

1        **A Large Language Model-based Platform for Real-Time Building Monitoring and**

2                   **Occupant Interaction**

3        **Abstract**

4        Effective management of indoor environments requires a comprehensive evaluation of health,  
5        energy consumption, and thermal comfort. However, real-time assessment of these factors is  
6        challenging due to the lack of integrated applications that combine IoT technology, real-time  
7        simulation, and user-friendly interfaces for communication. To address these challenges, this  
8        research introduces a novel platform specifically designed to manage health, energy consumption,  
9        and thermal comfort in smart buildings, leveraging IoT-based building information modeling  
10      (BIM), cloud computing, and an AI-powered conversational suggestion system based on the large  
11      language model (GPT). The platform integrates real-time monitoring, simulation, alerting, and  
12      persuasion capabilities to manage health, energy consumption, and thermal comfort, enabling  
13      responsive building environment controls by assessing tradeoffs among these dimensions and  
14      providing timely recommendations. Additionally, it employs persuasive techniques to encourage  
15      occupants to adopt environmentally-friendly practices. A case study in a university building  
16      demonstrated the platform's functionality and visualization capability. A survey assessing the  
17      persuasive system revealed high adoption rates—95.59% for switching rooms to improve indoor  
18      air quality and health, and 79.90% for adjusting clothing to enhance thermal comfort—indicating  
19      strong participant willingness to adopt sustainable practices through the platform's strategies. The  
20      key contribution of this research is the development of a comprehensive, real-time platform that  
21      enhances indoor environmental quality and sustainability through advanced monitoring, analysis,  
22      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 $t$

28

29 **1 Introduction**

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

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

57

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

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

82

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

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

109

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

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

131  
132 The manuscript is structured as follows: Section 2 reviews relevant literature. Section 3 details the  
133 study's methodology, including monitoring, simulation, and web app development. Section 4  
134 presents the case study results, followed by a discussion and future research directions in Section  
135 5. Section 6 concludes with a summary of key contributions.

136

## 137 **2 Literature review**

### 138 **2.1 Impacts of building environment factors on health, energy, and comfort**

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

142 factors related to the surrounding conditions influence occupants' comfort levels. Fanger's model,  
143 which underpins the ASHRAE-55 and ISO 7730 standards, is a widely recognized adaptive  
144 thermal comfort model that accounts for individual differences such as metabolic rate and clothing  
145 insulation [26]. This model was further refined to establish optimal comfort levels for occupants,  
146 utilizing the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) as key  
147 metrics [27]. Indoor air temperature has a profound effect on thermal comfort perception. Elevated  
148 indoor temperatures can cause discomfort and health issues like heat stress, potentially leading to  
149 more severe health problems [28,29]. Similarly, relative humidity is a critical component  
150 influencing thermal comfort and environmental satisfaction. Low humidity levels have been  
151 shown to increase fatigue among undergraduate students compared to higher humidity levels [30].  
152 Air velocity also influences thermal comfort, with studies showing that increased air velocity can  
153 lower mean skin temperature and alleviate thermal discomfort in hot and humid climates [31]. For  
154 instance, Zhou et al. [32] found a reduction in mean skin temperatures by 0.2°C–0.6°C for every  
155 1 m/s increase in air speed, although inconsistent ventilation patterns may reduce thermal comfort.  
156

157 Beyond thermal comfort, indoor health risks have gained significant attention in recent years due  
158 to the recognition of the role that built environments play in the spread of disease. Several disease  
159 outbreaks have been proven to be transmitted through the airborne route, such as measles [11],  
160 influenza [10], severe acute respiratory syndrome coronavirus (SARS-CoV) [33], and SARS-CoV-  
161 2 [12,34]. Numerous studies have explored the impact of various built environment parameters on  
162 the transmission dynamics of airborne pathogens. Factors such as temperature, humidity, and  
163 airflow rate have been identified as critical determinants that influence the survival, infectivity,  
164 and movement of pathogens within enclosed spaces [35]. For instance, research has shown that low  
165 humidity levels can enhance the stability and transmissibility of influenza viruses [36], while

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

170

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

182

## 183 **2.2 IoT-integrated digital twin**

184 The emergence of digital twin technology has revolutionized the field of asset management and  
185 monitoring, providing new opportunities for enhanced control and efficiency. Digital twin  
186 technology enables the creation of a virtual counterpart that mirrors the physical asset, leveraging  
187 the power of IoT to collect and integrate real-time data from sensors installed in the asset of interest  
188 [44–46]. Recent studies have explored IoT-integrated digital twin technologies to enhance building  
189 management practices. Zaballos et al. [47] focused on a smart campus concept involving the

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

211

### 212 **2.3 Communications technology in building management**

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

214 importance of sharing information with facility management teams. Various studies have  
215 developed different methods of sharing this information with users, including web-based and  
216 mobile applications. Mataloto et al. [52] developed an IoT system as part of a larger building  
217 energy management system (BEMS), including a platform that used data visualization templates  
218 to create a dashboard that allowed facilities management to identify appropriate actions that could  
219 lead to potential energy savings. Marinakis and Doukas [53] developed a recommendation system  
220 for intelligent BEMS in residential settings that was capable of pushing notifications when  
221 parameters exceeded certain thresholds as well as providing analytical, tailor-made  
222 recommendations and energy-saving tips. Fernando et al. [54] developed a web application that  
223 acted as a dashboard through which users could control the platform and access the energy  
224 consumption service. Ribino et al. [55] proposed a human-like social robot-based approach to  
225 monitoring indoor environment quality. Currently, communication systems in building operation  
226 and management applications primarily focus on tasks such as data visualization and notifications.  
227 Recommendations provided during communication are often targeted towards specific, singular  
228 objectives, such as reducing energy consumption or improving IAQ. However, there remains a  
229 significant gap in terms of the comprehensive analysis of tradeoff relationships between different  
230 dimensions such as energy, the indoor environment, and health risks within these systems. In  
231 addition, there is a notable knowledge gap associated with the integration of interactive tools that  
232 can understand and communicate with users in the field of building management systems (BMS).  
233 The effectiveness of these tools would be significantly increased should they be able to fully  
234 comprehend simulation results and current environmental conditions, as well as understand user  
235 concerns and preferences as expressed through natural language. Developments in this area are  
236 expected to bridge this knowledge gap and enhance communication between users and the BMS.  
237

