

Review

Human-building interaction for indoor environmental control: Evolution of technology and future prospects

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ARTICLE INFO

Keywords:

Human-building interaction
Topic modeling
BERTopic
Automatic control
Occupant centric control
Human-in-the-loop control

ABSTRACT

This paper presents a data-driven literature review of human-building interaction (HBI), which refers to the interaction between occupants and buildings. Through natural language processing-based text classification, the paper analyzed 907 literature sources and derived four research topics: automatic climate controller, automatic lighting controller, automatic window opener, and artificial intelligence. A meta-analysis was conducted to explore these topics from early to state-of-the-art technology. The meta-analysis revealed challenges and opportunities from the sensing, predicting, and control perspectives. Finally, the paper proposes future prospects to overcome these challenges, including increasing self-awareness in the environment, using multimodal sentimental feedback control, utilizing online and meta-learning, promoting collective control, and building infrastructure for field implementation. Eventually, HBI can also enhance the occupants' well-being by generating a more optimal indoor environment. In addition, the integration of advanced artificial intelligence can improve decision-making processes and increase the overall performance of automatic controllers.

1. Introduction

Previous research has found that due to the COVID-19 pandemic, people spend more than 90% of their time indoors, and there is a correlation between the indoor environment and people's health [1,2]. In this context, maintaining a comfortable indoor environment has been considered one of the essential services provided by buildings to improve occupants' comfort [3–5]. Accordingly, enhancing indoor environments for the operation of sustainable cities has become a major social concern [6–9]. Meanwhile, human-building interaction (HBI) technologies capable of providing indoor environments that maximize occupants' work performance, health, and well-being have received much attention [10–12].

HBI refers to a computer technology-based dynamic interaction process between intelligent buildings and their occupants [13]. Its main goal is to understand how people perceive, control, and interact with buildings from physical, spatial, and social perspectives. Additionally, HBI aims to develop innovative technologies that improve indoor environments through various information sets to enhance occupants' convenience and efficiency [14,15]. To measure and regulate environmental data in indoor environments, HBI must focus on the physical

environment where people interact and regularly reflect the occupants' status. Consequently, it is crucial to consider complex factors such as indoor and outdoor climate, occupants' behaviors, and user preferences and habits [16].

As shown in Fig. 1, four key components (i.e., human, building, environment, and interaction) constitute HBI as it focuses on improving the quality of human life and implements a built environment that can sense, predict, and control at various scales (individual building, community level, and city level).

Humans are the primary users and building occupants, determining how a building is used and occupied. They also provide various feedback on the indoor environment affecting their comfort levels. In the context of HBI, a building can be described as a human-made structure designed to ensure the safety and comfort of occupants, improve their quality of life, and achieve a specific goal. Controllable operating equipment (e.g., HVAC, lighting system, and automatic furniture) is also considered part of the building [17]. The *environment* is the totality of the surrounding conditions of an indoor space. In other words, it refers to an environment controlled by various sensors and devices within the building (e.g., temperature, humidity, CO₂ concentration, particulate matter, and illuminance) to suit the occupants' daily activities [18]. The interaction

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<https://doi.org/10.1016/j.autcon.2023.104938>

Received 9 March 2023; Received in revised form 4 May 2023; Accepted 11 May 2023

Available online 18 May 2023

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between humans and buildings is actively and passively conducted through various direct and indirect interface methods. As a result, these affect the occupants' experiences and behavior patterns. Passive interaction involves controlling the building system to minimize environmental impacts, for example, adjusting the indoor thermal environment via HVAC systems, thus affecting human thermal comfort. On the other hand, active interaction includes occupant actions that change the building management system or environment. These can include setting up specific values for window operation and heating control via interfaces [19].

The building and its environment defined by HBI can interact with each other through a new adaptive interface strengthened with sensing and computing (i.e., predicting and control) based on various devices [20]. First, it senses different information about occupants and the environment that affect the indoor environment and various environmental sensors installed inside the building [21]. Then, it predicts occupants' comfort, behavior, and occupancy based on the sensing data. Based on the predicted occupants' comfort, the operation system (i.e., equipment) installed in the building is controlled for the optimal and automated management of the indoor environment [22]. Consequently, indoor environment is improved, enhancing occupants' physical, mental, and social health and overall well-being.

This paper aims to conduct a data-driven literature review on HBI technology research. This approach is superior to traditional qualitative reviews in providing a more objective, systematic, and data-driven approach to synthesizing research evidence. The paper examined how HBI technology has advanced and evaluated its effectiveness in improving occupants' well-being. This review's findings provide insights into the current state of HBI technology and document the challenges, opportunities, and prospects in HBI research. The review is based on extensive academic literature source, including academic papers, conference papers, and review papers. The next section describes topic modeling methods to extract the research topic of HBI technology automatically. Then, in section 3, four research topics derived from the topic modeling are introduced, and technology development directions are organized chronologically. Section 4 discusses the challenges relative to HBI technology research from three perspectives: sensing, predicting, and control. Section 5 suggests five key prospects considered to address the limitations. Finally, section 6 presents the conclusions of this data-driven literature review.

2. Topic modeling

This literature review intends to explore HBI research trends and analyze its topic distribution to improve the indoor environment. The distribution was confirmed via topic modeling through natural language processing (NLP)-based text classification. Topic modeling automatically identifies research themes or topics hidden in literature sources. This establishes consistency and reliability by reducing the manual work required for the literature source selection and excluding researcher bias in the data-driven literature review [9]. Additionally, a broad literature scope can be summarized simply and in manageable form. In a data-driven literature review, topic modeling is conducted through four stages: (i) literature gathering, (ii) literature filtering, (iii) literature clustering, and (iv) cluster labeling.

2.1. Literature gathering

Before collecting the existing literature sources, four domains were defined based on the key components discussed on the introduction part.

- **Human domain:** Humans are the primary users and occupants of buildings. Therefore, they determine how a building is used, occupied, and provide feedback on the indoor environment. However, this domain was set for the general public, not for specific classes, such as patients, children, the elderly, or students.
- **Building domain:** In HBI, the building is designed, constructed, and operated to meet the occupants' preferences. However, the exterior space, temporary space, vehicles, airplanes, and public infrastructure, such as subway stations and airports, and structures for specific purposes were excluded from the building domain.
- **Interaction domain:** The interaction utilizes computer technologies to quantify the human desire to interact within buildings. Based on this, it then senses environmental data and predicts and classifies occupant preferences and comfort levels to include processes that automatically control building appliances [13].
- **Indoor environment domain:** This includes controllable factors (e.g., temperature, humidity, illuminance, and CO₂ concentration) that can be improved in real time due to occupant behaviors. However, uncontrollable factors (e.g., façade, furnishing, color, and textures)

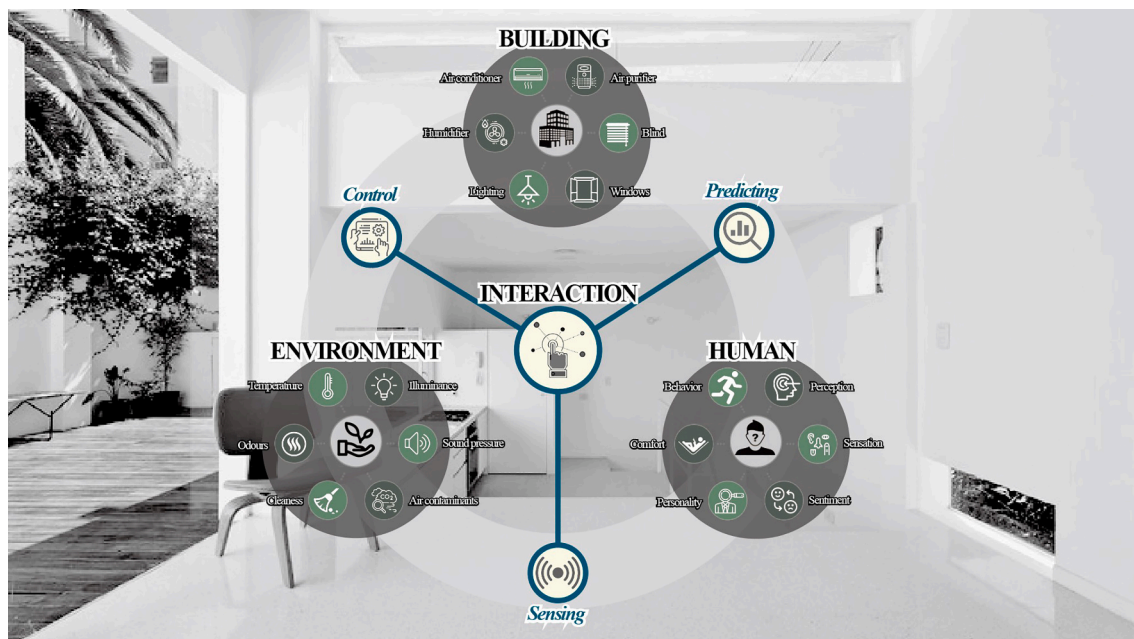


Fig. 1. Conceptual diagram of HBI.

difficult to change after completing building construction are excluded from this domain.

Table 1 shows logical grid for the main search terms, representing the previously defined domain and the corresponding alternative terms. The alternative terms were determined by referring to highly cited publications and organized using truncation operators (e.g., asterisk), Boolean operators (e.g., OR), and proximity operators (e.g., quotation marks). This review used advanced search builder from Scopus and Web of Science to collect existing literature sources. The scope of the advanced research was limited to “literature source that includes search terms in the title, abstract, and keywords,” “literature source written in English only,” “literature included in subjective areas such as architecture, engineering & construction, computer science, and environmental science,” and “literature source published in the form of peer-reviewed articles or conference proceeding papers.” As a result, 4868 literature sources were collected from Scopus and 2728 literature sources from the Web of Science.

2.2. Literature filtering

The primary selection process for the existing literature source collected from Scopus and Web of Science was performed considering suitability and relevance to the research topic of this paper. First, literature source representing different meanings from the domain defined in section 2.1 was eliminated. For example, literature source regarding research whose target of HBI technology application is not the built environment but the external environment or flight environment, and those that deal only with uncontrollable factors (e.g., furnishing, color, and texture) were eliminated. In addition, when it was difficult to select literature source only with the title, abstract and keywords, the full manuscripts were read for selection. All the above processes were carried out by a single author applying consistent criteria. As a result, a total of 907 literature source were selected. Then, the data frame was constructed to include the title, abstract, and keywords in rows for filtered literature source, and text preprocessing was then performed in the following order: (i) combining title, abstract and keyword; (ii) lemmatization (changing a word to root form); (iii) converting all text to lowercase; (iv) removing symbols, special characters, punctuations, and digits; (v) removing stop words (e.g., I, You, postposition, preposition, adjective and -thing, etc.); and (vi) n-gram extraction (in this paper, we used unigram and bi-gram).

2.3. Literature clustering

In this stage, the filtered literature sources was clustered according to the research topic via the BERTopic [25]. BERTopic (2022) requires less

Table 1
Logical grid of search terms.

