

# **A Large Language Model-based Platform for Real-Time Building Monitoring and Occupant Interaction**

## **Abstract**

Effective management of indoor environments requires a comprehensive evaluation of health, energy consumption, and thermal comfort. However, real-time assessment of these factors is challenging due to the lack of integrated applications that combine IoT technology, real-time simulation, and user-friendly interfaces for communication. To address these challenges, this research introduces a novel platform specifically designed to manage health, energy consumption, and thermal comfort in smart buildings, leveraging IoT-based building information modeling (BIM), cloud computing, and an AI-powered conversational suggestion system based on the large language model (GPT). The platform integrates real-time monitoring, simulation, alerting, and persuasion capabilities to manage health, energy consumption, and thermal comfort, enabling responsive building environment controls by assessing tradeoffs among these dimensions and providing timely recommendations. Additionally, it employs persuasive techniques to encourage occupants to adopt environmentally-friendly practices. A case study in a university building demonstrated the platform's functionality and visualization capability. A survey assessing the persuasive system revealed high adoption rates—95.59% for switching rooms to improve indoor air quality and health, and 79.90% for adjusting clothing to enhance thermal comfort—indicating strong participant willingness to adopt sustainable practices through the platform's strategies. The key contribution of this research is the development of a comprehensive, real-time platform that enhances indoor environmental quality and sustainability through advanced monitoring, analysis, and social interaction.

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## 24 Keywords

25 Building Management; Health; Energy; Thermal Comfort; Conversational Persuading System

26

## 27 Nomenclature

IoT	Internet of Things
BIM	Building Information Modeling
GPT	Generative Pre-trained Transformer
GHG	Greenhouse Gas
SBS	Symptoms of Sick Building Syndrome
AI	Artificial Intelligence
HVAC	Heating, Ventilation, and Air Conditioning
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
IAQ	Indoor Air Quality
BMS	Building Management Systems
LLM	Large Language Model
NLP	Natural Language Processing
BIM	Building Information Modeling
MEP	Mechanical, Electrical, and Plumbing
CO <sub>2</sub>	Carbon Dioxide
VOC	Volatile Organic Compounds
PM <sub>2.5</sub>	Particulate Matter with an aerodynamic diameter $\leq 2.5$ micrometers
PPM	Parts per Million
AWS	Amazon Web Services
Amazon EC2	Amazon Elastic Compute Cloud
API	Application Programming Interface
UI	User Interface
VAV	Variable Air Volume
$N_{total}(t)$	Building population at time step $t$
$N_i(t)$	Occupancy in space $i$ at time step $t$
$I_i(t)$	Number of infectors at time step $t$ in space $i$ at time step $t$
$\lambda_{infiltration,i}(t)$	Space infiltration air exchange rate in space $i$ at time step $t$
$\lambda_{ventilation,i}(t)$	Space mechanical ventilation rate in space $i$ at time step $t$
$k_{deposition}(t)$	Deposition rate of viruses at time step $t$
$k_{decay}(t)$	Decay rate for virus infectivity at time step $t$
$q$	Quanta generation rate
$V_i$	Volume of space $i$
IR	Local infection rate
$\mu(t)$	Number of quanta breathed by a susceptible occupant from time $t$ to $t + 1$

$P(t)$	Infection risk associated with time $t$
$T$	Space temperature
$RH$	Space relative humidity
$E_s$	Specific enthalpy
$p_v$	Vapor pressure
$p_s$	Saturated vapor pressure
$V_s$	Specific volume per kilogram of dry air
$C_m$	Moisture content
$p_b$	Barometric pressure
$CH$	County hospitalization data
$IHR$	Infection-hospitalization ratio
$N_i(t)$	Occupancy in space $i$ at time step $t$

## 1 Introduction

In the twenty-first century, sustainable buildings have emerged as a critical focus for both developing and developed nations [1]. Research indicates that the building sector is a major consumer of energy, accounting for approximately 30%–40% of global energy use and over one-third of greenhouse gas (GHG) emission [2,3], which significantly contribute to Global Warming and Climate Change [4,5]. As such, reducing energy consumption in buildings and achieving sustainability are imperative measures to mitigate these adverse effects. Beyond the aspect of energy use, human perception of indoor environments plays a vital role in sustainable building maintenance [6]. With individuals spending more than 90% of their time indoors [7], building configuration and operation greatly influence daily activities, performance and overall well-being. Human thermal comfort is widely recognized as a key factor in enhancing satisfaction within indoor environments [8,9]. Additionally, the last decades have seen a notable increase in respiratory infectious diseases (e.g., influenza [10], measles [11], SARS-CoV-2 [12–14]), profoundly affecting global, society, and the economy. More than 90% of infectious disease outbreaks occur indoors, particularly in densely populated public areas [15]. Therefore, alongside energy consumption and thermal comfort, health has become a pivotal dimension of building sustainability, necessitating robust monitoring and operational strategies to ensure occupant well-

being. Consequently, it is crucial to achieve real-time assessment and analysis of the tradeoffs between these three major dimensions, which prevents the proactive control of and response to pandemics. Facility management teams play an essential role in making informed decisions about control measures, and they must have a comprehensive understanding of the built environment. Beyond the management teams, building occupants are not merely passive users; they actively influence the environments through their interactions with building systems. These interactions significantly impact the thermal and energy dynamics of the buildings [16,17]. Hence, it is equally important to engage with and persuade occupants to actively participate in improving their quality of life and contributing to a healthy and sustainable environment. Such occupancy engagement is essential for the promotion and implementation of acceptable sustainable practices, which will lead to improved health outcomes, enhanced comfort, and reduced energy consumption.

Low-quality indoor environments can have negative effects on residents, leading to increased health issues such as respiratory problems, the exacerbation of asthmatic issues, headaches caused by pollutants, and symptoms of sick building syndrome (SBS) [18]. SBS is a condition in which occupants experience discomfort and health symptoms while spending time in a building, often associated with poor indoor air quality and inadequate ventilation. In addition, inadequate indoor environments can accelerate the spread of diseases, especially airborne viruses [19]. In addition to health concerns, suboptimal indoor environments can result in reduced performance, productivity, and discomfort among occupants [20]. Implementing effective building management measures is crucial for facility management teams to ensure a healthy and sustainable environment while reducing energy consumption. Hence, a timely awareness and understanding of the built environment are essential for facility management teams to make informed decisions and take appropriate actions. An additional challenge for facility management teams is that variations in

occupant behavior can lead to significant differences in the built environment and building energy consumption [21]. For example, studies have found that identical housing units can exhibit electricity consumption variations of up to 600% during certain periods of the year [22], while energy consumption in townhouses can vary by a factor of two [23]. These findings highlight the significant influence of human activities and decision-making on energy use and indoor environmental conditions. Improper occupant behaviors can also negatively impact living quality and the built environment, having adverse effects that not only influence the occupants themselves but also others sharing the same space. Conversely, the adoption of appropriate occupant behaviors can result in significant energy savings and contribute to a better indoor environment for all occupants. Therefore, the development of an integrated platform that caters to the needs of both facility management teams as well as that of occupants is significant for ensuring the maintenance of a sustainable and healthy built environment.

There are currently no existing integrated platforms that can consolidate the essential functionalities of monitoring, simulation, alerting, and persuasion in the context of smart building management. Three knowledge gaps present significant challenges in the development of such a service. Firstly, there is the absence of an integrated technology that consolidates all the necessary functionalities into a single platform. This platform should be capable of completing multiple tasks in real time, including data acquisition and processing, conducting simulations for different models, providing alerts and communication, and persuading occupants through an understanding of their preferences. Each of these capabilities is complex and requires advanced technological infrastructure to fully realize its functionalities. Secondly, there is the inability to simultaneously monitor and simulate variations in health, energy, and thermal comfort in real-time, while still considering both aspect-specific and mutually related parameters. Real-time health assessment

poses distinct challenges, primarily stemming from the complexity of retrieving timely epidemiological-related parameters from specific building locations. To implement effective measures for the protection of public health and safety within buildings, it is imperative to have access to up-to-date and location-specific data on epidemiological factors. The real-time assessment of energy consumption and thermal comfort also faces similar difficulties, including the development of reliable methods for the real-time simulation of occupancy fluctuations, which would enable the tradeoff analysis between health, energy, and thermal comfort. Finally, there is an absence of an AI-based application for the built environment that can interact with both facility management teams and occupants as well as promote healthy behaviors and energy-saving practices. This application should include functionalities, such as alerting facility management teams about abnormal situations (e.g., poor indoor environment, occupant discomfort, and health risks) while featuring a persuasive conversational system that attempts to convince occupants to adopt environmentally friendly behaviors, actively participate in improving their living conditions, and promote energy savings. However, current technologies lack these capabilities and often overlook the importance of occupant engagement in building management.

To address these knowledge gaps, this research proposes the development of an integrated platform for real-time building monitoring and communication aimed at improving overall building management. An IoT sensor network was deployed to enable real-time monitoring, which allowed for the collection of data such as room occupancy and air quality. Off-the-shelf occupant counters were used to determine room occupancy, while air quality sensors were used to measure the levels of indoor pollutants like carbon dioxide (CO<sub>2</sub>), volatile organic compounds (VOC), and fine particulate matter (PM<sub>2.5</sub>). Cloud computing technology was used to ensure real-time data acquisition, storage, processing, simulation of the health, energy, and comfort models, and tradeoff

analysis. The cloud-hosted platform also allowed for all functionalities to be accessed in real time through an integrated web-based application. To enable effective communication, the platform incorporates two key capabilities. Firstly, it provides visualizations of the monitored data and simulated results and is equipped with an alert system that notifies facility management teams of any abnormalities detected in the indoor environment. This capability primarily assists facility management teams with decision-making processes. Secondly, the platform provides recommendations and utilizes an AI-based communication system empowered by LLM to persuade building occupants and encourage them to adopt more environmentally friendly measures. By raising awareness of the positive impact of such behaviors on indoor environment quality and energy savings, occupants may be motivated to make conscious, environmentally friendly choices. In addition, the interaction between occupants and facility management teams allows for the adoption of occupant-preferred living environments and operation strategies, improving occupant satisfaction.

The manuscript is structured as follows: Section 2 reviews relevant literature. Section 3 details the study's methodology, including monitoring, simulation, and web app development. Section 4 presents the case study results, followed by a discussion and future research directions in Section 5. Section 6 concludes with a summary of key contributions.

## **2 Literature review**

### **2.1 Impacts of building environment factors on health, energy, and comfort**

The regulation of heating, ventilation, and air-conditioning (HVAC) systems significantly impacts human comfort and building energy usage [24]. Indoor thermal comfort is a crucial aspect affecting the well-being, health, and productivity of individuals within a built environment [25]. Various

factors related to the surrounding conditions influence occupants' comfort levels. Fanger's model, which underpins the ASHRAE-55 and ISO 7730 standards, is a widely recognized adaptive thermal comfort model that accounts for individual differences such as metabolic rate and clothing insulation [26]. This model was further refined to establish optimal comfort levels for occupants, utilizing the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) as key metrics [27]. Indoor air temperature has a profound effect on thermal comfort perception. Elevated indoor temperatures can cause discomfort and health issues like heat stress, potentially leading to more severe health problems [28,29]. Similarly, relative humidity is a critical component influencing thermal comfort and environmental satisfaction. Low humidity levels have been shown to increase fatigue among undergraduate students compared to higher humidity levels [30]. Air velocity also influences thermal comfort, with studies showing that increased air velocity can lower mean skin temperature and alleviate thermal discomfort in hot and humid climates [31]. For instance, Zhou et al. [32] found a reduction in mean skin temperatures by 0.2°C–0.6°C for every 1 m/s increase in air speed, although inconsistent ventilation patterns may reduce thermal comfort.

Beyond thermal comfort, indoor health risks have gained significant attention in recent years due to the recognition of the role that built environments play in the spread of disease. Several disease outbreaks have been proven to be transmitted through the airborne route, such as measles [11], influenza [10], severe acute respiratory syndrome coronavirus (SARS-CoV) [33], and SARS-CoV-2 [12,34]. Numerous studies have explored the impact of various built environment parameters on the transmission dynamics of airborne pathogens. Factors such as temperature, humidity, and airflow rate have been identified as critical determinants that influence the survival, infectivity, and movement of pathogens within enclosed spaces [35]. For instance, research has shown that low humidity levels can enhance the stability and transmissibility of influenza viruses [36], while



higher temperatures and increased airflow rates can help reduce the concentration and dispersion of airborne pathogens for influenza and SARS-CoV-2 viruses [37–39]. These findings underscore the importance of managing indoor environments in the context of mitigating the consequences of viral transmission.

To maintain sustainable building environments, the aim of managing and adjusting HVAC system settings remains centered on upholding thermal comfort and promoting health, albeit at the expense of energy consumption. The energy usage is contingent upon a multitude of factors, including external climatic conditions and internal variables such as occupancy rates, preferences, heat, and moisture levels [40–42]. HVAC systems play a vital role in regulating indoor temperature and humidity to sustain a comfortable indoor environment [43]. Notably, the COVID-19 pandemic has heightened the significance of indoor ventilation, thereby further amplifying the energy demands. However, the impacts of indoor environmental factors on health, energy, and comfort remain unclear during the monitoring process due to the lack of real-time simulation capabilities. This limitation hinders the ability to account for time-varying environmental factors and their timely effects on the tradeoff relationships between health, energy, and comfort.

