# MOBILE SENSING WITHIN SMART BUILDINGS: A SURVEY

**Siyuan Li**
School of Computer Science and Informatics
Cardiff University, UK
lis133@cardiff.ac.uk

**Yuhua Li**
School of Computer Science and Informatics
Cardiff University, UK
LiY180@cardiff.ac.uk

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

March 8, 2024

**ABSTRACT**

In recent times, there has been an increase in interest in mobile sensing systems. These systems integrate sensors with mobile devices like smartphones and robots, enabling data collection across varying locations. Such systems facilitate automated data acquisition by integrating specific sensors with mobile devices adapted to their intended objectives. Mobile sensing systems have the potential to replace static sensing systems to reduce the complexity of retrofitting buildings and minimise the overall number of sensors. This survey discusses the domain of the built environment and focuses on the building. It categorises the objectives of smart buildings and comprehends human requirements within the range of smart buildings through existing static sensing systems. Additionally, the survey categorises different mobile sensing by carriers and summarises the most suitable for different building objectives. By exploring mobile sensing systems across diverse environments, this study also evaluates the most fitting mobile sensing systems for various sensing scales and compares static sensing with mobile sensing systems.

***K*eywords** Building Environment, Sensors, Mobile Sensing

# 1 Introduction

For human life, the built environment encompasses vast domains. It not only includes the physical construction, but also the industries of human life cycles. To understand and monitor the quality of human life, new technologies have been integrated into the built environment, such as the Internet of Things (IoT) and mobile communication devices [1]. Among these, smart buildings and smart homes have a significant role, as people spend approximately 90% of their time indoors. The quality of the indoor environment significantly impacts occupants' health, comfort, and productivity [2, 3]. The impact of occupants' satisfaction on occupant productivity was recognised around the 1990s. Research has established a correlation between occupant satisfaction, indoor environment, and productivity, highlighting the need for comfortable indoor spaces. Retrofitting existing buildings in terms of lighting, heating, cooling and constructing new buildings improves worker productivity [4]. In 2004, studies showed the occupant's productivity could be reduced by 6-9% due to a poor indoor environment [5].

The IoT is a technology that integrates various hardware and software components, facilitating efficient storage, retrieval, processing, and data communication [6]. This development has led to smarter sensors, robust networks, and advanced data and signal processing technologies. Smart buildings, one of the main applications of IoT, have also benefited from this progress, becoming increasingly intelligent. By deploying IoT in smart building systems, smart buildings improve occupant health by utilising real-time sensor data to control appliances and optimise air quality. The objective of smart buildings is to achieve autonomy in data collection from the ambient human environment, facilitated by sensor-enabled devices. This autonomy fosters collaboration with occupants to monitor actuators, maximising occupant comfort, health, and energy efficiency [7]. Smart buildings serve distinct objectives aim at enhancing the overall quality of life. Based on existing applications, four primary objectives have been identified, namely occupant safety, occupant comfort and health, energy efficiency, and human activity recognition. Notably, most of these applications primarily rely on stationary sensors, which are immobile and fixed within a specific area, limiting their flexibility and adaptability to varying environmental conditions.

To improve the ability of the smart building system, there has been a notable increase in the utilisation of mobile sensing systems within smart buildings to reduce complexity, improve granularity, and expand the coverage area and flexibility of data sensing. The classification of existing mobile sensing systems can be predicated on various factors, including the application's objectives and the diverse types of mobile devices employed. The classification of the mobile sensing system depends on the object. It is divided into people-centric and environment-centric [8, 9] and Guo et al. [10] extend the classification of the mobile sensing system into user, ambient, and social awareness. There needs to be more specific categorisation dedicated to different types of motion sensors. For this survey, the classification is based on the carriers of the sensors, encompassing four types: 1) user-carried, 2) moving robot-carried, 3) drone-based, and 4) vehicle-based sensing systems. Each serves distinct purposes in data collection and analysis. The details of each mobile sensing system are provided in the following sections.

