Digital Twins for Healthier Spaces: A Scalable Framework for Monitoring Indoor Environmental Quality

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Abstract:

With an increasing focus on sustainability, human health, and productivity, there is a growing demand for efficient methods to monitor and manage indoor environmental conditions. However, existing monitoring platforms often face challenges related to high costs and limited scalability. This study presents a practical approach to developing a Digital Twin specifically designed for assessing indoor environmental quality (IEQ). A university campus office space served as the proof of concept, illustrating the implementation of the proposed Digital Twin workflow. The platform demonstrated stability with less than 3% data loss. The IEQ dashboard, along with thermal comfort visualization for various clothing types in the 3D environment, highlights the platform's effectiveness in monitoring IEQ and its potential to enhance indoor experiences. The proposed Digital Twin framework contributes to the growing body of knowledge by offering a scalable and cost-effective solution for indoor environmental monitoring. This study seeks to advance understanding of indoor environments and support data-driven decision-making to drive improvements.

1. Introduction

The Architecture, Engineering, and Construction (AEC) industry is increasingly adopting Digital Twin technologies to enhance collaboration and improve facility management (FM), including the monitoring of indoor environmental quality (IEQ) during the operation and maintenance phase (Zhao et al., 2022). At the same time, IEQ is gaining global attention due to the growing need to enhance indoor health and comfort in the post-pandemic era, particularly through IEQ monitoring and assessment platforms. (Cai et al., 2023; De La Hoz-Torres et al., 2022). Digital Twins offer a promising solution to achieve these goals by leveraging IoT technologies, platform services, 3D visualization, simulation and prediction, and providing historical, real-time, and predictive assessments for IEQ (Opoku et al., 2024). However, the application of Digital Twins for monitoring and improving IEQ faces several challenges, especially concerning the accessibility of a Digital Twin model of the built environment and the data integration across multiple disciplines (Gnecco et al., 2023).

A 3D model for a Digital Twin should accurately replicate the physical environment and seamlessly integrate with environmental data. Developing a dynamic and "living" Digital Twin for monitoring IEQ requires not only the integration of real-time sensor data but also the incorporation of predictive modeling and statistical analysis to enable informed decision-making. This requires enriching the data with historical trends and environmental simulations that allow for future performance forecasting. For example, IoT data integration requires customized sensor deployments for specific environments like classrooms, libraries, or offices (Mansor and Sheau-Ting, 2022). A single sensor often cannot meet all needs, necessitating the use of multiple sensors, which increases costs and leads to redundant data collection, making widespread adoption less feasible. Additionally, coordinating with IT departments, especially in large public buildings like universities, presents further challenges (Opoku et al., 2024). Most importantly, true Digital Twins not only represent the current state of the building but also provide the capability to simulate future scenarios, offering predictions about how changes in environmental conditions or building usage will affect IEQ.

While Digital Twins have the potential to significantly improve IEQ in the built environment by incorporating predictive analytics and decision-support mechanisms, they face several obstacles, particularly in terms of merging BIM models with 3D point clouds (Mengiste et al., 2023) and the high costs associated with IoT sensors and cloud services. These technical and financial barriers have hindered the widespread adoption of Digital Twins (Pregnolato et al., 2022). Faced with these challenges, this paper presents a practical Digital Twinning framework to generate a Digital Twin and propose a model-fused, cost-effective, and scalable Digital Twin platform for IEQ monitoring in a campus setting, paving the way for future Digital Twin applications in similar applications.

2. Literature Review

2.1 IEQ Reporting Criterion

IEQ is mostly composed of visual comfort, acoustics comfort, Indoor Air Quality (IAQ) and thermal comfort (Broday and Silva, 2022). AlGaithi and Kim (2021) investigated the IEQ in the United Arab Emirates by monitoring IAQ, thermal comfort and visual comfort. Abdul-Wahab et al. (2015) listed different indoor air pollutants across different countries and regions, including CO_2, NO_2, formaldehyde, CO, SO_2, PM2.5 and PM10, among others. Rana et al. (2013) conducted research on the utilization of Humidex as an indicator for evaluating indoor thermal comfort. However, the Humidex index proved to be insufficient in predicting sensations of coldness. Another index, Predict Mean Value (PMV), was also used by Kanna et al. (2022) to estimate the thermal comfort level in the indoor environment by measuring temperature, humidity, and wind velocity from the environment side. Fang et al. (2020) built a Cyber-Physical Human Centric System framework to improve the human's thermal comfort level while optimizing energy consumption at the same time. Tagliabue et al. (2019) used an IoT-based system and AI-based prediction to optimize IAQ. Srinivasan et al. (2023) investigated the relationship between the productivity and comfort of humans against the indoor sound level.

