

Decision Support for Building Thermal Comfort Monitoring with a Sustainable GenAI System

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Abstract— Staff expenses can account for up to 70% of business costs, with indoor conditions playing a critical role in employee health, behavior, and productivity. Optimal thermal comfort, typically around 21°C with 40-70% humidity, maximizes productivity. However, effective monitoring requires comprehensive data, particularly as energy regulations push for smarter building management. Although Building Information Modeling (BIM, a digital representation of a building's physical and functional characteristics) and sensor integration support facilities management, many existing systems are proprietary, expensive, and inflexible. To address these challenges, this study introduces *ThermalComfortBot*, a sustainable Generative Artificial Intelligence (GenAI)-powered Chatbot designed as an advanced Information System (IS). Utilizing Large Language Models (LLMs, AI models for natural language understanding) and Retrieval-Augmented Generation (RAG, a method that combines data retrieval with LLMs-generated insights), *ThermalComfortBot* integrates data from BIM, sensors, and other relevant sources. Built on open-source technology, it is cost-effective and fully customizable, allowing users to tailor datasets to their needs. The Chatbot delivers actionable insights through a Question-Answering (QA) interface, enabling data-driven decisions on thermal comfort to improve workplace conditions and enhance operational efficiency.

Keywords— *Thermal Comfort Monitoring, Generative Artificial Intelligence, Data-Driven Decision Support, Building Information Modeling, Sustainable Workplace Solutions.*

I. INTRODUCTION

Staff costs including wages, benefits, payroll, and associated taxes can represent a significant portion of a business's overall expenses [1]. A key factor influencing these costs is the indoor environmental conditions, which significantly affect employees' physiological and psychological well-being, habits, and productivity [2]. Among the elements impacting indoor environmental quality, temperature and humidity are crucial for maintaining thermal comfort. The UK Health and Safety Executive (HSE) defines thermal comfort as a balance of environmental, work-related, and personal factors that contribute to a comfortable workplace temperature [3]. Research [4] shows that optimal thermal comfort is essential for high productivity levels, with studies indicating productivity peaks at around 21°C. Excessive heat can cause fatigue, while cold conditions can lead to restlessness. Humidity is also vital for comfort, with the HSE recommending levels between 40% and 70%. Humidity below 30% can result in discomfort, such as dry eyes and skin, while levels above 70% can create a stuffy atmosphere. True comfort is achieved when temperature and humidity fall within this "comfort zone". Thermal comfort assessments should be tailored for summer and winter to maintain acceptable temperature and humidity levels throughout the year.

Data collection and environmental performance are key for building energy efficiency. Monitoring technologies, driven by regulations like the European Energy Performance of Buildings Directive (EPBD), promote smart systems. While BIM is a powerful tool in construction, its use has largely focussed on the design and construction phases [5, 6]. Integrating BIM with sensor data improves real-time monitoring, offering facility managers actionable insights and a user-friendly interface. However, many systems are proprietary, making evaluation and optimization difficult, leading to inefficiencies and higher costs. The absence of an open-source, integrated system hinders data aggregation and energy efficiency improvements. To tackle these challenges, this research investigates the following question:

- How can an IS integrate data from diverse sources, such as BIM and sensor data, and leverage advanced open-source technologies to support organizational decision-making in building thermal comfort?

To address these questions, this study introduces *ThermalComfortBot*, an integrated IS that operates as a Chatbot, designed to efficiently consolidate data from multiple sources. By leveraging advanced open-source GenAI technologies (i.e., systems capable of generating new insights from large datasets such as LLMs [8] and RAG [9]), *ThermalComfortBot* is designed to enhance thermal comfort monitoring and delivers substantial benefits. It seamlessly integrates BIM data, sensor data, and other relevant datasets essential for thermal comfort monitoring, offering organizations a comprehensive and up-to-date overview of their thermal environment. This integration improves decision-making by delivering timely, accurate insights that support data-driven choices regarding thermal comfort and help mitigate health risks. Additionally, *ThermalComfortBot* is built with sustainability in mind, emphasizing the reuse of existing LLMs instead of developing new systems from scratch, which can be resource intensive. This approach facilitates easy upgrades, ensuring that the system remains relevant as organizational needs evolve. Its cost-effective design minimizes development expenses, making *ThermalComfortBot* a practical solution for continuous building monitoring.

