Indoor Comfort Assessment Based on a Digital-Twin Platform

Chia-Ying Lin[1] and I-Chen Wu[2]

[1] Department of Civil Engineering, National Kaohsiung University of Science and Technology, Taiwan
[2] Department of Civil Engineering, National Kaohsiung University of Science and Technology, Taiwan
F112141104@nkust.edu.tw, kwu@nkust.edu.tw

Abstract –

Indoor comfort is shaped by many factors, such as thermal comfort, air quality, and lighting. Traditional building-management systems often struggle to bring all these elements together and make real-time adjustments. To tackle this challenge, this study develops a digital-twin platform that combines indoor-comfort assessment with intelligent environmental control to realize real-time monitoring, accurate analysis, and efficient management of various environmental parameters. The system is based on building information modeling (BIM) and incorporates real-time sensors and camera data, which are processed to assess and adjust core comfort factors. These include thermal indices (predicted mean vote and predicted percentage of dissatisfied), air-quality metrics (CO2 levels), and lighting conditions like illuminance and color temperature. The platform utilizes Unity for environmental simulation and visualization, integrating smart lighting and air-quality sensors to deliver real-time feedback and control. To demonstrate its application, the study focuses on three common scenarios in educational settings: classroom mode, relaxation mode, and presentation mode. The system can automatically fine-tune environmental settings to meet specific user needs and enhance comfort. The results show that the system successfully bridges monitoring and control across thermal comfort, air quality, and lighting, offering a practical and efficient solution for smart-building management.

Keywords –

Digital Twin; Building Information Modeling; Thermal Comfort; Indoor Air Quality; Visual Comfort.

1 Introduction

With the rise of modern smart-building technologies, there has been growing attention on creating human-centric indoor environments that prioritize comfort. This includes addressing key aspects like thermal comfort, air quality, and lighting. However, traditional building-management systems often fall short when it comes to real-time monitoring and control of these factors.

Research shows that integrating digital-twin (DT) technology with smart devices can effectively address the limitations of traditional management systems. For example, Tan et al. [1] developed a digital-twin Lighting (DTL) system that merges building information modeling (BIM) and computer-vision technology, enabling efficient energy use alongside real-time environmental control. Their testing demonstrated an impressive 95.15% decision-making accuracy and energy-cost savings of around 79%. Similarly, Leplat et al. [2] applied DT models for multivariate simulations, achieving a balance between visual needs, ecological concerns, and lighting design, further showcasing the versatility of DT technology.

To overcome these limitations, this study proposes an integrated system based on DT technology for assessing indoor comfort and enabling intelligent environmental control. By integrating BIM, Internet of Things (IoT) architecture, and smart devices, the system enables dynamic management and optimization of multiple environmental parameters, ultimately enhancing overall comfort and user experience.

The essence of DT technology lies in seamlessly connecting physical objects, virtual models, and data to simulate and enhance the operational efficiency of physical systems [3]. While BIM has been extensively used during the design and operational phases of buildings, it struggles with integrating dynamic data and enabling adaptive control, particularly when coordinating multiple systems like HVAC, lighting, and fire safety. Additionally, challenges persist in real-time data processing and achieving standardization [4]. As modern buildings place greater emphasis on health and efficiency, the need for dynamic management of thermal comfort, air quality, and lighting has become increasingly important in smart building design. For example, maintaining optimal temperature and air circulation can significantly boost physical well-being, while lighting tailored to user needs can improve mental health, reduce stress, and enhance productivity in both learning and work environments [5].

International standards play a crucial role in enhancing indoor environmental quality. The EN 12464-1 standard offers detailed guidelines for lighting across various spaces, focusing on achieving a balanced approach to health, psychological comfort, and visual needs [6]. Appropriate adjustment of environmental parameters is essential for ensuring comfort in different scenarios, as ideal color temperature and illuminance levels can vary greatly between relaxation and work settings [7].

