Framework of Occupant-Centric Measuring System for Personalized Micro-environment via Online Modeling

Mohammad Saleh Nikoopayan Tak[1] and Yanxiao Feng[2](✉)

[1] Hillier College of Architecture and Design, New Jersey Institute of Technology, Newark 07102, USA

[2] School of Applied Engineering and Technology, New Jersey Institute of Technology, Newark 07102, USA

yf43@njit.edu

Abstract. Indoor environmental comfort has become increasingly important, necessitating occupant-centric systems that provide personalized comfort. This trend is particularly notable in light of the increasing frequency of extreme weather events associated with global climate change. This paper proposes a novel framework integrating real-time occupant feedback, multi-sensor data fusion, online modeling, and intelligent sensor technologies to dynamically tailor indoor micro-environments. The framework collects diverse data on built environment and personal health using environmental sensors and wearable devices. It employs online machine learning algorithms to analyze the database and automatically adjust environmental conditions in real-time to match occupants' preferences. In implementing this framework, advanced encryption are utilized to enable swift, localized data processing while preserving privacy. Multi-sensor fusion techniques are leveraged to integrate heterogeneous sensor data into an accurate assessment of occupant comfort. The user interface facilitates occupant feedback to continuously refine the system's reinforcement learning model. By personalizing comfort in a responsive, privacy-aware manner, this framework is expected to enhance occupant well-being and satisfaction, potentially enabling significant energy savings by avoiding overcooling and overheating. The framework represents an innovative application of smart and computing technologies, including deep learning and data fusion, to advance beyond static environmental setpoints. In anticipation of testing, it shows promise in revolutionizing occupant-centric comfort, fostering the creation of more adaptive and resilient indoor spaces.

Keywords: Real-time modeling · Multi-sensor fusion · Adaptive adjustment

1 Introduction

The study of enhanced indoor environmental comfort has become increasingly critical in recent years, reflecting a broader recognition of its impact on human well-being and productivity, as well as its significance in building resilience amidst global climate

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change. This shift towards occupant-centric control systems emphasizes a personalized approach to comfort, necessitating a departure from traditional methods that rely on static setpoints and overlook the individual's dynamic experience of comfort.

The advent of smart sensing technologies and wearable devices represents a significant advancement, providing an abundance of personalized indoor comfort profiles that encompass both the built environment and personal health indicators. However, the industry faces persistent challenges in effectively harnessing this data to provide coherent, real-time insights that cater to the occupants' unique preferences. Critical issues include maintaining data consistency, protecting data privacy, and developing advanced data fusion techniques capable of adapting in real-time to individual needs.

Recognizing the strategic importance of responsive and sustainable living spaces, this research aims to address these challenges by proposing a novel framework that integrates smart sensing technologies, real-time occupant feedback, and cutting-edge machine learning algorithms. By employing intelligent sensing technologies and online modeling, the framework seeks to dynamically customizes indoor micro-environments to elevate comfort and well-being. This approach not only enhances the immediate experience of occupants but also cultivate a synergistic relationship between individuals and their living spaces, with a special emphasis on supporting vulnerable populations particularly affected by environmental stressors.

The proposed solution presents a paradigm shift in indoor environmental monitoring, positioning itself as a significant contribution to the field. It aims to bridge the gap between data availability and actionable comfort optimization, ultimately enhancing the synergy between humans and their built environments through advanced technology and innovative modeling techniques. The following sections will articulate the development of this responsive system, elucidating how it addresses existing gaps and establishes a new standard for indoor environmental control.

2 Related Work

The concept of adaptive thermal comfort has gained significant interest over the years as researchers recognize the limitations of conventional static comfort models based on heat balance theory (Yao et al., 2009). Static models, relying on fixed temperature setpoints, fail to account for temporal and individual variations in thermal perception (Huang et al., 2013). In contrast, adaptive models incorporate key factors such as outdoor climate, past thermal history, and occupant preferences to offer a more nuanced understanding of comfort (Kim et al., 2018).

Several studies have explored data-driven adaptive comfort models using machine learning techniques. Ghahramani et al. (2015) proposed an online learning system using reinforcement learning to automatically adjust HVAC setpoints based on user feedback. While a significant step forward, their system did not fully leverage the richness of data available from environmental sensors and wearable devices. Park and Nagy (2018) developed neural network models for predicting personalized thermal sensation using wearable sensors, improving upon conventional offline regression models.