Domain	Human	Building	Interaction	Indoor environment
Alternative terms			Interact*	
			OR	
	Human* OR	Building* OR	Predict*	“Indoor
	Person* OR	Home* OR	OR	environmental
	Individual*	House* OR	Control*	quality” OR
	OR	Housing* OR	OR	IEQ* OR
	Occupant*	Residential*	Classif* OR	“Indoor
	OR	OR	Manage*	environment*” OR
	User* OR	Indoor*	OR	“Built
	Customi*		Operat*	environment*”
			OR	
			Sens*	

Note: * is a truncation operator for searching zero or more characters in suffix/prefix; OR is a Boolean operator that any one of the search terms must occur to be retrieved; “” is proximity operator for searching an exact phrase.

effort for hyper-parameter tuning than the latent Dirichlet allocation (LDA), non-negative matrix factorization (NMF), and Top2Vec algorithm. In addition, the advantage of using BERTopic allows it to classify the text into different topics with high accuracy [26]. The following methods were used for BERTopic:

- **Embedding:** Paper embedding is the vectorization of filtered literature sources to convert them into numerical representations. Bidirectional Encoder Representations from Transformers (BERT) helps the filtered literature source to be embedded in accurate positions based on pre-trained data via the Wikipedia corpus database (2.3 billion words).
- **Dimensionality reduction:** In general, embedded literature source is characterized by high-dimensional data. However, since high-dimensional datasets may lead to performance degradation in clustering, Uniform Manifold Approximation and Projection (UMAP) which ensures better preservation of the global structure at high speed was used to reduce the dimensionality of document data [27]. UMAP is a novel method of reducing data dimensions that surpasses traditional methods like Principal Component Analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) in several ways. One of the key advantages of UMAP is its ability to preserve the overall data structure. While PCA can only identify linear relationships between variables, UMAP can detect more intricate non-linear relationships, making it particularly useful in visualizing datasets with many dimensions. Hyper-parameters of UMAP were as follows: (i) the number of components: 5; (ii) the number of neighbors: 20; (iii) minimum of distribution: 0.05; and (iv) distance metric: Euclidean.
- **Clustering:** Literature source with reduced dimensionality was clustered using the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). HDBSCAN performs superior in clustering non-linearly distributed data and is highly compatible with UMAP [28]. Another advantage of HDBSCAN is that it does not require the user to specify the number of clusters in advance. Hyper-parameters of HDBSCAN were as follows: (i) minimum number of cluster size: 12; (ii) minimum number of samples: 4; and (iii) distance metric: Euclidean.
- **Topic reporting:** Term Frequency-Inverse Document Frequency (TF-IDF) was used to derive important representative words for each cluster. TF-IDF increases proportionally as the frequency of a word that appears in a specific document increases. On the other hand, TF-IDF was awarded in inverse proportion as the number of documents in which the word was present increased. For this reason, TF-IDF helps to eliminate frequently appearing words, based on which a list of words that constitute the cluster and its weight was generated.

2.4. Cluster labeling

Because clusters are composed of word sets with similar meanings, it is important to classify them with the most representative topic. This paper used zero-shot text classification (ZSTC) to assign the optimal label to each cluster [29,30]. ZSTC has many advantages over traditional supervised learning methods: it reduces the need for labeled data, can handle new and unseen topics, and allows for more flexible and adaptive topic modeling. In addition, Facebook Bart-large-multi genre natural language inference, a crowd-sourced collection with 433,000 sentence pairs, was used for side information on ZSTC [31].

3. Topic representation

A total of four topics were automatically extracted from 907 existing literature sources using the BERTopic algorithm. Table 2 shows the five representative terms for the four topics and their relative importance.

Table 2 presents the ratio of five representative terms for Topic 1, which was the highest in HVAC (3.46%), followed by temperature

Table 2

Five representative terms for each topic.

Order	Topic 1	Topic 2	Topic 3	Topic 4
1	HVAC (3.46%)	Lighting (12.7%)	Learning (12.7%)	Window (27.1%)
2	Temperature (3.36%)	Visual (5.15%)	HVAC (8.13%)	Opening (20.4%)
3	Ventilation (2.24%)	Daylight (4.61%)	Deep (6.74%)	Behavior (13.4%)
4	Heating (1.80%)	Shading (4.11%)	Ventilation (3.65%)	Closing (5.53%)
5	Occupancy (1.61%)	Illuminance (2.84%)	Training (3.31%)	Outdoor (4.64%)

(3.36%), ventilation (2.24%), heating (1.80%), and occupancy (1.61%). The ratio of five representative terms for Topic 2 was the highest in lighting (12.7%), followed by visual (5.15%), daylight (4.61%), shading (4.11%), and illuminance (2.84%). The ratio of representative terms for Topic 3 was the highest in learning (12.7%), followed by HVAC (8.13%), deep (6.74%), ventilation (3.65%), and training (3.31%). Lastly, the ratio of representative terms for Topic 4 was the highest in window (27.1%), followed by opening (20.4%), behavior (13.4%), closing (5.53%), and outdoor (4.64%).

Table 3 reveals the results of optimal labeling for the four research topics using ZSTC. By referring to the keywords of the collected papers, candidate labels were determined as *automatic climate control*, *automatic lighting control*, *automatic window system*, and *artificial intelligence*. Accordingly, an automatic climate controller (62.8%) was chosen as the label of topic 1. The automatic climate controller is a system that automatically regulates the temperature, humidity, and air quality in a specific built environment. The label of topic 2 was selected to be an automatic lighting controller (29.7%). The automatic lighting controller adjusts the luminous environment and provides the desired illumination level. Artificial intelligence (AI) (49.7%), which enables interaction between occupants and various building devices, such as machine learning, deep learning, and reinforcement learning, was chosen as the label of topic 3. Lastly, the automatic window opener (34.9%) was selected as the label for topic 4. The automatic window opener is a device that automatically opens and closes windows in response to changes in temperature, humidity, CO₂, VOC, and PM2.5 and 10.

According to the topic proportion in Fig. 2, the automatic climate controller was the highest at 78.1%, followed by the automatic lighting controller (10.8%), artificial intelligence (AI) (4.55%), and automatic window opener and 1.55%, respectively). One reason for the high proportion of automatic climate controller studies in HBI technology research is the automatic control of the thermal environment, which is highly dependent on the well-being of occupants [32]. Another cause is that automatic climate controller is important in energy efficiency. It can help to reduce energy consumption by adjusting the temperature and humidity in response to occupancy patterns [33]. According to the topics in Fig. 2, HBI technology research has been actively conducted since 2014, and the number of relevant studies has increased five times by 2022. This development in research is due to technological advances, such as the advent of the ultrasonic wave, AI algorithm, Internet of Things (IoT) devices, blockchain, virtual reality, and augmented reality (AR) [34,35].

Table 3

Optimal labeling for the four research topics.

Candidate label	Automatic climate controller	Automatic lighting controller	Artificial intelligence	Automatic window opener
Topic 1	62.8%	1.97%	27.3%	7.87%
Topic 2	19.1%	29.7%	29.1%	22.0%
Topic 3	43.7%	1.58%	49.7%	5.0%
Topic 4	26.7%	26.4%	11.9%	34.9%

3.1. Automatic climate controllers

Automatic climate controllers sustain occupants' comfort regardless of the outside weather conditions. Over the past several decades, technological advances have transformed how automatic climate controllers heat, cool, and ventilate indoor environments, leading to the development of HBI technologies (refer to Fig. 3).

Classical control strategy primarily relied on temperature feedback. Typically, bang-bang controllers employed manual control methods, utilizing a thermostat to give temperature feedback. Despite their simple and intuitive implementation advantages, bang-bang controllers pose limitations in that they cannot accurately track the setpoint temperature due to frequent temperature overshoots and have disadvantages that might result from on-off operation [36].

PID controllers are developed to compensate for these limitations and can integrate proportional, integral, and derivative control to continuously monitor the differences between the desired setpoint temperature and the actual temperature. They can also correct the setpoint temperature of the heating and cooling unit through residual error [37–40]. But tuning its parameters can be a cumbersome process. The PID controller's performance may also decline if the operating conditions vary from the conditions under which it was tuned. Retuning or auto-tuning methods for the PID controller can be time-consuming and in certain applications, may not be suitable due to its disruptive nature during normal operation [41,42].

Based on the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) [43], many previous studies have proposed PMV-based climate control that quantifies the thermal state of the indoor space and operates the climate controller in the direction of PMV being the neural state and PPD being the minimal value [44–49]. This control strategy involves controlling building systems based on PMV and has been found to save energy while improving thermal comfort levels more than traditional temperature-based control. Although PMV-based controllers maintain indoor conditions that fall within a range of acceptable thermal comfort for most building occupants, two drawbacks exist. First, PMV-based controllers rely entirely on the mathematical model. Thus, they are more likely to fail to accurately reflect the actual thermal preference and comfort level of individual occupants in special situations. Second, PMV-based controllers use a one-size-fits-all approach, which can result in suboptimal thermal comfort levels for several occupants.

Ultimately, classical control strategies demonstrate limitations. The main disadvantage is that they do not consider the occupants' personal factors. Hence, the temperature may not be optimal for everyone, leading to complaints or discomfort. Classical control strategies lack operational flexibility because they fail to reflect specific individual preferences and establish the set point temperature of an entire building to an optimal value.

These limitations have been resolved by developing a new approach called occupant-centric control. The occupant-centric control can adjust the temperature based on the occupants' comfort levels instead of relying solely on a setpoint [50–54]. The occupants can adjust the temperature using their smartphones or other devices. This means every occupant can establish their own comfort level instead of relying on one fixed temperature for the entire building.

In the early days of occupant-centric control, methods that detected presence/absence based on passive infrared (PIR) sensors and ultrasonic sensors to operate automatic climate controllers were widely adopted [55–58]. Because occupancy presence is a binary factor that indicates either 0 or 1, where 0 stands for unoccupied and 1 stands for occupied, there is no need for a predefined model or an operating algorithm. For this reason, it is most widely used as it simplifies the operation of automatic climate controllers. Presence refers to the detection of whether there are people in each space or not. Detecting presence is generally done via image preprocessing. RGB images [59,58] and thermal images [61] are the major image types used for detecting presence.

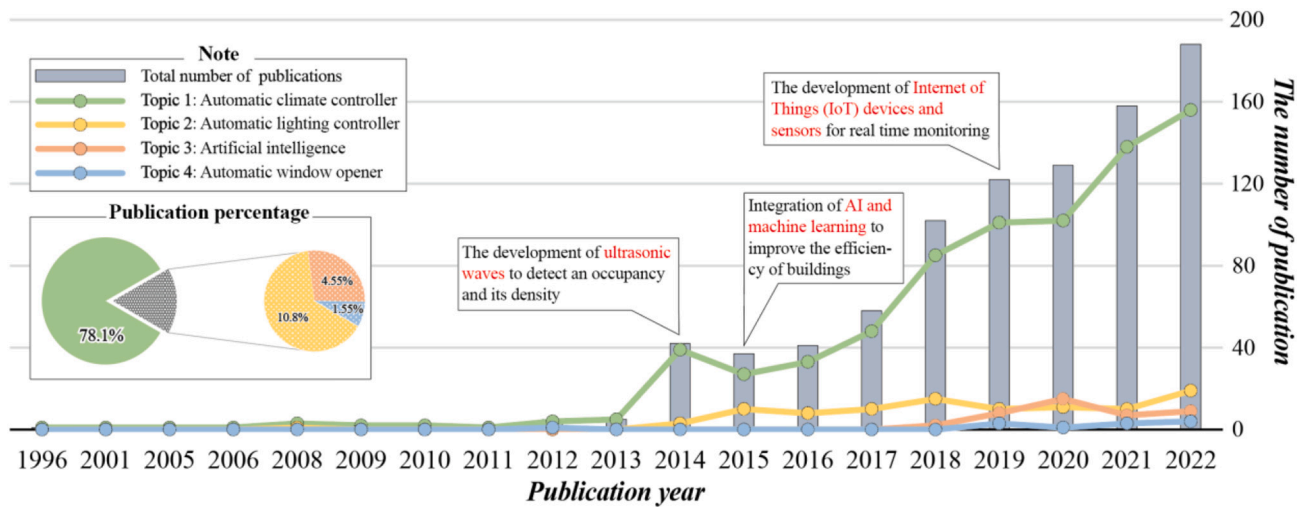


Fig. 2. Topic distribution over time (from 1996 to 2022 year).