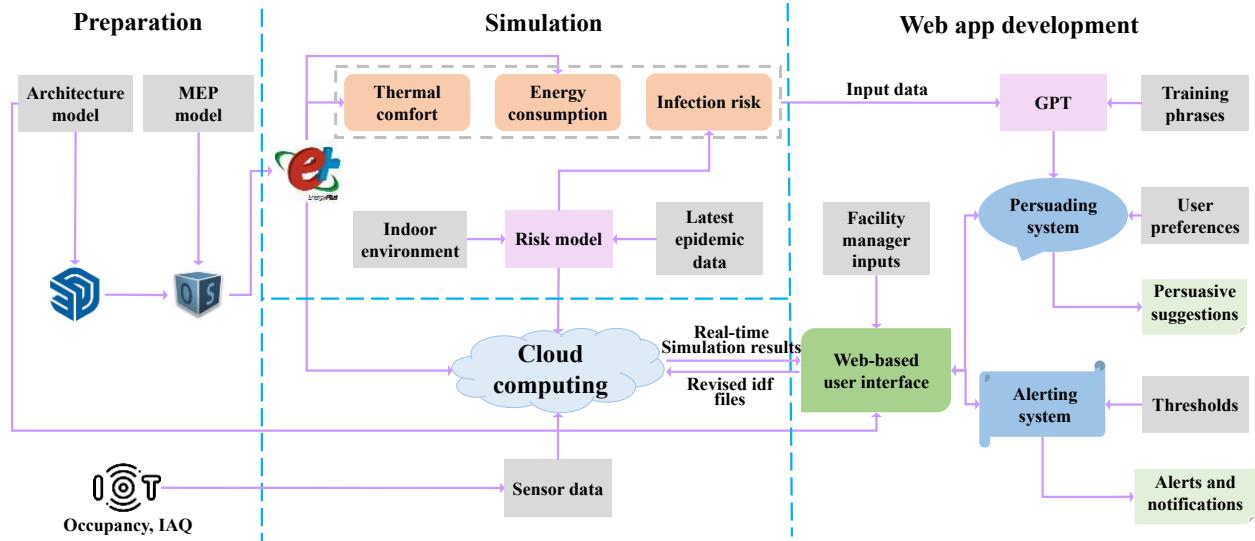
238 With the recent developments in natural language processing (NLP) as well as groundbreaking  
239 advancements in large language models (LLMs) such as ChatGPT, the integration of similar  
240 technology into communication systems is extremely promising. ChatGPT is an AI language  
241 model developed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

254

### 255 **3 Methodology**

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

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.



286

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

288

289 **3.1 Preparation**

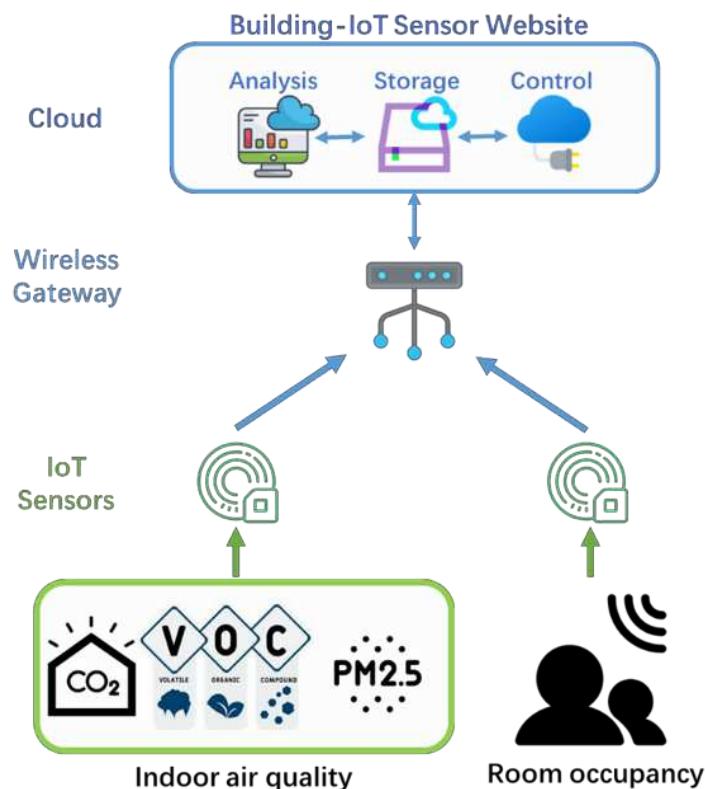
290 **3.1.1 Creating the building energy model**

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

298

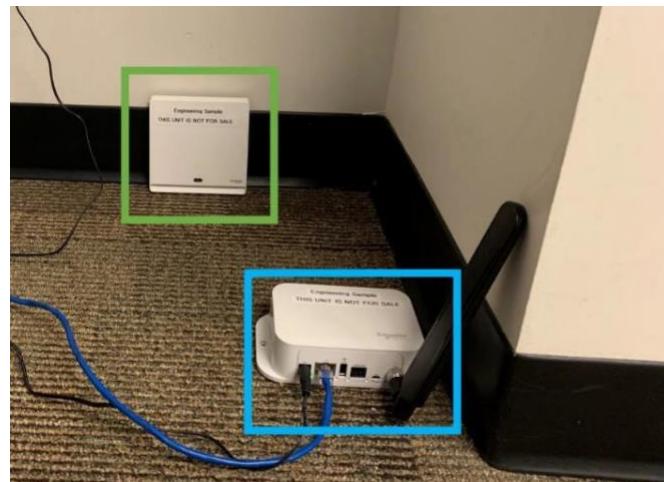
299 **3.1.2 Configuring the IoT sensing system**

