Human–Building Interaction Towards a Sustainable Built Environment: A Review

Devmane Suhas P.
School of Computer Science and Informatics
Cardiff University, UK
Devmanesp1@cardiff.ac.uk

Omer Rana
School of Computer Science and Informatics
Cardiff University, UK
RanaOF@cardiff.ac.uk

Charith Perera
School of Computer Science and Informatics
Cardiff University, UK
PereraC@cardiff.ac.uk

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Abstract

Human Building Interaction (HBI), a recently introduced emerging area, can be used for various purposes, including the development of better designs, constructions, and operations, as well as the support of building managers and occupants in meeting their goals. The expanding community of HBI researchers seeks to investigate the future of HBI research and design for an interactive built environment. Building managers and owners strive for energy-efficient, sustainable, and more livable buildings to improve and become 'smart.' Diverse buildings and urban spaces are individually designed and outfitted with various systems, components, and accessories. With the advent of the Internet of Things (IoT), these devices form a network of internet-connected 'things' that generate massive amounts of data. We can collect vast volumes of data in unprecedented numbers, providing critical insights that allow buildings to care for us by learning from acquired data and adjusting to our requirements.

This paper contributes to HBI by surveying various efforts to interact with buildings using IoT sensors and interconnected things to gain useful insights. Buildings, in our perspective, have distinct personalities and obligations to achieve their objectives. So, we are trying to incorporate them into reality. Considering a building to be a bio-inspired living architecture, we compare human anatomy to building anatomy to understand better the functions and operations that buildings can perform in their built environment. Thinking from this outlook allows us to investigate how sensors can help us achieve such building sustainability standards and what operations they perform to create an interactive built environment. This review paper aims to investigate the role of sensors in particular and to what extent they can provide various useful insights to building occupants and users to meet sustainability standards. We examine the most recent work on how people engage with and interact with buildings via various interfaces to achieve sustainability goals. Finally, some domain-specific challenges that limit human engagement and interactions with the built environment are discussed.

***K*eywords** Sustainable Buildings, Human Building Interactions, Knowledge Representation, Internet of Things, Semantic Interoperability

1 Introduction

Buildings are responsible for energy consumption, carbon emissions, water consumption, and many others to consider. Buildings have an impact on occupants' health, comfort, and well-being, as well as lowering productivity and overall quality of life [1]. Sensors and actuators are typically used to help building managers and owners to achieve cost-saving, efficient, and long-term goals.

We should consider potential opportunities to improve building performance through relevant standards [2, 3, 4, 5, 6, 7]. Human interaction and engagement with buildings are primarily intended to accomplish tasks, manage the built environment, and gather useful data from buildings in order to meet such desired sustainability goals. By integrating IoT [8] and sustainability standards, we can improve building sustainability, health, performance, and effectiveness to reduce the built environment's impact on the occupants and nature. Internet-connected sensor networks often provide a structured type of information with temporal and spatial characteristics that give a brief history of surroundings. In order to manage building operations and perform jobs, sensor networks are linked to site-specific technology stacks. Each built environment is unique and uses several methods for presenting metadata. Due to the heterogeneous nature of building types, their deployed sensor types and systems, subsystem, and connected networks prevent application portability. Additionally, it makes it difficult to design a unique framework that can be used to interact with various types of buildings. Hence, the adaptive layer topic is outside the scope of this paper, as shown in Figure 1.

To truly accomplish built environment sustainability, we should incorporate sustainability standards, various sensor networks, and citizen involvement and interaction in building operations.

This paper examines how various sensors can be used to analyze human-building interactions in built spaces and explore how sustainability requirements might be met using them. This review adds to the domain by addressing the following concerns, which are reflected in Figure 1.

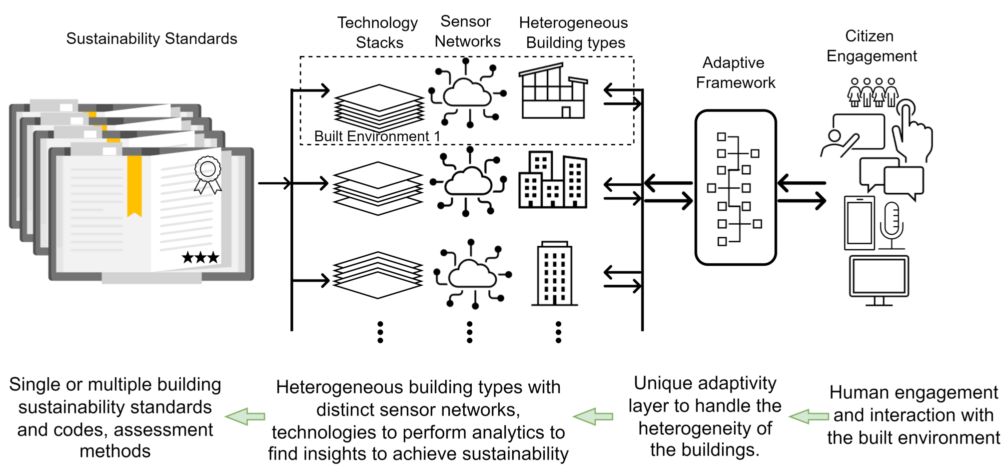

Figure 1: Human engagement and interaction with the built environment to achieve sustainability standards using sensor insights and adaptive layer

1. To analyze various sustainability standards for residential and commercial buildings and investigate various sensors used against factors impeding the achievement of desired sustainability goals.
2. To to examine some major sensors, analytics, and helpful insights used to achieve a sustainability standard.
3. To review the literature on how people engage and interact with the built environment and their necessity to participate in achieving sustainability goals.
4. To identify challenges in human engagement and sensor networks to achieve desired sustainability standards.

The following is how the article is organized: Section 2 compares smart building anatomy to human anatomy to better understand the role of various sensors in various systems in the built environment. Different human anatomy functions are logically compared to equivalent functions of building anatomy and components. Section 3 describes various sustainability standards and their scope of various factors in a built environment where sensors can help achieve sustainability. Among the standards mentioned, we explained some major factors affecting sustainability. We discussed the major impediments to sustainability and their causes, the various sensors used, and the critical insights.

Current trends and technologies are reviewed to understand the necessity of human engagement to achieve building sustainability. Section 4 describes sensor insights and factors that affect sustainability by utilizing an ontology of occupancy detection, thermal comfort, indoor air quality, and energy conservation. Section 5 reviews recent attempts to interact with the built environment using sensors and various interfaces. Section 6 explains some domain-specific challenges while excluding common IoT system challenges. Section 7 summarises the conclusion.

2 Anatomy of a Smart Buildings

Biology is beneficial in solving domain problems in various scientific branches such as biochemical, biomechanical, bio-electronics, bio-computing, and so on. Furthermore, due to future opportunities, bio-inspired or brain-inspired computing is on the rise. Humanoids are bio-inspired robotics with mechanical designs with biosensors, bio actuators, and bio-materials biologically inspired by eyes, muscles, and spider silk, respectively used in healthcare, manufacturing and maintenance, research, and space exploration, among other fields. We can construct a semantic network of interconnected systems by contrasting human anatomy with the anatomy of buildings. The table 1 compares human anatomy to interactive building anatomy containing similar systems mimicking similar functions. It shows how building systems are similar to human anatomy systems in that each system plays a unique and distinct role, yet all systems are interdependent.

Sensors play a pivotal role in mimicking the human nervous system as part of the built environment. We are thus focusing our efforts on building's communication system that mimics the human nervous system. The Human nervous system performs four major functions: Reception of general sensory information (touch, pressure, temperature, etc.), reception and perception of special sensations (taste, smell, vision, etc.), integration and processing of sensory information from various parts of the body, and response generation [9]. Similarly, various sensors help mimic the human nervous system to form an interactive communication system linked to all other building systems in the built environment. This happens in four stages (1) Sensation: the perception of changes occurring in the body. (2) Response: the brain generates a response for the body; (3) Integration: the processing of the response generated on the target; and (4) Control: the co-response of other body parts other than the target [10].

Human Anatomy Systems	Function	Building Anatomy Systems	Function	Interactive Building Components
Immune systems	Protect the body against outside invaders	Security and safety systems	Provide security to the built environment against theft, intruders	Alarms, surveillance, intrusion detectors, motion detectors, fire detectors, access systems, smoke detectors, window/door sensors, monitors, etc
Lymphatic and urinary system	Remove cellular waste and fluids	Drainage/sewer system	Remove wastewater, and gases outside buildings	Plumbing, surface water drainage, foul drainage systems, leakage sensors, and moisture detectors, ventilators
Endocrine and cardiovascular system	Deliver important substances to cells and organs for various functions	Power systems/electricity/gas	Provide various power sources to perform different tasks	Electricity supply, gas supply systems, water supply through pipes, heating systems, cables, etc
Respiratory system	Helps breathe, clear waste gases from the body	HVAC	Create a safe, convenient, healthy atmosphere to work by removing used air	Heating, ventilation, air-condition, humidifiers and dehumidifiers, scent, and air quality monitors, etc
Digestive and renal system	Digest, absorb nutrients from eaten food get energy, growth, and dump waste outside	Sanitation system	Remove and recycle waste products, keep the built environment safe and clean	Waste management, recycling, plumbing, cleaning service and supplies (soap/detergent, paper, hand sanitizer, etc)
Muscular system	Helps the body move	Motion systems	Allow occupants to move from one location to another	Elevators, escalators, moving walkways, trams, wheelchairs, carts, wayfinding, and traffic management
Nervous system	Control all movements, automatic responses to the outside world	Communication system	Detect, command, control, and communicate physical environmental factors	Phones, internet service, Wi-Fi, SCADA, Sensors networks, connected assets, etc
Skeletal and integumentary system	Support body structure and allows movement, etc	Structural body	Gives secure and solid structure to work and live	Foundation, permanent and flexible support structures, materials and facades, windows, doors, etc

Table 1: Comparison of human anatomy to the anatomy of an interactive building

The table 2 describes how sensors and devices help communication systems perform tasks in every stage of communication.

