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Automatic Indoor Thermal Comfort Monitoring Based on BIM and IoT Technology

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Abstract: Building Information Modeling (BIM) and Internet of Thing (IoT) integration technologies can improve operational efficiency in the operational phase of construction projects. Currently, research on the integration of BIM and IoT has yet to ensure secure data transmission and lacks real-time data processing capabilities. This study builds a framework to collect and analyze BIM and IoT data in real time. The framework is verified to be effective through a case study in an office building. The monitoring system can automatically calculate the Predicted Mean Vote (PMV) value, upload and update real-time temperature and humidity data, and visualize thermal comfort through heat maps. The proposed integration approach offers building management strategies to enhance thermal comfort in office environments, fostering a more inclusive and accommodating workspace that acknowledges the diverse cultural backgrounds of occupants.

Keywords: BIM; IoT; thermal comfort; dynamo; framework

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1. Introduction

People spend about 85% of their time indoors [1], so maintaining a comfortable indoor thermal environment is crucial for humans' working efficiency and health [2,3]. Thermal comfort is defined as "a psychological state that is used to express satisfaction with the thermal environment" by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers; it has no absolute standard and varies from person to person even in the same environment [4].

Previous studies have shown that the thermal environment should satisfy at least 80% of the occupants of the space [5,6]. Existing research about real-time environmental monitoring technology is primarily focused on outdoor settings. However, the determination of the comfortable indoor temperature is not directly related to the average outdoor temperature but is influenced by the thermal characteristics of the building envelope and its heating and cooling system settings [7]. This intricate relationship underscores the necessity for real-time indoor thermal monitoring.

Building Information Modeling (BIM) is widely used in the architecture, engineering, and construction (AEC) industry, and it has been defined in various ways by stakeholders with differing interests [8]. For designers, BIM serves as a digital tool that transforms design data into a digital format, thereby mitigating risks and optimizing options [9]. For contractors, BIM represents a process for mapping and managing data produced across the building's lifecycle [10]. This research defines BIM as a method for visually managing data to decrease errors and enhance the quality and efficiency of building operations [11,12]. BIM is not only pivotal in assessing building performance but also significantly improves environmental quality during the design phase [13,14]. However, it cannot autonomously integrate real-time external environmental data, thus requiring sensors and plugins to enhance visualization capabilities [15]. The Internet of Things (IoT) constitutes a network of interconnected intelligent devices, such as sensors and actuators. This network is characterized by its openness and extensive coverage, enabling these devices to exchange and respond to information [16]. IoT technology is widely applied daily, enhancing living standards and efficiency.

Previous reliance on cumbersome and inefficient questionnaires for capturing indoor thermal comfort data has shifted. Modern digital technologies streamline the acquisition of thermal environment data efficiently [17]. BIM and IoT technologies enable real-time thermal environment monitoring and significantly enhance life efficiency. The new technological solutions offer a more streamlined and practical approach for assessing and managing indoor thermal conditions.

Current research needs to address the challenges of unifying and simplifying the development process and securing and enhancing the real-time efficiency of BIM and IoT integration technologies [18]. A critical gap exists in examining these technologies during the operational and maintenance phases of smart buildings, particularly in real-time monitoring of indoor thermal environments. Additionally, existing studies primarily focus on improving managerial efficiency from an administrative viewpoint, often neglecting the vital aspect of user experience [19,20]. There is a pressing need for initiatives that provide building occupants with real-time visualizations of the thermal environment, a change that could significantly improve their indoor experience. Furthermore, most research on the cultural influences on thermal comfort assessment is limited to outdoor spaces or large buildings, leaving a notable lack of exploration into how cultural backgrounds affect thermal comfort in small indoor environments.

Considering the research gaps identified, this study aims to meticulously explore the following research questions:

1. How to develop a framework to effectively integrate BIM and IoT from the perspective of real-time monitoring?
2. How to develop and validate a real-time updated thermal comfort monitoring platform?
3. How can the BIM–IoT integration platform be applied to enhance indoor thermal comfort by considering occupants' preferences?

This research contributes to the field by developing a comprehensive framework for the effective integration of BIM and IoT technologies, specifically focused on enhancing real-time monitoring capabilities. Additionally, it aims to create and validate a real-time thermal comfort monitoring platform that leverages advanced IoT sensors and data analytics to provide continuous feedback on indoor environments. Furthermore, the study explores the application of the BIM–IoT integration platform in improving indoor thermal comfort by incorporating occupants' preferences, thereby promoting a more responsive and user-centered approach to building management. These contributions aim to bridge existing gaps in research and practice, ultimately leading to more efficient and comfortable indoor environments. The research begins with an introduction covering background and objectives, followed by a literature review highlighting key concepts and gaps. The methodology section explains how IoT and BIM technologies are used for data integration. An engineering building case study at Xi'an Jiaotong Liverpool University (XJTLU) was applied to test the framework's effectiveness. The discussion assesses advantages and disadvantages, and the conclusion summarizes findings and suggests future research directions.

2. Literature Review

2.1. BIM and IoT Application in the AEC Industry

Existing studies on BIM and IoT integration primarily concentrate on project design and construction phases. For example, Li et al. [21] focused on the construction phase, utilizing a platform supported by IoT and BIM technologies to monitor on-site workers' health and work conditions (duration and location). Similarly, Ismail [22] concentrated on the construction phase in building projects, with a systematic literature review demonstrating that integrating IoT sensors into program-counter components and linking them to a digital representation of the physical building in BIM facilitated real-time monitoring, predictive maintenance, and energy optimization, thereby significantly enhancing construction and energy efficiency. Lokshina et al. [23] primarily emphasized the design phase, employing blockchain as a security and control measure to ensure the integration of IoT and BIM technologies. They devised an intelligent system for a smart building, a concept eventually implemented in a museum project. Only a few studies addressing the amalgamation of BIM and IoT have delved into construction projects' maintenance and operational phases. Moreover, most of these studies emphasize enhancing operational efficacy, optimizing facility management, and maximizing interior space utilization, typically targeting managers and property owners [19,20].

2.2. Methods for Integrating BIM and IoT

Currently, a unified standard for integrating BIM and IoT technologies is absent, with existing methods falling into five distinct categories. The first method capitalizes on the extant databases and Application Programming Interfaces (APIs) of BIM tools, streamlining the import, export, and modification of BIM and sensor data. This method is particularly advantageous for elementary BIM models and a modest number of sensors, accommodating users with basic programming competencies. The second strategy entails converting BIM contextual information into a database that can be queried, laying the groundwork for devising a novel data schema that facilitates the integration of BIM and IoT, thus promoting efficient information retrieval [24]. The third method employs an advanced query language to optimize BIM and IoT integration for particular scenarios. Significantly, Alves et al. [25] devised BIMSL, a domain-specific language, to enhance facility management. The fourth distinguished methodology merges BIM with the Semantic Web, unifying BIM and sensor data into a consistent format that supports collaborative and interoperable data exchange, demonstrating strong potential for enabling extensive connectivity [5,26]. The fifth approach utilizes relational databases to facilitate data conversion within a Semantic Web framework, with sensor data archived as a time series in the database to forge a correlation with building data [27,28].

2.3. BIM–IoT Integration for Improving Thermal Comfort

Despite the limited number of studies examining the application of BIM and IoT integration technologies during the operation and maintenance phase, their significant contribution to enhancing indoor thermal comfort management efficiency in this phase has been recognized [10,29]. For instance, Marzouk and Abdelaty [30] employed sensors within subway environments to collect real-time temperature and humidity data to enhance visualization of metro elements and spaces pertinent to air quality. This initiative also aided operators in identifying areas potentially experiencing thermal comfort issues. The collected data were transmitted via routing nodes to a computer and integrated into the Revit 2022 model. Subsequently, the model processed temperature and humidity data using the Arduino Uno microcontroller and the external program Gobetwino. These data were then logged into an Excel file and linked to a Microsoft Access server database, enabling real-time updates and visualization within the BIM model. Zahid et al. [31] and Chang et al. (2018) [15] utilized Dynamo, a plugin accompanying Revit, preceding Excel, to facilitate the integration of building spatial data from BIM with temperature and humidity metrics archived in the database. These studies conducted a PMV analysis using the Python programming language, enabling facility managers to visualize color-coded comfort distributions derived from sensor data within the Revit model. Instead of adopting Revit as the user interface, Valinejadshoubi et al. [17] employed a smartphone application. Integrating BIM and IoT technologies facilitated the development of a system that enabled facility managers to swiftly identify and address issues stemming from HVAC failures or building envelope shortcomings. Arowoiya et al. [32] highlighted that integrating BIM and IoT technologies enhanced the accuracy of PMV and PPD calculations for traditional thermal comfort rating indicators, thereby improving building performance and energy efficiency.