Building on this foundation, this study incorporates smart-lighting and environmental-sensing technologies to create a DT-based system designed for the dynamic assessment and control of thermal comfort, indoor air quality, and lighting comfort. The system simulates three common scenarios: classroom mode, relaxation mode, and presentation mode, all aligned with the EN 12464-1 standard. Through experimental evaluations, it assesses the system's effectiveness in enhancing comfort and promoting health. This research offers a practical solution for managing indoor environments in smart buildings and serves as a reference for future human-centered architectural design.

2 System Framework

The system framework is shown in Figure 1. This study adopts the EN 12464-1 lighting standard to design three typical scenario modes: classroom mode, relaxation mode, and presentation mode. Lighting parameters were customized to align with the specific requirements of each scenario. The system integrates BIM with a DT platform to enable comfort simulation and environmental control. For data processing, IoT sensors gather real-time data on temperature, humidity, and carbon-dioxide (CO2) concentration, which are further complemented by image recognition technology for detailed analysis. All data are stored in a PostgreSQL database, supporting data visualization, dynamic updates to environmental models, and intelligent decision-making capabilities. The DT platform dynamically evaluates thermal comfort, indoor air quality, and lighting comfort, focusing on predicted mean vote (PMV), predicted percentage of dissatisfied (PPD) analysis, CO2 concentration heatmaps, and intelligent lighting control. PMV and PPD are important indicators in the ISO 7730 and ASHRAE 55 standards for assessing indoor thermal comfort. PMV represents the average thermal sensation of individuals in a given environment, while PPD estimates the percentage of people likely to experience discomfort. To maintain a comfortable indoor climate, PMV values are generally recommended to stay between −0.5 and 0.5.

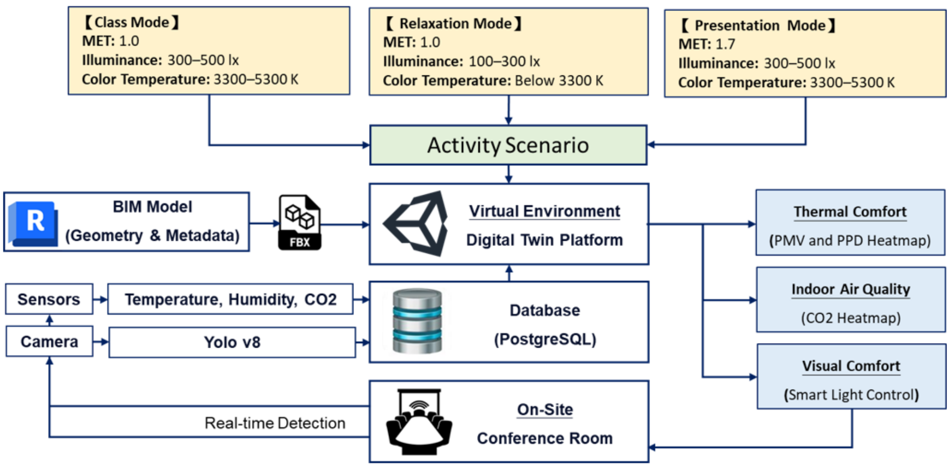
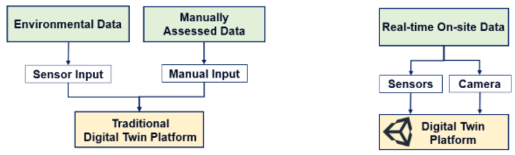


Figure 1. System framework for this research.

2.1 Conventional vs. Proposed Data Acquisition

Traditional DT platforms primarily rely on sensor data and manually entered information to construct digital models. However, this approach can lead to delays in data updates and human errors, making it difficult to reflect real-time changes in the indoor environment.

The proposed method improves automation and data timeliness by using sensors to continuously transmit environmental data, such as temperature, humidity, and CO2 concentration. Additionally, it integrates image-recognition technology to automatically estimate the number of occupants and their clothing insulation levels. These values are then used to calculate thermal comfort indicators like the PMV index. This reduces manual input errors and allows for real-time adjustments to environmental control strategies, making the DT model more responsive to actual conditions. A comparison of these two approaches is presented in Figure 2.



Conventional Approach Proposed Platform Method

Figure 2. Comparison of two data-acquisition methods.

