Utilizing Internet of Things in Human-Building Interaction to Support Sustainable Built Environments

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Human-Building Interaction (HBI) is an emerging field that enhances building design, construction, and operation by facilitating interactions between occupants and buildings. HBI supports managers and occupants in achieving energy efficiency, sustainability, and improved livability, driving the evolution of smart buildings. The Internet of Things (IoT) integrates diverse building systems into networks of connected devices, generating data that informs adaptive responses to occupant needs and promotes sustainable operations. This survey reviews the role of IoT sensors in HBI, emphasizing their potential to improve communication between buildings and occupants to achieve sustainability objectives. It examines how sensors can be used to generate actionable insights, helping stakeholders meet sustainability goals. To provide a focused analysis, this review is constrained to the two most prominent sustainability objectives identified in global standards: energy efficiency and health and well-being. We identify key factors, sensor types, and benefits shaping sustainable environments. Furthermore, we describe HBI advancements supporting sustainability, alongside challenges regarding IoT integration, occupant engagement, and system constraints. Finally, this review situates IoT sensors within HBI, linking human-building engagement and sustainability goals to provide a comprehensive understanding of their role in shaping smart, adaptive, and sustainable buildings.

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Social and professional topics** → *Sustainability*; • **Hardware** → *Sensor applications and deployments*.

Additional Key Words and Phrases: Sustainable Buildings, Human-Building Interactions, Internet of Things, Sustainability Monitoring

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1 Introduction

HBI is a new topic in Human-Computer Interaction (HCI) that aims to uncover research opportunities and challenges that may arise from discussions and debates by 2030 [9]. This field acknowledges the evolving landscape of technology and emphasizes the importance of understanding human values and priorities. It explores the relationship between people and the built environment, focusing on how buildings affect human experiences and how humans interact with, adapt to, and impact buildings and their systems [27]. As collaboration between humans and their surroundings deepens, particularly through integration of IoT and Artificial Intelligence (AI)—often termed AIoT—researchers increasingly explore the potential synergies within HBI, highlighting the need for ongoing scholarly inquiry and community engagement to realize its overarching goals. HBI aims

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to examine the building as a multifunctional system with three interconnected aspects: physical-material, spatial-configurational, and social-cultural [8]. Various research themes fall within these three dimensions, while others fall within all three dimensions.

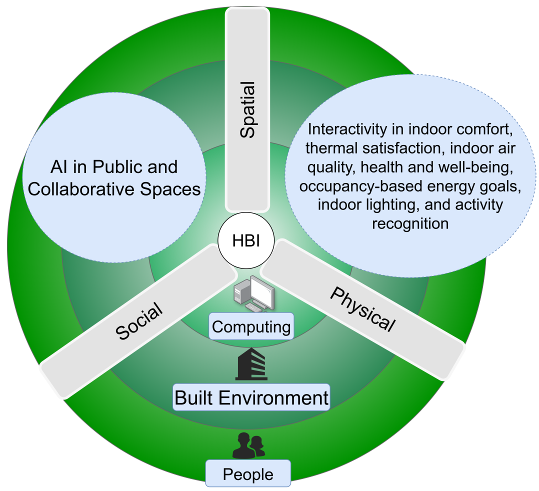

Fig. 1. Three dimensions of HBI research [8]

Figure 1 depicts these three dimensions of HBI research and their interconnections. The scope of HBI encompasses communication between humans and buildings to complete tasks through IoT devices, while also addressing occupants' feelings, emotions, and comfort, as buildings play a crucial role in shaping health, productivity, and overall quality of life [35]. This review fits within the spatial and physical dimensions as shown in Figure 1. People and buildings interact in various ways, and the Human-in-the-Loop (HITL) design contributes to the attainment of sustainability goals. Understanding the use of IoT devices, sustainable goals, and human-building engagement supporting HBI scope is crucial to achieving such a sustainable built environment.

Each smart building consists of heterogeneous systems/components and sensor/actuator networks to help building managers and owners achieve long-term, efficient, cost-effective, and sustainable goals. Figure 2 provides a high-level overview of sustainability standards and associated goals implemented across diverse building typologies, supported by heterogeneous sensor and device networks that facilitate human-building engagement. Building upon the physical and spatial dimensions of HBI illustrated in Figure 1, this review systematically examines the role of sensor technologies and human-building engagement in achieving key sustainability goals within the built environment. It encapsulates how human interaction with the built environment contributes to achieving these sustainability goals. It provides a visual summary of the key objectives of this review, aiming to enhance the understanding of sensor involvement in the HBI domain for smart buildings' sustainability by addressing the following objectives:

(1) Explore sustainability standards and their prominent prevailing sustainability goals contributing to HBI through IoT sensors. *(What sustainability standards, goals and key factors should be considered where IoT devices contribute to sustainability?)*
(2) Investigate the role of IoT-based sensing technologies, their analytics, and derived insights in enabling diverse sustainability applications, guided by prominent sensing approaches in the context of the built environment. *(How are IoT devices used to achieve sustainability goals?)*
(3) Explore different modalities of Human-building engagement, consisting of sensor involvement to achieve sustainable goals. *(What are the different human-building engagement approaches used to achieve these sustainability goals?)*

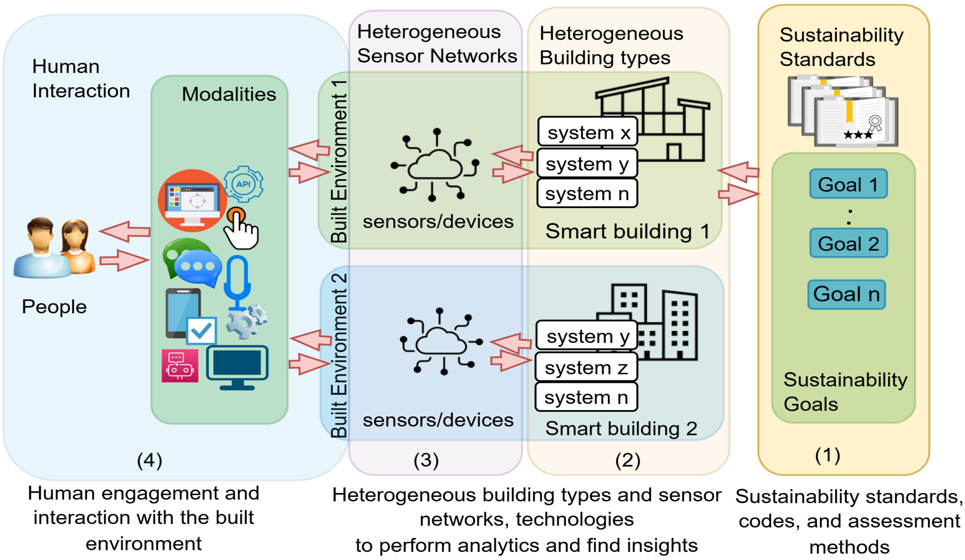

Fig. 2. IoT Sensors and Human Engagement Towards Sustainable Buildings

(4) Identify research challenges related to achieving sustainable goals through sensors and human-building engagement in HBI.

To address these objectives, we employed structured methodologies for literature selection, ensuring the inclusion of unique studies while excluding duplicates and identical work to avoid redundancy in the information gathered. Section 2 outlines the methodology used to select and analyze the literature. Section 3 reviews smart building sustainability, focusing on major standards (3.1) and goals (3.2) to contextualize IoT-enabled Human-Building Interaction (Objective 1). Section 4 discusses the role of sensors in enabling sustainability (Objective 2). Section 5 examines prominent sustainability goals and sensing approaches, highlighting how IoT technologies and analytics contribute to achieving them (Objective 2). Section 6 explores human interaction with buildings, emphasizing engagement modalities and sensor-driven interactions for sustainable goals (Objective 3). Section 7 provides a discussion of our findings and their broader implications. Section 8 identifies research challenges and directions for future work (Objective 4), followed by our conclusion in Section 9.

2 Methodology

2.1 Selection of sustainability standards and prominent goals

To address Objective (1), a comprehensive literature review was conducted using Google Scholar as the primary database to minimize publication bias. An advanced keyword-based search on sustainability-related terms (Figure 3) produced 10,100 initial results. From the initial corpus, 200 English-language articles were selected from the population using stratified sampling based on predefined criteria, using topic and abstract screening; further selection was discontinued once subsequent results were deemed irrelevant to the research scope. A thorough full-text analysis of 200 articles was conducted, and 160 of them contained sustainability standards. In order to determine their occurrence counts (frequency of mentions), a compiled list of sustainability standards was then created based on how frequently they appeared in the literature.

[1] [75] [2] [59] [3] [191]

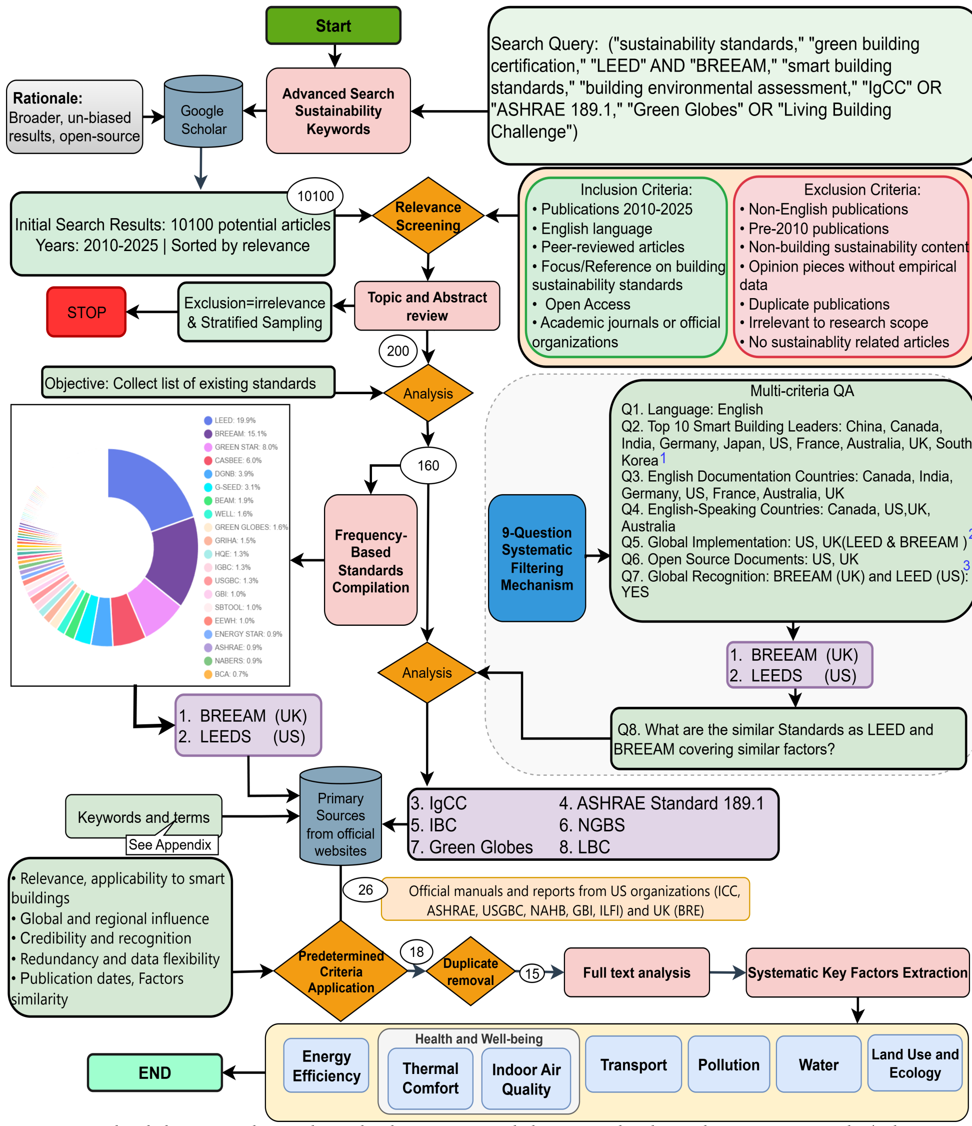

Fig. 3. Methodology used to select the key sustainability standards and recurring goals (Objective 1).