These previous approaches evaluate different aspects affecting the overall comfort of human beings. However, they do not provide a comprehensive evaluation of all the different factors altogether. To overcome this, Mujan et al. (2021) showed that it is possible to indicate the overall comfort level with a four-dimensional IEQ equation and categorize it on a scale from low to high, depending on the IEQ score. Similarly, Wang et al. (2024) proposed a softmax function to combine all the environmental indicators, which included temperature, humidity, PM2.5, and VOC, to reflect comfort and well-being in an indoor environment. In summary, establishing a comprehensive reporting criterion for IEQ, along with its associated sub-indicators, is essential for effectively monitoring environmental conditions. These data-driven insights will empower occupants to identify weaknesses and enhance the current environmental conditions.

2.2 Digital Twins for IEQ Monitoring

IoT plays an inequivalent role in collecting data from an indoor environment and reporting IEQ in real-time; the development of Cyber-Physical Systems (CPSs) for indoor human wellness takes advantage of IoT techniques to sense, analyze, and predict indoor environmental quality. In manufacturing and industry 4.0-related fields, CPSs and Digital Twins are correlated, but they do not represent the same concept (Tao et al., 2019). They both contribute to building the link between the real world and the virtual world. However, the core elements of CPS are sensors and actuators, while the core elements of a Digital Twin are data and models. With the integration of IoT data and 3D building models, a Digital Twin has the ability to gain spatiotemporal data insights and perform simulation and prediction, enabling strategic building management and informed decision-making (Zhao et al., 2022).

In 2021, Desogus et al. (2021) utilized an IoT system to monitor multiple indoor indicators in BIM models, achieving spatiotemporal insights beyond CPS solely, demonstrating the importance of Digital Twins in IEQ monitoring. Opoku et al. (2024) developed a Digital Twin to monitor the indoor conditions in a university library with the integration of IoT sensors and BIM models. Qian et al. (2024) developed a Digital Twin platform that monitored the IEQ of a traditional dwelling with the scalability of the platform for Computational Fluid Dynamics simulation, prediction and timely response.

2.3 Point of Departure

As shown before, different researchers have used different criteria, such as IAQ, Humidex, and PMV, to report the IEQ. Integrating an IoT platform with a 3D building model in a Digital Twin framework provides spatiotemporal insights into IEQ, surpassing traditional CPS.

Despite the advancement of reporting IEQ using CPS or Digital Twin, three challenges hindering the implementation of Digital Twin technology for IEQ monitoring: (1) Assessing IEQ is complicated by varying measurement standards and regulatory requirements across different countries, making it challenging to establish a unified approach to IEQ evaluation (Abdul-Wahab et al., 2015). To the best of the authors' knowledge, there is no standardized method for evaluating indoor environmental quality (IEQ) in office or laboratory environments within the United Arab Emirates in the context of this research. (2) The complexity of the Digital Twin process stems from the need to integrate diverse data sources, such as sensors, 3D models, and user inputs, into a cohesive system. This integration is often costly and technically demanding (Opoku et al., 2024). (3) There is a critical need for secure, real-time, and scalable monitoring platforms that provide continuous, reliable updates and maintain data integrity (García de Soto et al., 2022; Pärn, 2024) while adapting to changing environmental conditions.

These challenges emphasize the need for a cost-effective, scalable, and secure Digital Twin platform that can address these issues and offer practical applications in the built environment. In this paper, the IEQ index proposed by Mujan et al. (2021) was used to quantitatively report IEQ in real time using IAQ (PM2.5, CO_2, and VOC), thermal comfort (PMV), acoustic comfort (noise levels), and visual comfort (light intensity).

3. Methodology

3.1 Workflow of Digital Twinning

Digital Twinning is the process of establishing a Digital Twin platform and the related elements (i.e., instrumentation of the area of interest and development of a digital model) (García de Soto et al., 2023). The proposed Digital Twinning workflow used for this study is shown in Fig. 1.