The paper is structured as follows: Section 2 provides the background; Section 3 introduces *ThermalComfortBot*; Section 4 details the case study; Section 5 discusses the advantages and limitations; and Section 6 offers the conclusion.

II. BACKGROUND

The Architecture, Engineering, and Construction (AEC) industry employs BIM to enhance cost-efficiency, productivity, and project quality [7]. BIM provides a platform for managing complex building information and enables virtual visualization throughout a building's lifecycle. It

assesses energy efficiency by factoring in elements like orientation and materials while helping facility managers maintain thermal comfort through real-time sensor data visualization. Recent studies have increasingly focused on integrating BIM with sensing technologies, particularly by embedding sensor data into Industry Foundation Classes (IFC) formats i.e., an open standard developed by buildingSMART to enhance interoperability across BIM tools. This integration has led to various innovative approaches for environmental monitoring in buildings.

For instance, Lin and Cheung [10] developed a parking garage system that utilizes gas, temperature, and humidity data for informed decision-making. Desogus et al. [11] monitored building conditions with heat pumps and energy meters, delivering real-time data through the Dynamo platform. Kensek [12] improved façade design by integrating environmental sensors with BIM to process light, humidity, and CO2 data. Additionally, Zhong et al. [13] proposed a framework to manage temperature, humidity, noise, light, and air quality, while Opoku et al. [14] implemented a cloud-based digital twin to optimize thermal and air quality. Valinejadshoubi et al. [15] introduced an automated alert system for thermal comfort, and Wu and Li [16] developed COZyBIM to balance occupant comfort with energy efficiency. Further, Natephra and Motamedi [17] visualized live sensor data for real-time indoor insights, while Alavi et al. [18] identified discomfort factors through a BIM-based approach, and Shahinmoghadam et al. [19] focused on thermal comfort assessment with edge computing for real-time visualization. Lastly, ElArwady et al. [20] modeled indoor thermal comfort to facilitate active air conditioning control.

These studies underscore the limitations of proprietary BIM-sensor integrations for thermal comfort monitoring, primarily due to their closed-source nature, which complicates evaluation and optimization. The time and resources required to assess these proprietary systems can lead to inefficiencies and increased costs. Moreover, these solutions often rely solely on BIM and sensor data. Effective monitoring systems, however, should be adaptable to integrate a wider range of relevant datasets, such as HSE guidelines, weather data, occupancy records, and user feedback, without incurring additional resource demands. Integrated systems should provide actionable insights into informed decision-making and be customizable to promote cost-effective, sustainable solutions tailored for SMEs.

LLMs excel in Natural Language Processing (NLP) tasks and can enhance integrated ISs. While training LLMs is resource-intensive, reusing existing models supports sustainability. Various LLMs, including BLOOM [21], GPT-4 [22], and Llama [23] are available; however, they often face challenges with domain-specific queries, which can lead to inaccuracies. RAG addresses this limitation by retrieving relevant external information before generating responses, thereby improving accuracy [9]. RAG is applied across various fields [24] to improve QA and information retrieval. RAG enhances various domains, including medical information retrieval and financial QA [24]. In education, it analyzes tutoring dialogues for improved decision-making and is applied in life sciences. Additionally, RAG streamlines IT project requests, supports health education, and aids in disaster reporting. It also improves information extraction and planning processes while enhancing multilingual question-answering in HR documents [24]. Despite its potential, the

integration of LLMs in facilities management remains underutilized. However, leveraging these models could enable organizations to seamlessly synthesize data from BIM, sensors, and other relevant datasets.