A detailed dataset was created to quantify the occurrences of the standards in selected articles. To refine the scope, a questionnaire-based filtering mechanism was applied to identify the most relevant standards for smart buildings. Based on both inclusion/exclusion criteria and insights from the questionnaire, a subsequent full-text analysis was conducted to identify standards with similar factor coverage, particularly those aligning with the primary top two sustainability standards identified (i.e., LEED and BREEAM). This systematic screening process, guided by predetermined criteria, led to the selection of eight sustainability standards for detailed investigation. By accessing their official primary sources, we compiled a pool of 26 manuals and technical documents. After applying predefined criteria and removing duplicates, a final set of 15 sustainability standard documents was selected for full-text analysis to identify recurring key sustainability factors relevant to both new-construction and in-use building types. The factors identified across these 15 documents were then synthesized into seven recognized sustainability goal categories, as shown in Figure 3. This categorization consolidates the varied terminologies and metrics used across the standards. For more detailed information on the keywords, search strings, and selection criteria used, refer to Appendix Table 9.

2.2 Methodology for IoT sensors and human-building engagement

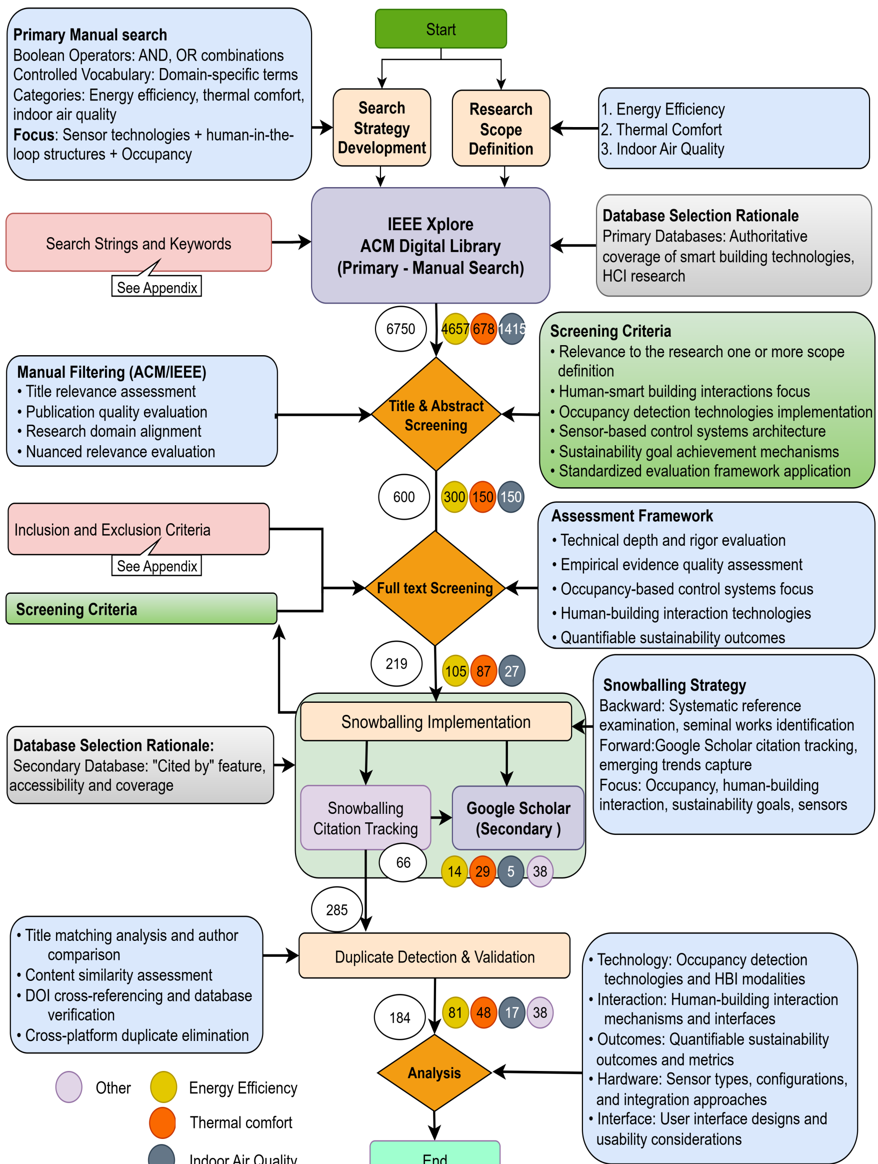

Fig. 4. Methodology used to select literature for objectives 2-4.

The methodology illustrated in Figure 4 is employed to address Objectives 2, 3, and 4. For more detailed keywords, search strings and selection criteria, see Appendix Table 9. This methodology aims to investigate how sustainability goals are realized through IoT sensors and human-building engagement in smart buildings. A multi-database approach combined manual and automated searches across ACM Digital Library and IEEE Xplore (primary databases) and Google Scholar (secondary database for citation tracking and snowballing). Boolean operators and controlled vocabulary were used to formulate systematic search queries for each category while ensuring focus on the research objectives.

This comprehensive search initially yielded 6,750 articles across three categories (Figure 4). Titles and abstracts were screened using predefined criteria emphasizing human-building engagement, occupancy detection and recognition, sensor-based control, and sustainability considerations, resulting in 600 articles. A standardized evaluation framework ensured consistency and minimized selection bias, while full-text review further assessed contributions to human-in-the-loop smart building systems, including occupancy-based controls, IoT interaction technologies, and measurable sustainability outcomes. Articles were also evaluated for rigor, relevance, empirical evidence, technical depth, and real-world applicability, leading to the selection of 219 articles for detailed analysis. To ensure comprehensive coverage and capture seminal works potentially missed by database searches, snowballing techniques were employed. Backward snowballing traced references in selected articles to foundational studies on occupancy detection, human-building interaction, and sustainability controls, while forward snowballing used Google Scholar and citation tools to identify recent works citing these studies, adding 66 relevant articles. This resulted in a robust corpus of 285 high-quality articles integrating foundational insights with innovations in energy efficiency, thermal comfort, indoor air quality, and other relevant topics, including human-building interfaces, multi-objective studies, and sensor technologies related to objectives 3 and 4. After removing duplicates, the final corpus consisted of 184 articles for detailed analysis, focusing on human-smart building interactions through diverse technological implementations such as mobile applications, user interfaces, sensor networks, and occupancy detection systems.

3 Smart Building Sustainability

3.1 Sustainability Standards

This section focuses on the first objective and explores widely adopted sustainability standards in smart buildings, focusing on common goals relevant to IoT sensing applications to guide subsequent analysis. There are numerous reasons why building sustainability is critical. Climate change is a real threat to the future, and buildings exacerbate its impact; we must not ignore the consequences for future generations. Most greenhouse gases are produced by heating and energy consumption in buildings, and to achieve net-zero targets, owners and managers must measure and reduce carbon emissions and energy consumption in the built environment.

Sustainable buildings play a crucial role in preserving and enhancing the quality of life by harmonizing with local climate, traditions, cultures, and environments. They contribute to occupants' well-being while nurturing local and global ecosystems throughout their lifecycle, safeguarding occupant health and productivity [32]. While the overarching goals of residential and non-industrial international codes align, specific design procedures and benchmarks vary. Various countries and territories have developed tailored standards for building design, construction, and operation, with only a select few adhering to broader international standards for global harmonization [184]. Following methodology from Figure 3, Table 1 summarizes notable benchmarks for achieving sustainability goals tailored to different built environments' unique contexts and regulatory frameworks.

Origin	Reference	Sustainability Standard	Coverage of Factors
UK	[36, 37]	Building Research Establishment's Environmental Assessment Method (BREEAM)	Management, health and well-being, energy, transport, water, resources, resilience, land use, and economy, pollution, etc.
US	[39]	Green Building Council's Leadership in Energy and Environmental Design (LEED)	Reduce contribution to global climate change, enhance individual human health, protect and restore water resources, protect and improve biodiversity and ecosystem services, promote sustainable and regenerative material cycles, enhance community quality of life, etc.
US	[14, 83]	International Code Council's 2012 International Green Construction Code (IgCC)	Life cycle assessment, site development and land use, material resource conservation and efficiency, energy conservation, efficiency and CO_2 emission reduction, water resource conservation, quality and efficiency, indoor environmental quality and comfort, etc.
US	[15]	American Society of Heating, Refrigeration and Air Conditioning Engineers ANSI / ASHRAE / USGBC / IES Standard (ASHRAE Standard 189.1)	Site sustainability, water use efficiency, energy efficiency, indoor environment quality (IEQ), materials and resources, construction and operations plans, etc.
US	[82]	The International Building Code (IBC) by the International Code Council (ICC)	Occupancy, fire and smoke protection, interior environment, fire protection systems, accessibility, energy efficiency, exterior walls, structural design, soil and foundations, building materials, electrical, mechanical, plumbing, elevators, and conveying, etc.
US	[19]	National Association of Home Builders ICC 700 National Green Building Standard (NGBS)	Resource efficiency, energy efficiency, water efficiency, IEQ, operation, maintenance and building owner education, remodeling, etc.
US	[72]	Green Building Initiative's ANSI/GBI 01-2010: Green Building Assessment Protocol for Commercial Buildings (Green Globes)	Sustainable sites, energy efficiency, water efficiency, materials and resource use, indoor environmental quality, emissions project/environmental management, etc.
US	[84]	The International Living Future Institute's Living Building Challenge, version 4.0 (ILFI-LBC)	Place, water, energy, health and happiness, materials, equity, beauty, etc.

Table 1. Some popular standards for Buildings focus on different building aspects.

The 2012 International Code Council International Green Construction Code (IgCC) sets minimum requirements for sustainable practices in both commercial and residential buildings, covering energy efficiency, water conservation, and indoor environmental quality. Similarly, the American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) ANSI/ASHRAE/USGBC/IES Standard 189.1 focuses on commercial buildings, but also offers guidance for high-performance residential projects with complex Heating, Ventilation, and Air Conditioning (HVAC) systems. The International Building Code (IBC), by the International Code Council, applies broadly to both building types, ensuring safety and sustainability in design and construction. Standards such as LEED (commercial) and the ICC 700 National Green Building Standard (NGBS, residential) provide tailored frameworks, while others like the International Living Future Institute's Living Building Challenge (ILFI-LBC) and the Building Research Establishment's Environmental Assessment Method (BREEAM) present comprehensive approaches relevant to both contexts. Together, these standards highlight diverse strategies for advancing sustainability across building types.

3.2 Sustainability Goals

Smart building management teams often focus on specific sustainability objectives; however, it is beyond the scope of this article to review all such goals. A review of Table 1 reveals that many factors are strongly associated with specific categories. Since most rating systems prioritize environmental aspects [21], this study focuses on key goals of Green Building Rating Systems (GBRS) such as LEED and BREEAM. LEED includes water, energy, materials, indoor quality, innovation, and transport [39]. In contrast, BREEAM covers energy, water, health, pollution, land use, ecology, transport, materials, waste, management, and innovation [36, 37]. Other standards highlight similar recurring factors (Table 1). This section emphasizes the shared sustainability goals across these systems.