## **2.2 IoT-integrated digital twin**

The emergence of digital twin technology has revolutionized the field of asset management and monitoring, providing new opportunities for enhanced control and efficiency. Digital twin technology enables the creation of a virtual counterpart that mirrors the physical asset, leveraging the power of IoT to collect and integrate real-time data from sensors installed in the asset of interest [44–46]. Recent studies have explored IoT-integrated digital twin technologies to enhance building management practices. Zaballos et al. [47] focused on a smart campus concept involving the

integration of BIM tools with IoT-based sensor networks. Their work aimed to monitor the environment, detect emotions, and provide insights into students, leading to the development of an updated digital twin for the campus. Tagliabue et al. [48] utilized digital twin technology to conduct a sustainability assessment of an educational building by employing an IoT-enabled dynamic approach involving real-time evaluation to provide user-centered control of sustainability criteria. This involved constant interaction between the digital twin and the sensors that monitored indoor comfort, air quality conditions, and energy behavior. The digital twin framework supported decision-making processes associated with sustainability. Yitmen et al. [49] proposed a modified cognitive digital twin model focused on using their cognitive ability to detect actions and reasons to inform dynamically processed optimization strategies. By integrating machine learning, cyber-physical systems, artificial intelligence, and IoT technologies, their model aimed to support decision-making in building lifecycle management. Shahinmoghdam et al. [50] developed a BIM- and IoT-based virtual reality tool for the assessment of real-time thermal comfort with 3D data visualization. Zhang et al. [51] designed a multi-indicator adaptive ventilation system for indoor air quality control, using real-time data from the IoT and a digital twin control platform. However, none of these studies utilized IoT-based digital twin technologies to monitor, model, and simulate health and infection risks associated with hazardous viruses. In addition, the ability to analyze the tradeoff relationships between health, energy, and thermal comfort in the context of smart building operations remains relatively unexplored. Addressing these limitations is essential for advancing the application of IoT-based digital twin technologies aimed at maintaining a healthy and sustainable built environment.

### **2.3 Communications technology in building management**

Communication is an essential component of smart building monitoring and operation due to the

importance of sharing information with facility management teams. Various studies have developed different methods of sharing this information with users, including web-based and mobile applications. Mataloto et al. [52] developed an IoT system as part of a larger building energy management system (BEMS), including a platform that used data visualization templates to create a dashboard that allowed facilities management to identify appropriate actions that could lead to potential energy savings. Marinakis and Doukas [53] developed a recommendation system for intelligent BEMS in residential settings that was capable of pushing notifications when parameters exceeded certain thresholds as well as providing analytical, tailor-made recommendations and energy-saving tips. Fernando et al. [54] developed a web application that acted as a dashboard through which users could control the platform and access the energy consumption service. Ribino et al. [55] proposed a human-like social robot-based approach to monitoring indoor environment quality. Currently, communication systems in building operation and management applications primarily focus on tasks such as data visualization and notifications. Recommendations provided during communication are often targeted towards specific, singular objectives, such as reducing energy consumption or improving IAQ. However, there remains a significant gap in terms of the comprehensive analysis of tradeoff relationships between different dimensions such as energy, the indoor environment, and health risks within these systems. In addition, there is a notable knowledge gap associated with the integration of interactive tools that can understand and communicate with users in the field of building management systems (BMS). The effectiveness of these tools would be significantly increased should they be able to fully comprehend simulation results and current environmental conditions, as well as understand user concerns and preferences as expressed through natural language. Developments in this area are expected to bridge this knowledge gap and enhance communication between users and the BMS.

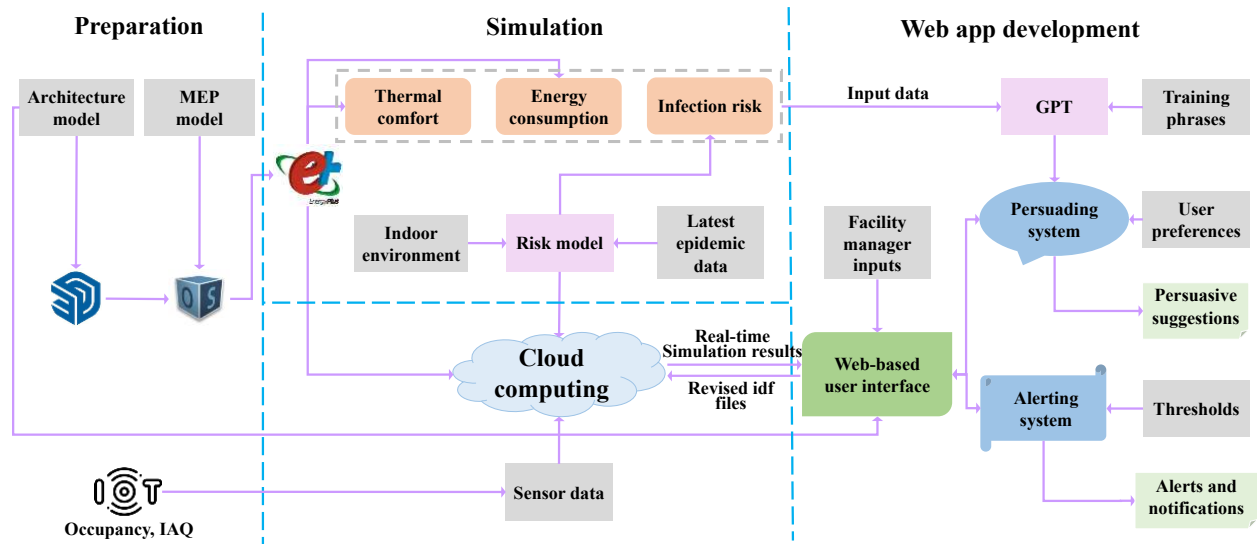
With the recent developments in natural language processing (NLP) as well as groundbreaking advancements in large language models (LLMs) such as ChatGPT, the integration of similar technology into communication systems is extremely promising. ChatGPT is an AI language model developed by OpenAI based on the GPT-4 architecture [56]. Trained in a diverse range of textual data, including scientific literature, technology articles, and other written sources, ChatGPT is designed to generate human-like text in response to user prompts. The GPT-4 model—upon which ChatGPT is built—has gained a considerable amount of attention in the field of NLP [57]. Its applications span various domains, including content generation, language translation, and virtual assistance. GPT-4 is exposed to a vast corpus of textual information during training, including books, articles, websites, and publicly available written content. Consequently, GPT-4 is uniquely capable of parsing the suggestion features present in BMS platforms, while also having the potential to persuade end-users to make rational changes to their behavior by providing them with an understanding of the current condition of the building. However, the integration of this technology into the field of BMS has not been explored in existing studies. Consequently, the novel and unique approach of integrating a GPT-based conversational system with simulation results in a BMS platform to provide persuasive suggestions holds significant promise.

### **3 Methodology**

The primary objective of this study is to develop a real-time building environment management system that leverages sensor data, simulation results, cloud computing, and a web app. This integrated approach aims to optimize building management by providing real-time insights and actionable recommendations for improving health, comfort, and energy efficiency. The proposed framework comprises three phases: preparation, simulation, and web app development, as illustrated in Figure 1.

262

263 In the preparation phase, a BIM of the target building was developed, composed of mechanical,  
264 electrical, and plumbing (MEP) as well as architectural components. This facilitates the  
265 development of the energy model used for the EnergyPlus simulation. Specifically, the  
266 architectural model was imported into SketchUp to represent the building envelope, while the MEP  
267 model was utilized to configure the HVAC system, which was further refined using OpenStudio.  
268 In addition, an IoT sensor network was set up in the building to enable the real-time monitoring of  
269 relevant indoor environment parameters and occupancy status. In the simulation phase, a  
270 comprehensive methodology was implemented to generate outputs describing energy  
271 consumption, thermal comfort, and infection risks based on the collected IoT data and building  
272 configurations. Energy consumption and thermal comfort were simulated through the EnergyPlus  
273 API, while infection risk was simulated using programming scripts that incorporated up-to-date  
274 disease data on the COVID-19 pandemic. During the web app development phase, the platform  
275 that integrated the entire process, ranging from data acquisition to data visualization, was designed  
276 and hosted on a web server environment. This phase focused on providing three primary features.  
277 Firstly, it involved the retrieval of IoT data and up-to-date disease data from cloud storage, which  
278 was then provided to the simulation process. Secondly, the app ran simulations and collected these  
279 results. Finally, the interactive app visualized and communicated the simulated outcomes to users  
280 through the integration of BIM and GPT technologies. The interactive app allowed real-time access  
281 to health, energy, comfort, and air quality information in selected rooms of interest. The developed  
282 platform integrated the three phases within a cloud environment, leveraging cloud computing  
283 technology to store IoT data, perform simulations, and host the web app on the same server. This  
284 integrated framework allowed for efficient computation and real-time communication with users  
285 based on monitored and simulated results.



**Figure 1.** Framework for the development of the web-based application.

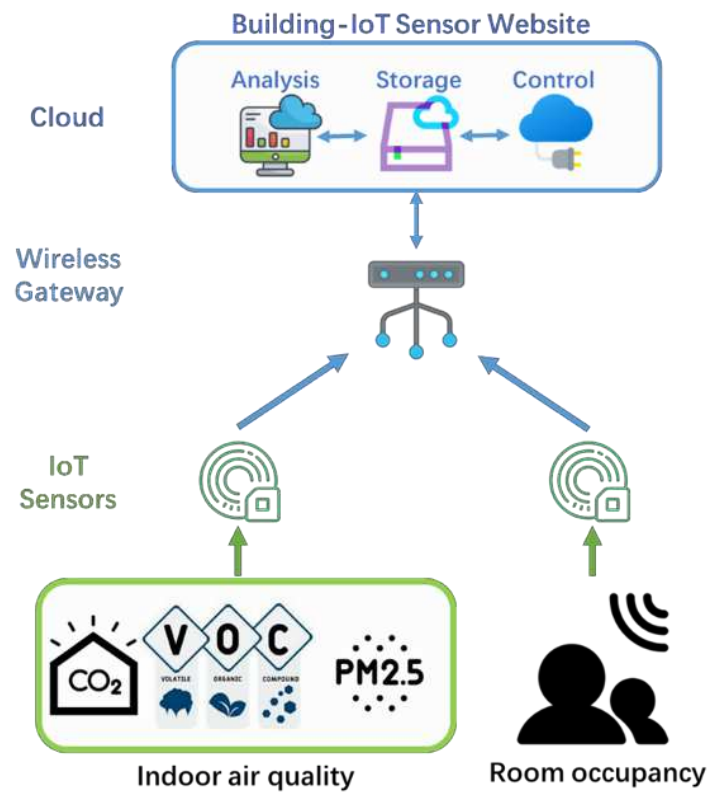
### 3.1 Preparation

#### 3.1.1 Creating the building energy model

The building energy model used in the simulations was generated by combining the building architecture model and the MEP model. The architectural model was imported into SketchUp, enabling adjustments to the building envelope to accurately depict the building envelope and streamline the energy simulations. The HVAC system of the building was subsequently incorporated into the model using OpenStudio based on the HVAC configuration from the MEP model. These modifications were then saved, resulting in a comprehensive model that could be used for energy simulations using EnergyPlus API.

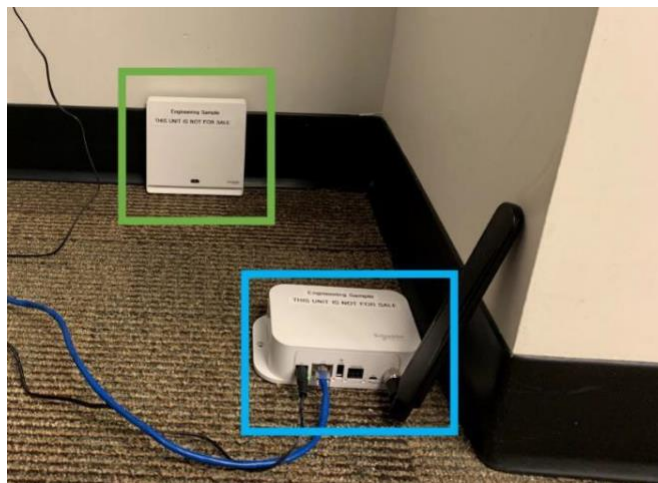
### 3.1.2 Configuring the IoT sensing system

An IoT sensing system was implemented in our case study area to allow for the real-time monitoring of the building environment. The off-the-shelf IoT hardware devices were used to collect data on air quality and occupancy at the room level. The architecture of this system is depicted in Figure 2, illustrating the components and their connections within the IoT sensing system.