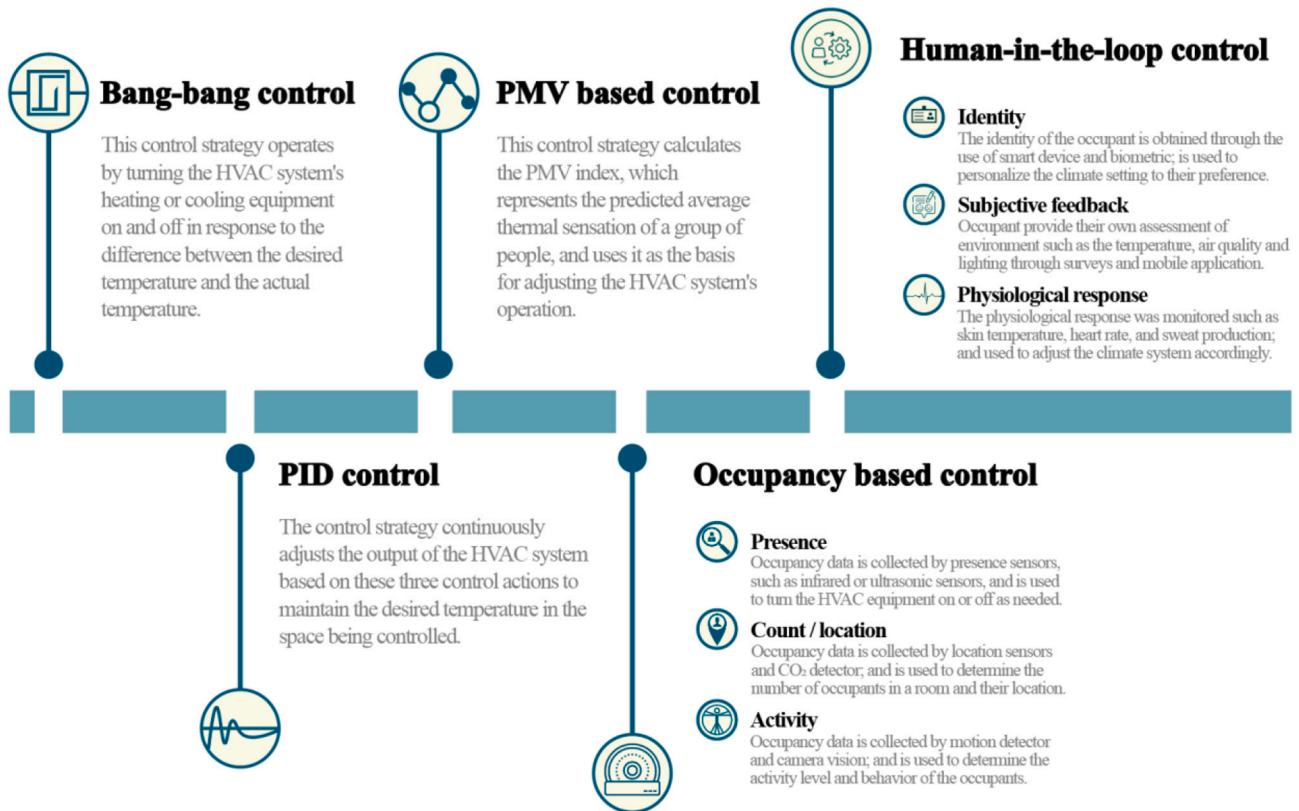


Fig. 3. Technical advance of automatic climate controller.

In addition, camera vision-based occupancy detection is also being widely adopted and is expected to replace passive infrared sensors and ultrasonic sensors in the near future. Introducing location-based systems (e.g., Wi-Fi, beacon, and GPS) enables the real-time collection of occupants' spatial coordinates. This system helped each occupant in the same indoor space but in different local positions to operate the automatic climate controller according to the standard of the local setpoint temperature [62,63]. Studies that utilized occupancy location to enhance occupants' comfort level with HVAC systems, such as adjusting the direction and speed of a fan, have been conducted. Similarly, introducing light beam sensors, camera networks, and CO₂ sensors helped detect the indoor space's occupancy level and density in real time and adjust the

supply air volume of automatic climate controllers, thus achieving energy savings [64,65]. In some studies, the setpoint temperature and airflow rate to maintain the indoor temperature constant were determined by detecting the occupancy level and density and calculating the heat emitted by occupants [66,64]. Additionally, the development of machine vision techniques made it possible to detect activities and metabolic levels of occupants, such as studying, exercising, and cooling through skeleton and volume-based models [68–71] and to predict the occupant clothing level (i.e., heat resistance of clothes) [72,73].

The next step in the evolution of occupant-centric control was a human-in-the-loop control incorporating occupants' feedback to optimize the indoor thermal environment continuously [74,14]. These

controllers allow occupants to provide feedback data and adjust the thermal state based on their comfort levels. In contrast to other controllers, these controllers allow for real-time adjustments, resulting in higher overall comfort. In a human-in-the-loop climate controller, three types of occupant feedback data are collected:

- **Identity:** This method operates the automatic climate controller by collecting only personal profiles that include occupant information as feedback data. In most cases, the occupant's user ID and media access control (MAC) address of the smartphone or IoT device are collected to detect a specific personal profile and operate the automatic climate controller according to the desired temperature, occupancy duration, and airflow rate determined by the occupant in advance [76,52]. However, this method has a disadvantage—each time the occupant goes in or out of the building, he or she needs to enter the desired thermal preference, which may threaten personal security [78].
- **Subjective feedback:** This method operates the climate controller by collecting subjective data, such as thermal preference, acceptability, and satisfaction perceived by the occupant in the indoor space as feedback data [79,80]. It is also a strategy to operate the automatic climate controller by reflecting the feedback data after requesting the occupant to accomplish a survey through a smartphone application or webpage at regular intervals to evaluate the thermal environment in real-time. Fukuta et al. [81] proposed a new survey method to gather occupant feedback data on individual comfort levels in human-in-the-loop HVAC control to reduce energy consumption and thermal discomfort. However, this method is not user-friendly because occupants must constantly update feedback data. In addition, it lacks consistency as the feedback data comes from subjective thinking. [15].
- **Physiological response:** This method operates the climate controller by collecting the physiological responses triggered by the occupant's autonomic nervous system as feedback data. This approach uses various sensors or wearable devices to collect the

physiological response data on the occupants' body temperature, heart rate, skin conductance, and other indicators and uses this information to regulate the climate controller accordingly [22,83–91]. In this way, the controller based on physiological responses provides a more precise, personalized, and thermal comfortable environment for occupants than subjective feedback. However, the most critical disadvantage of using physiological responses as feedback data is that occupants must constantly wear expensive wearable devices. In addition, some invasive sensors to measure physiological responses may cause discomfort or pain to occupants. Moreover, it is impossible to accurately measure the physiological response when the occupant falls asleep or engages in intense physical activities. Nevertheless, as the price of wearable devices has recently dropped, and the accuracy of the personal thermal comfort model has remarkably improved, human-in-the-loop control based on physiological responses is expected to become mainstream in the future [93–95].

3.2. Automatic lighting controller

Automatic lighting controllers are based on HBI technology that adjusts the brightness of the indoor environment according to environmental and human factors [96–98]. Over the years, the development of automatic lighting control has gone through several milestones and has been influenced by smart lighting technological advancement (refer to Fig. 4).

In the past, time-dependent and illuminance level-based control strategies were applied. A time-dependent control strategy controls lighting in an indoor environment by utilizing a pre-programmed schedule [99,100]. On the other hand, the illuminance level-based control strategy uses sensors to measure the illuminance and daylight factors [101,102]. Through sensing data, this control strategy adjusts the lighting according to the illuminance threshold. This strategy helps save energy by reducing the excessive use of artificial lighting, but it may not be suitable for an indoor environment that does not have

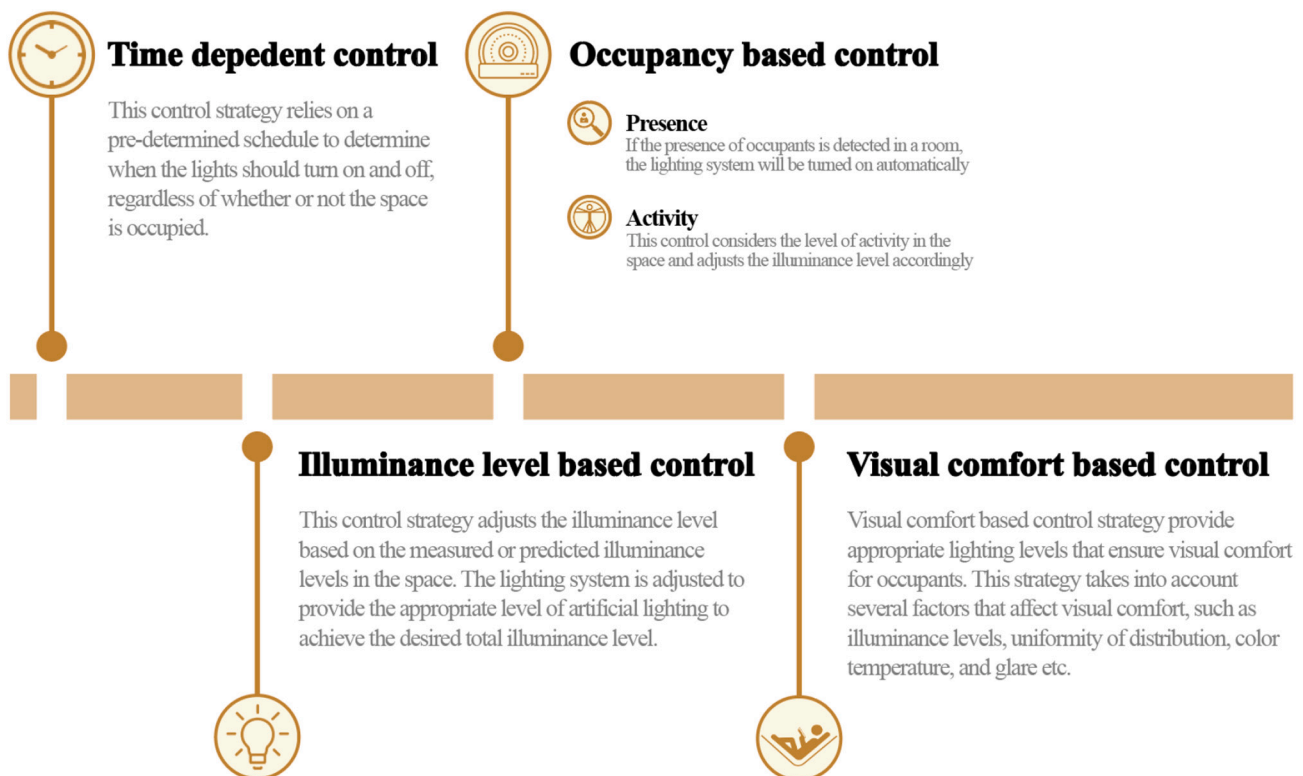


Fig. 4. Technical advance of automatic lighting controller.

windows or has limited access to daylight. Thus, early automatic lighting controllers simply turn lighting on or off based on a single variable, such as the time of the day, illuminance level, or daylight factors. The illuminance level-based control strategy offered a simple and straightforward approach to the automatic lighting controller, but it was difficult to adapt to changing conditions and meet new requirements.