- User-carried Sensing System: These mobile sensing systems have been further categorised into subgroups, namely smartphone and wearable sensors. It attains mobility through its portability, being carried by an individual. The smartphone sensing system leverages the smartphone's integrated sensors. In contrast, the wearable sensing system is designed to be worn by the user, and popular designs include the smartwatch and smart shirt. The range of movement of the system depends on the user's mobility, while the sensors predominantly collect data from the immediate environment surrounding the user.
- Mobile Robot and Station Carried Sensing Systems: The system integrates the necessary sensors with mobile robots or workstations, enabling the sensors to move. This configuration provides each sensor with a broader sensing range compared to static sensing. It is commonly applied in buildings or homes to monitor the surrounding environment of the occupants.
- Drones Sensing System: The system incorporates drones and sensors, enabling an expansive sensing range that surpasses other mobile sensing systems. By leveraging drones' fast speed and aerial capabilities, data can be efficiently collected from the air. This system is commonly employed in smart cities.
- Vehicle-based sensing systems: The system deploys fixed sensors on buses, bicycles, and cars, extending the sensing area and enhancing data collection for urban environments. This deployment is crucial in monitoring cities and contributes to a more efficient data collection approach for urban planning and management.

## 1.1 Existing Survey about the Smart Environment System

Several research survey papers have been published on smart environment applications. However, most of these surveys predominantly concentrate on traditional static sensing systems or only examine specific aspects of mobile sensing systems, such as smartphone sensing systems. A limited number of surveys simultaneously address multiple mobile

Table 1: Existing Review Paper

| Year | | 2015 | | | 2018 | 2019 | | | 2020 | 2021 | 2022 | 2023 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Author** | | [8] | [10] | [11] | [12] | [9] | [13] | [5] | [14] | [15] | [16] | [17] | This Paper |
| **Type of Mobile Sensing System** | **Wearable Sensor & Smartphone** | * | * | * | | * | * | * | | * | * | * | * |
| | **Mobile Station & Robot** | | | | | * | | | * | | | | * |
| | **Drone** | | | | * | | | | | | | | * |
| | **Install with Vehicle** | | | | | * | | | | | | | * |
| **Objective** | **Safety** | | * | | * | | | | | | | | * |
| | **Health & Comfort** | * | * | | * | | | | * | * | | * | * |
| | **Energy Efficiency** | | | | | | | | | | | * | * |
| | **Human Activity Recognition** | * | * | * | | * | | | * | | * | * | * |

sensing systems in smart environments. This section discusses the existing survey papers relevant to mobile sensing systems and smart building objectives, offering an overview of the current research landscape of mobile sensing systems in smart buildings. Table 1 shows the summary of the existing survey and compares the key elements of each survey.

Most of the existing surveys for mobile sensing systems focus on wearable sensors and smartphone sensing systems. The flexibility of smartphones, equipped with rich sensors, has driven the mobile sensing research area, making it an essential part of ubiquitous sensing. Macias et al. [8] aim to minimise the learning curves associated with the mobile sensing system where the complexity is high. The main objective of the existing survey for the wearable sensor and smartphone sensing system is health care. Rosario et al. [18] review the utilisation of smartphone sensing with movement and mobility to improve the well-being of populations vulnerable to falls or affected by chronic diseases. Kim et al. [13] review the fundamental principles of biosensor systems and effectively adapted them to design reliable wearable biosensors. Sempioinatto et al. [15] examines the utilisation of non-invasive wearable and mobile electrochemical sensors for collecting personal nutrition data to facilitate users in formulating personalised nutrition guidelines, enabling them to comprehend better and manage their health status. Besides health care, wearable sensors and smartphone sensing systems are crucial in human activity recognition. Attal et al. [11] review various classification methods employed for human activity detection using data from wearable sensors. Serpush et al. [16] review applications of human activity recognition of daily living with the location of the wearable sensor, data pre-processing and the recognition methods. Alsafery et al. [17] review the general smart building of human activity recognition systems with part of smartphone sensing systems. Guo et al. [10] and Dong et al. [5] also contribute to studying smart building systems with smartphone sensing integration, emphasising indoor environment control and healthcare.

Apart from the wearable sensor and smartphone system, Allaban et al. [14] conduct a systematic review on using in-home robotics for caring for older adults. Khan et al. [12] review examines current research and technologies deployed in ambient assistance, robot ecosystems, and social interaction.

### 1.2 Research Question

The survey answers the following question,

- **RQ1: What sensor data have researchers used to gather insights in the built environment?**
  Numerous applications within the built environment have been investigated, employing diverse sensors to align with smart building objectives. The selection of sensors in the built environment is based on the particular requisites. In general, temperature and humidity sensors, with their versatility, serve as the most prevalent choices applicable to various objectives. Furthermore, gas sensors encompassing CO, $CO_2$ , and P.M.2.5 components can potentially augment environmental health and safety. Specialized sensors, such as blood pressure and heart rate monitors, have been employed to meet specific demands. Certain studies have also introduced other sensors, like wind speed and wind direction detectors, to elevate result accuracy. These details are discussed in Section 3.