**Figure 2.** Architecture of the IoT system.

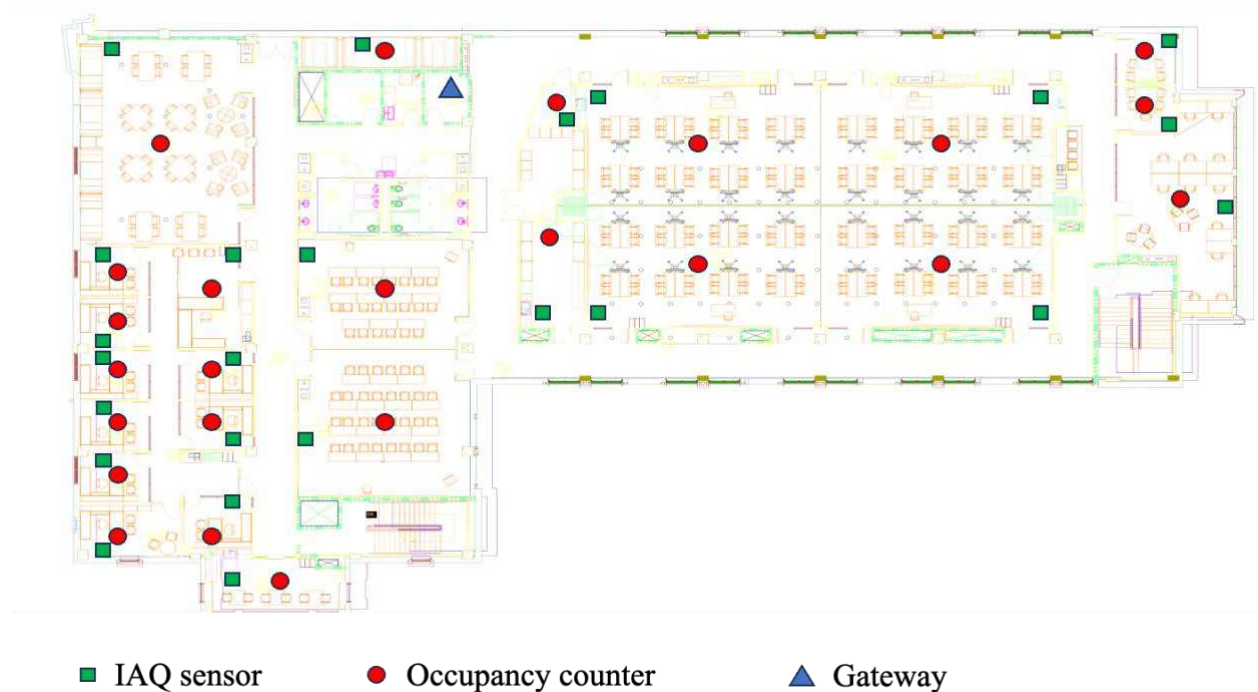
The IoT system consists of two main types of devices: IoT sensors and a wireless gateway. The off-the-shelf IoT sensors employed in the system included IAQ sensors for monitoring indoor air quality and a room occupancy sensor that tracked the number of people in the room. The IAQ sensors were composed of pollutant-specific sensors, including CO<sub>2</sub>, VOC, and PM<sub>2.5</sub> sensors, with data collected and measured in parts per million (PPM) for CO<sub>2</sub>, and micrograms per cubic meter (µg/m<sup>3</sup>) for PM<sub>2.5</sub> and VOC. The VOC sensors also measured the concentration of other pollutants, such as carbon monoxide, ethane, isoprene, and acetone. The system also collected other environmental data, such as temperature (°C), and relative humidity (%). The room occupancy sensor utilized overhead counters to count the number of occupants. The wireless gateway was used to manage the IoT sensors and was responsible for collecting data from the sensors and transmitting them to the Microsoft Azure Cloud Portal where it was saved and accessed by Amazon Web Services (AWS) for further analysis. Figure 3 presents an example of a set-up of the hardware environment, with the IAQ sensor highlighted in the green box, and the gateway highlighted within a blue box.



**Figure 3.** An example set-up of the hardware environment.



In addition to the hardware setup, a building-IoT sensor solution website was used to create a virtual representation of the case study site. In this virtual representation, different rooms were defined as spaces, facilitating the mapping and identification of device locations within the building. In addition, the website was used to create virtual devices, including the gateway and sensors, and synchronize them with their corresponding physical devices. The status and location of these devices were visualized on the website, with different shapes representing different devices (Figure 4).



**Figure 4.** Layout of hardware in the case study site.

### 3.2 Simulation

Once the IAQ and occupancy data have been collected from the off-the-shelf sensors, appropriate simulations were conducted utilizing the data. The simulation phase involves two main components: 1) energy consumption and thermal comfort simulation, and 2) infection risk simulation. The energy consumption and thermal comfort simulation were conducted using

EnergyPlus API. The default setpoints for the indoor environment were configured based on common operational scenarios. For example, during working hours, the heating and cooling setpoints were maintained at 22°C and 26°C, respectively, while during non-working hours, the setpoints were adjusted to 15.6°C and 26.7°C, respectively [58]. The outdoor air supply rate was set to 0.0094 m<sup>3</sup>/s per person [59], and an economizer operational temperature of 28°C was implemented. The default relative humidity range was set to be between 30%–60%, considering a comfortable living environment [60]. Real-time room occupancy was monitored using the occupancy sensor system, which was collected, transmitted, and saved on a Windows server hosted on an Amazon Elastic Compute Cloud (Amazon EC2). This integrated approach ensures that the simulation process uses up-to-date occupancy information, allowing for the accurate analysis and assessment of energy consumption, thermal comfort, and infection risks.

The web application allows facility managers to customize their desired setpoints for the indoor environment with the capability of reading idf files as text, a file format commonly used by EnergyPlus. When users input their desired setpoints, the application allows direct adjustments to the idf file by overwriting the original text. This functionality provides facility managers with a comprehensive understanding of the changes in energy consumption, thermal comfort, and infection risks associated with their desired settings, giving them insights into the effects of different HVAC operation strategies.

In the context of infection risk simulations, our approach considered the dynamic indoor environment within each zone, including factors such as temperature, humidity, and ventilation rate, as well as fluctuating occupancy levels. A derivative of the Wells–Riley equation was used to estimate room infection risk, which was developed and described in detail in our previous

publication [61]. This modified equation allows for the modeling of the hourly zone environment and occupancy changes, enabling a more comprehensive assessment of infection risks. All estimated infection risk data refers to the degree of infection risk at the time when the web app was executed. The hourly infection risk is estimated using Eq. 1.

$$\mu(t) = \frac{1}{N_{total}(t)} \times \bar{p} \times \Sigma_i \left( N_i(t) \int_t^{t+1} C_{quanta,i}(t, \tau) d\tau \right)$$

$$C_{quanta,i}(t) = \frac{I_i(t)q}{V_i K_{total,i}(t)} (1 - e^{-K_{total,i}(t)}) \quad (1)$$

$$K_{total,i}(t) = \lambda_{infiltration,i}(t) + \lambda_{ventilation,i}(t) + k_{deposition}(t) + k_{decay}(t)$$

$$I_i(t) = IR * N_i(t)$$

$$P(t) = 1 - e^{-\mu(t)}$$

$t$  is the time step with a step size of one hour.  $N_{total}(t)$  is the building population at time  $t$ .  $N_i(t)$  is the occupancy in space  $i$  at time step  $t$ , which is achieved from real-time sensing data.  $I_i(t)$  is the number of infectors at time step  $t$  in space  $i$ .  $\lambda_{infiltration,i}(t)$  is the space infiltration air exchange rate in space  $i$ ,  $\lambda_{ventilation,i}(t)$  is the space mechanical ventilation rate,  $k_{deposition}(t)$  is the deposition rate of viruses, and  $k_{decay}(t)$  is the decay rate for virus infectivity.  $q$  is quanta generation rate, set as 142 quanta/h according to the study conducted by Buonanno et al. [62].  $V_i$  is the space volume,  $IR$  is the local infection rate (%), estimated based on the latest epidemiological situation.  $\mu(t)$  is the number of quanta breathed by a susceptible occupant from time  $t$  to  $t + 1$ .  $P(t)$  is the infection risk associated with time  $t$ . Specifically, to account for the impact of environmental factors on the survival and persistence of viruses, the viral decay rate and viral deposition rate are calculated using Eq. 2 [63,64].

$$\left\{ \begin{array}{l} r = r_0 * \sqrt[3]{0.4/(1 - RH)} \\ k_{deposition} = 2\Delta\rho gr^2/(9\mu_a H) \\ k_{decay} = 16.9803 + 0.0622E_s - 0.796p_v - 21.95V_s \\ E_s = 1.007T - 0.026 + C_m(2501 + 1.84T) \\ p_v = p_s * RH/100 \\ V_s = (0.287 + 0.461C_m) * \frac{273.15 + T}{p_b} \\ C_m = 0.622p_v/(p_b - p_v) \\ p_s = 0.61078 \frac{17.2694T}{T + 237.99} \end{array} \right. \quad (2)$$

Where  $T$  is the space temperature,  $RH$  is space relative humidity,  $E_s$  is the specific enthalpy,  $p_v$  is the vapor pressure,  $p_s$  is the saturated vapor pressure,  $V_s$  is the specific volume per kilogram of dry air,  $C_m$  is the moisture content, and  $p_b$  is the barometric pressure.

### 3.3 Cloud computing

#### 3.3.1 Real-time data retrieval and storage

Real-time data was retrieved and stored using IoT sensors, including the latest updates on the epidemic situation. The IoT data is collected using sensors deployed throughout the building, which are then transmitted to the Amazon EC2 for storage and processing. Epidemic situation data is obtained through an API provided by Covid Act Now [65]. This API can be integrated into the cloud-based system, ensuring that the latest epidemic data is readily available for analysis and simulation. Specifically, the epidemic data provided include the county hospitalizations per 100,000 people. The infection rate is then estimated using Eq. 3:

$$IR = \frac{CH}{IHR * 100,000} \quad (3)$$

where  $IR$  is the county infection rate,  $CH$  is county hospitalization data,  $IHR$  is the infection-hospitalization ratio [66].  $IR$  is the prevalence parameter used in the risk simulation model.

### **3.3.2 Computation of health, energy, and comfort parameters**

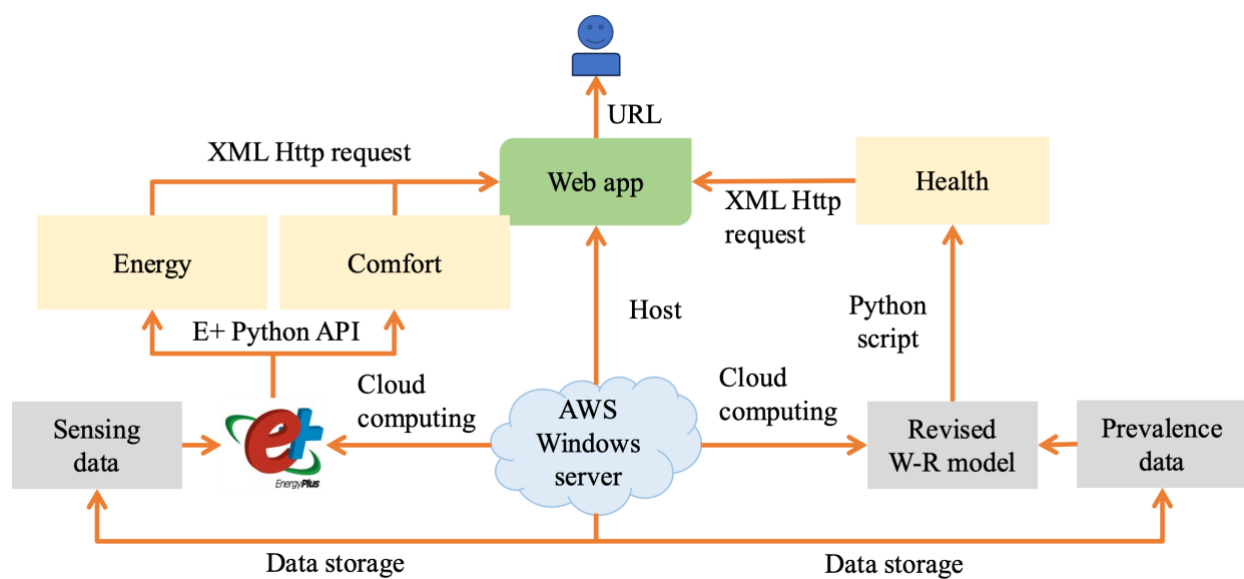
The cloud computing approach determines the health, energy, and comfort parameters through a combination of mathematical models and simulation programming on the cloud server. Health parameters are calculated using the Python implementation of a revised W–R model, which is then saved in a Windows server hosted within the AWS infrastructure. An interface was included in the Python script to facilitate the retrieval of prevalence data from the front end of the web app, allowing for seamless communication between the two scripts. The Windows server described above was specifically built using the EC2 service.

The Python API provided by the EnergyPlus simulation software was used to compute the energy consumption and thermal comfort parameters. This simulation software utilizes the building energy model, along with real-time occupancy data, to calculate energy consumption and assess thermal comfort. These Python scripts are responsible for triggering the simulation process as required as well as generating the relevant outputs pertaining to energy consumption and thermal comfort. Similar to the scripts responsible for the computation of health parameters, these Python scripts are stored within the same Windows server hosted on AWS, ensuring timely integration and accessibility.

