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REVIEW ARTICLE

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Smart sensors for Indoor Environmental Quality in residential smart buildings: a review

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ABSTRACT

The 2024 revision of the EU Energy Performance of Buildings Directive recognizes indoor environmental quality (IEQ) as a key complement to energy efficiency in promoting sustainable buildings and ensuring occupant comfort and well-being. This review approaches the subject of smart buildings from a multidisciplinary perspective, with a focus on residential applications. It examines four IEQ components: indoor air quality, thermal comfort, visual comfort and acoustic comfort. The discussion begins with technical standards and rating schemes, emphasising the physiological and psychological impacts of environmental conditions. It then investigates the state of research on smart sensors and IoT technologies, followed by recent advances in building management systems, particularly the integration of artificial intelligence for adaptive comfort control. Finally, the paper outlines future directions, including personalised comfort models, standardised assessment methods, scalable and interoperable sensor networks and privacy-preserving data strategies.

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Indoor environmental; quality comfort model; smart buildings; smart sensor; building management system; internet of things

1. Introduction

In the past decades, most of the focus related to building design and construction has been on improving energy efficiency. However, the advent of sustainably certified buildings does not seem to be conclusively correlated with a comparable improvement in occupant satisfaction with indoor spaces (Asmar, Chokor, and Srour 2014; Geng et al. 2019; Pastore and Andersen 2019). Therefore, the notion of IEQ has recently become an additional pillar in the design and operation of modern buildings. It includes IAQ, TC, VC and AC and directly affects occupant health and well-being while having an indirect impact on energy performance and sustainability (Deng et al. 2024; Rupp, Vásquez, and Lamberts 2015).

This paradigm is incorporated into the last revision of the EPBD (2024/1275) (European Commission 2024) published in May 2024, which highlights the importance of IEQ along with energy efficiency, introducing the for occupant-centric metrics, digitisation, and smart technologies in the built environment. This latter aspect is achieved by the introduction of the novel SRI, which is defined in the EPBD as a way to 'measure the capacity of buildings to use information and communication technologies and electronic systems to adapt the operation of buildings to the needs of the occupants and the grid and to improve the energy efficiency and overall performance of buildings' (European Commission 2024).

Therefore, the definition of the SRI emphasises the importance of automation in buildings, which can be improved by integrating smart sensors with IoT networks and BMS. These devices can collect real-time environmental data and, along with the feedback of the occupants, support adaptive control algorithms, allowing buildings to adapt proactively and dynamically to variable conditions (Dong et al. 2019; Genkin and McArthur 2023). However, the deployment of smart sensor networks presents challenges, such as sensor accuracy, spatial variability of environmental parameters, privacy and interoperability. These

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potential issues can be more prevalent in residential applications because of the greater variability in user behaviour and needs and architectural layouts (Calì et al. 2015; Clements et al. 2019).

Given this context, this review the state of the research on smart sensors in relationship to IEQ monitoring in buildings, with a particular focus on residential applications. Section 3 provides definitions of IEQ and its main components, along with their relevance in terms of the health and well-being of occupants, the technical standards currently in force and the different models and schemes from the literature. Section 4 focussed on the concept of smart building, analysing the available definitions and the main features. Section 5 is dedicated to smart sensors and includes an overview of network configurations from the literature and an analysis of the measurement devices dedicated to all the variables required for smart building operation. Section 6 describes the development of BMS, including the adoption of AI and ML techniques. Finally, Section 7 concludes the paper with a discussion of the challenges and future developments that have emerged from the review of the literature, including the need for standardised assessment methods, improved sensor accuracy, and scalable, privacy-preserving solutions.

Ultimately, this review highlights the multidisciplinary nature of the subject, linking technical innovations to the regulatory framework, highlighting the definition of IEQ and its components, their relevance in terms of human comfort and health, and the available rating schemes, and aims to provide support to researchers, technicians and policymakers in developing strategies and technologies for smart building construction, focussing on energy efficiency and occupant satisfaction and well-being.

2. Methods

This study focusses on the use of smart sensors to assess and guarantee adequate IEQ conditions for occupants in smart buildings, with specific attention to residential buildings, and aims to highlight the state of the research, along with the challenges that must be addressed to advance the efficacy of these systems and facilitate their adoption. Therefore, it addresses multiple topics, from the notion of IEQ, discussing its importance and application, to the available sensing technologies and their integration into IoT networks and BMS.

Research for this work has initially been conducted by querying both the Scopus and Web of Science databases, using the following keywords in various arrangements and combinations: *IEQ*, *rating system*, *smart sensor*, *healthy building*, *case studies*, *digital twin*, *smart building*, and *BMS*. The search results include original research papers, review papers and conference proceedings published in English from 2010 (with only a few exceptions) to 2024 (last update August 2024) and belong to the categories of *engineering*, *environmental science*, *energy* and *computer science*. After eliminating duplicates, the reference list has been expanded via a two-step process: first, through the *snowball technique* (a.k.a. *citation search* (Hirt et al. 2024)), and then via a more targeted search, to add information about specific subjects. The entire list was then screened for relevance to the topics studied in this review. Finally, European and US technical standards relevant to IEQ assessment and rating have been included, along with the data sheets of the devices presented in the literature, to provide the reader with full access to the list of their features. The whole process is summarised by the flow diagram represented in Figure 1.

Keyword relevance has been investigated considering the final selection of references from the scientific literature by highlighting co-occurrences. The outcome of this analysis is a network map of all keywords with at least five occurrences produced using the VOSviewer tool (van Eck and Waltman 2010), as shown in Figure 2. The size of each label represents its weight, while the distance between nodes is related to the strength of their connection, and the thickness of the links indicates the probability of co-occurrence. Finally, the nodes are coloured according to the average normalised citation number (i.e. the number of citations of documents related to a keyword divided by the average number of citations of the documents published in the same year to account for potentially higher citation numbers for older references). Figure 2 shows that *indoor thermal comfort* and *indoor air quality* are the most prevalent subjects among those related to *indoor environmental quality*, with a number of citations above average, demonstrating the research interest in those topics. At the same time, the reference list includes a significant number of manuscripts dedicated to *artificial intelligence*, *occupancy* and *building management system*, which have received an average number of citations, considering the normalization.

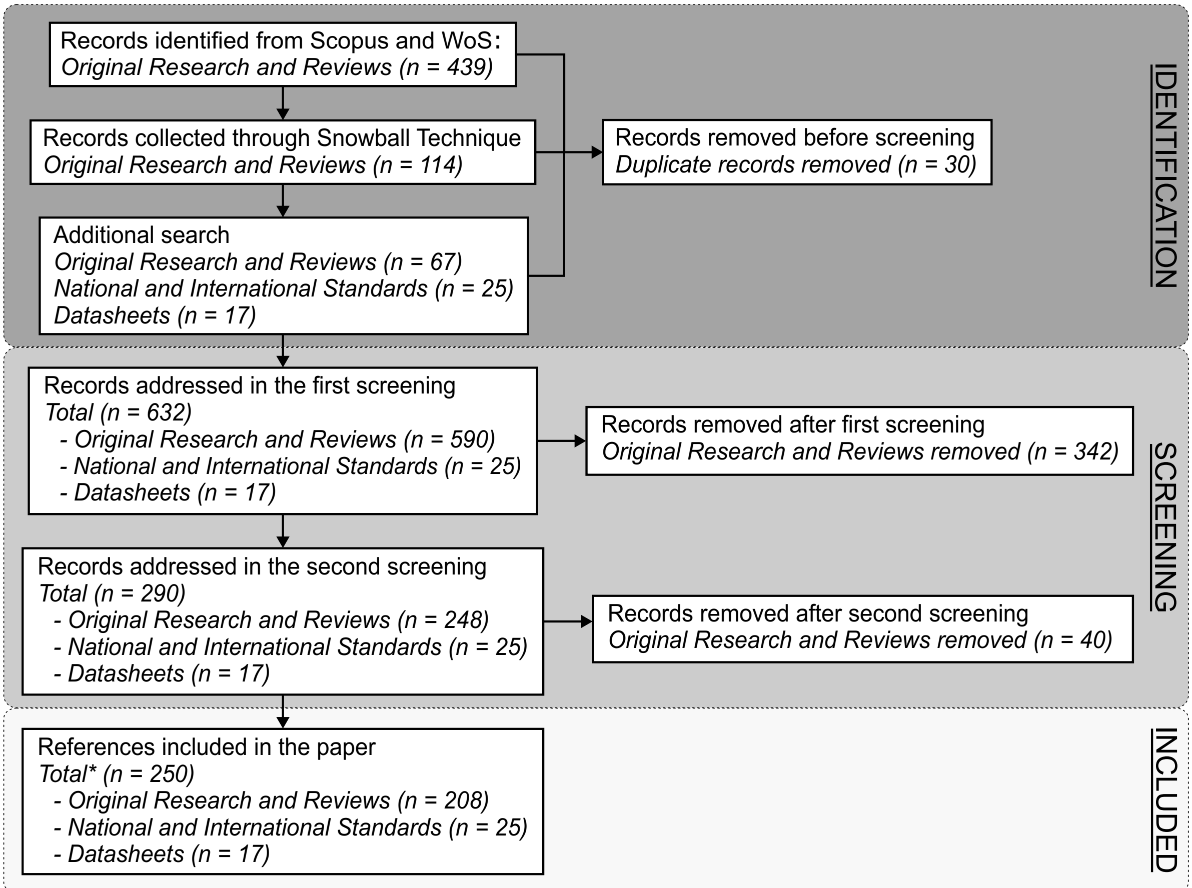

Figure 1. Flowchart describing the process followed to collect references for this review, divided into *identification*, *screening* and *included*. *Note: The total number of references excludes two works related to the search methodology followed in this work.

Finally, the research papers and the standards among the final reference list can be grouped according to their pertinence for the main topics investigated in this manuscript (*IEQ*, *standards and schemes, smart buildings, smart sensors and IoT*, *BMS* and *case studies*) to analyse their distribution in time: Figure 3 shows that most of them have been published after 2015, with a growth in interest over time, and that the scientific production dedicated to smart buildings and the description of case studies is even more recent overall. In general, Figure 3 shows that most of the references considered in this review have been published within the last ten years.

3. A comprehensive look at indoor environmental quality

This section is dedicated to the general concept of IEQ: starting from its latest definition and introducing the main components, an overview of the consequences related to indoor environmental conditions is presented, highlighting the comfort, health and productivity of the occupants. Finally, the standards and assessment schemes for IEQ are presented.

3.1. Definition

The IEQ refers to the indoor conditions in a building and is related to both the comfort and the health of the occupants. Its main components are TC, IAQ, VC and AC (Mui et al. 2016). More precisely, this concept describes an integral state of an occupant's subjective response to indoor environmental parameters such as the air temperature, humidity, CO_2 concentration, horizontal illumination, sound pressure

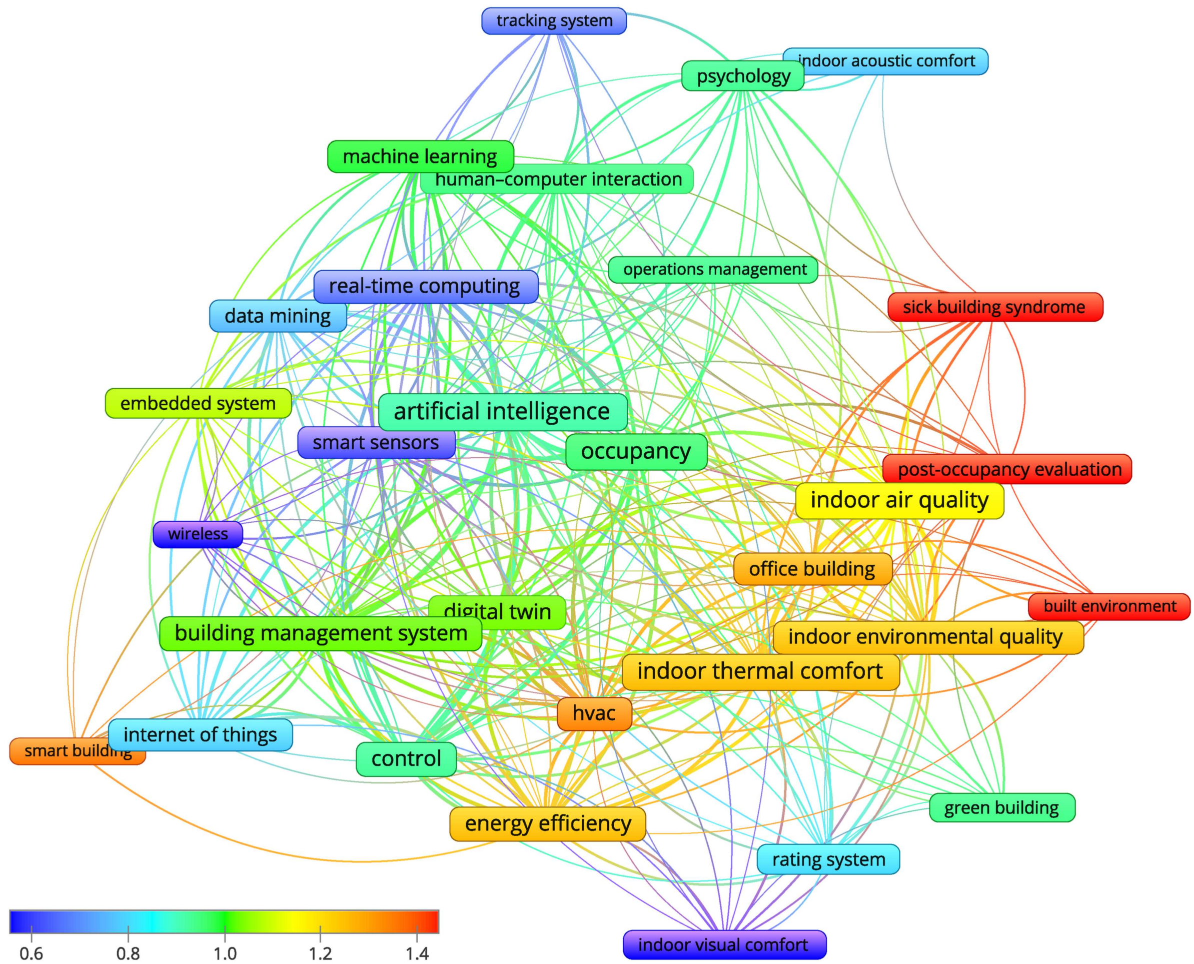

Figure 2. Keyword co-occurrence network, coloured according to the average normalised number of citations.

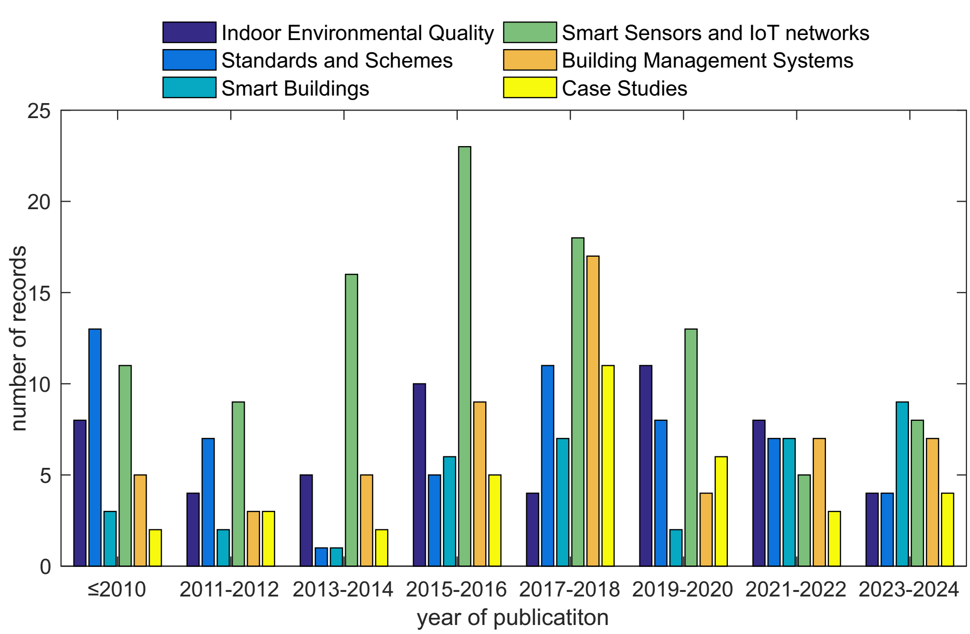

Figure 3. Number of research papers and standards included in the reference list, divided by year of publication and pertinence for the main topics investigated in this work. Each reference can potentially be considered relevant for more than one topic.

level and local air velocity (Mendell 2003). Moreover, this notion can also be extended to include daylight and views, pleasant acoustic conditions and occupant control over lighting and thermal settings. These elements contribute collectively to the whole perception (Deng et al. 2024) and can influence people's level of comfort (Sim et al. 2016). Additional aspects, such as layout, available space, furniture, and interior design, can also affect perceived comfort and well-being, although they are generally excluded from standardised comfort assessments (Zhang, Mui, and Wong 2023).