3.2.1 Energy Efficiency. We must reduce energy consumption and shift to renewable sources to mitigate climate change. BREEAM guidelines indicate that occupant behavior alone can increase residential energy use by up to 75% [36]. Demand-side management (DSM) strategies are crucial for optimizing energy use in buildings, covering areas such as lighting, transportation, ventilation, heating, cooling, distribution systems, and household appliances. Additionally, deploying renewable heating/cooling, temperature controllers, generator modulation, and efficient HVAC operation is crucial for enhancing energy efficiency and sustainability in smart buildings. ASHRAE Guideline 36:

High-Performance Sequences of Operation for HVAC Systems (G36) is a cornerstone document, on par with standards such as ASHRAE Standard 90.1 (Energy Standard for Buildings Except Low-Rise Residential) and ASHRAE Standard 62.1 (Ventilation and Acceptable Indoor Air Quality). G36 addresses a critical gap left by standard 90.1 and 62.1, which are mandatory for new construction and many renovations in most US jurisdictions. While standard 90.1 and 62.1 define requirements for health and efficiency in nonresidential buildings, they do not specify operational methods to achieve these standards. G36 provides a standardized toolkit of control techniques capable of significantly reducing building energy consumption. Initial studies indicate that retrofitting medium-sized commercial buildings with optimized Variable Air Volume (VAV) control sequences can reduce HVAC energy use by an average of 31% across different US climate zones [201].

3.2.2 Health and well-being. Indoor environmental conditions strongly influence occupants' physical and mental well-being. As people spend over 90% of their time in or around buildings [143], poor environments can cause serious health risks, particularly for vulnerable groups such as the elderly. According to BREEAM, poor Indoor Environment Quality (IEQ) can cause eye strain, cardiovascular and coronary issues, bronchial diseases such as asthma and allergies, dermatological and musculoskeletal problems, and psychological effects including headaches, fatigue, stress, anxiety, and depression. Smart buildings should provide safe, comfortable, and healthy environments that support occupants' health, well-being, and productivity by improving Indoor Air Quality (IAQ). Sustainability guidelines, such as BREEAM and LEED, recognize that thermal comfort is a crucial aspect of smart indoor buildings, as it enhances occupant health and well-being while also improving energy efficiency and long-term building performance.

3.2.3 Indoor Transport. Indoor transport systems in smart buildings are vital for enhancing sustainability. Elevators, escalators, walkways, conveyors, and material handling systems can be optimized to reduce energy use and improve efficiency. For instance, elevators can employ destination control to minimize stops, regenerative drives to recover braking energy, and predictive maintenance to prevent failures. Similarly, walkways and conveyors adjust speed to passenger flow, use regenerative braking, and activate only when occupancy sensors detect use. In industrial settings, material handling systems optimize routes, adjust speeds by load, and incorporate energy-efficient motors. Integrating sensors such as occupancy, light, and temperature/humidity further optimizes system operation, activating them only when needed and adapting energy use to conditions. By adopting these strategies, indoor transport systems significantly improve sustainability in smart buildings, supporting both occupant well-being and sustainable goals [2, 98].

3.2.4 Pollution. This category addresses the mitigation and prevention of pollution from asset placement and use. Avoiding indoor pollutants helps mitigate the adverse effects of flooding and emissions from air, land, and water on both the environment and occupants. Pollutants harm health and well-being over time. The United Nations' Sustainable Development Goals (SDGs) on "good health and well-being" aims to "reduce deaths and illnesses from hazardous chemicals and air, water, and soil pollution by 2030" [36]. Sensors enable monitoring and improving air quality, detecting refrigerant leaks, and reducing light and noise pollution. They also support land contamination mitigation, invasive plant detection, and prevention of airborne and waterborne pollution. Furthermore, sensors aid in lowering risks to the surrounding environment and monitoring fuel combustion and emissions.

3.2.5 Water. This category promotes sustainable water use throughout system operation and site life. It emphasizes minimizing leaks and reducing potable water use both indoors and outdoors. Sustainable buildings should conserve water and address scarcity while meeting future demand. According to the UK's National Infrastructure Commission (2018), halving leakage and lowering per capita use to 118 liters per person per day could supply water to 20 million more people by

2050. There is a clear link between water use, carbon emissions, and energy consumption, with sensors playing a vital role in leak detection, emission reduction, and water efficiency.

3.2.6 Resources and Resilience. This category promotes the responsible use of resources, materials, and waste. Users are expected to consider lifecycle environmental impacts of asset operations to minimize resource use. It encourages managing waste according to the waste hierarchy and assessing consumption within a circular economy. The resilience component focuses on an asset's vulnerability to risks such as climate change, local water pollution, material damage, and security threats. Building resilience involves assessing exposure, preparedness, and response to physical risks and hazards.

3.2.7 Land Use and Ecology. This sustainability goal emphasizes enhancing ecological value within and around buildings, while optimizing space use to improve occupant well-being and productivity. Assets are encouraged to recognize current and future environmental value on the property, as well as the impact of business activities. This enables the development of long-term management and maintenance plans that preserve and improve ecology. Green homes with planted areas, green walls, and roofs promote healthy indoor environments while supporting ecological preservation. In this context, IoT sensors enable real-time monitoring and optimization of environmental conditions, fostering a symbiotic relationship between human habitation and ecological integrity in smart buildings.

4 Sensors for sustainability

By reviewing the standards outlined in Table 1, this section examines how different IoT sensors and devices, along with their associated insights and applications, are employed to achieve diverse sustainability goals. Table 2 summarizes key factors and their relationship with sensor applications that support the realization of these sustainability objectives. The "Applicable Sensors/Devices" column provides an overview of the required sensor insights, while the "Sensor Insights/Applications" column explains their function. The selection is based on reviewed literature in this article and sustainability manuals (Table 1). While not exhaustive, this list covers unique and widely used sensors, with further details provided in the subsequent sections.

	Factors	Applicable Sensors/Devices	Sensor Insights/ Applications
Health and well-being	Thermal comfort	Temperature sensor, humidity sensor, thermostats, fan dimmers	Indoor air temperature, mean radiant temperature, air velocity, relative humidity, solar heat and draughts from the window, ventilation, heating/cooling system, mean radiant temperature
	Lighting/Visual comfort	Light Sensors (photoresistors (LDR), photodiodes, phototransistors, etc.), Photoelectric sensor, motion detectors, PIR sensors, microwave motion, day/night sensors, solar LED	Ambient light quantity, internal lighting level, external light level, glare and quality control
	Indoor air quality and ventilation	Occupancy, motion detectors, temperature, humidity, pressure sensor, carbon monoxide (CO),CO_2, hydrogen sulfide, sulfur dioxide, chlorine, nitric oxide, nitric dioxide, hydrogen, ethylene, ammonia, ozone, ethylene, halothane, isobutylene, ethanol, propane, butane, radon sensor/detector and monitors, smoke detector, motion	Pollutants, volatile organic compounds (VOCs), CO, CH_4, LPG, CO_2, ketones, organic acids, amines, aliphatic hydrocarbons, aromatic hydrocarbons CO_2, aroma, ventilation rate or fresh air, air velocity, moisture content, smoke, Air Handling Unit (AHU), filters, humidifiers, heat recovery units, air intakes, extracts and exhausts, terminal units, etc.
	Noise and acoustics	Sound sensor (microphones), vibration sensors, infrasound sensors	Background noise, privacy and interference, vibration
Water	Toilets, urinals, taps, basins, showers, bath, drinking, sanitation, washing, leakage, appliances, isolation valves etc.	Leak detectors, occupancy detectors, temperature sensors, pressure sensors, proximity detectors, time controllers, volume controllers, presence detectors and controllers, water control system, water quality sensors etc.	Stop overheating, leakage detections and prevention, pressure detection, water consumption monitoring, efficient appliances monitoring, recycling, effective flush volume (EFV), monitor water usage and time, maintaining and upgrading water systems, water levels etc.

Table 2. Sensor insights required to meet associated sustainability goals using sensor types

	Factors	Applicable Sensors/Devices	Sensor Insights/ Applications
Energy Sustainability	Lighting	Photoelectric sensor, motion detectors, PIR sensors, microwave motion sensors, day/night sensors, solar LED, light sensors, occupancy sensors (infrared), LDR, photodiodes, phototransistors	Ambient light quantity, internal and external light level, quantity, quality, glare, daylight, task type
	Heating water and refrigeration	Temperature sensor, pressure sensors, leak detectors	Temperature and pressure of water
	Heating/cooling and ventilation	Temperature sensors, smart thermostats, CO_2 sensors, humidity sensors, VOCs sensors, airflow sensors, pressure sensors, pressure transducers door/window sensors, leak detectors, hall-effect position sensors, thermostats	Air quality, fresh air replacement rate, temperature, humidity level, CO_2 level
	Humidity control	Humidity sensor	Humidity level
	Cooking	Thermostats, temperature sensors, pressure sensors, smart kitchen appliances, and home assistants	Energy-saving smart electronic devices
	Internal transport	Smart lift monitoring system	Usage of lifts and escalators, energy consumption
	Electric devices	Smart meters, current monitoring devices, dry contact sensors, pulse counters	Energy consumption rate, efficiency
	Occupants' lifestyle	Occupancy sensors, temperature sensors, smart devices, and gadgets	Usage of electronic devices, duration of use, over usage of electric devices
Transport	Lifts, escalators, elevators, moving walkways, conveyors, dumbwaiters, proximity to transport and amenities, modes of transport, Pedestrian and cyclist safety etc.	Motion, Load, Usage, Temperature, Vibration, Proximity, GPS, RFID, Traffic, Air quality, Energy consumption, Camera, Light sensors, Environmental sensors etc.	Movement and operational status, weight capacity and load distribution, usage frequency and patterns, operational temperature to prevent overheating, mechanical issues and wear, object detection, determine exact location relative to transport and amenities, track nearby facilities, Monitor transport flow and congestion, assess pollution levels related to transport modes, energy use monitoring, video surveillance for safety monitoring, lighting for visibility in pedestrian and cycling areas, monitor weather conditions affecting safety (e.g., ice, rain)
Pollution	Contamination, assets, moisture, tobacco, combustion, building materials, chemical storage, radon, particulates, refrigerants used, light pollution, watercourse, land contamination mitigation	Temperature and humidity, air quality, water quality and pressure, optical particle counters, soil contamination sensors, vibration sensors, leakage detection, gases, combustion, building materials, chemical storage, radon, light, flow, pH sensors, Particulate matter etc.	Nitrogen, phosphorus, potassium and pH, temperature, humidity, PM2.5, PM10, atmospheric pressure, light, VOC concentration, gas concentrations (CO_2, formaldehyde, Ozone (O_3), CO, CH_4, O_2, SO_2, NO_2, H_2, H_2S, NH_3 etc.), rainfall, radiation, water (level and pH, turbidity, oxygen level, temperature, chemical concentration, conductivity, total dissolved solids (TDS), pressure, quality, particulate matter levels, soil quality (pH, metal concentration, organic compound concentration, nutrient levels, moisture etc.), status and location of leakage, smoke detection, ambient temperature, light intensity and brightness, etc.
Resource and Resilience	Resource management, allocation, energy management, design, infrastructure, renewable energy sources, resource usage and comfort levels, scalability and flexibility, resilience planning, maintenance and upkeep, data security and privacy, water and waste management, climate Resilience etc.	Water alarms, leak alarm sensors, temperature sensors, lighting sensors, alarm systems, fire detectors, smoke detectors, air quality sensors, CO_2 sensors, early warning systems for natural and anthropogenic disasters, etc.	Fire safety management, evacuation, climate monitoring, climate-related transition risks, social risks, fire risk management, security risk assessment, recovery, outdoor/indoor air quality monitoring, etc.
Land Use and Ecology	Biodiversity, ecology and habitat preservation, green spaces and urban forestry, water and stormwater control, soil quality and erosion control, air quality and emissions control, energy efficiency and land use optimization, urban heat island mitigation, etc.	Acoustic, camera, infrared, soil moisture, temperature, light, CO_2, flow, rainwater, smart irrigation, water quality, soil pH, compaction, air quality, PM, VOC, smart meters, occupancy, solar radiation, waste level, smart sorting, surface temperature, reflective coating, flood, humidity etc.	Monitors wildlife, plant health, soil moisture, light, air and water quality, detects pollutants, controls irrigation, prevents flooding, tracks energy use, occupancy, waste levels, manages heat absorption, supports flood barriers and water conservation systems, etc.