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



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

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

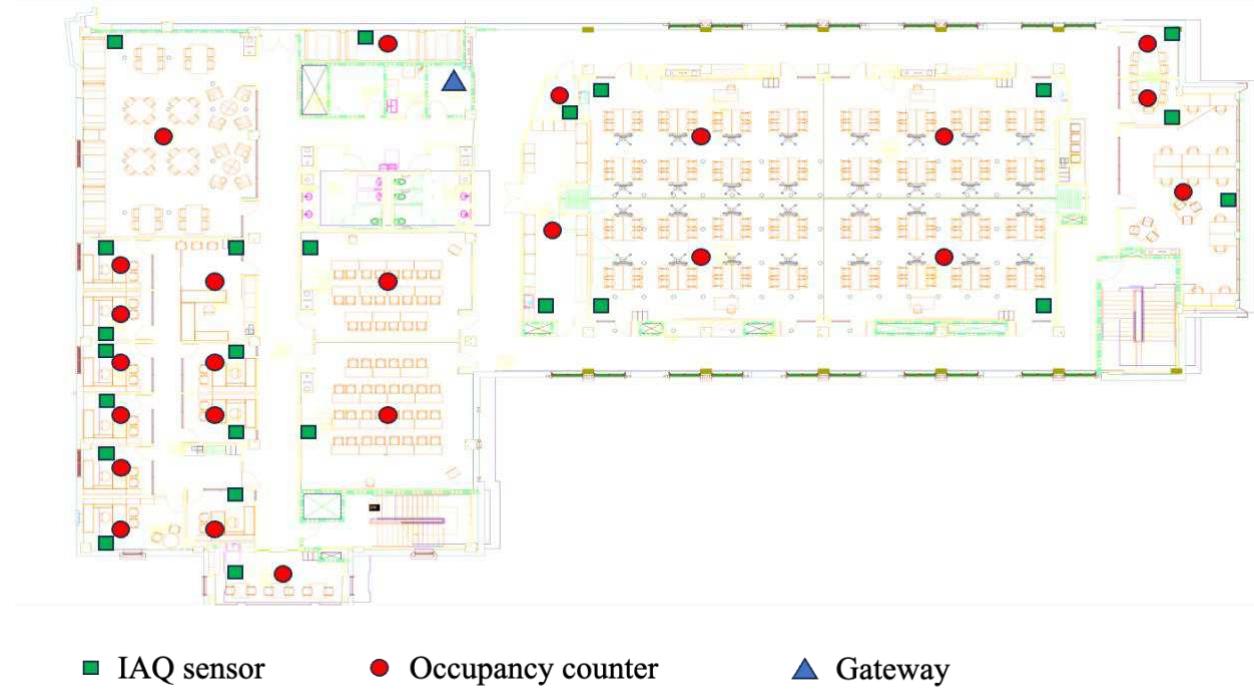


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321

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

322 In addition to the hardware setup, a building-IoT sensor solution website was used to create a virtual  
323 representation of the case study site. In this virtual representation, different rooms were defined as  
324 spaces, facilitating the mapping and identification of device locations within the building. In  
325 addition, the website was used to create virtual devices, including the gateway and sensors, and  
326 synchronize them with their corresponding physical devices. The status and location of these  
327 devices were visualized on the website, with different shapes representing different devices (Figure  
328 4).



329 ■ IAQ sensor      ● Occupancy counter      ▲ Gateway

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

331

332 **3.2 Simulation**

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

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

348

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

356

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

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

$$\begin{aligned}\mu(t) &= \frac{1}{N_{total}(t)} \times \bar{p} \times \sum_i \left( N_i(t) \int_t^{t+1} C_{quanta,i}(t, \tau) d\tau \right) \\ C_{quanta,i}(t) &= \frac{I_i(t)q}{V_i K_{total,i}(t)} (1 - e^{-K_{total}(t)}) \\ K_{total,i}(t) &= \lambda_{infiltration,i}(t) + \lambda_{ventilation,i}(t) + k_{deposition}(t) + k_{decay}(t) \\ I_i(t) &= IR * N_i(t) \\ P(t) &= 1 - e^{-\mu(t)}\end{aligned}\quad (1)$$

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

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

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

379

380 **3.3 Cloud computing**

381 **3.3.1 Real-time data retrieval and storage**

382 Real-time data was retrieved and stored using IoT sensors, including the latest updates on the  
 383 epidemic situation. The IoT data is collected using sensors deployed throughout the building,  
 384 which are then transmitted to the Amazon EC2 for storage and processing. Epidemic situation data  
 385 is obtained through an API provided by Covid Act Now [65]. This API can be integrated into the  
 386 cloud-based system, ensuring that the latest epidemic data is readily available for analysis and  
 387 simulation. Specifically, the epidemic data provided include the county hospitalizations per  
 388 100,000 people. The infection rate is then estimated using Eq. 3:

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

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

391

392 **3.3.2 Computation of health, energy, and comfort parameters**

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

400

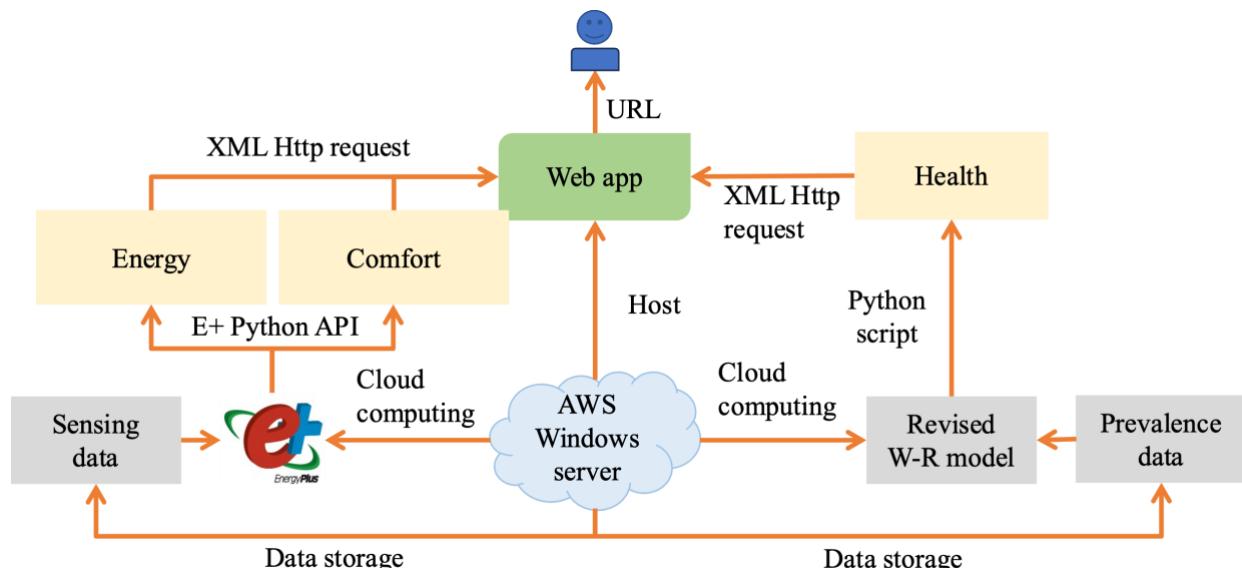
401 The Python API provided by the EnergyPlus simulation software was used to compute the energy  
402 consumption and thermal comfort parameters. This simulation software utilizes the building energy  
403 model, along with real-time occupancy data, to calculate energy consumption and assess thermal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

409

410 **3.3.3 App hosting**

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

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



430

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

432

433 **3.4 Web app development**

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

451

452 **3.4.1 Visualizations**

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

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

465

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

474

475 **3.4.2 Alerting system**

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

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

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

484 2. Relative Humidity: When the relative humidity falls below 30% or exceeds 60%, an alert will  
485 be sent to facility managers. This threshold is established because various bacteria species that  
486 contaminate humidification and air-conditioning equipment thrive outside this humidity range  
487 [60]. An alert will be sent to facility managers, informing them about these humidity-related  
488 issues. These issues can be mitigated through the activation of humidifiers or dehumidifiers at  
489 low or high humidity, respectively.

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

494 4. Indoor air quality (IAQ): An alert is triggered when the IAQ exceeds acceptable thresholds.  
495 These thresholds are set for specific parameters, which are 500 ppm [67], 15  $\mu\text{g}/\text{m}^3$  [68], and  
496 500  $\mu\text{g}/\text{m}^3$  [69] for the concentration of CO<sub>2</sub>, PM<sub>2.5</sub>, and VOCs, respectively. Exceeding these  
497 thresholds indicates that the IAQ may pose potential health risks, and facility management  
498 teams should take actions to address the situation, such as increasing the room ventilation rate  
499 or reducing the concentration of pollutants.