The research mentioned above primarily utilizes BIM and IoT integration technologies to furnish building operation managers and facility technicians with data for evaluating indoor thermal comfort. This approach neglects the preferences of building occupants who seek to comprehend their thermal environment directly [31]. Moreover, these investigations predominantly employ the Predicted Mean Vote (PMV) as the index for thermal comfort assessment, a metric that may prove challenging and less intuitive for the layperson. Building users would benefit more from directly transforming temperature and humidity readings into visual graphics, facilitating an immediate and clear understanding of their thermal surroundings.

In addition to the limited research focusing on building occupants' preferences for indoor thermal comfort, these studies demonstrate significant limitations. Given building occupants' lack of familiarity with specialized thermal comfort metrics, Dave et al. [33] introduced Otaniemi3D, a platform designed to furnish users with essential thermal comfort data, including temperature and humidity readings. Additionally, the platform enabled occupants to utilize an app to adjust room HVAC equipment settings. However, they overlooked the variance in thermal comfort preferences among different occupants, potentially leading to frequent HVAC adjustments and consequent equipment wear. Naheed and Shooshtarian [34] found that cultural background contributed to variations in thermal perception, preferences for specific thermal conditions, expectations of comfort, and clothing choices. In that context, culture encompassed various factors, including ethnic customs, climate, and economic conditions. Lam et al. [35] and He et al. [36] highlighted the impact of clothing on thermal satisfaction. Individuals who required additional layers for religious or aesthetic reasons tended to be more adaptable to uncomfortable temperatures.

Operating from a unified premise, Salamone et al. [37] and Shahinmoghadam et al. [38] persisted in employing the PMV as the evaluative metric for disseminating information on the indoor thermal environment to the broader building user base. Specifically, [37] introduced an integrated framework that leveraged nearable and wearable technologies, parametric modeling, and machine learning to evaluate and enhance the thermal comfort conditions for occupants. This methodology surpassed the constraints of conventional physical models through the analysis of occupants' psychophysical conditions, the application of IoT solutions, user feedback, and machine learning techniques. Nevertheless, such indicators and data may need to be more relevant to the average building occupant, who is predominantly disinclined to invest time in comprehending their implications. Ref. [38] investigated a system architecture that utilized real-time computation of PMV and Predicted Percentage of Dissatisfied indices, augmenting BIM-based visualizations in Virtual Reality settings with real-time monitoring data from IoT devices. The system employed sensors and edge computing devices to calculate average radiant temperatures derived from thermal imagery in near real time. While attempting to employ VR as a user interface to improve environmental interaction, the expensive cost of VR equipment and its cumbersome use should have been addressed, rendering the proposed framework impractical for everyday applications. Overall, extant research needs to concurrently meet the criteria for practicality, metrics intelligibility, and development cost-efficiency.

2.4. Summary of the Research Gaps

The above literature review identified gaps in the current research on BIM and IoT integration. Primarily, this integration has been extensively explored in the design and construction phases, where it assists in design adjustments, enhances construction safety, and monitors progress. However, few studies have examined BIM and IoT applications in the operation and maintenance phase, focusing mainly on improving efficiency for managers. These studies typically address automated responses, such as activating air conditioning when temperatures rise or alerting managers to deactivate cooling equipment when temperatures drop, aiming to save energy and provide convenience for managers and owners.

Most studies on integrating BIM and IoT technologies focus on new, unfinished construction projects. For example, automated management of building equipment requires that the equipment be remotely controllable or pre-equipped with necessary features. Research on using BIM and IoT to enhance old buildings is limited.

There are various methods to integrate IoT and BIM, such as using APIs to connect IoT and BIM data or developing new query languages. However, practical case studies to verify the feasibility and stability of these methods are lacking.

The potential of IoT technology to monitor indoor thermal comfort has not been fully explored. Most studies focus on using IoT to optimize building energy consumption, with fewer studies aimed at enhancing the thermal comfort experience for users.

Current thermal comfort assessments rely mainly on periodic questionnaires, which are intrusive and do not provide real-time data [39]. In environments like Sino-foreign universities, the diverse thermal comfort needs due to cultural and climatic differences are not adequately addressed by existing methods. There is a need for research to develop a platform that allows building users to choose a personalized thermal environment.

3. Research Methodology

To achieve the research objectives and solve the research question, this research was conducted according to the process shown in Figure 1. The process began with presenting questions through an introduction and a comprehensive literature review to identify existing knowledge and gaps. The analysis highlighted key research gaps, such as the lack of a unified integration method for BIM and IoT, insufficient case studies validating the reliability and practicality of this integration, and a lack of focus on enhancing users' indoor thermal comfort assessments. From these gaps, specific research questions were formulated, including how to effectively integrate BIM and IoT, realize real-time thermal environment monitoring, and present thermal data visually. The research objectives were then defined to address these questions, aiming to integrate BIM and IoT safely and efficiently, achieve real-time monitoring, and provide clear visualizations of thermal data. To solve these questions, the research methodology employed BIM tools' APIs and a relational database, utilizing the Revit model platform and measuring key parameters such as temperature, humidity, and PMV, with heat maps used for visualization. This approach aimed to offer users reliable information to improve their indoor thermal comfort satisfaction. A practical case demonstration was conducted in Room 577 of XJTLU's Engineering Building, with the research concluding by drawing insights from the findings and case study. This structured approach ensured a comprehensive exploration and practical validation of the integration of BIM and IoT technologies for enhancing indoor thermal comfort.

To successfully visualize the indoor thermal environment, this study used IDW to calculate the correlation values of interpolation points, as shown in Equations (1)–(3).

$$d_i = \sqrt[2]{(x - x_i)^2 + (y - y_i)^2} \quad (1)$$

$$w_i = \frac{1}{{d_i}^p} \quad (2)$$

$$Z_{(x,\ y)} = \frac{\sum_{i=1}^{n} w_i \times Z(x_i, y_i)}{\sum_{i=1}^{n} w_i} \quad (3)$$

d_i: distance from the discrete point to the interpolating point.

(x, y): interpolating point coordinates.

(x_i, y_i): discrete point coordinates.

w_i: the weighted value of the interpolation point.

p: power parameter that controls the rate at which the weights decrease with distance, typically >0, here taken as 2.

$Z_{(x,y)}$: estimated value of interpolated point with coordinate (x, y).
$Z_{(x_i,y_i)}$: the value of a discrete point.
n: total number of discrete points.

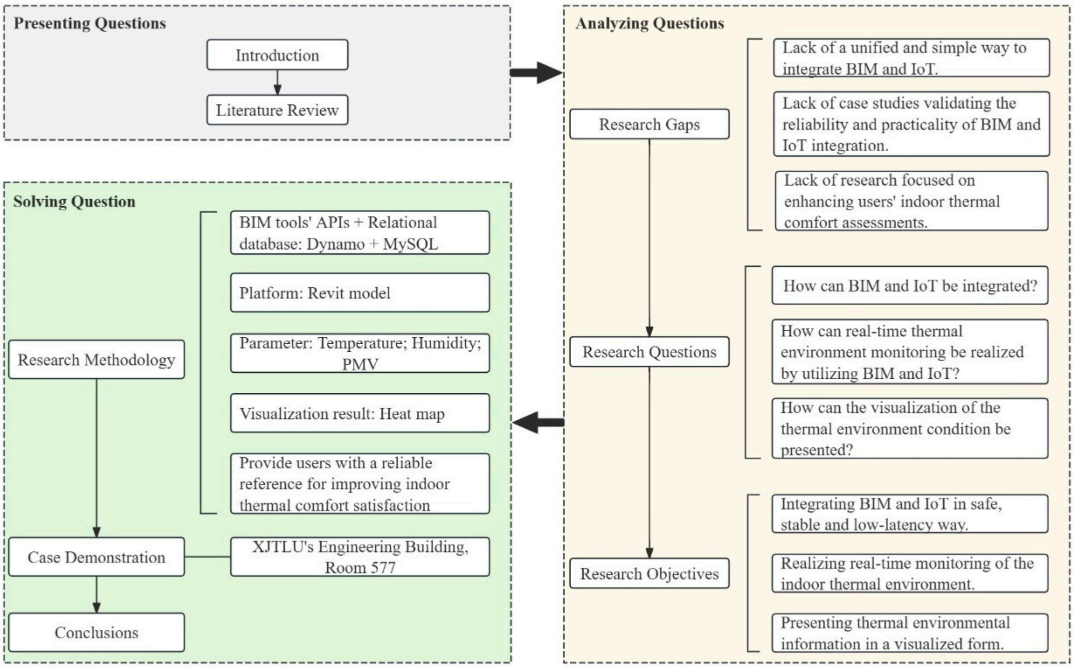


Figure 1. Research framework.

In this research, the proposed framework depicted in Figure 2 encompassed four primary units: the data collection unit, the data transmission unit, the data sorting and updating unit, and the visualization unit. Detailed descriptions of these units are provided in the subsequent sections.