2.2 Data Processing and Integration Workflow

First, this study uses Revit 2023 to create a BIM model that accurately reflects the characteristics of the experimental environment. To preserve material appearance during the modeling workflow, 3ds Max was used for material conversion. Autodesk-native materials were transformed into Physical Materials to avoid material loss during export. Following this step, the model was exported in FBX format for seamless integration into the Unity platform, supporting the development of the DT.

The system integrates mass data from diverse data sources, including temperature and humidity sensors, CO2 sensors, image recognition tools, and smart lighting systems. Real-time environmental data are obtained from temperature and humidity sensors, while image recognition is applied to detect room occupancy and evaluate clothing insulation levels (Icl), which are then used to calculate PMV and PPD values. Indoor air quality is assessed by monitoring and calculating CO2 concentrations using dedicated sensors. Moreover, the smart-lighting system manages dynamic lighting control based on predefined comfort parameters. This integrated dataset is processed to generate visual outputs, such as PMV and PPD heatmaps, CO2 concentration heatmaps, and lighting simulation scenarios. These visualization results can help users better understand environmental conditions and make informed decisions about adjustments.

The system utilizes continuous data streaming and real-time feedback mechanisms to dynamically adjust indoor environmental parameters, addressing the need for real-time monitoring and enhancing comfort in smart buildings. The following sections will provide a detailed overview of the analysis and implementation methods for thermal comfort, indoor air quality, and visual comfort.

2.3 Thermal Comfort Analysis

This study provides a detailed analysis of indoor thermal comfort primarily by using the PMV and PPD indices to assess comfort under various environmental conditions. The PMV index, introduced by Danish engineer Fanger [8], measures human thermal comfort in a specific setting. It takes into account several environmental factors, such as air temperature, radiant temperature, air velocity, and relative humidity, as well as personal factors like clothing insulation and metabolic rate. The calculation formula is as follows:

$$\mathrm{PMV} = (0.303\mathrm{e}^{-0.0036\mathrm{M}} + 0.028) \times \{ \mathrm{M} - 3.05 \times 10^{-3} \times (5733 - 6.99\mathrm{M} - \mathrm{p_a}) - 0.42 \times (\mathrm{M} - 58.15) - 1.7 \times 10^{-5} \times \mathrm{M} \times (5867 - \mathrm{p_a}) - 0.0014 \times \mathrm{M} \times (34 - \mathrm{t_a}) - 3.96 \times 10^{-8}\, \mathrm{f_{cl}} \times [(\mathrm{t_{cl}} + 273)^4 - (\mathrm{tr} + 273)^4] - \mathrm{f_{cl}} \times \mathrm{h_c} \times (\mathrm{t_{cl}} - \mathrm{t_a}) \} \quad (1)$$

The parameters used in the formula are summarized in Table 1, while the PMV index categorizes thermal sensations into seven levels, as shown in Figure 3.

For PMV calculation, the following data are obtained from IoT sensors:

- Air temperature (ta): Measured using the AM2320 temperature and humidity sensor.
- Water vapor pressure (Pa): Calculated based on the relative humidity measured by the AM2320 sensor, using the equation (see Equation (2)), where RH represents the relative humidity.

$$\mathrm{Pa} = \mathrm{RH} \times 10 \times \mathrm{e}^{\left(16.6536 - \frac{4030.183}{\mathrm{ta}+235}\right)} \quad (2)$$

Other parameters are computed programmatically as follows:

- Metabolic rate (M): Assigned based on the type of activity, e.g.,
  1. Resting (sitting): 60 W/m²
  2. Light walking (office walking):100 W/m²
- Mechanical work (W): Assumed to be 0, as typical classroom environments do not involve significant physical exertion.
- Clothing surface temperature (tcl): Determined iteratively based on the mean radiant temperature (tr) and air temperature (ta):

$$\mathrm{tcl} = 35.7 - 0.028M - Icl \times [3.96 \times 10^{-8} \times fcl \times (tcl + 273)^4 - (tr + 273)^4 + fcl \times hc \times (tcl - ta)]; \quad (3)$$