Human Nervous System	Interactive Buildings Communication	Description
Sensation	Sensing and connectivity	Sensors receive data from the environment and send the data to the target location for processing further via different communication protocols
Response	Data processing	Once the data is accepted, the software performs some kind of processing on it.
Integration	Actions/User Interface	The processed data is used to perform actions on the actuators via communication protocols or processed data is sent back to the occupant with useful insights or information
Control	Automation and customization	While performing a single action, custom rules and settings are used to adjust other relevant tasks or settings without the need of the user.

Table 2: A constructed environment's stages of communication resemble the human nervous system

Before delving into the sensors used to achieve the human-building interaction goals, it is critical to understand why they are being used. Most of reasons are related to meeting the goals of building managers or owners, such as achieving sustainability standards or providing a comfortable experience for their occupants.

3 Sustainability standards

There are numerous reasons why building sustainability is critical. Climate change is a real threat to the future, exacerbated by buildings, and we must not ignore the consequences for future generations. The majority of greenhouse gases are produced by heating and energy consumption in buildings [11]. To achieve the net-zero target, owners and managers must measure and reduce carbon emissions and energy consumption in the built environment. Conversely, the outdoor environment impacts our buildings, their occupant's health, and energy consumption [12].

Sustainable buildings can preserve and improve the quality of life while blending in with the local climate, tradition, culture, and environment.

Sustainable buildings improve and sustain the local and global ecosystems throughout the building's life cycle while protecting occupant health and productivity. The overall goal of all residential and non-industrial international codes is similar, but the procedures and recommended set points in designs differ. Some countries and territories have their own customized standard code for building design, construction, and operation, and only a few adhere to other international standards to achieve global standardization. Table 3 provides some illustrations of useful benchmarks for attaining sustainability and pertinent objectives based on the location and jurisdiction of the built environment.

Origin	Reference	Sustainability Standard	Coverage of Factors
US	[13]	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	[14, 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 plans for operation, etc.
US	[16]	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	[17]	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 enhance biodiversity and ecosystem services, promote sustainable and regenerative material cycles, enhance community quality of life, etc.
USA	[18]	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.
USA	[19]	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.
USA	[20]	The International Living Future Institute's Living Building Challenge, version 4.0 (ILFI-LBC)	Place, water, energy, health and happiness, materials, equity, beauty, etc.
UK	[2]	Building Research Establishment's Environmental Assessment Method (BREEAM)	Management, health and wellbeing, energy, transport, water, resources, resilience, land use, and economy, pollution, etc.

Table 3: Some popular standards for Buildings focusing on different building aspects.

Researchers have created innovative building architectures ([21, 22, 23, 24, 25]etc.), frameworks([26, 27, 28, 29, 30] etc.), and prototypes ([31, 32, 33] etc.) to achieve such sustainability standards, which can be studied further to gain a more in-depth understanding of the benefits of making our buildings more liveable. A sustainable built environment can be achieved using sensors and various communication technologies. These built environments are intelligent enough to make decisions based on data collected from our daily activities. IoT devices enable us to interact with them and control our environment, allowing us to operate our built environment comfortably and safely. Human-building interaction benefits from the semantic representation of the built environment. Further subsections discuss these sustainability goals and the relevant sensors used to achieve them.

3.1 Health and Wellbeing

The internal environmental conditions of a building have a significant effect on our physical and mental well-being. Over 90% of all people's lives are spent in or near buildings, with the rest spent traveling between them [34]. Higher-risk individuals, such as the elderly, disabled, and sick, can suffer from various other health effects caused by their environment, many of which can be severe and even fatal[35]. Eye strain, cardiovascular and coronary problems, bronchial complaints including asthma and allergies, dermatological complaints, musculoskeletal problems, and various psychological effects such as headaches, fatigue, stress, anxiety, and depression are all associated with building's Indoor environmental quality [2].

Intelligent buildings should provide safe, comfortable, and healthy environments to their occupants internally and externally and support their residents' health, well-being, and productivity. In order to reduce psychological and social stress levels, promote human well-being, develop a productive and healthy built environment, and enhance productivity and overall sustainability, it is essential to consider the occupant's stochastic and challenging psychological behavior over the entire life span of a smart built environment [36]. Referring to UK's new standards, new homes will be required to emit 31% less CO_2 in 2025 than in 2021 [37][38], and new homes should be fit for the future by reducing emissions by at least 75% to deliver greener buildings [39].

Indoor environment quality (IEQ) is an essential factor influencing occupant's health, comfort, and productivity. A well-balanced ventilation system ensures that there is always enough air for all areas. HVAC systems are outfitted with various adjustable sensors and actuators, commonly managed by today's Building Information Modeling (BIM) software. To provide fresh air supply, Variable Air Volume (VAV) dampers automatically regulate the zonal airflow rate of the supply air and room/duct pressure based on the occupancy detection, CO_2 level, or other factors measured by air quality sensors. The aspects of the built environment that impact occupants' health and well-being are included in Table 4. [1]

	Factors	Applicable Sensor Types	Sensor Insights and Applications
Health and Wellbeing	Thermal comfort	Temperature sensor, humidity sensor, thermostats, fan dimmers	Indoor air temperature, mean radiant temperature, air velocity, relative humidity, solar heat, and draughts from window, ventilation, heating/cooling system, mean radiant temperature
	Lighting levels	Light Sensors (photoresistors (LDR), photodiodes, phototransistors, etc)	Ambient light quantity, internal lighting level, external light level
	Lighting control	Photoelectric sensor, motion detectors, PIR sensors, microwave motion sensors, day/night sensors, solar LED	Quantity, quality, glare, daylight
	Indoor air quality and ventilation	Occupancy, motion detectors, temperature sensors, humidity sensors, pressure sensor, carbon monoxide (CO), CO_2 sensors, hydrogen sulfide, sulfur dioxide, chlorine, nitric oxide, nitric dioxide, hydrogen, ethylene, ammonia, ozone, ethylene, halothane, isobutylene, ethanol, propane, butane many, radon sensor/detector and monitors, smoke detector, motion sensors, occupant behavior	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, 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

Table 4: Factors affecting health and wellbeing showing sensors scope

3.2 Energy

To keep climate change from worsening, we must reduce our energy consumption and use more renewable energy sources. According to estimates, behavior can increase residential building energy consumption by up to 75% [2]. Demand-side management (DSM), monitoring energy performance, lighting, transportation, ventilation, heating, cooling, and distribution, electric devices, renewable heating and cooling, temperature controllers, generator and generator modulation, HVAC control and run-time management, and so on are examples of energy consumers.

Energy sustainability can be attained by performing tasks like calculating and monitoring the energy efficiency of installed services, systems, external lighting, and elevators, improving renewable energy generation capacity, energy monitoring, and management capabilities, performing energy audits, reporting energy consumption, monitoring emissions reduction, paying attention to operational energy performance, minimizing car trips, reducing traffic, and many other things.

All homes and businesses must strictly adhere to new energy efficiency standards to reduce energy consumption and bills to protect the environment. For example, the United Kingdom's new standards aim for all homes to be highly energy-efficient, as heating and powering buildings currently account for 40% of total energy consumption [40]. Under the Climate Change Act 2008, amended in 2019, the United Kingdom is committed to achieving net-zero GHG emissions by 2050 [11]. In 2019, energy usage in residential buildings accounted for 13% of the UK's GHG emissions, and HVAC systems accounted for 47.7% and 51% of energy consumption in residential and office buildings, respectively [41]. The table 5 shows various energy-consuming factors that can be monitored, changed, and improved using sensors and devices.

[1] The middle column lists various sensors that can measure and regulate the relevant factor by configuring the appropriate entity parameters. This right column displays numerous sensor insights each can extract to fulfill sustainable built environment goals.

	Factors	Applicable Sensor and Devices	Sensor Insights and 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 sensor, smart thermostats, CO_2 sensors, humidity sensors, VOCs sensors, airflow sensors, pressure sensors, pressure transducers door/window sensors, leak detectors, hall-effect position sensor, 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

Table 5: Factors affecting Energy usage showing sensors scope

3.3 Transport

Innovative lifts can help reduce greenhouse gas emissions from transportation in the built environment. Air pollution not only harms animals and plants but also has an impact on biodiversity and crop yield. Air pollution causes 4.2 million premature deaths worldwide, and reducing air pollution levels can reduce the burden of diseases from stroke, heart disease, lung cancer, and respiratory diseases [2]. Indoor path planning in buildings can help reduce energy consumption. Table 6 shows different components where sensors will contribute to the transport-related sustainability achievement goals.