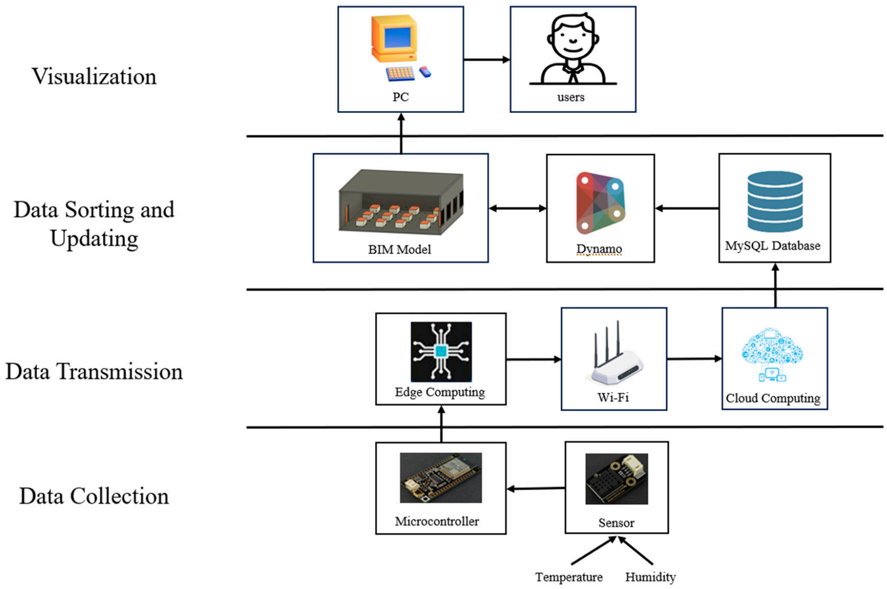


Figure 2. The framework of the proposed visualization platform.

3.1. Data Collection

The data collection unit consisted of microcontrollers connected to temperature and humidity sensors. This research employed the ESP32 microcontroller to communicate air temperature and relative humidity data in the room. Although the ESP8266 microcontroller is similar in size and supports Wi-Fi communication at a lower cost, the ESP32's dual-core processor offers better Wi-Fi performance compared to the single-core ESP8266. Therefore, the ESP8266 was not considered for this research.

The DHT-20 Digital Temperature and Humidity sensor was used in this study. The DHT-20 measures temperatures from −40 to 80 °C with a resolution of 0.01 °C and a measurement error of ±0.5 °C. It also measures humidity from 0 to 100% RH with a resolution of 0.024% RH and a measurement error of ±3% RH. The choice of the DHT20 sensor, despite its ±0.5 °C accuracy not aligning with the ASHRAE 55-2020 requirement of ±0.2 °C, may be justified by considering several factors: the application context, cost-effectiveness, and acceptable risk levels. The DHT20 sensor offers improved accuracy compared to the DHT11 used in previous research, which has a temperature error of ±2 °C [38]. In scenarios where budget constraints exist or where high precision is not critical for decision-making, the DHT20's performance is sufficient for indoor environment monitoring and data collection. Additionally, integrating the sensor into a larger BIM–IoT framework enabled real-time data aggregation and analysis, potentially mitigating the sensor's accuracy limitations through averaging multiple measurements and correlating them with other environmental factors. This pragmatic approach allowed for effective thermal comfort monitoring while balancing cost, complexity, and acceptable measurement tolerances.

3.2. Data Transmission

In terms of data transmission, this study leveraged edge computing and cloud computing technologies to develop microcontroller Wi-Fi connectivity and database connections within the Arduino IDE 2.2.1 platform using C++ language code. The edge computing aspect allowed for real-time data processing and decision-making at the microcontroller level, reducing latency and improving responsiveness [40]. Concurrently, cloud computing facilitated the storage, analysis, and management of large data sets in a scalable manner. The microcontroller connected to Wi-Fi, enabling seamless data transmission to the cloud, where advanced computational resources handled extensive data processing tasks. This integrated approach ensured efficient and reliable data flow from the sensors to the database, enhancing the overall system's performance and robustness.

3.3. Data Sorting and Updating

The data sorting and updating unit consisted of a MySQL database integrated with a BIM system. This study used the MySQL platform to develop the relational database, which stored and updated data captured by sensors. It employs Structured Query Language (SQL) to manage and retrieve data efficiently, supports multi-user access, and processes large data sets effectively. The database schema consisted of tables designed to handle the required data. Due to software incompatibilities with newer MySQL versions, such as version 8.0, and to ensure stability and compatibility with Arduino and the Dynamo platform, this study adopted MySQL version 5.7. The temperature and humidity data collected by sensors were sent to the online MySQL database at the frequency specified by the code.

The BIM system consisted of a Revit model and several Dynamo scripts. The Revit model was created using Revit 2022 software to store building space information. Dynamo, a plugin seamlessly integrated with Revit, enables real-time feedback and modifications through dynamic connections and it allows users to create custom design scripts, enhancing productivity, reducing errors, and maximizing the benefits of BIM technology [41]. Therefore, this study chose Dynamo over creating another API to connect sensor data with the BIM model, ensuring stable operation. This module mainly extracted and integrated space information stored in the Revit model with the temperature and humidity time-series data stored in MySQL. The integrated data were then imported into the corresponding properties of Revit model components.

3.4. Visualization

Given that humans are naturally adept at interpreting spatial and visual information, heat maps can instantly and intuitively convey temperature data [33]. To better visualize thermal comfort, this study used Revit as the user interface to display visualizations processed and generated by Dynamo nodes. By leveraging Revit's 3D modeling capabilities, users could more easily view the temperature distribution across different spaces, while Dynamo nodes handled real-time sensor data processing to create the corresponding heat maps. This combination not only enhanced data visualization but also enabled users to more easily understand and utilize this information to optimize indoor thermal comfort.

4. Case Study

4.1. Framework of the Thermal Comfort Monitor Platform

4.1.1. Data Collection

In this case study, Revit 2022 was used to model a PhD office in the Engineering Building of Xi'an XJTLU (Figure 3). The office's selection reflected XJTLU's unique position as a Sino-foreign, comprehensive, international university with a diverse population. This diversity was critical, encompassing a broad spectrum of thermal comfort preferences influenced by varied cultural backgrounds and climatic experiences. For example, cultural practices and clothing preferences, such as lighter attire in warmer climates versus traditional sarees, indicated differing thermal comfort thresholds [42]. These variations underscored the importance of considering a wide range of comfort levels in the study. Additionally, the office's communal use by multiple PhD candidates, rather than a single occupant, presented a unique scenario for evaluating shared thermal comfort perceptions. The office's desk arrangement supported self-selection, empowering students to choose their preferred seating in contrast to conventional university-assigned seating. This strategy fostered autonomy by aligning with individual seating preferences, directly supporting the study's objective: to use visual feedback to enable occupants to tailor their seating choices for enhanced personal comfort and satisfaction with the indoor thermal environment.

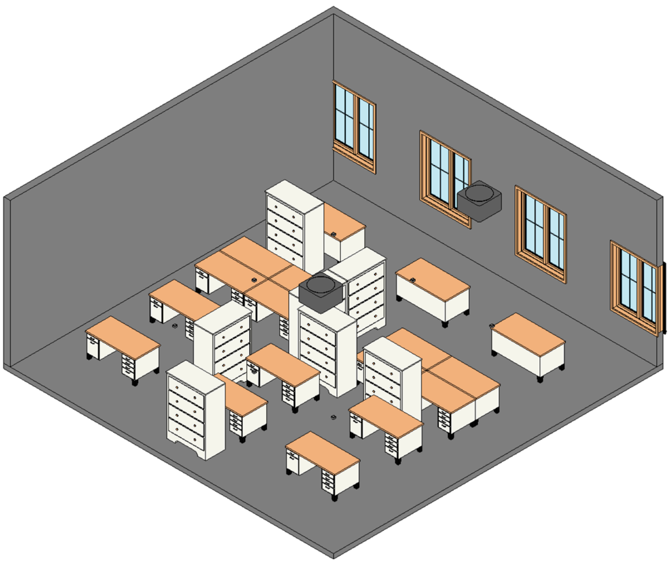
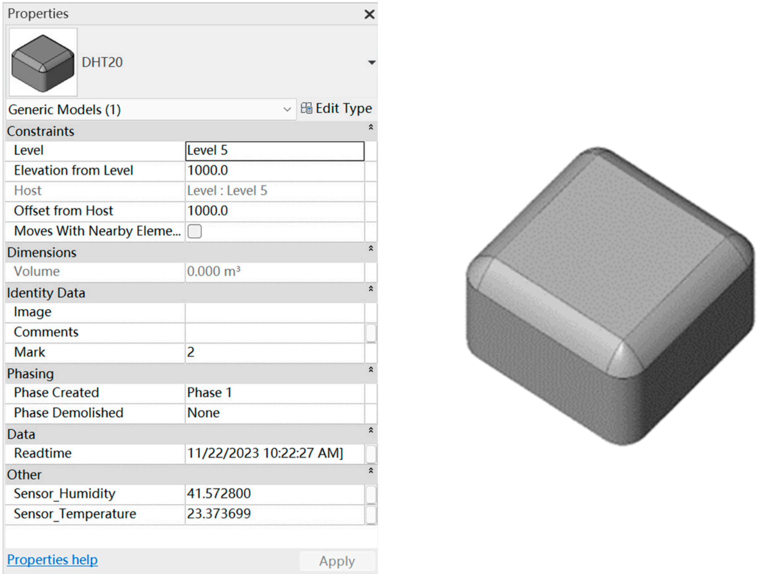


Figure 3. Revit model of PhD office.