- **RQ2: What insights have research studies gathered using mobile sensing systems in built environments?**
  Mobile sensing remains a minor part of smart built environment research. Leveraging its mobile capabilities, it allows for capturing data within human surroundings, mainly focusing on human activity recognition and health monitoring of the environment and humans themselves. Additionally, researchers have utilised this mobility to decrease sensor numbers and alleviate data collection dead zones. These details are discussed in Section 4.

- **RQ3: What are the potential techniques for gathering insights indoors using outdoor mobile sensing systems?**

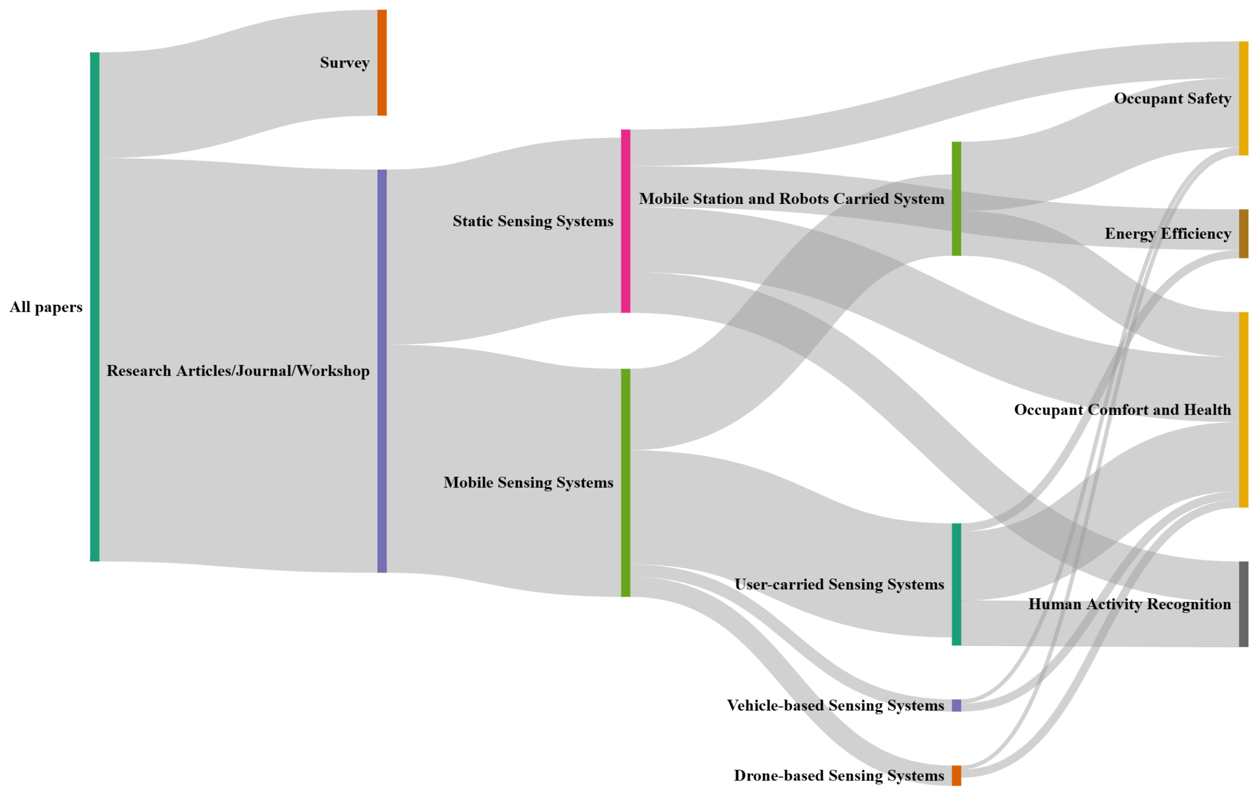


Figure 1: Summary for all papers in this Survey

The two primary outdoor data collection technologies are drone-based and vehicle-based sensing systems. Transitioning vehicles from outdoors to indoors faces limitations due to scaling issues. However, the data analysis and storage methods employed can still be applicable. For instance, setting up data stations along the movement path can reduce device storage requirements. Additionally, exploring Simultaneous Localization and Mapping (SLAM) with drones in indoor environments represents a novel area that enhances the potential of drone-based sensing systems for indoor data collection in the future.