The development of automatic lighting controllers shifted toward the occupancy-based control strategy. This control strategy uses occupancy sensors to detect the presence and activity type and adjusts the lighting accordingly [103,104]. When a room is unoccupied, lighting can be turned off or dimmed, and when occupancy is detected, lighting can be turned on or brightened. Occupancy-based control strategy classifies the required data into two categories: presence and activity.

- **Presence:** This is a method of operating the automatic lighting controller by detecting the occupant's presence through monitoring equipment, such as the PIR sensor, vision camera, CO₂ sensor, RGB and thermal image, or ICT components of a mobile device, such as Wi-fi and Bluetooth [105–108]. Zou et al. [108] calculated the non-occupancy time of the indoor space via a statistical approach and suggested the energy potential when the lighting was turned off during the non-occupancy time. Lee et al. [105] created a dimming lighting controller that combines general illumination, dimming, and technology for recognizing the occupant's location. Various occupancy scenarios have been studied and proposed for controlling lighting systems based on occupancy detection.
- **Activity:** This strategy controls lighting as it reflects the occupant's activity in the indoor space [21,110–112]. The automatic lighting controller adjusts the illuminance level and correlated color temperature (CCT) based on the task type, such as reading, writing, or computer work. Chun and Lee [112] classified occupant activity into five modes (i.e., studying, dialog, watching, walking, and rest) via image processing and suggested the optimal CCT. Choi et al. [115] devised a personalized lighting control system using IoT and smart devices. This system was used to calculate the user's activity and fatigue levels in real-time via a mobile application and a cloud-based platform and provide the optimal illuminance level and CCT.

From the late 2010s to 2020s, visual comfort-based lighting controls that reflect visual comfort levels that the occupant perceives for the luminous environment to adjust the illuminance and CCT in the indoor space appeared. This control strategy helped create the optimal luminous environment considering the task being performed, the time of day, illuminance, and the preferences of occupants [116–118]. Cheng et al. [103] developed a closed-loop satisfaction-based system to obtain an optimal lighting control strategy using improved reinforcement learning. Park et al. [98] presented LightLearn based on reinforcement learning to consider indoor environment's factors (e.g., illuminance, temperature, and humidity) and individual occupant behavior. It was found that LightLearn balances visual comfort and energy consumption successfully. Kandasamy et al. [121] used an artificial neural network and internal model control to develop personalized lighting control that considers occupants' preferences.

As the importance of occupants' wellness has been highlighted, many studies have explored occupants' visual comfort, psychological factors, eye health, and productivity under various luminous environments [122,123]. In addition, observational studies on physiological features using eye-tracking glasses and electroencephalogram methods have been actively conducted to select physiological indicators according to luminous environments [124–126]. In the light of the recent research trend analysis, it is expected that a technology that collects real-time data on physiological and psychological factors to automatically control lighting will be developed in the future [127].

3.3. Automatic window opener

To discharge pollutants produced from living in a closed space and improve the indoor air environment, the importance of natural ventilation, which is the exchange of air between the inside and outside of the building, has been stressed for a long time [128]. An automatic window opener has established itself as one of the HBI technologies capable of performing more efficient natural ventilation, considering occupants' comfort levels for indoor air quality and indoor and outdoor environmental conditions in a smart building [129,130]. Over the past several decades, technological advances have transformed how automatic window openers ventilate indoor environments, leading to the development of HBI technologies.

In the past, weather-based and multivariable-based control strategies were applied to develop automatic window openers. First, the weather-based control strategy collects outdoor weather data (e.g., outdoor temperature, precipitation, wind speed, particulate matters, and other pollutants) from weather stations and automatically operates windows or doors according to the predefined rule-based algorithm [131,132]. Second, the multivariable-based control strategy adjusts the indoor environment considering the collected weather data and environmental and non-environmental data measured using various monitoring devices. To be more specific, studies considering environmental data (i.e., the indoor and outdoor temperature, relative humidity, dust concentration, solar radiation, noise level, etc.) have been mainly conducted to establish a natural ventilation strategy to effectively remove indoor pollutants and maintain an optimal thermal environment [133–136].

In an adaptive behavior-based control strategy, environmental data and the occupants' behavioral patterns are considered at the same time [137]. In most studies, the adaptive behavior of the occupant opening or closing the window was detected via FIR sensors, while environmental parameters, such as temperature, humidity, and CO₂ concentration, were collected via environmental parameters. In addition, a binary classification model was developed using adaptive behavior as a response variable and environmental parameters as predictor variables [138–140]. The related studies suggested the automatic window control strategy through a deterministic approach [141,142]. However, a stochastic approach has been used more often to address the limitations caused by the trade-off issue of various environmental data and the inability to reflect occupants' comfort level, [138,143,145]. The adaptive behavior-based control strategy classifies the monitored environmental parameter into two categories:

- **Temperature:** Occupants may open windows to regulate indoor temperature and improve their thermal comfort. They may open windows to allow fresh air and natural ventilation if the indoor temperature is too high or too low. D' Oca and Hong [147] found that indoor and outdoor temperatures were the primary determinants of the occupant's window opening behavior. Herkel et al. [148] developed a statistical model based on not indoor and outdoor temperature data and outdoor humidity data to calculate the probability of window opening.
- **Indoor pollutants:** Occupants may open windows to improve indoor air quality if they perceive that the air inside the building is contaminated or stale. They may open windows to allow for fresh air. If the concentration of indoor pollutants is too high. Cali et al. [149] showed that the most important factors affecting the window opening behavior were the time of day and the CO₂ concentration. Kim et al. [144] proposed an automatic ventilation control algorithm considering CO₂, total volatile organic compounds (TVOC), and particulate matter. They found that CO₂ and TVOC were the primary determinants of the occupant's window opening behavior.

3.4. AI technologies

AI technologies have played a crucial role in improving HBI

technology, especially in controlling IEQ, including automatic climate, lighting, and window controllers. Detailed AI methodologies used in HBI have evolved over time (refer to Fig. 5).

Before AI technologies became popular, most studies focused on using rule-based algorithms in the development process of automatic controllers [151,152]. These algorithms control automatic controllers based on a set of predefined rules. General predefined rules are specific events, including occupant behavior and environmental conditions. For example, when people enter or leave a building, HVAC, lighting, and windows are automatically controlled according to the predefined conditions, and appropriate actions are taken until these conditions are met. Despite their advantages of automating the building [153], the rule-based algorithms have many limitations, including inflexibility [154]. Because these algorithms rely only on a fixed set of rules, they cannot respond to changing environmental conditions and occupant comfort levels in real time. Another limitation is their limited decision-making capability. These algorithms only perform decision-making based on predefined conditions and thus fail to cope with unexpected or unusual situations.

As technology advances, academic research focuses on fuzzy logic algorithms. Unlike traditional rule-based algorithms, fuzzy logic algorithms offer several advantages that make them more attractive to engineers and researchers [155,156]. Fuzzy logic algorithms can deal with uncertainty and inaccurate information more intuitively. These algorithms use probabilistic concepts to define the degrees of truth or membership values in a linguistic variable. Thus, unlike rule-based algorithms that perform dichotomous decision-making with incomplete information, they can perform logical inference. This enables automatic controllers to operate more robustly and flexibly.

The next step in evolution was the advent of model-based algorithms, which utilized mathematical models to represent complex relationships and make predictions based on multiple variables [76,157–160]. While fuzzy logic algorithms compensate for uncertainty by allocating

intervals to linguistic terms, model-based algorithms deal with uncertainty through mathematical models, showing better performance in a complex relationship. In addition, these algorithms help increase predictive accuracy as they control the environmental condition by reflecting several variables simultaneously. In summary, model-based algorithms offer a more sophisticated approach to decision-making. They are better suited for complex and data-rich applications than rule-based and fuzzy logic algorithms.

With the rise of small-sized IoT devices and the availability of big data, data-driven algorithms emerged as a game-changer. These algorithms utilize machine learning techniques to automatically learn from sample data to make classifications and predictions. Unlike model-based algorithms, which make decisions based on mathematical models, data-driven algorithms make decisions based on data patterns, thus exhibiting excellent adaptability to real-time situations and occupants' feedback [98,19,162–166,168]. In addition, they can be scaled up to handle relatively large amounts of data, making them suitable for big data applications. In addition, despite the involvement of many computing technologies, it is easier to implement and interpret when compared to model-based algorithms that require expertise in mathematics and statistics. Machine learning techniques that are commonly adopted in data-driven algorithms are composed of the following four methods [169]:

- Non-linear method:** This machine learning technique deals with non-linear relationships between predictor and response variables. Unlike linear methods, the non-linear method can capture non-linear patterns of data and can thus be applied to data with non-linear relationships. Examples of non-linear methods include support vector machines (SVM) [94,170,171], K-nearest neighbors (KNN) [172,173], and Naïve Bayes [173,174]. According to Feng et al., 2022b., SVM is the most widely used algorithm for developing a thermal comfort prediction model and performs well in classifying data samples through a hyperplane.