In the developed Revit model, nine DHT-20 virtual sensors and 17 virtual desks were integrated. The model featured a "Room" object that delineated the office space, with each sensor programmed to simulate environmental conditions by displaying parameters like "reading time", "temperature", and "humidity", as depicted in Figure 4a. Each virtual sensor and desk in the Revit environment was assigned a unique ID to reflect their physical counterparts accurately. Given the absence of a pre-existing DHT-20 sensor template in the

Revit library, a custom sensor component was created using a standard family template for this research, detailed in Figure 4b.



(**a**) (**b**)

Figure 4. (**a**) The property field of the created component. (**b**) Three-dimensional front view of the created component.

The successful deployment of the IoT system in this study was achieved through the synergistic integration of Arduino, MySQL, and Dynamo. These technologies are fundamental to constructing the system's architecture, enabling precise data collection, storage, and processing. A comprehensive analysis of their interconnected roles is provided in the subsequent sections.

4.1.2. Data Transmission

The Arduino platform utilized in this study supports Wi-Fi-enabled microcontroller development and seamless integration with edge and cloud computing, enabling environmental data captured by sensors to be stored in a MySQL database. Additionally, the platform manages sensor activation cycles, incorporating a 30 min hibernation period post-activation to optimize energy efficiency. This design not only conserves energy but also aids in clarifying the operational status for users during sensor and microcontroller initialization.

This research established a new MySQL connection named "DC" on the MySQL 5.7 platform using port 3308. Under this connection, a new schema named "test_data" was created, which included nine tables named "testID". These tables were designed to store sensor data independently. The structure and data types for these tables were detailed in Table 1. Each table used an automatically generated "ID" as its primary key. The "Readtime" parameter also recorded the date and time when data were entered.

Table 1. A MySQL table holds elements and their data types.

Parameter	Type
ID	Int (11)
Temperature	float
Humidity	float
Readtime	datetime

4.1.3. Data Sorting and Updating

For automated data visualization, the nodes in Dynamo were organized into six key modules: MySQL database connections, data sorting, reference point generation, sensor coordinate acquisition, interpolation, and heat map coloring. Detailed descriptions of the primary functions and nodes within each module are provided in the following sections.

The MySQL database connection was established using the Slingshot suite, configuring the "Connection.MySQL_ConnectionString" node with server ID, port number, user ID, password, command timeout, and connection timeout settings. Subsequently, the "Query.MySQL_Query" node received the connection string, a Boolean true value, and the SQL query to access and query database tables. Details on the configuration and use of these nodes are illustrated in Figure 5.

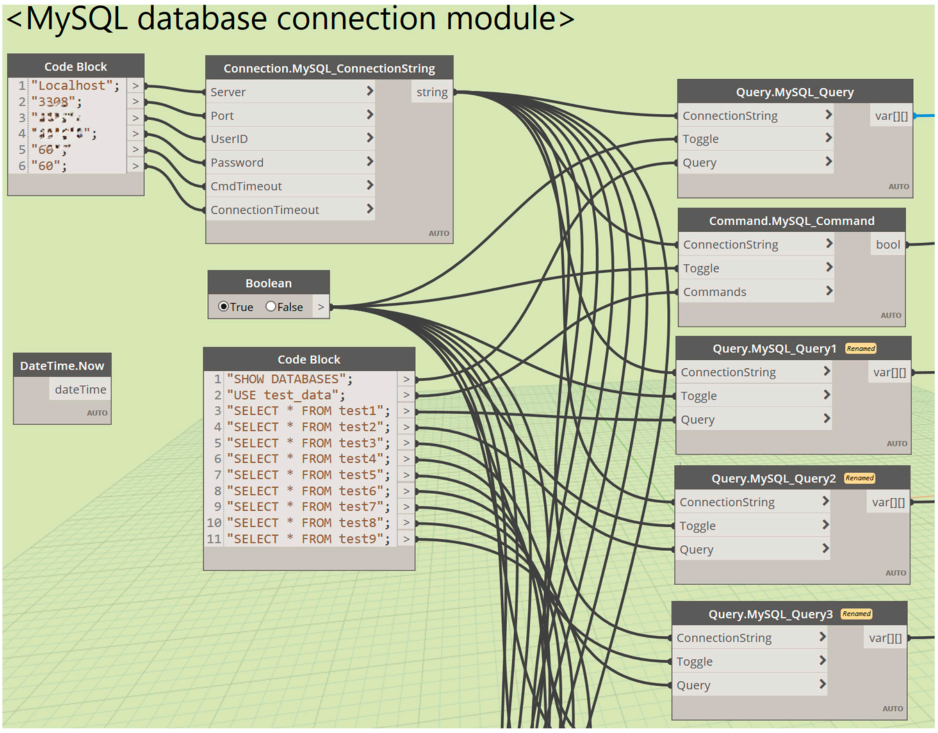


Figure 5. MySQL database connection module of Dynamo.

The data sorting module's primary function was to segregate temperature, humidity, and reading times in a table, assigning them to the corresponding virtual sensors' property fields. Critical nodes in this process included "List.GetItemAtIndex" for selecting specific table columns (referred to as lists in Dynamo) and "Element.SetParameterByName" for mapping these values to properties in the Revit model. Upon selecting a Revit model element and specifying parameters, the "Element.SetParameterByName" node automatically updated the relevant fields with the latest data. Details on node functionality, connections, and execution outcomes are illustrated in Figure 6.

The reference point generation module was designed to obtain the uniformly distributed point coordinates of the plane space of the target office for later temperature interpolation calculation. Firstly, the grid's fineness that divided the target office's floor space into small planar squares had be determined. Next, the boundary and the corner points on the boundary of the target office were obtained by going over the "Element.BoundingBox" and "BoundingBox.Min/MaxPoint" nodes, respectively. Lastly, the grid dimensions required to achieve the previously determined level of grid refinement were calculated, and the "Point.ByCoordinates" node was used to generate the center reference point for each grid; the grid accuracy determined in this research was 25 × 25. Since PhD students in the office predominantly spent their time seated and working, this study focused on temperature and humidity effects 1 m above the ground. Accordingly, sensors and reference points were positioned 1 m off the floor, ensuring the z-axis coordinates for both were consistently at that height. Further details about this module can be found in Figure 7.

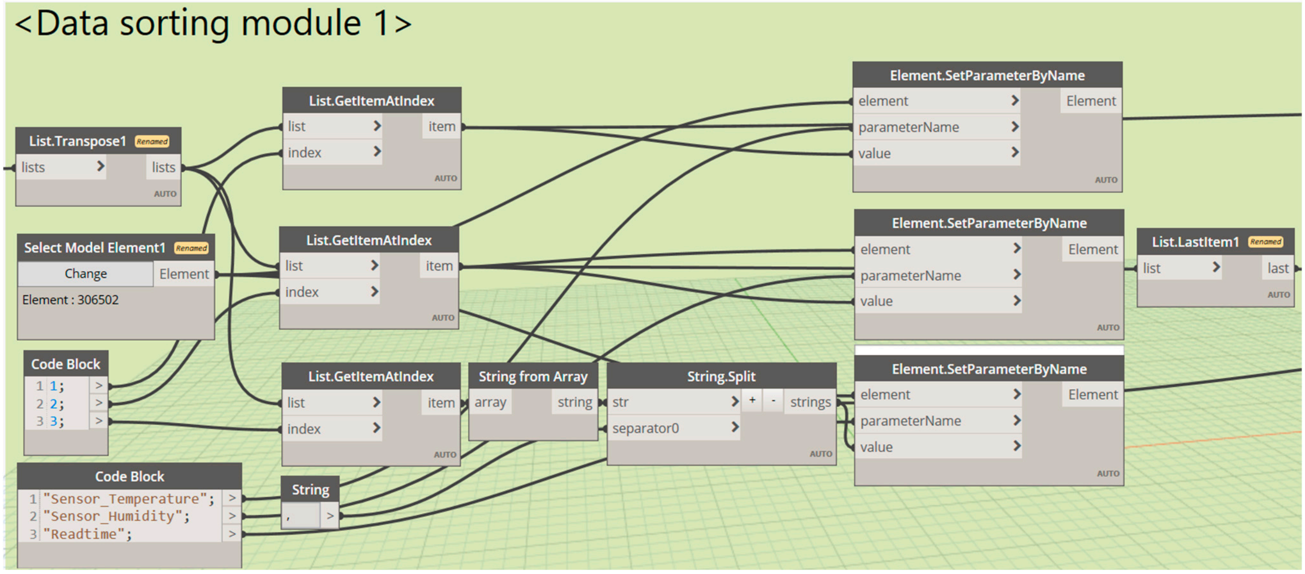


Figure 6. Data sorting module of Dynamo.