Table 2. Sensor insights required to meet associated sustainability goals using sensor types (continued)

5 Prominent Sustainability Goals and Sensing Approaches

In Section 4, we examined factors contributing to sustainability goals. Given the breadth of the field, it is not possible to review all goals or sensor approaches. As noted by independent analyses of rating systems mentioned at the end of the methodology Figure 4, sustainability frameworks heavily prioritize environmental quality and resource consumption. Consequently, the review is limited to two key goals: energy efficiency and health and well-being. In addition, two standard sensing methods, occupancy detection, and activity recognition are considered, as they support multiple sustainability goals.

5.1 Prominent Sustainability Goals

Based on the frequency-based standards compilation described in Section 2.1 (Figure 3), "Energy efficiency" and "Health and well-being" were identified as the highest-frequency compliance categories. Factors such as temperature, lighting, humidity, CO_2 levels directly affect both occupant health and building sustainability. Among these, thermal comfort and indoor air quality are most emphasized in the literature as they make up the majority of the presented literature.

5.1.1 Energy Efficiency. Integrating IoT sensors with complementary technologies presents a promising pathway for enhancing energy efficiency in smart buildings. As buildings remain among the largest electricity consumers globally, innovative strategies for demand reduction are essential. A key factor lies in understanding occupant interactions with the built environment, which strongly influence energy use. Occupant-based models enable precise energy management by supporting individualized decision-making processes [22]. For instance, occupancy-driven HVAC systems [18, 28, 95, 122, 142], coupled with integrations based on application programming interface (API) or graphical user interface (GUI) [20, 30, 44, 51, 91, 182, 190, 202], provide occupants with personalized, actionable suggestions for conservation. Connected thermostats further generate rich datasets on user interactions and temperature preferences [81]. Leveraging these datasets, personalized recommendations can optimize thermostat set points according to occupancy patterns, thereby improving energy efficiency [147].

Several Machine Learning (ML)-based models have been demonstrated to aid in energy efficiency and thermal comfort [63, 89]. These models include regression models [86] for forecasting energy consumption and disaggregated forecasting techniques [177] for enhancing forecast accuracy across various energy-consuming systems, such as HVAC and lighting, which further contribute to energy optimization. Architectures that combine ML, deep learning, and gamification offer further promise, enabling enhanced energy efficiency while simultaneously minimizing environmental impact [110, 151, 165, 178]. For example, deep-reinforcement ML models, such as Long Short-Term Memory (LSTM), are increasingly being applied to building anomaly detection, contributing to overall energy optimization efforts [69, 160, 194]. Furthermore, the use of open datasets in conjunction with real-time sensor data supports the design and development of AI-driven solutions in smart homes that align with sustainability goals [108]. Edge computing frameworks, such as fog computing, provide substantial energy savings over traditional cloud-based approaches in intelligent buildings [87]. By adopting such integrative strategies, IoT sensors can transform energy efficiency practices, promoting operational paradigms that are both sustainable and environmentally responsible. Sensor-based approaches for energy sustainability encompass data-driven and AI techniques for forecasting energy demand and optimizing real-time system control. Key efforts focus on predictive modeling of heating/cooling loads and building occupancy, often leveraging machine learning and deep learning methods. These insights support optimized system control, particularly for HVAC systems, through advanced strategies such as Model Predictive Control (MPC) and Deep Reinforcement Learning (DRL). A review of the literature reveals numerous IoT sensor devices contributing to energy efficiency in diverse ways. Table 3 summarizes these sensors, their insights, and applications, highlighting select unique sensor-application combinations.

5.1.2 Health and well-being: Thermal Comfort. Thermal comfort is commonly defined as the "state of mind which expresses satisfaction with the thermal environment" [173]. The literature collected here converges on two core themes: (1) standard, building-wide control approaches often fail to

Reference	Year	Sensors	Analytics	Insights	Applications
[113]	2014	Temperature sensors	optimization algorithm, setpoint optimization, temperature-comfort correlation	Occupant thermal comfort profile, thermal comfort index	Occupant driven thermal comfort to save energy
[44]	2019	temperature, humidity, environmental sensors, CO_2, airflow meter/anemometer, velocity sensors, MEMS sensors	Big data analysis, influential factor analysis, smart sensing and data analysis	Air contamination, VOCs, HCHO, Air velocity, temperature, humidity, turbulence, air volume	interior comfort and saving energy, energy savings using controlling indoor environmental contamination, monitor contamination
[142]	2018	Temperature sensors, AHU and the VAV sensors	EnergyPlus building simulator, OMOPSO optimizer	PMV, Thermal comfort level, power consumption	Temperature setting schedules of air-conditioning systems to save energy, to save energy while maintaining thermal comfort
[203]	2018	Temperature, humidity, contact, motion, occupancy sensors	Machine Learning (ML): Support Vector Regression (SVR), Recurrent Neural Network (RNN)	EnergyPlus: Ambient factors, temperature, HVAC data, heat source information	Occupancy detection, Energy efficiency, security monitoring
[135]	2018	Temperature, humidity and environmental sensors (PM sensor)	Indoor air sensing and automation (IASA) system, Rule-Based Control Logic	temperature, air quality, fan status, air particulate matter	Energy conservation while Air quality improvement
[66]	2017	Environmental sensors, PIR	Binary and multiclass classification	occupancy status	Enhancing automated building energy management systems by improving the prediction of the building's energy consumption
[118]	2012	RFID, HVAC system sensor AHU VAV (airflow volume)	Energy-saving strategies, cooling or heating and distribution	Stationary and mobile occupant detection, zonal occupancy, activity tracking, HVAC (such as temperature, humidity, airflow, pressure, damper position)	RFID based occupancy detection system to control HVAC operation for energy efficiency, demand-driven HVAC operation strategies for energy efficiency, activity monitoring for energy efficiency, reduce HVAC related energy consumption
[31]	2016	RFID	ADL recognition algorithm, decision Trees	Spatial information by RFID tags (Indoor positioning system), indoor tracking system in real-time,	Activity of Daily Living (ADL), Zonal activity detection for energy efficiency
[38]	2018	CO_2 sensors,2 temperature and humidity sensor	ML-based occupancy estimation systems (gradient boosting, k-nearest neighbours (KNN), linear discriminant analysis, and random forests.)	relation between the CO2 and occupant state	CO_2 based occupancy estimation for energy efficiency
[97]	2017	Temperature, humidity, microphone, ranging and light sensors	Non-parametric clustering method (mean shift), Hidden Markov models (HMMs)	Zonal activities, activity time, number of occupants	Energy conservation through zonal activities
[28]	2014	Temperature, contact, motion, occupancy sensors, airflow meter/anemometer, velocity sensors	Blended Markov Chain (BMC) occupancy prediction model	Thermal load and occupancy of each zone	Optimal HVAC control for energy savings while staying within the comfort bounds of the occupants, Occupancy and comfort based HVAC control for energy savings
[85]	2019	Motion sensor, magnetic sensor, temperature sensor	Fuzzy control system to control electric valve	Occupancy status, temperature	Smart central heating system for energy savings, occupancy-based heating control for energy efficiency
[12]	2018	Hall effect sensor ACS712	Current and voltage analysis	Electricity/current and voltage measurement	Current and energy monitoring
[172]	2019	Temperature sensor	Gaussian Process (GP) model, Neural Network model	Heater temperature, water temperature, air temperature, optimized heating schedules	Human behavior-based optimal hot water schedule to save energy on heating
[157]	2017	Temperature, Light, motion sensor, surveillance camera, light and HVAC control systems	Thermal analysis, stress analysis on smart LEDs	Zonal damper opening or closing, ANSYS based visualization for sensor values and status	Smart cooling system controlled by IoT devices for energy efficiency, monitoring temperature, pressure and flow velocity from the ducting and the living areas

Table 3. Energy efficiency experiments to meet sustainability standards using sensors and different analytics methods

capture occupant heterogeneity, and (2) occupant-driven, sensor-rich, and zone- or person-centric approaches promise improved comfort and energy outcomes but remain incompletely validated in long-term, real-world deployments. Established thermal standards, including ASHRAE 55:2017, ISO 7730, and EN 16798, provide a helpful reference (Predicted Mean Vote (PMV)/Predicted Percentage of Dissatisfied (PPD) indices) for determining acceptable comfort levels; however, numerous studies have highlighted their practical limitations. Jones [204] and later analyses contend that PMV/PPD-based on steady-state, population-wide models may not accurately reflect the preferences of individuals and small groups. Empirical surveys and field studies (e.g., [58, 60]) consistently show that even when set points are aligned with standards, occupants report dissatisfaction, pointing to the discrepancy between standardized criteria and subjective experiences in real environments. Large-sample surveys [58, 60] and targeted office studies [146] consistently document occupant dissatisfaction driven by lack of local control and overcooling in warm seasons. Parkinson [146] draws attention to a gender gap in particular, as women report feeling more uncomfortable in common areas. This is consistent with earlier research on how age and gender affect thermal perception [100, 161, 162, 171]. More physiological or clinical investigations [137] focus on the health effects of poor ventilation and indoor conditions, emphasizing respiratory outcomes rather than subjective comfort. Together, these results illustrate that subjective surveys, physiological studies, and standards-based evaluations each capture different aspects of the problem; reconciling them requires multimodal measurement and multimetric evaluation protocols.

Comparative analyses across the literature reveal a clear hierarchy of control granularity: traditional building-wide HVAC strategies prioritize simplicity and central energy control, but often result in thermal heterogeneity and occupant complaints. Studies [68, 79] demonstrate that zonal air handling and Personal Comfort Systems (localized fans, heated/cooled seating, microclimate devices) can reduce energy consumption while better matching individual preferences. However, many Personal Comfort Systems (PCS) studies are short-term or simulated; longitudinal field evidence of occupant adoption, maintenance requirements, and actual energy savings at scale remains limited. Occupant-centric thermal comfort strategies have been reviewed [198], highlighting approaches such as dynamic blind control, adaptive artificial lighting management, and occupancy-based thermostat control. Recent HBI work emphasizes sensor-actuator networks and data-driven models [34, 64, 71, 90, 133] to enable occupant-centric control. Open datasets and demonstrators (e.g., [67]) provide valuable starting points; however, there is wide variability in sensor types (thermostats, anemometers, CO_2 monitors, wearables), placement, sampling rates, and preprocessing-making cross-study comparisons challenging. Several studies [80, 120], and [119] propose new indices or data-driven metrics that move beyond fixed temperature bands. Von Frankenberg [186] aligns satisfaction metrics with the ASHRAE scale. Overall, the promise of ML and AI for personalization is clear. However, the literature often fails to report robust out-of-sample validation, equity across demographic groups, or practical considerations for privacy and interoperability. Given the role of thermal comfort in health and well-being, IoT sensors such as smart thermostats are essential for optimizing energy use and improving occupant comfort in smart buildings [124, 187].

Multiple studies identify demographic differences in well-being: gender [146, 161, 162, 171], age [100], and the special needs of older people [109]. These findings indicate that a single thermostat is insufficient. However, many sensor/PCS intervention studies do not stratify results by these demographic factors, or their sample sizes are too small to draw firm subgroup conclusions. This is a key empirical gap: interventions must be tested for differential effects and for the risk of exacerbating inequities. Mishra [137] and related work emphasize that ventilation and air quality are central to health outcomes and may interact with thermal strategies (for example, increased fresh-air supply alters thermal loads). The relationship between respiratory health and thermal control, which can sometimes result in reduced ventilation to conserve energy, is not well explored.