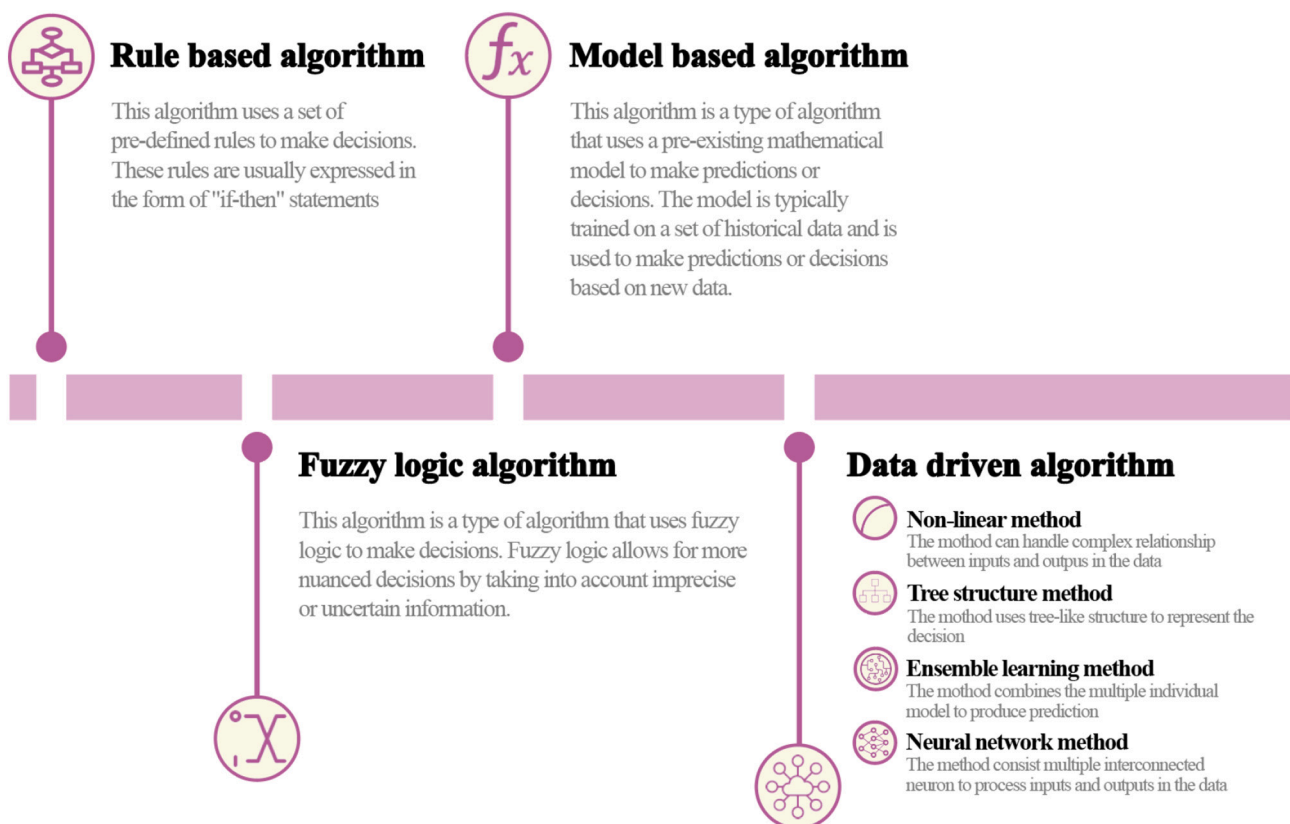


Fig. 5. Technical advance of AI technology.

- **Tree-structure method:** This machine-learning technique uses a tree-like structure to represent the decisions and their consequences. Examples of decision trees include classification and regression trees (CARTs) and random forests (RFs) [87,176].
- **Ensemble learning:** This machine-learning technique combines multiple individual models to produce a more accurate and reliable prediction. Collective intelligence is more potent than any single model. Examples of ensemble learning include gradient boosting [94,170], adaboost [173], and XGboost [145,178].
- **Neural network:** This machine learning is inspired by the brain's structure and function. It processes many input features using several interconnected neurons and generates output values. Neural networks play a vital role in interpreting complex and non-linear relationships relatively easily. Recently, with the rise of computing power and the development of efficient activation functions, the proportion of neural networks in HBI technology has risen. Examples of neural networks include multi-layer perceptron (MLP) [173,91], convolutional neural networks (CNN) [84,181–185], recurrent neural networks (RNN) [186], and graph neural networks (GNN) [187–189]. CNN can be efficiently used when preprocessing physiological response data with multiple channels or classifying occupant information through image feature extraction. RNN is a network used to predict time series data. Generally, it can be frequently used for sentiment classification of occupants through life logging or speech. GNN can analyze occupant interactions, behavior modeling, and interactive patterns in a shared indoor environment.

4. Identified challenges and opportunities

Several challenges and opportunities in predicting and control process were identified after reviewing the existing literature source on HBI technologies.

4.1. Challenges in sensing process

Implementing HBI technologies requires sensing various types of data [190]: (i) environmental data (e.g., temperature, humidity, illuminance, and CO₂); (ii) occupancy data (e.g., presence, number, activity, and clothing level); (iii) subjective feedback (e.g., self-reported sensation, preference, acceptability, and satisfaction); and (iv) physiological response (e.g., body temperature, heart rate, and skin conductance). The sensing data is then used to develop prediction models representing the interactions between occupants and buildings.

The following challenges were determined after the data-collecting process:

- **Non-detected local zone:** Extensive and accurate measurement of environmental data is vital to manage indoor environments and operate automatic controllers. Despite the need for many monitoring devices to measure the environmental data for all points in the indoor space, their implantations in actual buildings seem impossible due to budget challenges and spatial inefficiency. In the meantime, a single point-based measurement method using few monitoring devices results in a non-detected zone in which there is no environmental data for the local indoor space. Therefore, to measure and predict environmental data of the non-detected zone, advanced sensing technologies such as 3D distribution maps using spatial interpolation methods [191–193], robot-based mobile sensing systems [194,195], and wearable environmental sensors [196,197] are being introduced.
- **Difficulty in self-awareness in indoor environment:** In human-in-the-loop control, automatic controllers are mostly operated based on occupants' subjective feedback on the indoor environment. However, due to limited knowledge, occupants may not be aware of all the components that contribute to the indoor environment, such as air temperature, illuminance, CO₂ concentration, and airflow rate. In

addition, prior experiences and expectations can influence occupants' perception of an indoor environment, leading to biases that negatively affect their self-awareness. Kong et al. [198] presented test results showing that occupants should be provided with numerical data displayed via monitoring devices in real time because they are not clearly aware of the indoor environment at present. To improve self-awareness in indoor environments, a method of providing alert information whenever management criteria are exceeded [199,200], and advanced sensing technologies such as indoor environment visualization that combines AR with computational fluid dynamics (CFD) [201,202] have been suggested.

- **Lack of social dynamics and personality traits:** Existing literature source failed to reflect the social dynamics of a group to which the occupant belongs and the occupant's personality traits. In fact, occupant behavior is influenced by social dynamics (e.g., norms, religion, and cultures) and personality traits (e.g., attitude, knowledge, and extraversion), which can also affect occupant satisfaction, comfort, and work performance. For example, introverted occupants prefer a quiet environment and dimmed lighting, while extroverts prefer more open space with bright lighting. Occupants with different social dynamics and personality traits may also have different preferences for lighting, temperature, and air quality, which can play a critical role in shaping the perception of the indoor environment [203]. Recently, some studies attempted to demonstrate the effects of social dynamics and personal traits on occupant behavior patterns through statistical methods using various sociological models or questionnaire forms [203–205].
- **Excessive requests for occupant feedback:** The occupant's subjective feedback plays a crucial role in occupant engagement with the HBI system [16]. Current HBI control strategies tend to request excessive and frequent feedback from the occupant. For example, occupants are required to periodically evaluate sensation, satisfaction, and preferences for indoor environmental factors, such as indoor thermal, visual, acoustic, and air environment. Accordingly, it is predicted that spending a lot of time on these evaluations will be quite bothersome to occupants. In addition, occupants may perceive excessive and frequent requests as intrusive or annoying, leading to decreased satisfaction and engagement with the HBI system [207,208]. To overcome these shortcomings, it is important to design the feedback mechanisms in a human-in-the-loop control carefully [209]. For instance, in addition to increasing the time interval between requests for feedback so that the occupant can control the indoor environment simply and intuitively, it is essential to introduce new indicators that can integrate each feedback on the thermal, visual, acoustic, and air environment.
- **Absence of standardized/generalized sensors:** The existing literature sources on HBI aimed to analyze what kind of data had statistical significance with environmental factors and whether they could be factors. Various sensors are used in recent studies. For example, some studies used thermocouples to measure skin temperature, while others used smart wristbands or infrared cameras. However, not every occupant wears smart wristbands or EEG caps in actual buildings. Furthermore, the sensors used in most studies are existing sensors and are not specialized for buildings. Moreover, one sensor may collect limited data types, and it may not be efficient for the building owner to install all the necessary sensors. Consequently, there is a need to develop building-specific sensors fixed to the building that can collect occupant feedback. In addition, it is necessary to find a way to collect occupant feedback by sharing the data of sensors possessed by individual occupants without installing them in the building. Ultimately, standardized sensing technologies that can be applied generally should be proposed. If given options of standardized HBI sensing technologies, building owners can then decide what type of sensors should be installed in their buildings more easily. In addition, economically efficient sensors capable of

collecting strong indicators with a small number of sensors are needed to implement HBI technologies.

- **Data insecurity and invasion of privacy:** Recently, as the value of big data has been emphasized in all industries, there have been increasing concerns about data security and invasion of privacy [210]. HBI technology also starts from collecting occupant feedback data that often contains sensitive personal information, such as images, subjective preferences, physiological responses, gender, daily habits, and so on; this is often confidential information that should not be disclosed to an unauthorized group [211,78]. Accordingly, ensuring the security of occupant feedback data should take priority because it maintains the privacy and confidentiality of the individual occupant who provides the data, complies with personal ethics and public communication law, and can help obtain a good reputation from users. In this context, research has been undertaken to enhance the occupant feedback data security via blockchain-based data encryption. For instance, there is a trend to encrypt occupant's activity/clothing level, location, presence, preference, and physiological data by means of blockchain technologies, including blockchain-distributed ledgers [213,214] and smart contract [78].

4.2. Challenges in predicting process

HBI technologies use many machine learning techniques to predict occupant comfort models, such as SVM, KNN, CART, RF, Gaussian approach, MLP, and CNN. Many indicators evaluate the prediction accuracy: precision, recall, area under the receiver operating characteristic curve, Gini-index, and F1 score. In the predicting process, existing literature sources have identified the following three challenges:

- **Insufficient sample data:** Most of the HBI technologies designed to predict occupant comfort were developed through laboratory research involving recruiting specific subjects and conducting experiments rather than field research with a randomly selected target population [169]. Therefore, it is dangerous to generalize the HBI technologies of several studies because each paper has different criteria for calculating the number of subjects, and the physical information (e.g., age, height, and weight) of the subjects also varies greatly [215]. Martins et al. [93] conducted a systematic review of papers that proposed a thermal comfort model and revealed that the criteria for the subjects were inconsistent. The number of subjects recruited ranged from 3 to 576, and the ratio of male subjects was far higher than that of female subjects. In addition, there were racial differences in body composition from country to country where the experiments were carried out. As a result, insufficient sample data can be a challenge when developing an HBI technology for occupant comfort. However, a few approaches be taken to address this issue: data augmentation, transfer learning [217], and ensemble learning [218]. Besides the sample data quantity mentioned above, the inconsistency of sample data during the experimental process is also an important challenge. Factors causing inconsistency to deteriorate data quality are largely classified into two categories. First, the interference effect caused by various devices used in the experiment is a factor that distorts the subject's response [87,12,88,220]. For example, the consistency of responses may vary greatly depending on the wearability of the many wearable devices required to measure the subject's physiological response or attitude. Second, the subject's biorhythm is another factor that distorts the response [87,94]. For example, the amount of sleep, smoking, or alcohol consumption the previous day hinders the perception of the indoor environment. Therefore, an experimental design considering the biorhythm of the subject in a homogeneous indoor environment should be created to maintain consistent sample data quality.
- **The disadvantage of offline learning:** Most HBI technologies are based on offline learning, done by fixed data and not updated to new data in real-time [94,222,172]. Therefore, all the prediction models

are trained only once in the early stages and are then used to predict the occupant's comfort level without the additional adjustment of hyper-parameters. The applicability of offline learning decreases because of several known disadvantages. First, when data distribution varies with time, offline learning models can be unstable in predicting these changes. Second, offline learning models can be biased if the training data is not representative of the real-world population, leading to poor performance when applied to new, unseen data. Third, the model needs to be trained whenever the training set changes, and the training process may be complicated and time-consuming. Finally, the biggest drawback of the offline learning model is that a large amount of data is needed to train one model, which can be difficult to obtain and time-consuming. However, HBI infrastructure for online learning has recently been built due to intelligent sensor technology and computing technology Development [224–226].