	Factors	Applicable Sensor and Devices	Sensor Insights and Applications
Transport	Lifts, escalators, elevators, walkalators(moving walk), conveyors, dumbwaiters, material lifts, stairway lifts, wheelchair lifts	Occupancy sensor, motion detectors, weighting sensors and load cells, current sensors, current transducers, energy monitors, air quality sensors, CO_2, temperature sensors, humidity sensors, fire detectors, smoke detectors, parking sensors	The efficiency of elevator, access control, monitor energy usage, occupancy, guidance to the right elevator, air quality, the comfort of occupants

Table 6: Sources of indoor transport and possible sensor insights for sustainability

3.4 Pollution

This category deals with mitigating and preventing pollution brought on by the placement and utilisation of an asset. Avoiding indoor pollutants makes it easier to lessen the adverse effects that flooding and air, land, and water emissions have on the environment and its inhabitants. Pollutants negatively impact health and well-being over time. The United Nations has designated "good health and well-being" as one of its SDGs, with the goal of "significantly reducing the number of deaths and illnesses from hazardous chemicals and air, water, and soil pollution and contamination by 2030" [2]. If any, watercourse pollution and pollution associated with indoor chemicals should be prioritised in sustainable buildings. The sensors support the achievement, measurement, and improvement of local air quality as well as the detection and monitoring of refrigerant leaks, the reduction of light pollution, the mitigation of land contamination, the awareness of invasive plant species contamination, the control and prevention of both airborne and waterborne pollution, the reduction of pollution risk to the surrounding environment, the reduction of acoustic pollution, and the monitoring and reduction of various types of fuel combustion and emissions. Table 7 depicts several pollution sources and sensor types that can be utilised to gain valuable insights that can be used to establish a sustainable built environment further.

	Sources of Generation	Sensor Type	Sensor Insights and Applications
Pollution	Contamination, assets, moisture, tobacco, combustion, building materials, chemical storage, radon, particulates, refrigerants	Temperature and humidity sensors, air quality sensors, pressure sensors, optical particle counters	Nitrogen, phosphorus, potassium and pH, temperature, humidity, PM2.5, PM10, atmospheric pressure, light, TVOC in the air environment, CO_2, formaldehyde, O_3, CO, CH_4, O_2, SO_2, NO_2, H_2, H_2S, NH_3, rainfall, radiation, gases, water level, pressure, quality

Table 7: Factors affecting pollution and showing sensors scope

3.5 Water

Sustainable buildings should save water and reduce water consumption over the lifetime of the building with no leaks, aiming to reduce the number of people suffering from water scarcity while also meeting future demand. If we cut leakage by half and reduce per capita consumption to 100 litres per person per day, we could provide enough water for over 20 million more people by 2050. [42]. Water consumption, energy consumption, and carbon emissions are all interconnected. Sensors are deployed to increase water efficiency, prevent leaks, and thus reduce emissions. There has been some debate about a practical and effective method for installing sensors in water networks to detect and locate failures [43].

Table 8 shows different types of water consumption sources that can be monitored and controlled by respective sensors and their insights.

	Consumption Sources	Applicable Sensor and Devices	Sensor Insights and Applications
Water	Toilets, urinals, taps, showers, bath, drinking, sanitation, washing, leakage, appliances	Leak detectors, occupancy detectors, temperature sensors, pressure sensors, proximity detectors, time controllers, volume controllers, presence detectors and controllers, water control system, water quality sensors	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

Table 8: Factors affecting water usage showing sensors scope

3.6 Resources and Resilience

Building resilience considers an asset's exposure to physical risks and hazards preparedness and response. We should use optimised resource use, reuse, and recycling to achieve a sustainable and green environment. Sensors may aid in the circular use of physical resources and the reuse of recycling facilities. Laser, weightage, and ultrasonic sensors are used in intelligent waste bins for waste classification, hazardous waste identification, and waste monitoring.

Table 9 shows different sensors and their necessary insights for the applications.

	Sensors/Devices	Sensor Insights and Applications
Resilience	Water alarm, 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	Fire safety management, evacuation, climate monitoring, climate-related transition risks, social risks, fire risk management, security risk assessment, recovery, outdoor/indoor air quality monitoring

Table 9: Factors affecting on building resilience and possible sensor insights for sustainability

3.7 Land Use and Ecology

This pillar of sustainability standard aims to maximise the ecological value of a building's existing features and the surrounding area, both indoors and out. Green homes are more concerned with optimising space utilisation for improved occupant health and productivity. Planted areas, green walls, and green roofs, as well as the ecological features of the planted area, can be tracked, monitored, and automated in the built environment using moisture, soil, air quality, and temperature sensors. It has also been observed that occupants prefer a pleasant environment and visual content in their workspaces, such as urban or natural views, which aids productivity and well-being [44].

4 Sensor Insights

There are numerous applications and reasons for installing sensors, and multiple tools and methods can be used to analyse such data. Factors such as temperature, humidity, CO_2 levels, and much more influence the indoor environment and contribute to the health of occupants and the building's sustainability. However, it is necessary to consider the significant factors that prevent buildings from becoming environmentally friendly and sustainable first. This section discusses three primary goals for achieving sustainability: thermal comfort, indoor air quality, and energy sustainability.

4.1 Sustainable Goals

4.1.1 Thermal Comfort

Building managers strive for energy efficiency without jeopardising occupant health and well-being. Traditional HVAC systems have been shown to use lower temperature setpoints to save energy. However, lower temperatures do not constantly improve human thermal comfort. From a recent survey [45], it has been seen that occupants are dissatisfied with the building's indoor environment due to a lack of control over the acoustic and thermal environment in terms of temperature and air movement. Dynamic control of HVAC systems appears to be a viable option to achieve thermal comfort while conserving energy. Therefore, it is essential to take human thermal comfort and occupant-driven control of the built environment into account.

D'Oca Simona [46], surveyed interactions at work and occupants' perceived comfort, satisfaction, and productivity to find their relationships. It has been established that both natural and artificial lighting can impact productivity, as can indoor thermal comfort and indoor air quality. Finding the gender and age-related thermal comfort level, acceptability, and preference to achieve a trade-off against energy usage is a hot topic. As a result of overcooling in the US during warm weather, people are dissatisfied with their thermal comfort in the office, and women are more likely to be unsatisfied with their environment [47]. Schellen, L. et al. [48, 49], Veronica S. et al. [35] study that the thermal comfort and preferences for the different gender are nearly the same. While Ferenc Kalmár [50], Nigel A. et al. [51] found the contrary results. Finding such correlations can significantly help us to design solutions for elderly care [52].

Different sustainability standards have defined their respective thermal desirability levels in terms of standards such as ASHRAE's standardized scale of thermal desirability. ASHRAE's standard 55:2017 describes thermal environmental conditions for human occupancy. Similarly, ISO 7730 uses the same approach to analytical determination and interpretation of thermal comfort [53]. Other European standards, such as EN 16798, provide room ventilation and conditioning requirements [54]. These standards have developed several indices of thermal comfort. They have given standard acceptable temperature ranges for the buildings. However, data-driven acceptable temperature ranges are more comprehensive than their standards [55]. Thermal comfort can be defined as "that condition of mind that expresses satisfaction with the thermal environment" [56], and the PMV and the PPD indices can express these comfort limits.

- *Predicted mean vote (PMV)*: seven-point thermal sensation scale ranging from *-3:too cold* to *+3:too hot*.
- *Predicted percentage of dissatisfied (PPD)*: a quantitative prediction of the percentage of thermally dissatisfied occupants.

However, PMV has been shown to be inaccurate in predicting comfort for a small group of people [57]. As a result, additional experiments were conducted for small groups of occupants to predict comfort levels using the indices mentioned above and other factors that affected occupant comfort [58]. For the long-term thermal comfort evaluation, additional indices are proposed in addition to indices from ISO 7730, EN 16798, and ASHRAE 55 standards [59]. Nadine F. et al. [60] attempted to modify and map occupants' thermal satisfaction, preference, and desirability to the ASHRAE scale. To draw valuable insights and design the right IEQ-built environment, ASHRAE provides open-source, global thermal databases from offices, classrooms, housing, and other locations in a few countries [61]. In order to design future HBI applications, a rigid thermal desirability evaluation method must be defined.

Building ventilation must respond to CO_2 levels in the environment in order to meet health and safety standards. CO_2 exposure could have physiological and psychological consequences for building occupants. A. Mishra et al. [62] examined physiological effects on respiratory functions, indicating the need for additional research on living in a poorly ventilated indoor environment. Thomas P. et al. [63] used machine learning models to predict thermal pleasure using neurophysiological parameters. It is vital to reduce HVAC energy usage while keeping occupant comfort. HVAC systems that use sensor data and analytics to learn about individual occupants' thermal comfort create a more sustainable built environment by reducing energy consumption while improving occupant thermal comfort [64]. A much higher airflow rate is required to improve safety and thermal comfort in HVAC systems. Over traditional building-level air control, zonal air handling can help achieve energy and health sustainability standards [65]. However, When compared to overall HVAC power usage, Personal Comfort Systems (PCS) use focused local cooling or heating of the environment shows more energy saving [66]. To handle the tradeoff between energy goals and comfort satisfaction, future HBI requires integrated sensor and actuator network research systems [67]. Temperature set-points for zones or rooms are used in traditional HVAC systems. Smart thermostats, room anemometers, intelligent fans, HVAC sensors, occupancy sensors, and smart wearables can all be linked for inter-device communication, with data stored locally or in the cloud. This data can apply analytics such as machine learning (ML) and artificial intelligence (AI) to make decisions and carry out actions to achieve long-term goals. Considering all the preceding points, we can see how critical it is to consider thermal comfort to achieve good health and well-being standards. Table 10 describes how researchers use sensors to achieve thermal comfort to meet health and well-being requirements.