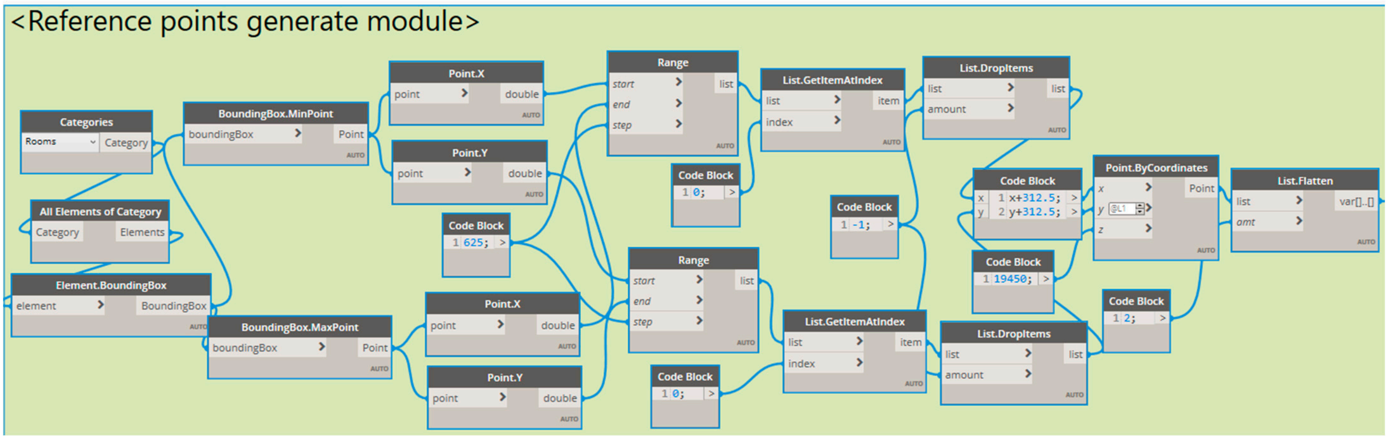


Figure 7. Reference point generation module of Dynamo.

In the sensor coordinate acquisition module, acquiring the spatial coordinates of virtual sensors was straightforward when these sensors were pre-placed in the Revit model. The primary node, "FamilyInstance.Location", input elements from the virtual sensors, generating a list of their locations. Figure 8 illustrates the nodes used in this module and their connections.

In the interpolation module, temperature values for each grid square were calculated using the inverse distance weighted (IDW) interpolation method, implemented through the "Python Script" node. IDW interpolation, a commonly used deterministic model in spatial interpolation, is frequently utilized to generate climate-dependent heat maps [4]. Figure 9 illustrates how the IDW interpolation formula was implemented in IronPython2 within the "Python Script" node.

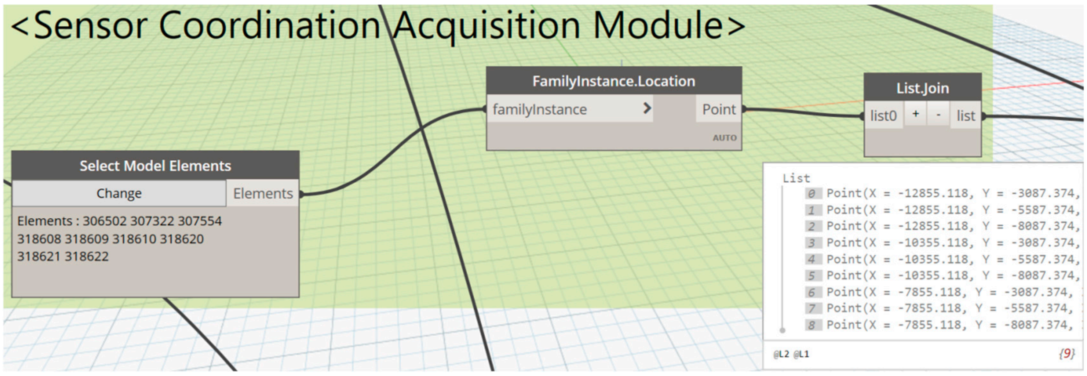


Figure 8. Sensor coordination acquisition module of Dynamo.

```python
import math

# Converts coordinates to Point objects
2 usages
def to_point(coord):
    if isinstance(coord, Point):
        return coord  # If it is already a Point object, return it directly
    elif isinstance(coord, (list, tuple)) and len(coord) == 3:  # If the input is a list or tuple of length 3
        try:
            return Point.ByCoordinates(float(coord[0]), float(coord[1]), float(coord[2]))
        except:
            raise ValueError("Unexpected coordinate format")  # Conversion failure to lift exception
    else:
        raise ValueError("Unexpected coordinate format")  # The lifting error does not meet any of the above conditions

# Use IDW for interpolation
1 usage
def idw_interpolation(known_coords, known_temps, unknown_points, p=2):
    known_points = [(to_point(coord), temp) for coord, temp in zip(known_coords, known_temps)]
    interpolated_values = []  # Create a new list to store the interpolation results
    # Go through every position you want to interpolate
    for up in unknown_points:
        up_point = to_point(up)
        numerator, denominator = 0, 0
        for kp in known_points:
            d = up_point.DistanceTo(kp[0])  # Calculate the distance between an unknown point and a known point
            if d == 0:
                interpolated_values.append(kp[1])
                break
            w = 1 / (d ** p)  # Calculated weight
            numerator += w * kp[1]
            denominator += w
        else:
            interpolated_values.append(numerator / denominator)
    return interpolated_values

# Get 25 points of coordinate input
all_coords = IN[0]
# List of 9 sensor temperatures
sensor_temps_data_list = [IN[i] for i in range(1, 10)]
# Coordinating points for the sensor
sensor_coords = IN[10]

# Get the latest temperature data from each sensor temperature list
latest_temps = [temps[-1] for temps in sensor_temps_data_list]

# The temperature values of corresponding points are obtained by interpolation method
interpolated_temps = idw_interpolation(sensor_coords, latest_temps, all_coords)

OUT = interpolated_temps
```

Figure 9. Python code for calculating temperature at each point using IDW interpolation.

4.1.4. Visualization

The heat-map coloring module converted interpolated data into visual heat maps, facilitating more accessible access to thermal comfort data. The process involved three central nodes: “Color Range”, “Math.RemapRange”, and “Element.OverrideColorInView”. Initially, RGB values were input into the “Color Range” node, which accepted only values between zero and one. The "Math.RemapRange" node adjusted the interpolated values to that range to accommodate this. Using the "Element.OverrideColorInView" node, the final step, applied the colors to selected elements. Detailed descriptions of node usage and connections appear in Figure 10.

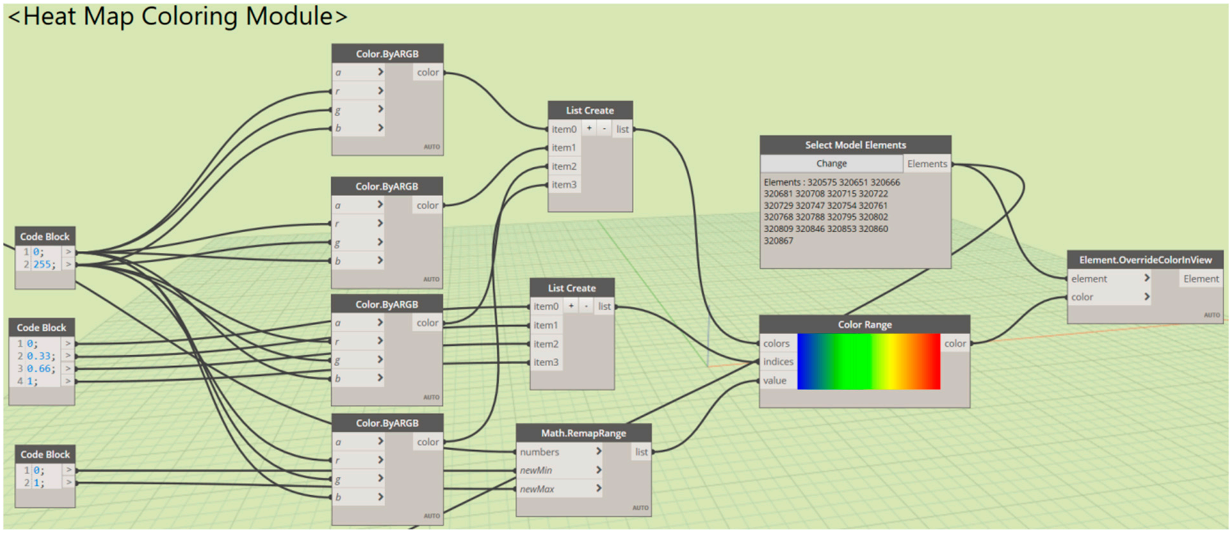


Figure 10. Heat-map coloring module of Dynamo.