### 1.3 Research Methodology and Contribution

The research methodology encompasses searches on several platforms, including the ACM Digital Library, IEEE Xplore, and Google Scholar. ACM TAAS, ACM TOSN, ACM MobiSys, and ACM IMWUT were studied separately for more specific studies. Two primary categories of keywords are employed during the research process. The first category of keywords relates to the built environment, including terms such as "smart building", "smart home", "smart city", "smart environment", and "built environment". The second category of keywords is associated with various data-sensing methods. It encompasses phrases such as "sensing systems", "mobile sensing systems," "autonomous sensing systems", "robots", "drones in smart environments", "wearable sensors", and "smartphones." These two sets of keywords were combined in search queries, for instance, "smart buildings" AND "sensing systems" and "smart buildings" AND "mobile sensing systems".

A total of 128 research papers were selected. Depending on the different types of papers, they are divided into surveys and others. The other papers are furthermore divided depending on the smart building objectives and types of mobile sensing systems. Figure 1 shows the Sankey diagram of this survey.

Based on the existing review, the contribution of this survey in

- Review the existing research on smart building objectives, encompassing occupant safety, comfort, health, energy efficiency, and human activity recognition.
- A novel classification is proposed for mobile sensing systems categorising.
- The comparison is conducted between static and mobile sensing systems.
- The distinctions between various mobile sensing systems are highlighted, emphasising differences in sensor employment limitations and data collection scales and exploring future directions for mobile sensing technologies.

The survey was organised into six sections. Section 2 discusses the built environment, including the impact and domain. Section 3 focuses on the diverse applications of stationary sensors and categorises them based on different smart building objectives. Section 4 examines existing mobile sensing systems, encompassing various types. In section 5, a comparative analysis is conducted between stationary sensors and mobile sensing systems while also considering the prospects of mobile sensing. Finally, section 6 provides a concise summary of the entire survey.

## 2 Built Environment

The built environment encompasses a wide domain, encompassing all elements surrounding human-made structures. This domain goes beyond mere physical construction to contain the design and management of buildings, the transportation systems linking these structures, and the public spaces facilitating human activities. The built environment plays an essential role in shaping the quality of life, impacting society, fostering sustainability, and driving economic development [19, 1].

### 2.1 Important of the Built Environment

The built environment exerts both direct and indirect influences on humans. Direct effects emanate from environmental quality, while indirect effects encompass behavioural influences. Current research concerns the built environment's impact on health and sustainability.

One area of exploration is the relationship between the built environment and physical activity, which strongly correlates with overall health. This linkage emphasises the inherent interdependence between the built environment and the spectrum of health. The impact of the built environment on physical activity can be featured into five primary aspects [20]: i) Density, which refers to the concentration of people, buildings, and functions; ii) Diversity, encompassing the proximity of walking destinations to residential areas; iii) Design, including pedestrian-friendly small-scale elements like street lights and benches; iv) Accessibility to destinations, which measures the ease of travel between origin points and destinations; and v) Distance to transportation facilities, including the distance from home to transport station and workplaces. In addition to physical activity, obesity, an important health factor, is influenced by both physical activity levels and diet. Research indicates a correlation between the distance to food sources and physical activity facilities, with individuals residing over 1.8 miles from a grocery store showing higher Body Mass Index (BMI). Moreover, a higher concentration of entertainment facilities is associated with an increased incidence of overweight individuals [21].

Regarding mental health, environmental characteristics play a significant role. Evans [22] asserts that environmental characteristics impact mental health. Specifically, factors such as high-rise housing, residential floor level, housing quality, neighbourhood quality, and greater residential density are associated with higher levels of psychological distress. Strategic furniture placement has been observed to enhance social interaction and reduce passive, isolated behaviours between psychiatric patients. Providing privacy has proven beneficial for severely retarded adults and psychiatric patients, leading to improved functioning and an enhanced ability to regulate social interaction. Specifically designed environments for individuals with Alzheimer's have shown positive results, including reduced disorientation and fewer behavioural problems.

Sustainability encompasses various aspects of the building sector, from construction materials to diverse building types. Even individual behaviours contribute to its impact [23]. To achieve sustainability, the larger scale, such as transportation facilities, proves more feasible than addressing it locally, such as modifying individual user behaviours [24].