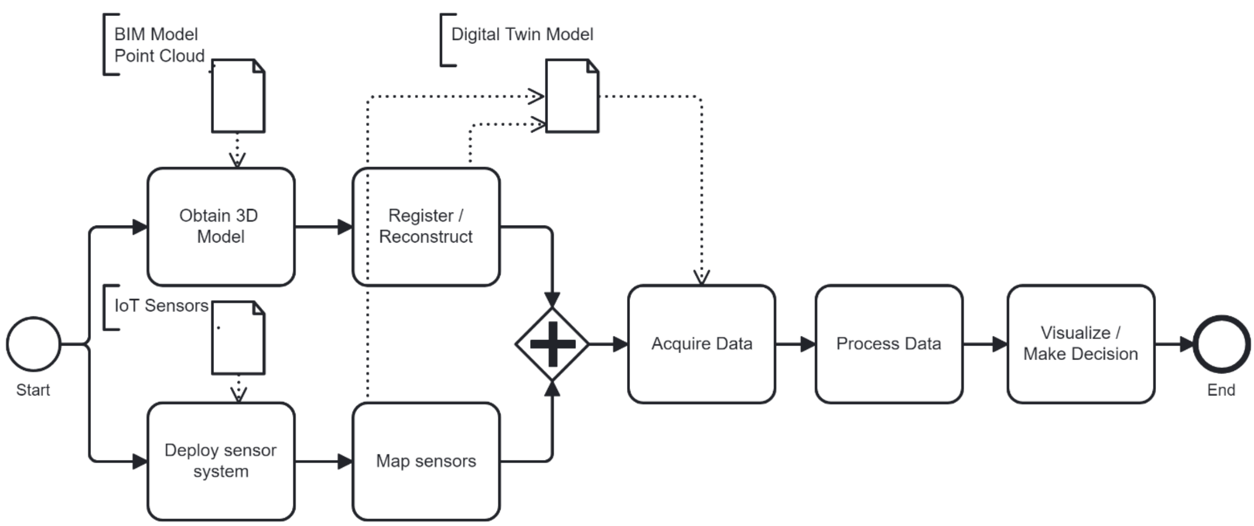

Fig. 1 Workflow for the development of the proposed Digital Twin platform

3.1.1 Obtain 3D Model

The development of a 3D model involves two possible methods depending on the availability of an existing BIM model (Darko et al., 2024). If a BIM model of the building is available, the basic geometric features of the physical environment can be extracted and used directly. However, BIM models are not always readily accessible due to ownership restrictions, file format compatibility issues, or the lack of one for renovated buildings. In these cases, point clouds that are obtained from 3D scanning techniques are used to visually reflect the status of the current indoor environment and digitally reconstruct the building model. Technologies such as laser scanning (i.e., LiDAR) or photogrammetry can capture precise spatial data (Hosamo and Hosamo, 2022).

A preliminary 3D model containing basic geometric information and high-quality texture from point cloud data is adequate to build a Digital Twin platform for IEQ monitoring. To use a preliminary 3D building model in the Digital Twin platform to monitor the IEQ, the basic geometric information is extracted from the BIM or in the case of 3D point cloud. Then the point clouds are cleaned from noise and downsampled, reducing the density to make it light and workable. When a BIM model is not available or is not up to date, this is a practical way to obtain the 3D model for the Digital Twin platform.

3.1.2 Deploy Sensor System and Map Sensors Location

Deploying the sensor system involves sensor selection, sensor build and sensor installation. The selection of the sensors is driven by the data requirements and their reliability, cost, and compatibility. In the case of IEQ, environmental parameters of four different IEQ components are required:

- *Indoor Air Quality (IAQ)*: sensors need to monitor indoor air quality parameters, such as CO_2, PM2.5, and VOC, and to be placed strategically near air circulation.
- *Acoustic Comfort*: noise sensors need to monitor noise levels, such as decibels.
- *Thermal Comfort*: thermal comfort is evaluated by PMV. Sensors need to measure temperature, humidity, wind velocity, human insulation (i.e., clothing), and metabolic rate, which are the inputs of PMV. For indoor environments and normal indoor activities, wind velocity and metabolic rate can be assigned as constant values (Zahid et al., 2021).
- *Visual Comfort*: light sensors that measure the light intensity, such as lux, should be installed (at the height of human eyes).