- Clothing surface area factor (f_{cl}):

$$\mathrm{fcl} = \begin{cases} 1 + 1.29\mathrm{Icl}, & \text{if } \mathrm{Icl} \leq 0.78\,\frac{\mathrm{m^2 k}}{\mathrm{w}}\text{; and} \\ 1.05 + 0.645\mathrm{Icl}, & \text{otherwise} \end{cases} \quad (4)$$

- Convective heat transfer coefficient (h_c):

$$hc = \begin{cases} 2.38 \times |tcl - ta|^{0.25} \\ \text{if } 2.38 \times |tcl - ta|^{0.25} \geq 12.1 \times Var^{0.5}. \\ 12.1 \times Var^{0.5}, \text{ otherwise} \end{cases} \quad (5)$$

Finally, all parameters are applied to the PMV equation for calculation. The resulting PMV values are visualized using a heatmap, providing an intuitive representation of indoor thermal comfort distribution.

In this study, the metabolic rate (M) is a key parameter for PMV calculation and is determined based on the activity-type table from ISO 7730 and ASHRAE 55 standards, as shown in Table 2. The metabolic rates are set as follows for different scenarios: 1.0 MET for classroom and relaxation scenarios and 1.7 MET for presentation scenarios, ensuring accurate PMV calculations. The PPD index is derived from PMV, which indicates the percentage of people likely to feel dissatisfied:

$$PPD = 100 - 95 \times \exp(-0.3353\ PMV^4 - 0.2179\ PMV^2) \quad (6)$$

When the PMV value is close to zero, the PPD value reaches its minimum, suggesting that most individuals are thermally comfortable. Conversely, as the absolute value of PMV increases, the PPD value approaches 100, reflecting a greater dissatisfaction.

To enhance the dynamics and accuracy of the PMV index, this study integrates YOLOv8 for real-time human detection, recording the number of individuals entering and leaving the space. YOLOv8 is a high-performance object detection framework capable of rapidly identifying and tracking the number and movement of individuals in an environment [10]. These occupancy datasets are used as input parameters for the PMV calculation, enabling real-time comfort evaluation. Additionally, this study employs the UNet (ResNet50) deep-learning model to identify clothing types, such as long sleeves and short sleeves, for calculating clothing insulation levels, thus providing critical data for accurate PMV assessment. The recognition results from UNet are shown in Figure 4.

Table 1. The meanings of the parameters in the PMV formula.

Parameter	Description
M	Metabolic rate (heat generated by the human body)
W	External work (amount of work performed by the body)
t_a	Air temperature (temperature of the ambient air)
t_{cl}	Clothing surface temperature (temperature felt on clothing surface)
t_r	Radiant temperature (mean temperature of surrounding surfaces)
f_{cl}	Clothing thermal resistance (resistance of clothing to heat conduction)
h_c	Convective heat transfer coefficient (efficiency of heat transfer between air and skin)
p_a	Water vapor pressure (pressure of water vapor in the air)
I_{cl}	Clothing thermal resistance (clothing's resistance to heat)

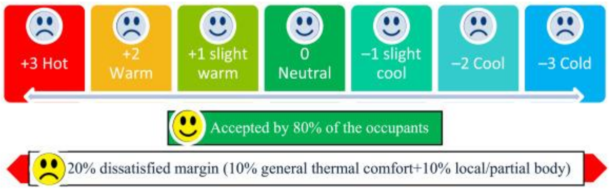


Figure 3. Definitions of PMV values according to ASHRAE [9].

Table 2. Activities corresponding to human metabolic rates.

Activity Type	M (W/m²)	M (MET)
Rest – Lying	40	0.7
Rest – Sitting	60	1.0
Rest – Standing	70	1.2
Office – Writing/Reading	60	1.0
Office – Typing	65	1.1
Office – Walking	100	1.7
Office – Organizing Items	120	2.1

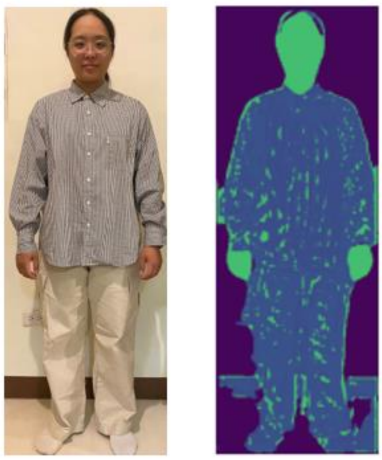


Figure 4. Recognition results for clothing insulation level.