Furthermore, the built environment is closely related to patterns of life. Patterns of life are regular and repetitive activities that provide insight into behaviour. Hou et al. [25] indicate the built environment impact the people's travel pattern which is a kind of pattern of life. For instance, for elders, they tend to prefer the short distance travel and make a convince transportation system near their residence particularly important [26]. A well-designed built environment can positively influence an individual's life pattern.

### 2.2 Enhancing the Built Environment

As mentioned in the previous paragraph, the domain of the built environment is wide. Addressing health and sustainability, the U.S. local agency divides it into three primary segments [24]: transportation system for the connection between construction, land use, and housing. Different constructions in the built environment have different requirements [1].

In examining the impact on public health, physical activities are essential to several diseases, e.g. obesity [21] chronic and infectious disease [20]. Depending on the public health, the built environment has several different categories. Frank and Engelke [27] investigate the correlation between physical activities and the built environment. The built environment is categorised into transportation systems, land development patterns, and micro-scale urban design. Transportation systems serve as the link between activities. Land development patterns play a role in structuring activities and impacting trip distances. Micro-scale urban design is particularly relevant to pedestrians and bicyclists, encompassing features like streets equipped with sidewalks, bike lanes, and crosswalks. Within this category, the focus lies solely on the elements of design that pertain to physical activity. Gary W. Evans [22] believe the built environment affects mental health through the following domains: i)housing, including house type, floor level, housing quality, and neighbourhood quality; ii) institutional settings, including psychiatric facilities and Alzheimer's facilities; iii) crowding, including noise, indoor air quality, and light; iv) personal control; v) social support; and vi) restoration.

Regarding sustainability in retrofitting building environments, Kylili et al. [28] introduce the key performance indicators to achieve sustainability for retrofitting the building environments, including the generic, atmosphere, land use, water resources, ecology, noise, visual impact, indoor quality, energy, reuse, waste management, and public health.

## 3 Smart Building Objective

The historical development of stationary sensor systems in smart buildings has been more extended than that of mobile sensing systems. Most of the existing applications for smart buildings are static sensing systems. To gain deeper insights into the requirements of smart buildings, this section explores existing applications of static sensing systems in smart buildings with their objectives. From the aspect of smart building objectives, we can provide a better understanding of the role that mobile sensing systems contribute to smart buildings and the differences in utility compared with static sensing systems.

For optimal indoor environmental conditions, thermal comfort, visual comfort, voice comfort, and indoor air quality play pivotal roles in ensuring energy efficiency [29]. Dong et al. [5] have extensive research to enhance indoor environmental control, focusing on energy efficiency, thermal and visual comfort, and indoor air quality. Tang et al. [30] categorises the smart indoor environment into convenience, comfort, energy efficiency, and security. Apart from environmental control for occupant comfort and energy efficiency, occupant safety and human activity recognition systems are also important for smart buildings. The taxonomy in this section broadens the categories from Dong et al. [5] and Tang et al. [30] to encompass occupant safety and human activity recognition systems, thus expanding beyond comfort and energy efficiency.

This section explores each of these different areas of the built environment: data collection, pre-processing, data analysis, and data results. The table provides clarification for each section. Figure 2 illustrates the taxonomy of smart building objectives and provides details for this section.