4.1.2 Indoor Air Quality (IAQ)

Because people spend 90% of their time indoors [68], it is evident that occupants and built environment both influence each other positively or negatively. To minimize the consequences on the occupants, it is necessary to focus on achieving healthy air quality in all building types. The concentration of particulate matter, organic gases, inorganic gases, vapours, and odours that affect human comfort, well-being, health and safety, and work performance is referred to as IAQ [69]. Smart buildings necessitate a delicate balance of IAQ optimization. Measuring CO_2 concentration alone is insufficient to achieve the health sustainability criteria. According to the above standards, several variables must be addressed while constructing and renovating a building's indoor environment to fulfil health requirements.

According to the International WELL Building Institute (IWBI), different building materials, paints, fabrics, and cleaning products emit volatile organic compounds (VOCs). Acetaldehyde, acetone, benzene, dichloromethane, formaldehyde, naphthalene, phenol, tetrachloroethylene, toluene, trichloroethane, and xylene are just a few examples of common VOCs listed by ASHRAE [70]. Other examples include CO, CO_2, PM2.5, ozone, radon, ammonia, and others. ASHRAE's standard 62.1 specify minimum ventilation rates and other measures to provide indoor IAQ that is acceptable to human occupants and minimizes adverse health effects. It is also required to think of energy conservation while improving IAQ. Sensors used to capture the indoor environment quality also helps to increase the occupants'

Reference	Year	Sensors	Dataset	Analytics	Insights	Applications
[72]	2022	Thermostat	Temperature readings	BrickSchema, mortar testbed application	Overcooling overheating fault detection and diagnostics	Long term thermal comfort evaluation
[73]	2021	Temperature sensor	Temperature readings	Questionnaire	Sex/age Vs thermal comfort	Thermal comfort
[74]	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
[75]	2021	Lux meter, light sensors	Illuminance readings	DGP	Glare discomfort	Glare discomfort
[76]	2021	Flame sensor, gas sensor/ smoke sensor	Temperature readings, a smoke sensor value	Arduino programming	Smoke/ flame indicators	Notifications, alarms, Water sprinklers, safety
[77]	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
[78]	2021	Anemometer, tachometer	Air speed, fan speed	Math: airspeed coverage index, cooling effect	Behavior of fans, quantity, direction, room geometry, and furniture density	Thermal comfort
[?]	2019	Temperature, humidity, luminosity, and wind speed	Temperature, humidity, radiant temperature, wind speed, luminosity, and PMV	Custom ontology + sentiment analysis	Measure and optimize participant's thermal satisfaction	Thermal comfort
[79]	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
[80]	2019	Bluetooth smart[81] heart rate sensor, IButton DS1923	Heat 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
[82]	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
[83]	2018	Passive infrared motion sensors, contact sensor	Door contact, room occupancy	ML: classification by random forests	Sleep time and quality, dailly habits, utility usage tracking	Activity recognition, occupancy dependent comfort, auto-schedule
[58]	2015	AeoTec MultiSensor: motion, temperature, light, humidity, vibration, UV sensor, wearable devices	Air, skin temperature, body air temperature,humidity, activity and sweat level, GSR, metabolic rate, thermal and comfort sensation, indoor location	ML: random forest and gaussian-kernel SVM	Infer/predict occupant's thermal comfort	Individual/small group thermal comfort prediction

Table 10: Thermal comfort experiments to meet sustainability standards using sensors and different analytics methods

comfort and energy savings to meet sustainability standards [71]. Building systems should efficiently provide an excellent environment to avoid impacting the occupants and environment. HVAC systems are widely installed to control the building's indoor environment, which circulates good air and temperature to the building zones. Zonal level air handling provides higher indoor air quality by increasing the air change rate in HVAC systems in buildings as compared to the building level air control [65].

Environmental sensors such as CO_2, humidity, temperature, VOCs, and many more are widely installed in green buildings to get the right environment, and sensor data is used further to take healthier actions. Green buildings improve people's health and well-being and contribute to resilient climate infrastructure by producing fewer emissions.

Many developing countries are suffering from air pollution, such as PM2.5. Several cities have air quality monitoring stations to warn people about the concentration of air pollutants to protect people's health from the harm caused by air pollution. Indoor PM2.5 can be controlled to some extent if HVAC systems or individual air filtering systems are manipulated promptly and correctly. Windows are essential in indoor air quality, glare protection, brightness control, and sunlight control. Window placement and shape should be designed with the occupants in mind rather than the architect to meet the occupants' comfort and satisfaction [84]. According to the study findings, thermal comfort factors such as temperature, airflow, and humidity significantly impact occupant perception of indoor air quality more than pollutant levels [85]. The indoor environment can be maintained to satisfy the occupant by soliciting feedback or conducting limited surveys of their comfort level and adjusting the relevant environmental parameters [86].

COVID-19 has affected millions of people. Poor air quality has been shown to increase COVID-19 infection in indoor spaces. Agarwal et al. [87] reviewed different factors affecting indoor air quality and several possible air quality improvement techniques with thermal quality and safety of occupants to avoid such consequences again. Table 11 shows some studies that use IoT sensors to monitor and control the IAQ.

Reference	Year	Sensors	Analytics	Insights	Applications
[88]	2021	RGB, thermal, depth, LiDAR, and ultrasound	-	Window status with many modalities, states, distances, and angles	Sensor data analysis and window state classifiers, thermal comfort, energy conversation, IAQ
[68]	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
[79]	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, air flow control, air cleansing, energy saving, peristome shifting	Health, comfort, and saving energy indoor
[89]	2019	Electroencephalogram (EEG) : Emotiv EPOC	ML: Classification LDA, SVM pattern recognition	Classify mental states under different	CO_2 level, IAQ control, mental health monitoring
[90]	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

Table 11: Thermal indoor environment quality studies employing sensors and other analytics methods to accomplish sustainable standards

4.1.3 Energy Sustainability

Danish Iqbal et al. [91] used an edge computing framework and concluded that intelligent buildings that use fog computing to connect their devices would save more energy than those that use cloud computing. Cloud computing platforms such as IaaS, PaaS, and SaaS [92] have grown significantly over the last decade. However, it contains security and vulnerabilities that must be addressed when implementing such models [93]. Several domains are provided by IoT cloud platforms, including application development, device management, system management, data management, analytics, deployment management, monitoring management, visualisation, and research can be used to achieve sustainable goals [94]. To achieve such human-in-the-loop architecture, machine learning, deep learning, and gamification [27] can achieve energy efficiency while minimising environmental impact. Deep reinforcement learning-based models [95] are widely used in applications such as building anomaly detection.

The LSTM model is used in a federated learning system to detect anomalies with low latency [96]. In addition to data collected from live sensors, open data sets can be used to design and develop smart home AI solutions capable of achieving sustainability goals [97]. Numerous communication technologies and protocols, such as LoRa and BLE, can be used to reduce energy consumption by IoT sensors and devices. LoRa modules consume little energy, and multiple modules can be linked to a single gateway. Over the last four years, more than 50 buildings in Sydney and Australia have used LoRa-enabled innovative emergency light solutions to save energy and improve cost-effectiveness [98]. Smart home infrastructures can use sensors more effectively to save energy as technology and IoT advance. Occupants interact with the built environment differently, resulting in varying energy consumption rates. Occupancy-driven HVAC systems can be used to save energy, which is explained in the subsection.

Such an agent/occupant-based model of occupants and their impact on electric/gas energy use in commercial buildings has been developed and can be used with energy modelling software and for individual occupant-centric decision-making [99]. The intelligent building API can also suggest potential energy-saving actions to building occupants [100]. Connected thermostats generate massive amounts of valuable data that can be analysed for occupant-thermostat interactions to improve understanding of occupant energy use behaviours [101]. Furthermore, personalised thermostat recommendations can provide automated suggestions to setpoints based on occupancy to control the temperature, thereby saving energy [102]. Machine learning is widely used in various architectures/frameworks to achieve sustainability standards. A machine learning-based regression model can forecast future energy consumption while considering other factors influencing energy consumption, such as climate change [103]. Thokala N et al. [104] proposed that disaggregated forecasting yields accurate results for lighting, HVAC system, and total power consumption forecasting. ML and deep learning algorithms assist the energy disaggregation technique in profiling energy usage, what and when appliances are used, their corresponding energy consumption (profiling), and appliance relationships [105].