2.4 Air Quality Analysis

This study analyzes indoor air quality by focusing on the distribution and dynamic changes of CO2 concentrations, which are visualized using heatmaps. This visualization provides an intuitive illustration of spatial CO2 levels across indoor areas, along with real-time concentration trends, thereby providing essential data for assessing and regulating indoor air quality. To further quantify the air exchange demand, the model proposed by Coley and Beisteiner [11] is used to calculate the indoor–outdoor CO2 exchange rate. The calculation formula is:

$$\mathbf{C_t} = \mathbf{C_{ex}} + \frac{\mathbf{G}}{\mathbf{Q}} + \left(\mathbf{C_{in}} - \mathbf{C_{ex}} - \frac{\mathbf{G}}{\mathbf{Q}}\right) \times \mathbf{e}^{-\left(\frac{\mathbf{Q}}{\mathbf{V}}\right)\mathbf{t}}. \quad (7)$$

In this formula, the parameters represent the following: C_t is the indoor CO2 concentration at time t (ppm), C_{ex} is the outdoor CO2 concentration (ppm), C_{in} is the initial indoor CO2 concentration (ppm), G is the indoor CO2 generation rate (ppm/h), Q is the ventilation rate (m^3/h), and V is the indoor space volume (m^3).

To accurately compute air exchange values, the following data are obtained from IoT sensors:

- Outdoor CO2 concentration (C_{ex}): Measured using the DS-CO2-20 sensor, representing the CO2 level in the outdoor environment (ppm); and
- Initial indoor CO2 concentration (C_{in}): Measured using the DS-CO2-20 sensor, representing the initial CO2 concentration inside the space (ppm).

Other parameters are derived from computational models as follows:

- CO2 generation rate (G): Determined based on the number of occupants in the space. Each person produces a certain amount of CO2 per second. In this study, the average human CO2 emission rate is assumed to be 40 mL/min.
- Ventilation rate (Q): The ventilation volume per cycle is set at 50 m^3. Accordingly, the ventilation rate is determined using:

$$Q = \frac{50}{60 \times 60}\ (m^3/s)\ . \quad (8)$$

- Indoor space volume (V): The experimental space has a volume of 118.62 m^3.
- Indoor CO2 concentration over time (C_t): The CO2 level at time t is determined based on ventilation and generation rates:

$$Ct = Q \times T\ (ppm). \quad (9)$$

This study integrates sensor data with computational modeling to accurately capture dynamic CO2 concentration changes within indoor environments, enhancing real-time monitoring and decision-making, as illustrated in Figure 5.

Furthermore, this study combines heatmap visualization with mathematical modeling to develop a dynamic air-exchange recommendation system. CO2 heatmaps provide a spatial representation of indoor CO2 distribution, enabling the system to identify high-concentration areas for targeted air-quality regulation. The air-exchange formula is then applied to predict concentration changes and determine the necessary ventilation rate. For example, in scenarios where CO2 levels exceed the threshold, the system may recommend an exchange rate of 50 m3/hr.

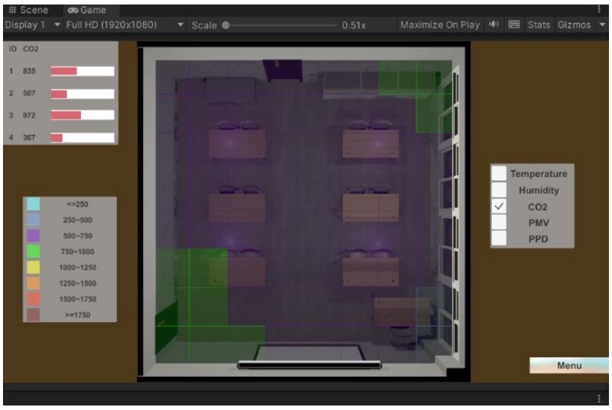


Figure 5. CO2 heatmap.