Mapping the sensors involves georeferencing or associating each physical sensor's position in the real world with its corresponding location in the 3D model. This ensures that the data from each sensor is accurately displayed in its corresponding location in the virtual environment, which allows for spatiotemporal features in the data analysis.

3.1.3 Acquire and Process Data

After the 3D building model and sensor data are generated and mapped correspondingly, data from the deployed sensors is collected via an IoT network, which transmits real-time information on IEQ parameters to the IoT platform. Based on that information, the IEQ can be calculated. All the raw data and processed data are securely stored for further analysis and visualization, including simulation, prediction and optimization for building management.

3.1.4 Visualize

The final stage of the workflow is to make the model and data accessible through visualization tools for monitoring and to help occupants and decision-makers make informed decisions. The 3D model visualization enables occupants and different stakeholders to navigate the 3D model of the building, visualizing the real-time environmental conditions. The dashboard used for IEQ monitoring can display the overall sensor statuses, readings, historical data and predictions.

3.2 Digital Twin Platform

Fig. 2 shows the key elements of an efficient, robust, and scalable Digital Twin platform. The main elements of the different stages of Digital Twinning are summarized next.

3.2.1 Multi-source data/model

As mentioned in Section 3.1, multi-source data are from air quality sensors, temperature sensors, light sensors, noise sensors and digital models. The sensors communicate with the IoT platform using a reliable wireless communication protocol (e.g., Zigbee, Bluetooth, MQTT, etc.) (Opoku, 2024). A BIM model and 3D point clouds are integrated into the Digital Twin environment for visualization, and the model remains static unless significant changes occur. The integration of the static model is indicated by a dashed line in Fig. 2. The monitoring platform incorporates static 3D model and dynamic sensor readings, which is indicated by a solid line in Fig. 2, to deliver spatiotemporal visual insights.

3.2.2 Containers

Containerization is a cost-effective technology that packages and runs software applications in isolated environments. Containers can be deployed and managed using different platforms, a popular one being Docker (Zhang et al., 2020). Docker has several advantages, including modularity and ease of updates. In addition, by utilizing containers, the platform can leverage TCP/IP communication to efficiently host multiple services on a single host operating system, enhancing cost efficiency, security (with proper configuration), and scalability for future expansion.

Four basic containers are essential for a Digital Twin platform to monitor IEQ: (1) IoT platform, (2) database, (3) data analysis, and (4) web application. The IoT platform container is responsible for the communication and operation of the IoT sensors; the database container stores the data from the IoT platform and results from the data analysis; the data analysis container processes the sensor data and performs statistical and assessment analysis, such as assessing current IEQ condition or predicting future IAQ; the web application container hosts the web services such as real-time monitoring, 3D model visualization, and dashboards.

The final aspect of Digital Twinning emphasizes the importance of a well-designed front-end user interface in the web application. It is essential to ensure that the connection established with the Digital Twin is secure, protecting user interactions and preventing data leakage. This ensures reliability and trustworthiness in user engagement with the platform.

A container-based approach enables the system to be modular, meaning each component can be developed, updated, or scaled separately without affecting other parts of the system.

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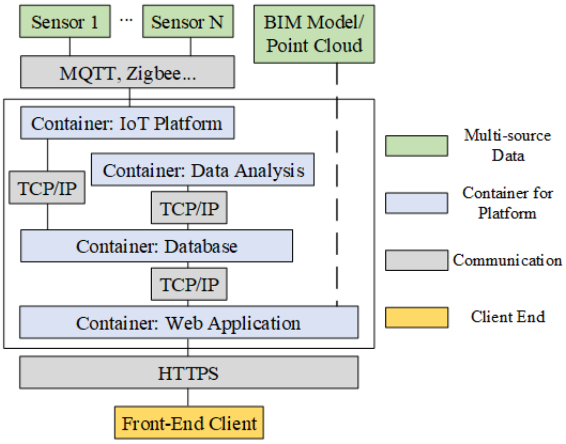


Fig. 2 Main elements of the Digital Twin Platform

3.3 Scaling of Digital Twin Platform

The proposed platform integrates multi-source data from the physical world into the Digital Twin model and allows for flexibility in the number and types of sensors based on the specific requirements for different environments. Containers, which form the backbone of the platform, can be easily replicated and deployed across multiple buildings or environments without requiring significant changes to the architecture. Security does not suffer as the system scales up since only the web application container is exposed to the public, being securely accessed by mobile devices through HTTPS connections.