### **3.3.3 App hosting**

The web app is hosted on a Windows server, which serves as a repository for IoT data and the Python scripts responsible for cloud computing tasks. This integrated setup allows for the smooth integration of the app and the computing environment. Python scripts that handle various calculations and simulations are triggered by the web app whenever necessary. To facilitate this dynamic interaction, the web app sends inputs to the programming scripts via an XMLHttpRequest

object. This enables users to provide inputs through the web app's user interface (UI), which are then passed on to the scripts for processing. The outputs generated by the Python scripts are read by the web app using the same XMLHttpRequest object and are promptly presented using the app's UI, providing users with relevant information in real time. This hosting configuration establishes a cohesive ecosystem in which the web app and programming scripts collaborate harmoniously, ensuring a seamless and efficient user experience. Furthermore, the web app eliminates the need for users to install additional software, as all of the provided functions are easily accessible through a simple URL. This streamlined approach enhances the app's ease of use, in terms of both setup and interactivity, allowing a broader range of potential users to benefit from its functionalities. The app is not only designed for facility management teams but also for occupants, workers, or anyone temporarily present in the building. By removing the requirement for software installation, the app becomes more inclusive and user-friendly, catering to a wider audience and ensuring convenient access to its features. The flowchart of the proposed cloud computing system is shown in Figure 5.



**Figure 5.** Flowchart of the cloud computing system

### **3.4 Web app development**

The web app developed in this study incorporates several key components aimed at assisting with facility management practices. Firstly, the app allows for the 3D visualization of the building model and time series data visualization, allowing for the real-time monitoring of the building environment. These visualizations aid facility managers by providing them with a comprehensive understanding of the current state of the facility. Facility managers can adjust the setpoints of the indoor environments based on their preference, while also providing them with any changes in the energy consumption or building environment that may arise as a result of these changes. In addition, an alert system allows facility managers to promptly identify and address any abnormalities or deviations from the desired conditions by providing timely alerts and notifications. An AI-based persuasion system was also developed to encourage desirable occupant behaviors and preferences. This integrated system provides facility managers with a deeper understanding of occupant-preferred measures, fostering effective interactions between occupants and facility managers. By leveraging AI technologies, this system offers personalized recommendations and suggestions to optimize both occupant satisfaction and facility management efficiency. Together, these components encompass a robust methodology that integrates visualization, alerts and notifications, and AI-based persuasion systems that allow facility managers to effectively monitor, respond to, and engage with the built environment and its occupants.

#### **3.4.1 Visualizations**

The web app was developed using the NodeJS and Bootstrap frameworks, creating a user-friendly interface that facilitates efficient data visualization and interaction. One notable feature of the app is the 3D visualization of the building architectural model made possible through its integration with Autodesk Platform Services. This functionality allows users to select specific rooms of

interest and observe them highlighted within the 3D building model. The 3D view of the building model can also highlight specific rooms to emphasize the presence of any abnormalities, drawing attention to rooms that require immediate attention or further investigation, aiding in effective decision-making and the prioritization of actions. The 3D building model is also fully interactive, allowing users to zoom in, pan around, and explore different parts of the building. This immersive and interactive visualization system enhances the user experience and provides users with a better spatial understanding of the layout of the building. Example visualization of the 3D building and the described functions can be found in Section 4.

The app is also capable of visualizing the fluctuation of key parameters over time. Line plots are used to illustrate the dynamic changes in energy infection risk, energy consumption, and thermal comfort in specific rooms, allowing users to easily observe trends and identify potential areas of concern. Line plots are also utilized to visualize room temperature, humidity, and ventilation, providing insights into indoor environmental conditions. Finally, line plots are also used to show the cumulative infection risks of each room, allowing users to assess their individual infection risks based on the time spent in each room. This information can be used for high-infection risk alerts and proactive measures. Sample line plots can be found in in Section 4.3.

### **3.4.2 Alerting system**

An alerting system was integrated into the app to provide comprehensive guidance and support to facilities management. This system utilizes simulation results associated with the user's selected room to proactively trigger alerts. An alert can be triggered based on the following conditions:

1. Cumulative Infection Risk: If the cumulative infection risk exceeds a predetermined threshold (e.g., 1%), then an automatic alert is triggered, notifying facility managers of potential health



risks and providing recommendations on various mitigation measures, such as increasing ventilation, reducing room occupancy, and implementing disinfection strategies such as the use of ultraviolet lights.

2. Relative Humidity: When the relative humidity falls below 30% or exceeds 60%, an alert will be sent to facility managers. This threshold is established because various bacteria species that contaminate humidification and air-conditioning equipment thrive outside this humidity range [60]. An alert will be sent to facility managers, informing them about these humidity-related issues. These issues can be mitigated through the activation of humidifiers or dehumidifiers at low or high humidity, respectively.

3. Thermal Comfort: Alerts are pushed if the thermal comfort levels deviate from predefined thresholds, such as when the predicted mean vote (PMV) exceeds 1 or falls below -1. This allows facility managers to take timely action in response to comfort-related concerns, such as adjusting the room temperature setpoints.

4. Indoor air quality (IAQ): An alert is triggered when the IAQ exceeds acceptable thresholds. These thresholds are set for specific parameters, which are 500 ppm [67], 15  $\mu\text{g}/\text{m}^3$  [68], and 500  $\mu\text{g}/\text{m}^3$  [69] for the concentration of  $\text{CO}_2$ ,  $\text{PM}_{2.5}$ , and VOCs, respectively. Exceeding these thresholds indicates that the IAQ may pose potential health risks, and facility management teams should take actions to address the situation, such as increasing the room ventilation rate or reducing the concentration of pollutants.

### 3.4.3 AI-based persuasion system

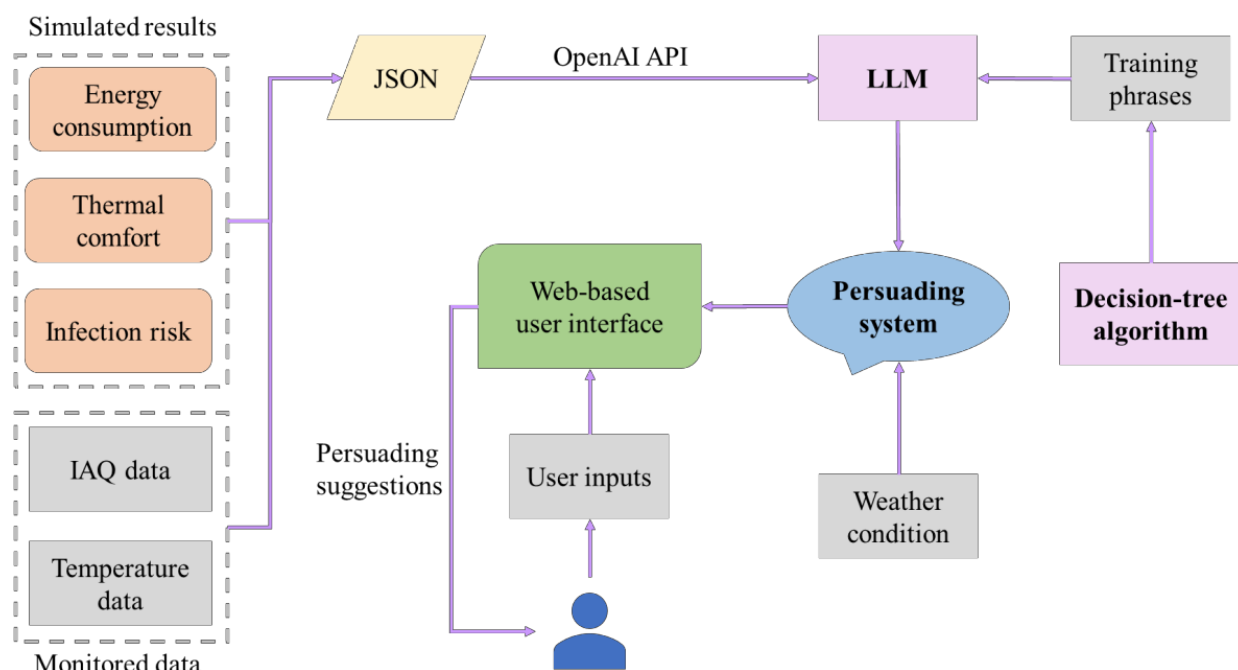
The functionality of the web app extends beyond facility managers and can cater to the needs of other users, such as occupants or workers, by providing them with information about the facility as well as receiving and providing suggestions to their concerns. In addition to the visualization

capabilities described earlier, the app incorporates an AI-based persuasion system that offers personalized suggestions to this user group through the use of conversations informed by the current environment data and simulation results. This persuasion system takes the form of a conversational interface powered by the highly regarded GPT-4 LLM [70]. This LLM has been specifically optimized for conversational tasks and is thus highly effective at generating meaningful responses.

The LLM has three main functions: data retrieval, data comparison, and the provision of suggestions. After the web app simulates the current state of the building, the real-time environmental data from IoT sensors (such as IAQ and temperature) and the simulation results (including energy consumption, thermal comfort, and infection risk) are automatically transmitted to the GPT model through the OpenAI API [71] in the JSON format. The LLM then utilizes the retrieved JSON data to identify differences between neutral conditions (e.g., an indoor temperature set at 24°C) and current conditions, such as variations in simulated energy use. The LLM is trained using predefined decision-tree-based training phrases to provide conversational suggestions to end-users. To ensure accurate responses, a manual check is performed after each training session.

Users can engage with the app's conversational UI to express their concerns, share their feelings, or ask questions about the current environment. The LLM is capable of providing relevant and personalized responses based on the real-time data it receives. This comprehensive approach allows the app to provide users with appropriate guidance and effectively address their specific concerns, fostering an informative, user-centric experience. The fundamental concepts behind the persuading system are founded in the tradeoff relationships between health, energy, and thermal comfort. Two adaptive persuasion algorithms were developed in this study: one focused on the

occupant's perception of thermal comfort and the other on their perception of the IAQ. These qualities are important for occupants, as they directly relate to what occupants can feel and are most concerned about in an indoor environment. The persuasion algorithms are presented using a decision-tree format and are utilized as training data for the GPT. Specifically, they were provided in the form of descriptive phrases, allowing the model to learn and understand how to generate effective and persuasive suggestions. Figure 6 provides a comprehensive illustration of the entire process.

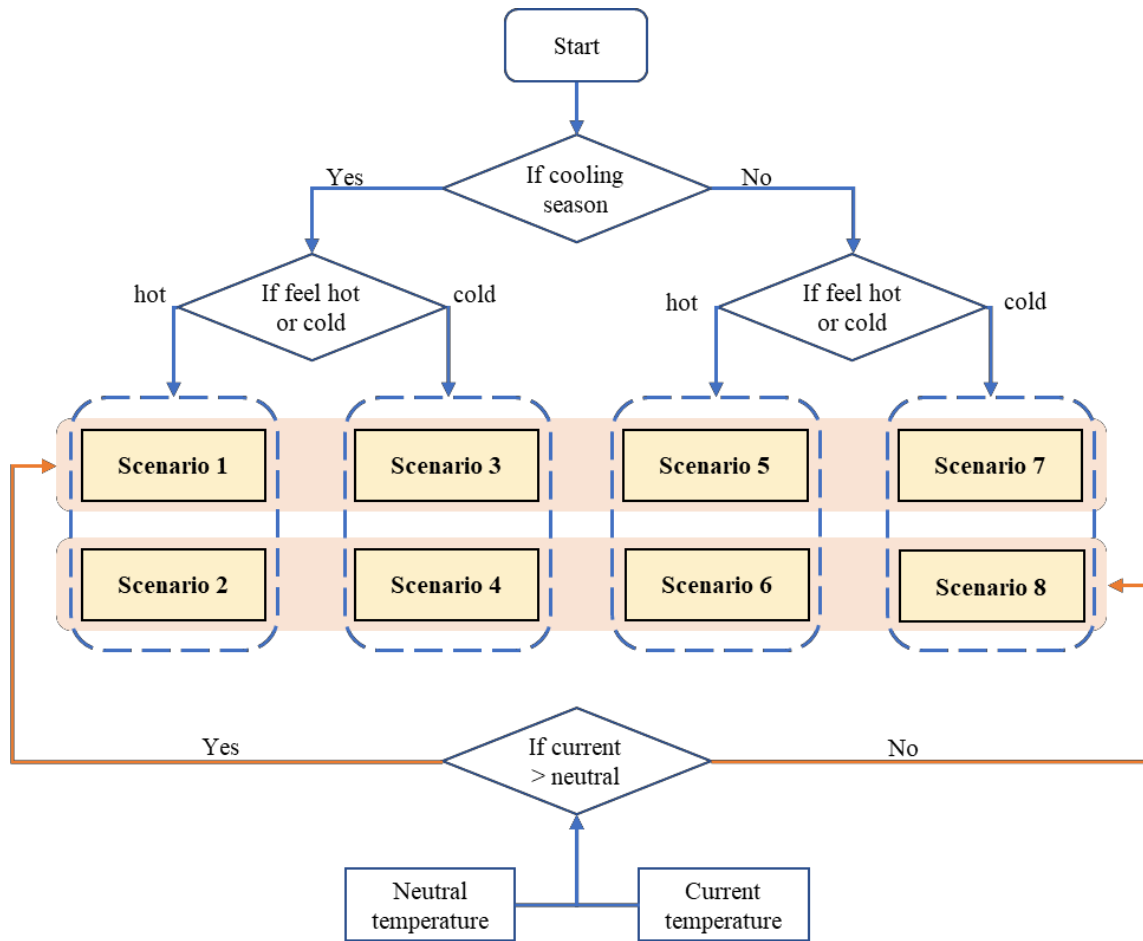


**Figure 6.** Integrated operations of the AI-based persuasion system.

### 3.4.3.1 Adaptive persuasion algorithm based on user perception of thermal comfort

The first of the two adaptive persuasion algorithms utilized in the app focuses on the user's perception of thermal comfort. The algorithm involves three decisions, with the result of each decision based on user input or environmental conditions. A demonstration of how outputs are generated by the persuasion algorithm is shown in Figure 7. The algorithm distinguishes between

544 cooling and heating seasons based on the current date retrieved from the device's system time,  
545 focusing solely on these periods because discomfort is more likely during these seasons. During  
546 the shoulder season, when neither cooling nor heating is necessary, dynamically adjusting the  
547 temperature setpoints is not required, as the indoor temperature is likely to remain within the  
548 comfortable range. Therefore, to prioritize energy savings, the algorithm is only active during the  
549 cooling and heating periods. After identifying the current weather conditions, the algorithm obtains  
550 the occupant's thermal perception through the conversational interface, capturing their feelings  
551 about the state of the indoor thermal environment. It then compares the current temperature—  
552 acquired from real-time IoT sensing data—with the preset neutral temperature (e.g., 24°C). The  
553 simulation results under current and neutral conditions are then used to calculate the difference in  
554 energy use. Based on the outcomes of these three decisions, the algorithm generates eight  
555 distinct scenarios, with specific suggestions and persuasive phrases formulated for each scenario.