A key challenge in harnessing the full potential of sensing data is the development of robust data fusion techniques. As Li et al. (2017) discussed, combining data from heterogeneous sensors is non-trivial due to differences in sampling rates, measurement uncertainties, and synchronization issues. To address this, Dai et al. (2017) proposed a wearable multi-sensor fusion scheme using a hidden Markov model to integrate temperature, humidity, and heart rate data for personalized thermal comfort estimation. Liu et al. (2019) combined infrared imagery, CO2 sensors, and humidity data to estimate personalized comfort. However, research gaps remain in the fusion of the breadth of data needed for holistic comfort monitoring.

Privacy preservation is another critical consideration in adaptive comfort systems that rely on personal data. Lin et al. (2016) applied differential privacy techniques to smart meter data in buildings, enabling analytics while preserving individual privacy. Access control mechanisms, such as attribute-based encryption, restrict data access to only authorized users, facilitating the secure sharing of sensitive comfort-related data (Liang et al., 2015). Integrating such solutions can facilitate the wider adoption of personalized comfort systems. Federated transfer learning allows the training of a model across multiple organizations without sharing raw data (Liu et al., 2019). Despite these advanced techniques, effectively integrating them into holistic comfort frameworks remains an open challenge.

Overall, while significant research has explored adaptive thermal comfort and data-driven HVAC control, opportunities exist to develop a holistic framework addressing key gaps related to multi-sensor fusion, online learning, and privacy preservation. This research aims to fulfill this potential and advance the state-of-the-art. It introduces an adaptive framework designed to address these limitations by leveraging advanced computing-enabled architecture, integrating multivariate data sources, and employing privacy-preserving online machine learning algorithms. The proposed approach is expected to significantly advance occupant-centric and responsive indoor comfort.

3 Framework Design

In the realm of indoor environmental comfort, the proposed framework represents a significant departure from the conventional, static systems by introducing an occupant-centric model that leverages real-time data analytics and personalized environmental control. The proposed framework transcends conventional measurement systems by incorporating several layers of innovation, particularly in adaptive control, privacy preservation, and data integration (See Table 1). These advancements not only enhance the occupant experience but also contribute to the field of human-computer interaction (HCI) by offering fine-tuned control and increased transparency in system operations. This section outlines the structure of the proposed system and the envisioned applications that underscore its potential impact, especially in sensitive environments such as assisted living facilities.

Table 1. Key features of the proposed framework.

Feature	Traditional Approach	Proposed Framework
Modeling Approach	Static, based on fixed setpoints	Adaptive, based on real-time data and user feedback
Control System	Rule-based using temperature thresholds	Online learning model continuously optimized based on updated database
Data Sources	Measurements from individual wired sensors	Multi-sensor data fusion from environmental sensors and wearables devices
Responsiveness	Low, relying on fixed schedules	High, real-time adaptation possible
Personalization	Minimal, generalized group comfort zones	High, customized to individual via physiological feedback
Privacy Management	Limited considerations for data privacy	Encryption and federated learning for privacy preservation

3.1 System Architecture and Integration

As illustrated in Fig. 1, this framework signifies an evolution from the 'traditional measurement' process, which relies on offline modeling to set comfort temperatures based on general data, to an 'occupant-centric measurement' system. This system prioritizes the individual's experience by integrating a multitude of sensors that collect both environmental and personal data. It marks a shift to 'online modeling,' where the comfort zone is no longer static but rather a 'neutral comfort zone' that can be fine-tuned in real-time in response to active occupant feedback.

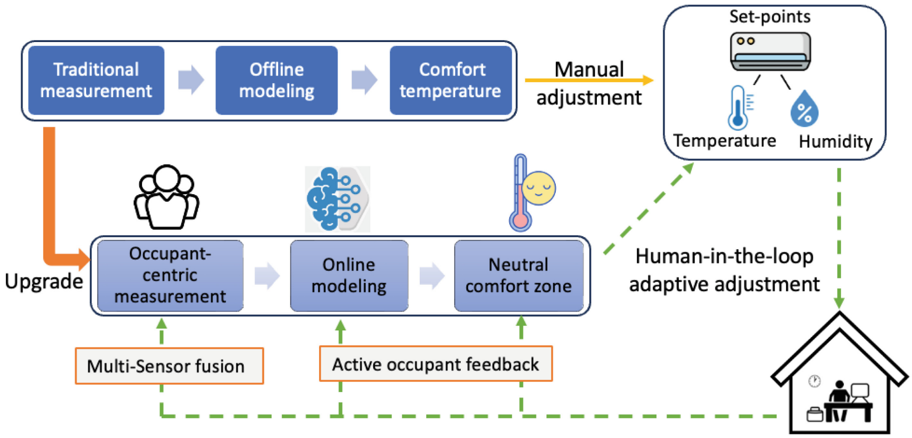

Fig. 1. Upgraded occupant-centric measurement and adjustment system.