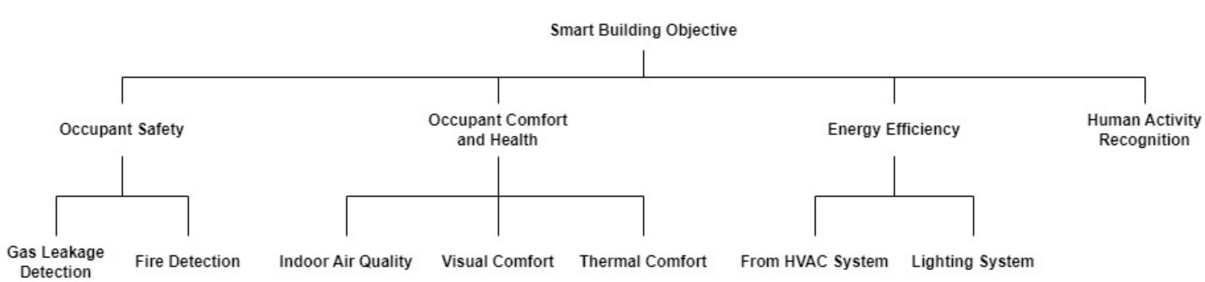


Figure 2: Taxonomy of Smart Building Objective

### 3.1 Occupant Safety

In smart buildings, ensuring occupant safety is essential. Occupant safety systems are specialised and focused on fire and gas leakage detection. Each year, thousands of residents are affected by fire outbreaks, leading to significant consequences and impacts on their lives. Three primary factors can lead to the fire accident [31]: i) combustion of material, gas and electrical circuit, ii) improper equipment maintenance and machinery overheating, and iii) malicious actions. Two methods for data collection can be utilised to detect fires at an early stage: multi-sensor detection, which involves using gas, temperature, or smoke sensors, and image recognition, which assesses whether a fire is present in a specific area. Table 2 has some examples of occupant safety systems discusses in this paragraph. It includes information on built environment raw data collection, pre-processing methods, data analysis techniques, and the corresponding results obtained for each system.

Table 2: Summary of the Occupant Safety Applications

| Application | Ref | Built Environment | Raw Data Input | *Pre-processing* Data Analysis Methods | Data Results |
|---|---|---|---|---|---|
| Fire Detection | [32] | Indoor environment: home | CO, $CO_2$, Smoke, Temperature | *Remove the missing data* K-NN, Decision Tree | Fire, no Fire, maybe Fire for fire early warning |
| | [33] | Indoor environment | CO, Smoke concentration, Temperature | *Kendall-tau algorithms* Back propagation Neural Network | Probility of fire for early fire warning |
| | [34] | Indoor environment: Building/Home | Flame, Smoke, Temperature, Humidity, Light Intensity | *Normalisation* Bayesian Classifier | Fire and no fire state with low-cost and power efficiency sensor |
| | [35] | Any place with fire | Fire and Non-fire video, addition challenging non-fire images | *Out of all the frame extracted, randomly sampled few images for final test set* Light-weight Neural Network | 93.91% accuracy (Own dataset), 96.53% Accuacy (Foggia's dataset) with real-time visual response of fire state |
| | [36] | Any place with fire | Open-Source Images Video Frames, Robmarkcole and Glenn-Jocher data set | *Dataset augmentation* YOLOv6 | 93.48% accuracy for real-time fire detection |
| Gas Leakage Detection | [37] | Indoor environment: Industry | LPG, Methane, and Benzene | If/then condition | Gas concentration between 200 to 10000 ppm with fast response time |
| | [38] | Indoor environment: Industry | LPG | If/then condition | Detect gas leakage with 95% collected data accuracy |

In multi-sensor fire detection methods, the choice of specific sensor configurations and their deployment varies based on individual system requirements and design. Commonly used sensors include Carbon Monoxide (CO), Carbon Dioxide ($CO_2$), and temperature sensors. Furthermore, flame, smoke, methane gas, benzene, and compressed natural gas sensors are employed to detect the state and gases indicative of fire at an early stage. Bhoi et al. [32] have developed a fire early warning system that utilises supervised machine learning algorithms, namely k-nearest neighbours algorithm (K-NN) and decision tree algorithms. This system classifies fire situations into three categories: fire, not fire, and maybe fire, based on pre-defined threshold values for CO, $CO_2$, smoke, and temperature data. On the other hand, Maltezos et al. [31] have integrated additional sensors, including flame, liquefied petroleum gas (LPG), and compressed natural gas (CNG) sensors, into their fire detection system. This enhanced system leverages an edge computing framework, allowing for multiple sensor nodes and high scalability. When the collected data surpasses the predefined thresholds, the system triggers an alert to call the fire service. However, the complexity of fire situations arising from different materials poses a challenge, as setting up thresholds to cover all scenarios becomes difficult. To address this, Wu et al. [33] employed the Back Propagation Neural Network (BPNN) with multiple inputs and outputs, incorporating numerous fire parameters in the model. Similarly, Khalid et al. [34] integrated various input data, such as flame, smoke, temperature, humidity, and light intensity, into a Bayesian classifier for their fire detection system. The selection of low-cost sensors further enhances the system's cost-effectiveness and efficiency in fire detection. To avoid false alarms, Saeed et al. [39] employed a mobile communication system. When the sensor in the system detects abnormal data, the user will receive an alert message. The system will share the information with the local service if the user confirms the fire outbreak.