500

### 501 **3.4.3 AI-based persuasion system**

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

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

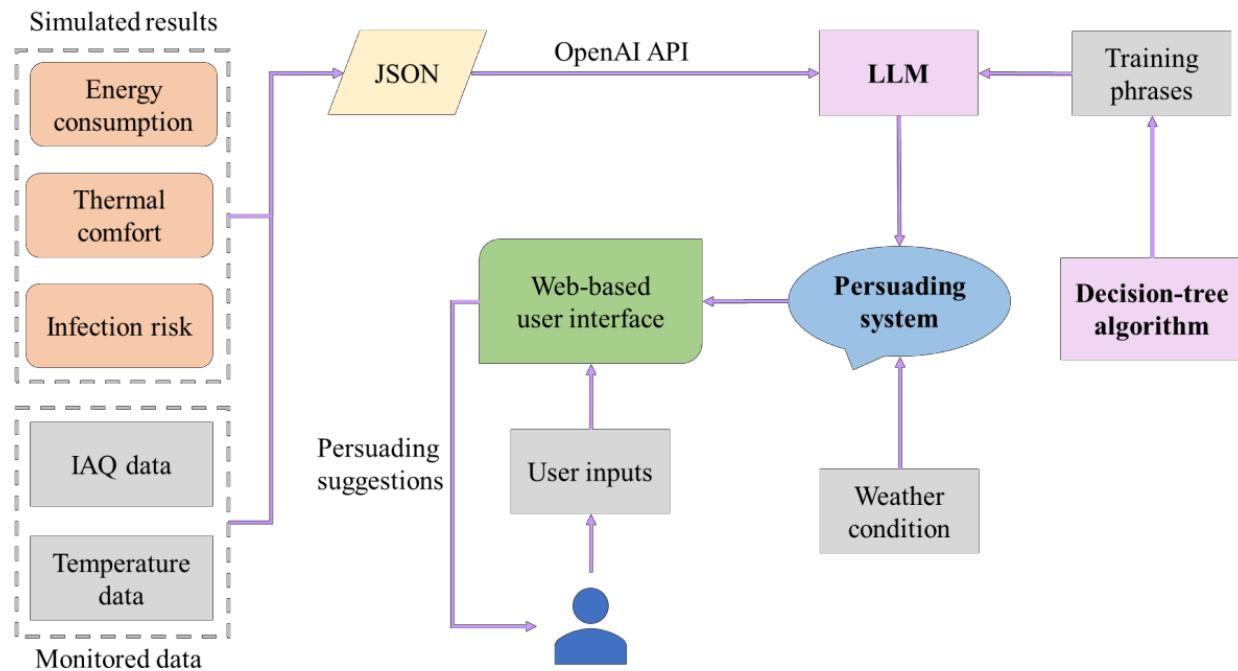
511

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

521

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

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



536

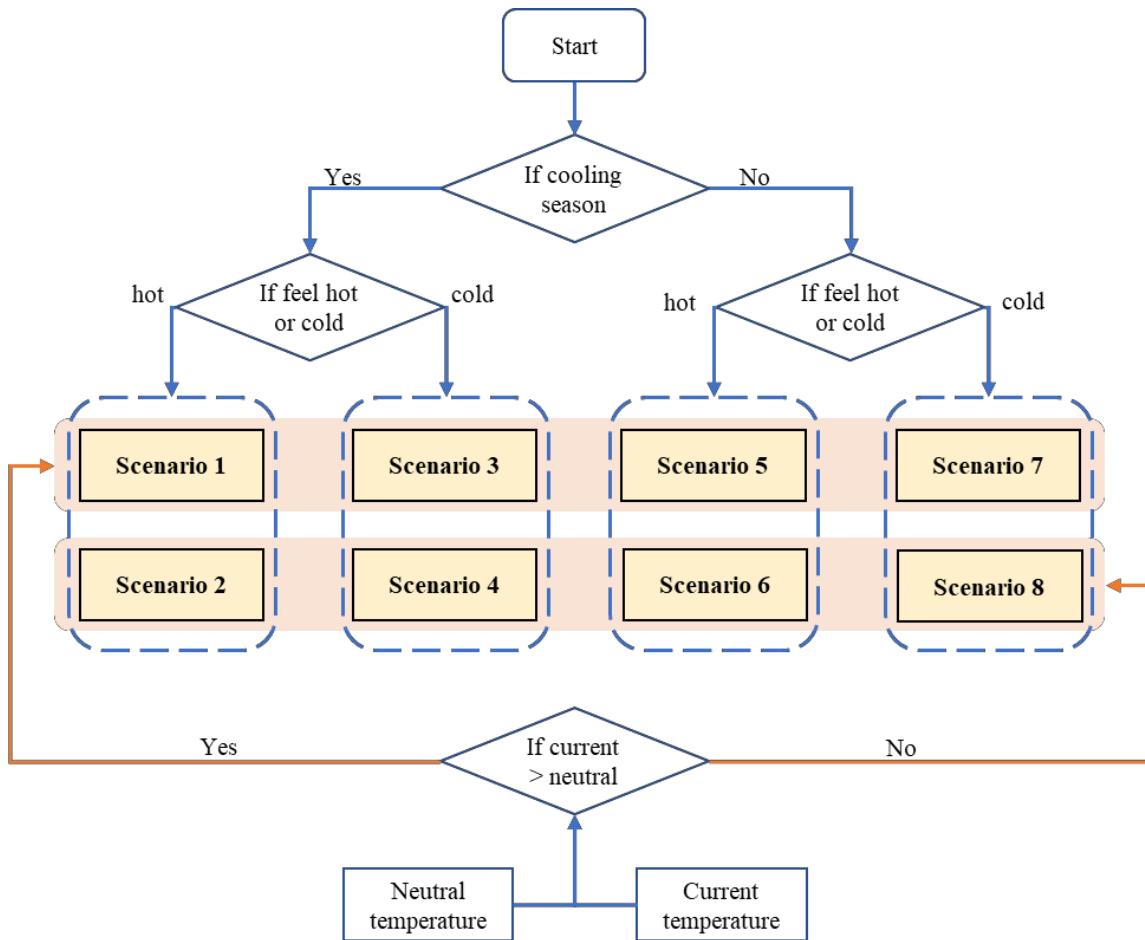
537 **Figure 6.** Integrated operations of the AI-based persuasion system.

538

#### 539 **3.4.3.1 Adaptive persuasion algorithm based on user perception of thermal comfort**

540 The first of the two adaptive persuasion algorithms utilized in the app focuses on the user's  
 541 perception of thermal comfort. The algorithm involves three decisions, with the result of each  
 542 decision based on user input or environmental conditions. A demonstration of how outputs are  
 543 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.



556

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

559

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

568 encouraging the active participation and collaboration of occupants.

569

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

574 • Scenario 1 (cooling season, the user feels hot, and the current temperature is higher than  
575 neutral): Shall I communicate with the facility managers and advise them to lower the indoor  
576 temperature? Alternatively, if you are comfortable adjusting your clothing to lighter attire, it  
577 could potentially save an estimated  $Y$  kWh of energy (where  $Y$  is the number retrieved from  
578 the result of cloud-computed energy simulation). Please let me know your preference regarding  
579 contacting the facility managers.

580 • Scenario 2 (cooling season, the user feels hot, and the current temperature is lower than neutral):  
581 The current temperature is already below the neutral level, and further lowering it may cause  
582 people to feel cold. In this situation, I recommend considering removing some clothing to help  
583 you feel more comfortable and alleviate your thermal discomfort.

