is maintained throughout the subsequent time intervals.

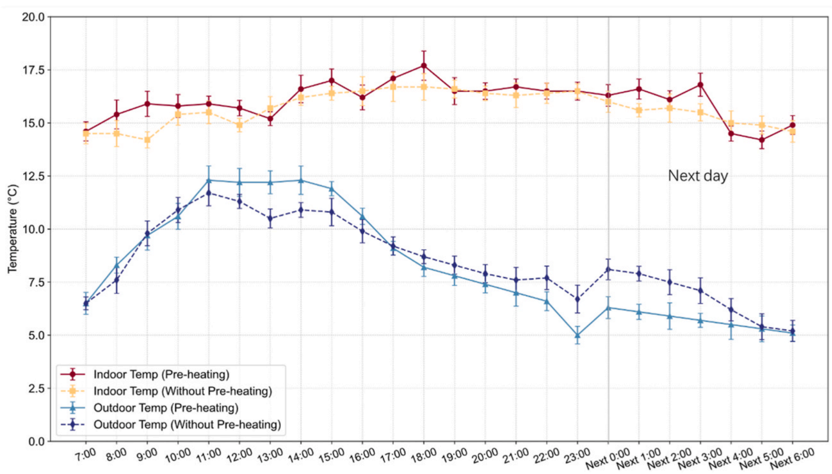


Fig. 10. Average indoor and outdoor temperature comparison (With and without pre-heating).

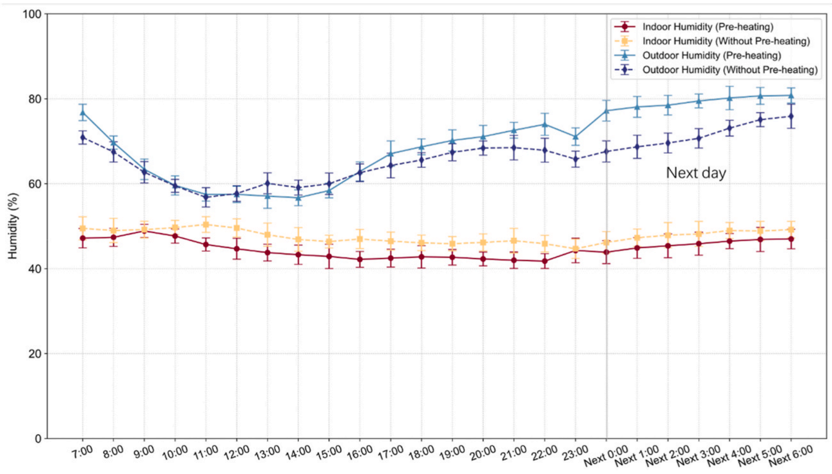


Fig. 11. Average indoor and outdoor humidity comparison (With and without pre-heating).

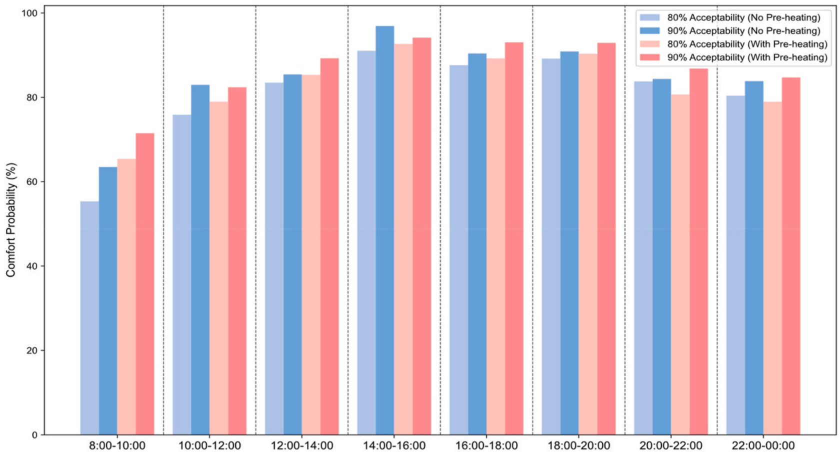


Fig. 12. Thermal comfort probability with and without pre-heating.

Table 8
The average value of thermal comfort votes.