According to Standard ANSI/ASHRAE 55-2004 (2004), TC is defined as,

> *that condition of mind which expresses satisfaction with the thermal environment.*

According to Ganesh et al. (2021) and Navada, Adiga, and Kini (2013), the parameters related to TC can be divided as follows:

a. Environmental factors, including the indoor air temperature, relative humidity, air velocity and mean radiant temperature;

b. Personal factors that depend on the individual characteristics of a person, including metabolic rate, clothing insulation, sex, age, and weight.

In addition, climatic, geographic and cultural factors should also be considered in the evaluation of TC but are currently overlooked in most assessment methods (Horr et al. 2016).

As far as IAQ is concerned, ASHRAE Standard 62.1-2016 (2016) defines good air quality as follows:

> *air in which there are no known contaminants at harmful concentrations as determined by cognizant authorities and with which a substantial majority (80% or more) of the people exposed do not express dissatisfaction.*

In fact, IAQ is a multidisciplinary phenomenon and is determined by the many pathways in which chemical, biological and physical contaminants eventually become a part of the total indoor environmental composition (Tham 2016). Dealing now with VC, the European standard EN 12665 defines it as:

> *a subjective condition of visual well-being induced by the visual environment* (En 12665: 2024).

According to Carlucci et al. (2015), its assessment includes the evaluation of:

a. The amount of light;

b. The uniformity of light;

c. The quality of light in rendering colors;

d. The prediction of the risk of glare for the occupants.

The study conducted by Ko et al. (2022) revealed that VC can also be improved by window view quality. Its assessment should consider daylight, views and building orientation but should also be flexible enough to not prevail over other requirements.

Finally, AC is defined in Frontczak and Wargocki (2011) as:

> *a state of contentment with acoustic conditions.*

The main factors include the sound pressure level, exposure time, frequency composition and repetition over time (Rocca et al. 2022). However, overall perception can also be influenced by the urban context, envelope acoustic performance, person-related factors, situational factors and the environmental context (Torresin et al. 2019).

3.2. Importance

People spend 90% of their time indoors, making IEQ a central aspect of modern building design. In this context, the concept of a *people-centred* building has been promoted in the literature (Jin et al. 2018), considering the health, comfort, well-being and productivity of the occupants as effects of improved comfort levels (Devitofrancesco et al. 2019).

According to Asadi, Mahyuddin, and Shafigh (2017), poor IEQ is caused mainly by elevated IAP concentration, indoor temperature and relative humidity. These conditions can cause physiological stress, reduced cognitive function and chronic health problems (Heidary et al. 2023), as well as an increased possibility of developing SBS (Zhang, Mui, and Wong 2023). Among the components of IEQ, indoor air quality (IAQ) plays a predominant role in the protection of human health, since it directly influences short- and long-term physiological results.

Indeed, inadequate IAQ levels can lead to various consequences: some pollutants are considered more hazardous and are associated with respiratory diseases, cancer, immune deficiencies, and organ diseases affecting the liver and kidneys (Tham 2016). In particular, the study conducted by Patino and Siegel (2018) highlights the elevated concentration of $PM_{2.5}$ in social houses due to cigarette smoking in buildings, revealing it as the primary cause of health issues related to IAQ. Furthermore, poor IAQ can facilitate the transmission of infectious diseases and increase the incidence of health symptoms in occupants, such as mucous membrane irritation, airway issues, headaches, a lack of concentration, fatigue, allergic reactions, asthma, etc. (Altomonte et al. 2020). Other pollutants may not be directly harmful but still negatively influence comfort, productivity and overall performance (Xiang et al. 2013). For example, according to Wolkoff (2013), odour appears to be one of the IAQ factors capable of influencing occupant perception, despite not necessarily being related to adverse health effects. Finally, it is important to clarify that the research shows that symptoms are correlated with the level and duration of exposure (Snyder et al. 2013).

Similarly, uncomfortable thermal conditions can cause illnesses or other effects, such as shivering and sweating, which are more closely related to the well-being of the occupants than to severe health issues (Sim et al. 2016).

The work of Choi and Zhu (2015) indicates that VC is a key component of IEQ, particularly in workplace environments where occupant health and productivity are critical. Other studies have revealed that glare and reflected light negatively impact user satisfaction in computer-based tasks (Choi, Loftness, and Aziz 2012), while natural light provides physical and psychological benefits to building occupants (Dahlan and Eissa 2015). Moreover, our eyes are not only responsible for vision but also crucial in stimulating our body's circadian system, which sets the pace of almost every process in our bodies (Altomonte et al. 2020).

According to Sakellaris et al. 2016, the results obtained through a cross-European survey demonstrate that AC is the most important IEQ component associated with occupant comfort, particularly satisfaction with overall noise. Noise levels represent the most significant factor that affects sleep quality, concentration, and overall performance (Muzet 2007). Hongisto (2005) explored different sources of disturbance: a predictive model demonstrated that it is not the sound level of speech that determines its distracting power but its intelligibility. On this matter, the STI quantifies how clearly a spoken message can be perceived and understood in an environment affected by background noise and reverberation, and the results show that high STI values correspond to a reduction in the performance of the occupant.

Finally, a review by Rupp, Vásquez, and Lamberts (2015) highlights that the IEQ strongly influences human performance and productivity: maintaining high comfort conditions improves the quality of life and productivity of work. Indeed, the work by Fisk (2000) estimates the annual economic benefits of improved IEQ in the United States, including reduced health-related costs and increased worker performance, thereby underscoring the significant potential of this research domain. Therefore, similar to energy efficiency improvements, a significant push toward better IEQ could be driven by financial incentives Parkinson, and de Dear (2019), highlighting the costs associated with inadequate indoor conditions, particularly in office environments (Zhang et al. 2023). The challenge lies in achieving high IEQ standards according to occupant perceptions without increasing energy consumption (Choi and Yeom 2017; Kaushik et al. 2020). A potential solution is proposed in the manuscript by Deng et al. (2024), where the authors suggest combining smart sensors with occupant feedback as an effective approach to achieve both energy efficiency and indoor comfort. This topic will be discussed in more detail in Section 4. Another suggestion proposed by Qabbal, Younsi, and Naji (2022) recommends to incorporate IEQ during the design phase, especially for AC and VC, investigating envelope geometry, technology and indoor space design (Horr et al. 2016). Table 1 summarises the relationship between IEQ category effects on occupants.

3.3. Standard and schemes

The IEQ is linked to a wide range of parameters, constraints and assessment methods. The overall level of IEQ in buildings depends on the interactions among various parameters (Nimlyat 2018). The work by Wei

Table 1. IEQ categories and effects on occupants.

References	IEQ category	Environmental parameters	Health effects	Well-being and productivity
(Sim et al. 2016)	TC	Air temperature, relative humidity, air velocity and mean radiant temperature	Illnesses	Shivering and sweating
(Tham 2016)	IAQ	Indoor air pollution (IAP)	Respiratory diseases, cancer, immune deficiencies, and organ diseases affecting the liver and kidneys	Influence comfort, productivity, and overall performance
(Patino and Siegel 2018)	IAQ	$PM_{2.5}$	Biggest chronic health impact among common residential indoor pollutants	
(Choi and Zhu 2015)	VC	Glare and reflected light		Reduce user satisfaction
(Muzet 2007)	AC	Noise		reduce sleep quality, concentration, and overall performance
(Hongisto 2005)	IEQ	Speech transmission index (STI)		Reduction in occupant's performance
(Heidary et al. 2023)	IEQ	Elevate indoor air pollution (IAP) concentration, indoor temperature, and relative humidity	Chronic health issues	Physiological stress, reduced cognitive function
(Rupp, Vásquez, and Lamberts 2015)	IEQ			Enhances quality of life and work effectiveness
(Zhang, Mui, and Wong 2023)	IEQ		Sick building syndrome (SBS)	

et al. (2020) provides a review of fourteen green building certification schemes to assess the IEQ levels in offices and hotels. The outcome counts 19 parameters to assess TC, 39 for IAQ, 20 for AC and 12 for VC. Given this complexity, the amount of data required for a comprehensive assessment of IEQ often exceeds the capabilities of currently available sensors in terms of economic and technological feasibility. A detailed discussion is provided in Section 5. To simplify the process, only a limited number of parameters are typically monitored, according to their importance and influence on IEQ. For instance, (Jin et al. 2018) proposed temperature, humidity, illuminance, CO_2, VOC and PM as the main parameters. However, other studies have highlighted the limitations of relying on a narrow set of variables for IAQ assessment; For instance, (Pastore and Andersen 2019) stated that relative humidity and CO_2 concentration are insufficient to accurately reflect occupant satisfaction.

Another major challenge in this field is the development of assessment frameworks that are able to incorporate occupant feedback. To address this, (Geng et al. 2019) propose to separate IEQ assessment into an objective part, which compares measurements to thresholds provided by standards, and a subjective part aimed at evaluating occupants' perceptions registered through surveys. The work by Meir et al. (2009) highlights the importance of POE as a tool to guarantee that new buildings are able to respect increasingly demanding standards of comfort, safety, cost-effectiveness and sustainability. Indeed, in (Meir et al. 2020), POE is used to identify potential flaws in various phases of the building life (i.e. design, construction, commissioning and building/user interaction) while indicating useful corrective feedback. These questionnaires are based on human perception (Ganesh et al. 2021), and their objective is to assess psychological factors. Although individual variability may limit their comprehensiveness, well-designed surveys remain highly effective. The BUS occupant survey Bordass, Leaman, and Eley (2016), For instance, systematically translates occupant feedback into actionable data, enabling case-specific analyses, benchmarking across a broader database, and providing robust support for decision-making. In this sense, user feedback constitutes an integral part of a structured process that improves both individual buildings and collective knowledge. Subjective evaluation techniques are also included in Annex F of CEN/TR 16798-2 (CEN 2019).

General IEQ assessment based on its four components relies on EN 16798-1:2019 (Standard CEN/TR 16798-2:2019). The standard classifies dwellings into four different categories based on the occupants PPD. In parallel, ANSI/ASHRAE/IES Standard 90.1-2016 (2016) is considered equivalent to EN 16798-1:2019 and ensures compliance with energy requirements. However, as highlighted in (Wargocki et al. 2021), a clear reference framework is needed to define which variables should be measured and how different outcomes should be weighted. Since EN 16798-1:2019 builds upon the reference standards of each individual domain, namely, TC, IAQ and VC, a more detailed overview of these component-specific standards is provided.

ISO 7730 (ISO 2005) and ASHRAE 55 (Standard ANSI/ASHRAE 55-2004 2004) are the reference standards for the evaluation of TC and are widely adopted in scientific research (Daum, Haldi, and Morel 2011; Navada et al. 2013; Nicol and Humphreys 2002; Rupp, Vásquez, and Lamberts 2015; Khovalyg et al. 2020). These standards define acceptable thermal environments based on the PMV, which represents the average value predicted by the subjective judgement of a group of people in a given environment, and PPD, which refers to a quantitative measure of thermal comfort. With respect to TCs, adaptive criteria are aimed at setting acceptable indoor temperatures in buildings without mechanical cooling. The method can be applied under specific conditions based on the building type, occupant behaviour, metabolic rate, clothing insulation and seasonal period. The purpose is to have a dynamic indoor temperature setpoint that permits energy savings and enhances occupant involvement and adaptation. The assessment is conducted through the evaluation of the operative temperature, as prescribed by CEN/TR 16798-2 (CEN 2019). However, several studies have pointed out limitations in their accuracy, particularly due to the variability of human perception influenced by different cultural habits, climate conditions and individual factors (Niza and Broday 2022). Among these individual factors, clothing insulation plays a crucial role in perceived TC. In this context, Zhang (2010) explored the impact of clothing on thermal sensation by applying a modified Gagge model to simulate transient heat and moisture transport through clothing systems, offering a more dynamic and personalized approach to TC evaluation Ghaddar, Ghali, and Chehaitly (2011).

Related to the variability of human perception, (Kim, Schiavon, and Brager 2018a; Kim et al. 2018b) introduced the concept of personal comfort model for TC with the aim of predicting an individual's thermal comfort response. This approach identifies the specific comfort needs of each individual and provides the desired environmental conditions required to satisfy them. This information can then be used to operate the HVAC system, as indicated by Jung and Jazizadeh in their work (Jung and Jazizadeh 2019). The main features of a personal comfort model are as follows:

a. Treating the individual as the unit of analysis;
b. Collecting both direct feedback and personal data from occupants;
c. Measuring environmental parameters;
d. Prioritizing cost-effective and easily obtainable data;
e. Adopted a data-driven approach in order to increase the flexibility and adaptability of the model.

Results showed improvements in the prediction accuracy (20%–40% higher than that of convectional comfort models) and enhanced data diversity. Issues arise when individual feedbacks are not enough to train the model, mainly because of the decrease in occupant participation. Another work (Choi and Yeom 2017) focused on personal models reveals the possibility to assess TC through skin temperature measurements on the wrist (front), upper arm, and waist. Gender and BMI, which refer to the ratio between body weight and height of the human subject, were also considered. The study carried out in an experimental chamber reveals a level of accuracy of 95% compared to the responses registered with surveys. However, issues arise due to the discomfort and invasiveness of the body sensors.

IAQ assessments refer to ANSI/ASHRAE Standard 62.1-2022 (Standard ANSI/ASHRAE Standard 62.1-2016) and ANSI/ASHRAE Standard 62.2-2022 (Standard ANSI/ASHRAE 62.2- 2022), the latter being specifically focused on residential buildings (Calì et al. 2015; Berger et al. 2022; Khovalyg et al. 2020), by calculating the minimum requirements for ventilation. Additionally, EN 16798-1 (Standard CEN/TR 16798-2:2019 2019) specifies ventilation rates with three different methods:

- Perceived IAQ: based on comfort criteria. The total ventilation rate is calculated by combining two components: the ventilation required for occupant bio effluents and the ventilation required for building material/system emissions;
- Substance concentration limits: these are based on health criteria. The required ventilation rate to dilute an individual substance is calculated using a steady-state mass balance formula based on the pollutant's generation rate and the maximum permissible guideline concentration;
- Predefined ventilation flow rates: minimum rates estimated to meet both health and perceived air quality, typically expressed as flow rates per person, per unit floor area, or air change rates;

Given the large number of parameters involved, a major challenge is to identify the most reliable indices (Pourkiaei and Romain 2023). A literature review of IAQ conducted by Wolkoff (2013) categorises pollutants according to their effects on occupants:

• priority compounds (benzene, formaldehyde, nitrogen dioxide, naphthalene);

• perceived air quality compounds (acetic acid, hexanal, 2-butoxyethanol, 2-ethylhexanol, hexanoic acid, limonene, phenol);

• sensory irritation compounds (acetic acid, acrolein, ammonia, 2-ethylhexanol, formaldehyde, glutaraldehyde, hydrogen peroxide, isopropenyl-6-oxo-heptanal, methacrolein, methyl-naphthalenes, 1-octen-3-ol, 4-oxopentanal, ozone, peroxy-acetic acid, phenol);

• performance-deteriorating compounds (carbon dioxide);

• long-term effect compounds (ultrafine/fine particles, $PM_{2,5}$, soluble transition metals);

This classification provides a catalogue where pollutants can be selected according to the assessment objective. Priority compounds are defined according to the WHO's Indoor Air Quality Guidelines (World Health Organization 2010) and the Risk Assessment on Indoor Air Quality (SCHER) (Wojciech et al. 2007). As indicated by Salis et al. (2007), IAQ indices can be defined in different ways. Some are specific to a single pollutant, while others are aggregated using various approaches, such as simple aggregation, aggregation by source, aggregation by health impact or aggregation by potential concentration. A crucial challenge when using aggregated indices is to avoid eclipsing (i.e. masking information) and ambiguity (i.e. false alarms).

At the standardization level, it is necessary to refer to ISO 16000 series, which provides recognized methodologies for the assessment of indoor air pollutants. These documents define sampling strategies, measurement techniques and evaluation protocols for a wide range of chemical and microbiological contaminants (Standard ISO 16000-3: 2011; Standard ISO 16000-16: 2008; Standard ISO 16000-2: 2004; Standard ISO 16000-4: 2011; Standard ISO 16000-5: 2007; Standard ISO 16000-6: 2011 ; Standard ISO 16000-18: 2011). The interpretation and classification of the measured data against acceptable thresholds are addressed by ISO 16000-41:2023 (2023), which confirms that evaluation should be based on guide values derived from external authorities (e.g. WHO or national regulations), as the ISO document itself does not establish universally applicable numerical limits for individual pollutants.

Considering the VC assessment, the most important standard is EN 12665:2024 (En 12665: 2024), which establishes a terminological reference for the visual environment, while BS EN 12464-1:2021 (Standard EN 12464-1; 2021) specifies requirements and methodologies for the parameters, including minimum illuminance, maximum unified glare rating, minimum color rendering index and correlated color temperature for indoor environments.

The most relevant AC standard is ISO 1996-1:2016 (Standard ISO 1996-1:, 2016), which defines the parameters and assessment procedures, and ISO 1996-2:2017 (Standard ISO 1996-2: 2017), which focusses on the determination of sound pressure levels, which is applicable for both residential and non-residential buildings. According to (Mahdavi et al. 2023), the standard is based on the following performance variables:

a. A-weighted equivalent sound pressure level, normalized with respect to reverberation time – $L_{Aeq,nT}$ [dB(A)];

b. Noise from service equipment in buildings considering the maximum sound pressure level – $L_{AF\,max,nT}$ [dB(A)];

c. Installation noise [dB(A)].