584 • Scenario 3 (cooling season, the user feels cold, and the current temperature is higher than  
585 neutral): The current temperature is already higher than the neutral level. In this case, I  
586 recommend wearing an additional light blanket if you're still feeling chilly.

587 • Scenario 4 (cooling season, the user feels cold, and the current temperature is lower than  
588 neutral): The current temperature is below the neutral level. I will inform the facility managers  
589 to increase the temperature cooling setpoint, which will help save energy by  $Y$  kWh.

590 • Scenario 5 (heating season, the user feels hot, and the current temperature is higher than  
591 neutral): The current temperature is above the neutral level. I will communicate with the

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

- 594 • Scenario 6 (heating season, the user feels hot, and the current temperature is lower than neutral):  
595 The current temperature is already below the neutral level, and further lowering it may cause  
596 people to feel cold. In this situation, I recommend considering removing some clothing to help  
597 you feel more comfortable and alleviate your thermal discomfort.

- 598 • Scenario 7 (heating season, the user feels cold, and the current temperature is higher than  
599 neutral): The current temperature is already higher than the neutral level, and further increasing  
600 it may cause people to feel hot and lead to higher energy consumption. In this situation, I  
601 recommend removing some layers of clothing to help you feel more comfortable and reduce  
602 the need for additional adjustments to the indoor temperature.

- 603 • Scenario 8 (heating season, the user feels cold, and the current temperature is lower than  
604 neutral): Should I communicate with the facility managers to increase the temperature?  
605 Alternatively, you could put on more layers of clothing to help us save Y energy. Please let me  
606 know your preference regarding contacting the facility managers.

607

#### 608 **3.4.3.2 Sample training phrases and training process**

609 This section provides a comprehensive illustration of the training process through sample training  
610 phrases. Taking advantage of the LLM, all training phrases were formulated in natural language.  
611 The simulated and monitored data were transferred and demonstrated to the LLM by employing  
612 the following phrase: “Below is a JSON format simulation result of a building's room level  
613 infection risk, energy usage in kWh, ventilation rate in air change per hour, humidity condition in  
614 %, thermal comfort in PMV, temperature condition in °C, and indoor air quality in ppm. The  
615 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

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

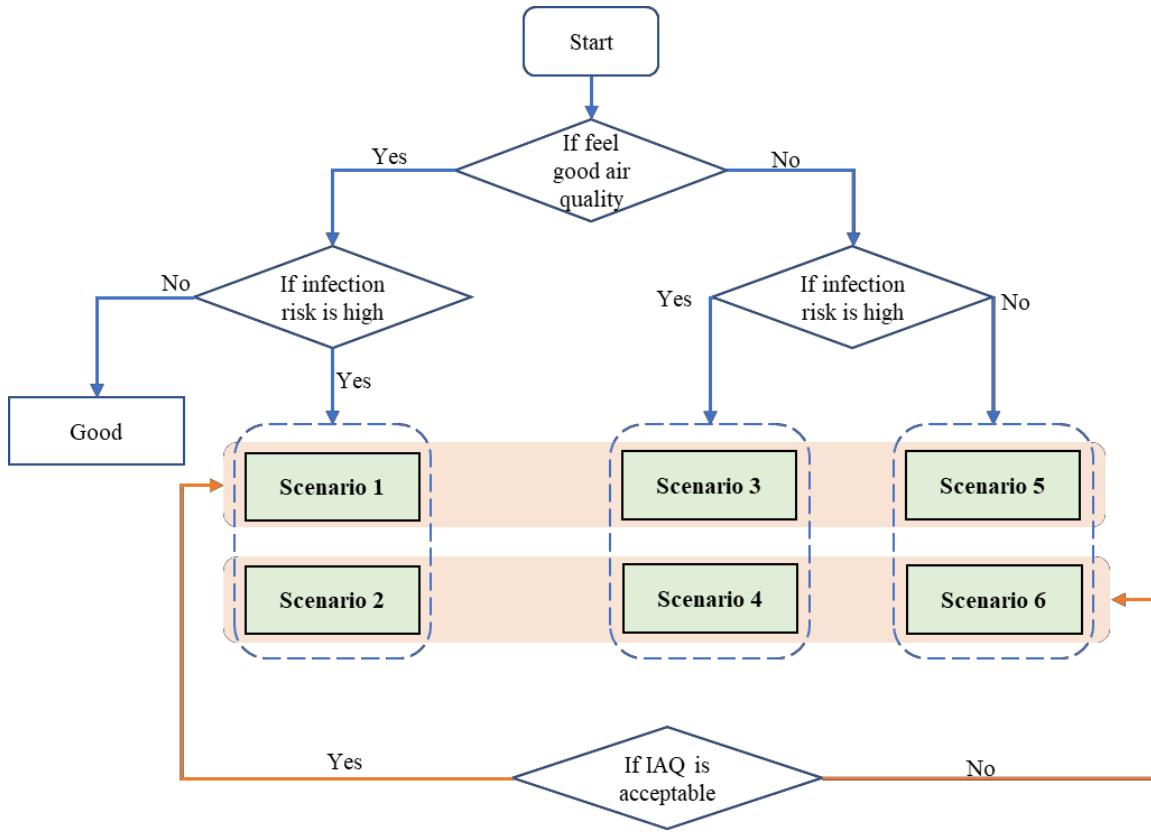
645

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

652

### 653 **3.4.3.3 Adaptive persuasion algorithm based on user perception of IAQ**

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



663

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

666

667 The system considers two crucial factors: the health risks associated with airborne diseases and air  
 668 pollutants. The system acquires the infection risk through real-time simulation results, while the  
 669 health risks related to air pollutants are obtained from the IoT monitoring system. The algorithm  
 670 presents users with different mitigation measures, allowing them to choose the option that best  
 671 aligns with their preferences. The persuasion system's initial strategy is to encourage occupants to  
 672 consider moving to another room, which helps to reduce potential health risks while minimizing  
 673 the need for the extensive implementation of mitigation measures, thus promoting energy and cost  
 674 savings. Furthermore, the system acts as a communicative link between the building occupants  
 675 and the facility management teams, providing insights into occupant preferences and needs. This  
 676 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).