2.5 Visual Comfort and Intelligent Control

This section focuses on visual comfort and intelligent smart control, combining international lighting standards with advanced technologies to optimize lighting design and enable dynamic management for various scenarios in educational spaces.

First, lighting parameters for each scenario are defined based on the EN 12464-1 standard. The system then adjusts the lighting according to the activity type, aiming to strike a balance between comfort and energy efficiency. To assess the performance of smart luminaires under different conditions, an illuminance meter was used to measure brightness in specific zones. These measurements help map the relationship between actual brightness and illuminance, facilitating in-depth analysis of the lighting environment.

For intelligent control, the system integrates Yeelight smart luminaires with the Unity development platform. By enabling LAN control, the system establishes communication with the luminaires and uses TCP protocols to send commands for remote operation. To make it user-friendly, an intuitive interface was developed, allowing users to easily adjust brightness and color temperature with sliders and buttons. This setup supports the simulation of multiple lighting scenarios, showcasing the design's practicality and flexibility.

2.5.1 Scenario Parameter Definition

To balance lighting comfort and energy efficiency, this study establishes indoor lighting parameters for educational spaces in accordance with the EN 12464-1 standard. Key parameters like illuminance and color temperature are tailored for each scenario and adjusted based on user requirements.

As shown in Table 3 and referencing the EN 12464-1 standard's color temperature classification, neutral tones were selected for scenarios requiring focused attention, while warm tones were used in relaxation modes to promote users' psychological comfort. The standard also offers specific lighting recommendations for educational spaces, as summarized in Table 4. This study uses the abovementioned tables as a reference. Lighting parameters were tailored to meet the needs of each scenario, with detailed configurations presented in Table 5.

Table 3. Classifications of lighting color [4]

Color Appearance	Correlated Color Temperature (TCP) K
Warm	Below 3300 K
Intermediate	3300 to 5300 K
Cool	Above 5300 K

Table 4. Lighting requirements for educational buildings [4].

Type of Room, Task, or Activity	Maintained Illuminance (lx)	Remarks
Classrooms, tutorial rooms	300	Lighting should be controllable.
Lecture hall	500	Lighting should be controllable.
Student common rooms and assembly halls	200	

Table 5. Recommended lighting parameters for different scenarios based on EN 12464-1 standards.

Scene	Illuminance Range (lx)	Color Temperature Range (K)
Class Mode	300–500 lx	3300–5300 K
Relaxation Mode	100–300 lx	Below 3300 K
Presentation Mode	300–500 lx	3300–5300 K

2.5.2 Smart Luminaire Control System

To enable real-time adjustments, this study developed a user interface (UI) on the Unity platform, offering users with an intuitive way to control the luminaires. Through sliders and buttons on the interface, users can instantly adjust the brightness and color temperature, simulating different lighting scenarios based on contextual needs. To further enhance automation and adaptability, this study integrates a real-time occupancy-based lighting mode switching mechanism. Using YOLOv8 for human detection, the system monitors the number of people entering and exiting the space and dynamically adjusts the lighting mode according to predefined thresholds:

- Activation Threshold: When eight or more individuals enter the room, the system automatically switches to Classroom Mode or Presentation Mode, ensuring appropriate illumination for learning or presentation activities.
- Delay Mechanism: A one-minute delay is applied before switching modes to confirm stable occupancy and to prevent frequent unintended fluctuations.
- Deactivation Threshold: If the number of occupants drops to three or fewer, the system transitions to Relaxation Mode, minimizing unnecessary energy consumption when the room is sparsely occupied.

This system integrates automated mode-switching with manual control via the Unity-based UI, enhancing user experience while ensuring optimal lighting conditions and energy efficiency.