4.3. Challenges in control process

The concept of control in HBI technology involves using actuators and other control systems to influence human behavior or environmental conditions. In the control process, the existing literature sources have identified the following three challenges:

- **Interdependence of each automatic controller:** Multifarious automatic controllers work to provide an integrated and optimal indoor environment. The interdependence of these controllers means that they should be designed to ensure information sharing and operation in harmony to improve the occupant's comfort level. However, in the human-in-the-loop control strategy, different kinds of occupant feedback are required for each automatic controller. For example, automatic lighting controllers require feedback on visual comfort perceived by the occupant, whereas automatic climate controllers tend to require feedback on thermal comfort. Accordingly, occupants should provide feedback for each independent environmental factor (i.e., thermal environment, luminous environment, acoustic environment, and air quality). Many studies have shown that environmental factors interact with one another and affect occupants through complex processes [227,228]. Therefore, a new indicator that evaluates the many overall environmental factors of space from an integrated point of view is needed to consider these controllers' interdependence.
- **Dispersed comfort zones:** As HBI technologies are being improved to reflect the feedback of individual occupants, they are becoming hyper-personalized. However, there are generally several occupants in a room, or a zone controlled by one environmental controller, and feedback from each occupant may cause conflicts among the occupants. For example, if half of the people think the room is too hot and the other half feels cold, the climate controller might fail to satisfy anyone. As these individual occupants' feedback conflicts have been steadily increasing, various attempts have been made recently to solve these conflicts. These efforts can be largely grouped into two different approaches, as Malkawi and Srinivasan [201] have suggested. The first approach is to provide a physical solution, which introduces various personal comfort systems, such as chairs for local heating and cooling [229,230]. In addition, there is a method to divide the shared space further and thus reduce the number of people controlled by one controller [201]. Another approach is establishing a collective control strategy to resolve differences in individual occupants' feedback. This approach seeks to determine the setpoint according to the ratio of occupants' feedback or quantitatively calculate the individual's comfort range through various methods such as Fuzzy, Bayesian, and reinforcement learning, which makes it possible to determine the optimal environmental setpoint and allows the proposed model to control the indoor environment [231–233].

- **Absence of existing building codes, regulations and guidelines:** Existing building codes, regulations, and guidelines have been proposed under the assumption that it is appropriate to control buildings based on average occupants [69], but recent literature source has demonstrated that occupant centered controlling is more efficient in various aspects, such as occupants' satisfaction and energy [235,236]. HBI technologies continue to evolve rapidly, making it difficult for building codes and regulations to keep pace and leading to conflicts between the HBI controlling process and existing building codes, regulations, and guidelines. The recently proposed standards, such as WELL, can potentially lead markets for HBI technologies with the aim of occupants' health and well-being [238]. The introduction of occupant-centered building codes and regulations that reflect this new paradigm is expected to accelerate the implementation steps of HBI technologies further.
- **Difficulty in real-world implementation:** Studies regarding HBI technologies mostly target sensing and predicting processes and HBI controlling processes, including actuators, have received relatively little attention. In addition, each process tends to be developed individually, and there is a lack of research that integrates all three elements. However, technologies for transferring and automation to each technical part are essential to implement the human-in-the-loop system properly [238]. In the meantime, the current HBI technologies are still at the level of conceptual development. No element has been developed up to the standardized physical layer (e.g., user interface and actuators) that stakeholders can refer to when making decisions. Therefore, research is needed to implement the sensing and prediction process integrated with a controller, including an appropriate IoT device, for which infrastructure is required.

5. Proposal of prospects

5.1. Increasing self-awareness in indoor environment

To address challenges such as “non-detected local zone” and “difficulty in self-awareness,” this section proposes methods to increase occupants' self-awareness in indoor environments through various

advanced sensing technologies (refer to Fig. 6. To increase the self-awareness of the occupant, environmental data for all points in the indoor space need to be measured. Then, a method for information delivery that allows occupants to perceive the indoor environment must be devised.

First, the following two methods are suggested to prevent a non-detected zone in the indoor space:

- **Mobile robot-based sensing system:** The monitoring devices currently used in HBI technology are mostly fixed to the walls or columns, which makes it impossible to measure data in segmented points between spaces with no monitoring devices installed [239]. A mobile robot-based sensing system that measures environmental data while moving the line of flow entered with a predefined algorithm is capable of resolving the aforementioned limitations while, at the same time, helping to obtain more economical and spatial benefits when compared to traditional stationary sensors [194,240,241]. This mobile system estimates the blind spot through spatial interpolation. Yang et al. [240] present a novel approach of using a mobile robot with a LIDAR and CO₂ sensor quickly identify and locate contamination sources. The real-world experiments show that mobile systems were superior to traditional stationary sensors in terms of accuracy and granularity. Troncoso-Pastoriza et al. [241] presented a mobile platform that utilizes spatial interpolation and machine learning to accurately represent indoor environments.
- **Wearable environmental sensor:** A wearable environmental sensor is proposed as another solution to overcome the limitations of the non-detected local zone. Occupants can wear the portable sensor manufactured in a non-invasive way to measure the environmental data around the occupant and can measure the ambient environment for a long time [196,197]. In addition, it is possible to measure the entire movement range of occupants in the indoor space and thus secure a wider range of data than the range measured using traditional stationary sensors. Gnecco et al. [197] conducted an experiment in which participants wore a device to continuously monitor temperature and relative humidity while answering a daily survey about thermal comfort.

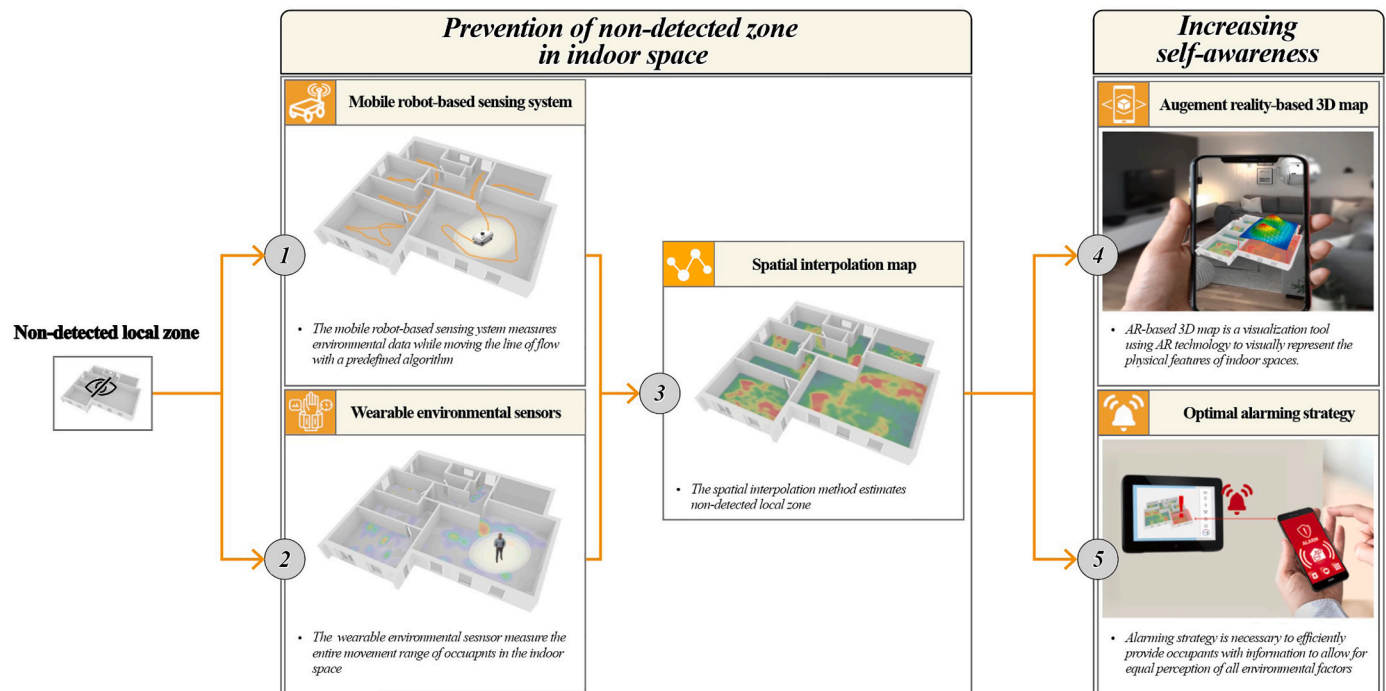


Fig. 6. Conceptual diagram for increasing self-awareness in indoor environment.

Second, there are two methods to allow occupants to actively or passively check the environmental data measured using the monitoring device and improve the self-awareness of the indoor environment:

AR-based 3D map: AR can be easily implemented using an application in a smart device. HBI technology can change how occupants make decisions and interact with environmental data via AR. Second, there are two methods to allow occupants to actively or passively check the environment data measured using the monitoring device and improve the self-awareness of the indoor environment:

- **AR-based 3D map:** At present, AR can be easily implemented using an application in a smart device. HBI technology can change how occupants make decisions and interact with environmental data via AR. An AR-based 3D map is a visualization tool using AR technology to represent the physical features of indoor spaces visually. This 3D map can be viewed via the smart device or the head-mounted display and is used to visualize the indoor environment's thermal conditions, airflow patterns, and other elements in real time [201,202]. Recently, with the use of various building information modeling (BIM) tools, the entire indoor space can be converted to a point cloud, and environmental data can be entered for each point. The environmental data for each point is calculated using a CFD simulation. After being made compatible with the AR technology, the simulated environmental data for each point in the space is augmented to allow occupants to directly experience and perceive the indoor environment, thus improving self-awareness in indoor environment.
- **Alarming strategy:** A continuous alarming feedback strategy for indoor environments is considered the simplest method to improve self-awareness [199,200]. However, there are limits in terms of occupants actually checking the indoor environment. In addition, since each occupant has different dominant senses for environmental factors, the sensitivity may vary depending on each environmental factor. Therefore, it is necessary to efficiently provide occupants with information to allow for the equal perception of all environmental factors, and it is important to establish occupant-centered optimal alarming strategies.
- This 3D map can be viewed via the smart device or the head-mounted display and is used to visualize the indoor environment's thermal conditions, airflow patterns, and other elements in real time [201,202]. Recently, using various building information modeling (BIM) tools, the entire indoor space can be converted to a point cloud, and environmental data can be entered for each point. The environmental data for each point is calculated using a CFD simulation. After being made compatible with the AR technology, the simulated environmental data for each point in the space is augmented to allow occupants to directly experience and perceive the indoor environment, thus improving self-awareness in an indoor environment.
- **Alarming strategy:** A continuous alarming feedback strategy for indoor environments is considered the simplest method to improve self-awareness [199,200]. However, there are limits in terms of occupants actually checking the indoor environment. In addition, since each occupant has different dominant senses for environmental factors, the sensitivity may vary depending on each environmental factor. Therefore, it is necessary to efficiently provide occupants with information to allow for an equal perception of all environmental factors, and it is important to establish occupant-centered optimal alarming strategies.