III. PROPOSED SYSTEM

ThermalComfortBot is a GenAI-driven decision support system developed to help building analysts monitor and analyze thermal comfort within buildings. By integrating multiple datasets, *ThermalComfortBot* can answer inquiries about temperature and humidity fluctuations or comfort issues across different building areas. This system provides responses in text format, making it easier for analysts to understand and address comfort-related concerns efficiently. Figure 1 illustrates the seamless integration of datasets to deliver text outputs for analyst inquiries, as detailed below:

Step 1 - Analyst Query Input: The process begins when a building analyst formulates a specific query, such as identifying temperature or humidity anomalies within the building. The analyst enters this query into the *ThermalComfortBot* prompt, an interface that allows the user to specify issues or areas of interest. This initial step sets the stage for *ThermalComfortBot* to retrieve and process data that is directly relevant to the analyst's question.

Step 2(a) - Data Retrieval from Relevant Sources: Once the query is entered, *ThermalComfortBot's* retrieval mechanism is activated. It searches through various data sources to find the most relevant information, including:

- *BIM data*, which provides insights into the building's structure.
- *Weather data* to understand how outdoor conditions may influence indoor temperatures.
- *Sensor data* collected from different locations within the building, offering precise sensor readings.
- *Historical maintenance records* that reveal previous issues, impacting current thermal conditions.
- *HSE guidelines* to align with regulatory standards for indoor comfort.
- *User feedback* on thermal comfort, providing insights from occupants' perspectives.

The datasets mentioned above were selected based on the literature analysis in Section 2. Additionally, other datasets can be incorporated as needed, ensuring the system remains adaptable and flexible.

Step 2(b) - Data Processing with the LLM: Once the relevant data is retrieved, *ThermalComfortBot's* LLM specifically the Llama 3.1 model developed by Meta [24] processes it to generate comprehensive responses. We selected Llama for its powerful capabilities in NLP and its open-source nature, which allows for effective data interpretation and response generation in our study. However, developers are free to choose other models based on their specific requirements. The LLM uses the retrieved data to contextualize the answer, ensuring it aligns with the specifics of the analyst's question, such as identifying temperature or humidity fluctuations in particular rooms or patterns across different time periods.

Step 3 - Generating Responses: *ThermalComfortBot* output provides a summary of key findings, such as high-temperature spikes or notable anomalies in specific rooms or times.

IV. CASE STUDY

The proposed system, *ThermalComfortBot*, is applied in a case study involving the strategic placement of temperature and humidity sensors throughout a building floor (see Fig. 2). Sensors were positioned at various locations, with readings taken from May to September 2018 at a sampling interval of 1 second. This setup tracks temperature and humidity variations across four key locations: Room 1 Window, Room 1, the Landing, and the Bathroom. The goal is to assess the impact of these variations on occupant comfort, providing building analysts with actionable insights to optimize indoor

environmental conditions. Room 1 and its window are essential for understanding the impact of external climate on indoor conditions, especially regarding heat exchange. The Landing, as a central area, influences nearby rooms and contributes to the home's thermal balance, while the Bathroom provides insights into the effects of humidity and moisture on occupant comfort.

As a preliminary assessment of the utility of the system, the study aims to compare temperature and humidity across monitored locations. Table 1 outlines key questions using *ThermalComfortBot*, showcasing temperature and humidity anomalies for in-depth analysis.