The core of the proposed framework is smart wearable devices to measure an array of individual physiological metrics, including skin temperature, metabolic rate, and heart rate, along with portable environmental sensors to collect data on environmental factors such as air temperature, relative humidity, airflow, illuminance, acoustics, and indoor air quality. Physiological signals from wearables will be encrypted at the device before transmission for analysis. Through the sophisticated fusion of these diverse datasets, the system customizes the micro-environment at an individual level, taking into account factors factors such as age and seasonality.

The wearable device is supported by a platform—a smartphone APP that enables users to access data analytics insights and update their environmental preferences. This platform offers personalized feedback to individual data profile for continuously model training and optimization. Feedback from occupants is not merely passive data; it is an essential input that continuously informs the online learning model. This model evolves with each interaction, refining its suggestions and automatic adjustments to ensure they align more closely with the individual's preferences and well-being. Consequently, the mobile platform can actively send recommendations to the user, thereby promoting a human-in-the-loop adjustment system to enhance both comfort and energy efficiency.

The connection of wearable sensors and environmental has been tested for building system integration through a wireless mesh network protocol that allows data integration for IoT sensor networks. To synchronize sensing data from multiple data sources at the same time stamps, utilizing the processing platform with a web server to store, transfer and process data, is being increasingly explored (Feng and Wang, 2023). The processed outputs will feed into the online learning model to estimate and identify the neutral comfort zone. Such a platform has great potential for seamless integration with HVAC, lighting, and other building management systems to enact personalized comfort adjustments.

3.2 Implementation of the Proposed Framework

The proposed framework specifically emphasizes the feedback loop integrated into the model and showcases the practical application of this system in residential and commercial buildings such as an assisted living facility. In this setting, the system can either suggest adjustments to the occupant or staff or, if integrated with the building management system, automatically modify environmental conditions such as HVAC settings, lighting, and window positions to optimize comfort without requiring manual intervention. A control framework for the implementation is described in Fig. 2.

The described integration facilitates two key scenarios: staff-mediated adjustments where the system sends notifications to staff to take action, and automated environmental adjustments. In the latter situation, the system interfaces directly with building controls, offering a seamless response to occupants' needs. This dual capability ensures the system's versatility, allowing it to adapt to varying degrees of automation across different facilities.

Online Machine Learning. The proposed framework stands at the intersection of advanced technology and human-centric design. The adaptive control framework represents the next generation of environmental comfort systems. It moves beyond static,

Fig. 2. Assisted living facility scenario.

one-size-fits-all settings, utilizing a combination of real-time data and occupant feedback to create a living environment that adjusts to the changing conditions and preferences.

The proposed online framework evaluates the state of the indoor environment in real-time, including the occupant's current comfort level, and takes actions that maximize a predefined function with continuously updated database. This function is tailored to prioritize occupant comfort, as well as energy efficiency, thereby aligning with the goals of sustainable and occupant-centric design. The efficacy of the prediction model in such scenarios is supported by research by Wei et al. (Automation Conference, 2017), which highlights the potential of deep reinforcement learning in reducing energy consumption while maintaining comfort.

Explainable Artificial Intelligence (XAI). Transparency in AI-driven systems is a growing field of interest, particularly in scenarios where the user's trust and understanding of the system's decisions are crucial. The proposed framework incorporates XAI principles to demystify the AI's decision-making process. By leveraging techniques such as feature visualization and saliency mapping, which have been discussed in detail by Samek et al.'s (IEEE, 2017), the system provides users with understandable explanations for the AI's actions.

The system's XAI component tackles a significant challenge in HCI: the frequently opaque nature of AI algorithms. By implementing guidelines from Gunning's work (Defense Advanced Research Projects Agency (DARPA), 2017), we ensure that users are not alienated by the complexity of AI. Instead, they are provided with an interface that offers clear, concise explanations for the AI's adjustments to the indoor environment. This not only enhances user satisfaction but also encourages more meaningful interaction with the system, potentially leading to more accurate feedback and further refinement of the AI model.

By integrating online machine learning and XAI, the framework respects the dynamic nature of human comfort, prioritizes energy efficiency, and values the trust and engagement of the occupants, embodying the true spirit of human-centered design in smart building systems.

3.3 Evaluation Criteria and Hypothetical Outcomes

The proposed system will integrate into a constructed environment, bringing together a network of web servers, smartphone APP, environmental sensors, and personalized wearable devices. The integration strategy will address compatibility, data communication protocols, and system scalability. The evaluation of the system will primarily be based on three aspects, including data synchronization, interface friendless and reliability, and energy efficiency.