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

709

#### 710 **3.4.3.5 Majority-preference based environment control algorithm**

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

719

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

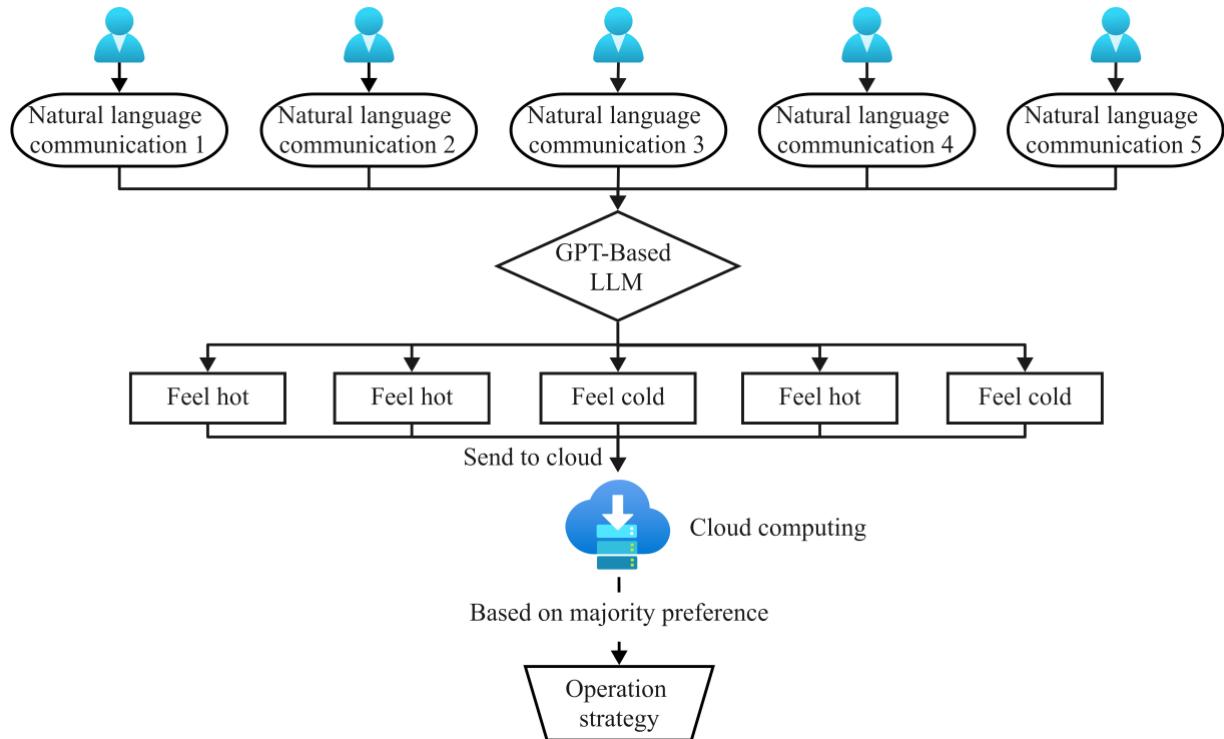
725 allowing for real-time updates and access by the app. This cloud-based storage ensures that the  
726 data is always up-to-date and can be accessed timely to make informed decisions. The app  
727 continuously updates the preference data as new feedback is received, ensuring that the decisions  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

729

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

736

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



745

746

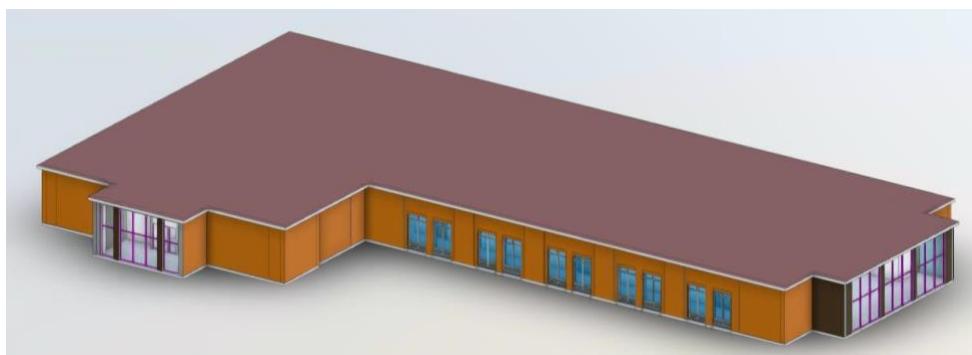
747

748 4 Case study

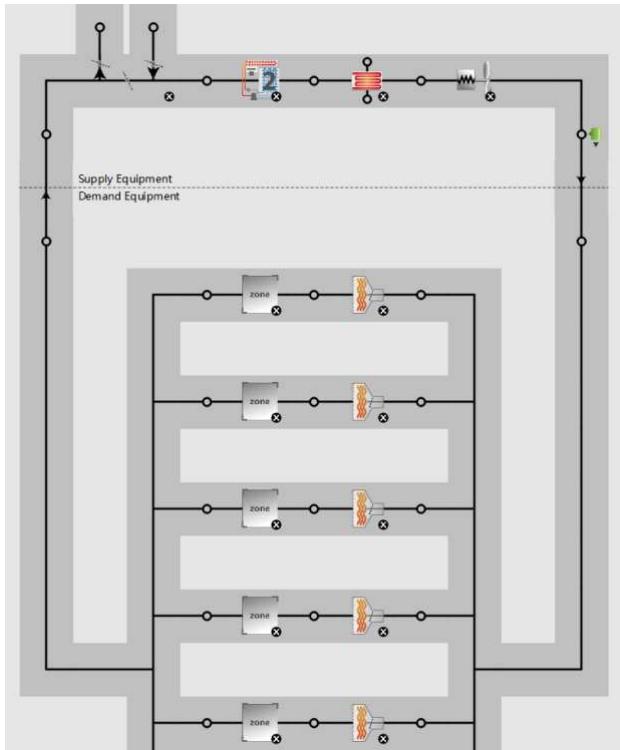
This section presents the development of a real-time, cloud-based, integrated platform aimed at monitoring three major aspects of building management, including energy consumption, thermal comfort, infection risks, and overall building environments, as well as communicating this information to users. 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.

759 **4.1 Energy model generation**

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



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

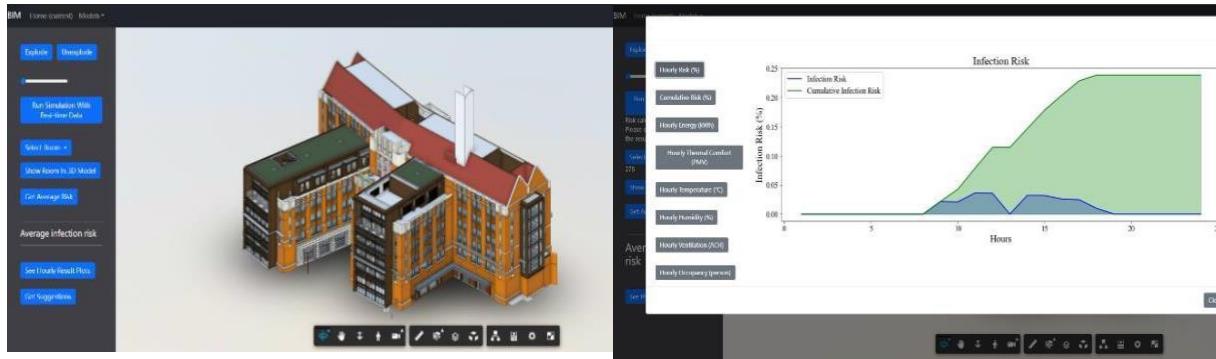


776 **Figure 11.** Diagrammatic representation of the HVAC configuration in the selected building

777 section.