To enable remote operation, the "LAN Control" feature is activated in the Yeelight application, allowing luminaires to receive commands over the local network. The system then sends a UDP broadcast request to detect available luminaires, retrieving their IP addresses and ports to establish a stable connection. Once connected, TCP communication is used to transmit JSON-formatted commands, enabling functions such as turning the luminaires on/off, adjusting brightness, and modifying color temperature.

3 Case Study

This study selected the BIM Research Center of the Department of Civil Engineering at the National Kaohsiung University of Science and Technology as the experimental site, covering an area of approximately 45.62 m^2. To simulate the indoor lighting environment, the space was divided into four primary zones, with one light fixture positioned at the center of each zone, as shown in Figure 6. In line with the space's lighting requirements, this study used four Yeelight Moonshadow

550 ceiling lights, evenly distributed to meet demands of visual comfort. This configuration significantly improves light uniformity, reduces glare, and enhances overall visual comfort.

To demonstrate the application of the DT platform, this section uses "Relaxation Mode" as an example to assess indoor comfort through system operation and analysis. The platform integrates real-time environmental monitoring and visualization technologies, enabling a comprehensive evaluation of thermal comfort, air quality, and visual comfort.

For air-quality analysis, the system uses CO2 heatmaps to display real-time comfort levels across different zones, based on continuous data from four CO2 sensors. Additionally, the system offers real-time recommendations for the necessary air-exchange rate based on the monitoring results, allowing users to adjust air quality effectively.

For thermal comfort, the system utilizes the PMV/PPD index to monitor real-time environmental data and employs heatmap visualization to display the distribution of thermal comfort, as shown in Figure 7. Experimental results show that overall thermal comfort within the space stays within standard ranges, thereby satisfying the needs of human comfort.

In terms of visual comfort, under "Relaxation Mode", the lighting is set to a warm, low-light mode with a color temperature below 3300 K. This design effectively reduces the light intensity and creates a relaxed and comfortable atmosphere. The UI of the DT platform displays key parameters such as lighting intensity, color temperature, and thermal comfort metrics, as shown in Figure 8. Experimental results reveal that the virtual images generated by the DT platform align closely with the real-world environment, further validating the accuracy and reliability of the system's data, as shown in Figure 9.

To ensure data accuracy, this study used an illuminance meter to measure the brightness of smart lights and their corresponding illuminance levels in different scenarios. Measurements were taken at the center of the space, as shown in Figure 10.

During the testing, the brightness of the smart lights was gradually adjusted from 10% to 100%, with readings taken every 10%. The recorded illuminance values were then compiled into a reference table, as shown in Table 6, which displays the illuminance distribution in the space under different brightness settings. This approach ensures systematic and precise data collection, providing a robust foundation for lighting comfort analysis and validation of the smart-lighting control system.

Figure 6. Spatial lighting configuration diagram.

Figure 7. PMV heatmap

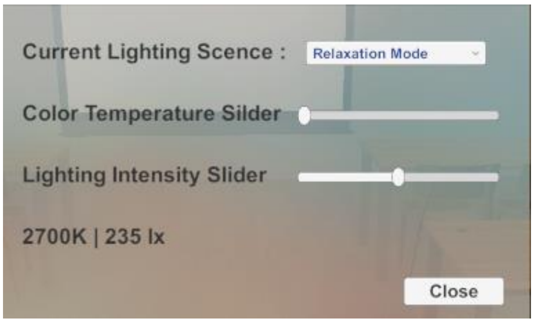
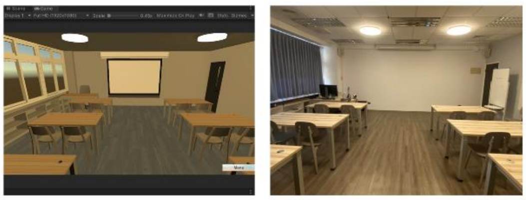


Figure 8. Parameter setting in relaxation mode.



(a) in Unity environment (b) on-site

Figure 9. Comparison of virtual and physical scenes.