ThermalComfortBot Prompt

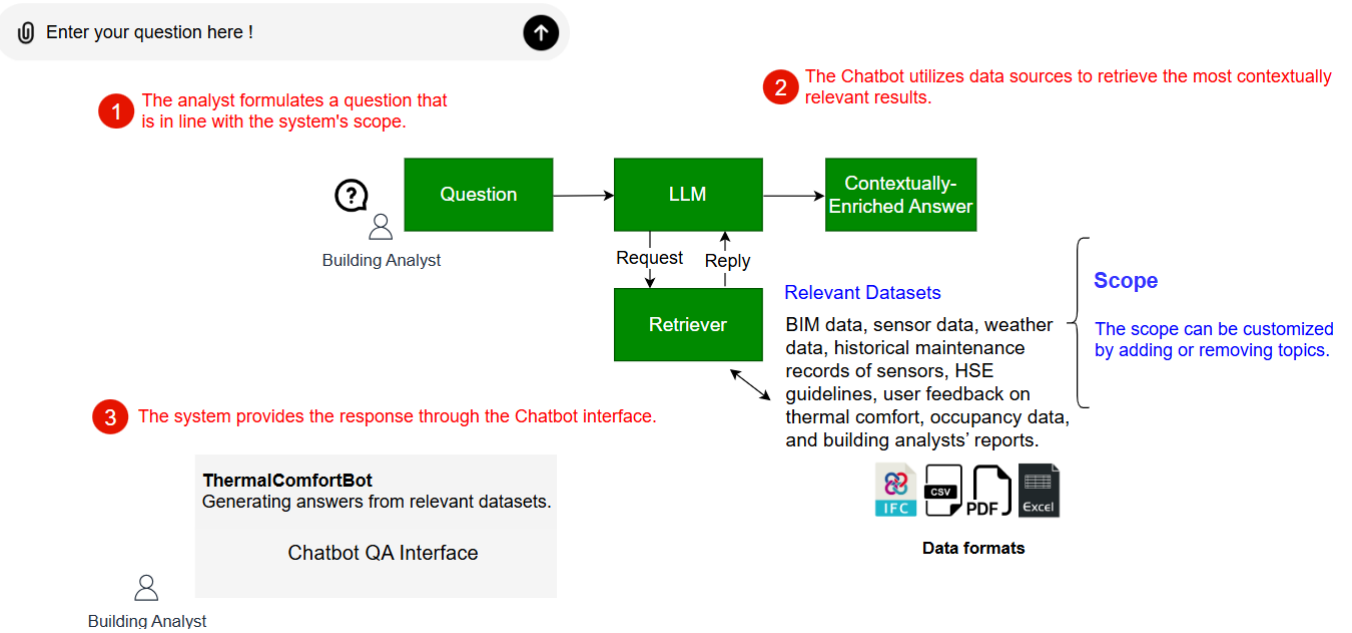


Fig. 1. ThermalComfortBot: Seamlessly Integrating Datasets to Provide Textual Outputs for Analyst Inquiries

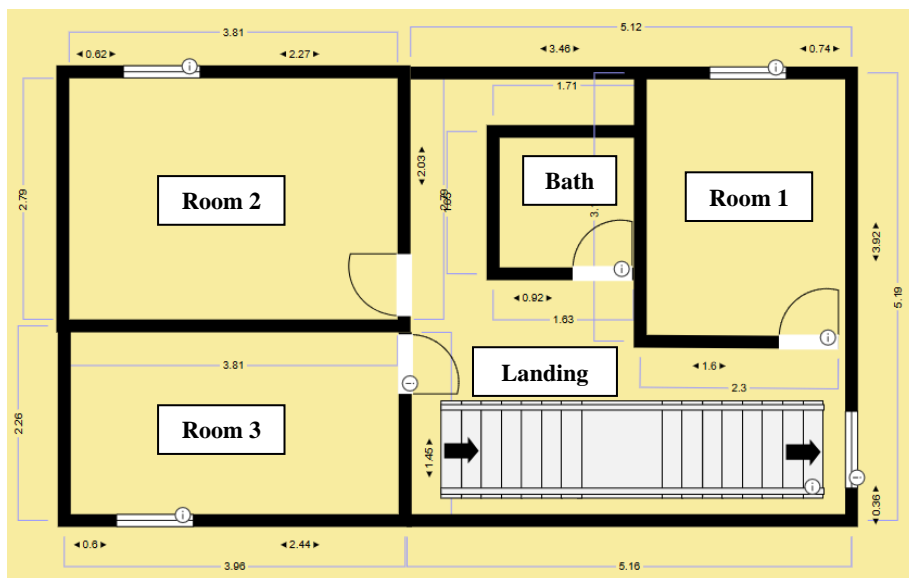


Fig. 2. Floor plan illustrating the case study implementation.

TABLE I. TO IDENTIFY ANOMALIES IN TEMPERATURE AND HUMIDITY DATA ACROSS DIFFERENT AREAS OF THE HOUSE.