To give a comprehensive review, in Table 2 are listed the main standard reference used in literature for the evaluation of IEQ, including the list of parameters monitored and the assessment methodologies discussed so far.

In the literature, many frameworks are present for IEQ evaluation. The EU ALDREN project developed the TAIL protocol (Wargocki et al. 2021), with the intent of creating a unified index to determine the IEQ. The framework is based on the evaluation of the four categories through the following parameters: operative temperature for TC, ventilation rate, CO_2 concentration, formaldehyde, $PM_{2.5}$, radon, benzene, relative humidity and visible mould for IAQ, sound level for AC and illuminance level and daylight factor for VC. The final score is determined by the lowest quality level among the four IEQ components.

Table 2. Monitoring parameters of standards for indoor environmental quality evaluation.

Standard reference	Parameter monitored	Assessment methodology
	Thermal comfort (TC)	
EN ISO 7730:2005 (Standard ISO 7730: 2005), EN 16798-1:2019 (Standard CEN/TR 16798-2:2019 2019)	Predicted mean vote (PMV) and predicted percentage dissatisfied (PPD)	Analytical determination through six physical and personal input variables (metabolic rate, clothing insulation, air temperature, mean radiant temperature, relative air velocity, and water vapour pressure). Categories based on occupant's expectation levels are defined as follow: • A: PPD < 6%, −0.2 < PMV < 0.2 • B: PPD < 10%, −0.5 < PMV < 0.5 • C: PPD < 15%, −0.7 < PMV < 0.7
	Local thermal discomfort (e.g. draught rate, radiant asymmetry)	PPD calculation: derived from measurements of local air velocity, vertical air temperature difference and floor surface temperature range. The evaluation method is equivalent to PMV-PPD.
CEN/TR 16798-2 (Standard CEN/TR 1679 8-2:2019 2019)	Subjective responses	Questionnaire using a 7-point thermal sensation scale.
	Operative temperature	Measuring period of at least one week, preferably approximately three weeks, for both the summer and the winter seasons. Thresholds are based on the outside temperature.
	Indoor air quality (IAQ)[a]	
ISO 16000-2 (Standard ISO 16000-2: 2004), ISO 16000-3 (Standard ISO 16000-3: 2011)	Formaldehyde, other carbonyl compounds (aldehydes/ketones)	Active sampling (short-term): 5–60 min or up to 24 h (long-term). Compliance checking typically uses a 30-min sampling period.
ISO 16000-4 (Standard ISO 16000-4: 2011)	Formaldehyde	Diffusive sampling (long-term): 24–72 h, providing a time-integrated average concentration.
ISO 16000-5 (Standard ISO 16000-5: 2007), ISO 16000-6 (Standard ISO 16000-6: 2011)	Volatile Organic Compounds (VOCs, VVOC, SVOC)	Active sampling: recommended flow rates 20–200 ml/min. At least two parallel samples with different volumes are suggested. Samples should be analyzed within 4 weeks.
ISO 16000-7 (Standard ISO 16000-7: 2007)	Airborne asbestos fibers	Variable duration: for leakage sampling (high flow rate), only a few minutes. For background comparison, routine samples should exceed 4 h.
ISO 16000-16 (Standard ISO 16000-16: 2008)	Moulds, filamentous fungi (microorganisms)	Filtration (long-term): typical sampling durations 0.5 h to several hours.
ISO 16000-18 (Standard ISO 16000-18: 2011)	Moulds, filamentous fungi (microorganisms)	Impaction (short-term): 1–10 min. Recommended collecting parallel samples at 50, 100, 200 l.
	Visual comfort (VC)[b]	
BS EN 12464-1:2021 (Standard EN 12464-1: 2021)	Maintained illuminance	On-site photometric measurement: determined using illuminance meters calibrated for spectral luminous efficiency and cosine correction. Standard values for maintained illuminance 100 lx
	Illuminance uniformity	Calculated metric: ratio of minimum to mean illuminance, derived from the gridded array measurements on the reference surface. The range varies from 0.4 to 0.7 depending on the activity.
	Unified glare rating limit (UGR_L)	Analytical determination: This method is verified either by the UGR tabular method (under standard room/luminaire symmetry conditions) or by calculation using the UGR formula, which requires input on luminance distributions of luminaires. The UGR_L values should be within 10–28.
	Cylindrical illuminance	Calculated metric: derived as the average of four vertical illuminance measurements taken at the measurement point. The parameters should not be lower than 50 lx with a uniformity of 0.10 for general purposes
	The colour rendering index (R_a) and correlated colour temperature (T_{cp})	Verification of the source specification: This verification is based on photometric data provided by the manufacturer, ensuring a minimum R_a (e.g. 80 or 90) and T_{cp} range (e.g. 4000 K ≤ T_{cp} ≤ 6500 K).
	Acoustic comfort (AC)	
ISO 1996-2:2017 (Standard ISO 1996-2:2017)	A weighted equivalent sound pressure level, maximum sound pressure level [dB(A)]	Sampling time comprises at least three periods when the noise exhibits cyclic behaviour. The microphone placement must comply with the standard specifications, distinguishing between indoor and outdoor positioning. Threshold values are established on the basis of the disturbance response, using 95% prediction intervals.

[a] According to ISO 16000-41:2023 (2023), threshold values are provided by external authorities.
[b] No specific values for residential building. Thresholds refer to common values presented in BS EN 12464-1:2021 (Standard EN12464-1 2021) for different purposes.

Importantly, this protocol assigns significant importance to IAQ evaluation on the overall IEQ score by considering a fairly extensive list of factors that can affect it. On the other hand, the literature provides several methods to assess a unified IEQ indicator, and the most common approach to combine them is (Wei et al. 2020):

$$\mathrm{IEQ} = w_1 \cdot \mathrm{TC}_I + w_2 \cdot \mathrm{IAQ}_I + w_3 \cdot \mathrm{AC}_I + w_4 \cdot VC_I, \tag{1}$$

where TC_I, IAQ_I, AC_I and VC_I are the scores for the four IEQ components at the same scale (e.g. 0…100), while $w_1 \ldots w_4$ are the corresponding weighting factors. Then, the definition of these four coefficients has become the main issue and has been the subject of multiple studies. For example, (Ncube and Riffat 2012) proposed weighting factors based on the relative importance of each parameter, which is evaluated using a correlational method called the POM, which involves field measurements and questionnaires to determine the relative importance of each of the contributors to the perceived IEQ. The resulting weighting factors are TC = 0.30, IAQ = 0.36, AC = 0.18, and VC = 0.16. On the other hand, the sustainable building method (Devitofrancesco et al. 2019) provides a model to evaluate the IEQ index based on the building usage during the operational phase. The evaluation is divided into two layers: 5 specific categories related to IEQ comfort (TC, IAQ, VC, AC and electromagnetic pollution) and a series of indicators for each category. In addition to addressing a weighting factor for each comfort component, the model also assigns a weighting factor for each indicator within its category. The IEQ categories are weighted according to their relative importance with respect to some goals and criteria chosen by the system developers, while the indicators are based on three criteria:

a. *Importance* of the indicator with reference to indoor environmental quality concepts and issues;

b. *Governability*, which reflects the possibility for the owner of the building, the manager or the customer to modify the specific phenomenon represented by the indicator;

c. *Stability*, namely, the expected duration of the impact on sustainability after the interventions.

The method described in (Piasecki et al. 2017; Piasecki and Kostyrko 2018) involves calculating the PPD for the most significant parameter in each category and then estimating the weighting factors accordingly. In addition, the framework provides an estimate of the accuracy of the model prediction. The simplest model adopts an arithmetic average of the four components (Larsen et al. 2020; Piasecki 2019), thus assigning equal importance to each, while others define that the weighting of IEQ categories should be based on the results of the survey of the inhabitants or determined by regression analysis (Heinzerling et al. 2013). Finally, LEED proposes a certification that is able to compare different buildings in the design and construction phases. The assessment includes nine thematic areas, one of which is related to IEQ. The evaluation is based on prescriptive requirements aligned wmajor standards such as ASHRAE. The weighting factors are considered as follows: TC = 0.06, IAQ = 0.47, AC = 0.12, and VC = 0.35 (Lee and Kim 2008). However, there are inconsistencies among scoring IEQ and occupant satisfaction: studies conducted through POE on LEED-certified buildings (Asmar, Chokor, and Srour 2014; Guo et al. 2021; Amasyali and El-Gohary 2016; Habibi 2020) demonstrate that achieving high rating levels does not correspond to higher satisfaction with the workspace, even if the certified buildings outperform the non-certified.

In addition to these models, alternative schemes not based on equation (1) have emerged. TripleA-reno combined labelling (Magyar et al. 2021) includes several aspects, such as energy performance, IEQ and occupant well-being. The evaluation is performed considering:

a. *Energy performance indicators* selected according to the most relevant existing certification schemes, the Level(s) reporting framework and several EU projects. The features include the energy efficiency class, calculated and measured total primary energy use, calculated and measured delivered energy use, share of renewable energy sources, and area-weighted average thermal transmittance;

b. *The well-being and IEQ indicators* focused on the characteristics of the technical building system. The indicators are control of the heating/cooling system, supply air flow per person, air-tightness of windows and doors, exterior shading, radiant heating/cooling system, and radiant temperature asymmetry;

c. *The measured well-being and IEQ indicators* provide on-site measurements to occupants to inform which environmental parameters should be improved. Measurements include operative temperature, relative humidity, CO_2, TVOC, formaldehyde, $PM_{2.5}$ and PM_{10}.

Table 3. Schemes from literature for IEQ assessment.

Schemes	IEQ category	Assessment method
Impact of clothing on thermal sensation (Ghaddar, Ghali, and Chehaitly 2011)	TC	Modified Gagge model.
Personal comfort model (Kim, Schiavon and Brager 2018a; Kim et al. 2018b)	TC	Identifies specific comfort needs of each individual.
Local body skin model (Choi and Yeom 2017)	TC	Assessment of personal TC through local skin measurements, gender and BMI.
TAIL protocol (Wargocki et al. 2021)	IEQ	Lowest quality level among the four IEQ
Passive Observational Method (POM) (Ncube and Riffat 2012)	IEQ	Based on Equation (1), POM to assess weighting factors.
Sustainable Building Method (Devitofrancesco et al. 2019)	IEQ	Based on Equation (1). Assessment of weighting factors for IEQ categories based on importance and their relative indicators according to three criteria.
PPD method (Piasecki et al. 2017; Piasecki and Kostyrko 2018)	IEQ	Based on Equation (1). Calculation of the PPD for each parameter and estimation of the weighting factors accordingly.
Arithmetic average method (Larsen et al 2020; Piasecki 2019)	IEQ	Based on Equation (1). Assigning equal importance to each IEQ category
Occupant survey method (Heinzerling et al. 2013)	IEQ	Based on Equation (1). Assessment of weighting factors based on occupants feedback
LEED certification (Lee and Kim 2008)	IEQ	Based on Equation (1). Assessment of weighting factors based prescriptive approach of ASHRAE standards
TripleA-reno combined labelling (Magyar et al. 2021)	IEQ	Percentage of the maximum achievable score considering the same system
POE methodology (Pastore and Andersen 2019)	IEQ	It does not provide a unique IEQ index

The final score is obtained by summing all the scores of the components and expressing them as a percentage of the maximum achievable score considering the same system, highlighting areas for improvement and supporting building retrofitting. (Pastore and Andersen 2019) introduces a POE methodology used to assess the comfort quality of office buildings in Switzerland certified under the local Minergie label (Minergie). The assessment includes a monitoring phase consisting of a long-term campaign in which parameters such as temperature, relative humidity, and illuminance are continuously recorded, as are spot measurements of temperature, relative humidity, and CO_2 concentration. In parallel, occupant feedback is collected through surveys, following an approach similar to the monitoring methodology. The assessment approach does not yield a unified IEQ index; instead, individual parameters are independently evaluated. Table 3 provides an overview of the most relevant assessment methods found in the literature and discussed above.

This review of the literature highlights the absence of a unified method for IEQ assessment. Experts typically develop their own evaluation schemes based on major standards, yet the integration and management of all this information remains a challenge. A more technical perspective, focused on sensor technologies, their regulation, and the use of recorded data, will be explored in Section 6.1.

4. Smart buildings

As awareness of the impact of indoor environmental conditions on the health, comfort and productivity of occupants continues to grow, there are evident advancements in the built environment related to this aspect, i.e. the development of smart buildings. These buildings are increasingly being designed and built not only to improve energy efficiency but also to monitor and improve IEQ through the use of integrated technologies. This section explores the evolving definitions and key characteristics of smart buildings, which integrate automation, IoT, and AI to optimise energy efficiency, the comfort of occupants and adaptive functionality. Although some definitions emphasise autonomous systems with minimal human intervention, others require greater occupant involvement or hybrid AI collaboration.

4.1. Definition of smart buildings

Currently, there is a lack of consensus on the definition of smart building, in broad terms, it is defined as *a building that uses advanced automation and other technologies to manage building processes, reduce energy use and improve occupant comfort*. A common definition of Smart Buildings refers to buildings that autonomously adapt to users and environmental needs through systems such as the BMS, IoT, and AI (Genkin and McArthur 2023; Kumar et al. 2021; Heidary, Rao and Fischer 2023; Lillstrang et al. 2022). Therefore, smart buildings can be defined as cyber-physical systems that use sensing, data analytics and control to provide the necessary services (Jin et al. 2018). Works from the literature also describe their behaviour based on this principle of adaptability, which is also their main difference from standard buildings with automation, as they rely on continuous feedback from users and surrounding environmental factors to adjust their behaviour (Heidary, Rao and Fischer 2023; Ekwevugbe et al. 2017). Genkin and McArthur (2023) presented the B-SMART architectural framework, which defines smart buildings as systems equipped with autonomous capabilities such as self-configuration, self-optimisation, self-healing and self-protection enabled by AI. This framework highlights the integration of layered automatic control loops, real-time monitoring and intelligent interaction between the environment and users. According to (Yang et al. 2022), predictive forecasting and real-time monitoring are major components of smart buildings, which require data-driven decision-making and the use of digital twins and blockchain technology. Others find them as environments that make use of ML and IoT for real-time decisions (Habiba et al. 2024; Floris et al. 2021). All these definitions underscore a significant shift in the notion of smart buildings from static, predefined automation to dynamic, intelligent systems capable of autonomously adapting their operations in response to user behaviour and real-time environmental variations relative to an established performance baseline. This is aligned with the definition of SRI. The SRI was first formally introduced by the European Union in the 2018 revision of the EPBD, specifically under Directive (EU) 2018/844 (European Commission 2018). This directive laid the legal foundation for the SRI, aiming to assess a building's capacity to use smart technologies to optimize energy efficiency, adapt to occupant needs and respond to grid signals (European Commission 2025). However, this evolution has not led to a universally accepted definition, which becomes evident when examining the variability in scope and focus across the existing literature.

Although most definitions agree on the use of automation and the integration of technology, there are differences in scope. On the one hand, some refer to an energy-efficient building with BMS as smart building (Chen et al. 2021; Kumar et al. 2016), while others take a holistic perspective, describing smart buildings as operationally aware and implementing occupant-centric features such as self-healing and self-optimising (Habiba et al. 2024; Genkin and McArthur 2023). Furthermore, some articles seem to be more ambiguous, without actually defining a certain term, rather than acquiring features from a case study using an example (Malkawi et al. 2023; Ntafalias et al. 2024). Differences emerge in the autonomics range and technical requirements: while some studies (Genkin and McArthur 2023; Sharma et al. 2024) position smart buildings as fully autonomous systems that require minimal human intervention, others (Cascone et al. 2017) underline the need for human oversight, especially with respect to ethical and operational challenges, including data privacy and integration of legacy systems.

The different definitions reveal the multidisciplinary nature of smart building research, with studies from an engineering perspective focusing on aspects such as automation and energy systems, while studies with a more human-centric perspective focus on comfort and adaptability, which often prioritise hybrid human and AI collaboration due to technical and ethical limitations (Cascone et al. 2017; Habiba et al. 2024). The emphasis on adaptability (Heidary, Rao, and Fischer 2023) suggests a shift toward dynamic definitions that include emerging technologies such as digital twins and blockchain, which can be seen as future smart building paradigms, offering new opportunities and solutions for data integrity, security, and system integration (Yang et al. 2022; Habiba et al. 2024; Heidary, Rao, and Fischer 2023). However, the lack of standardised definitions implies that smart buildings are context-dependent (Yang et al. 2022) and shaped by regional standards, device maturity and people needs. Subsequent research should aim to establish a unified definition that bridges the gap between technological and human-centric aspects.