**Figure 7.** Outputs of the persuasion algorithm according to the occupant perception of indoor temperature and environmental conditions.

The contents of the persuasion system were developed by considering the tradeoff between energy consumption and thermal sensation. If changing temperature setpoints will result in increased energy use, the system initially recommends that users change their clothing levels to reduce energy consumption. If changing setpoints will reduce energy use while also satisfying user thermal requirements, the system will suggest adjusting setpoints accordingly. To enhance user engagement, the system provides suggestions while demonstrating the energy savings achieved by user actions. This approach helps users better understand the impact of their behavioral changes while making the system more persuasive, improving thermal comfort and energy conservation by

encouraging the active participation and collaboration of occupants.

In each scenario, multiple recommendations are offered to users, allowing them to choose their preferred course of action. The system then responds according to user choices and informs the facility management teams of the user's preference. The detailed persuading phrases based on different scenarios are as follows:

- Scenario 1 (cooling season, the user feels hot, and the current temperature is higher than neutral): Shall I communicate with the facility managers and advise them to lower the indoor temperature? Alternatively, if you are comfortable adjusting your clothing to lighter attire, it could potentially save an estimated Y kWh of energy (where Y is the number retrieved from the result of cloud-computed energy simulation). Please let me know your preference regarding contacting the facility managers.
- Scenario 2 (cooling season, the user feels hot, and the current temperature is lower than neutral): The current temperature is already below the neutral level, and further lowering it may cause people to feel cold. In this situation, I recommend considering removing some clothing to help you feel more comfortable and alleviate your thermal discomfort.
- Scenario 3 (cooling season, the user feels cold, and the current temperature is higher than neutral): The current temperature is already higher than the neutral level. In this case, I recommend wearing an additional light blanket if you're still feeling chilly.
- Scenario 4 (cooling season, the user feels cold, and the current temperature is lower than neutral): The current temperature is below the neutral level. I will inform the facility managers to increase the temperature cooling setpoint, which will help save energy by Y kWh.
- Scenario 5 (heating season, the user feels hot, and the current temperature is higher than neutral): The current temperature is above the neutral level. I will communicate with the

facility managers to lower the temperature heating setpoint, which will help save energy by Y kWh.

- Scenario 6 (heating season, the user feels hot, and the current temperature is lower than neutral): The current temperature is already below the neutral level, and further lowering it may cause people to feel cold. In this situation, I recommend considering removing some clothing to help you feel more comfortable and alleviate your thermal discomfort.
- Scenario 7 (heating season, the user feels cold, and the current temperature is higher than neutral): The current temperature is already higher than the neutral level, and further increasing it may cause people to feel hot and lead to higher energy consumption. In this situation, I recommend removing some layers of clothing to help you feel more comfortable and reduce the need for additional adjustments to the indoor temperature.
- Scenario 8 (heating season, the user feels cold, and the current temperature is lower than neutral): Should I communicate with the facility managers to increase the temperature? Alternatively, you could put on more layers of clothing to help us save Y energy. Please let me know your preference regarding contacting the facility managers.

### **3.4.3.2 Sample training phrases and training process**

This section provides a comprehensive illustration of the training process through sample training phrases. Taking advantage of the LLM, all training phrases were formulated in natural language. The simulated and monitored data were transferred and demonstrated to the LLM by employing the following phrase: “Below is a JSON format simulation result of a building's room level infection risk, energy usage in kWh, ventilation rate in air change per hour, humidity condition in %, thermal comfort in PMV, temperature condition in °C, and indoor air quality in ppm. The outcomes pertain to each room, with the ‘ZoneRoomNumber’ key indicating the room numbers.

616 Please respond to user questions based on this data.” In this phrase, the key was defined and stored  
617 in the JSON data.

618

619 To quantify the energy saving attributed to user behavior, the LLM was trained to generate  
620 simulated results based on a neutral temperature (e.g., 24°C). These outcomes are subsequently  
621 employed to conduct a comparison between the simulated results under current and neutral  
622 temperature conditions. Here are the training phrases that illustrate this process: “Displayed below  
623 is the result data in JSON format based on neutral temperature. The ‘ZoneRoomNumber’ key  
624 indicates the room number, and the ‘ZoneHourlyEnergy’ key presents room-level energy usage  
625 computed at the neutral temperature. To calculate energy savings, integrate the baseline data  
626 represented by the neutral temperature result with the previously provided simulation result based  
627 on the current temperature. By subtracting the room-level energy usage depicted in the neutral  
628 temperature result data from the corresponding data in the simulation conducted at the current  
629 temperature, you can quantify the energy conserved. Proceed to inform the user about the amount  
630 of energy saving.”

631

632 Here are the example training phrases of the decision tree-based algorithm, utilizing the first  
633 branch of the decision tree – “during cooling season, when the user feels hot,” with Scenarios 1  
634 and 2. The phrase is as follows: “If the user feels hot, respond with two suggestions, presenting  
635 them together. The first suggestion is: Should I communicate with the facility managers and  
636 recommend lowering the indoor temperature? The second suggestion is: If you're open to adjusting  
637 your clothing to lighter attire, it could potentially save energy. Please inform me of your preference  
638 regarding contacting the facility managers. Provide full information, and no more additional  
639 suggestions beyond these. If the user then expresses the need for you to contact the facility

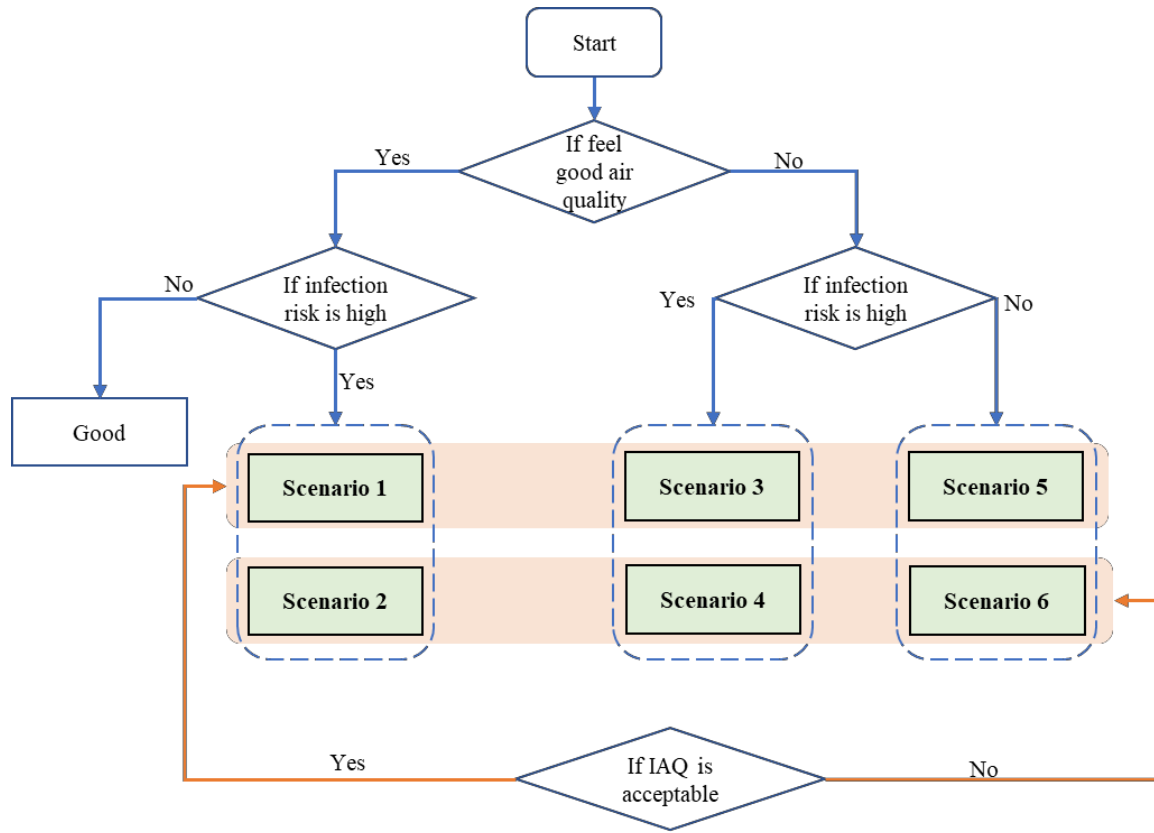


manager, inform them that you will take care of it. If the user indicates they don't require your assistance, express gratitude for their energy-saving contribution and furnish them with the amount of energy saved for an hour based on the simulation and baseline data. Begin by asking the user for their choice. Display the energy-saving result exclusively if the user selects the second option mentioned above.”

For each scenario, similar training phrases are formulated according to the weather condition, user feelings, and current room temperature. The intent behind these phrases is to suggest strategies for enhancing thermal comfort and offering energy-saving recommendations that align with the ongoing circumstances, and guarantee the accurate and appropriate recommendations for users based on the scenarios. Coupled with the NLP capabilities of the LLM, the algorithm comprehends various user inputs and offers a range of sentences to articulate the suggestions.

#### **3.4.3.3 Adaptive persuasion algorithm based on user perception of IAQ**

Like the algorithm described in Section 3.4.3.1, this algorithm generates responses based on three key decisions (Figure 8), involving a consideration of the environmental conditions, user perception, and health risks. It first prompts the user to input their perception of the air quality through the conversational interface of the application. It then compares the current infection risk level to a predefined risk threshold to determine if the room's infection risk is high. Finally, it evaluates the IAQ with close consideration of the concentration of air pollutants such as CO<sub>2</sub>, PM<sub>2.5</sub>, and VOC. This data is gathered in real-time through IoT sensing devices and compared against preset thresholds as demonstrated in Section 3.4.2. From this data, the algorithm generates outputs based on one of six scenarios.



**Figure 8.** Outputs of the persuasion algorithm according to the occupant perception of the IAQ.

The system considers two crucial factors: the health risks associated with airborne diseases and air pollutants. The system acquires the infection risk through real-time simulation results, while the health risks related to air pollutants are obtained from the IoT monitoring system. The algorithm presents users with different mitigation measures, allowing them to choose the option that best aligns with their preferences. The persuasion system's initial strategy is to encourage occupants to consider moving to another room, which helps to reduce potential health risks while minimizing the need for the extensive implementation of mitigation measures, thus promoting energy and cost savings. Furthermore, the system acts as a communicative link between the building occupants and the facility management teams, providing insights into occupant preferences and needs. This promotes the adoption of preferred mitigation measures, leading to a healthier environment, energy

677 savings, and improved occupant satisfaction. The detailed persuading phrases based on different  
678 scenarios are as follows:

679 • Scenario 1 (the user feels good, infection risk is high, and IAQ is acceptable): Although the air  
680 quality in this room may feel comfortable, it's important to be aware that the current infection  
681 risks are high. To address this concern, I strongly recommend moving to another room. The  
682 healthy room numbers are Z (recommended rooms are determined based on risk simulation).  
683 Would you be willing to move to one of these healthier rooms? (Response from the user). If  
684 moving to another room is not feasible for you, I can promptly contact the facility management  
685 teams to implement one of three mitigation measures: 1. An increase in room ventilation. 2.  
686 Room disinfection procedures. 3. Occupancy control measures. Which of these mitigation  
687 measures would you prefer?

688 • Scenario 2 (the user feels good, infection risk is high, IAQ not acceptable): While you may  
689 currently feel good, it's crucial to be aware that both the infection risks and the air quality in  
690 this room are not at an acceptable level. To address these concerns, I strongly suggest moving  
691 to another room, such as room Z<sub>1</sub>, Z<sub>2</sub>, or Z<sub>3</sub>. If you do not wish to or cannot change rooms, I  
692 can contact the facility manager to increase the ventilation rate in this room.