The platform can operate independently without relying on external cloud service, making it an ideal solution for localized, smaller-scale applications.

4. Case Study

An office space with an approximate area of 80 m^2 on campus of New York University, Abu Dhabi was equipped as proof of concept to illustrate the implementation of the proposed Digital Twinning workflow.

4.1 Digital Twin Setups

4.1.1 Model Reconstruction

The point cloud of the space was obtained by the Leica BLK-360 scanner (Fig. 3a). The data was imported into the open-source game engine Unity 3D to generate a 3D geometrical model (Fig. 3b).

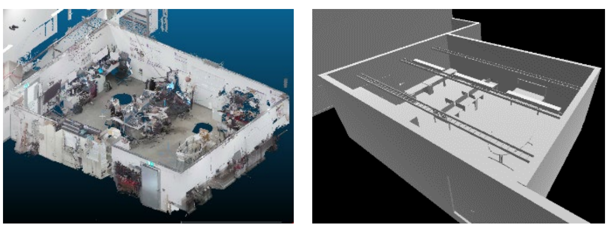

(a) Point Cloud (b) 3D Geometrical model

Fig. 3 3D Model visualization in Unity 3D

4.1.2 Data Acquisition

The sensors used are listed in Table 1. The overall plane view of the location of the different sensors is shown in Fig. 4.

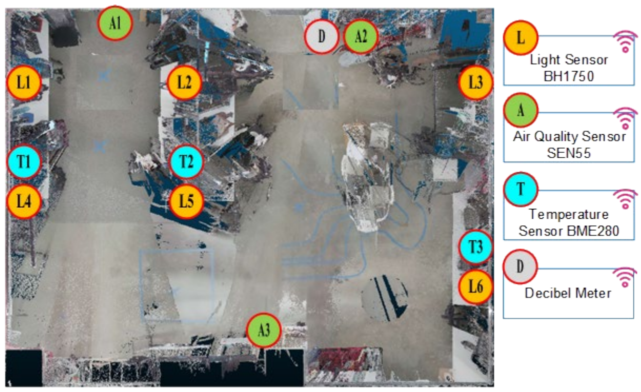


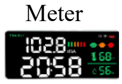
Fig. 4 Plan view of testing area with sensor type and location

The SEN 55, BME 280 and BH 1750 sensors do not possess communication modules that support MQTT or Bluetooth. To ensure communication with the IoT platform, these sensors were connected with ESP 32 modules to provide them with Wi-Fi communication capabilities and the data are transferred through the MQTT protocol. The decibel meter has a Wi-Fi connection to ensure the data transfers to the IoT platform.

4.1.3 Docker Containers

The platform used for the container-based approach was Docker. The Docker framework containing all the containers was hosted on a Synology DiskStation DS1821+, Network Attached Storage (NAS) (Synology, 2024).

Table 1 Summary of sensors used and main characteristics

Sensor	Domains	Parameter	Sampling Time	Range
SEN55 	Air quality, thermal comfort	Temperature	60 s	-10 ~ 50 (°C)
		Humidity		0 ~ 90 (RH)
		Particulate Material (PM 1, 2.5, 4, 10)		0 ~ 1000 μg/m³
		VOC		0 ~ 500 VOC Index
BME280 	Thermal comfort	Temperature	10 s	-40 ~ 85 (°C)
		Humidity		0 ~ 100 (RH)
Sound Meter 	Acoustic comfort	Decibel	1.5 s	30 ~ 130 (dBA)
BH1750 	Visual comfort	Light Intensity	60 s	0 ~ 65535 (lux)

The NAS provides a robust environment for running Docker containers that manage data acquisition, storage, analysis, and visualization. This local deployment ensures centralized management, cost efficiency, and enhanced security for all components of the system. The deployed containers are as follows:

- *Home Assistant container:* Home Assistant is an open-source IoT platform that supports a wide range of networks and integrations for indoor environmental quality (Khusnutdinov et al., 2018; Strand, 2023). Communication between the sensors and Home Assistant is facilitated through ESP 32 modules using the ESP Integration in Home Assistant, allowing for real-time data collection.
- *MySQL container:* the sensor data is stored in a MySQL database on the Synology NAS within a Docker container. A separate database container ensures efficient communication between the IoT platform and data analysis services.
- *Data processing container:* an Alpine Linux Docker container running on the NAS controls multiple Python scripts designed to analyze sensor data from the database. These scripts are executed by Linux's CRON jobs, which are scheduled to run hourly.
- *Web application container:* the web-based user interface is developed in a Django framework hosted in another Alpine Docker container. This container also hosts JavaScript, WebGL, and HTML to create interactive visualizations and dashboards. Through a responsive and secure web interface, users can monitor live sensor data, view historical trends, and engage with the Digital Twin system.