4.2. Smart building characteristics

Smart buildings are revolutionising urban infrastructure, providing seamless integration of automation, energy efficiency, sustainability and occupant-centric design through cutting-edge technologies such as IoT, AI, and data-driven systems. The set of definitions presented shows that a core strength of smart buildings comes from self-optimisation capabilities that empower BMS and AI-backed frameworks such as B-SMART (Genkin and McArthur 2023) to enable autonomous control of energy consumption, HVAC and lighting (Malkawi et al. 2023). However, this dependency on automation leads to issues, especially in terms of security and interoperability, with IoT networks raising ethical concerns about data privacy and cybersecurity (Cascone et al. 2017). In addition, predictive analytics and ML, such as CNN-RNN hybrid models (Sharma et al. 2024) and SVR-based HVAC control strategies (Anselmi and Moriyama 2017), have shown strong potential to forecast energy demand and improve efficiency. However, for some solutions, such as electrochromic smart windows, which can change their light transmission properties, studies reveal trade-offs: while significant energy savings are achievable, maintaining consistent visual comfort in all building zones remains a challenge (Budaiwi and Fasi 2023). Likewise, designs for green buildings promote sustainability through passive ventilation and recycled resources (Lu et al. 2021), but studies dispute that this universally leads to enhancement of IEQ, with problems such as overheating in well-insulated environments (Karimi et al. 2023; Nimlyat 2018; Noor et al. 2021). With the use of RL algorithms and mobile sensing robots, occupant-centric functionalities are aimed at enhancing comfort (Bouktif and Ahmad 2023; Jin et al. 2018), but their efficacy can be compromised by sensor accuracy (e.g. CO_2-based misestimation of occupancy) and privacy concerns of ubiquitous monitoring (Navada et al. 2013; Cascone et al. 2017).

These contradictions highlight the importance of balanced and adaptable systems that optimise efficiency and human well-being. An example of this is the use of multi-sensor fusion, which combines data from multiple sensors to produce more accurate, reliable or comprehensive information (Ekwevugbe et al. 2017), and digital twin simulations (Yang et al. 2022), which could reduce the trade-off between comfort and energy, while blockchain and federated learning may enable data security (Yang et al. 2022; Cascone et al. 2017). Future developments should focus on scalable hybrid renewable energy systems (e.g. solar biomass) (Dong and Andrews 2009), occupant-in-the-loop automation to increase responsiveness (Bouktif and Ahmad 2023; Floris et al. 2021) and standardized interoperability protocols for the unification of legacy and smart infrastructures (Heidary, Rao, and Fischer 2023). In the end, the diffusion of smart buildings will depend on interdisciplinary answers that merge technological advancements with a balance of ethical, occupant-driven, and climate-responsive designs to meet the sustainability objectives and ever-changing needs of people.

4.3. Role of building management system and its function in smart buildings

The building management system is the core of smart buildings, providing a central monitoring and control platform for the built environment. The main functions of BMS are the management of HVAC systems, lighting, energy consumption and security systems (Li et al. 2019; Malkawi et al. 2023; Genkin and McArthur 2023) and uses data from connected sensors and actuator networks to maximize energy savings and comfort in real time (Li et al. 2019; Genkin and McArthur 2023). For example, BMS can adjust the HVAC system based on occupancy patterns and ambient factors (such as CO_2 concentrations and ambient temperatures), achieve optimal IAQ and TC (Akbar et al. 2015; Qabbal, Younsi, and Naji 2022) and control the lighting system, often using occupancy sensors to reduce energy consumption by shutting down lights in empty spaces (Sim et al. 2016; Zou et al. 2017). It also supports fault detection and diagnosis and allows proactive maintenance and continuous operations to optimize the performance of building systems (Shen et al. 2017; Habiba et al. 2024).

In smart buildings, data collection and analysis are at the core of BMS capacity. In order to improve building system monitoring and control, BMS relies on real-time data from various types of sensors, including temperature, humidity, CO_2 and occupancy sensors (Li et al. 2019; Malkawi et al. 2023). Modern technologies such as AI and the IoT enable predictive analytics and ML models to enrich BMS' advantages: for example, supervised machine learning model can estimate energy consumption patterns and optimize HVAC operations, generating significant energy savings (Chen et al. 2021; Shapi et al. 2021). IoT integration provides smooth connections between sensors, actuators and BMS, allowing system dynamics to adapt to ambient environments (Floris et al. 2021; Heidary et al. 2023). Furthermore, BMS platforms increasingly incorporate advanced analytics and ML algorithms (e.g. k-NN, SVM, and ANN) for monthly and peak energy consumption forecasting while also supporting data-driven control algorithms for occupancy prediction and HVAC unit status inference (Shapi et al. 2021). Advanced deep learning approaches, including hybrid models combining CNN and RNN, are being integrated into BMS platforms for short-term heat energy consumption prediction, supporting more sophisticated energy management strategies in smart buildings (Sharma et al. 2024).

Traditionally, smart buildings have made use of various sensors to gather information on occupancy patterns and optimize energy-consuming facilities. However, despite the advancements in BMS technology, several challenges and limitations persist. First, sensor accuracy and calibration are two major challenges that can deeply affect the quality and reliability of collected data (Painter, Brown, and Cook 2012; Akkaya et al. 2015). For instance, miscalibrated sensors might prompt the HVAC or lighting systems to change status when they should not, compromising energy efficiency and occupant comfort (Painter, Brown, and Cook 2012). Furthermore, privacy concerns exist, especially regarding the use of occupancy detection systems with cameras or other potentially invasive technologies (Shih 2014; Akkaya et al. 2015). Finally, the deployment of effective smart building solutions is further complicated by integration challenges, such as the need for BMS compatibility, since manufacturers do not necessarily use the same standards (Habiba et al. 2024).

Moreover, there is an ongoing discussion around the extent that green building certifications, including IEQ, ensure real comfort conditions. Although studies have focused on the certification of green buildings, it has been observed that it does not necessarily guarantee comfortable conditions in all aspects, since TC and AC are not considered consistently (Horr et al. 2016; Karimi et al. 2023). The literature reveals diverse viewpoints on whether BMS achieves the goals of energy efficiency and comfortable indoor environments. Advanced BMS functionalities, including adaptive systems control and real-time data analytics, are associated with remarkable results on both fronts (Li et al. 2019; Chen et al. 2021). For example, data-driven adaptive HVAC control results in decreased thermal dissatisfaction in the range of 5%–40%, together with energy savings of 15%–33% (Papadopoulos et al. 2023). Nevertheless, other works highlight several limitations, such as the dependence on correct sensor data, as well as the risk of privacy breaches with invasive surveillance tools (Painter, Brown, and Cook 2012; Akkaya et al. 2015). Various technological advancements in digital twins and AI-driven predictive models, among others, are providing solutions to these challenges, since a digital twin can provide near real-time data and insights to facilitate maintenance and optimization of building operations (Yang et al. 2022; Puiu and Fortis 2024).

The evolution of BMS is moving towards highly adaptive, occupant-centric systems based on emerging technologies (e.g. AI, IoT, digital twins) to enhance its features and capabilities. Adaptive control strategies will further gain traction, dynamically adjusting building operations with real-time data and feedback from occupants to find the best trade-offs between energy efficiency and comfort (Salamone et al. 2018; Papadopoulos et al. 2023).

5. Smart sensors

The effectiveness of BMS highlights the importance of accurate and reliable data collection, along with properly designed IoT networks. This section is dedicated to the sensing technologies available for IEQ monitoring in smart buildings. After a general overview, the key sensors dedicated to the main environmental variables (i.e. air quality, temperature and relative humidity, acoustics, and light) are investigated. Although occupancy evaluation is not strictly involved in IEQ monitoring, it is included in this literature analysis because of its relevance in energy savings and personalized comfort (particularly in residential settings). Finally, all-in-one and wearable smart sensors have been investigated due to the recent growth in importance on the market.

5.1. Overview

Sensors are at the core of a smart building: they collect data on environmental parameters and occupation, providing valuable information to assess IEQ and guarantee comfort conditions while optimising system management to reduce energy consumption (Dong et al. 2019). In detail, the notion of smart sensors was introduced in the literature around the early 2000s: they are nodes in an IoT network, and their hardware may include memory, a computational device and a wireless communication device, along with the sensing element itself. They can also include software for monitoring and signal processing and can provide control signals to actuators connected to the network (Lim 2001). Therefore, smart sensors can also have the ability to post-process the output of the sensing element and perform self-diagnosis (Bayart 2001) and self-calibration (Kenny 2005) procedures. As stated in (Mozaffari et al. 2019), smart sensors constitute the so-called *edge* layer of the overall network: due to their computational capabilities, they can process data and limit the bandwidth required for transfer to other layers. The same work lists two other requirements to allow the integration of smart sensors into an IoT network:

a. They need to be logically connected to each other to combine data and improve precision;
b. They need to be highly energy efficient.

Since the effectiveness of an IoT network relies on its architecture, which needs to be scalable and able to manage, transfer and analyse collected data, much focus has been dedicated to this topic in recent years. An interesting approach applied to public buildings with an existing communication infrastructure was presented by Calvo et al. (2022): it is based on the highly flexible and scalable *edge-fog-cloud* paradigm, namely, sensing nodes, IEQ concentrators (local storage, configuration, etc.) and cloud services (e.g. data analytics, storage, prediction, weather forecasting, etc.). Similarly, the work by Kumar et al. (2021) suggests a general architecture layout that can be applied to any context and follows the evolution of the smart building over the years and is based on three layers: the *sensing or perception layer*, which is responsible for collecting data, including those related to occupant preferences (e.g. set points for temperature and relative humidity); the *processing or network layer*, which organises and processes information; the *reproduction or application layer*, which uses processed data to understand the interaction between users and equipment and, finally, improves the performance of the latter in delivering services to the users themselves. This framework aims to track the environmental quality and use of indoor spaces and improve building management and maintenance. A similar three-phase concept was presented by Li et al. (2019) and can be summarised as *monitoring*, *diagnostic* and *intervention*. The monitoring phase is mainly based on the real-time sensor network but can also include the collection of information on occupant satisfaction. The diagnostic phase is based on data-mining techniques and statistical analysis and is focused on identifying performance losses and providing possible interventions to improve energy efficiency, IEQ and occupant satisfaction. Finally, the intervention phase focusses on developing and validating optimisation strategies, such as automatic controls and occupant behaviour. Finally, Genkin and McArthur (2023) ascribe the smart sensor network to the *real-time data zone* of the *building knowledge repository* inside the B-SMART architecture. This zone needs to support high rates of data inserts and updates, along with fast operations when needed, and to store at least 24 h of collected information to allow for real-time analysis. For older data and technical specifications, the *historical data zone* is available inside the architecture. This approach treats smart buildings as *autonomic cybernetic systems*, which are computing environments capable of minimising the human intervention required in response to changes, either internal or external.

In terms of overall efficacy in guaranteeing high levels of IEQ in smart buildings, a dedicated sensor network should be designed that considers the spatial distribution of environmental variables (Calvo et al. 2022). This issue is addressed in an experimental study by Clements et al. (2019), which evaluated the efficacy of a *living lab* research facility to conduct human-subject research: when thermal conditions are considered, the authors measured up to 3 °C of temperature deviation between the set-point and desk temperature when windows were not shaded and significant variation between desks due to layout, human presence, orientation, etc. The same work highlights spatial variability in lighting and auditory conditions variation in background sound levels between 32 and 43 dBA). The distribution of indoor pollutant concentrations can also be spatially non-uniform, as stated in Xiang et al. (2013). Such variability requires a sufficiently refined sensor network to allow adequate monitoring of environmental conditions, at least in the most commonly used locations inside an indoor space (Dong et al. 2019). This is also demonstrated in Mohammadi, Assaf, and Assaad (2024), where a set of four sensing stations is used to evaluate the spatial distribution of temperature in a compact space (3.2 × 5.2 m room) in real time. A more targeted approach can be adopted in working environments such as office buildings, where sensors can be located on desks to

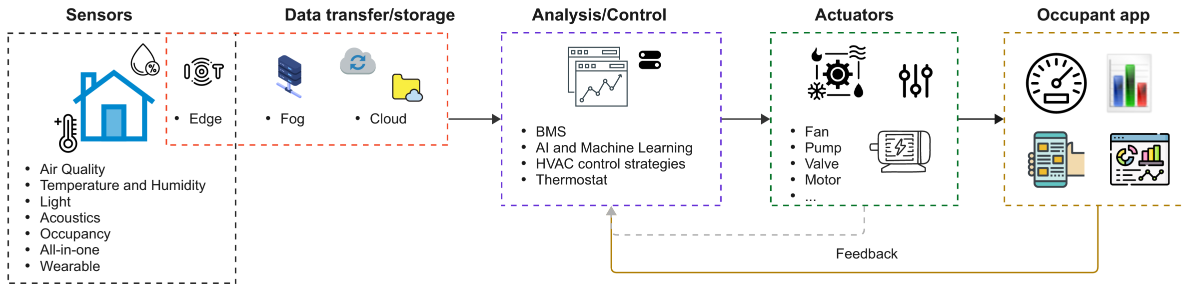

Figure 4. IEQ control workflow.

evaluate environmental variables locally (Salamone et al. 2017; Parkinson et al. 2019). When IAQ is considered to evaluate personal exposure to pollutants, it presents the same kind of challenges due to the spatial and temporal variability of their concentration, as highlighted in Qabbal, Younsi, and Naji (2022). As far as lighting quality and visual comfort in office environment are concerned, the paper by Pandharipande and Caicedo (2015) presented a smart lighting system that involves luminaires equipped with occupancy and light sensors. Due to its granular application, it is able to mitigate energy consumption by actuating each luminaire separately only when and where required by the presence of a user and dimming the level to take into account the available daylight (to guarantee the minimum illuminance of 500 lux in occupied areas and 300 lux in unoccupied areas, as indicated by the standard EN 12464-1 (EN1 2021). However, despite the observed energy savings, the authors identify the role of daylight on lighting control as one of the technical challenges that would be mitigated by the introduction of automatically controlled blinds to lower glare. Finally, in recent years, smart sensors dedicated to residential settings have been made available on the market (LSI LASTEM S.R.L.- Sphensor TM; RENSON - Sense; leapcraft - AmbiNode; Fybra S.R.L. - Fybra Home): they can be located inside rooms according to the needs of the occupants and provide useful information about the IEQ. However, their placement is limited by the interior arrangement of the rooms, and readings might not reflect the conditions at the exact location of the occupants (for instance, sensor readings taken from one side of a room may not accurately reflect the environmental conditions on the other side). Building on the concepts of smart sensors, IoT layers and scalable architectures discussed above, the general control workflow of a smart building is illustrated in Figure 4. The diagram presents how heterogeneous sensor data (e.g. air quality, temperature, humidity, light, acoustics, and occupancy) are collected and transferred across edge-fog-cloud layers for further processing, storage and analysis. Furthermore, the analysis and control layer, which can constitute AI- and BMS-driven control logic, enables optimized HVAC strategies, which are implemented via actuators (fans, pumps, valves, motors, etc.). Additionally, the workflow emphasizes the continuous feedback loop between occupants, sensing infrastructure, and intelligent control systems, ensuring optimal occupant comfort and well-being.

5.2. Key sensors

The analysis of works in the literature dedicated to IEQ and smart buildings highlights the state-of-the-art and future trends in sensing devices that can be integrated into smart sensors, together with the sensors already available on the market. The purpose is to list the main technologies available to address several components of the IEQ, along with the potential limitations and issues that should be considered when effectively deploying IoT networks and smart sensors in residential buildings. Moreover, greater emphasis is given to devices that involve low-cost sensors oriented toward a do-it-yourself approach (Table 4), since the vast number of variables required for IEQ monitoring can lead to a growth in the complexity and cost of smart sensor networks, potentially hindering their diffusion in the market.

Table 4. List of low-cost sensing elements for IEQ, including the works from literature where they are discussed (column *Refs.*). Measurement range and accuracy are reported, when available.

Sensor	Features		References	Notes
		Air quality		
K-30 (Datasheet K-30 2022)	NDIR CO_2 sensor	0…5000 ppm ±30 ppm	(Salamone et al. 2017; Pandharipande and Caicedo 2015) (Weyers et al. 2017) (Weekly et al. 2015)	Equipped with automatic baseline correction
Telaire T67xx modules (Amphenol Sensors)	NDIR CO_2 sensor	0…2000 ppm ±30 ppm	(Ekwevugbe et al. 2017) (Candanedo and Feldheim 2016) (Dong and Lam 2011)	Equipped with self-calibrating algorithm
S8 (Datasheet, S8 2022)	NDIR CO_2 sensor	400…2000 ppm ±70 ppm	(Wolf et al. 2019)	Maintenance-free, available in a low-power version
CSS811 (Datasheet CCS 811 2020)	MOX sensing element, directly measures TVOC concentration and evaluates eCO_2	0…1187 ppb TVOC 400…8192 ppm eCO_2	(Calvo et al. 2022)	Low-cost, calibrated to a typical mixture for indoor environment, baseline correction every 24 h, affected by low operational precision
TGS2602 (Datasheet, TGS2602, 2018)	MOX sensing element, VOCs	1…30 ppm	(Snyder et al. 2013) (Wolf et al. 2019)	This technology can be used to monitor CO, O_3 and NO_x
GP2Y1010AU0F (Datasheet, GP2Y1010AU0F, 2018)	PM monitoring through light scattering	100 $\mu g\ m^{-3}$ ±30%	(Snyder et al. 2013) (Qabbal et al. 2022)	It does not discern between $PM_{2.5}$ and PM_{10} (GP2Y1030/31AU0F can detect both, DN7C3CA007/DN7C3D015 is dedicated to $PM_{2.5}$)
Temperature and Relative Humidity				
DHT22 (Datasheet, DHT22 2012)	Capacitive temperature and relative humidity sensor	0…100% ±5% RH −4080 °C ±0.2 °°C T	(Mui et al. 2016) (Qabbal et al. 2022) (Salamone et al. 2017) (Candanedo and Feldheim 2016)	Reported accuracy do not agree between different works (values reported here are referred to data provided by the manifacturer)
Telaire T9602 (Datasheet, Telaire T9602 2018)	Capacitive polymer RH sensor, proportional to absolute T sensor	20…80% ±2% RH 2040 C ±0.5 °°C T	(Weyers et al. 2017)	Reliable low-cost option
BME680 (Datasheet, BME680 2024)	RH, T, VOC and pressure sensor	0…100% ±3% RH 4085 °C ±1°C T	(Mohammadi et al. 2024)	Compact and low-power-consumption 4-in-1 sensor
		Light		
TSL2561 (Datasheet, TSL2561 2025)	Photodiode	0.1…40000 lux	(Mui et al. 2016) (Candanedo and Feldheim 2016)	Separate detection of infra-red and full-spectrum light, comparable performance to laboratory grade instruments
		Acoustics		
Grove Sound Sensor (Datasheet, Grove 2015)	Electret microphone, LM358 amplifier	40…90 dBA	(Mui et al. 2016) (Parkinson et al. 2019) (Qabbal et al. 2022) (Zikos et al. 2016)	

5.2.1. Air quality

IAQ in buildings has a direct effect on the health and well-being of their occupants. It is affected by several parameters, such as the concentrations of various gases (e.g. CO_2, CO, NO_x, SO_x, etc.), VOCs and PM (Heidary et al. 2023). Therefore, different sensors are dedicated to each category, and a practical implementation of Smart Sensors in residential Smart Buildings would require a careful selection of the most relevant quantities to be measured.