Although heat-map generation did not directly incorporate PMV values, nodes calculated and recorded the PMV for each mesh square in the corresponding object's attribute column. The PMV formula, written in Iron Python, was implemented in Dynamo via the "Python Script" node, as shown in Figure 11. Since office occupants primarily engaged in sedentary activities like typing, the metabolic rate was 1.1 met. Adequate mechanical power was maintained at 0 W/m^2, a standard for indoor thermal comfort assessments. Experiments conducted in autumn reflected typical lightweight long-sleeved office attire, setting clothing insulation at 0.96 clo. A nominal value of 0.1 m/s was used for the relative wind speed parameter without relative wind speed sensors. Adequate mechanical power is consistently assumed to be zero in indoor thermal comfort assessments.

Table 2 outlines comfort levels across PMV ranges, providing general guidelines based on typical temperature preferences. A PMV of zero is generally considered comfortable, although individual preferences can vary, affecting comfort perception. For example, while a PMV of −1 may be comfortable for some, others may find a PMV of +1 more to their liking.

As illustrated in Figure 12, a complete rundown of all the nodes in the Dynamo produced a smooth heat map that met the design requirements.

Table 2. Comfort level corresponding to PMV index.

PMV Index	−3	−2	−1	0	1	2	3
Feeling	Cold	Cool	Slightly Cool	Neutral	Slightly Warn	Warm	Hot

```python
import sys
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *

dataEnteringNode = IN

import math
1 usage
def calculate_PMV(ta, rh, met, clo, vel):
    ta = float(ta)
    # Convert temperatures from Celsius to Kelvin for the formula
    ta_kelvin = ta + 273.15
    # Convert relative humidity to a fraction
    rh = rh / 100.0

    # Constants
    pa = rh * 10.0 * math.exp(16.6536 - 4030.183 / (ta + 235.0))
    icl = 0.155 * clo
    m = met * 58.15
    w = 0

    # Insulation factor of clothing
    if icl <= 0.078:
        fcl = 1.0 + 1.29 * icl
    else:
        fcl = 1.05 + 0.645 * icl

    # Heat transfer coefficient by convection
    hc = 12.1 * math.sqrt(vel)

    # Heat transfer coefficient by radiation
    hr = 4.7

    # Internal heat production
    m_internal = m - w

    # Thermal sensation
    pmv = ((0.303 * math.exp(-0.036 * m) + 0.028) * (
        m_internal - 3.96 * fcl * (ta_kelvin ** 4 - ta_kelvin ** 4)
        - fcl * hc * (ta_kelvin - ta_kelvin) - 0.42 * (m_internal - 58.15)
        - 0.0173 * m * (5.867 - pa) - 0.0014 * m * (34 - ta)) - 3.5
    )
    return pmv

# List of temperatures
temperatures = IN[0]
# Average relative humidity
average_humidity = IN[1]

# Calculate PMV for each temperature using the provided average humidity
pmv_results = [calculate_PMV(t, average_humidity, 1.1, 0.74, 0.1) for t in temperatures]

OUT = pmv_results
```

Figure 11. Python code for PMV calculation.

4.2. Case Demonstration

This research applied the ASHRAE 55-2020 standard [43] to evaluate indoor thermal comfort. The case study was conducted during the transition from autumn to winter, a period that potentially affects thermal perceptions. According to ASHRAE Standard 55, the acceptable indoor temperature range is from 22.2 °C to 26.4 °C, assuming the relative humidity remains between 30% and 60%.

This study employed a real-world scenario in a PhD office at XJTLU to validate the proposed thermal comfort visualization method. The experimental setup, including a DHT-20 sensor, an ESP32 microcontroller, and a portable power source, is depicted in Figure 13. Figure 14 shows the office's spatial layout and the sensors' placement. Data collection occurred at 30 min intervals over 24 h from 10:00 a.m. on 21 November 2023 to 10:30 a.m. on 22 November 2023. The windows remained closed throughout the data collection period. Air conditioner 1 was turned on after sunset (19:00) and turned off after the last person left the office at night (22:30); air conditioner 2 was not used. The outdoor temperature ranged from 13 to 20 °C, while the relative humidity was about 41%.

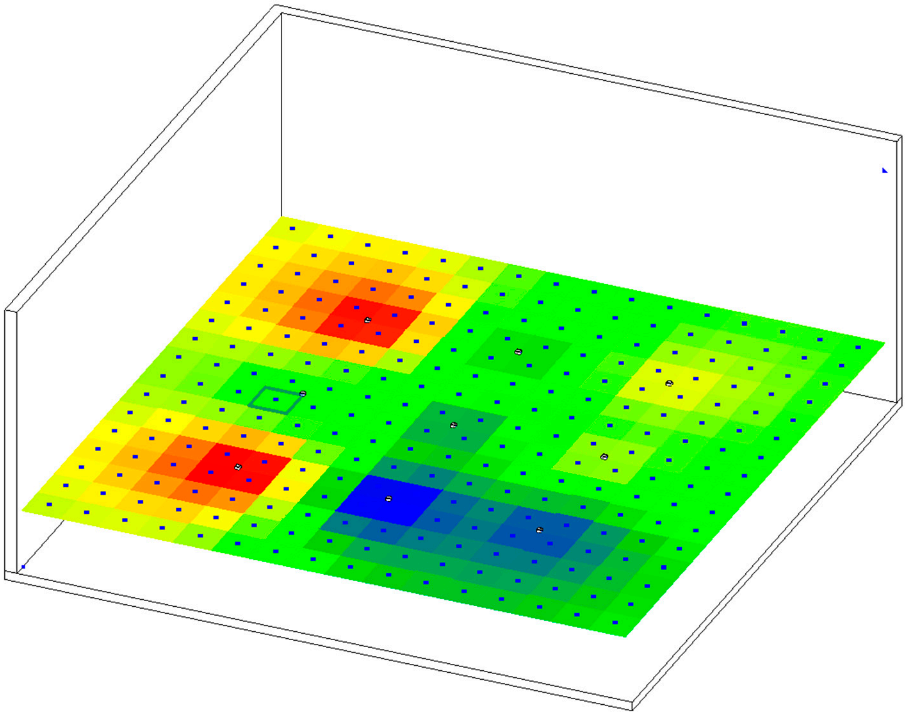


Figure 12. Heat-map test-run results in the Revit model.

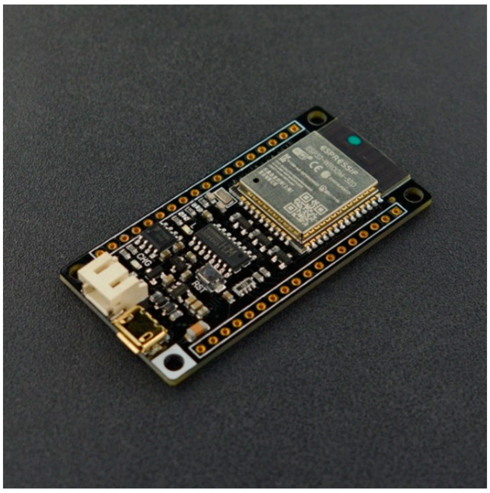


Figure 13. Data acquisition devices in the case.

Figure 15 illustrates the data collected by individual sensors, highlighting minor diurnal variations in temperature and humidity, with slight differences in the readings among sensors. After the heating was activated for two hours, a notable increase in temperature was observed across all sensors, peaking at approximately 10:30 PM. Temperatures returned to their baseline levels two hours after the heating was turned off, maintaining stability with few fluctuations. As for humidity, a modest decrease was recorded two hours after the heating began, returning to normal levels once the heating was deactivated. The humidity readings from the nine sensors showed consistent variations.

During the data collection period, as shown in Figure 15a, the highest and lowest temperatures were recorded as 25.6778 °C by sensor 4 at 23:36 and 21.0904 °C by sensor 7 at 10:03, respectively. The temperature fluctuated by as much as 4.5 °C in the same office on the same day. Given the human body's thermal perception threshold of approximately 0.5 °C to 1 °C, it is crucial to provide users with visualized environmental data to assist in selecting optimal seating [44].