		Average thermal sensation	Average thermal comfort	Average thermal preference	Average thermal acceptation
Without pre-heating	Entering	−0.91	−0.75	1.09	3.78
	15 min after entering	−0.47	−0.31	0.34	4.13
	30 min after entering	−0.06	0.22	0.53	4.34
	1 h after entering	0.03	0.35	1.04	4.73
Pre-heating	Entering	0.19	0.50	0.78	4.44
	15 min after entering	0.41	0.81	0.47	4.94
	30 min after entering	0.47	0.69	0.53	5.00
	1 h after entering	0.28	0.78	1.09	5.13

3.3.2. AC energy consumption evaluation

If the 2 h before occupant arrival and the first hour after occupant arrival are defined as the “pre-heating period,” we calculated the energy consumption differences for each AC unit during the experimental period at 7:00, 8:00, and 9:00 a.m., as shown in Table 9. The total energy consumption during the pre-heating period across all three air conditioning units was 10.78 kWh. This demonstrates that

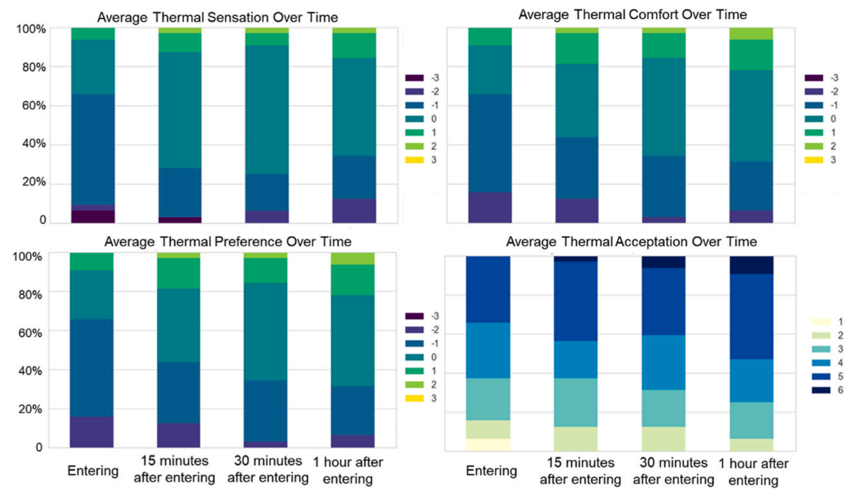


Fig. 13. Thermal comfort distribution without pre-heating.

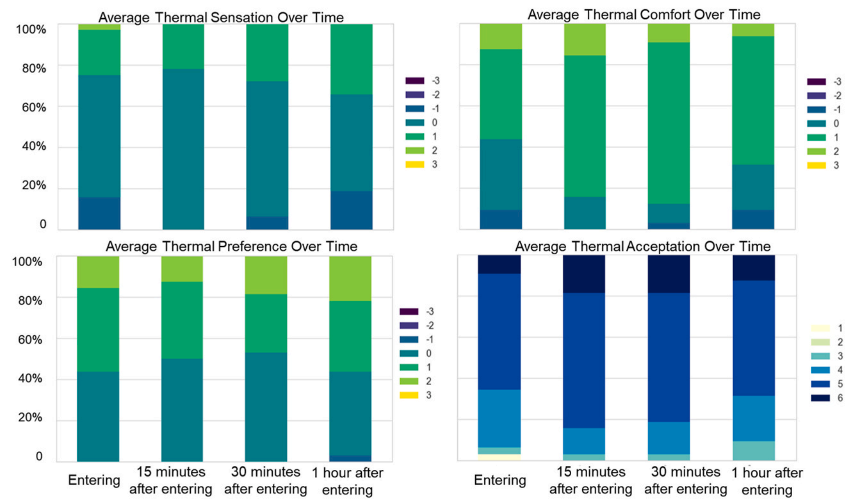


Fig. 14. Thermal comfort distribution with pre-heating.

pre-heating is an energy-intensive process, primarily due to stabilizing indoor temperatures before occupant arrival. Considering an average of eight occupants during the experimental period, the additional energy cost per occupant is approximately 1.35 kWh per person. Compared to the scenario without pre-heating, the energy consumption during the pre-heating period is 1.14 times higher. However, the additional energy consumed during this period accounts for only 0.98 % of the total energy consumption for the entire day, indicating that the extra energy cost of pre-heating is relatively minimal. This highlights the trade-off between achieving thermal comfort through pre-heating and the associated energy cost. While pre-heating ensures a comfortable indoor environment upon arrival, the process incurs a significant energy overhead. Further optimization of pre-heating schedules and air conditioning unit settings could help mitigate this energy cost while maintaining occupant comfort.