No.	Question	Answer
1	What anomalies can be identified from the temperature data comparison of all areas?	<i>General Observations:</i> The Room 1 Window sensor (Sensor 30) shows the most frequent high-temperature spikes. Sensors 28 (Bathroom) and 38 (Landing) mostly remain within range but sometimes reach the higher threshold. <i>Summary of Key Anomalies:</i> High-Temperature Spikes in July 2018. Low-Temperature Drops in early May 2018.
2	What anomalies can be identified from the humidity data comparison of all areas?	<i>Sensor-Specific Anomalies:</i> Room 1 Window (Sensor 31) shows frequent high-humidity readings above the threshold, while Room 1 (Sensor 45) exhibits consistent high-humidity anomalies. The Landing (Sensor 39) occasionally exceeds the threshold but has fewer anomalies overall. In contrast, the Bathroom (Sensor 29) has the fewest anomalies, suggesting more stable humidity levels. <i>Temporal Distribution:</i> Early Period: Few anomalies from April to early May; Peak Period: Most anomalies from mid-May to late August, possibly due to seasonal or environmental factors.

V. DISCUSSION

ThermalComfortBot is a system designed to monitor thermal comfort in buildings, harnessing the capabilities of GenAI to deliver actionable insights. By integrating temperature and humidity data from strategically placed sensors throughout a building, *ThermalComfortBot* allows building analysts to effectively evaluate and optimize indoor environmental conditions. This approach enhances occupant comfort while contributing to energy efficiency and sustainability in building management. With timely monitoring and analysis, *ThermalComfortBot* empowers decision-makers to make informed choices regarding Heating, Ventilation, and Air Conditioning (HVAC) adjustments, insulation improvements, and other modifications necessary for optimal thermal comfort. A key feature of *ThermalComfortBot* is its ability to detect anomalies in temperature and humidity data. By employing advanced LLMs, the system flags unusual readings that may indicate potential issues such as inadequate ventilation or insulation problems. This proactive management approach enables building operators to address concerns before they escalate, minimizing discomfort for occupants and reducing energy consumption associated with inefficient systems.

Sustainability is a core feature of *ThermalComfortBot*, leveraging pre-trained LLMs to minimize the environmental impact of creating new models. This approach conserves computational resources while enhancing efficiency. The system is adaptable, allowing customization for various building types and environmental conditions without extensive retraining. By optimizing thermal comfort, it reduces dependence on heating and cooling systems, cutting energy consumption and carbon footprints, thereby supporting sustainability goals. However, the study has limitations. It lacks detailed discussions on sensor placement, relies primarily on temperature and humidity data from HSE guidelines and BIM, and focuses exclusively on the open-access Llama model, which could be expanded. Currently, *ThermalComfortBot* is designed for detecting anomalies in temperature and humidity, but future work should address additional objectives, including:

- *Comparative Analysis:* Examining temperature and humidity across multiple locations to identify spatial variations and assessing responses to external conditions, crucial for improving energy efficiency and maintaining consistent comfort.
- *Correlation Studies:* Exploring relationships between internal areas and external environmental conditions to better understand energy dynamics and comfort levels.

- *Trend Monitoring:* Tracking short and long-term fluctuations in temperature and humidity on weekly, monthly, and seasonal scales, essential for identifying recurring seasonal patterns.
- *Seasonal Variation Analysis:* Focusing on summer months when temperature and humidity levels rise, analyzing these changes to evaluate cooling system performance and determine necessary improvements for sustained comfort.

Additionally, future work should include a comprehensive system evaluation to ensure the effectiveness and reliability of the generated insights.

VI. CONCLUSIONS

This study introduces *ThermalComfortBot*, which integrates BIM, sensor data, and other relevant datasets using advanced LLMs and RAG, with its implementation demonstrated in a residential building case study. Through the QA system interface, it provides actionable insights that enable data-driven decisions, enhancing workplace environments and offering SMEs a cost-effective, customizable solution. Chatbot supports timely monitoring, optimizing indoor conditions, and proactively identifying anomalies in temperature and humidity to address potential issues before they escalate. Its sustainability is further enhanced by reusing pre-trained LLMs, reducing environmental impact [25, 26]. While *ThermalComfortBot* shows great potential for improving thermal comfort and energy efficiency, future work should focus on incorporating additional building-specific datasets, conducting a detailed system evaluation to assess response accuracy, and exploring the use of other open-source LLMs to improve the quality and comprehensiveness of generated insights.

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