Reference	Year	Sensors	Dataset	Analytics	Insights	Applications
[156]	2022	Thermostat	Temperature readings	BrickSchema, mortar testbed application	Overcooling overheating fault detection and diagnostics	Long-term thermal comfort evaluation
[195]	2021	Temperature sensor	Temperature readings	Questionnaire	Sex/age vs. thermal comfort	Thermal comfort
[130]	2021	Heart rate sensor, NTC thermistors, galvanic skin response (GSR) sensor, environmental humidity, and temperature	Human biometric data, wearable sensors data	ML: regression models (SVM, Neural Network, Random Forest)	PMV, radiation temperature, clothing temperature, environment temperature, and humidity	Human thermal comfort estimation
[104]	2021	Lux meter, light sensors	Illuminance readings	DGP	Glare discomfort	Glare discomfort
[92]	2021	Flame sensor, gas sensor/ smoke sensor	Temperature readings, a smoke sensor value	Arduino programming	Smoke/ flame indicators	Notifications, alarms, Water sprinklers, safety
[54]	2021	CO_2 sensors, temperature sensors, airflow meters/anemometer (HVAC)	CO_2, temperature, and ventilation rate	ML: bayesian modeling (logistic regression)	Thermal comfort predictions	Thermal comfort
[125]	2021	Anemometer, tachometer	Air speed, fan speed	Math: airspeed coverage index, cooling effect	Behavior of fans concerning the number of fans, the direction of operation, room geometry, and furniture density	Thermal comfort
[144]	2019	Temperature, humidity, luminosity, and wind speed	Temperature, humidity, radiant temperature, wind speed, luminosity, and PMV	Custom ontology + sentiment analysis	Measure and optimize participants' thermal satisfaction	Thermal comfort
[44]	2019	MEMS-sensors, velocity, temperature, humidity, turbulence smart sensors, CADR air purifier	Temperature, humidity, VOCs, HCHO, air quality	Cloud IoT platform	Air conditioning monitoring, automated air flow control, air cleansing	Thermal comfort, indoor air quality, energy saving
[123]	2019	Bluetooth Smart [153] heart rate sensor, IButton DS1923	Heart-rate, activities, wrist, ankle, and body temperature	ML: LDA, regLogistic, svmRadial, KNN, NB, rpart, j48, PART, C5.0, treebag, rf, extraTrees, gbm	Personal thermal comfort	Thermal comfort via wearables
[134]	2018	DHT22 relative humidity and air temperature sensor, K-30 CO_2 sensor, pressure based transducer	Temperature, humidity, CO_2	ML: logistic regression	Thermal comfort Predictions	Adjust environment by occupancy
[127]	2018	Passive infrared motion sensors, contact sensor	Door contact, room occupancy	ML: classification by random forests	Sleep time and quality, daily habits, utility usage tracking	Activity recognition, occupancy dependent comfort, auto-schedule
[80]	2015	AeoTec MultiSensor: motion, temperature, light, humidity, vibration, UV sensor, wearable devices	Air temperature, humidity, skin temperature, near body air temperature, activity level and sweat level, GSR, metabolic rate, thermal sensation, comfort sensation, indoor location, and activity	ML: random forest and gaussian-kernel SVM	Infer/predict occupant's thermal comfort	Individual/small group thermal comfort prediction
[113]	2014	Temperature sensor	Building Management System (BMS) temperature setpoints: indoor and outdoor temperature	Temperature-comfort correlation (TCC) model: setpoint optimization algorithm	Predict thermal preference, model-driven temperature setpoints	Thermal comfort, energy conservation.
[94]	2014	Motion, sound, door status, temperature, and humidity, wifi module CO_2, light and passive infrared sensor	Sensor time series database	Fuzzy rule-based descriptive and predictive model	Occupants preferred thermal zone in HVAC	Thermal comfort

Table 4. Thermal comfort experiments to meet sustainability standards using sensors and different analytics methods

This may create a trade-off between long-term health, energy consumption, and perceived comfort. A recurring methodological problem in the reviewed studies is fragmentation, characterized by heterogeneous metrics (subjective surveys, physiological measures, PMV/PPD), diverse experimental designs (lab versus field, short-term versus longitudinal), and limited use of open benchmarks. Although Foldvary-Ličina [67] provides open thermal datasets, the field lacks widely accepted benchmarking tasks and standardized assessment protocols to enable reliable comparisons between control algorithms and PCS.

In addition to technical performance, many papers (e.g., [58, 60]) highlight perceived control, usability, and organizational constraints. Zonal and PCS approaches introduce complexity in maintenance, cost, and occupant behavior; few studies provide a full lifecycle or cost-benefit analysis that includes installation, maintenance, and user training. Interoperability between legacy building systems and modern IoT solutions is often assumed but seldom assessed. Current advancements shift focus from static building-wide setpoints to person- and zone-aware control, enhancing comfort and energy balance. However, challenges remain, such as limited representative trials, fragmented metrics, and insufficient attention to health-energy trade-offs and deployment costs. To address these issues, coordinated interdisciplinary studies are needed, combining sensor-rich interventions with thorough social, economic, and health evaluations. Table 4 explores how sensor-based approaches are used with sensor analytics, insights, and applications for achieving thermal comfort goals discussed in this subsection.

5.1.3 Health and well-being: Indoor Air Quality (IAQ). Indoor Air Quality (IAQ) management is critical in smart buildings, as people spend approximately 90% of their time indoors, creating reciprocal occupant-environment influence [143]. COVID-19 highlighted IAQ's urgency, linking poor air quality to increased infection risks [6]. IAQ encompasses particulate matter, gases, vapors, and odors affecting human comfort, health, and performance [143], requiring optimization beyond simple CO_2 metrics. Standards from International WELL Building Institute (IWBI) and ASHRAE (e.g., 62.1) specify minimum ventilation rates and address pollutants including VOCs like formaldehyde, benzene, and toluene from building materials and cleaning products [16]. Additionally, ISO 16000 sets the "how-to" for assessing IAQ, and ASHRAE 62.1 sets the "what" for what constitutes acceptable IAQ and how to achieve it through ventilation. IoT sensors enable pollutant monitoring and HVAC control, enhancing comfort while pursuing energy savings [48]. However, a critical hardware-software gap exists: despite the proliferation of low-cost sensors for VOCs and particulate matter [46, 128], systematic reviews reveal that most studies neglect in-situ calibration, undermining data reliability [44]. Additionally, LoRaWAN protocols provide substantially lower indoor coverage than estimated, requiring denser, costlier infrastructure [121]. This disconnect between assumed and actual hardware performance fundamentally challenges IAQ monitoring validity.

Methodological frameworks split between *data-driven machine learning* and *knowledge-based ontological reasoning*. Data-driven approaches utilize time-series forecasting with Gated Recurrent Units (GRU) for proactive comfort zone maintenance [46], or Deep Reinforcement Learning (DRL) for optimal, adaptive HVAC control that balances energy cost and comfort [194]. Conversely, knowledge-driven systems employ ontologies for formal environmental modeling, enabling semantic reasoning for situation classification and control recommendations [4]. A critical trade-off emerges: superior *black-box* DRL performance [194] sacrifices interpretability, while ontological systems [4] offer transparency but lack nuanced learning capabilities. This performance-explainability gap hinders user trust and system validation.

Human factors complicate IAQ management, as occupants' air quality perception is more influenced by *thermal comfort factors* like temperature and humidity than actual pollutant levels [57]. Architectural decisions such as window placement should prioritize occupant comfort [24], while occupancy information enables demand-driven control, with non-intrusive estimation from environmental sensors emerging as key research [73] for both IAQ and energy savings.

In developing countries suffering from high outdoor PM2.5 pollution [207], indoor levels can be mitigated through prompt and correct adjustment of HVAC or air filtration systems. The field faces a precarious research gap: sophisticated, data-hungry algorithms [46, 194] rely on potentially fragile, uncalibrated low-cost sensor data. Future work must bridge this hardware-software divide through *hybrid neuro-symbolic models*, which combine machine learning's adaptive power with ontologies' formal safety guarantees. Moreover, the field requires a shift from simulation-based validation toward long-term, in-situ field studies (e.g., [128]), to prove real-world robustness and socio-technical viability. Table 5 presents a non-exhaustive list of previously unseen studies that use IoT sensors, analytics, insights, and applications to monitor and control IAQ.

Reference	Year	Sensors	Analytics	Insights	Applications
[62]	2021	RGB, thermal, depth, LiDAR, and ultrasound	window detection algorithms with Lepton module code, Python, VeloView, Intel Realsense, Intel rs-capture	Window status with many modalities, states, distances, and angles	Sensor data analysis and window state classifiers, thermal comfort, energy conservation, IAQ
[206]	2020	Dust sensor, temperature and humidity sensor	Air pollutant concentration, air quality sub-index by mathematical analysis	Detect the level of fine particles, smoke particles, dust concentration, temperature and humidity level	SMS alerts, monitor, control, and improve IAQ
[44]	2019	Micro Electro-Mechanical System (MEMS) sensor: PM10, PM2.5, TVOC, HCHO, temperature, RH, CO_2	Statistical analysis on cloud web app system using mass balance model of IAQ	Contamination monitoring, airflow control, air cleansing, energy saving, peristome shifting	Health, comfort, and saving energy, IAQ index and indoor pollutants finding to take actions
[168]	2019	Electroencephalogram (EEG) : Emotiv EPOC	ML: Classification LDA, SVM pattern recognition	Classify mental states under different IAQ conditions	CO_2 level, IAQ control, mental health monitoring
[45]	2014	Aerosol particle counter: PM2.5, PM10, temperature, humidity, pressure, wind speed	ML: neural networks	Monitor pollutants level of PM10 and PM2.5, temperature humidity and wind speed	HVAC operating time and HVAC air filter replacement suggestion
[128]	2018	CO_2, ozone (O_3) with MOX sensors, temperature, relative humidity sensors	Root-mean-square-error (RMSE), Artificial Neural Networks (ANN) based calibration models training on cloud server with tensorflow	Multi-pollutant monitoring, ambient O_3 and CO_2 measurements	Wearable platforms such as wrist-worn, attached to belts or backpacks for indoor/outdoor IAQ monitoring, health and fitness trackers
[61]	2023	Temperature, humidity, and CO_2 sensors, VOC, light sensors, motion sensors	Data processing on PowerStudio SCADA (Supervisory Control And Data Acquisition) central server	Temperature and humidity level in each of the classrooms, and percentage of CO_2 measured in the air	Room scheduling, Occupancy-based services, monitoring and adjusting CO_2 levels, lighting, temperature, and humidity, monitoring energy efficiency, energy cost savings
[194]	2023	FLIR One Pro RGB-thermal cameras, Jetson Nanos, and temperature/humidity sensors	Deep Q-network in simulation models to predict the new building state	PMV calculations and Air Quality Index (AQI)	PMV ASHRAE 55 scale for air quality, thermostats for user thermal comfort, HVAC airflow control for IAQ, lighting/visual comfort based on occupancy
[182]	2022	Netatmo weather stations consist of temperature, humidity, barometric pressure, carbon dioxide concentration and noise pollution sensors	statistical and machine learning methods such as Naive Forest, ARIMA, ARX	Estimate and forecast energy consumption, and CO_2 footprint	To reduce CO_2 footprint from indoor energy savings, social Smart Metering, smart thermostat solutions
[103]	2024	Dust sensors (PM), temperature, relative humidity, NO_2, C_2H_5OH, VOC, CO, CO_2	Kernel Change Point Detection (KLCPD) algorithm	VOC levels, CO_2 concentrations, PM concentration, combined pollution spread patterns, actionable insights	Human-in-the-Loop labeling for activities, split air conditioning for IAQ, indoor zonal pollution monitoring

Table 5. IAQ studies employing sensors and other analytics methods to accomplish sustainable goals

5.2 Prominent Sensing Approaches

As mentioned earlier, we will explore the two main sensing approaches that frequently occur, based on the methodologies used to achieve multiple sustainability goals: occupancy detection and activity recognition.