4.2 Prominent Sensing Approaches

4.2.1 Occupancy Detection

Building occupants influence energy use significantly. Occupancy detection techniques are essential for thermal comfort levels, indoor air quality analytics, and energy efficiency monitoring. Occupancy-driven thermal comfort minimizes energy consumption in systems such as HVAC and indoor environment control such as lighting control. Detecting people's presence and monitoring their flows in different locations could provide valuable insights for building management to make intelligent decisions, such as human-in-the-loop HVAC operations [106] and innovative lighting systems, among other things. Depending on the application, different technologies and sensors can detect occupancy, people count or flow through direct sensing with various sensors and indirect sensing with activities tracking in the built environment, such as desktop activities, WiFi logs, and server logs. Similarly, users' and IoT devices' localization and positioning are noteworthy. RFID-based localization (passive and active) is adaptable, cost-effective, and energy-efficient, and it can be used for indoor localization, location sensing, and tracking [107]. Different wireless technologies, such as ultra-wideband (UWB), SigFox, RFID, Ultrasound, LoRa, acoustic, cameras/vision, and many more, are also available to help you locate devices and people using localization techniques [108].

Occupancy sensors are used in various intelligent building applications, including energy and space optimization. PIR sensors are widely used for automatic lighting and building environment control (HVAC), intrusion detection, and occupancy detection (security). Occupancy sensors should respond in real-time with high accuracy, resolution, low deployment cost and latency, and the appropriate communication protocols that meet standards and are non-intrusive. Selecting a sensor with the appropriate specifications for the application is vital. Like other sensors and actuators, PIR sensors are prone to failure due to various causes that can be identified and diagnosed using data mining (statistical) and external hardware. Other physics-driven fault detections and diagnostic techniques for PIR sensors have also been highly accurate [109]. Analogue output passive infrared devices, such as Panasonic's PIR Motion Sensor PaPIRs, are simple to connect to Arduino boards and detect lateral movement within a 5m range [110].

Depending on the application, different sensors are used for occupancy detection, counting, positioning, and identification [111]. Table 12 shows the number of sensors used in three application scenarios that can be used in tandem for multi-occupancy in space.

Occupancy Detection	Occupancy Counting	Occupancy Positioning
PIR/Motion, light, doppler radar, ambient conditions, RGB, WiFi, RFID, GPS, door reed switch, door counter, appliance use, electricity load, chair status, etc.	CO_2, ambient conditions(except CO_2), depth, RFID, chair, door counter, WiFi, infrared, PIR/motion, cameras, door counter	WiFi, RFID, BLE, ultra-wideband, light barrier, depth, etc.

Table 12: Use of sensors for occupancy detection, counting, and positioning

When sensor data is available, machine learning can detect an occupant's presence and count the number of occupants present [112]. Building occupancy can also be monitored using simulations and many traffic modelling software available. It is necessary to consider the user's privacy and the security of the sensor data that occupancy sensors collect because it may contain valuable information about the individual occupant. It is necessary to implement the appropriate mitigation strategies for the applications [113].

HVAC systems account for nearly half of all energy consumption in buildings. Occupancy-driven HVAC control provides more significant energy savings in conjunction with other energy-saving techniques. Furthermore, in large zones with multiple AHUs, the detection of zonal occupancy can be used to save energy and improve occupant comfort [114]. Zonal occupancy can be used to set the suitable environmental parameters based on each occupant's feedback and opinion and adjust parameters so that maximum votes for setpoints or the average of opinions are taken into analytics to satisfy the maximum zonal occupant's comfort [115]. The table 13 shows different analytics on occupancy detection by sensors for various sustainable goals.

4.2.2 Activity Recognition

Activities of daily living (ADL) in smart-home environments are a hot study topic. The behaviour of a building's occupants can significantly impact its performance, including energy consumption and indoor air quality. To achieve a higher level of sustainability, occupant interactions with the building can be linked to energy usage, comfort conditions, adaptive adjustments, and satisfaction level [116]. It is essential to comprehend how building occupants react to the indoor environment and energy consumption in their daily activities. Many applications, such as health and elderly care, rely on activity recognition [52]. Several approaches are presented to recognise the occupants' daily activities, such as cooking, eating, sleeping, etc. Non-sensor-based/indirect sensing (cameras, WiFi logs, etc.) or sensor-based activity detection are also possible; however, this article will focus on sensor-based approaches.

A significant challenge of sustainable development is to perceive changing occupant behaviour to improve energy efficiency. Understanding the occupant's behaviour is complex, and we should consider the risks and opportunities when designing activity recognition [117]. Monitoring meaningful activities with devices supports sustainability standards like health and comfort, energy efficiency, and a healthy built environment [118]. Jordan Tewell et al. [119] are concentrating on receiving finer-grained activities for applications such as determining an individual's activity. Such activities help people meet their emotional, creative, intellectual, and spiritual needs. Various systems and frameworks have been developed for recognising occupants' activities to self-manage their lives and well-being, primarily implemented in healthcare and elderly care [119]. A diverse set of motion, pressure, and beacon sensors are implemented to collect data from the built environment and used to recognise activities using trained AI reasoning modules, which can then predict activities to perform the automated task. Such trained systems set rules and make intelligent decisions based on collected data to save energy, improve environmental quality, and occupant assistance and comfort. Federico et al.[120] used fog-based activity recognition for better performance over cloud-based applications. The figure 2 illustrates the relationship between the standards, sensors, human-building interactions, and sustainability factors discussed earlier.

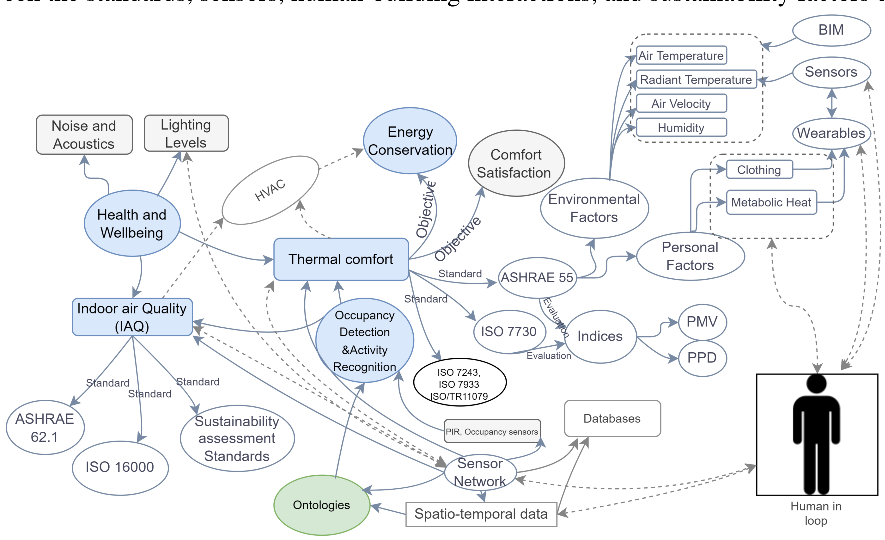

Figure 2: Ontology of standards, sensors, human-building interactions and factors affecting sustainability [121, 16, 3, 69, 67, 70, 122, 123, 45, 124, 82, 64, 125, 59, 30, 126]

5 HBI for sustainability

Interactions between humans and buildings can be visual, textual, virtual, gestural, spoken, and so on. Speech interaction and control are central to devices such as Google Home, Amazon Echo with Alexa, and Google Assistant. Anbarasan et al. [33] used speech and gestures to help older people control home appliances and perform tasks. For interaction and visualisation, smartphone-based applications and APIs are used. However, smartphones are more likely to attack smart

Reference	Year	Sensors	Analytics	Insights	Applications
[129]	2021	TENG-based gait sensor	Deep learning: residual dense-BiLSTM,	Activity recognition and individual identification	Activity recognition, individual identification, and personal health care
[130]	2020	Laser doppler vibrometer	Deep learning CNN	Home activities recognition	Energy and water saving, energy monitoring, electrical safety
[32]	2019	Intel RealSense depth camera D415 and microsoft kinect camera	Object detection system YOLOv3 on raspberryPi	Occupancy, number of people	Energy efficiency, indoor environmental quality
[131]	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
[132]	2018	Temperature	Swarm-based optimizer, EnergyPlus simulator, OMOPSO algorithm	Temperature schedules for thermal comfort, energy conservation	Improved thermal comfort and energy efficiency
[133]	2018	EnergyPlus: Ambient factors, temperature, HVAC data, heat source information	ML: support vector regression (SVR), recurrent neural network (RNN)	Occupancy detection	Energy efficiency, security monitoring
[134]	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 wellbeing
[135]	2018	Occupancy sensor data, HVAC dataset	ML: Nonlinear autoregressive network with exogenous inputs (NARX)	Occupancy prediction, estimation of number of occupants	Energy efficiency
[136]	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
[137]	2017	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
[138]	2017	Air quality sensors, VOC	ML: classification	Occupancy detection (Binary)	Energy consumption
[139]	2016	Massachusetts Institute of Technology (MIT) smart home dataset	Deep learning: quick propagation (QP), levenberg marquardt (LM) and batch back propagation (BBP) artificial neural networks ANNs	Activity recognition	Energy saving, security, health care and home care
[29]	2014	Temperature, occupancy sensor, HVAC data	Model predictive control MPC framework	HVAC control, occupancy prediction	Energy efficiency
[140]	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
[141]	2012	WiFi-connected devices e.g. smartphones, mobiles	WIFI wireless APs, indoor positioning system (IPS) algorithm	Web UI occupancy, zonal occupancy detection and tracking, monitoring	HVAC/lighting automation

Table 13: Different analytics on occupancy detection and recognition by sensors for various sustainable goals

homes [127]. Using frameworks such as SenseRT, which provides a visual representation of all processes for better interaction, it is possible to monitor in-building real-time sensor data flow and data analysis with minimal latency for crucial applications [128].