693 • Scenario 3 (the user feels bad, infection risk is high, IAQ is acceptable): Thank you for  
694 expressing your concerns. The current room's infection risk is indeed not at an acceptable level  
695 for maintaining a healthy environment. (At this point, the same recommendations from  
696 Scenario 1 will be provided).

697 • Scenario 4 (the user feels bad, infection risk is high, IAQ is acceptable): Thank you for  
698 acknowledging the concerns. It is crucial to note that both the infection risk and the air quality  
699 in the room are not at a healthy level. (Same recommendations from Scenario 2 will be  
700 provided).

- Scenario 5 (the user feels bad, infection risk is low, IAQ is acceptable): Although you feel unwell, please note that the room environment is healthy and has an acceptable level of air quality. However, considering your discomfort, I recommend taking a break outside the building to refresh yourself.
- Scenario 6 (the user feels bad, infection risk is low, IAQ not acceptable): Thank you for expressing your concerns. The air quality in this room is not at an acceptable level, which can potentially affect your performance and well-being. (Same recommendation from Scenario 2 will be provided).

#### **3.4.3.5 Majority-preference based environment control algorithm**

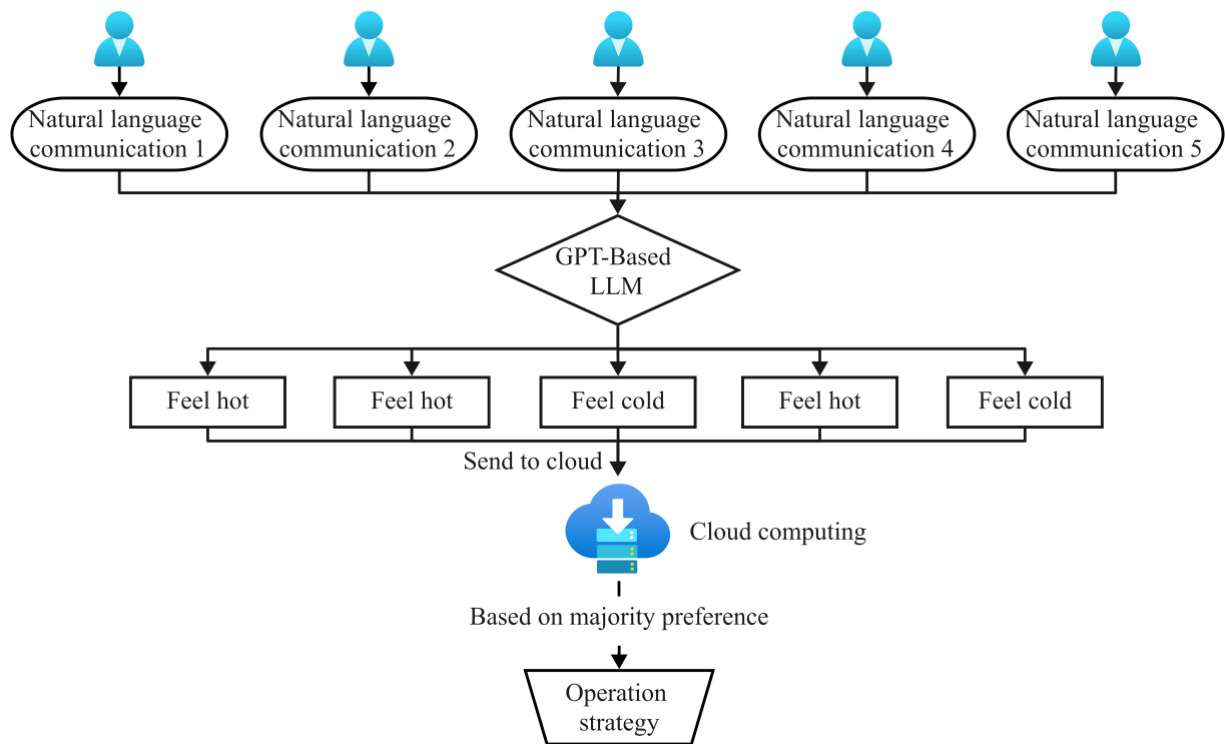
In scenarios where occupants in the same room have opposite preferences, the app employs a decision-making algorithm based on majority feedback to ensure overall satisfaction. This process leverages the capabilities of the GPT-4 model to analyze communication logs and generate preference data, which is then used to guide adjustments in the building environment. When multiple occupants provide feedback about their comfort levels or preferences, the app collects and analyzes this data to determine the majority preference. This approach ensures that environmental adjustments, such as temperature or ventilation changes, align with the preferences of the majority, promoting a balanced and satisfactory indoor environment for most occupants.

The GPT-4 model plays an essential role in this process by generating tags based on the communication logs of the occupants. Each time an occupant interacts with the app and expresses a preference (e.g., feeling too hot or cold), the GPT-4 model analyzes these interactions and assigns tags that represent these preferences. These tags are then aggregated to provide a clear picture of the overall preferences within a room. The generated preference data is saved in the cloud,

allowing for real-time updates and access by the app. This cloud-based storage ensures that the data is always up-to-date and can be accessed timely to make informed decisions. The app continuously updates the preference data as new feedback is received, ensuring that the decisions reflect the current preferences of the occupants.

To implement this algorithm, the app follows several steps: 1) it collects feedback from all occupants in the room through the conversational interface; 2) GPT-4 analyzes the communication logs and generates preference tags for each occupant; 3) the tags are aggregated in the cloud to determine the majority preference; 4) based on this majority preference, the app makes decisions about environmental adjustments; and 5) the app continuously updates the preference data as new feedback is received, ensuring that decisions remain relevant and accurate.

For example, in a room with ten occupants where six occupants report feeling too hot while four report feeling too cold, the GPT-4 model tags these preferences and saves them in the cloud. The app aggregates this data and determines that the majority of occupants prefer a cooler environment. Consequently, the app will adjust the temperature settings to lower the room temperature, aligning with the majority preference. By using majority feedback and leveraging the analytical capabilities of GPT-4, the app ensures that the environmental conditions in shared spaces are optimized for the greatest number of occupants, enhancing overall comfort and satisfaction. The flowchart of the Majority-preference based environment control algorithm is shown in Figure 9.



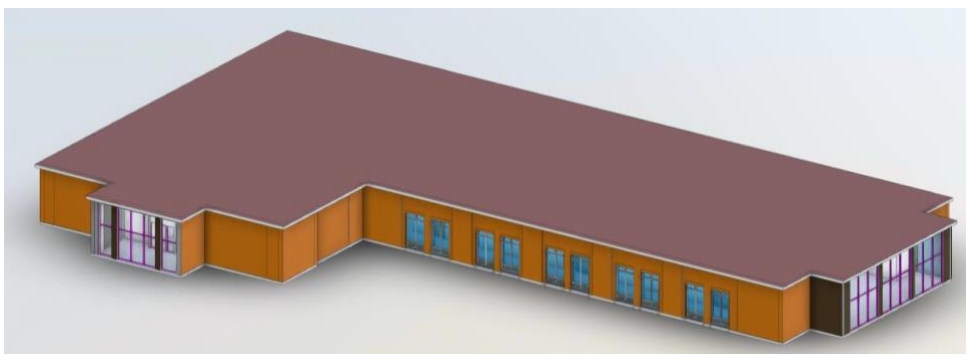
**Figure 9.** The flowchart of the Majority-preference based environment control algorithm

#### 4 Case study

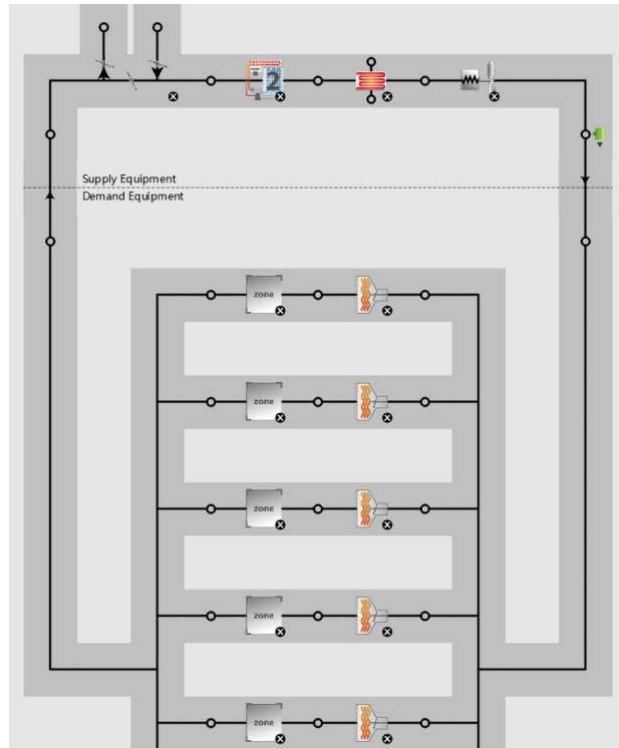
This section presents the development of a real-time, cloud-based, integrated platform aimed at monitoring three major aspects of building management, including energy consumption, thermal comfort, infection risks, and overall building environments, as well as communicating this information to users. The infrastructure integrates various components, such as sensor APIs, web servers, cloud computing, and EnergyPlus simulations. The UI of the web app was designed to communicate the dynamic information collected to facility management teams. To demonstrate the application's capabilities, a case study was conducted using a section of the Zeanah Engineering Complex, the largest academic building on the campus of The University of Tennessee, Knoxville, with the results of the simulation presented within the app. This platform offers a comprehensive solution for real-time monitoring, analysis, and communication in building management scenarios.

#### 4.1 Energy model generation

The capabilities of the platform were demonstrated by using a specific section of the Zeanah building as a case study. The selected region included the left wings of the second floor, which is composed of various spaces, including seven classrooms, thirteen offices, two laboratories, one learning space, one wellness room, two restrooms, two stair rooms, one electric room, and one data room. The total area of this building section is approximately 1848.9 m<sup>2</sup>, and the layout of the building is presented in Figure 10. The HVAC systems employed in the building include three centralized variable air volume (VAV) systems equipped with economizers. Figure 11 illustrates a sample configuration of a deployed HVAC system. The building uses both gas and electricity as primary fuel sources. The heating system utilizes gas boilers, while the cooling system uses a packaged air conditioning unit (PACU). A VAV box with a reheat function is installed within each zone to regulate the airflow and temperature. The architectural model was imported into SketchUp using OpenStudio plugin to accurately represent the building envelope and facilitate the energy simulation process. OpenStudio was then used to incorporate the building's HVAC systems into the model based on the configuration provided in the MEP model. These modifications resulted in a comprehensive model for energy simulation using EnergyPlus as described in Section 3.2.



**Figure 10.** The architectural configuration of the selected building section.

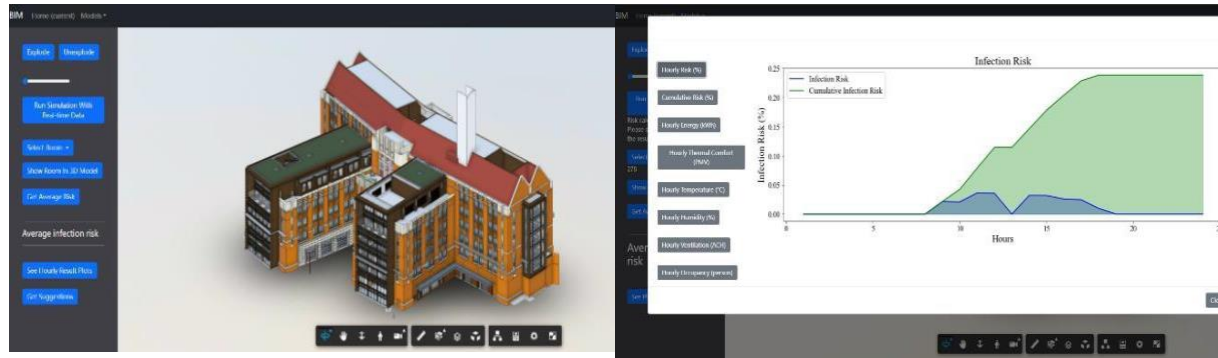


**Figure 11.** Diagrammatic representation of the HVAC configuration in the selected building section.

## 4.2 Web app UI

The web app UI was designed with a focus on user-friendliness and clarity. Emphasizing simplicity and intuitive navigation, the interface is easy to use and comprehend. The concise design, paired with a single-page display, allows users to efficiently access and absorb information. The core design principles and features are demonstrated on the main page of the web app (Figure 12).