5.2.1 Occupancy Detection: The literature details a diverse technological landscape for monitoring building occupancy, count, and flow, employing both direct sensing and indirect activity tracking. For localization, studies highlight cost-effective, RFID-based systems [112] alongside a wider spectrum of wireless technologies such as ultra-wideband (UWB), SigFox, and LoRa to locate devices and people [200]. While ML algorithms can effectively enhance the detection and counting of occupants [188], the requisite data collection raises critical privacy and security concerns. In response, some research proposes privacy-preserving options, such as Kinect cameras that use depth-sensing technology [53, 193]. Effective deployment hinges on sensors that offer real-time response, high accuracy, low deployment cost, and non-intrusive protocols. Crucially, as the literature underscores, selecting the right sensor is fundamentally application-dependent [77]. Sensors can be used in three application scenarios *(1) Occupancy Detection* (PIR, MW, Ultrasonic, Radar, RGB, IR, ToF, LiDAR, CO_2, VOC, Temperature & Humidity, Sound, WiFi, BLE, RFID/NFC, Door counter, Chair/Floor Pressure, RF Sensing), *(2) Occupancy Counting* (CO_2, VOC, Depth, RFID, Chair/Floor Pressure, Door counter, WiFi, IR, ToF, LiDAR, Radar, Ultrasonic, Cameras, RF Sensing), and *(3) Occupancy Positioning* (WiFi, RFID/NFC, BLE, UWB, Depth, IR, ToF, LiDAR, Radar, Ultrasonic, RF Sensing, Vibration, Chair/Floor Pressure). Many of these sensors can be used in tandem to monitor multi-occupancy spaces effectively [99].

5.2.2 Activity Recognition: Beyond mere presence, understanding Activities of Daily Living (ADL) is identified as a crucial factor influencing building performance, especially energy consumption and indoor air quality. Research posits that linking energy usage, comfort, and satisfaction directly to residents' interactions is key to achieving greater sustainability [96]. This necessitates a deeper comprehension of how occupants react to their indoor environment, a concept central to applications like elderly care [109]. While various sensor-based and non-sensor-based approaches exist for recognizing activities like cooking or sleeping, the focus of this review is on sensor-based methods. However, the inherent complexity of human behavior presents both risks and opportunities in system design [115]. Frameworks developed primarily for healthcare aim to help individuals self-manage well-being by monitoring meaningful activities [176]. Recent advancements underscore the synergy between IoT sensors and sustainability, evidenced by studies on data-driven approaches in smart homes [11], the pursuit of finer-grained activity data for elderly care [176], and the development of fog-based systems for improved performance over cloud-based alternatives [50]. Table 6 presents a range of recent studies on occupancy detection and activity recognition using sensors, highlighting their application toward single or multiple sustainability goals.

6 Human Interaction with Buildings

While previous sections detailed how IoT devices enable buildings to achieve sustainability goals, a critical analysis must also examine the reciprocal relationship: the complex and evolving nature of human communication with the building as human-building interactions contribute directly to achieving sustainability objectives such as energy efficiency, health and well-being, and user comfort. The literature reveals a clear trajectory towards adaptive architectures where data empowers occupants, shaping the future of HBI [164]. This shift is driven by occupant demand for greater environmental control [154], which necessitates a critical review of interaction modalities. The push for more intuitive interfaces is evident in the exploration of speech and gesture controls, which have shown promise in assistive contexts [17]. However, this trend introduces a significant tension with inclusivity, as these modalities may not be suitable for individuals with specific disabilities. This highlights the necessity of multimodal approaches that combine various communication modes to cater to diverse user groups, a principle supported by recommendations from the W3C and research on accessible displays [10, 55]. The challenges of integrating these diverse modalities are addressed in numerous studies that underscore the difficulty of achieving sustainability goals without effective occupant collaboration through interfaces [26, 29, 41, 105]. Beyond common modalities, more novel methods like eye and head tracking are also being investigated for both interaction and activity recognition [88]. Conversational AI (e.g., virtual assistants) is increasingly

Reference	Year	Sensors	Analytics	Insights	Applications
[117]	2021	TENG-based gait sensor	Deep learning: residual dense-BiLSTM (Bidirectional LSTM)	Activity recognition and individual identification	Activity recognition, individual identification, and personal health care
[174]	2020	Laser doppler vibrometer	Deep learning CNN	Home activities recognition	Energy and water saving, energy monitoring, electrical safety
[138]	2019	Intel RealSense depth camera D415 and Microsoft Kinect camera	Object detection system YOLOv3 on raspberry pi	Occupancy, number of people	Energy efficiency, indoor environmental quality
[56]	2018	Metal oxide semiconductor, temperature / relative humidity sensor DHT-22, VOC sensor, multi-channel gas sensor MEMS, NDIR CO_2	ML: linear regression, classification	Activity recognition via indoor odors classification	Health and safety, indoor air quality
[142]	2018	Temperature	Swarm-based optimizer, EnergyPlus simulator, OMOPSO algorithm	Temperature setting schedules for thermal comfort PMV, energy conservation	Improved thermal comfort and energy efficiency
[203]	2018	EnergyPlus: Ambient factors, temperature, HVAC data, heat source information	ML: SVR, RNN	Occupancy detection	Energy efficiency, security monitoring
[149]	2018	Massachusetts Institute of Technology (MIT) smart home data set	ML: Uncertain Pattern-Discovery Method	Activity prediction and recognition, human behavior	Energy efficiency, health and well-being
[73]	2018	Occupancy sensor data, HVAC dataset	ML: Nonlinear autoregressive network with exogenous inputs (NARX)	Occupancy prediction, estimation of number of occupants	Energy conservation and IAQ via occupancy
[38]	2018	CO_2 sensor	ML: gradient boosting (GB), k-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), and Random Forests (RF)	Relation between CO_2 and occupant	Wireless sensor network for environmental monitoring, occupancy detection for applications
[135]	2018	Air quality sensor- Utah-modified Dylos sensor (UMDS), PM2.5, PM10, smart thermostat, temperature, humidity sensor	Rule-based declarative control logic	Automated fan control, monitor air pollution, air quality	Energy conservation, indoor air quality
[66]	2017	Air quality sensors, VOC	ML: classification	Occupancy detection (Binary)	Energy consumption
[132]	2016	Massachusetts Institute of Technology (MIT) smart home dataset	Deep learning: quick propagation (QP), Levenberg Marquardt (LM), and batch backpropagation (BBP) and ANNs	Activity recognition	Energy saving, security, health care and home care
[28]	2014	Temperature, occupancy sensor, HVAC data	Model predictive control MPC framework	HVAC control, occupancy prediction	Energy efficiency
[111]	2013	PIR, CO_2, plug meter, temperature, humidity, lux, current transducer, light sensor		Energy usage of end-loads, energy use analysis, load state estimation, occupancy estimation, utility estimation, time-series analysis	Energy efficiency and monitoring
[116]	2012	WiFi-connected devices, e.g. smartphones, mobiles	WIFI wireless APs, an indoor positioning system (IPS) algorithm	Web UI occupancy information, zonal occupancy detection and tracking, monitoring	HVAC/lighting automation
[118]	2012	Ultra-high frequency (UHF)RFID equipment (915MHz-100m range), readers	Server location statistics, proximity-based algorithm KNN	Time, tag IDs, tag model, battery life, RSSI readings, last contact time, and contact count	Demand-driven HVAC operation, Energy conservation
[197]	2012	Lighting sensor, sound sensor, motion sensor, CO_2 sensor, temperature sensor, relative humidity sensor, PIR sensor, door switch sensor	Back-propagation (BP), ANN algorithm	Occupants quantity, lighting, sound, motion, CO_2 concentration, temperature, relative humidity, reflector (infrared) count, door status and count, motion count, average variables	Demand-driven HVAC, occupancy Monitoring, Energy conservation
[178]	2018	Camera, sound/noise, motion, temperature, humidity, and light sensor	OpenCV image processing, transfer learning, unsupervised, Supervised, and Semi-supervised learning	Occupants quantity, lighting, sound, motion, temperature, humidity, motion count	Building efficiency via IoT-based BMS, occupancy monitoring, energy conservation, HVAC efficiency

Table 6. Different analytics on occupancy detection and activity recognition by sensors for various sustainable goals

powered by large language models (LLMs) and advanced AI technologies, enabling users to interact naturally without requiring prior knowledge of the environment. These systems can support a wide range of objectives, from information retrieval to task automation. In contrast, ontology-based assistants and traditional ML driven systems [126] operate differently, with varying levels of accuracy, adaptability, and scope. However, the comparative effectiveness and limitations of these approaches are not yet fully understood. Smartphone applications remain a dominant modality, with frameworks like SenseRT enabling real-time data visualization and interaction [183]. This concept of user empowerment is powerfully demonstrated in prototypes like "WindowWall", where a simple interface allows residents to make decisions about lighting and views that directly impact building sustainability [24]. The evolution of interaction extends into immersive realities, where technologies like Augmented Reality (AR) and Virtual Reality (VR) are being leveraged for building management and control [167]. Major technology firms are heavily investing in this space, developing platforms that center user interaction within Extended Reality (XR) environments [152]. Prototypes utilizing AR for HVAC control [5] and cross-reality simulations to assess inhabitant experiences [140] exemplify the shift towards more intuitive, spatially aware building management. Although wearable technology aids in comfort management, its integration with real-time HVAC operations has not been fully investigated [99].

Automation, mobile robotics and Autonomous Mobile Robots (AMRs) are increasingly used for environmental sensing and condition prediction [169]. A critical trade-off emerges: while these systems offer efficiency in path planning and operation, their reliance introduces significant vulnerabilities, including cybersecurity threats and system failures that can compromise safety and privacy. Additionally, natural language queries are simplifying access to complex sensor data, allowing non-technical users to retrieve and visualize time-series information without programming skills [185]. The integration of IoT sensors is also transforming traditional Building Management System (BMS) into intelligent platforms capable of real-time asset monitoring and optimized scheduling [136, 178]. The most significant leap comes from the application of ML for predictive maintenance. A substantial body of recent work demonstrates that ML-driven strategies can optimize appliance scheduling [166], predict facility failures [33, 205], and improve overall system reliability [7]. As systematic reviews confirm [42], integrating ML with BMS offers a powerful pathway to enhanced efficiency, reduced costs, and more resilient smart systems. Table 7 compares the reviewed modalities for sustainability goals, while Figure 5 illustrates the spectrum of Human-Building engagement from direct to indirect modalities of interaction.

7 Discussion

Figure 6 depicts the pathway from human-building interaction to standardized sustainability goals. Occupants engage via interfaces (e.g., Voice/Text, Extended Reality), while IoT sensors and networks provide data for activity and occupancy recognition. This enables management of key goals-health, well-being, and energy efficiency by regulating thermal comfort, IAQ, and lighting. Thermal comfort, for instance, is evaluated using environmental and personal data (e.g., PMV) to meet standards like ASHRAE 55. Overall performance is then assessed against sustainability frameworks such as LEED and BREEAM.