Table 14 lists recent works to achieve a sustainable built environment using various sensors to achieve respective sustainability goals.

	Sensors												Sustainability standard					
Reference	Temperature sensor	Humidity sensor	Flame sensor, gas sensor/ smoke sensor	Cameras	Environmental sensors	CO_2 sensor	Wearable sensor: temperature, heart rate etc	RFID	Lux meter, light sensors	Contact/motion/occupancy sensors	Airflow meters/anemometer	Velocity sensors	Energy Efficiency	Health and wellbeing	Thermal comfort	Indoor air quality	Occupancy detection or prediction	Safety/security
[72] [73]	✓														✓			
[75]									✓					✓				
[76]			✓															✓
[77]	✓					✓					✓				✓			
[78]											✓				✓			
[123]	✓	✓							✓		✓	✓			✓			
[80]							✓								✓			
[82]	✓	✓				✓									✓		✓	
[83]										✓						✓	✓	
[58]	✓	✓					✓		✓	✓				✓	✓			
[122]	✓												✓		✓			
[79]	✓	✓			✓	✓					✓	✓	✓			✓		
[89]	✓													✓				
[132]	✓												✓				✓	
[133]	✓	✓								✓			✓				✓	✓
[135]										✓						✓	✓	
[137]	✓	✓			✓								✓			✓	✓	
[138]					✓								✓					
[142, 143, 144]								✓					✓				✓	
[145]	✓	✓				✓				✓			✓				✓	
[136]						✓							✓			✓	✓	
[146]							✓										✓	
[32]				✓													✓	✓
[147, 148]				✓													✓	
[149]	✓	✓							✓				✓					
[29]	✓									✓	✓	✓	✓				✓	
[30]	✓	✓				✓			✓	✓					✓			
[150]					✓								✓				✓	

Table 14: Reviewed literature on sensors usage to achieve sustainability standards

Such devices may not be appropriate for all users, including the deaf and people with disabilities. Screen readers and accessible displays may be appropriate for this group of people [21]. A combination of different modes of communication with buildings may be the solution for covering all types of occupant groups. Multimodal interaction for users is recommended and explained by W3C [151]. Various experiment [152, 153], reviews [154] and case studies [155] have recently demonstrated the importance of human-building interaction and the challenges of achieving sustainability standards through occupant collaboration with the system via various interfaces (textual, spoken, gestures, etc.). Eyeblink, eye movement, and head motion can also be used for interaction and activity recognition [156]. A key consideration in developing and implementing any innovative building technology is human interaction in the context of cyber-physical systems. Offering occupants the opportunity to influence their built environment's physical, spatial, and social impacts is a critical component of HBI design [157]. HBI is a new topic proposed by human-computer interaction researchers that aims to uncover research opportunities and challenges that may arise from discussion and debate by 2030. HBI is an interdisciplinary domain for interacting with architecture and urban areas, focusing on 'environments' to benefit from HCI theories and practices.

HBI is primarily concerned with architecture and sees 'time' and 'scale' as primary challenges in defining the future. It combines the fields of architecture and building interaction design. HBI also focuses on developing creative strategies for dealing with emerging phenomena such as artificial intelligence and new modalities of engagement in built environments. As a result, achieving HBI goals will necessitate extensive study and research from current communities.

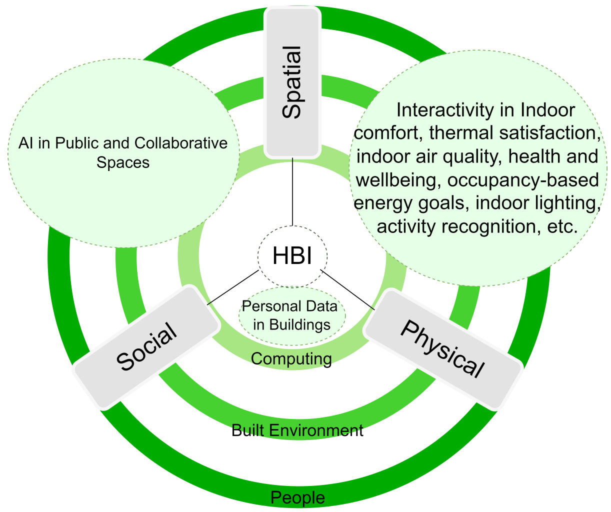

Figure 3: Three dimensions of HBI research and interconnected aspects [158]

HBI is a sophisticated field of study focusing on human values, needs, and priorities while achieving common goals like improving efficiency, cost, and sustainability in built environments. This collaboration between humans and the built environment began with the advent of IoT, and many researchers are investigating how they can further benefit from HBI. Domains such as Smart Homes[159, 160, 154, 52, 161], Autonomous Buildings [162], Robotic Home [163], Ubiquitous Domestic Environment [164], Intelligent Building [165], Living Building [166] can be a subset of "in" future, HBI.

The goal of human-building interaction is to examine the building as a multifunctional system with three interconnected aspects: physical-material, spatial-configurational, and social-cultural [158]. Various research themes fall within these three dimensions, while others fall within all three dimensions. For example, human comfort research questions may range from physical (Indoor Environmental Quality) to spatial (visual attributes, such as zonal temperature). Various recent attempts demonstrate methodological development and design-related scope for HBI. The Figure 3 depicts three dimensions of HBI research and their interconnections. IoT and intelligent building technologies are critical for achieving goals such as a comfortable indoor environment. The scope of HBI includes communication between humans and buildings to complete tasks using devices and taking care of occupants' feelings, emotions, and comfort. For example, Bohyeon Lim et al.[167] conducted a qualitative experiment to distract patients and occupants from anxiety and discomfort in a hospital waiting area by implementing an interactive environment in the waiting area using a TV monitor, which is shown to be ineffective. The experiment demonstrates the need for HBI capable of meeting occupants' functional, aesthetic, comfort, health, and safety needs and their anxiety. David Kirsh [168] investigated the thinking of HCI practitioners and architects and concluded that architects play an essential role in designing the user-centric interface.

Michelle Annett et al.[169] conclude that by implementing HBI, the next generation of workshops could benefit from intelligent sensing in the built environment. This experiment demonstrates the importance of HBI, who addresses technical and philosophical challenges in the built environment. Furthermore, HBI can be used to interact with the built environment and its occupants by giving the user control over comfort levels and assessing valuable information within the built environment. Using this concept of an adaptive built environment, Patrick Bader et al.[170] created a prototype 'WindowWall' by mounting a bright window on a wall and designing it so that the user can control the outside view and natural indoor lighting via a smartphone interface. Such displays provide valuable information on the screen to residents, allowing them to make decisions and take actions that contribute to the building's sustainability.

Augmented Reality (AR) is a real-time presentation of digital information combined with the real world [171]. In many fields, including marketing and tourism, virtual reality (VR) uses head-mounted displays to display information depicting a virtual environment to the user [172]. Mixed Reality, Extended/Cross Reality (XR), and Immersive Reality (IR) are technologies with various meanings and applications for simulating the real world[173]. Different simulation programmes, such as EnergyPlus, Modelica, Radiance, and MATLAB/Simulink, are widely used in building management and can be linked to one another via the HABIT toolkit, which was recently proposed by Jared Langevin et al. [174]. Table 15 compares several interfaces utilized or studied by researchers to regulate, monitor, and perform operations toward sustainability goals for interaction between the building and building stakeholders.

References				Interaction Interface
Focused on Sustainability Standards			Others	
Health and Wellbeing	Energy	Indoor Environment Quality		
[175, 176, 33, 177]	[178, 179]	-	[180, 152, 181, 182, 183, 33]	Conversational AI: speech/text
[23, 184]	[23]	[23, 184]	[185]	Extended Reality (XR) (AR+MR+VR)
[170]	[128, 186]	[170, 186]	[187, 188, 189]	Visualization and monitoring (monitors, displays, etc)
[32, 190, 191, 192]	[193]	-	[101, 33]	ML based applications using algorithms (Camera, gestures, postures, etc.)
[194, 195]	-	-	-	Robots
[76, 27, 155, 153]	[27, 84, 100, 174, 102]	[76]	[26, 30]	Applications/software, widget, frameworks, interface, smartphone APIs
[86, 64, 123, 46, 196]	[64]	[46, 196]	-	Surveys and feedback

Table 15: Potential human interaction interfaces used to communicate with buildings

Companies such as Meta Platforms, Inc., Microsoft, PTC Inc., Apple, and Deloitte have created devices and technologies that allow users to interact with reality. There are significant differences between AR and VR. VR experiences can be fully immersive, semi-immersive, or non-immersive. These technologies can be used in HBI to interact with one another in order to achieve user-centred management goals and sustainability standards. Nguyen B. et al.[23] used semi-immersive cross-reality simulation to determine how a responsive wall influenced common inhabitants' experience of space in their everyday homes. This experiment further investigates the use of HBI in architecture for human-centred design. AR can be used to control HVAC in self-aware intelligent buildings. Muhammad Aftab et al.[185] tested such a prototype to achieve human-building interaction, which provides intuitive user interfaces for building systems and captures the physical structures, properties, and materials of buildings to enable real-time building simulation and control via augmented reality. AR-enabled systems recognise building geometry, visualise simulations, and respond to user input. Intelligent indoor environments in homes include various types of smart devices and home assistants for security, planning, entertainment, and others. According to a recent survey by Samantha Reig et al.[197], occupants expect their future devices to have more control over their physical environment. Adaptive architectures or adaptive buildings are powered by data collected from various technologies embedded in the environment and shared with people, and they will shape our future human-building interactions [25].