CO_2 is one of the key indicators related to IAQ (Wargocki et al. 2021): it can be used to address the efficacy of the ventilation system in providing fresh air intake and controlling the air change rate through a demand-controlled strategy (Nassif 2012) and is related to the outdoor concentration and occupant presence and activity as a consequence of their metabolism (Dong et al. 2019). For instance, the study by Laverge et al. (2015) shows that the highest concentrations observed in residential buildings are detected in bedrooms. Therefore, CO_2 concentration can be used as a control variable to manage the ventilation system since it can be used as a proxy for the occupancy level. In this way, it is possible to achieve a healthy indoor environment and mitigate energy consumption at the same time (Nassif 2012; Wang et al. 2018; Zikos et al. 2016; Wolf et al. 2019). However, when it is used for this purpose, the location of CO sensor installation becomes paramount (Zikos et al. 2016; Wolf et al. 2019), as discussed in §Section 5.2.5. Moreover, according to (Erickson and Cerpa 2010; Zikos et al. 2016), the slow response of CO_2 sensors to build-up can make the ventilation control less effective, making their calibration and accuracy critical (Nassif 2012). Even though in past works electrochemical sensors were considered among the most promising in terms of cost and durability (Park et al. 2003), the devices mentioned in more recent works are generally based on the NDIR operating principle, which is implemented by several commercially available sensing modules, such as the K-30 (Datasheet, K-30 2022) (used in Pandharipande and Caicedo 2015; Weyers et al. 2017; Weekly et al. 2015; Salamone et al. 2017) and various versions of the Telaire (Amphenol Sensors) sensor (mentioned in (Ekwevugbe et al. 2017; Candanedo and Feldheim 2016; Dong and Lam 2011). They feature measurement range equal to 0…5000 ppm and 0…2000 ppm, respectively, with an accuracy around ±30 ppm, and both are equipped with a baseline correction or a self-calibration algorithm. NDIR is also implemented in the S8 (Datasheet, S8 2022) miniature CO_2 sensor (range 400…2000 ppm, accuracy ± 70 ppm, maintenance-free according to the manufacturer) mentioned in the work by Wolf et al. (2019), which is available in a low-power version. Sensors based on this principle are generally compact and stable to fluctuations in temperature and relative humidity, while their sensitivity is affected by the path length, and the calibration procedure can pose some issues (i.e. self-calibrating single beam devices can assume 400 ppm as background CO_2 as default) (Snyder et al. 2013). Finally, another approach is the indirect measurement of the so-called equivalent CO_2 (eCO_2) performed by the CCS811 sensor (Datasheet, CCS811 2020): this quantity is tied to TVOCs concentration (which is measured directly) and is considered to provide an acceptable representation of the actual CO_2 concentration evolution. This sensor is used in (Calvo et al. 2022) due to its lower cost, but the authors have observed a lack of operational precision and plan to search for an alternative.

Even though the CO_2 concentration is sometimes used as the sole indicator for IAQ (Devitofrancesco et al. 2019) and to quantify the need for fresh air in indoor spaces (Nassif 2012), there are other factors that need to be taken into account, especially in urban areas, where a higher ventilation rate can increase the indoor pollutant concentration (Kumar et al. 2016), hence the requirement for effective filtration. Moreover, only inspecting for CO_2 does not consider the emissions from building materials (Painter et al. 2012). This complex relationship, demonstrated by the measurements presented in (Qabbal, Younsi, and Naji 2022), highlights the necessity for more in-depth monitoring, including of pollutant gases, VOCs and PM. Indeed, beside CO_2, there are several potential variables to monitor when assessing IAQ: as an example, the TAIL protocol (Wargocki et al. 2021), aimed at evaluating the IEQ in offices and hotels, also includes the concentration of formaldehyde, benzene and $PM_{2.5}$. This list was expanded further by Qabbal et al. in their experimental evaluation of a university building (Qabbal, Younsi, and Naji 2022) by considering VOCs and CO_2 concentrations as well. Finally, some works only analyse VOCs (Xiang et al. 2013; Calvo et al. 2022) or PM (Weyers et al. 2017).

This lack of consistency suggests that there is not a general definition for a minimum set of variables to be continuously measured when addressing the IAQ of an enclosed environment, but it can depend on several factors (e.g. use, location, and construction technology, etc.). As far as residential buildings are concerned, an interesting review presented by Rojas et al., (2024) shows a collection of papers investigating different combinations of parameters, leading the authors to observe a lack of standardized methods to assess IAQ, along with a lack of long-term experimental studies. However, a study aimed to identify guidelines for specific VOCs rather than TVOC in the UK (Shrubsole et al. 2019) reported generally low concentrations of VOCs with health impact after few months after construction, possibly indicating that TVOC monitoring is adequate in residential settings. It also indicates that source control is the preferential strategy to mitigate their concentration and reduce exposure of the indoor population, along with good ventilation practices to dissipate residues.

Considering current sensing technology, many studies involving pollutants and VOCs use passive samplers (Derbez et al. 2014a; Derbez et al. 2014b; Langer et al. 2015; Kauneliene et al. 2016; Piasecki 2019), which are adequate for experimental study but are not of practical use in a smart sensor network since they need to be periodically collected and analysed. In Calvo et al. (2022), TVOCs are measured with the previously mentioned CCS811 (Datasheet, CSS811 2020), which is based on a solid-state metal oxide semiconducting (MOX) gas-sensing element (Zampolli et al. 2005). It is very compact and low-power, has a range of 0-1187 ppb, is calibrated to a typical compound mixture for an indoor environment and features an automatic baseline correction with a 24-h period. Another gas sensor based on MOX technology is TGS2602 (Datasheet, TGS2602 2018), with a detection range of 130 ppm, as mentioned previously (Xiang et al. 2013). Furthermore, metal oxide semiconductors are an inexpensive option to monitor CO, O_3 and

NO_x (Snyder et al. 2013). Finally, PM monitoring is most commonly performed through the light scattering technique, which is inexpensive and compact but does not provide direct mass measurements and can have issues with ultra-fine particles (Snyder et al. 2013). For example, the GP2Y1010AU0F sensor used in the work by Qabbal, Younsi, and Naji (2022) to monitor $PM_{2.5}$ is a low-end basic model produced by SHARP/Socle Technology (Datasheet GP2Y1010AU0F, 2018), with a declared measurement accuracy of 100 µg· m$_{-3}$ ±30%. However, despite the information reported in (Qabbal, Younsi, and Naji 2022), this sensor is unable to discern between $PM_{2.5}$ and PM_{10} according to the manufacturer. Nevertheless, there are other components that have this ability (e.g. GP2Y1030/31AU0F detects $PM_{2.5}$ and PM_{10} separately, and DN7C3CA007/DN7C3D015 is solely dedicated to $PM_{2.5}$).ata supporting the findings of this study are avai

5.2.2. Temperature and humidity

One of the most relevant components of IEQ is TC. Although it is affected by several parameters, according to the well-known Fanger model (Fanger 1967), the most commonly monitored parameters are temperature and relative humidity. More precisely, this model is based on measurements of both air and mean radiant temperatures since it needs to evaluate simultaneously the convective and radiative heat exchange between the human body and the surrounding environment. In practice, the indoor TC is empirically assessed by measuring the air and operating temperatures. However, there are IEQ protocols, such as the recently published TAIL (Wargocki et al. 2021), that evaluate the thermal environment through the air temperature only. This simplification is based on the assumption that, in low-energy buildings, the difference between these two quantities is negligible; for instance, a study by Dawe et al. (2020) investigated the difference between air temperature and mean radiant temperature over 200k pairs of measurements from field and laboratory analyses and shows that the median absolute difference is 0.4 °C, regardless of the building type or the system type and operation, which is well below the temporal or spatial fluctuation. This result is also supported by the work of Kontes et al. (2017), which obtains a similar outcome for buildings with high thermal mass when solar and internal gains are properly taken into account, while more caution is required with buildings with lower thermal mass.

As far as sensors are concerned, there are several options available on the market (Dong et al. 2019), with different levels of precision and accuracy, ranging from less than ±0.5 C to around ±0.1 C. To ensure stability and address any drift, they require regular calibration. A low-cost solution to measure both air temperature and relative humidity at the same time is the capacitive-type sensor DHT22 (Datasheet, DHT22 2012), which is used as part of a smart sensor to assess TC in a retrofitted university building in Lille (France) (Qabbal, Younsi, and Naji 2022). In this paper, it is declared to measure relative humidity and air temperature in the range of 0%…100% and −40…80 °C, respectively, with ±5% and ±2 °C accuracy. This same sensor is also used in few other works from the literature: first, a study by Mui et al. (2016), aimed at developing a predictive IEQ calculator, which is based on few sensors available on the market; second, an occupancy detection algorithm based on the sampling of several environmental variables and involving statistical learning models (Candanedo and Feldheim 2016); and, finally, a low-cost do-it-yourself device to monitor environmental parameters and control heating, cooling, ventilation and lighting presented in (Salamone et al. 2017). Even though it is nominally the same device, its specifications seem different in some aspects (i.e. relative humidity range and accuracy of 0…100% and ±2% or ±3%, respectively, and temperature accuracy of ±0.5 °C). Importantly, the temperature accuracy reported in all the studies seems to be in disagreement with the value of ±0.2 °C declared by the manufacturer in the data sheet (after factory calibration in a dedicated thermostatic chamber), and no explanation for this issue is provided in any case. For this reason, the data included in Table 4 refer to the data sheet provided by the manufacturer. Another commercially available device is the Telaire T9602 (Datasheet, T9602 2018), which includes a capacitive polymer relative humidity sensor (±2% accuracy in the 2080% range) and a proportional to absolute temperature sensor (±0.5 °C accuracy in the 2040 °C range). An example of its application can be found in (Weyers et al. 2017), where it is used to develop an IEQ platform dedicated to classrooms and based on low-cost components. According to the authors, this sensor has been selected for its reliability, and its connection to the main board of the Smart Sensor platform has been defined keeping in consideration its sensitivity to heat sources, since the heat radiated by the microcontroller or other sensors could interfere with the accuracy of data readings. A third option mentioned in the literature is the

BME680 sensor (BME 2024): it is used to monitor temperature and relative humidity to provide a real-time evaluation of the spatial and temporal distributions of PMV in a study by Mohammadi et al. (2024). In this work, the measurement range and accuracy declared are −4085 °C and ±1 °C for temperature and 0…100% and ±3% for relative humidity. Importantly, this is actually a very compact and low-power 4-in-1 sensor capable of monitoring gas concentration and pressure and, therefore, a potentially convenient solution for IoT devices.

Among the all-in-one smart sensors (see §Section 5.2.6 for a detailed discussion), a noteworthy solution in terms of temperature and relative humidity measurement is the one described in the paper by Parkinson et al. (2019), called SAMBA. In detail, the housing of this device includes two main components: a *main unit* and a *satellite element*, which includes all sensors involved in local TC assessment: air and operative temperature (NTC thermistor, range 050 °C, resolution 0.1 °C) relative humidity (capacitive, range 595%, resolution 0.1%) and air velocity (bi-directional thermal anemometer, range 01 m/s, resolution 0.01 m/s). This solution is adopted after testing, instead of a single-housing unit, to address potential measurement biases due to waste heat from other components (e.g. power-conditioning circuits and other sensors).

Finally, many studies related to IEQ in general and indoor TC specifically involve different kinds of monitoring station (Lan et al. 2011; Painter et al. 2012; Ekwevugbe et al. 2017; Devitofrancesco et al. 2019; Piasecki 2019). However, even though these clusters of sensors equipped with a dedicated data-logger are able to provide a complete environmental monitoring solution, they are intended for research and experimental use and do not present any interest in everyday domestic applications in smart sensor networks.

5.2.3. Light

As stated in Section 3.2, VC is an important component of IEQ that directly affects occupant productivity, especially in office buildings. When integrated in an IoT network, light sensors (i.e. photometric sensors) can be used to control the activation and intensity of luminaires according to daylight availability to reduce electricity consumption while ensuring human comfort (Yan et al. 2017; Navada et al. 2013; Heidary et al. 2023). However, the effectiveness of this approach largely depends on the placement of these sensors in the built environment in relation to the locations typically occupied in indoor spaces (Heidary et al. 2023; Dong et al. 2019). Moreover, even though VC can be based only on illuminance and daylight factors (Wargocki et al. 2021), other aspects can be taken into consideration in the control strategy of the lighting system, such as the colour temperature ratio, glare, light spectrum, etc. (Dong et al. 2019). An example of sensor-based lighting control is presented in (Pandharipande and Caicedo 2015), where photometric sensors are used in combination with occupancy sensors in a distributed architecture to detect human presence and control IoT-ready luminaires to guarantee 500 lux on used working stations and 300 lux everywhere else. The system, which requires calibration against the dimming levels of the luminaires, is controlled through an optimised algorithm, which shows promising results when compared to a simple PID control but is largely affected by the unknown effects of daylight on the sensor planes (i.e. available daylight on the working plane might differ from the one perceived by the sensor on the ceiling due to unmapped reflections). This work also highlights several technical challenges: first, due to the importance of daylight, the control algorithm needs to be able to account for blinds and movable shading devices; second, the control system must consider the effects of daylight penetration in the indoor space and the lighting design (i.e. luminaire location, spacing, etc.); finally, user satisfaction needs to be monitored and considered in the control strategy. Light sensors are also used in some cases to provide indications of occupancy in rooms (Candanedo and Feldheim 2016).

A low-cost photometric sensor available on the market is the TSL2561 (Datasheet, TSL2561 2025), which is based on a photodiode and is mentioned in some works in the literature (Candanedo and Feldheim 2016; Mui et al. 2016): it has a range of 0.140000 lux and is able to detect infrared and full-spectrum light separately. Although it is a do-it-yourself option, it performs comparably to laboratory-grade instruments when involved in VC assessment (Mui et al. 2016).

5.2.4. Acoustics

The sound pressure level is generally used in rating schemes to address indoor AC in buildings (Devitofrancesco et al. 2019; Wargocki et al. 2021; Rocca et al. 2022), since it has been correlated with subjectively perceived noise discomfort (Huang and Griffin 2012) and subsequent performance in a work setting due to its impact on speech intelligibility (Hongisto 2005) (which is evaluated through the dedicated STI (Devitofrancesco et al. 2019). Moreover, as mentioned in §Section 3.2, it has been demonstrated that ambient noise in a residential context can disrupt sleep quality, inducing tiredness and reducing daytime performance, with a detrimental effect on overall health (Muzet 2007).

However, despite its significance, not many works in the literature involve indoor AC measurement, in comparison to the other components of IEQ: in some cases, the sampling campaign is based on laboratory-grade equipment (Devitofrancesco et al. 2019; Lan et al. 2011; Huang and Griffin 2012; Piasecki 2019), which would not be useful in an IoT network inside a residential Smart Building, while in other manuscripts, the sound pressure levels are used only as a mean to estimate occupancy levels (Ekwevugbe et al. 2017; Zikos et al. 2016; Dong and Andrews 2009), rather than to evaluate AC itself.

On the other hand, some studies involve compact and commercially available low-cost sensors that can be used in an IEQ-oriented smart sensor: one example is the Grove Sound Sensor (Datasheet, Grove 2015), which includes an electret microphone and an LM358 amplifier, and generates an analog output. This device is used in studies that adopt a do-it-yourself approach: For instance, Mui et al. (2016) described a smart sensor (*IEQ calculator* in the paper) based on compact low-cost sensors and compared its accuracy against laboratory-grade equipment by correlating the two IEQ calculations in an office environment. However, among all the measurements, which generally show high accuracy and sensitivity (i.e. $R^2 > 0.95$, $p > 0.7$), the sound pressure level is characterized by a worse performance (i.e. $R^2 > 0.65$, $p > 0.45$), possibly due to background noise fluctuations. Nevertheless, the authors still consider it acceptable, due to the small contribution of AC to the overall IEQ in their model. An electret microphone is also adopted in other cases: first, in the bespoke PCB described in (Parkinson et al. 2019), to measure the sound pressure level (range 4090 dBA, resolution 0.1 dBA). Second, in the work of Zikos et al. (2016), it is used to register acoustic events that are tied to human presence and occupancy level, with a high degree of efficiency in terms of both accuracy and protection of privacy. Finally, this type of device is used in the Smart Sensor described in (Qabbal, Younsi, and Naji 2022), but results about AC are not presented in the manuscript.