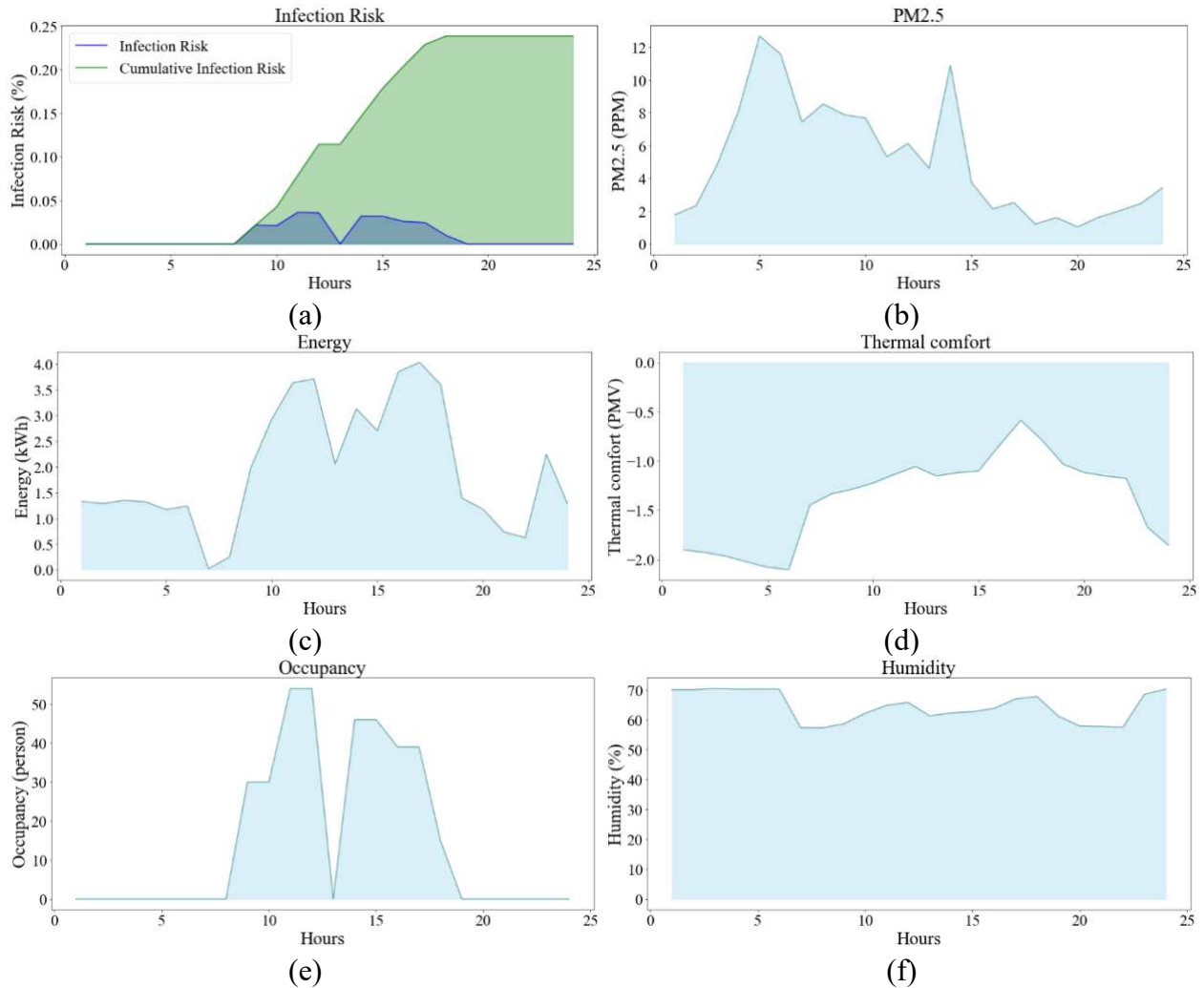
(a)

(b)

**Figure 12.** The UI of the web app. (a) Main page and (b) simulation results visualized using line plots.

### 4.3 Sample simulation results

A test simulation was conducted to demonstrate the visualization capabilities of the web app. This simulation utilized data and information specifically collected from classroom 278, located on the second floor of the Zeanah building. The simulation was performed for a whole day using weather and IoT data retrieved on June 22, 2023. The simulated hourly outcomes included infection risk, cumulative infection risk, energy consumption, and thermal comfort. Room temperature, relative humidity, occupancy, and the concentration of different pollutants were monitored by the IoT sensors. Figure 13 illustrates the time series results of the simulation and monitoring for room 278, as would be presented within the app's UI.



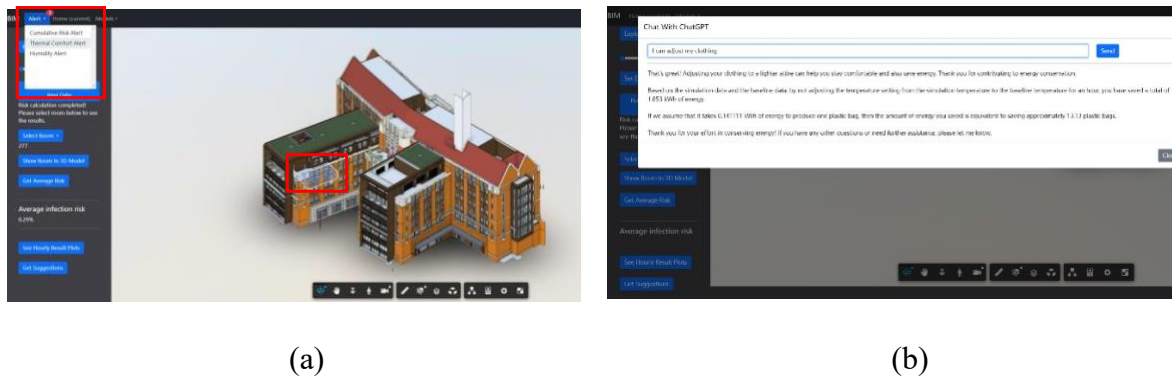
**Figure 13.** Simulation results from a sample room. Hourly outcomes included: (a) infection risk (%); (b) PM<sub>2.5</sub> (PPM); (c) Energy consumption (kWh); (d) Thermal comfort (PMV); (e) Occupancy (no. of persons); (f) Relative humidity (%).

#### 4.4 Alerting system and conversational persuasion system

The app's alerting system is designed to automatically trigger when predefined thresholds are exceeded. Popup alerts are displayed immediately after the user selects a room. To provide a comprehensive view of the alerts related to the selected room, all identified alerts are presented using a dropdown menu. Users can conveniently explore the dropdown menu and select specific problems they are interested in and access the relevant suggestions. In addition, the app utilizes a

persuasive conversational interface powered by GPT-4 to provide appropriate suggestions and recommendations. Users can engage in a conversation-like interaction to receive personalized suggestions based on user inputs and current environmental conditions.

Figure 14 illustrates the visual representation of the alerting system and the conversational interface within the app. This user-friendly design allows users to easily navigate and access alert information, obtain tailored suggestions, and engage in interactive conversations to enhance their experience and address specific concerns.



**Figure 14.** The UI of (a) The alerting system and (b) the GPT-powered suggestion system.

In addition to offering persuasive strategies, the AI-empowered conversational persuasion system also encourages user participation by offering the user several energy-saving tips by considering the tradeoffs between energy consumption, thermal comfort, and infection risks. By explicitly informing the user of the amount of energy saved, this approach helps occupants better understand the positive effects of their actions and promotes responsible behavior. Furthermore, the system not only encourages positive occupant behavior but also provides multiple mitigation measures that occupants can choose from. These measures can be implemented by the facility management teams, offering occupants a range of options based on their preferences to address their specific needs. Figure 14(b) illustrates an example of the persuasion system's response when the user feels

overly hot in a room. The system suggests adjusting their clothing as a potential solution that addresses the user's discomfort. To enhance the persuasiveness of these suggestions, the app presents the estimated potential energy savings that can be achieved through clothing adjustments. By indicating the potential energy savings and environmental benefits tied to specific actions, users are encouraged to adopt sustainable behaviors, resulting in a more informed and eco-conscious user experience.

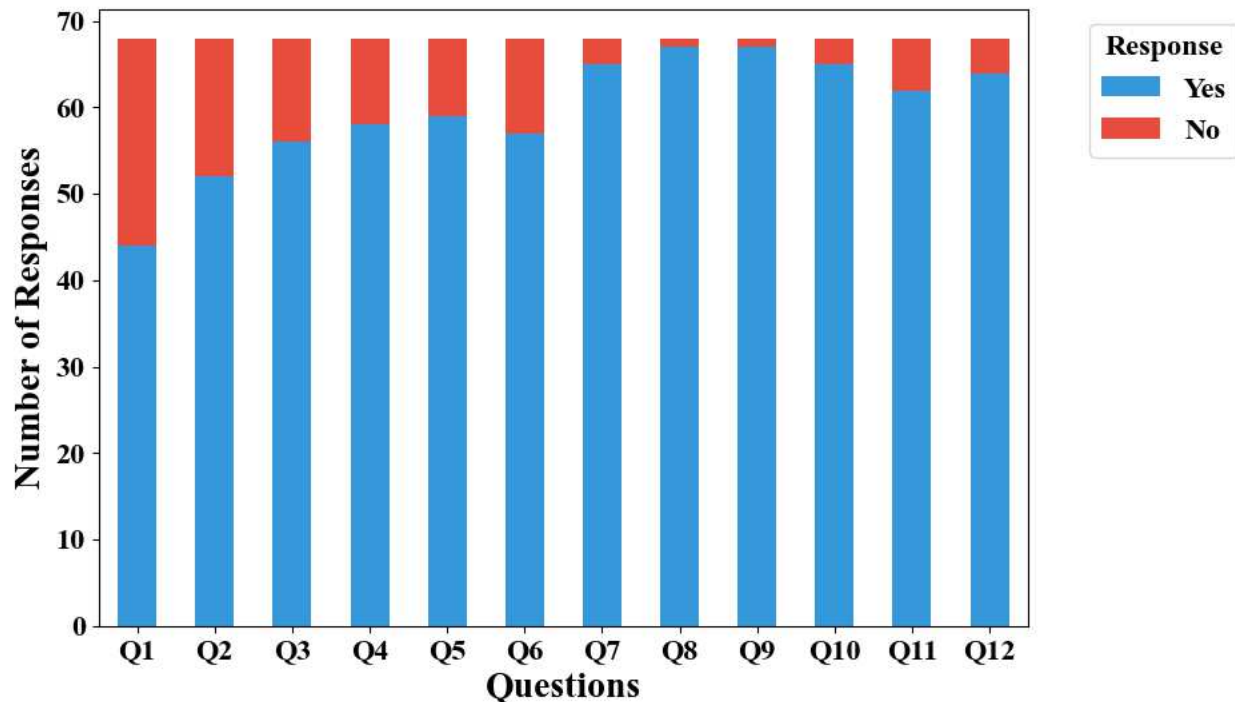
A sample conversation between the LLM-powered persuasion system and an occupant is provided in Table 1, demonstrating the interactive nature of the system and how it facilitates informative discussions. This dialogue exemplifies the interactive capabilities of the LLM-powered assistant, allowing for personalized suggestions and engaging conversations.

**Table 1.** Sample conversation between the LLM-powered assistant and an occupant.

Occupant	I feel hot in room 278.
Assistant	<p>I'm sorry to hear that you're feeling hot in room 278. I have two suggestions for you:</p> <ol style="list-style-type: none"> <li>1. Should I communicate with the facility managers and advise them to lower the indoor temperature?</li> <li>2. If you are willing to adjust your clothing to a lighter attire, it could potentially save energy.</li> </ol> <p>Please let me know your preference regarding contacting the facility managers.</p>
Occupant	I can adjust my clothing.
Assistant	<p>That's great! Adjusting your clothing to a lighter attire can help you stay comfortable and save energy. Thank you for contributing to energy conservation.</p> <p>Based on the simulation data, by not adjusting the temperature setting for an hour, you have saved a total of 1.853 kWh of energy.</p> <p>Thank you for your effort in conserving energy! If you have any other questions or need further assistance, please let me know.</p>

#### 4.5 Capability of the persuasive system

Surveys were conducted to graduate students majored in civil engineering in Nanjing Tech To validate the effectiveness of the developed persuasive system, a survey was conducted with 68 university students to assess their willingness to adopt environmentally friendly measures. The survey included 12 questions, each representing scenarios from two adaptive persuasion algorithms: one based on user perception of thermal comfort (Section 3.4.3.1) and the other on IAQ perception (Section 3.4.3.3). Participants were presented with scenarios and corresponding suggested actions, choosing "yes" or "no" to indicate their willingness to take the proposed measures. The scenarios covered six questions related to thermal comfort perception (Q1 to Q6) and six related to IAQ perception (Q7 to Q12), as shown in Figure 15 and Table S1 (Appendix A). The detailed survey questions are listed in Appendix B.



**Figure 15.** Participant willingness of adopting environmentally friendly measures

Figure 15 indicates that a majority of participants are willing to adopt environmentally friendly

measures for energy-saving purposes, highlighting the effectiveness of the persuasive system in promoting sustainable behaviors. Notably, suggestions for achieving better indoor air quality and health by switching rooms had a higher average adoption rate (95.59%) compared to suggestions for adjusting clothing to enhance thermal comfort (79.90%). This difference suggests that participants prioritize air quality, particularly during pandemic concerns, over thermal comfort adjustments, which can be difficult to achieve if clothing options are limited or if a blanket is not readily available. Overall, the strong positive response across all scenarios demonstrates the system's capability to encourage sustainable practices through its persuasive strategies, supporting its potential for building energy conservation.