Additionally, we monitored the energy consumption of the air conditioning system. Over four non-pre-heated days, the total energy consumed by the air conditioning was 137.57 kWh. In contrast, on four pre-heated days, the total energy consumption dropped to 126.78 kWh. The daily energy consumption results are illustrated in Fig. 15. The charts show that the peak load during days with pre-

Table 9
Energy consumption difference with and without pre-heating for different AC (kWh).

	AC 1	AC 2	AC 3
7:00	0.01	0.00	2.35
8:00	0.88	1.12	3.55
9:00	−0.42	−1.22	4.51

heating occurs earlier than those without pre-heating. This shift in peak load timing can be attributed to the pre-heating process, which requires the air conditioning system to ramp up earlier to achieve the desired temperature when occupants arrive. This earlier peak load during pre-heated days improves occupant thermal comfort during critical periods (e.g., morning entry) and contributes to a more stable and efficient energy consumption profile. However, we acknowledge that multiple factors, including outdoor temperature, humidity, and solar irradiation influence the observed reduction in total energy consumption. We conducted an uncertainty analysis to account for these variables, quantifying the possible impact of climatic variations on the results. The detailed hourly analysis, combined with the uncertainty assessment, provides a more robust evaluation of the proposed pre-heating strategy and its potential for improving energy efficiency in real-world building operations.

4. Discussion

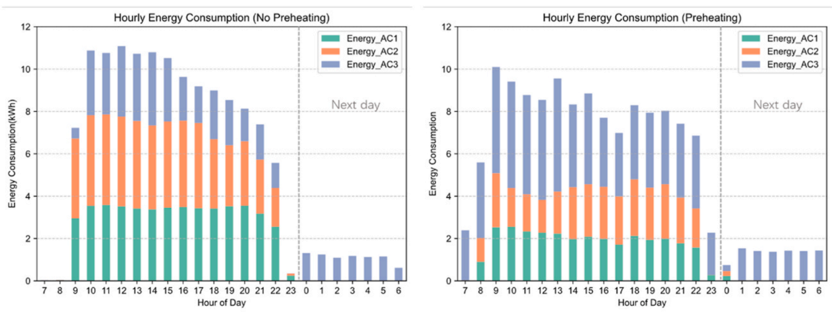
The study proposes a comprehensive OCC process encompassing data integration, analysis-based predictions, actual control mechanisms, and evaluation systems. Compared to innovative environmental control solutions [43,60], the proposed workflow leverages IoT devices to coordinate environmental factors, diverse OBs, and multiple energy-consuming devices. Experimental results demonstrate that the OCC method significantly enhances indoor occupant comfort with minimal energy consumption. Below, we discuss the study's broader implications, the challenges associated with its implementation and scalability, and potential directions for future research.

This workflow integrates data collection and analysis technologies using IoT systems, adhering to ASHRAE thermal comfort standards. It accurately measures key parameters such as indoor temperature to ensure improved thermal comfort for occupants. However, since this study focuses primarily on user feedback, factors such as clothing insulation and metabolic rate, critical for evaluating thermal comfort as outlined in ANSI/ASHRAE Standard 55, were not directly included. Additionally, we established a basic thermal comfort model to evaluate the benefits of temperature adjustments and validated its assumptions through a thermal comfort questionnaire. This approach is not a strictly controlled experiment but is designed to align more closely with real-world engineering applications. In practical scenarios, it is challenging to standardize factors such as occupant movement and clothing, so our research focuses on applicability and feasibility in real-life contexts. Future research will incorporate clothing insulation and metabolic activity data to provide a more comprehensive and precise evaluation of thermal comfort and further analyze its relationship with pre-heating strategies.