Several sensors generate data with a timestamp to gain a comprehensive understanding of processes over time and monitor system performance. Databases like InfluxDB, Kdb+, Graphite, Prometheus, and RRDtool are widely used to store temporal aspects of sensors that are not stored in SQL structures [198]. MySQL, a traditional SQL database, and MongoDB, a NoSQL database, are used to store IoT data, and both have advantages and disadvantages. As a result, selecting the appropriate database depends on the application's requirements [199]. Natural language queries can be sent to the database to retrieve sensor time series data with visualisation to make crucial decisions and perform additional operations. Andrew Rocha et al.[175] recently developed a search engine system capable of querying the database in natural language to retrieve sensor time series data with graph visualisation. For example, they asked a simple natural language question: *You are looking for sensors that detect room temperature. Can you provide a list of sensor names associated with room temperature?* As a result, the query retrieves time-series sensor data.

6 Research Challenges

IoT technology brings a set of typical difficulties. New technologies, techniques, software, and strategies are being formulated to overcome these problems. Some typical problems have a significant impact on sustainability and should be considered. We have seen sustainability standards thus far, as well as human involvement, a variety of built-environment interfaces, sensors, and their insightful data. We have seen the reasons for the necessity for such sustainability requirements combined with human participation to achieve building sustainability. Along with basic issues, we have dealt with issues that limit human interaction to create a sustainable built environment. Additionally, there are still some challenges with combining sensor networks and built-in technologies to achieve the sustainability goals of the building.

6.1 Sensors: Placement, Type and Quantity Selection

To achieve the desired efficiency and sustainability standards, the location of the various sensors should be considered. Furthermore, to understand the environment well, the sensors should be placed in an appropriate location to receive the appropriate conditions for the application. For example, demand-controlled ventilation saves energy while preserving acceptable indoor air quality. To achieve these objectives, researchers discovered that the location of the CO_2 sensor is critical in a CO_2-based demand control system [200]. Furthermore, determining the appropriate number of sensors to perform the application/task is critical to reducing energy consumption and resource usage and achieving long-term goals. Adding more sensors generates more data, necessitating more storage space and processing power to analyse. When designing the sensor network architecture, it is critical to determine the minimum number of sensors required while maintaining the same accuracy, performance, energy efficiency, and coverage rate [201], which can be discovered using various frameworks [202]. In some scenarios, such as a sensor network, where each node sends different data to the receiver, the data collection process is enhanced by adding additional nodes to send the packets [203]. Smart metres in buildings can detect anomalies and power theft without compromising observability if placed in the right location and position [204].

6.2 Human Engagement and Interaction

One of the issues in the built environment is selecting the correct communication interface so that the building can connect with any user and cover the highest amount of human interaction. Recent HBI research focuses on the direct occupant-driven environment for overall sustainability. Building users frequently experience problems with their built environment due to a lack of understanding about the factors affecting their environment and how they can be controlled. In addition, most occupants do not have direct access to the building's system.

Building professionals typically have access to information that residents do not. Therefore, building managers and owners may need the training to comprehend their environment fully. Building managers and owners must give important information to inhabitants through various techniques, such as giving building information sheets, digital displays, input and output devices, mobile APIs, and others, to establish a sustainable built environment. Allowing users to manipulate and manage as many features of their personal spaces as feasible would assist them in accomplishing these goals. The infrastructure and framework can be designed to prepare and motivate users to take action, making them an integral part of the building ecosystem [205].

One of the challenges in IoT is enabling the user to control smart devices to perform operations or commands to achieve desired tasks [206]. Therefore, users must understand how to control or perform actions in order to perform specific operations. One simple solution is to provide a graphical user interface (GUI) to help users understand what components, sensors, and actuators are installed and how they work. GUI's are extremely useful for analysing data over time or visualising performance. Other voice-based user interfaces, such as Google Home and Amazon Echo/Alexa, have been developed in the current era to assist users who are unfamiliar with the structure. Users do not need to interrupt their activities and can send voice commands to the voice receiver from any location without moving to the GUI input device. Voice interfaces are the most goal-oriented and basic type of UI for non-technical users. Conversational AI allows us to interact with technology using our natural language(voice/text) [152]. The voice messaging system [180] demonstrates the utility of using voice messages to communicate with users who cannot read or write.

Several companies are already using AI-powered chatbots for customer service and communication in .a variety of domains. For example, gesture-based communication is safer and easier for people with disabilities or the elderly [190]. Another problem is dealing with natural language diversity in order to express intent. Perception of the right intent should be prioritised to avoid incorrect operations by IoT systems. This problem can be solved using ML training models to understand the user's intent and other technologies and approaches.

The prime advantage of using conversation AI in buildings is that it benefits everyone, regardless of whether the user has expert knowledge or not. Voice commands, GUI, and touch UIs (and mid-air gestures) are other current alternatives to human building interactions [207]. We can control the built environment in terms of system management by implementing such a robust and automated network of smart devices in the buildings.

6.3 Heterogeneity and Interoperability

A few challenges in building an adaptive and interoperable bridge between the built environment and people are the heterogeneity of custom sensor deployments, their types of storage databases, their analytics techniques, and the technology they use. Varying protocols used by sensors—such as Bluetooth, WiFi, ZigBee, LoRa, and Modbus—use different frequencies, ranges, power requirements, and security standards. For improved communication and accuracy, multiple protocols are utilised for different purposes. Protocols are chosen based on complexity, importance, data quantity, bandwidth, range, energy usage, sensor quantity, technologies, and platforms where data must be transferred. Depending on the application, application layer protocols such as DDS, CoAP, AMQP, MQTT, XMPP, and HTTP REST are chosen. Different device layer protocols (LTE, Z-Wave, WiFi, etc.), Network layer protocols(6LoWPAN, IPv4/IPv6, etc.), and routing protocols are some reasons for the heterogeneity of sensors and their network.

Besides the standard protocols, Riccardo Giambona et al. [208] tried to modify or combine them for their application, such as MQTT+, which also adds to the heterogeneity and interoperability issues. Consequently, heterogeneity poses many challenges, particularly in security and privacy. On the other hand, Interoperability in IoT is critical, and several methods, such as hub-based [209] and platform-based [210], are being tested and experimented with to achieve interoperability. The interoperability issues can be classified into six types and seen from different perspectives due to heterogeneity [211]. According to LCIM [212] [213], the interoperability model consists of 7 layers ranging from 0 to 6, where the 7th level is the highest, as shown in Table 16.

Layer Name	Description	Examples
(L6) Conceptual	Fully specified, a common conceptual model of a system exposing all concepts, assumptions, constraints, etc.	DoDAF, SysML
(L5) Dynamic	Producing and consuming the definitions of meaning and context	UML artifacts, DEVS
(L4) Pragmatic	Description of the service to access relevant data, the meaning of terms and methods	Taxonomies, ontologies, sequence diagrams, OWL
(L3) Semantic	Common reference model which focuses on the meaning of terms, relations, language, etc.	Dictionaries, semantic graphs
(L2) Syntactic	Common structured data format for information exchange	XML,SOAP,CSV
(L1)Technical	Refers to a communication protocol for network connectivity	OSI, TCP/IP

Table 16: Interoperability levels and examples.

The question is how we might make our building more adaptable to its understanding of the built world. One approach is to adapt Knowledge Representation and Reasoning(KRR) to build such infrastructure consisting of sensors and their properties. The knowledge representation (KR) domain was concerned with representing knowledge by creating an appropriate representation language and applying reasoning to the represented knowledge to solve complex tasks [214]. The web can be transformed into a distributed knowledge base and application platform using semantic web technology, allowing businesses to leverage the value of the vast amount of available information and services [215]. Adding a semantic layer to data generated by various sensors in the built environment significantly improves energy efficiency, cost optimization, occupant comfort and satisfaction and contributes to meeting sustainability standards.

For AI and web researchers, an ontology is a document or file that officially describes the relationships between terms through taxonomy and a set of rules. In addition, it introduces the meaningful vocabulary of various domain aspects. The World Wide Web Consortium (W3C) recommends the recently created Web Ontology Language (OWL) [216, 217], a web ontology language based on description logic that encompasses RDF, RDFS, SPARQL, etc., as a highly successful standard for ontology development. In addition, various ontology development tools, such as 'Swoop' [218] and 'Protege' [219], are available to save developers time.