778 **4.2 Web app UI**

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



783 (a)

784 (b)

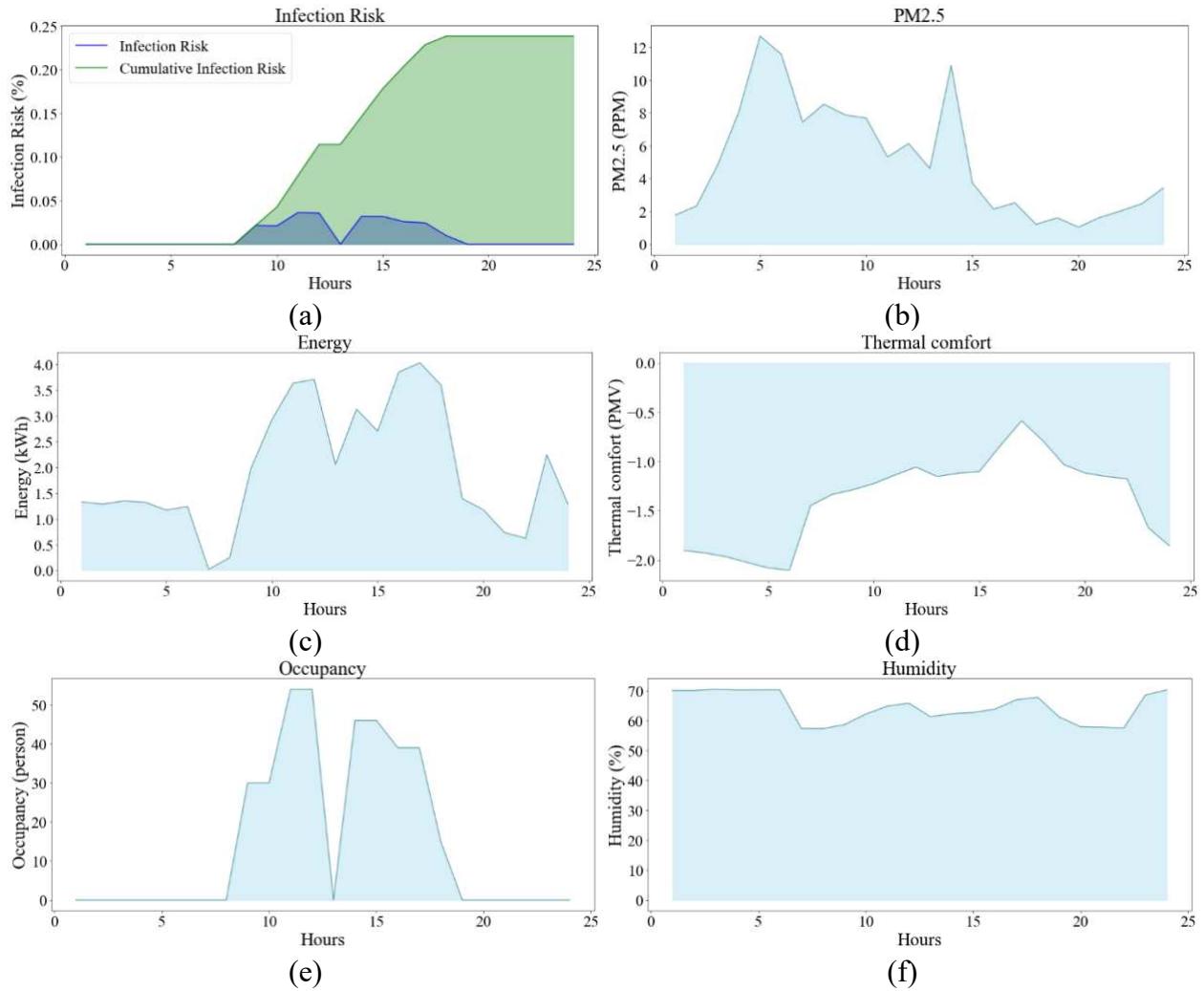
785 **Figure 12.** The UI of the web app. (a) Main page and (b) simulation results visualized using line

786 plots.

#### 787 **4.3 Sample simulation results**

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

796



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

800

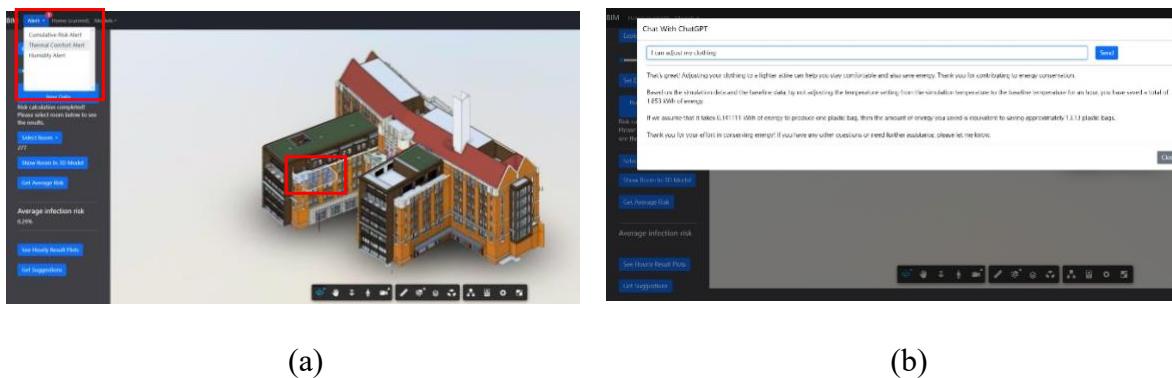
#### 801 **4.4 Alerting system and conversational persuasion system**