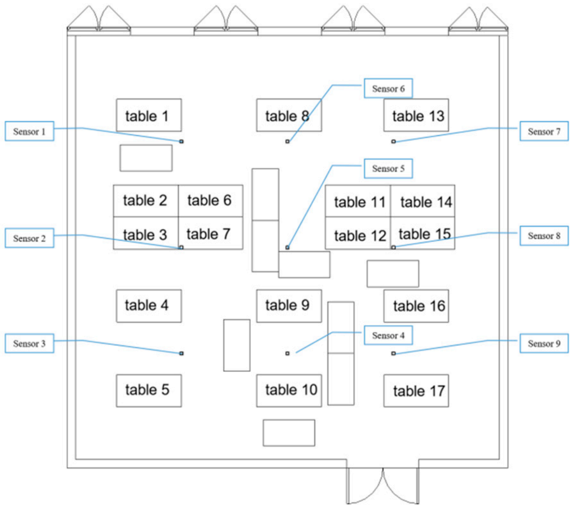


Figure 14. Sensors and tables' location.

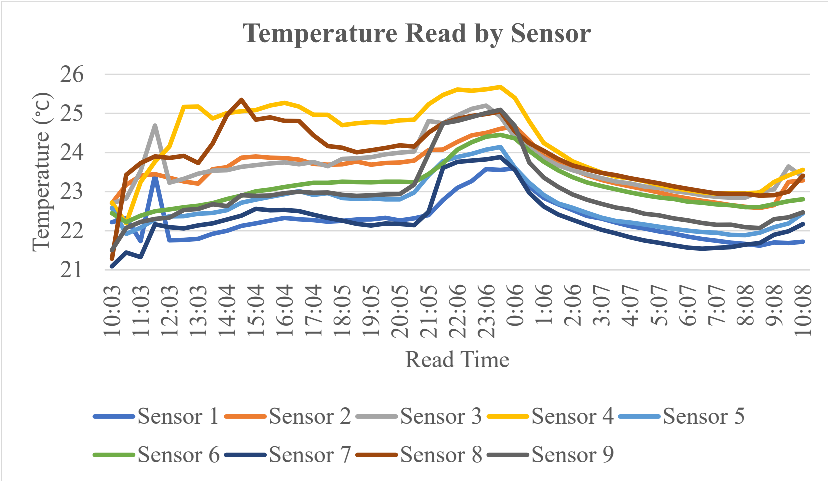
As shown in Figure 15b, relative humidity levels ranged from a low of 38.7733% at 12:33 by sensor 4 to a high of 50.648% at 10:03 by sensor 1. As both values were within the ASHRAE 55 standard's comfort range and given the lower human sensitivity to humidity variations compared to temperature, excluding humidity from heat map calculations was both practical and conserved resources.

Figure 15 shows the maximum and minimum temperature and humidity values recorded by each sensor, demonstrating that the office's conditions typically met the ASHRAE 55 recommended comfort ranges for temperature (22.2 °C to 26.4 °C) and humidity (30% to 60%) during the data collection period. While the minimum temperature occasionally dropped below that range, such instances were brief. They occurred late at night when the office was unoccupied, suggesting that the overall comfort standards were generally upheld.

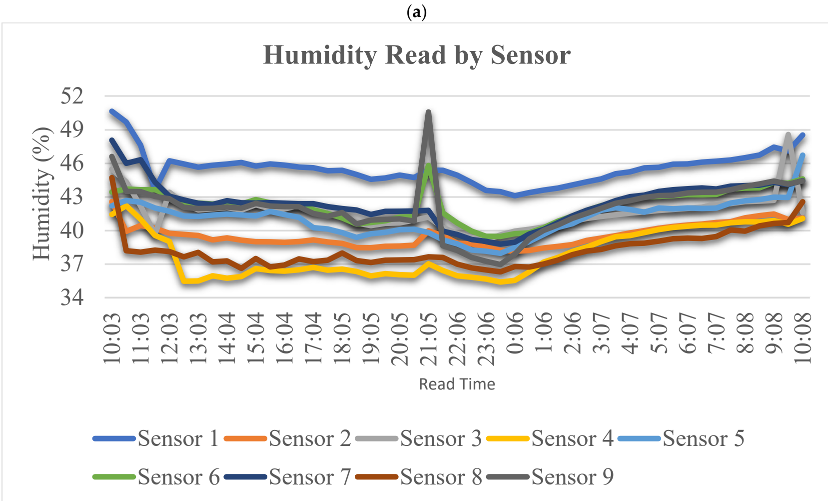
Figure 16 presents the results of the proposed method for visualizing the indoor thermal environment through BIM and IoT integration, developed by the research institute. It shows that during active office hours (10 a.m. to 7 p.m.), without heating, the temperature around desks 1, 8, and 13 was within the neutral range, while the temperature around desks 9, 10, 14, and 15 was in the warm range.

Heating was activated at 7:30 p.m., causing desks 11 to 15 to warm up compared to other areas rapidly. Desks 1, 2, 3, 6, and 7 exhibited superior insulation, retaining heat for a significantly longer duration after the heating was deactivated, as documented in Figure 16. The analysis also showed that desks 4, 5, 16, and 17 were largely unaffected by the heating, remaining cooler throughout the study period compared to other desks.

After 24 h of data collection, PMV, temperature, and humidity fluctuations remained within the predefined acceptable ranges, with thermal comfort levels during active periods showing no significant deviations. PMV values during the case study were maintained between –0.4 and 0.4, indicating conditions generally perceived as comfortable. Thus, all areas, whether depicted as red or blue on the heat map, were likely to meet most occupants' comfort needs. When choosing a seat, students should consider their personal temperature preferences; for example, desks 9, 10, 14, and 15 were suited for those preferring warmth, while desks 4, 5, 16, and 17 were better for those who preferred cooler conditions. It is important to note that seasonal adjustments may be required, particularly in summer when heating vents are converted to cooling vents, and individuals sensitive to cold may need to reevaluate their seating choices based on the latest operational data.

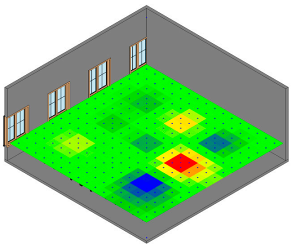


(**a**)

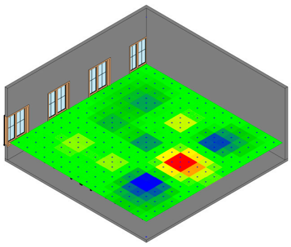


(**b**)

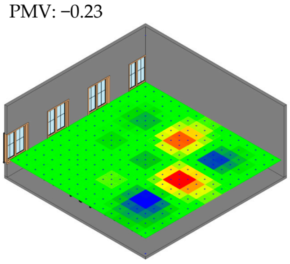
Figure 15. (**a**) Temperature read by sensors 1–9; (**b**) Humidity read by sensors 19.



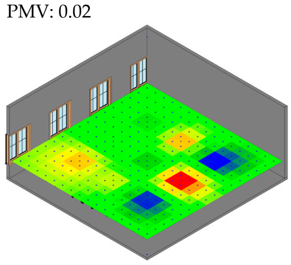
- Time: 21/11/2023 10:03:39
- Average temperature: 22.14 °C
- Average humidity: 45.01%
- PMV: −0.23



- Time: 21/11/2023 13:34:07
- Average temperature: 23.13 °C
- Average humidity: 40.70%
- PMV: 0.02



- Time: 21 November 2023 16:34:07
- Average temperature: 23.50 °C
- Average humidity: 40.97%
- PMV: 0.11



- Time: 21 November 2023 19:35:27
- Average temperature: 23.34 °C
- Average humidity: 40.07%
- PMV: 0.07

Figure 16. *Cont*.

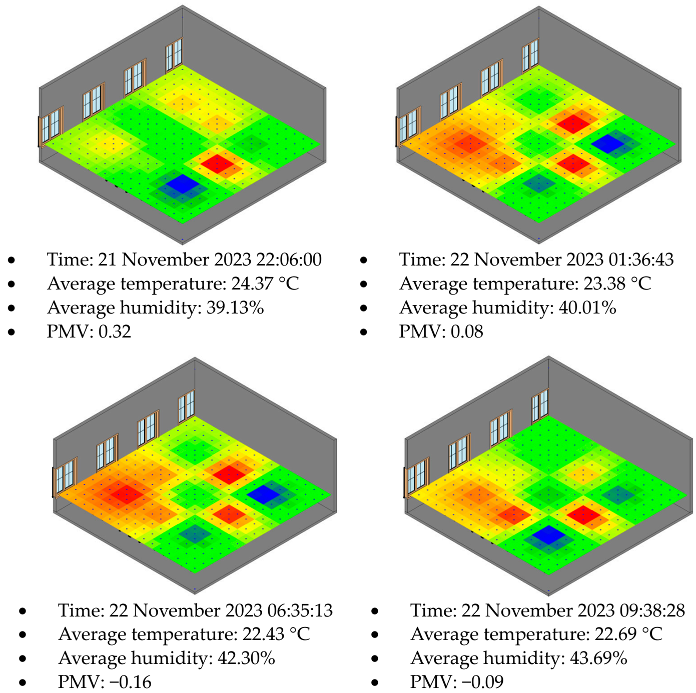


Figure 16. Screenshots of heat maps in the Revit model for different periods.