5.2.5. Occupancy

Although occupancy monitoring is not strictly related to IEQ assessment, significant research effort has been dedicated to this topic in recent years. Indeed, information about occupancy (i.e. human presence, number of occupants, type of activity, location in space, identification) can be integrated into the BMS and facilitate improvements in energy efficiency and personalised environmental comfort (Jung and Jazizadeh 2019; Wang et al. 2005; Lam et al. 2014; Pandharipande and Caicedo 2015; Zikos et al. 2016; Chen et al. 2016; Candanedo and Feldheim 2016; Shrubsole et al. 2019; Kim and Srebric 2017; Sun et al. 2020): as an example, a control strategy for HVAC systems based on room occupancy prediction is presented in (Erickson and Cerpa 2010), which leads to 20% potential energy savings. A similar approach is the subject of (von Bomhard et al. 2016), where measurement-based occupancy prediction is used to control the activation of the heating system in each room separately. The work by Capozzoli et al. (2017) involves the definition of an occupancy-based energy saving strategy for the HVAC system, which leads to 14% average energy savings during the investigated period. In (Jia et al. 2017), the VAV boxes are controlled according to an *occupancy-location model*, with a specific focus on privacy protection. In fact, a significant portion of the research effort in the last year has been dedicated to the definition of reliable predictive algorithms for occupancy, which are based on direct or indirect measurements (Wang et al. 2018; Jia et al. 2017; Kleiminger et al. 2014; Zuraimi et al. 2017), which can also be used in building numerical simulation and the definition of digital twins (Capozzoli et al. 2017; Page et al. 2008; Duarte et al. 2013; D'Oca and Hong 2015; Mahdavi and Tahmasebi 2015; Davis and Nutter 2010; Chen et al. 2015; Yan et al. 2017). The list of all sensors and techniques mentioned in this section is summarized in Table 5.

Table 5. List of sensors and techniques to detect occupancy-related data in buildings. The works from literature where they are discussed are reported in column *Refs*.

Method		Technology	References	Notes
Direct	Image-based sensor	Infrared, visible light and luminance cameras	(Zou et al. 2017) (Shih 2014) (Sun et al. 2020) (Benezeth et al. 2011) (Labeodan et al. 2015) (Jiang et al. 2016)	It can track occupants location, number, activity and identity it is costly, limited by occlusions, requires storage and computing power, presents privacy issues
Direct	Image-based sensor	Depth sensor	(Galcık and Gargalik 2013) (Seer et al. 2014) (Diraco et al. 2015)	It can count and locate occupant without identification (privacy preservation)
Direct	Motion sensor	PIR	(Ekwevugbe et al. 2017) (Weyers et al. 2017) (Labeodan et al. 2015) (Shen et al. 2017) (Wahl et al. 2012) (Raykov et al. 2016)	Assesses occupancy by detecting movements and requires a time delay to avoid misreading vacancy, people counting can be performed with appropriate configurations
Direct	Radio-based sensor	RFID	(Raykov et al. 2016) (Li et al. 2012) (Ranjan et al. 2013)	Identifies occupants through radio tags with a univocal identification code (terminal based)
Direct	Threshold/ mechanical sensor	Reed switches, door badges, piezoelectric mats or infrared beams	(Agarwal et al. 2010)	Interaction with openings is required for the system to function
Indirect	Environmental variable	CO_2 concentration	(Qabbal et al. 2022) (Calì et al. 2015) (Zuraimi et al. 2017) (Jiang et al. 2016)	Requires machine learning or predictive algorithm, observed accuracy above 80%, it can have issues since CO_2 is a transient phenomenon
Direct	Combined measurements	CO_2 concentration and PIR	(Akkaya et al. 2015) (Gruber et al. 2014)	Improved accuracy in estimating occupancy level
Indirect	Combined measurements	CO_2 concentration and other IEQ variables	(Dong and Andrews 2009) (Zikos et al. 2016) (Dong et al. 2010) (Chen et al. 2017)	Improved accuracy in estimating occupancy level
Indirect	Other techniques	Webcams, mouse and keyboard activity, chair sensors, Wi-Fi connection, electricity consumption	(Newsham et al. 2017) (Zhao et al. 2015) (Zou et al. 2017) (Labeodan et al. 2015) (Zou et al. 2018; Becker and Kleiminger 2018)	Potential privacy issues
Direct	Motion sensor	mmWave	(Gu et al. 2019) (Pegoraro et al. 2022) (Liu et al. 2024) (Zhang et al. 2025) (Haipeng et al. 2021) (Zhang et al. 2023)	Effective in localizing multiple people simultaneously, sensitive to small movements, privacy-preserving

In terms of direct measurement, the review by Dong et al. (2019) indicates the following categories of sensors: *image-based sensors*, *motion sensors*, *radio-based sensors* and *threshold and mechanical sensors*.

The first group, which includes infrared, visible light and luminance cameras, is generally adopted in office buildings for security purposes (Benezeth et al. 2011; Shih 2014; Labeodan et al. 2015; Zou et al. 2017) and can be used to track occupants or identify their location, number, activity and identity. The main limitations of this approach, as confirmed in (Sun et al. 2020), are due to its cost, its limited coverage caused by occlusions, the complexity of the algorithms required and the concerns due to privacy infringement (Jiang et al. 2016). This last issue can be addressed by using depth sensors instead of cameras, since it has been demonstrated that depth data can count and locate occupants, even in crowded environments, but are not suitable for personal identification, hence preserving privacy (Galcık and Gargalik 2013; Seer et al. 2014; Diraco et al. 2015) when no RGB camera is involved.

Motion sensors (i.e. PIR sensors, ultrasonic Doppler, mocrowave Doppler, photosensors, etc.) are generally adopted to control artificial lighting and HVAC for energy saving purposes. These devices are effective in detecting occupancy presence, but are unable to count subjects or detect small movements, thus providing a false control signal when occupants are not moving for a long time (Heidary et al. 2023; Akbar et al. 2015; Guo et al. 2010; Song et al. 2014), leading to potential discomfort or increased energy consumption. PIR sensors, which measure changes in infrared light emitted by objects in their field of view, are cost-effective options that are frequently used in non-residential settings to detect occupant presence (Ekwevugbe et al. 2017; Weyers et al. 2017). More precisely, since these sensors detect movements, which are discrete events, a time delay value (e.g. 15–60 min) is defined to avoid misreading vacancies due to immobility, and the space is considered to be occupied during this period. The appropriate setting of this parameter is necessary to avoid false absence detection (i.e. underestimation of the delay) or a reduction in potential energy savings (i.e. overestimation of the delay) (Shen et al. 2017).

However, it has been shown that a false ON state can be triggered by warm currents from HVAC systems (Labeodan et al. 2015). Finally, the work of Wahl et al. (Wahl et al. 2012) demonstrated that a PIR sensing network can also be used to estimate people count, by installing sensors in pair and supporting them with one of two distributed algorithms proposed in the paper, which are defined to perform the count estimation using the directional information from the sensor pairs, possibly including the sensor masking time. In (Raykov et al. 2016), a single PIR sensor combined with an ML model was shown to be capable of performing this same task, even if at a lower accuracy than more state-of-the-art techniques.

Radio-based sensors can detect occupant presence using radio signals. For instance, RFID can sense people using tags with a univocal identification code and therefore can be considered a *terminal-based* detection system (Wu and Wang 2019). In (Li et al. 2012), where this technology is used to develop an occupancy detection system that can be used to run demand-driven HVAC operations, RFID is considered a valuable alternative to image-based and motion sensors since it is cost effective, adequately accurate, and able to detect multiple stationary subjects while not requiring a line of sight and on-board storage. In their work, Ranjan et al. (Ranjan et al. 2013) introduced the so-called *RF Doormat system*, which includes two separate RF sensing zones (one on each side of a door), RFID ankle bracelets with passive tags (i.e. no battery requirement) and a door-crossing detection algorithm. This system is tested in a residential setting as a way to infer people's room location and has an accuracy of 98%. A similar approach is presented in the work of Hnat et al. (Hnat et al. 2012), where the authors use ultrasonic range-finding sensors as primary devices at the doorway.

As far as threshold and mechanical sensors are concerned, they are able to record occupants' presence in an enclosed environment through their interactions with either windows or doors, and they can be reed switches, door badges, piezoelectric mats or infrared beams. These systems can either require direct interaction with the occupants (i.e. door badges) or operate autonomously, but in all cases, they are prone to errors when counting occupants (e.g. multiple people crossing an infrared beam at the same time). A reed switch is used in the work of Agarwal et al. (Agarwal et al. 2010) in combination with a PIR motion detection device to detect occupancy in a single room office. This *synergy presence node design* uses the signal from both sensors in a dedicated algorithm that allows for a high degree of accuracy and, according to the authors, could lead to 10%–15% potential energy savings with the introduction of an occupancy-driven HVAC control strategy.

Along with direct occupancy measurements, which present several issues (invasiveness, cost and complexity of the hardware, installation requirements, privacy intrusion) despite good accuracy, significant research effort is dedicated to indirect measurement techniques that infer the occupancy level by analysing its effect on environmental variables that are already monitored for IEQ (Viani et al. 2014). For instance, in (Qabbal et al. 2022), CO_2 is considered a proxy for occupant density in indoor environments: its concentration in occupied classrooms increases significantly, with a strong correlation with the number of people. Jiang et al. (Jiang et al. 2016) described an ML algorithm that processes smoothed CO_2 measurements and counts the occupants, showing accuracies between 89% and 94% when tested in a large office with up to 35 occupants (assuming a tolerance of 4 people). A comparable outcome is shown in (Zuraimi et al. 2017), where CO_2 readings combined with dedicated prediction models (physical or statistical) are used to estimate the number of occupants in a lecture theatre. However, according to the review by Shen et al. (Shen et al. 2017), zone-level occupancy estimation based on CO_2 readings can be challenging since CO_2 transport is an intrinsically transient phenomenon and can be influenced by the furniture layout and the distance between the sensor and the occupants, as demonstrated in (Calì et al. 2015). For this reason, several works suggest to combine CO_2 readings with other sensing techniques, such as PIR (Akkaya et al. 2015; Gruber et al. 2014) or other environmental variables (Dong and Andrews 2009; Zikos et al. 2016; Dong et al. 2010; Chen et al. 2017), to increase accuracy. Finally, other manuscripts, which are more focused on office buildings, suggest other means to collect occupancy information, such as webcams, mouse and keyboard activity, chair sensors, Wi-Fi connections, electricity consumption (Newsham et al. 2017; Zhao et al. 2015; Zou et al. 2017; Zou et al. 2018; Labeodan et al. 2015; Becker and Kleiminger 2018).

Finally, in recent years, much interest has been gathered by the so-called mmWave, which can be used not only for effective wireless communication but also for privacy-preserving sensing technology to detect human presence in smart buildings, since it is effective in localising multiple people simultaneously (without the need to wear dedicated devices such as RFID), recogniSing vital signs (i.e. breath, heartbeat, and chest motion pattern) (Gu et al. 2019) and identifying motion and activity patterns (Pegoraro et al. 2022; Liu et al. 2024; Zhang et al. 2025). This technology has the ability to map the indoor static environment and detect even small dynamic human movements because the short wavelength of the source signal that is sufficient to capture millimetric motions (Haipeng et al. 2021), overcoming the limitations of other motion sensors like PIR. According to a comprehensive overview by Zhang et al. (Zhang et al. 2023), mmWave can be used for several applications and is a promising technology for the integration of IoT networks in smart buildings, allowing them to interact with occupants through gestures, monitor daily activities to customize services, monitor health status and evaluate perceived IEQ.

5.2.6. All-in-one

In the last decade, there has been flourishing research endeavour dedicated to the so-called all-in-one smart sensors, which are compact devices that include several sensing components dedicated to different environmental variables, are generally wireless and connected to the local network, are able to store and post-process collected data and, finally, communicate with a central node (i.e. the cloud layer mentioned in §Section 5.1). This section is meant to be a collection of examples, including both prototypes mentioned in the literature and commercially available products, and is not intended to be a comprehensive list.

As far as research works are concerned, much of the focus is dedicated to do-it-yourelf low-cost solutions. In the work by Quabbal et al. (Qabbal et al. 2022), the authors use an in-house developed smart sensor to assess the IAQ and TC of a classroom in a retrofitted demonstrator building located in Lille (France). It is based on a Raspberry Pi 3 B$^+$ board in a compact box casing; it can measure several air quality parameters (CO_2, CO, formaldehyde and $PM_{2.5}$), along with the air temperature, relative humidity, noise level and light availability, and is integrated into the BMS to modulate the ventilation system according to the CO_2 concentration. The results of the measurement campaign in relationship to a survey conducted among students show a general thermal discomfort (i.e. too hot and dry) and were also used to highlight a direct correlation between CO_2 concentration and the number of occupants. A fairly advanced solution is the one presented in (Parkinson et al. 2019): the device, called SAMBA by the authors and already discussed in §Section 5.2.2, has been carefully designed to be deployed in office settings on desks. As previously mentioned, its housing has been designed not only to be aesthetically pleasing but also to avoid measurement biases to sensors that could be heat sensitive (i.e. temperature, relative humidity and air velocity). It is not only able to monitor light availability (illuminance, 020000 lx, range 1 lx) and noise level (sound pressure level, 40…90 dBA, 0.1 dBA) but also able to provide a fairly extensive IAQ assessment by sampling CO_2 (NDIR, 0…5000 ppm, 1 ppm), CO (electrochemical, 0…50 ppm, 0.1 ppm), formaldehyde (electrochemical, 0…2 ppm, 0.01 ppm) and TVOC (photoionization, 10…2000 ppb, 10 ppb). All the combined sensors constitute an IoT network that sends data to a cloud server aimed at assessing data quality and providing transformation, analysis and visualization though a dashboard accessible by the end-user. Finally, Salamone et al. (Salamone et al. 2017) describe in their paper another solution aimed at office buildings, called 'Open-source Smart Lamp': more specifically, the work involves two prototypes of smart desk lamps, both of which are based on the do-it-yourself philosophy, tested in the same scenario and aimed at optimizing different IEQ aspects. The first is equipped with a DHT22 (Datasheet, DHT22, 2012) placed at the base of the lamp to avoid influence from heat-emitting elements (e.g. light bulb) and addresses the indoor TC by managing the air conditioning system according to temperature and relative humidity monitoring. The second prototype includes two elements: a monitoring device with a K30 (Datasheet, K-30 2022) CO_2 sensor and a photoresistor, wirelessly connected to a receiving station that manages the ventilation system and the light according to the readings. The results show an improvement in indoor conditions, along with the potential for customization and adaptation due to the do-it-yourself approach. Finally, a different goal is at the core of (Labeodan et al. 2015), where chairs equipped with sensors are used to monitor occupancy in an office room to be potentially used to drive the HVAC system. More in detail, micro-switches are hidden by cushions and connected to a wireless transmitter, and the collected data are transmitted only when a change in status is registered (i.e. closing or opening of the switches). A direct comparison between chair recordings and a more common CO_2 estimated occupancy shows a significant discrepancy between the two approaches, with a better performance of the former. However, the authors highlight that such a fast response can be detrimental to the overall HVAC system performance and needs to be filtered by the control algorithm.

Focussing now on commercially available smart sensors, there are several options: all measured quantities, with the respective ranges and accuracies, are reported in Table 6. The first device in this group is also involved in (von Bomhard et al. 2016), which is aimed at the development of an individual-room heating system that is activated on the basis of occupancy monitoring extrapolated from the CO_2 concentration and modulated according to temperature and relative humidity measurements. It is achieved using the Netatmo (Datasheet Netatmo) Smart Sensor, which communicates IEQ parameters via a dedicated smartphone app and regulates the heating system through wireless radiator thermostats. These sensors collect data every 5 minutes and are able to record noise levels as well, providing an adequate IEQ monitoring solution that does not require to be wall-mounted and is flexible in terms of placing options. Another commercial solution is Sphensor by LSI Lastem (Datasheet Sphensor), which includes few models dedicated to different aspects of IEQ, that can communicate with the same gateway. They can be either located on horizontal planes using a dedicated base, wall-mounted or suspended from the ceiling. A desk option is also Sense by Renson (Datasheet RENSON): it includes sensors for all the main variables involved in IEQ but is particularly geared toward IAQ monitoring, with a dedicated LED

Table 6. Main features of the commercial All-in-one Smart Sensors.