All data transfers between the sensors and the Docker containers are securely managed within the locally deployed Wi-Fi network. This ensures that all communications remain internal and protected from external threats. Furthermore, the web application is made publicly accessible via a Cloudflare tunnel, allowing users to access the system securely from outside the network.

4.1.4 Data Security

The Digital Twin platform is designed to provide open public access to sensor data while ensuring the security and integrity of the underlying system. To securely serve the public-facing dashboard, all external connections pass through a Cloudflare Tunnel, ensuring end-to-end HTTPS encryption. This setup protects against man-in-the-middle attacks and ensures that all data remains confidential during transmission. Since Cloudflare Tunnel acts as a secure proxy, no direct access to the Django server is possible from external networks. The MySQL database is hosted locally and is only accessible by the Django application, ensuring that the database is not directly exposed to the internet.

4.2 Data Validation

4.2.1 Statistical Sensor Data

As shown in Table 1, sensor data was collected at varying sampling intervals. To ensure that the IEQ index is calculated at consistent time points despite varying sensor sampling intervals, a time-weighted averaging method is applied, which aggregates the sensor data within uniform one-hour windows, calculated as Equation (1). In addition to the time-weighted average, the maximum, minimum, first-quartile, and third-quartile values during that window were also computed (e.g., Fig. 5).

$$\bar{s} = \frac{\sum[s_{t_i} \cdot (t_i - t_{i-1})]}{t_n - t_0} \quad (1)$$

where $\bar{s}$ = the time-weighted average
s_{t_i} = the sensor reading at t_i
t_0, t_n = the start and end time of the selected time window

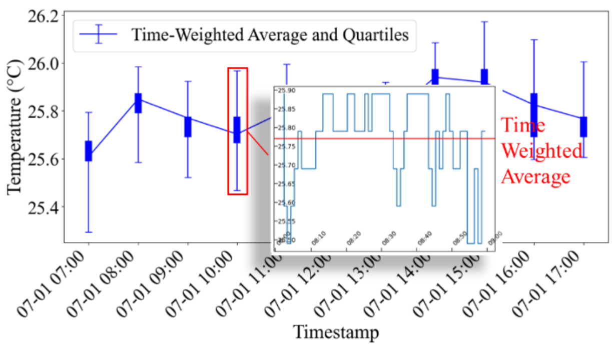


Fig. 5 Example of time-weighted average and box-plot chart (maximum, minimum, first quartile, and third quartile) for temperature data

4.2.2 Sensor Network Stability

The monitoring period used for this paper is from May 1st to October 11th, 2024. During that time, 3,936 one-hour windows and 6,403,200 sensor readings were stored in the database. A negligible amount of data (less than 3%) was missing from some sensors (Table 2) due to connectivity issues that required manual rebooting. The small amount of missing data did not impact the calculation of the IEQ.

Table 2 Summary of data collected by the different sensors from May 1st to October 11th, 2024

Record Name	Valid Record Count	Valid Stats Count	Missing Stats Count
BME 1 Temp	127,187	3,838	98 (2%)
BME 2 Temp	44,203	3,936	0
BME 3 Temp	122,398	3,936	0
SEN 1 Temp	83,393	3,848	88 (2%)
SEN 2 Temp	55,747	3,936	0
SEN 3 Temp	35,337	3,936	0
BME 1 Humidity	180,900	3,838	98 (2%)
BME 2 Humidity	91,089	3,936	0
BME 3 Humidity	178,040	3,936	0
SEN 1 Humidity	121,625	3,848	88 (2%)
SEN 2 Humidity	98,506	3,936	0
SEN 3 Humidity	95,278	3,936	0
SEN 1 PM2.5	692,892	3,848	88 (2%)
SEN 2 PM2.5	813,360	3,936	0
SEN 3 PM2.5	814,997	3,936	0
SEN 1 VOC	134,231	3,848	88 (2%)
SEN 2 VOC	172,835	3,936	0
SEN 3 VOC	168,805	3,936	0
BH 1	47,595	3,936	0
BH 2	80,543	3,936	0
BH 3	72,165	3,936	0
BH 4	82,896	3,936	0
BH 5	80,593	3,936	0
BH 7	73,303	3,936	0
Decibel	1,935,282	3,884	52 (1%)