Besides assessing thermal comfort, the energy consumption of plug-in devices and HVAC systems is also monitored. The analysis identified instances where appliances were left on when individuals left, indicating significant energy-saving opportunities. This evidence supports the development of automated mechanisms to turn off non-essential devices when rooms are unoccupied, thereby significantly reducing energy consumption and improving the operational efficiency of building management. This strategy aligns with the principles of smart building design, optimizing energy use based on actual occupancy and behavior patterns. Integrating occupancy sensors or IoT-based systems can automatically control appliances, ensuring they operate only when necessary, thus helping to conserve energy.

The proposed workflow is dedicated to enhancing energy efficiency while improving the thermal comfort of occupants, making it a cornerstone for developing smart buildings during colder seasons. With our pre-heating initiative, we've substantially lifted the entry-time thermal comfort from −0.91 to 0.17 and increased the thermal acceptability score from 3.78 to 4.38. This strategy focuses on the well-being of occupants, demonstrating the potential of smart building technologies to dynamically cater to user needs and leading to more streamlined and responsive building management approaches. The pre-heating experiment improves the initial thermal perception of occupants, ensuring a welcoming and comfortable environment from the moment they enter.

While the case study demonstrated promising results, its current scope is limited to scenarios involving air conditioning pre-heating. Future research should explore a broader range of OCC scenarios to unlock more energy-saving opportunities without compromising occupant comfort. Additionally, the study's reliance on historical operation data reveals a potential area for further



a) Average hourly energy consumption without pre-heating

b) Average hourly energy consumption with pre-heating

Fig. 15. Average hourly AC energy consumption for case study office during the experiment.

development. Expanding the research to include online occupant feedback for model adjustments can significantly enhance the adaptability and responsiveness of environmental control strategies, leading to better outcomes in energy savings and occupant satisfaction. It is essential to recognize that occupants exhibit certain inertia in managing indoor environments, indicating that future research needs to more accurately define the real needs of occupants within building spaces.

This study illustrates the workflow's adept use of IoT technology and data analytics to facilitate efficient and sustainable environmental management in smart buildings, simultaneously improving occupant comfort. The platform exemplifies the vast capabilities of IoT and intelligent data analysis in revolutionizing building management practices.

5. Conclusion

This study addresses two major limitations of existing approaches: the limited practical application of OCC and the lack of a comprehensive process for its implementation. To overcome these challenges, we propose a complete implementation process for OCC, enhanced by advanced machine learning and IoT technologies, demonstrating its practical application potential in optimizing thermal comfort and energy efficiency in smart buildings. Through this complete process of real-time smart control, the proposed OCC strategy has been validated in practice, significantly improving occupant comfort, customizing indoor environments to actual usage patterns, and effectively reducing energy consumption. The principal conclusion is summarized below.

- Thermal evaluations indicated that the case study room's conditions fell outside the comfort range for 15.3 % of the observed period, with over 71.1 % of discomfort events occurring in the morning. This underscores the importance of pre-heating strategies in addressing transitional thermal discomfort.
- Integrating high-performance machine learning models, particularly the Xgboost model with 95 % accuracy, provides a robust foundation for predicting OB and advancing dynamic OCC frameworks.
- Pre-heating strategies significantly improved occupant comfort, raising the entry comfort level from −0.96 to 0.17 and thermal acceptability from 3.88 to 4.44. These results validate the real-world effectiveness of pre-heating in enhancing indoor environments. During the experimental period, the average additional energy consumption per person per day during the pre-heating period was 1.35 kWh, representing an increase of approximately 0.98 % overall energy consumption. However, this extra energy cost can be mitigated through optimized scheduling and more efficient daily air conditioning management.
- A web-based platform, named OBIoT, is proposed to implement the entire workflow.

These findings contribute to the growing body of research on smart building management, offering a practical framework for balancing occupant preferences with sustainability goals. The study highlights the value of integrating advanced technologies and real-time data processing to dynamically respond to occupant needs, paving the way for more adaptive and energy-efficient building systems.

CRediT authorship contribution statement

Yue Yuan: Writing – original draft. **Chengcheng Song:** Validation, Software. **Kejun Zeng:** Visualization, Validation. **Liying Gao:** Validation, Data curation. **Yu Huang:** Writing – review & editing. **Yixing Chen:** Supervision, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve readability and detect spelling/grammar mistakes. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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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