5.2. Multimodal sentimental feedback control

To address the various challenges mentioned in Section 4, such as *lack of social dynamic and personality trait*, *excessive requests for occupant feedback*, and *interdependence of each automatic controller*, this section proposes methods for predicting sentiment and automatically

controlling indoor environments with the use of various types of information the occupant possesses. The analysis of occupants' sentiments has advantages—it is easy to reflect individual personality traits and specific social dynamics. Moreover, it can automatically identify the occupants' preference without separate subjective feedback. However, the biggest advantage is that the feedback (i.e., thermal comfort, visual comfort, and air quality) that the occupant perceives and provides for each indoor environment factor can be represented as a single indicator from an integrated point of view.

The sentiment determines a given situation's emotional intensity, positivity, negativity, or neutrality [185,242–245]. In the context of HBI, sentiment estimation included ascertaining the emotions and perspectives of an individual towards their surrounding environment (e.g., HVAC, lighting, and windows) [246]. The main purpose of sentimental feedback control is to identify how occupants perceive the indoor environment and to provide optimal control strategies to interact with buildings based on these emotions. In general, multimodal methods that consider non-linguistic information can estimate sentiment more accurately than unimodal methods that estimate sentiment by considering only linguistic information [247]. Moreover, in buildings equipped with infrastructure that can collect non-linguistic information, the multimodal method is optimized for predicting occupants' sentiment. In addition, since third-party sentiment estimation is made possible not by self-reported sentiment by the individual but by a system and model, it is possible to predict and control the collective sentiment of a group to which several occupants belong [248,249]. Fig. 7 shows a conceptual diagram of multimodal sentimental feedback control.

In raw data sensing, various data related to an individual's sentiments are collected through sensors, cameras, or other monitoring devices. The raw data to be measured for sentiment estimation are primarily classified into six categories: lifelog, facial expression, (iii) physiological data, voice, environmental data, and personality.

- **Lifelog:** Lifelog-based estimations include gathering the raw data related to an individual occupant's daily routines and habits to determine their sentiments. [250]. The main lifelong data to be collected comprises SNS postings written by occupants, conversations on messenger services, and conversations with people around the occupant in the form of text data. NLP can be used in lifelog-based sentiment estimations to analyze text data in lifelog. NLP (e.g., text classification) can provide an in-depth understanding of an occupant's sentiments toward their indoor surroundings [251]. Recently, there has been a growing tendency to analyze sentiment and the subject of lifelog texts through BERT, a pre-trained language model developed by Google.
- **Facial expression:** In this estimation method, camera sensors capture images of the occupants' faces, and computer vision techniques are used to analyze the facial expressions [252]. The pre-trained ImageNet model can predict the occupant's sentiment in real-time through a database that stores facial expressions that convey different feelings and sentiments [253].
- **Physiological data:** This estimation entails sensing physiological data (e.g., heart rate, skin conductance, and body temperature) to represent a building occupant's sentiment [246,254].
- **Voice:** This estimation involves using vocal cues, like pitch and tone, to determine an occupant's sentiment. The method records speech, analyzes vocal characteristics with software, and determines the individual's sentiment.
- **Environmental data:** This estimation predicts the occupant's sentiment based on the collected environmental data, such as temperature, humidity, and illuminance. For example, high temperatures and low humidity levels can lead to discomfort, while poor air quality can lead to feelings of irritation and frustration. [185,255,256]
- **Personality trait:** Personality traits have a significant impact on sentiment. Even if occupants with different personality traits are in

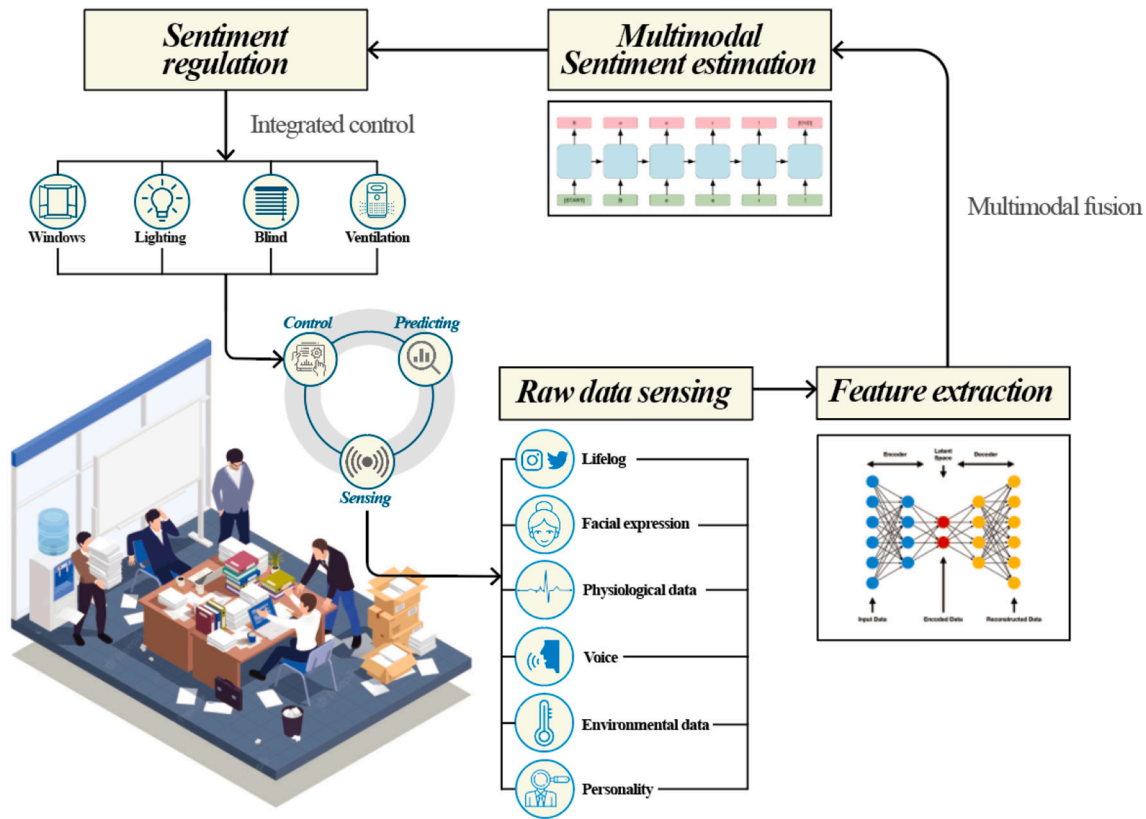


Fig. 7. Conceptual diagram of multimodal sentimental feedback control.

the same environment, their sentiment patterns will differ [203–205,257,258]. In general, personality traits tend to be initially determined by test papers because they are unique elements for each individual that do not change over time, unlike the variables mentioned earlier. The Big Five model is a widely accepted test that describes personality traits based on five dimensions: openness, conscientiousness, extroversion, agreeableness, and neuroticism [259]. In addition, the Myers-Briggs Type Indicator (MBTI) and The Personality Assessment Inventory (PAI) are also available. Recently, studies have been undertaken to predict personality traits through user-generated content (e.g., self-narratives, blogs, tweets) without separate examination [260,261].

In the feature extraction stage, raw data is processed to extract relevant features that can be used to determine the occupant's sentiment. This may involve filtering out background noise, detecting specific patterns in the data, or transforming the data into an easily analyzed format. In general, feature extraction was done via databases such as Handcrafted, fastText, BERT, physiological feature extraction, OpenSMILE, and OpenFace. Then, numerical sentiment estimation was performed by training the extracted features using various data-driven algorithms (e.g., SVM, RF, and ANN). If there was only one occupant, the personal sentiment was estimated, and collective sentiment was estimated if there were two or more occupants. Lastly, the estimated sentiment is used to regulate the occupants' comfort levels in the indoor environment. This may involve providing feedback to the individual, such as suggesting automatic building control to alter the sentimental state, such as adjusting illuminance or temperature. Various technologies could potentially be utilized to achieve the objective of automatically regulating the indoor environment based on anticipated sentiments. These may include artificial computer vision, natural language processing, and affective computing. Using these technologies, it is possible to create algorithms that analyze signals such as facial

expressions, gestures, and speech to forecast emotions. This information can then be utilized to adjust the indoor environment automatically, such as lighting, temperature, and sound, to create a more comfortable and pleasant experience for the occupants. Overall, a range of technologies and approaches can be explored to accomplish the aim of automating the control of the indoor environment based on anticipated sentiments.

5.3. Online and meta learning

To address the challenges mentioned in Section 4, such as *insufficient sample data* and *disadvantage of offline learning*, this section deals with methods to improve the performance of HBI technology (i.e., human-in-the-loop control) through online and meta-learning models. First, online learning is used to make up for the disadvantages of existing offline learning (i.e., batch learning) and can update the prediction model immediately and efficiently through a pre-specified data-driven algorithm at the same time as new and unseen data are collected [224–226]. In this way, automatic controllers can learn and adjust to changes in the occupancy feedback data over time. However, hyper-parameter tuning needs to be performed in online learning whenever new data is generated. Moreover, data privacy and data size issues arise. Localized learning is a training a model on a small local dataset rather than a centralized dataset. Localized learning is useful when the data is too large to be processed by a single system or when data needs to be kept on the device to protect privacy. In addition, prediction models can be effectively trained even in offline modes where data is not shared with a centralized server.

Second, meta learning is a potential solution to the problem of insufficient training data. It is also a “learning-to-learn” approach that makes it easier to apply models to new tasks and environments with limited training data (refer to Fig. 8). Meta learning can be classified as a subfield of (i) few-shot learning and (ii) transfer learning. In general

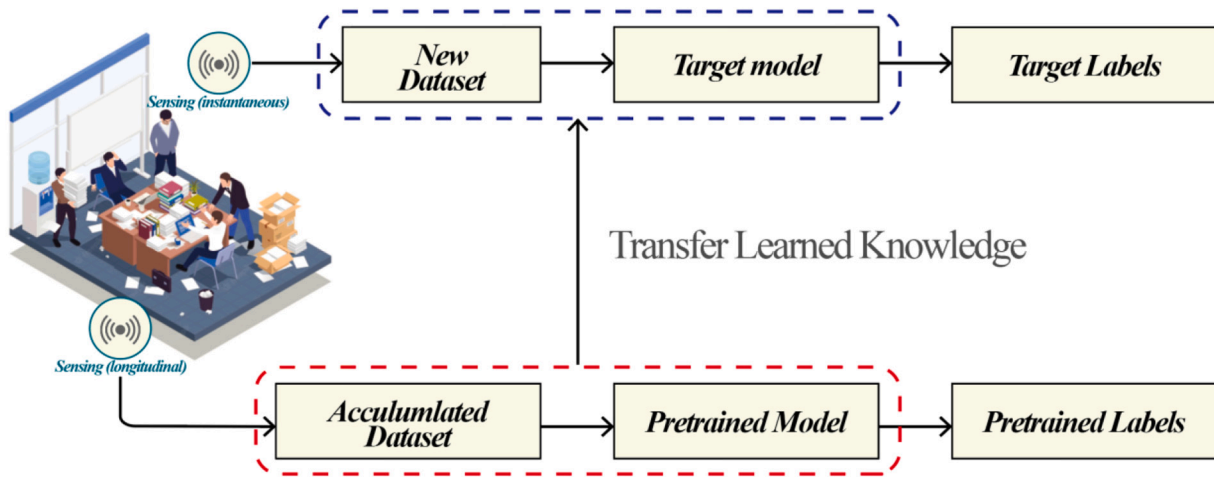


Fig. 8. Conceptual diagram for online and meta learning.

cases, few-shot learning is often used as a synonym for meta learning. The objective of few-shot learning is to train a model that generalizes tasks to new ones, even when there are only a small number of training data. Likewise, transfer learning is a machine learning technology that applies a model trained on one task to another related task [217,262]. Meta learning can be seen as a form of transfer learning because it aims to transfer prior knowledge learned from the related task to a new task. Sufficient data and its diversity are significant in meta learning. The more data available, the better the meta-learning model can learn the common features and patterns. The data should include various conditions, such as different temperatures, humidity levels, clothing types, activities, and so on.