4.3 IEQ Reporting and Visualization

4.3.1 Real-time IEQ Index Reporting

The IEQ index reported uses the average for field studies in office buildings according to Equation (2) (Mujan et al., 2021).

$$I_{IEQ} = 0.35 I_{IAQ} + 0.285 I_{TC} + 0.195 I_{AC} + 0.17 I_{IL} \quad (2)$$

Where I_{IEQ} indicates the IEQ index, I_{TC}, I_{IAQ}, I_{AC}, and I_{IL} indicate the thermal comfort component index, the indoor air quality component index, indoor acoustics comfort component index, and indoor visual comfort component index, respectively. I_{TC}, I_{IAQ}, I_{AC}, and I_{IL} are derived from the Predicted Percentage of Dissatisfied (PPD) of each comfort component or sensor reading (e.g., PPD_{VOC}, $PPD_{PM2.5}$, PPD_{AC}, and so on). Depending on the value of the I_{IEQ}, the IEQ level can be categorized from low to high. This study follows the categories proposed by Mujan et al. (2021): high (75%-100%), medium (50%-75%), moderate (25%-50%), and low (0%-25%).

The IEQ dashboard is visualized using Django + JavaScript and is accessible to users from a public web application (Castaño Molina et al., 2024). The inputs of the I_{IEQ} use the hourly average data of the sensors in each category in this study. An example of the values for the different indices derived from the sensor readings at 14:00, October 11, is shown in Fig. 6. OI that case, the I_{IEQ} was 64.1%, which falls in the medium category. When looking at the components that make up the I_{IEQ} it can be seen that thermal comfort achieves the highest score (94.9%) while indoor air quality has the lowest score (37.8%).

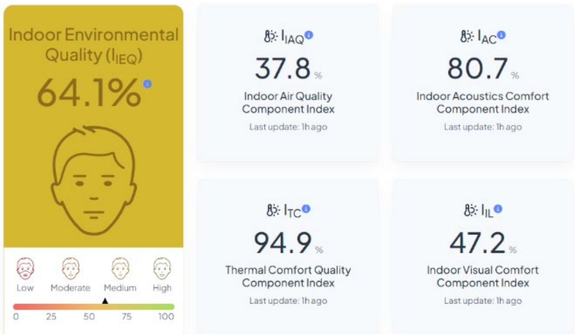


Fig. 6 Example of I_{IEQ} taken on October 11th 2024 at 14:00

4.3.2 Historical Records and Sub-comfort Index

The dashboard also shows the historical records of each sub-comfort indices (Fig. 7). For I_{IAQ}, the scores of the relevant parameters are 62.2% and 12.1% for PPD_{VOC} and $PPD_{PM2.5}$, respectively (Fig. 7 (a)), indicating a high VOC level and a low PM2.5 level–the higher value is taken for I_{IAQ}. Reviewing the historical data reveals that the I_{IAQ} fluctuates between day and night, indicating VOC accumulation during the day and dissipation at night. VOC values should be closely monitored, and further action should be taken if elevated VOC levels persist (e.g., by making ventilation adjustments, checking HVAC filters, etc.). For I_{TC}, the PPDTC of 5.1% reflects a satisfactory thermal comfort (Fig. 7 (b)). The historical thermal comfort index remains steady at a satisfactory level. For I_{AC}, the score of PPD_{AC} is 19.3%, indicating acceptable acoustics comfort (Fig. 7 (c)). The historical record also shows that the acoustics comfort remains stable at an acceptable level. For I_{IL}, the score of PPD_{IL} is 52.8%, indicating that visual comfort is dissatisfying (Fig. 7 (d)). It is worth noticing that I_{IL} value also included the time outside office hours when the lights are turned off. The I_{IL} value during regular office hours (e.g., 9 am to 5 pm, from May 7th to October 11th, 2024) is calculated from the database the result is 41.2 % (or a PPD_{IL} of 58.8%), which still could be considered a low visual comfort and the need for additional artificial lighting or increased daylight access.