References	Product name		Description
(Datasheet Netatmo)	Netatmo (Netatmo)	*Recording frequency:*	every 5 min
		Relative humidity:	0. . . 100% ±3%
		Air temperature:	0. . . 50 °C ±0.3 °C
		CO_2 sensor:	0. . . 5000 ppm
		Sound meter:	35. . . 120 dB
(Dtatasheet Sphensor)	Sphensor (LSI Lastem)	*Relative humidity*:	0. . . 100% ±2% (±1.5% 0. . . 80%)
		Air temperature:	-30. . . 60 °C ±0.2 °C (±0.1 °C 20. . . 60 °C)
		Atmospheric pressure:	600. . . 1100 hPa ±0.6 hPa
		Lux*:	0.1. . . 90 klx ±5 lx (5 directions)
		UV-A*:	0. . . 200 µW·cm−2 ±5% VL
		VOC*:	0. . . 60000 ppb ±15% ethanol/ ±10% H2
		PM (1, 2.5)*:	0. . . 100 µg·m−3±10 µg·m−3 (100. . . 1000 µg·m−3±10%)
		PM (4, 10)*:	0. . . 100 µg·m−3±25 µg·m−3 (100. . . 1000 µg·m−3±25%)
		CO_2*:	0. . . 5000 ppm ±(50 ppm + 3% meas.value)
(Datasheet Sense)	Sense (Renson)	*Relative humidity*: *Air temperature*: *CO_2*: *Sound*: *VOC*: *Light*:	0. . . 100% (±2% 10. . . 90%)
		Air temperature:	-10. . . 60 °C (±0.2 °C 0. . . 60 °C)
		CO_2:	400. . . 5000 ppm (±5% + 40 ppm 400. . . 2000 ppm)
		Sound:	29. . . 120 dBA
		VOC:	relative (i.e. signals changes in VOCs)
		Light:	not specified
(Datasheet Fybra Home)	Fybra Home (Fybra)	Measures *relative humidity*, *temperature*, *CO_2* and *VOCs*	
(Datasheet AmbiNode)	Ambinode (Leapcraft)	*Relative humidity*: *Air temperature*: *CO_2*: *Barometric pressure*: *PM 1, 2.5, 4, 10*: *Lux meter*: *Sound*: *TVOC*†: *Formaldehyde*†: *Ozone (O_3)*†:	1. . .99% ±2%
		Air temperature:	-20. . . 60 °C ±0.5 °C (±0.2 °C 10. . . 40 °C)
		CO_2:	0. . . 5000 ppm ±30 ppm ±3%
		Barometric pressure:	300. . . 1100 hPa ±6 Pa
		PM 1, 2.5, 4, 10:	±15 µg·m−3
		Lux meter:	0. . . 10000 lm·m−2
		Sound:	30. . . 110 dBA ±1 dB
		TVOC†:	0. . . 1000 ppb
		Formaldehyde†:	0. . . 5000 ppb ±10 ppb
		Ozone (O3)†:	0. . . 2000 ppb ±10 ppb
(Datasheet Elisya)	Elisya (Focchi)	Measures *indoor and outdoor relative humidity*, *indoor and outdoor temperature*, *indoor and outdoor CO_2*, *indoor and outdoor noise*, *indoor and outdoor radiation*, *internal surface temperature*, *external brightness*, *rain*	

Notes: *available on the advanced models, †optional add-on sensors.

colour scheme to communicate the CO_2 concentration to the occupants, bypassing the need for an app for this purpose. A product with similar features and purpose is Fybra Home by Fybra (Datasheet Fybra Home), which specifically monitors IAQ, along with hygro-thermal conditions. On the other hand, a wall-mounted solution is Ambinode by Leapcraft (Datasheet AmbiNode), which is a smart sensor dedicated to IEQ in general and can evaluate occupancy trends and space use without the use of privacy-infringing methods. According to the manufacturer, its software platform is integrated with AI algorithms that provide support in HVAC management for energy efficiency and general fault detection (i.e. system performance, mould growth risk, toxic gases, etc.). Finally, Elisya by Focchi (2025) is a different solution, mainly intended for office buildings: it integrates the IoT technology into the glazed façade of the building and monitors light availability, CO_2 concentration, noise level, precipitations and outdoor hygro-thermal conditions, and is integrated into the BMS to monitor IEQ conditions, also providing automated actions for thermal, visual and acoustic comfort.

5.2.7. Wearable

According to the review work by Dong et al. (Dong et al. 2019), wearable sensors can be used not only to collect individual occupancy data and environmental parameters (i.e. air temperature, relative humidity), but also personal parameters such as skin temperature, heart rate and perspiration rate. This allows us to evaluate their specific thermal perception of the indoor environment, collecting the data necessary for individual comfort evaluation. In fact, physiological responses are related to the perception of the four main IEQ dimensions, and more precisely, they can be the consequence of a single or multiple dimensions (i.e. TC, IAQ, AC and VC). A review by Kong et al. (Kong et al. 2023), aimed at providing a set of guidelines for physiological response measurement for future IEQ research and wearable sensor development, included an interesting table that correlates several physiological responses to the IEQ factors that affect them. Its content is replicated in Table 7.

On this note, the work by Choi and Yeom (Choi and Yeom 2017) demonstrated the link between the whole-body TC and the local skin temperature in several locations, especially on the forehead, neck, arm and wrist (with the last two being the most accurate). This variable, along with BMI and sex, allows for a

Table 7. Relationship between physiological responses and IEQ factors, as reported in (Kong et al. 2023).

Physiological response	Unit	IEQ factor			
		TC	IAQ	AC	VC
Blood pressure	mmHg	✓	✓	✓	✓
Heart rate/Heart rate variability	ms	✓	✓	✓	✓
Respiration rate	bpm	✓	✓	✓	
Electrodermal activity	μS	✓	✓	✓	
Skin blood flow	$W \cdot m^{-2} \cdot Hz^{-1}$	✓	✓		✓
Core body temperature	°C	✓		✓	✓
Brain activity	mV	✓	✓		
Skin temperature	°C	✓	✓		
Salivary α-amylase	$U \cdot ml^{-1}$	✓	✓		
Eye blinking rate	bpm		✓		✓
Rectal temperature	°C	✓			
Oral temperature	°C	✓			
Pulse rate/Pulse rate variability	ms	✓			
Muscle activity	mV	✓			
Sweat rate	$\mu L\ cm^{-2}\ min^{-1}$	✓			
Eye dryness	mm		✓		
Forced expiratory volume	L		✓		
Forced vital capacity	L		✓		
pCO_2	mmHg		✓		
PaO_2	mmHg		✓		
$ETCO_2$	mmHg		✓		
Peak expiratory flow	$L \cdot min^{-1}$		✓		
SaO_2	%			✓	
Degree of eye opening	$L \cdot Lmax^{-1}$				✓
Eye movement	deg				✓
Gaze direction	deg				✓
Pupil size	mm				✓
Melatonin level	$pg \cdot mL^{-1}$				✓

95.87% accurate estimate of thermal sensation. This outcome is also confirmed in (Sim et al. 2016), where the attention is focused on the wrist skin temperature in combination with personal thermal sensation models in sedentary office conditions. Therefore, wearable devices such as smart wristbands or watches, already fairly common, could be easily integrated into the IoT network of a smart building and provide a reliable mean to assess the indoor TC in any environment, particularly when used in combination with personal comfort models dedicated to home environments (Kim, Schiavon, & Brager 2018). In (Cheng and Lee 2014), it is suggested that these devices could also play a more active role, such as detecting the sleeping state of occupants and adjusting the smart air conditioning accordingly to improve human comfort and well-being and mitigate energy consumption.

Finally, it should be noted that modern commercial wearable devices are equipped with sensors and technologies that make them an effective tool to monitor occupancy, in terms of human presence, activity level and location in space (Ekwevugbe et al. 2017; Zhao et al. 2015). However, this specific use can pose significant issues in terms of privacy and security that need to be addressed, especially in residential settings.

6. Management system

This section provides a concise overview of modern BMSs, emphasising their role in optimising IEQ through multisensory integration and adaptive controls. It briefly addresses the trade-offs between unified and parameter-specific IEQ assessments, the value of the feedback of the occupant and the ongoing challenges related to privacy, interoperability and scalable context-sensitive system design.

6.1. Smart building management system

A systematic analysis of studies from the literature emphasises the critical importance of incorporating data from multiple sensors, such as temperature, humidity, CO_2, VOC, occupancy, lighting and noise levels, to achieve comprehensive and efficient smart building management systems (Navada, Adiga, and Kini 2013; Ogundiran, Asadi, & da Silva 2024). Most works highlight that integration is an absolute prerequisite, as it plays a vital role not only in efficient environmental monitoring but also in enabling adaptive system control approaches, thus also contributing to the integration of IEQ and user satisfaction data (Dong et al. 2019; Lillstrang et al. 2022; Navada, Adiga, and Kini 2013). Several researchers have proposed frameworks that facilitate real-time integration of heterogeneous data from heterogeneous sources, such as BIM-based platforms and IoT middleware, enhancing real-time decision-making and emphasising the effective interaction and scalability of systems (Choi and Yeom 2017; Ogundiran et al. 2024). Occupancy detection is a common topic, where multisensor fusion, (e.g. passive infrared (PIR, CO_2, RFID) and HVAC and lighting management improvements can lead to energy savings of 10 to 44% (Dong and Lam 2011; Zhao et al. 2015; Nagy et al. 2015). One striking unifying theme is the contextualisation of parameters according to what matters for the specific application: for example, temperature and CO_2 are often presented as primary determinants of TC and IAQ, respectively, while parameters such as noise and lighting are accepted as secondary parameters but are still considered valuable due to their influence on productivity and well-being (Calì et al. 2015; Lillstrang et al. 2022; Shen et al. 2017; Sim et al. 2016). Research findings support the establishment of parameter hierarchies for operational decision-making, with studies demonstrating that strategic prioritisation of variables can significantly improve both data processing efficiency and user interface design effectiveness (Diraco et al. 2015). Furthermore, the study supports the increasing relevance of user feedback systems in real-time monitoring and control systems by recommending the implementation of subjective feedback loops to enhance system responses and adapt environmental conditions to match the preferences of the occupants (Kim et al. 2018; Kumar et al. 2016; Salamone et al. 2018; Weyers et al. 2017; Erickson and Cerpa 2012). As discussed in detail in § 3.3, the limitations of aggregated IEQ indices are further discussed, suggesting that certain IEQ factors (e.g. PMV for thermal comfort and CO_2 for air quality) should be prioritised to allow more actionable information for occupants (Parkinson et al. 2019; Wei et al. 2020).

Despite the general consensus on the value of sensor integration, several studies reveal divergent views on the use of a unified IEQ index. While some propose comprehensive indices for simplicity and benchmarking (Ogundiran et al. 2024), others argue that such aggregation obscures parameter-specific dynamics, thus reducing actionable insight for users and system operators (Navada, Adiga, and Kini 2013; Salamone et al. 2018). These differences reflect a broader debate about usability versus granularity in data representation. Furthermore, there are conflicting opinions on whether hierarchical parameter prioritisation is universally applicable. Some studies criticize this approach for being context-dependent and overly rigid, potentially neglecting user diversity and real-time adaptability (Lillstrang et al. 2022; Sim et al. 2016). There is also a noted gap in how studies define the weight of subjective user feedback, with some treating it as auxiliary data and others advocating for its centrality in system responsiveness (Kumar et al. 2016; Guo et al. 2010).

The contradictions surrounding IEQ indices versus parameter-specific reporting point to a fundamental tension between data simplification and transparency. Although a single index may offer streamlined reporting, it can undermine the interpretability of critical environmental factors. This is particularly significant in user-centric models, where occupants may prefer tailored feedback on distinct parameters such as CO_2 or light levels, especially in dynamic environments such as schools or offices where conditions and occupant needs fluctuate frequently (Lillstrang et al. 2022; Candanedo and Feldheim 2016; Navada, Adiga, and Kini 2013). The debate on parameter hierarchy further reveals that smart building systems must strike a balance between standardised frameworks and contextual customisation. For example, what constitutes a primary parameter in a healthcare facility (e.g. air purity) may differ significantly from the priorities in an educational or residential setting. The implication is that smart management platforms must be flexible enough to accommodate scenario-specific hierarchies while still enabling holistic integration. Moreover, the mixed treatment of user input in the literature underscores a transitional phase in the smart building design philosophy, from sensor-dominant models to human-in-the-loop systems. This transition signals a growing appreciation for user agency and comfort perception, highlighting the need for further development of interfaces that effectively capture and integrate real-time occupant feedback into environmental control systems (Kumar et al. 2016; Weyers et al. 2017).

6.2. AI and machine learning

Along with data collection and interpretation, advanced decision-making is one of the prerogatives in BMS for smart buildings. In this regard, AI and ML approaches integrated with predictive analytics for adaptive comfort modeling are promising areas for unit management in the context of individual comfort control for occupants. In fact, multiple studies have shown that AI-based strategies are able to identify and respond effectively to the changing preferences of occupants and changing environmental conditions. Random forest and Gaussian process classification, for example, have been successful in modelling and forecasting TC conditions with a high degree of precision even in naturally ventilated buildings, demonstrating their robustness and flexibility (Kim, Schiavon and Brager 2018; Li et al. 2017). Even RL, namely, learning from the responses of the occupants and parametrising a set point to refine comfort and energy consumption over time, is presented as a potential method (Kim and Hong 2024). For instance, the use of hybrid ML models by merging decision trees with real-time sensory data enhances individual-level comfort predictions, leading to a shift from stochastic-based (i.e. as portrayed by international standards) to more occupant-centred models (Png et al. 2019). These tools allow systems to reasonably predict human behaviour and their physical interactions with the surrounding environment, which is a clear transition from reactive to proactive and contextual building management strategies (Dong et al. 2010; Wang et al. 2020).

Although there are some promising trends, the existing database of research contains significant contradictions. Many studies have expressed concerns about the generalisability of AI models due to limited training datasets or highly specific experimental settings (Haipeng et al. 2021; Chen et al. 2013). Debate also arises regarding the reliability of occupants' feedback, which often underlies supervised learning methods. Some researchers propose training models with these subjective TC votes (Raykov et al. 2016), while others are less convinced about their validity, citing the variability from one occupant to another, along with the possible data sparsity (Newsham et al. 2017; Feng and Li 2017). A second important trade-off is between model complexity and practicality (i.e. accuracy versus ease of implementation): highly accurate models (e.g. deep learning architectures) are often not practical for real-time implementation due to their computational complexity (Bengea et al. 2015). On the other end of the spectrum, less complex models may not accurately account for individual nuances of comfort adaptation, resulting in less than ideal performance in heterogeneous or dynamic settings (Jiang et al. 2016).

These inconsistencies highlight the need to balance model accuracy with interpretability and scalability. Existing models and approaches are much limited in their ability to develop broadly applicable solutions that can be generalised across building types, climates and user populations. This underscores the need for improved data collection methodologies, such as passive tracking (e.g. using WiFi or PIR sensors Raykov et al. 2016; Zou et al. 2017) or multimodal sensory absorption (e.g. integrating CO_2, temperature and motion data), which can minimise the reliance on subjective user feedback while preserving adaptability to individual preferences (Li et al. 2017). Furthermore, with the trade-off between precision and response time, the need for innovative algorithms to create lightweight AI models that retain predictive performance but are low in energy and processing requirements will become critical. These findings reveal critical challenges in smart building development, customisation must not compromise practicality in avoiding intrusive emotion-monitoring systems (Kim and Hong 2024), and high-accuracy predictions must not introduce operational delays or risks such as faulty HVAC control damaging infrastructure (Bengea et al. 2015).

Newer studies are progressively focussing on hybrid AI systems that combine multiple algorithms or learning paradigms to improve flexibility and resilience (Png et al. 2019; Ghahramani et al. 2014). For the purpose of continuously refining comfort predictions based on changing occupancy behaviour, real-time learning (especially through reward or transfer learning) is becoming increasingly popular. It also highlights how the integration of edge computing with IoT technologies enables distributed low-latency decision-making at the device level (Kim and Hong 2024; Wang et al. 2020). There is also a growing awareness of the need for uniform assessment criteria and a benchmarking dataset to facilitate comparative research and the repeatability of AI-based comfort models (Dong et al. 2010; Feng and Li 2017). Future research should explore cross-disciplinary approaches between psychology, behaviour and physiology to enable more complete and human-centred adaptive comfort systems.

6.3. HVAC control strategies

HVAC systems are essential to provide TC and IAQ in buildings but contribute to approximately 40%–50% of their overall energy use. The focus of research on intelligent control strategies is to maximise HVAC operation performance because of increasing energy costs and environmental issues. The developments in HVAC have included human-in-the-loop systems (Shen et al. 2017; Tien et al. 2022), adaptive real-time control (Jia et al. 2017) and DCV using IoT sensors, ML and occupant feedback, which allow for increased efficiency without sacrificing comfort (Shen et al. 2017).

Human-in-the-loop HVAC systems use occupant feedback to dynamically adapt the thermal environment. There are a few direct feedback methods, such as users can manually enter preferences for comfort into smartphone apps and wearable devices (Erickson and Cerpa 2012) or the Web interface (Habibi 2020) for explicit comfort adjustment. For example, the Thermovote system allows office users to vote on thermal satisfaction using an app, leading to a 67% increase in perceived comfort and 10.1% reduction in energy consumption (Erickson and Cerpa 2012). However, this approach also has frictions because it requires a certain amount of active user participation and can have low adoption rates in the long run. The implementation of direct feedback methods (i.e. PIR sensors, CO_2 monitors and thermal imaging) can mitigate this friction by inferring occupancy and comfort levels without the user having to provide input themselves. The *occupant preference-based thermal control* framework applies this approach in a university lecture hall and found a comfort improvement of 63% with a predictive model based on historical occupancy to make proactive adjustments to HVAC settings (Lam et al. 2014). However, there are also indirect methods such as sensor networks (Zhao et al. 2015; Guo et al. 2010) and wearable devices (Sim et al. 2016) that do not require active interaction, but these methods may lack nuance in multi-occupant spaces where individual preferences vary. Indeed, studies show that while AI-driven personal comfort models (Kim et al. 2018; Li et al. 2017) can adapt to individual needs, they struggle to reconcile conflicting preferences in shared environments (Ghahramani et al. 2014).