Modality Group	Outcomes/Applications	Sustainability Goals		
		Energy Efficiency	Thermal Comfort	Indoor Air Quality
Extended Reality (XR) (Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR)) systems	Immersive visualization and collaborative design for planning and retrofits. Converts energy, comfort, and IEQ data into interactive formats. Engages stakeholders and supports training on sustainable practices.	[5, 163]	[5, 140, 148]	[5, 140]
Software, Platforms & Interfaces (Dashboards, Mobile Apps, Widgets, Building Management Systems, APIs, Wearable Haptic Devices with apps, Touch Screens)	Real-time monitoring and feedback on comfort, energy, and IEQ. Transforms sensor data into actionable insights and enables automation. Wearables and haptics provide tactile alerts for environmental changes or energy-saving opportunities. Enhances personalization and engagement.	[3, 5, 10, 12, 13, 17, 20, 24, 29, 30, 40, 41, 43, 47, 51, 61, 65, 74, 76, 81, 91, 101, 102, 105, 107, 110, 114, 122, 131, 134, 138, 139, 147, 159, 165, 170, 175, 178, 180, 182, 189, 190, 194]	[1, 3, 5, 10, 24, 29, 41, 49, 51, 52, 61, 65, 70, 74, 76, 81, 91, 94, 105, 114, 122, 131, 134, 139, 147, 158, 178, 194, 199]	[3, 5, 10, 13, 44, 51, 61, 65, 74, 91, 94, 103, 114, 128, 141, 151, 182, 194, 202]
Gesture & Posture Recognition (Hand gestures, posture detection)	Touch-free interaction with HVAC and lighting. Detects thermal discomfort and automatically adjusts conditions. Uses ML and computer vision for adaptive control and natural interaction.	[3, 10, 17]	[3, 10, 23]	[3, 10, 23]
Conversational AI (Speech, Text-based Chatbots based on LLMs or ontologies)	Natural language control of thermal, lighting, and ventilation systems. Improves comfort with personalized dialogue. Engages occupants in energy-saving behaviors through clear explanations and targeted suggestions.	[10, 17, 41, 78, 105, 126]	[10, 41, 78, 105, 126, 155, 158, 159]	[10, 78, 126, 155]
Physical & Robotic Systems (Mobile Robots, Robotic Arms)	Autonomous task execution (e.g., shading, cleaning, targeted heating/cooling). Provides continuous sensing and optimizes movements to minimize energy consumption. Enhances resilience and supports dynamic building operations.	[129]	[106, 155]	[129, 155, 196]

Table 7. Literature distribution for human-building modalities

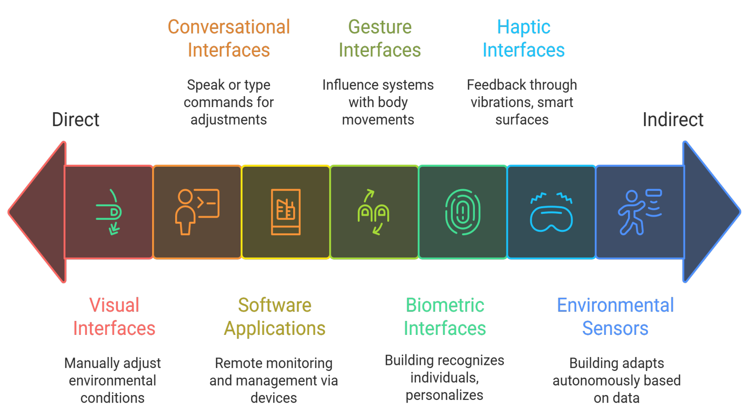

Fig. 5. Human-building modalities: direct to indirect control

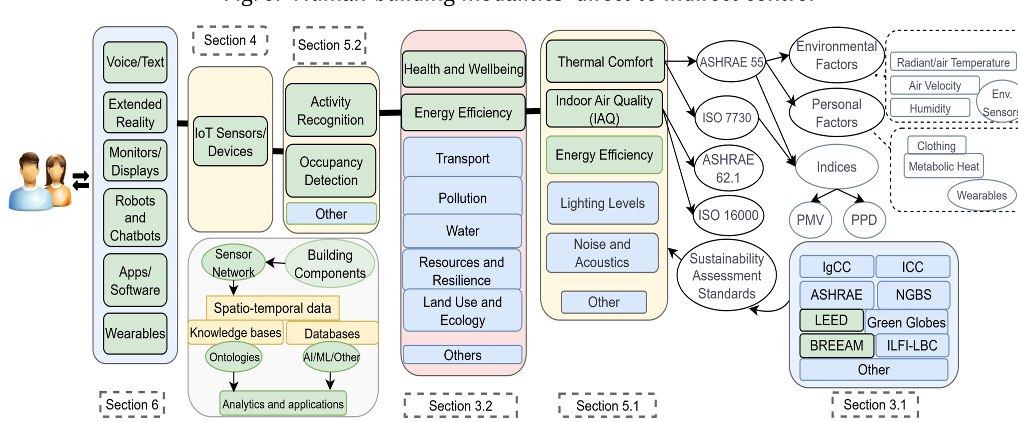

Fig. 6. Overview of discussed literature

The integration of various sustainability standards, including LEED, BREEAM, and others, emphasizes the need to adhere to internationally recognized protocols. While Section 3 identified broader sustainability factors such as water conservation, indoor transport, and land use as integral to standards like BREEAM and LEED, our literature analysis reveals that HBI research remains heavily skewed toward energy efficiency and thermal comfort. These "non-energy" factors remain underexplored in the context of interactive, occupant-centric technologies. Environmental and human factors such as air temperature, air velocity, and metabolic heat illustrate the complex interplay between human and building systems and highlight the need for further analytics and more sophisticated control regulators. The diagram's structure highlights the critical need to balance trade-offs between competing sustainability goals, informed by data-driven insights from IoT sensor networks. This underscores the need for ongoing research to enhance these technologies and their higher degree of involvement with occupants, in addition to addressing some other vital issues of interoperability, data security, and personalized control, thereby releasing the full potential of smart buildings and sustainable buildings.

Major sensing applications include activity recognition and occupancy detection for achieving different sustainability goals. These approaches enable buildings to adapt in real-time to occupant behavior, resulting in optimized energy use while maintaining desired comfort levels. The diagram alongside depicts the relationship between particular sustainability goals and standards: ASHRAE 55 and ISO 7730, respectively. Figure 7 in the Appendix compares the sustainability goals from previous sections, linking them to contributing factors and relevant sensors/sensor types. To summarize, Table 8 compares some of the unique sensors/device types used to achieve sustainable goals, including the occupancy detection and recognition techniques discussed.

	Sensors/Sensor Types											Sustainability			
Reference studies and experiments	Temperature sensor	Humidity sensor	Cameras, smart cameras (e.g. Kinect)	Environmental sensors	CO_2 sensor	Wearable sensor: temp., heart rate etc	RFID	Lux meter, light sensors	Contact/motion/ occupancy sensors	Airflow/anemometer/ velocity sensors	Current/Voltage/ thermostats sensors	Energy Efficiency	Health and well-being: Thermal comfort	Health and well-being: Indoor air quality	Occupancy detection or recognition
[156, 195]	✓												✓		
[54]	✓				✓					✓			✓		
[125]										✓			✓		
[144]	✓	✓						✓		✓			✓		
[123]						✓							✓		
[134]	✓	✓			✓								✓		✓
[127]									✓					✓	✓
[80]	✓	✓				✓		✓	✓				✓		
[113]	✓											✓	✓		
[44]	✓	✓		✓	✓					✓		✓		✓	
[142]	✓											✓	✓		✓
[203]	✓	✓							✓			✓			✓
[73]	✓	✓			✓	✓			✓			✓		✓	✓
[135]	✓	✓		✓								✓		✓	✓
[66]				✓								✓			
[31, 118, 150]							✓					✓			✓
[197]	✓	✓			✓				✓			✓			✓
[38]					✓							✓		✓	✓
[93]						✓									✓
[138, 145, 179]			✓									✓			✓
[97]	✓	✓						✓				✓			
[28]	✓								✓	✓		✓			✓
[94]	✓	✓			✓			✓	✓				✓		
[192]				✓								✓			✓
[181]	✓							✓	✓			✓			
[85]	✓								✓			✓			
[12]											✓	✓			
[172]	✓										✓	✓			✓
[157]	✓		✓					✓	✓	✓		✓			✓
[74]	✓	✓							✓		✓	✓	✓		✓
[178]	✓	✓	✓	✓				✓	✓			✓	✓		✓

Table 8. Reviewed literature on sensors usage to achieve sustainability standards

8 Research Challenges and Directions

8.1 Research Challenges

The rapid spread of IoT technology is leading to a wide range of problems in various disciplines. We have identified several research challenges that are closely linked to the discussions in the previous section and our research goals. These challenges address significant barriers to effective human-building engagement, which are essential for achieving sustainability. Addressing these issues is crucial for meeting our primary objectives of developing smart buildings that are sustainable, energy-efficient, and centered around user needs.

8.1.1 Data Integrity and Reliability. The effectiveness of human-building engagement depends entirely on data quality. As discussed in Section 5.1.3, while low-cost sensors for VOCs and particulate matter are widely available, they often lack in-situ calibration, which undermines the validity of IAQ monitoring [44, 128]. Furthermore, the reliance on advanced systems like AMRs for environmental sensing introduces vulnerabilities such as system malfunctions and cybersecurity threats that can compromise both data integrity and occupant safety [169]. If occupants perceive that building operations do not align with their physical reality, the resulting erosion of trust leads to manual overrides, curtailing the sustainability goals established by standards. Although machine learning calibration (e.g., [128]) and sensor fusion methods exist to improve accuracy, infallible data remain an indelible part of any truly conclusive HBI work.

8.1.2 The Perceptual Gap: Reconciling Objective Data with Subjective Comfort. A recurring theme in the literature is the "perceptual gap" between measurable environmental data and subjective human experience. Findings in Section 5.1.2 highlight that standard indices like PMV and PPD often fail to capture individual heterogeneity, with occupants frequently reporting dissatisfaction even when set points align with international standards such as ASHRAE 55 [58]. This is exacerbated by demographic differences—such as the gender gap in thermal perception where women report higher discomfort due to overcooling in common areas [146]—and the specific needs of older populations [109, 171]. Bridging this gap requires moving beyond averages toward multimodal, person-centric measurement protocols that incorporate subjective feedback rather than relying solely on global evaluations.

8.1.3 The Interaction Paradigm: Designing for Occupant Agency. For the HBI system to operate efficiently, its interface should transform complex building data into insights for users who may not be familiar with this domain. Section 6 revealed a clear trajectory toward occupants demanding greater environmental control. However, the push for advanced modalities like speech or gesture controls introduces a tension with inclusivity, as these may exclude individuals with specific disabilities or limited digital literacy [10]. While interfaces like "WindowWall" empower users to make sustainable decisions [24], the challenge remains to design multimodal interfaces that provide clear, actionable insights without overwhelming the user or creating a "digital divide" in comfort and control. As noted in Section 8.1.6, over-reliance on smartphone apps may exclude elderly individuals [127], necessitating the adoption of universal design principles.

8.1.4 The Optimization Dilemma: Balancing Competing Goals. As synthesized in Section 7, smart buildings must manage a trade-off between competing objectives: individual comfort, collective well-being, and building-level energy efficiency. For instance, Section 5.1.2 noted that overcooling in warm seasons consumes energy while also causing significant occupant discomfort [146]. Similarly, reducing ventilation to conserve energy can create a trade-off with long-term respiratory health, a link that remains insufficiently explored in current HBI research [137]. Energy conservation is often at odds with meeting the preferences of thermal, air quality, and lighting parameters –

often described as the "politics-of-the-thermostat". To mitigate such conflicts, algorithms must find "Pareto-optimal" solutions that are not only computationally efficient but also socially accepted. Future studies should focus on developing AI-based predictive models and control algorithms that consider user preferences, usage trends, and environmental factors. Feedback mechanisms that allow occupants to adjust the settings could be incorporated into the system, offering flexibility and enhancing energy efficiency and occupant satisfaction.

8.1.5 The Engagement Conundrum: Sustaining Long-Term Participation. The success of HBI systems depends on sustained participation, yet many systems suffer from the "novelty effect," where user enthusiasm declines sharply after initial deployment. While Section 5.1.1 suggests that gamification and deep learning architectures offer promise for enhancing energy efficiency [110, 165], these interventions must be carefully balanced to avoid feedback fatigue and eventual abandonment. Sustaining behavioral change requires a transition from extrinsic rewards to intrinsic motivators, such as social impact and a sense of achievement, underpinned by a foundation of data privacy and trust.