Because of the benefits of KRR, several ontologies [220, 221, 222] have been developed to handle smart device interoperability. For example, Marjan Alirezaie et al. [223] proposed a framework for a smart environment that can perform context recognition based on activities and events in the home. This Semantic Sensor Network (SSN) ontology describes sensors and their observations, the procedures that go with them, the relevant features of interest, the samples used, their observed properties, and actuators [224]. SSN implements a horizontal and vertical modularization architecture for its elementary classes and properties, which includes a lightweight but self-contained core ontology called SOSA (Sensor, Observation, Sample, and Actuator) [221].

Furthermore, the Building Topology Ontology (BOT) is a minimal ontology for describing the core topological concepts of a building that can be used in conjunction with other ontologies. Using such ontologies can make it easier for humans to interact with the built environment by translating user-defined actions into sensor commands that address interoperability issues in smart spaces [26]. Conversely, ontology-based activity recognition approaches can be effective for various applications[225]. A knowledge graph allows buildings to think more intelligently. Knowledge graphs transform heterogeneous building data into meaningful non-heterogeneous graphs that can be transformed into data that most ML models accept [226]. We can efficiently and effectively link and utilise data from disparate sources using knowledge graphs, such as real-time sensor data, occupancy data, environmental conditions data, and others.

Managing sensor interoperability while achieving specific sustainability goals is a serious challenge. Certain sensors can be used to achieve a variety of goals. For instance, employing CO_2 sensors to manage emissions, improve health and welfare, and maintain energy use. The Figure 4 illustrates typical sensors and the different combinations that can be made of them to satisfy sustainability objectives.

6.4 Building Metadata Schema Representations

To achieve semantic relationships between buildings, developing a unique metadata representation technique for each type is necessary. Metadata schema can be used to deploy portable building applications to solve various problems, meet sustainability standards, and resolve interoperability issues between heterogeneous buildings. One approach is to create metadata using the 'tags' used in Project Haystack [227], which can be built automatically with minimal expert involvement [228]. Bharathan Balaji et al.[229] introduced 'Brick', an open-source uniform metadata schema for buildings that describes physical, logical, and virtual assets in buildings and their relationships. Brick outperforms previous systems such as Project Haystack, Industry Foundation Classes (IFC)[230], BIM, BOT, and Smart Appliances REFerence Ontology (SAREF). The Brick+ ontology replaces this Brick ontology by Gabe Fierro et al.[231], which helps to bridge the gap between existing ad-hoc, informal metadata practises and interoperable formal systems by addressing interoperability and consistency issues in tagging systems. Expanding this research, the team have also created an open testbed for portable building analytics called 'Mortar' which spans over 90 buildings and contains over 9.1 billion data points.

Unstructured building data/metadata can be converted to Brick using the scrabble framework [232], which reduces the effort of mapping multiple buildings and learns from buildings that have already been mapped to the schema with minimal input from domain experts. The method and system presented by brick authors Gabe Fierro et al.[233, 234] can be used to convert existing metadata sources, such as gbXML, BuildingSync, Project Haystack, and Modelica, that are produced at various stages of the building lifecycle and have different metadata presentations into a valid brick model that can be continuously maintained throughout the building lifecycle. Building metadata can be easily normalised using graphical user interfaces such as Plaster for users unfamiliar with ML and programming interfaces that use scrabble and other algorithms [235]. Machine learning can be used semi-automatically to create metadata

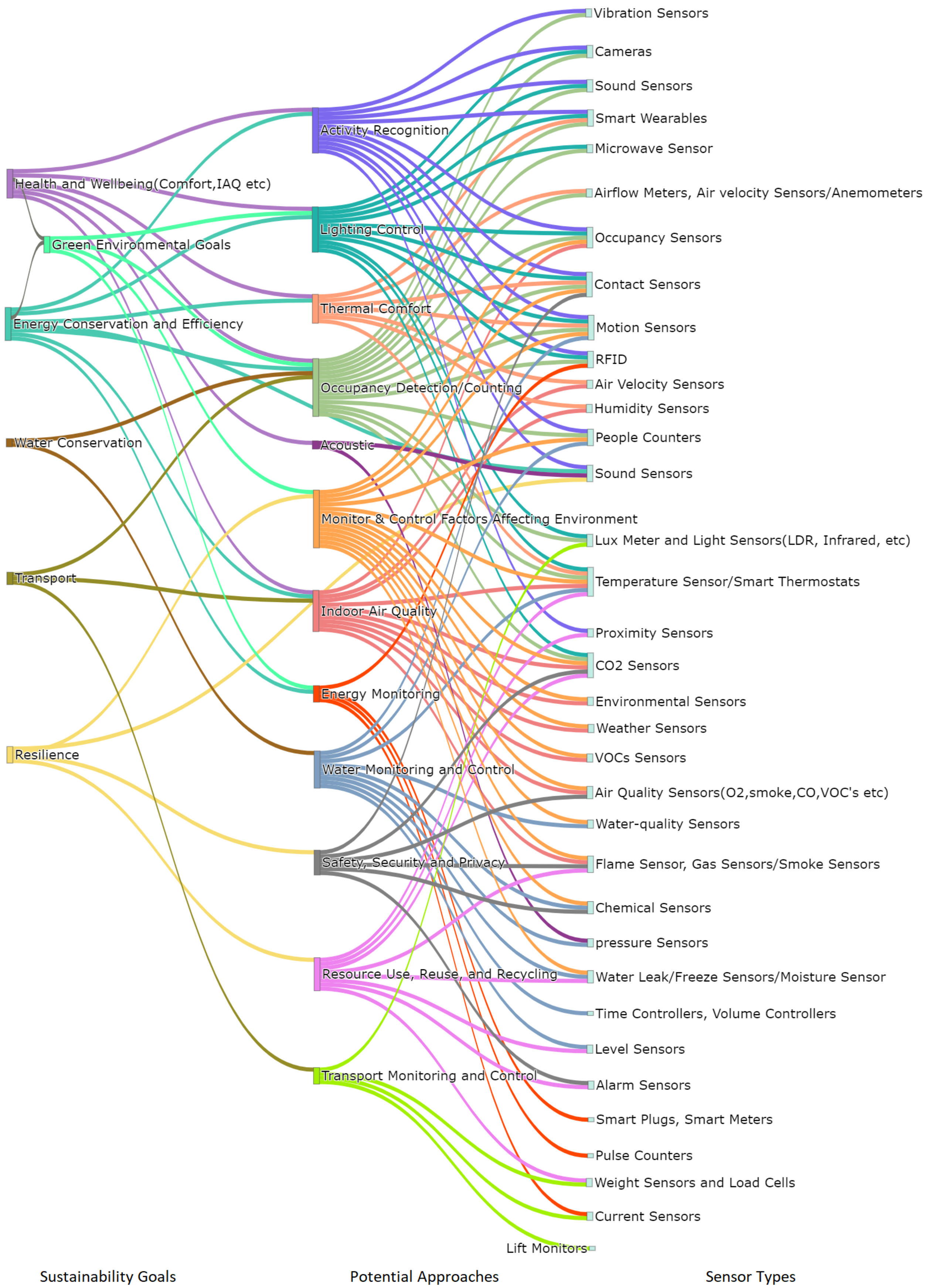

Figure 4: Commonly used sensor combinations to achieve sustainability goals

from existing Building Automation Systems (BAS) datasets [28]. Furthermore, frameworks such as Zodiac [236] can classify, name automatically, and manage many sensors based on active learning from sensor metadata deployed in a large network. While BIM allows for the seamless exchange of information about the built environment, it has the complexity of an open standard data schema, IFC. Therefore, researchers created tools that use Brick, BOT, PROPS, and BEO to convert IFC data into a unified knowledge graph that can be queried using SPARQL and SQL queries [237]. Using ontologies and creating knowledge graphs improves building automation and human-building interaction.

7 Conclusion

We examined various sustainability standards for residential and commercial buildings used in various countries to achieve various management goals and sustainable targets such as green buildings. Some sustainability standards are applicable internationally, and meeting such standards is a top priority to avoid future consequences. We looked at some of the major factors influencing human health and wellbeing and how sensor insights can be used to achieve health and sustainability goals. Previous human-building interaction research shows that indoor transportation, water, and land use are not given as much attention to achieve a sustainable built environment as other factors such as thermal comfort, indoor environment, and energy efficiency. We compared the built environment to human anatomy to understand the need for specific sensors in various building systems to archive a sustainable and safe environment. We use an ontology diagram to show the importance of balancing trade-offs between occupancy-driven thermal comfort, indoor air quality, health and wellbeing, and energy sustainability. Several sensors require analytics, and relevant insights are examined to achieve a sustainable built environment. Various interfaces for interacting with the building to accomplish tasks and achieve sustainability standards-related goals are reviewed. Further human-building interactions and their scope are examined using current methodologies, such as semantic web technologies, to achieve HBI goals. This review concludes that we should encourage building occupants to engage and interact with the built environment to achieve a sustainable built environment. For interaction with the variety of built environments, further study is required. Additionally, we addressed some of the HBI and sustainability challenges while ignoring some domain-specific challenges in the IoT system.

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