5.4. The need for collective control

Existing literature source to develop HBI technologies is limited in terms of implementation in actual spaces usually filled with more than one occupant [78,263]. Different feedback from occupants causes conflicts in the controller, and solutions that resolve these conflicts should

be proposed to succeed in satisfying the majority of occupants. As described in Chapter 4, approaches addressing the different feedback from occupants include (i) a physical solution and (ii) a collective control strategy establishment (refer to Fig. 9). Methods such as personal comfort systems or shared space segmentation can intuitively solve the problem but pose limitations as a general solution. Accordingly, future work needs to focus on a collective control strategy that is universally available in various spaces.

Existing literature source that proposed collective control strategies applied consensus methods in which approaches determine the setpoint mainly through (i) the feedback ratio or (ii) comfort range. For example, when the temperature control request is blowing at a specific rate, the set temperature is maintained as it is determined that most occupants are satisfied with the thermal environment. On the other hand, if it exceeds a certain rate, the temperature is controlled according to the rate of feedback requesting warmer or cooler air temperature [264]. Meanwhile, when the average point of the comfort zone of occupants whose comfort zones do not overlap is set as the setpoint, all occupants are very likely to suffer discomfort. In this case, another method utilizes

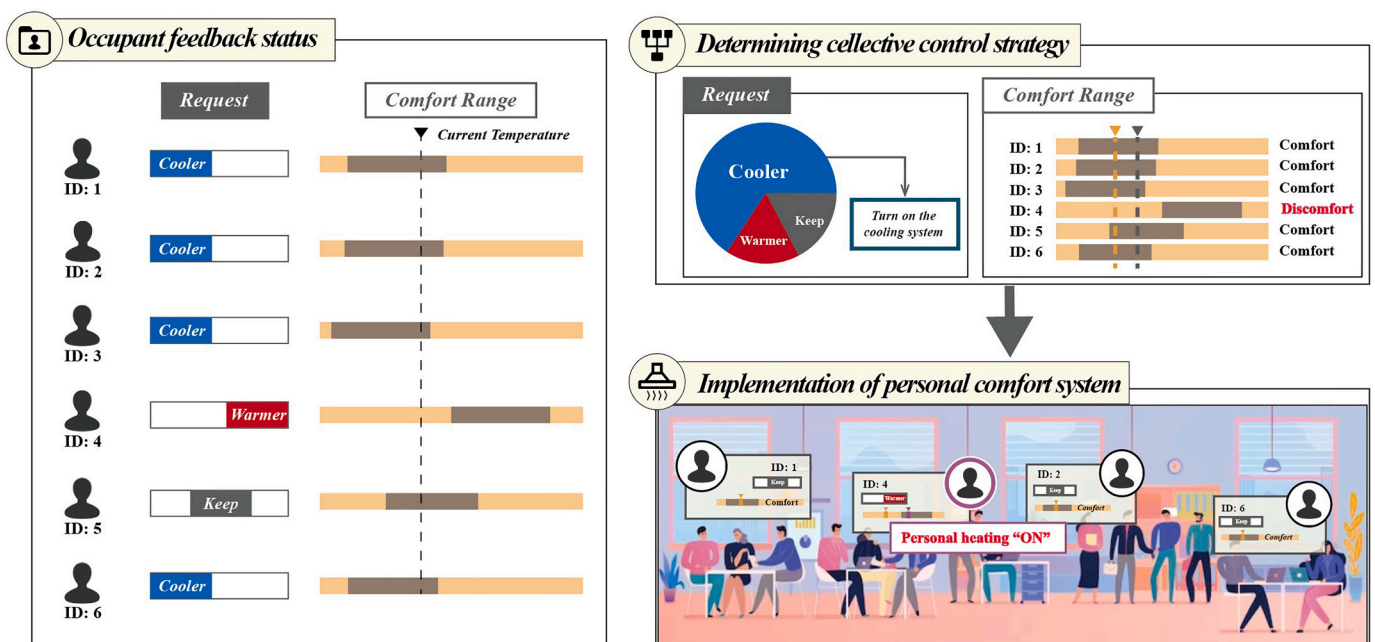


Fig. 9. Conceptual diagram of collective control strategy.

a fuzzy pattern recognition method to calculate the allowable discomfort range of occupants and perform optimization based on the range [233]. To intensify the benefits of HBI technologies, a collective control strategy can be used to make most occupants more comfortable. Such technologies as personal comfort systems can then be used to resolve some of the remaining problems without causing further discomfort.

5.5. Infrastructure of field implementation

Despite a growing number of literature source focused on developing HBI technologies, it is still difficult to find cases in which these technologies are implemented in actual buildings [265,266]. In addition, there has been an increasing gap between the developmental speed of the conceptual models and technologies and the speed of field implementations. Barriers to field implementations lie in insufficient infrastructure to implement HBI technologies. Hence, this research suggests three future directions to help remove these barriers.

First, advanced data encryption should be developed to secure confidential personal data and to gain social consensus and reputations from occupants. Data insecurity and invasions of privacy are one of the most sensitive issues when it comes to implementing HBI technologies [267]. According to Wei et al., the problem of privacy security for IoT data and privacy protection of data can be resolved by combining blockchain approaches with IoT [268]. Current blockchain technologies can be divided into public, private, and consortium blockchain approaches. In general, private blockchains with low accessibility and openness are mainly used to increase IoT data security in smart homes with HBI technologies or similar technologies. However, since decentralization is low, the risk is high when data is subject to attacks. Therefore, the possibility of using a consortium blockchain, which combines functions from both public and private blockchains with high decentralization of data storage, has been highlighted [268]. As such, blockchains can be used as an optimal method for data encryption. However, users need to select the appropriate type of blockchain, and relevant research needs to be undertaken in the future on how this can and should be carried out.

Second, integrating and standardizing three HBI processes (i.e., sensing, predicting, and controlling) should be more proactively sought. The conceptual development of the individual process has been made in various studies. However, each technology has failed to reach the physical layer, and there is a lack of cases in which all three processes are implemented in an integrated manner. Therefore, future work should integrate the three processes in actual buildings. Moreover, HBI technologies should be developed in line with the standardized physical layer (e.g., user interface, ubiquitous sensors, and actuators) that stakeholders can refer to when making decisions. This standardization is closely related to commercialization. Thus, future work should additionally consider the economic benefits of HBI technologies. In particular, there is a need to develop an innovative technology capable of sensing occupant feedback data via sensors in a building without relying only on occupants' wearable devices. Most of the previous studies found that data collected using existing sensors such as eye trackers and smartwatches have environmental factors and statistical significance. However, in this case, the implementation of HBI technology can be done under the premise that all occupants in the building possess such private sensors. To overcome such limitations, the demand for ubiquitous sensors development has increased, and it has become possible to collect visual signs such as occupancy, heart rate, and respiratory rate via sensing technologies like Doppler-radar-based sensors attached to the ceiling [263]. However, such technologies have limitations in that the scope of a subject is limited to a single occupant. Or various premises are needed. In the future, it is expected that demand for research designed to develop economically efficient sensors capable of collecting various types of occupant feedback data will continue to increase.

Finally, building codes, regulations, and guidelines should be amended to be more occupant centered to reduce discrepancies with HBI

technologies. Existing building codes, regulations, and guidelines are based on traditional construction practices, and they mainly focus on technical aspects of building design and operation related to energy efficiency and indoor air quality. However, with growing interest in occupants' well-being and health, such standards as WELL that reflect such demands have begun to be introduced, and an analytical approach that existing standards should support a more flexible design approach based on HBI has been proposed [269]. Therefore, to reduce the gap between existing building codes, regulations, and guidelines, and HBI technology, research proposing amendments or new standards needs to promote the successful implementation of HBI technology further.

6. Conclusions

Recently, as much attention is focused on rapidly developing interaction technologies (e.g., ChatGPT and Google Bard), the demand for human-computer interface (HCI) research is also increasing. In a built environment where people spend more than 90% of their time, HCI is one of the top priority technologies that must be applied inevitably. The HCI application in the built environment is often called human building interaction (HBI). This data-driven literature review performed a meta-analysis of the HBI technology so that the researchers can explore future values in line with the latest trends. Based on the result of topic modeling using the natural language processing-based text classification regarding 907 literature sources, the following four research topics were summarized: automatic climate controller, automatic lighting controller, automatic window opener, and artificial intelligence. Then, the evolution of technology from early studies to state-of-the-art works was investigated for each research topic.

As a result of qualitative reviews, some challenges were found in terms of sensing, predicting, and control processes. First, in the sensing process, the main challenges were the non-detected local zone, which is not precisely measured by the sensor, the lack of a method for self-awareness of the indoor environment, and data insecurity and invasion of privacy. Second, there were major challenges in the predicting process, including the disadvantages of offline learning, insufficiency of sample data, and inconsistency of data quality collected by existing literature sources. Third, in the control process, the main challenges were that each automatic controller was not compatible, that the personal comfort zone of individual occupants was not considered, and that there were no existing building codes, regulations, and guidelines. To overcome these challenges, it is necessary to conduct research by referring to the following five prospects:

- Non-detected local zones in indoor spaces can be prevented through mobile robot-based sensing systems and wearable environmental devices. In addition, AR-based visualization methods with appropriate alarming strategies can facilitate occupants' self-awareness of indoor environmental quality.
- Active research is needed on how to estimate the sentiment of occupants by collecting lifelog, facial expression, physiological response, voice, environmental data, and personality. If it is possible to implement an automatic building operation that can improve the indoor environment by estimating occupant's sentiment, indoor environment can be changed to a preferred environment without submitting separate subjective feedback.
- Online learning solves the disadvantage of offline learning, which requires hyper-parameter tuning of the model whenever new and unseen data occurs. In addition, we propose to develop high-accuracy models with a small number of sample data through few-shot learning and transfer learning.
- Because existing HBI technologies were developed focusing on individuals, the disadvantage of causing friction in multi-use facilities used by groups occurred. A personal comfort system and collective control strategy can provide all occupants with an optimal indoor environment.

- It is necessary to establish a sandbox infrastructure that enables field implementation to solve institutional and social awareness obstacles that hinder the development of HBI technology.

This data-driven literature review can play a leading role as a knowledge-based systematic guide for future research on human-building interaction for controlling the indoor environment. In this paper, HBI technology is divided into sensing, predicting, and control process, but the same programming language, platform, and user-interactive design may be needed to implement these technologies in the real world. Since many literature source only emphasized conceptual approaches and individual technologies, it is important to share infrastructures such as Annex 79 and integrate technologies through them. From the aforementioned point of view, this review presented the technical and policy directions for HBI technology to researchers, engineers, and policy-makers. Since many unexplored future directions require a multidisciplinary approach, they will be resolved through joint research between different technological bases.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT; Ministry of Science and ICT) (NRF-2021R1A3B1076769).

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