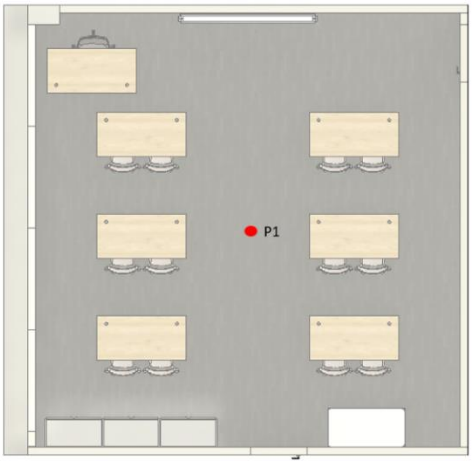


Figure 10. Sampling diagram for illuminance measurements.

Table 6 Measured illuminance values corresponding to lamp brightness levels.

Lamp Brightness (%)	Average Illuminance (lx)
10%	178 lx
20%	235 lx
30%	294 lx
40%	347 lx
50%	397 lx
60%	459 lx
70%	511 lx
80%	564 lx
90%	609 lx
100%	652 lx

4 Conclusions and Future Work

This study used three typical scenarios—classroom mode, relaxation mode, and presentation mode—as case studies to validate the application value and reliability of the digital-twin (DT) platform in assessing indoor comfort conditions. The results demonstrated that the DT platform effectively provides an intelligent and visualized solution for indoor comfort management. It achieves this through real-time environmental parameter monitoring, thermal comfort analysis from predicted mean vote and predicted percentage of dissatisfied, visual comfort assessment, and continuous CO2 concentration tracking. These capabilities collectively improve the quality of indoor environments and accommodate the diverse needs of users across different scenarios.

Future research could broaden the application scope of the DT platform by integrating additional environmental parameters, such as acoustic characteristics and indoor movement patterns. This would enable a more comprehensive assessment and control of comfort. Moreover, with advancements in artificial intelligence and Internet of Things technologies, the incorporation of deep-learning models for user-behavior prediction and adaptive environmental control will be crucial for enhancing the platform's application value. These future developments will enable more accurate and efficient solutions for smart-building management and will contribute to the design of sustainable spaces.

References

[1] Y. Tan, P. Chen, W. Shou, and A. M. Sadick. Digital twin-driven approach to improving energy efficiency of indoor lighting based on computer vision and dynamic BIM. *Energy and Buildings*, 270:112271, 2022.

[2] L. Leplat, C. López-Alfaro, A. Styve, and R. D. S. Torres. NorDark-DT: A digital twin for urban lighting infrastructure planning and analysis. *Environment and Planning B: Urban Analytics and City Science*, 23998083241272099, 2024.

[3] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks. Characterising the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 29:36–52, 2020.

[4] M. Hauer, S. Hammes, P. Zech, D. Geisler-Moroder, D. Plörer, J. Miller, and R. Pfluger. Integrating digital twins with BIM for enhanced building control strategies: A systematic literature review focusing on daylight and artificial lighting systems. *Buildings*, 14(3):805, 2024.

[5] J. A. Veitch and G. R. Newsham. Lighting quality and energy-efficiency effects on task performance, mood, health, satisfaction, and comfort. *Journal of the Illuminating Engineering Society*, 27(1):107–129, 1998.

[6] CEN. EN 12464-1: Lighting of work places - Part 1: Indoor work places, 2002.

[7] Q. Wang, H. Xu, F. Zhang, and Z. Wang. Influence of color temperature on comfort and preference for LED indoor lighting. *Optik*, 129:21–29, 2017.

[8] P. O. Fanger. *Thermal Comfort. Analysis and Applications in Environmental Engineering*. Danish Technical Press, Copenhagen, 244 p.p., 1970.

[9] K. Karyono, B. M. Abdullah, A. J. Cotgrave, and A. Bras. The adaptive thermal comfort review from the 1920s, the present, and the future. *Developments in the Built Environment*, 4:100032, 2020.

[10] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma. A review of Yolo algorithm developments. *Procedia Computer Science*, 199:1066–1073, 2022.

[11] D. A. Coley and A. Beisteiner. Carbon dioxide levels and ventilation rates in schools. *International Journal of Ventilation*, 1(1), 2002.