## **5 Discussion**

This study proposes the use of an innovative real-time integrated platform for building management that integrates a variety of features from building environment monitoring to the effective communication of information with the express purpose of fostering a healthy and sustainable built environment. To demonstrate the capabilities of the platform, a case study was conducted within a section of Zeanah Engineering Complex in Knoxville, Tennessee. The building's architectural model and MEP model were used to create a building energy model, which served as the basis for the digital twin. An IoT sensor network was deployed throughout the selected study area to allow for comprehensive building monitoring. This network continuously collects real-time data on various environmental factors in each room, including temperature, humidity, as well as the concentrations of pollutants such as CO<sub>2</sub>, PM<sub>2.5</sub>, and VOC. The platform conducts simulations at the room level to assess three major aspects that are essential for building sustainability: health, energy consumption, and thermal comfort. The UI of the platform facilitates information sharing and visualization for facility management teams and occupants and uses an

enhanced communications system involving a conversational persuasion system to provide occupants with a user-friendly experience.

## **5.1 Health aspects of building management**

The occurrence of several severe pandemics over the past two decades, including influenza, SARS, and COVID-19 pandemic, has emphasized the critical significance of health considerations in building management. Although the threat of the COVID-19 pandemic has subsided recently, the need to prevent potential disease outbreaks remains essential due to the pandemic's devastating impact on human lives and the economy. Airborne transmitted diseases pose a particularly severe threat due to their potentially rapid spread and limited means of transmission control. Indoor environments, often lacking adequate ventilation in typical operation scenarios, can become breeding grounds for airborne viruses. Hence, the development and implementation of a health-focused platform that monitors indoor environments is vital in curbing potential disease outbreaks. In addition to disease transmission, traditional concerns about IAQ continue to be significant in building management. Low-quality indoor environments can adversely affect occupants' health, leading to increased absenteeism due to SBS as well as reduced productivity and performance among occupants and workers. SBS is primarily caused by contamination from various pollutants and insufficient indoor ventilation [72]. Consequently, IAQ detection was also considered in this study as a means of mitigating health risks and ensuring a healthier and more productive indoor environment.

It is essential to recognize that mitigation measures, such as increased ventilation, can effectively address health risks arising from both airborne diseases and pollutants. However, these two aspects should be considered separately to improve building performance. During pandemics, it becomes

crucial to prioritize the reduction of disease transmission; consequently, room ventilation rates must be set to higher levels to enhance air circulation and minimize the risks of infection. Despite the implementation of these measures, the infection risks can remain high depending on the current state of the epidemic, while the IAQ can remain at low levels. Conversely, during non-pandemic periods, priority shifts to the management of IAQ during building operations. Maintaining a high-quality indoor environment is essential to promote the well-being and productivity of occupants and workers.

## **5.2 Interoperability achieved by cloud computing**

To conduct real-time energy simulations, researchers often rely on additional software for programming and data storage. In general, the energy simulation process is conducted locally before the data is transferred to a cloud server for retrieval. For instance, Pang et al. [73] introduced a framework for the real-time performance assessment of entire buildings, utilizing Building Controls Virtual Test Bed (BCVTB) as the software platform to which inputs from the Energy Management and Control System (EMCS) were provided. The acquired data were then sent to EnergyPlus for simulation, with the results archived in a separate database. Pallonetto et al. [74] proposed a grid co-simulation software platform that integrated BCVTB with a MySQL database using Java Database Connectivity (JDBC). By accessing the database, this platform allowed for real-time simulation and visualization through a web application. However, such approaches still require the local installation of BCVTB software, which poses challenges to users, impacting accessibility and ease of use. The need for additional software installation may limit user's access to information, especially in the context of the wide variety of user devices, excluding potential users who may not require the app for professional purposes but still seek information or interaction about the building environment. In this study, a cloud-based integrated platform was



developed to address these problems. This technology allows for interoperability within the same device, eliminating the need for additional software installation. This cloud-based approach supports cross-platform accessibility, allowing users to easily access the platform from any device and at any time (as long as they have Internet access) through the simple use of a URL. This innovation allows for room-level monitoring and simulation, laying the foundation for efficient building operations.

### **5.3 Human-centric conversational persuasion system**

In recent years, there has been a growing emphasis on human-centric building operation technologies, driven by an increased recognition of the significance of human perception and satisfaction in establishing a comfortable and sustainable building environment. This emphasis is rooted in the fundamental understanding that humans are the primary users and occupants of buildings. In this context, Abdelrahman et al. [75] introduced a spatial-temporal occupant preference sampling method, leveraging BIM technology, to optimize personal comfort. The participants were asked to answer thermal comfort questionnaires during their work activities. Favero et al. [76] proposed human-in-the-loop methods for occupant-centric building operation with the focus on human thermal perception. Through the recruitment of participants, trials were conducted involving varying thermal exposures, and participants were required to provide feedback on thermal perception at predefined intervals. However, these approaches overlook the challenges associated with fostering occupants' willingness to provide frequent feedback through surveys in real-world building operation applications. Furthermore, it has been observed that individuals may be less inclined to engage with surveys featuring repetitive questions and lacking in responsive interactions in accordance with the feedback they provide. Bresa et al. [77] identified occupant preferences and predicted the likelihood of occupant interactions based on behavioral

science theory. This research indicated the fact that prevailing building control methods often fall short of aligning with the viewpoints and preferences of building occupants. This research found that the primary motivation for individuals to interact with building controls is their desire to contribute positively to energy conservation. This finding underscores the significance of energy savings as a major expected outcome, which is in accordance with the motivator for encouraging occupant interaction in our app.

This study introduced an innovative AI-based conversational persuasion system powered by GPT as the large language model that can generate personalized responses to specific user inputs. The development of this conversational system expands the scope of human-centric interactive services in the context of smart building operations. While such technologies are finding wide usage in fields like healthcare and services, it has not been extensively applied to the field of building management for indoor environments. This conversational system bridges this gap, allowing facility management teams to promptly address occupant needs and preferences. It also enhances occupant participation and fosters a healthier and more sustainable building environment. This system offers significant improvements in the interactive process compared to traditional conversational agents or chatbots. Traditional chatbots tend to provide consistent, rigid responses to similar questions, leading to user boredom and dissatisfaction due to repetitive interactions. However, the integration of a LLM-empowered interface as a conversational tool addresses these issues while introducing several advantages. Firstly, the widespread usage and human-like interface of LLM contribute to improving the users' trust and acceptance of the information provided, establishing credibility and fostering user engagement. Furthermore, the ability of LLMs to generate diverse sentences during communication ensures dynamic and varied conversations enhances the overall user experience, and makes interactions more engaging and enjoyable. This

contributes to increased user satisfaction and promotes sustained user engagement with the system.

The monitoring data and simulated results are automatically transferred to the GPT model in real time. Through a comprehensive, predefined set of training phrases, the system gains the ability to understand the current environmental conditions and respond appropriately to user inputs by providing accurate and relevant responses. In particular, information regarding the tradeoffs between health, energy use, and thermal comfort serves as a powerful motivator, causing building occupants to actively engage with and embrace energy-saving strategies. The use of human-like conversational tones to demonstrate energy savings allows occupants to gain a sense of awareness regarding their actions and informs them of their direct impact on the building's overall performance. This creative approach allows for the effective and relatable visualization of energy consumption, making it easier for occupants to understand the extent of the environmental implications of their daily activities. This engagement encourages occupants to take a more active role in enhancing indoor environments and living quality through their participation.

While this study estimates indoor infection risks for specific viruses, environmental factors like temperature and humidity can affect different pathogens differently, especially when multiple are present, highlighting the need for further exploration to determine optimal indoor environments and mitigation measures. Another limitation is our reliance on a student population for participant feedback, which may introduce participation bias, as students might be more inclined to collaborate or may not fully express their feelings about thermal comfort and indoor air quality, potentially leading to unrepresentative data. Future studies should explore long-term and personalized feedback mechanisms to enhance the willingness of information sharing. In addition, although we focus on controlling mechanical ventilation systems, it is important to acknowledge

the positive impact of natural ventilation on indoor health; future research could enhance the platform by incorporating multiple types of ventilation systems. Studies on human behavior could lead to more effective persuasive methods, improving user experience and encouraging greater participation and interaction. Future research directions include conducting quantitative assessments of the platform's performance, such as evaluating the efficacy of comfort, health, and energy-saving measures, and quantifying occupant participation and behavior modification achieved through its use.

## **6 Conclusion**

The COVID-19 pandemic and other severe airborne diseases have underscored the critical need for effective health monitoring in facilities management, as improper strategies can have serious public health implications. Consequently, the simultaneous monitoring of health risks, energy consumption, and thermal comfort is now essential for maintaining sustainable built environments. This study introduces a real-time, cloud-based integrated platform that significantly advances adaptive built environment management. The platform stands out for several key reasons:

- **Consolidated Functionality:** It combines all essential functionalities into a single system, ensuring efficient data exchange and interoperability across devices.
- **Real-Time Simulation:** It enables real-time simulations of critical aspects of smart building management—specifically health, energy, and thermal comfort—using data from IoT sensing networks and cloud computing technologies.
- **AI-Based Persuasion:** The platform features an AI-based conversational agent designed to encourage healthy occupant behaviors and energy-saving practices, effectively balancing the tradeoffs between health, energy, and thermal comfort.

A survey conducted to assess the effectiveness of the persuasive system revealed high adoption rates (95.59%) for suggestions related to improving indoor air quality and health, compared to 79.90% for adjusting clothing to enhance thermal comfort. This indicates a strong willingness among participants to adopt sustainable practices under the platform's persuasive strategy.

By providing real-time, room-level information and comprehensive views of the building environment, the platform allows facility management teams to visualize the impact of their decisions and adjust environmental setpoints accordingly. The integrated persuasion system further enhances interactions between occupants and management, promoting behaviors that support sustainability. By taking occupant preferences into account, the platform not only improves occupant satisfaction but also contributes to the overall sustainability of the building. A case study conducted in a university building section demonstrated the platform's capabilities and the extensive information it can provide, reinforcing the potential for this system to drive energy conservation and sustainable practices.

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## Appendix A

**Table S1.** Distribution of survey responses on participant willingness.

Answers	Q1	Q2	Q3	Q4	Q5	Q6
Yes responses	44	52	56	58	59	57
No responses	24	16	12	10	9	11
Yes rate (%)	64.71	76.47	82.35	85.29	86.76	83.82
No rate (%)	35.29	23.53	17.65	14.71	13.24	16.18
Answers	Q7	Q8	Q9	Q10	Q11	Q12
Yes responses	65	67	67	65	62	64
No responses	3	1	1	3	6	4
Yes rate (%)	95.59	98.53	98.53	95.59	91.18	94.12
No rate (%)	4.41	1.47	1.47	4.41	8.82	5.88

## Appendix B

Below are the survey questions depicted in Section 4.5.

1. In summer, you feel a bit hot, and the current room temperature is slightly higher than the optimal temperature (e.g., 24°C). We suggest that you wear cooler clothing to save some energy. Compared to directly lowering the air conditioning, would you be willing to accept this suggestion?

2. In summer, you feel a bit hot, but the current room temperature is already lower than the optimal temperature. We suggest that you remove a few layers of clothing to cool down. Would you be willing to do this?

3. In summer, you feel a bit cold, but the current room temperature is actually higher than the optimal temperature. We suggest that you wear more clothing or use a blanket so that you don't have to increase the air conditioning. Would you be willing to do this?

4. In winter, you feel a bit hot, but the current room temperature is already lower than the optimal temperature. We suggest that you remove a few layers of clothing to cool down. Would you be willing to do this?

5. In winter, you feel a bit cold, but the current room temperature is already higher than the optimal

1061 temperature. We suggest that you wear more clothing so that you don't have to increase the heating.  
1062 Would you be willing to do this?

1063 6. In winter, you feel a bit cold, and the current room temperature is indeed slightly lower than the  
1064 optimal temperature. We can ask the management to increase the heating, but you can also wear  
1065 more clothing to save energy. Would you be willing to do this?

1066 7. You feel that the indoor air quality is good, but according to calculations, the risk of infectious  
1067 disease transmission in this room is high. We suggest that you move to a room with a more suitable  
1068 environment. Would you be willing to move?

1069 8. You feel that the indoor air quality is not very good, and the risk of infectious disease  
1070 transmission in this room is high. We suggest that you move to a room with a more suitable  
1071 environment. Would you be willing to move?

1072 9. You feel that the air quality is poor, but in fact, the indoor air quality is good. However,  
1073 according to calculations, the risk of infectious disease transmission in this room is high. We  
1074 suggest that you move to a room with a more suitable environment. Would you be willing to move?

1075 10. You feel that the indoor air quality is poor, and indeed the air quality is quite bad. At the same  
1076 time, the risk of infectious disease transmission in this room is high. We suggest that you move to  
1077 a room with a more suitable environment. Would you be willing to move?

1078 11. You feel that the indoor air quality is poor, but in fact, the indoor air quality is good, and the  
1079 risk of infection is low. Although you feel uncomfortable, the overall environment is good. We  
1080 suggest that you take a temporary break outside to relax and alleviate discomfort. Would you be  
1081 willing to do this?

1082 12. You feel that the indoor air quality is poor, and indeed the air quality is quite bad, but the risk  
1083 of infection is low. We suggest that you move to a room with better air quality. Would you be  
1084 willing to move?

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