Data collection and synchronization will be multifarious, encompassing environmental parameters (e.g., temperature, humidity, air quality) and personal physiological signals (e.g., heart rate, skin temperature) obtained via wearable technology. The cornerstone of the proposed system is its data processing capability, employing data fusion techniques for immediate data storage and preprocessing. Simultaneously, the time-stamped data should be obtained and integrated for online modeling.

The user interface will be meticulously crafted, following the principles of user-centered design, to ensure not only intuitiveness and ease of interaction but also the utmost reliability. This reliability will be ingrained in every aspect of the interface, fostering user confidence in the system's consistent performance. Additionally, the interface will facilitate seamless occupant feedback, empowering users to confidently personalize their environmental settings. Recognized as a critical touchpoint, the interface will play a pivotal role in enhancing occupant engagement.

A comparative analysis of energy consumption before and after the system implementation will provide insights into its efficiency. It is hypothesized that the system's ability to tailor environmental conditions to individual needs will lead to significant energy savings, reducing unnecessary heating, cooling, or lighting adjustments.

4 Discussion

The proposed system is expected to significantly enhance indoor comfort levels, and this personalization is anticipated to lead to increased occupant satisfaction and well-being. In the long term, the system could contribute to improved occupant health and productivity, as personalized comfort has been linked to these factors in existing literature. For example, Frontczak et al. (2012) found that occupants reported improved health, satisfaction, and productivity when they had control over their indoor environment. Similarly, Kim and de Dear (2012) demonstrated long-term reductions in sickness in occupants of buildings with enhanced comfort systems. The proposed system dynamically aligns HVAC and lighting to occupant presence and preferences, reducing unnecessary energy use while enhancing indoor comfort.

The framework's flexibility suggests it could be adapted for various building types and environments, thereby broadening its applicability and impact. The system's potential to cater to the specific needs of vulnerable populations, such as the elderly or those with health conditions, highlights its societal value. Its capacity for personalization and privacy preservation positions it as a valuable contribution to future smart building solutions.

While innovative, the proposed framework has certain limitations that must be acknowledged. Primarily, its effectiveness is yet to be validated in real-world environments. This testing phase is crucial for understanding practical challenges and the system's adaptability to diverse settings. Furthermore, the framework faces notable challenges due to its reliance on sensor accuracy and the complexity of integration with various building management systems. Ensuring the privacy and security of sensitive data, despite the advanced techniques employed, remains an area requiring vigilant attention and continuous improvement.

In contemplating the future development of this system, a broader perspective is necessary-one that not only addresses the current limitations but also enhance the system's capabilities. An intriguing and crucial avenue for future research is exploring the integration of indoor comfort systems with external climate prediction models. This integration forms the basis of what can be termed the occupant-centric building resilience framework. This expanded framework goes beyond optimizing indoor comfort in the present; it envisions enhancing building resilience in response to climate change. Integrating real-time external climatic data enables the system to proactively adjust to environmental changes, ensuring the sustained comfort and well-being of occupants even under fluctuating external conditions. The holistic approach surpasses traditional paradigms of indoor comfort systems that often operate independently of external environmental factors. The novelty of this approach lies in its proactive nature-anticipating and responding to external weather patterns, rather than merely reacting to internal environmental changes.

5 Conclusion

This paper has introduced a comprehensive framework for occupant-centric measurement and adjustment within indoor environments, designed to enhance comfort through personalized micro-environment control. The proposed framework represents a significant shift from conventional static models, advocating for a system that dynamically adjusts to individual preferences using real-time data and feedback. The novelty of the framework lies in its integration of multi-sensor data fusion, online modeling, and intelligent sensor technologies. It is designed to handle and respond to a diverse range of inputs from both the built environment and the occupants themselves, providing a level of personalization not previously achieved in existing systems. Theoretically, this approach has been suggested to enhance the immediate occupant experience and foster a harmonious relationship between individuals and their living spaces.

This research makes dual contributions. Firstly, it tackles the challenges of data consistency and privacy in smart environments by implementing advanced computing. Secondly, it introduces a system capable of real-time adaptability, thereby enhancing the responsiveness of indoor comfort control measures. The paper has additionally outlined an occupant-centric building resilience framework as a direction for future work, proposing the integration of indoor comfort models with climate prediction to proactively adapt to external environmental changes. This future work aims to extend the application scope of the framework and contribute to building resilience in the face of climate variability.

In conclusion, while the proposed framework is yet to be validated in situ, it provides a blueprint for the future of intelligent building systems, where comfort, energy efficiency, and user privacy are at the core of design and operation. The expected results of this research are anticipated to lead to the development of more adaptive and resilient living spaces.

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