New solutions like the *smart token-based scheduling algorithm* (Png et al. 2019) use decentralised designs to speed up systems, and augmented reality interfaces (Mohammadi et al. 2024) provide a new way to engage with them. However, a comparative study (Murakami et al. 2007) shows that users prefer passive systems since they are less likely to cause problems. Indeed, one of the biggest problems with human-in-the-loop systems is finding a balance between privacy (keeping data collection from being intrusive) and usability (making it easy for users to use). Studies offer a number of alternatives, such as federated learning, where decentralised AI models digest data on user devices and only send back anonymised information for HVAC optimisation (Li et al. 2017). Another way to understand how users behave over time is to use automated occupant profiling with ML algorithms, reducing the need for frequent manual changes (Behzadi et al. 2023). In another study, Peng et al. (Peng et al. 2017) used binary presence detection to change the temperature set-points, depending on an estimate of how many people will be present at that moment. In addition, the use of CO_2 and motion sensors that do not require any physical interaction provides occupancy data without identification, hence preserving privacy, but might not be detailed enough for personalised comfort (Kim and Srebric 2017). Despite these advances, privacy concerns persist, particularly in workplaces and shared residential spaces. The *collective decision algorithm* (Li et al. 2017) proposes to solve this problem by combining anonymous comments from many people to make the group more comfortable. However, it still requires an opt-in agreement. Another study (Zhao et al. 2015) used anonymised data, which improved the detection accuracy from 62% to 95%.

6.4. Case studies

The case studies revealed that the technological landscape of the IEQ-oriented BMS is characterised by advanced sensor networks, predictive modelling and adaptive control systems (Cascone et al. 2017 ; Erickson and Cerpa 2012; Dong et al. 2010). Real-time monitoring is also well spread, from low-cost sensor networks (Weyers et al. 2017) (e.g. SKOMOBO for monitoring IAQ in classrooms) to large and dense sensor architectures (Malkawi et al. 2023) (e.g. HouseZero's temperature, humidity, and CO_2 sensors), with the latter integrating more than 300 sensors for the control of both HVAC and lighting across hybrid control layers. Occupancy detection is also a significant driver, using either direct measurements or indirect CO_2-based algorithms (Calì et al. 2015,Jiang et al. 2016,Lu et al. 2011), 3D depth sensors (Galcık and Gargalik 2013; Seer et al. 2014; Diraco et al. 2015), and occupancy patterns deduced from WiFi (Zou et al. 2017; Zou et al. 2018). Predictive HVAC control is a key feature in the smart building prototype, including hybrid CNN-RNN models for the prediction of energy needs (Sharma et al. 2024) and model predictive control for the optimisation of TC (Bengea et al. 2015; Goyal et al. 2015). When it is incorporated within BMS for energy management, as in federal Canadian buildings, it can achieve energy savings of up to 15% by means of anomaly detection (Shen et al. 2017). A study on comfort modeling investigated techniques ranging from PMV TC (Anselmi and Moriyama 2017) to participatory frameworks, such as Thermovote, which defines HVAC set points through occupant voting (Salamone et al. 2018). However, there are discrepancies in sensor accuracy (e.g. CO_2 sensors' limitation in regional applications (Shen et al. 2017; Calvo et al. 2022) and prevalence (e.g. RFID-based system infeasibility for large environments (Li et al. 2012; Behzadi et al. 2023; Kofler et al. 2012) and privacy (Wang et al. 2020; Kofler et al. 2012).

Energy efficiency and comfort usually compete when IEQ factors are integrated within BMS logic. For example, DCV paradigms are energy saving, but they can underperform in steady-state conditions, potentially leading to pollutant accumulation (Lu et al. 2011;O'Neill et al. 2020), and personalised comfort systems (e.g. smartphone-controlled HVAC (Li et al. 2017; Ortiz et al. 2020)) are difficult to operate in multi-occupant spaces. Adaptive granularity is also found in lighting systems, where luminare-based sensors can save 30.8% (Feyzi and Mojallali 2024) but suffer computational burdens in centralised designs (Pandharipande and Caicedo 2015). The dependence on real-world data, as explained in the Danish residential heat meter case study (Sharma et al. 2024), increases validity but reveals discrepancies in applicability across different climates. Studies such as (Li et al. 2019; Shen et al. 2017; Zhao et al. 2015; Kofler et al. 2012) attempt to balance energy efficiency and occupant comfort by performing dense sensor deployment to record parameters such as CO^{-3}, temperature and occupancy. For example, at Hotel ICON (Hong Kong Li et al. 2019), a three-step BMS cycle (monitoring, diagnosis, intervention) is tested to strike for performance-based optimization of the operation of the fan coil unit, according to the comfort needs of the occupants and the situational operating patterns. Other methods use motion sensors (Peng et al. 2017), dense sensor networks (Wang et al. 2020), CO_2 data (Jiang et al. 2016), human feedback (Erickson and Cerpa 2012), and hybrid deep learning techniques (Sharma et al. 2024) to adapt HVAC and lighting dynamically. However, the manner in which IEQ parameters are integrated into the BMS logic is highly variable. Some case studies prioritize TC through PMV indices (Anselmi and Moriyama 2017), IAQ via the CO_2 concentration (Choi and Yeom 2017) or visual comfort via adaptive lighting (Pandharipande and Caicedo 2015). This variability demonstrates that there is no one-size-fits-all approach to the integration of IEQ, and the outcomes are largely determined by context, including the type of building and the pattern of use.

Sensor accuracy can sometimes present issues: even though the performance of low-cost IAQ sensors can be adequate when compared to recommended readings and be sufficient to assess the overall condition of the indoor climate while providing great scalability (Weyers et al. 2017), CO_2-based occupancy predictors used to control ventilation can perform poorly in the presence of high airflow rates (Gruber et al. 2014), especially when the sensor is located inside the room and not in the exhaust air duct (higher measurement fluctuations lead to inconsistent behaviour). Ethical issues, such as privacy risks of IoT occupancy tracking (Cascone et al. 2017), are often not adequately examined, and limited research has been proposed to mitigate them (e.g. lightweight cryptography). Occupancy prediction models (e.g. KNN algorithms (Peng et al. 2017)) fail on unusual patterns, while TC models such as PMV often do not agree adequately with subjective feedback, especially in residential environments (Becker and Paciuk 2009). Scalability represents another challenge (Kofler et al. 2012): on the one hand, centralised systems (e.g. Hotel ICON's triadic BMS Li et al. 2019) require large capital, on the other hand, decentralised solutions (e.g. do-it-yourself IoT solutions Salamone et al. 2017) suffer from interoperability issues.

Results discrepancies add additional complexity to the subject. For example, the measured occupancy-based optimal (MOBO) controllers obtained 40% energy savings in HVAC simulations but only 30% savings in field empirical tests because the logic of the AHU was not ideal (Goyal et al. 2015). In addition to performance indicators, discrepancies also occur between official environmental quality certification metrics and user satisfaction. As discussed in §3.3, many LEED-certified buildings do not achieve high occupant satisfaction despite accomplishing high IEQ scores (Asmar, Chokor, and Srour 2014; Altomonte et al. 2019). This ignores cultural and contextual factors: wrist skin temperature models (Dong and Andrews 2009; Sim et al. 2016) may not generalise to all demographics, and daytime harvesting strategies are highly dependent on the geographical orientation of users (Navada, Adiga, and Kini 2013). These incongruities highlight the importance of adaptive and context-sensitive BMS in mediating occupant preferences while respecting technical feasibility and energy efficiency.

To overcome these limitations, future applications should focus on adaptive learning and occupant-centred reconfigurability. Participatory systems (e.g. Thermovote (Erickson and Cerpa 2012) and OPTC frameworks (Lam et al. 2014)) show the possibilities of human-in-the-loop control, but such systems clearly need yet another coherent feedback mechanism to not overwhelm the user. Hybrid methods, such as federated learning for personalised comfort models (Ghahramani et al. 2015), may alleviate the issue of data privacy and improve accuracy. Scalability can be provided by modular BMS architectures, such as the KNX-BACnet with hybrid system (Malkawi et al. 2023), assuming that interoperability standards (e.g. in IoT protocols (Calvo et al. 2022)) are defined and consistently implemented.

7. Challenges and future developments

The analysis of the literature demonstrates that the assessment and management of IEQ in smart buildings is a multidisciplinary endeavour that must be tackled at different levels and from multiple perspectives, presenting challenges that need to be addressed in future research developments.

First, standards and schemes addressing IEQ in buildings require further investigation, due to their relevance for both the design phase and the management phase throughout a building life cycle, especially in residential settings. On the one hand, there is currently no consensus on the weighting of each IEQ component in the overall performance, since it depends on several factors, ultimately suggesting that a single index may not always be required and each component could be considered independently, as in the TAIL protocol. Moreover, additional effort is needed to investigate further the combined impact of different IEQ factors and their effects on occupant health and well-being. This approach provides a robust set of tools to support technicians during the design phase. On the other hand, it has been observed that careful design does not always align with occupants' perceptions of IEQ during the use of the building, especially when statistically-based schemes are adopted for small groups, such as in residential settings. Therefore, it is essential to recognise the needs of individual occupants and further develop personalised comfort models that can be deployed during the use phase of a building to assess perceived comfort levels. This would also enable the consideration of several parameters currently neglected by standards, such as different regional, cultural, climatic and building characteristics, and the definition of specific scoring systems, while maintaining a common base framework.

Second, a crucial factor to achieve high levels of perceived IEQ is the adoption of a well-designed network of smart sensors, which also needs a high degree of flexibility and scalability to accommodate changes in requirements throughout the lifetime of a building. One of the most critical challenges is the effect of the spatial distribution of environmental variables on the accuracy of the monitoring system. This issue should be considered when designing the sensor network in a smart building and can be more prevalent in residential contexts where the disposition of the furniture, and therefore that of the occupants, can be less predictable than in office environments. Further research on this subject could result in guidelines to support this design process. Considering the technology of Smart Sensors themselves, future efforts should focus on further improving their accuracy, since it significantly affects the quality and reliability of the collected data and therefore the efficacy of the BMS. Furthermore, the selection of sensing elements should be limited to the most relevant environmental variables for the specific building category to reduce the energy consumption of the network and the general installation cost, thus facilitating their diffusion in the market. If we focus on the main IEQ components, the following considerations arise:

a. There is a lack of consistency in the monitoring strategies for IAQ. Past works suggest that in residential buildings VOCs typically fall below potentially hazardous concentrations only a few months after construction and that simple source control can be an effective strategy, along with direct measurement of CO_2 concentration and TVOC sampling. In this context, an adequate air change rate and effective PMs filtration can maintain high levels of IAQ.

b. To evaluate TC, the air temperature is generally accepted as a substitute for the operating temperature, especially when highly insulated buildings are considered. This approach can therefore simplify Smart Sensor design but may require adjustments in cases of significant radiative asymmetry (e.g. next to windows).

c. When assessing VC, studies have shown that the efficacy of light sensors is greatly affected by internal reflections, which should be mapped to allow the system to perform correctly. Moreover, the BMS needs to be able to manage both artificial and natural light to guarantee a comfortable environment from the visual standpoint, which requires integration into the IoT network of actuators to control shading devices.

d. Experimental studies involving AC evaluation are less prevalent in the literature than those dedicated to other IEQ components, showing the need for further investigations, especially in residential settings. The sound pressure level is generally sufficient to characterise AC, and low-cost sensors are available on the market. However, their accuracy seems to be significantly worse than that of lab-grade instruments, especially in the presence of background noises, and should be a focus of future research.

Even though not required by any IEQ model, occupancy monitoring is a useful tool to support the BMS in a smart building in improving energy performance and guaranteeing adequate indoor conditions. However, it constitutes an intrusion of personal privacy, especially in residential applications. On this topic, mmWave technology seems to be a promising solution, both in terms of performance and privacy, and in the future, it could also provide a way for occupants to interact with the IoT through gestures. Alternatively, environmental variable monitoring (e.g. CO_2 concentration and acoustic events) can serve as a meaningful proxy for occupancy evaluation, balancing system effectiveness and privacy for users.

However, privacy concerns extend to all data collected by the IoT network, especially when they are sent off-site to a cloud computing layer. This creates a significant vulnerability that requires further development.

Finally, the effective operation of a smart building is largely based on its BMS, and recent research trends include the adoption of AI and ML techniques. The accuracy of these approaches is tied to the complexity of the models, along with the reliability of the smart sensor network. However, further developments should strive to find a trade-off between model accuracy and practicality, since complex models can be too computationally intensive for real-time implementation, despite their accuracy, while simpler ones can be easier to implement but might compromise user comfort due to lower precision. Moreover, another limitation of AI and ML algorithms is that they are trained on limited or context-specific datasets, reducing their ability to generalise across different building types and, therefore, limiting their potential diffusion in the market. Finally, the efficacy of the BMS in maintaining adequate IEQ and satisfying occupant requirements also relies on the ability to collect their feedback. However, it can be challenging to engage user to actively provide feedback, potentially resulting in low adoption rates due to fatigue. A potential solution to address this issue could rely on the adoption of wearable sensors (e.g. smart watches, fitness bands or rings) to monitor physiological responses and assess comfort levels without requiring active user participation. This could also enable the ML algorithms to effectively predict occupant behaviour and their interactions with the surrounding environment, leading to a clear transition from reactive to proactive and context-aware building management strategies. On this note, occupants may also need the support of technicians in the training process of the autonomic BMS to make it more effective.

8. Conclusions

This review investigates the literature dedicated to IEQ assessment and management in smart buildings through IoT networks and smart sensors, with a special focus on residential buildings. The list of references includes the European and US technical standards currently in force, along with the research papers published since 2010 (with only a few exceptions).

Due to the broad scope of this work, it has been possible to observe several trends that have developed in the research landscape in recent years. Significant effort has been dedicated to the definition of IEQ models, for instance, with the introduction of personalised comfort models. Studies on smart sensors are focused more on environmental measurement issues (i.e. the effects of spatial and temporal fluctuations) and their integration with BMS, rather than on the sensing elements themselves. The only exception is occupancy sensors, which have been the subject of several manuscripts investigating various approaches. Finally, another fast-developing field of research is related to BMS, and the implementation of ML techniques and AI. Although BMS has been demonstrated to be an integral part of the functionality of smart buildings, challenges remain to be overcome, such as measurement accuracy due to sensor placement, privacy and system integration. Whether it is AI or IoT, the fast-paced development in technology provides a silver lining to these issues, further indicating that computerization in BMS, for a future that is both effective and occupant-centric, is the correct path.

This review of the literature has shown that the IEQ in smart buildings is a multidisciplinary topic that can be addressed from both the engineering side and the occupant perspective. This means that future developments will require a multidisciplinary approach involving predictive models that can consider occupant preferences; minimal smart sensor and IoT networks that optimise the balance between affordability, efficacy and usability; a greater focus on data safety and privacy protection; and, finally, improved and frictionless interactions between autonomic BMS and users, potentially through the combined use of AI and unobtrusive wearable sensors, which would use occupant feedback to enable smart buildings to behave proactively in the pursuit of satisfactory IEQ and energy efficiency. It is evident that sensor- and IoT-based IEQ management systems are highly dependent on an uninterrupted power supply and connectivity. With increasing climatic exacerbations and potential energy disruptions, future developments must therefore prioritise the resilience of smart sensor networks, ensuring adequate IEQ and occupant safety during temporary failures. Nevertheless, as extreme events become more frequent, designers should still be aware of passive design strategies that can help to sustain acceptable IEQ conditions when active technological systems are compromised.

Authors contributions

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All authors revised it critically for intellectual content and the final approval of the version to be published. All authors agree to be accountable for all aspects of the work.

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Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article.

Acronyms

AC	acoustic comfort
AHU	air handling unit
AI	artificial Intelligence
BMI	body Mass Index
BMS	building management system
CNN	building management system
DCV	demand controlled ventilation
EPBD	energy performance of building directive
HVAC	heating, ventilation and air conditioning
IAP	indoor air pollution
IAQ	indoor air qualityu
IEQ	indoor enviromental quality
IoT	internet of things
LEED	leadership in energy and environmental design
ML	machine learning
mmWave	millimiter-wave
NDIR	non-dispersive infrared
PIR	passive infra-red
PM	particulate matter
PMV	predicted mean vote
POE	post-occupancy evaluation
POM	passive observational method
PPD	predicted percentage of dissatisfied
RFID	radio frequency identification
RL	reinforced learning
RNN	recurrent neural network
SBS	Sick Building Syndrome
SRI	smart readiness indicator

STI	speech transmission index
TC	thermal comfort
TVOC	total volatile organic compound
VAV	variable air volume
VC	visual comfort
VOC	volatile organic compound

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