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

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

810

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



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

816

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

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

832

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

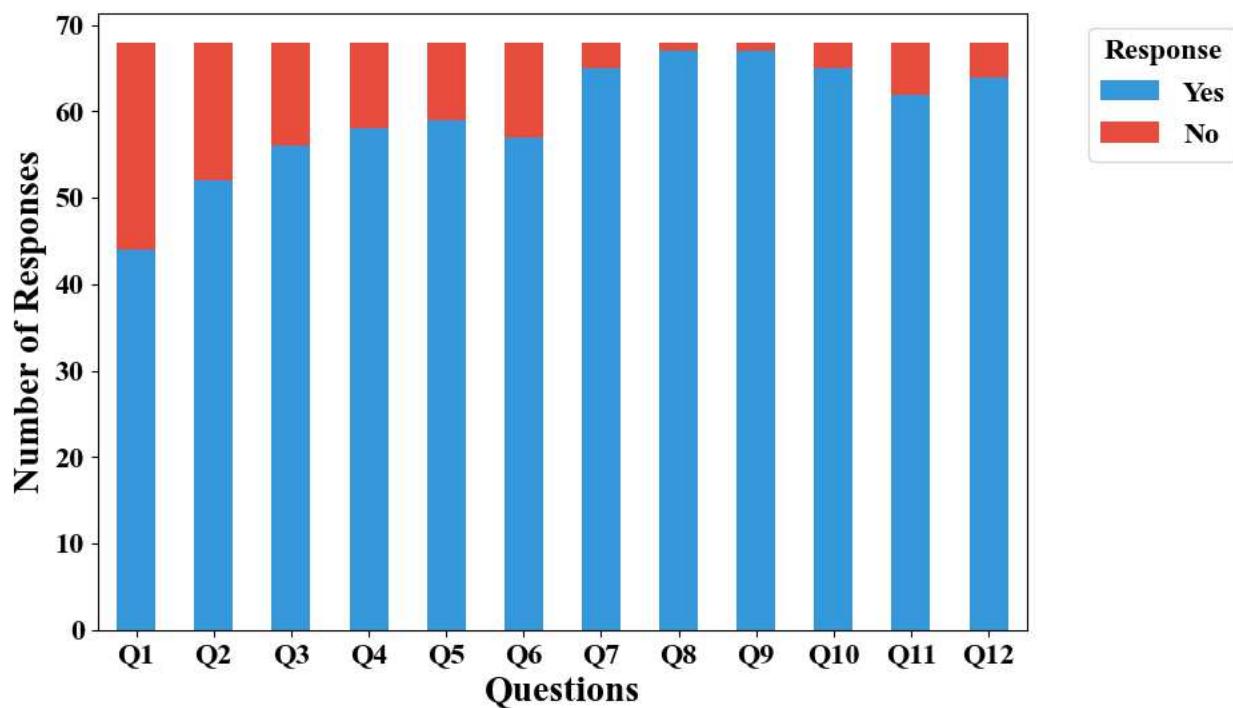
837

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

Occupant	I feel hot in room 278.
Assistant	I'm sorry to hear that you're feeling hot in room 278. I have two suggestions for you: 1. Should I communicate with the facility managers and advise them to lower the indoor temperature? 2. If you are willing to adjust your clothing to a lighter attire, it could potentially save energy. Please let me know your preference regarding contacting the facility managers.
Occupant	I can adjust my clothing.
Assistant	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. 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. Thank you for your effort in conserving energy! If you have any other questions or need further assistance, please let me know.

839 **4.5 Capability of the persuasive system**

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



850

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

852

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

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

863

## 864 **5 Discussion**

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

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

880

### 881 **5.1 Health aspects of building management**

882 The occurrence of several severe pandemics over the past two decades, including influenza, SARS,  
883 and COVID-19 pandemic, has emphasized the critical significance of health considerations in  
884 building management. Although the threat of the COVID-19 pandemic has subsided recently, the  
885 need to prevent potential disease outbreaks remains essential due to the pandemic's devastating  
886 impact on human lives and the economy. Airborne transmitted diseases pose a particularly severe  
887 threat due to their potentially rapid spread and limited means of transmission control. Indoor  
888 environments, often lacking adequate ventilation in typical operation scenarios, can become  
889 breeding grounds for airborne viruses. Hence, the development and implementation of a health-  
890 focused platform that monitors indoor environments is vital in curbing potential disease outbreaks.

891 In addition to disease transmission, traditional concerns about IAQ continue to be significant in  
892 building management. Low-quality indoor environments can adversely affect occupants' health,  
893 leading to increased absenteeism due to SBS as well as reduced productivity and performance  
894 among occupants and workers. SBS is primarily caused by contamination from various pollutants  
895 and insufficient indoor ventilation [72]. Consequently, IAQ detection was also considered in this  
896 study as a means of mitigating health risks and ensuring a healthier and more productive indoor  
897 environment.

898

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

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

909

## 910 **5.2 Interoperability achieved by cloud computing**

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

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

932

### 933 **5.3 Human-centric conversational persuasion system**

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

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

956

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

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

975

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

988

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

998 the positive impact of natural ventilation on indoor health; future research could enhance the  
999 platform by incorporating multiple types of ventilation systems. Studies on human behavior could  
1000 lead to more effective persuasive methods, improving user experience and encouraging greater  
1001 participation and interaction. Future research directions include conducting quantitative  
1002 assessments of the platform's performance, such as evaluating the efficacy of comfort, health, and  
1003 energy-saving measures, and quantifying occupant participation and behavior modification  
1004 achieved through its use.

1005

## 1006 **6 Conclusion**

1007 The COVID-19 pandemic and other severe airborne diseases have underscored the critical need  
1008 for effective health monitoring in facilities management, as improper strategies can have serious  
1009 public health implications. Consequently, the simultaneous monitoring of health risks, energy  
1010 consumption, and thermal comfort is now essential for maintaining sustainable built environments.  
1011 This study introduces a real-time, cloud-based integrated platform that significantly advances  
1012 adaptive built environment management. The platform stands out for several key reasons:

- 1013 • Consolidated Functionality: It combines all essential functionalities into a single system,  
1014 ensuring efficient data exchange and interoperability across devices.
- 1015 • Real-Time Simulation: It enables real-time simulations of critical aspects of smart building  
1016 management—specifically health, energy, and thermal comfort—using data from IoT  
1017 sensing networks and cloud computing technologies.
- 1018 • AI-Based Persuasion: The platform features an AI-based conversational agent designed to  
1019 encourage healthy occupant behaviors and energy-saving practices, effectively balancing  
1020 the tradeoffs between health, energy, and thermal comfort.

1021

1022 A survey conducted to assess the effectiveness of the persuasive system revealed high adoption  
1023 rates (95.59%) for suggestions related to improving indoor air quality and health, compared to  
1024 79.90% for adjusting clothing to enhance thermal comfort. This indicates a strong willingness  
1025 among participants to adopt sustainable practices under the platform's persuasive strategy.

1026

1027 By providing real-time, room-level information and comprehensive views of the building  
1028 environment, the platform allows facility management teams to visualize the impact of their  
1029 decisions and adjust environmental setpoints accordingly. The integrated persuasion system  
1030 further enhances interactions between occupants and management, promoting behaviors that  
1031 support sustainability. By taking occupant preferences into account, the platform not only  
1032 improves occupant satisfaction but also contributes to the overall sustainability of the building. A  
1033 case study conducted in a university building section demonstrated the platform's capabilities and  
1034 the extensive information it can provide, reinforcing the potential for this system to drive energy  
1035 conservation and sustainable practices.

1036

1037 **Acknowledgement**

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1039 greatly appreciate the support from the National Science Foundation.

1040

1041

1042 **Appendix A**1043 **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

1044

1045 **Appendix B**

1046 Below are the survey questions depicted in Section 4.5.

1047 1. In summer, you feel a bit hot, and the current room temperature is slightly higher than the  
 1048 optimal temperature (e.g., 24°C). We suggest that you wear cooler clothing to save some energy.  
 1049 Compared to directly lowering the air conditioning, would you be willing to accept this  
 1050 suggestion?

1051 2. In summer, you feel a bit hot, but the current room temperature is already lower than the optimal  
 1052 temperature. We suggest that you remove a few layers of clothing to cool down. Would you be  
 1053 willing to do this?

1054 3. In summer, you feel a bit cold, but the current room temperature is actually higher than the  
 1055 optimal temperature. We suggest that you wear more clothing or use a blanket so that you don't  
 1056 have to increase the air conditioning. Would you be willing to do this?

1057 4. In winter, you feel a bit hot, but the current room temperature is already lower than the optimal  
 1058 temperature. We suggest that you remove a few layers of clothing to cool down. Would you be  
 1059 willing to do this?

1060 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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