8.1.6 The Accessibility Divide: Ensuring Interoperability and Equity. HBI presents a dual accessibility divide. The first element presents a technological barrier, indicating a severe lack of semantic interoperability. Buildings in a fragmented ecosystem of proprietary systems struggle to share data effectively and interpret one another's systems. This constraint limits scalable HBI applications, which are both cost-effective and resource-efficient. As mentioned in Section 6, standardized data frameworks, such as Brick Schema [25], aim to create a common language for building data; many legacy systems remain isolated. The second aspect is the so-called "digital divide" related to the human factor. Digital overdependence and especially an overreliance on smartphone apps or complex digital interfaces may exclude particular users, such as elderly individuals, those with disabilities, or those with limited digital skills, creating an inequitable dual system of comfort and control. The strategy for remedying this lies in strong adoption of Universal Design (UD) principles to develop redundant, multimodal interfaces. If voice commands, touch, or simple manual controls are incorporated, users will be empowered to interact with the system and benefit fully from it. Without standardized data models that can map real-time sensor data to recognized standards like LEED or BREEAM (discussed in Section 3), the potential for autonomous, cross-platform sustainability optimization remains limited.

8.2 Research Directions for Sustainable Human-Building Interaction

Important research avenues that address unique opportunities and challenges in the HBI sustainability paradigm are identified in the reviewed literature. These directions focus on how human well-being, the environment, regulations, and intelligent systems interact. Together, these directions outline a design methodology for buildings that are efficient, healthy, and regenerative.

8.2.1 Advancing Occupant-Centric Adaptive Systems for Personalized Well-being. The next frontier for HBI lies in moving beyond static comfort models to create truly personalized and adaptive building experiences. This research direction focuses on the physical comfort factors of lighting, thermal comfort, and air quality, intending to enhance psychological well-being. Adaptive systems must then be established that determine occupant preferences and physiological needs in real-time. There should be an integration of sensor data from the IoT with direct feedback from occupants to build environments for stress alleviation, cognition enhancement, or mental well-being, essentially taking away their isolation and making buildings active partners for their occupants.

8.2.2 Leveraging AI and Data Analytics for Continuous Performance Optimization. For buildings to be truly sustainable, they must constantly learn and change. The goal of this research direction is to improve performance through the use of advanced data analytics, AI, and AIoT. The creation of energy consumption prediction models, the identification of operational inefficiencies, and autonomous system modifications should all be part of future research. Introducing closed-loop operations—collection, analysis, and action—using real-time data for optimizing resource management, from HVAC to vertical transport in buildings, ensures that informed decisions are made using data for efficiency upgrades, renewable energy integration, and, of course, continuous improvement throughout the building's life.

8.2.3 Developing Standardized Frameworks for Interoperability and Compliance. The lack of standardization is another obstacle preventing large-scale HBI operations. The goal of research is to ensure interoperability between different types of IoT devices and building management systems by developing standardized frameworks, architectures, and data models. Research should be conducted to develop and implement open standards that can seamlessly map real-time sensor data to recognized IEQ and sustainability criteria, such as WELL and BREEAM. The provision of these standardized blueprints paves the way for reliable benchmarking procedures, regulatory compliance, and the integration of new technologies into both new and existing building stock.

8.2.4 Transforming Buildings into Holistic and Regenerative Ecosystems. A smart building should not be considered as a static structure that uses resources, instead it should be considered as a dynamic entity that is responsive and regenerative. It is a more comprehensive approach to design that combines the principles of social and environmental sustainability with human-centered design. Investigations will necessarily include the use of eco-friendly along with pollution-free materials and applying circular economy concepts to minimize the entire life-cycle impact of a building. The aim is to develop building frameworks that allow buildings to adapt to the needs of their occupants.

9 Conclusion

We explored the critical role of Human-Building Interaction (HBI) in achieving sustainability goals through the strategic deployment of IoT-based sensors. By reviewing global sustainability standards (Objective 1), we established that thermal comfort, indoor air quality, and energy efficiency are the highest-frequency compliance categories, thereby serving as the primary focus of this review. We examined how insights derived from targeted sensors can effectively address these specific objectives through occupancy detection and activity recognition. Our analysis highlights that while current HBI research has matured in optimizing energy and thermal comfort, significant disparities exist in broader sustainability applications. As noted in the Discussion, critical areas such as indoor transportation, water conservation, and land use remain underexplored within the HBI domain, despite their prominence in certification frameworks like LEED and BREEAM. Additionally, we have highlighted six key challenges: (i) the reliability of sensor data necessitating hybrid models for improved accuracy, (ii) the need for real-world validation of conceptual algorithms, (iii) the perceptual gap between objective measurements and subjective comfort, (iv) the optimization dilemma of balancing competing sustainability goals, (v) the engagement conundrum of maintaining long-term user participation, and (vi) the accessibility divide in ensuring system interoperability and equity across diverse user populations. Future research should prioritize developing hybrid sensor-based models that bridge the gap between objective data and subjective preferences. Ultimately, sustainable smart buildings require more than technological advancement; they demand personalized adaptive approaches that integrate the full spectrum of sustainability goals-beyond just energy and climate-to foster active, long-term engagement between occupants and their built environments.

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Appendix

Referenc	Keywords and terms	Example search strings [4]	Criteria for Inclusion/exclusion	
Table 1	Sustainable building standards, green certifications, environmental assessment, net-zero energy, LEED, BREEAM, IgCC, ASHRAE Standard 189.1, IBC, NGBS, Green Globes, LBC	("building sustainability standard" OR "green building certification" OR "environmental building assessment" OR "sustainable construction standard") AND (framework OR system OR protocol OR guideline)(Returned initial results=10100)	Relevance to sustainability goals, applicability to smart buildings, global and regional influence, credibility and recognition, redundancy and data flexibility, publication dates	
Table 3	Energy efficiency, energy conservation, smart buildings, IoT, thermal comfort, HVAC optimization, machine learning, occupancy detection, sensor analytics, indoor air quality, power consumption monitoring, RFID, smart sensors, multi-objective optimization	[All: Energy efficiency] AND [All: smart buildings] AND [All: iot] AND [All: sensors] AND [E-Publication Date: (01/08/2015 TO 31/08/2025)] (Returned initial results, ACM=4344, IEEEXplore =313)	Sensors used to achieve energy related sustainability goals (energy savings, efficiency), publication year and analytics, scope and limitations, applicability to energy efficiency related sustainability goals, study type, database resource	1. Lack of originality or insufficient research insights 2. Unclear research objectives, context, or methodology 3. Inadequate data analysis or unsupported conclusions 4. Duplicated findings from previously published studies 5. Multi-scope research beyond defined parameters
Table 4	Thermal comfort, smart buildings, personalized comfort, IEQ, sensors (wearable, temperature, air quality), occupant behavior, participatory approaches, energy conservation, elderly care, thermal comfort prediction	[All: Thermal comfort] AND [All: smart buildings] AND [All: iot] AND [All: sensors] AND [E-Publication Date: (01/08/2015 TO 31/08/2025)] (Returned initial results, ACM=595, IEEEXplore =83)	Sensors used to achieve thermal comfort related sustainability goals, publication year, scope and limitations, analytics used, study type, database resource, applicability and relevance to occupant thermal comfort	
Table 5	Indoor air quality (IAQ), indoor environment quality (IEQ), smart buildings, sustainable buildings, (air quality, CO2, particulate matter, IoT-enabled, EEG, multi-modal) Sensor, machine learning, predictive modeling, pollution control	[All: indoor air quality] AND [All: iot sensors in smart buildings] AND [E-Publication Date: (01/08/2015 TO 31/08/2025)] Returned initial results, ACM=1336, IEEEXplore =79)	Sensors used to achieve indoor air quality related sustainability goals, Publication year, Scope and limitations, Dates, Domain, Study type, Database resource analytics used, Applicability to indoor air quality sustainability goals	

Table 9. Keywords and Search Strings for Sustainable Smart Buildings Literature Review

[4] Equivalent search strings are used in IEEE Xplore

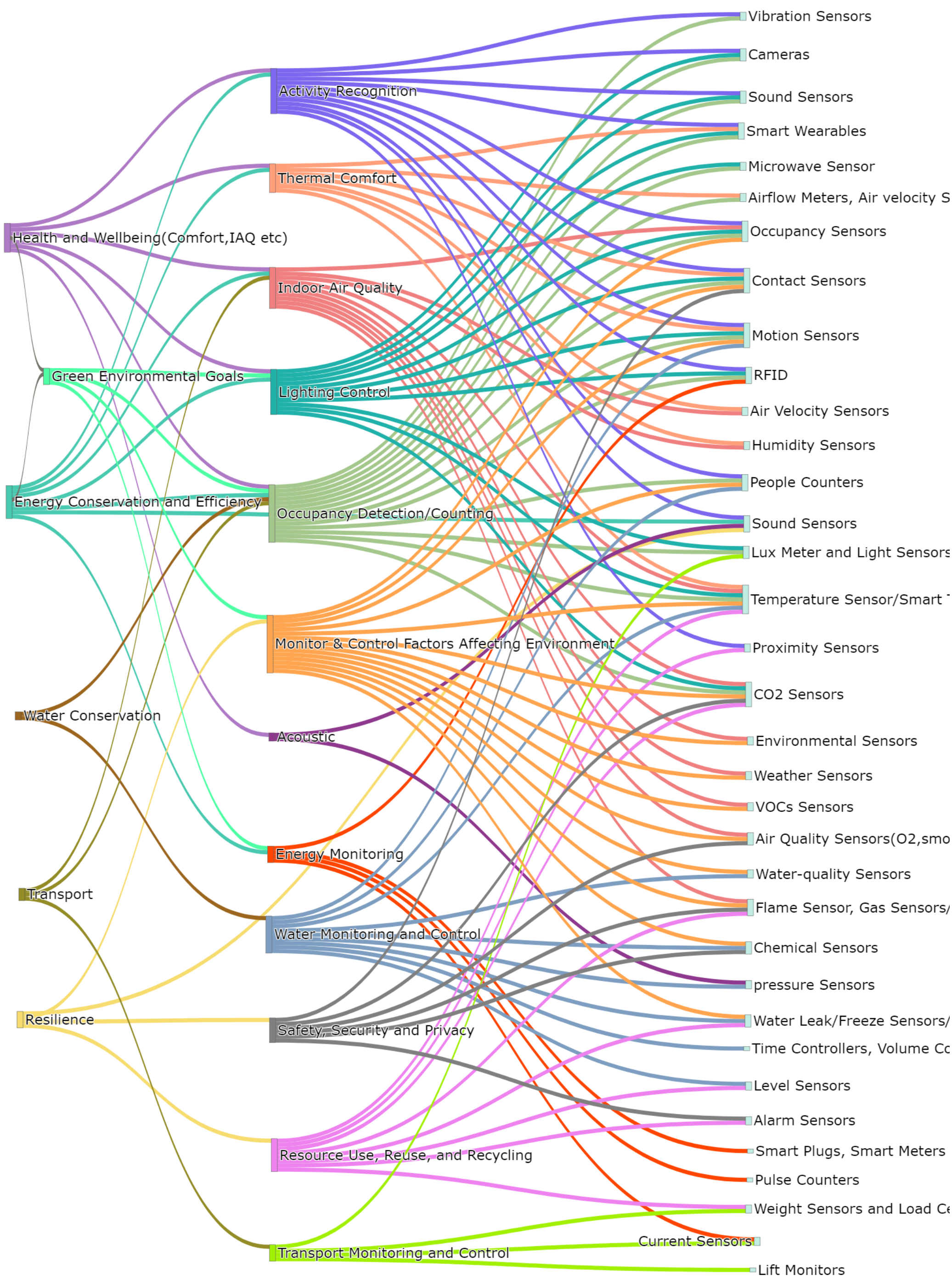

Fig. 7. Commonly used sensor combinations to achieve sustainability goals (better viewed in colors)