(a) Indoor Air Quality

(b) Thermal Comfort

(c) Acoustics Comfort

(d) Visual Comfort

Fig. 7 Example of different IEQ components (i.e., sub-comfort indices) taken on October 11th, 2024 at 14:00

4.3.3 Location-based Thermal Comfort Prediction

Not only are the real-time and historical IEQ monitored and displayed on the dashboard, but also a continuous heat map of temperature is generated in Unity 3D. The heat map is generated using an interpolation algorithm, with the sensors mapped in a coordinated location. The snapshot from October 11th, 2024, is shown in Fig. 8, showing a clear visual representation of temperature distribution for the monitored area.

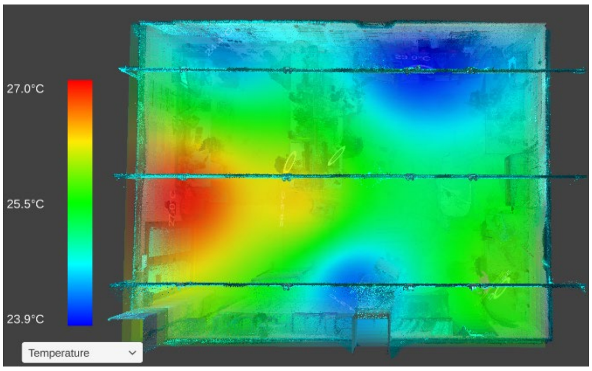


Fig. 8 Real-time temperature heatmap from a top-view.

Moreover, the Predicted Mean Vote (PMV) of an occupant at any location within the monitored area can be estimated using interpolated temperature and humidity data, along with assumed clothing insulation values according to ASHRAE Standard (2017): light clothing (trousers and short-sleeve shirt) and warm clothing (trousers, long-sleeve shirt, and suit jacket). That allows users to visualize how different clothing insulation levels impact thermal comfort (example in Fig. 9). In this case, the PMV values (0.4 and 0.9 for light clothing and warm clothing, respectively) fall within the neutral thermal comfort range [-1, +1]. The PMV of 0.4 lies in the optimal comfort range [-0.5, +0.5], indicating that light clothing is better suited for that environment compared with warm clothing.

Fig. 9 Real-time location-based PMV prediction

5. Limitations

In this study, only a specific set of low-cost sensors and a local Wi-Fi network were tested. While the experimental results demonstrate the effectiveness of the Digital Twinning workflow, the validation was limited to a single office space. One notable limitation of the platform is the network's range, which restricts the size of the testing environment. Scaling the platform to larger areas would require addressing these network limitations, potentially through the deployment of a reliable Zigbee network or integration with a building-wide Wi-Fi system. Additionally, the platform has not yet been validated across diverse indoor environments, such as residential, industrial, and educational spaces. Targeted assessments in these settings are necessary to further evaluate the platform's effectiveness in monitoring IEQ under varying conditions.

6. Conclusion and Future Work

This study demonstrates the potential of Digital Twin systems for monitoring and visualizing indoor environmental quality (IEQ) by integrating an IoT platform, 3D visualization, data integration, and containerized deployment. These systems enable data-driven decision-making to enhance indoor conditions.

Low-cost sensors were used to measure air quality, thermal comfort, visual comfort, and acoustic comfort. A 3D model (developed in Unity) combined geometrical and point cloud data for real-time visualization, while heatmaps allowed an intuitive understanding of environmental conditions. Docker containers deployed on a Synology NAS simplified the management of components like Home Assistant, MySQL, data processing scripts, and the web interface. This modular approach reduced costs and enhanced security by managing data transfers locally. The system showed stability, with less than 3% data loss, while the dashboard displayed real-time and historical IEQ data. The virtual environment also demonstrated thermal comfort insights through heatmaps and clothing suggestions based on PMV values.

Future research could focus on three key areas: (1) Predictive Maintenance and Machine Learning: Introducing predictive algorithms and leveraging machine learning could address sensor failures and optimize building automation, such as temperature control. (2) Enhancing the IEQ Framework: Refining the IEQ equation to better suit specific locations and incorporating real-time occupancy data or user feedback could improve accuracy. (3) Scaling the Platform: Expanding the platform from individual spaces to larger areas, such as entire floors or buildings, could demonstrate its scalability and broader applicability.

This study provides a foundation for scalable, secure, and cost-effective Digital Twin systems for IEQ monitoring, paving the way for more advanced applications and larger-scale implementations.

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