4.3. Thermal Comfort Feedback

In this study, a survey was conducted after office personnel adjusted their seating arrangements based on the heat map presented in Section 4.2. The survey was involved 17 occupants, of whom 14 agreed to participate, resulting in a response rate of 82.35%. This response rate is considered acceptable according to previous research benchmarks, which typically recognize a response rate above 70% as sufficient for drawing meaningful conclusions [34]. The feedback from diverse culture groups are shown in Table 3.

Table 3. Thermal comfort survey results after seat adjustment.

Country	Number	Satisfied	Neutral	Unsatisfied
China	7	5	2	0
India	3	2	1	0
Baxi	1	1	0	0
Nigeria	2	1	1	0
Sri Lanka	1	1	0	0
Total	14	10	4	0

The survey results indicated a generally positive response to the seating arrangement adjustments made by office personnel, with a total of 10 out of 14 respondents (71.4%) reporting satisfaction with their thermal comfort. Notably, participants from China showed the highest level of satisfaction, with five out of seven respondents feeling comfortable after the adjustments. This may be due to cultural factors that prioritize communal well-being in work environments, leading individuals to be more accepting of changes designed to enhance comfort for the group. Conversely, the responses from Nigeria and India, where participants expressed a mix of satisfaction and neutrality, suggest variations in cultural norms regarding thermal comfort and acceptance, highlighting the complexity of how different backgrounds influence perceptions of comfort.

5. Discussion

This research introduced a framework that integrated BIM and IoT technologies to visually represent the indoor thermal environment for building occupants. Due to the general unfamiliarity with PMV indices among non-specialist users and the limited impact of relative humidity on perceived comfort, the heat maps generated did not include PMV indices or relative humidity as variables. Nonetheless, these metrics are calculated within Dynamo and are accessible to users requiring detailed real-time data on temperature, humidity, and PMV through the Revit model's property bar, as shown in Figure 17.

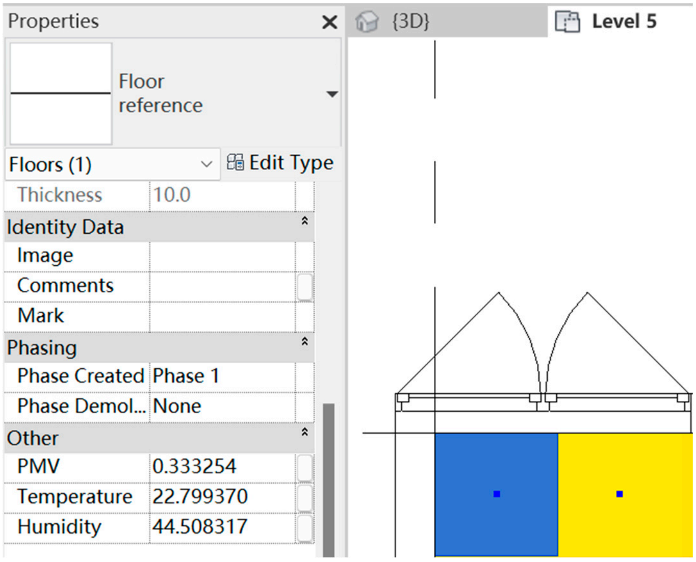


Figure 17. Details of the Revit model property bar.

5.1. Contributions

The proposed research framework significantly improves the timeliness of monitoring indoor thermal environments, enhancing efficiency compared to the traditional questionnaire-based approach, often protracted from design to result analysis. This framework notably shortens the time from sensor data collection to the presentation of visual information to building occupants, reducing it to a few seconds. This research advances indoor thermal environment visualization by presenting data and using thermal maps to provide a clear and immediate perception of thermal conditions. Moreover, this framework enhances data transmission security during BIM and IoT integration by utilizing MySQL's SSL/TLS encryption and setting defined access rights for MySQL administrators. Additionally, the framework supports future functional enhancements and expansions by incorporating new nodes in Dynamo. Notably, this approach reduces the traditionally high costs associated with BIM and IoT integrations by eliminating the need to develop new applications and Web pages. Instead, it leverages existing architectural design software for the user interface and employs visual programming tools, thus decreasing the dependence on specialized personnel.

The proposed BIM–IoT integration framework emphasizes the practical needs of ordinary users by focusing on temperature, the most direct and understandable indicator of thermal comfort. Using real-time highest and lowest temperature values as boundary indicators for heat-map coloring, this approach offers more intuitive and easily understandable information than Chang et al.'s [15] method of using PMV values. Users can quickly identify the hottest spots in a classroom at any given time. Furthermore, the study enhances the precision of indoor thermal environment monitoring with a resolution of one pixel per 0.16 square meters, which is particularly suitable for small, densely populated indoor spaces. This framework also provides more detailed information for personalized user choices compared to Dave et al.'s [33] approach of generating a single-color block based on average temperature, thereby simplifying how building occupants perceive and interact with their environment. By avoiding complex, technical indices, this approach enhances usability and applicability in daily operations, ultimately improving the overall user experience in indoor environments.

For the thermal comfort feedback, the varying levels of satisfaction can be attributed to diverse cultural beliefs and practices surrounding comfort and climate adaptation. For instance, individuals from India and Nigeria may have different thresholds for thermal comfort due to their distinct regional climates and cultural histories. In India, the exposure to both humid and dry climates might lead to a greater variability in comfort levels among individuals when faced with temperature changes. On the other hand, the participants from Nigeria expressed more ambivalence, with one person feeling neutral about their comfort level. This could indicate a potential disconnect between the heat map data and the personal comfort preferences of respondents, reinforcing the idea that cultural context significantly informs individual responses to environmental adjustments.

To enhance overall thermal comfort in office environments, building management strategies should consider these cultural differences in workplace thermal preferences. Firstly, implementing a flexible seating arrangement policy that allows employees to choose their own seating based on real-time thermal data can accommodate diverse preferences. Additionally, offering personalized climate controls, such as desktop fans or localized heating, may help individuals adapt their microenvironments. Furthermore, regular training sessions and workshops exploring cultural perspectives on thermal comfort can foster greater awareness among staff about the varying thresholds for comfort experienced by their colleagues. By integrating these strategies, building management can create a more inclusive and comfortable work environment that recognizes and responds to the cultural backgrounds of all employees.

5.2. Limitations

The framework proposed in this research introduces innovative approaches but also exhibits notable limitations. The data collection phase needs to fully account for the influence of human activities, such as the heat generated by prolonged computer use, which may skew sensor readings and fail to represent the environmental conditions accurately. The accuracy of the DHT20 sensor may slightly influence the monitoring of occupant comfort levels. Future research should utilize more precise temperature sensors, such as PT100 (RTD) and thermocouples, to enhance scientific rigor and ensure that findings accurately reflect indoor environmental conditions. Moreover, the analysis focused primarily on temperature as a key determinant while overlooking other critical factors like carbon dioxide levels, which are essential for a comprehensive assessment of the thermal environment.

The proposed framework's scope is less applicable for entities outside the construction sector due to the requirement for specific software, such as Revit, which may not be a cost-effective investment for these groups. Furthermore, the system lacks exception-alert mechanisms, a critical omission that fails to notify administrators of issues like connectivity disruptions. The framework also needs more interactive or feedback mechanisms, providing visual data without supporting user engagement and limiting its effectiveness in creating a responsive, user-centered environment. Additionally, relying on mobile power sources without a strategy for long-term data monitoring calls into question its sustainability.

6. Conclusions

This research developed a customized relational database schema and employed cloud and edge computing to collect and analyze BIM and IoT data in real time. It created a platform that transformed indoor thermal data into context-based visualizations, such as heat maps displayed within a Revit model. This platform facilitated real-time monitoring of the indoor thermal environment, enabling users to choose spaces that aligned with their comfort preferences, which could enhance productivity by optimizing environmental conditions.

Future work will enhance user interaction with the platform by developing a more interactive feedback system, allowing the platform to recommend spaces based on real-time environmental data and user preferences. Additionally, users can immediately respond by adjusting equipment settings, enhancing the system's responsiveness. Further research will focus on optimizing the power supply system and applying the methodology in various settings to evaluate its long-term viability across different scenarios.

The significant contribution of this research is its innovative approach to integrating real-time sensor data with BIM models, which involves projecting detailed visualizations of the thermal environment directly onto these models. This enhancement allows building occupants to accurately gauge indoor conditions and select seating based on their comfort preferences. The proposed framework streamlines the decision-making process for facility managers by providing actionable insights and empowers occupants by offering choices that cater to individual comfort needs. Furthermore, this study enhances indoor thermal comfort by incorporating the preferences of occupants from diverse cultural backgrounds, thereby promoting a more user-centered approach to building management strategies.

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