For image processing systems, the sensor collects the environment image as the input and uses machine learning to identify the environment state. Jadon et al. [35] created a lightweight neural network architecture called FireNet. The architecture contains 14 layers with pooling, dropout and a 'Softmax' output layer. This allows fire detection in real-time with visual feedback. The YOLO (You Only Look Once) algorithm is widely recognised and utilised for object detection in image analysis. Saydirasulovich et al. [36] employed YOLOv6, the newest version of the YOLO algorithm, for real-time fire detection tasks.

The gas leakage detection system primarily focuses on preventing fire outbreaks by detecting and alerting gas leaks before they lead to hazardous situations. The gas leakage detection system does not rely on machine learning for data analysis to identify fire incidents. Instead, the primary objective is to detect gas leaks and prevent potential fire outbreaks promptly. In the context of fire prevention in industries, Kodali et al. [37] proposes a safety gas leakage detection system. This system is designed to detect gas leaks, specifically liquid petroleum gas, natural gas, and benzene, which are common culprits in fire breakouts within industrial settings. When an abnormal state is detected, the system sends a warning message to the user via SMS. Another study by Salameh et al. [38] presents an integrated end-to-end wireless network, connecting LPG sensors in a seamless communication manner. This network enables early gas leakage detection within 50ms.

### 3.2 Occupant Comfort and Health

The building's impact on occupants' satisfaction is mainly related to indoor air quality, thermal, and visual [40, 41]. Data collected from various sensors and visual interfaces are utilised to enhance user satisfaction and improve comfort levels. Table 3 presents an overview of the data processing techniques employed in the occupant comfort and health systems discussed in this section. It includes information on built environment, raw data collection, pre-processing methods, data analysis techniques, and the corresponding results obtained for each system.

Indoor air quality is essential to occupants' health and comfort, with certain pollutants posing health risks. Sources of indoor air pollution include furniture, construction materials, smoking, cooking, and human respiration. Pollutants such as particulate matter, volatile organic compounds (VOCs), CO, $CO_2$, and organic substances can adversely affect human health [51, 52]. To monitor indoor air quality, Benammar et al. [53] designed a real-time modular end-to-end IoT platform, measuring various parameters, which include $CO_2$, CO, $SO_2$, $NO_2$, $O_3$, $CL_2$, ambient temperature, and relative humidity for health and comfort monitoring. To enhance indoor air quality, accurate sensing data is essential, and understanding the distribution of air pollutants in the indoor environment is crucial. Research has shown that within a single room, the distribution of $CO_2$ does not vary significantly for different positions of the $CO_2$ sensor [54]. This implies that $CO_2$ sensors can be randomly placed throughout the room to monitor and assess $CO_2$ levels effectively without affecting accuracy. Additionally, outdoor air quality also impacts indoor air quality. Integrating indoor and outdoor air quality data optimises the Heating, Ventilation, and Air Conditioning system (HVAC) and enables adaptive control. A monitoring system in an office setting incorporates indoor sensor data and outdoor air pollution data from the Internet, using an artificial neural network (ANN) with a Purification Time Inference (PTI) based model to predict the time for HVAC to reduce PM2.5 concentrations and optimise the air quality [43]. Furthermore, Xiahou et al. [42] developed an air monitoring system that collects and analyses data using an autoregressive integrated moving average model (ARIMA) to predict $CO_2$ concentrations in the coming hours. These approaches contribute to better indoor air quality management, ensuring occupants a healthier and more comfortable environment.

Thermal comfort plays a crucial role in occupant health and productivity [44]. Various models are employed to predict occupant thermal satisfaction using different sensor data. ASHRAE, the American Society of Heating, Refrigerating and Air-Conditioning Engineers, has published several standards and guidelines for building comfort. Different from the air quality, thermal conditions also depend on individual preferences, necessitating occupant questionnaires. For instance, Yang et al. [45] utilise a data-driven model with the ASHRAE RP-884 dataset, including a thermal questionnaire with eight variables, to predict personal thermal comfort. Merabet et al. [44] collect data from ten occupants by themself based on the ASHRAE 55/2021 standard and propose a predictive machine learning model using logistic regression to understand occupant thermal comfort levels in smart buildings based on the ASHRAE PMV model. Ono et al. [46] adopt an optimised control framework for individual comfort models to experimentally and comparatively assess thermal comfort resolutions at individual and group levels. Real-time questionnaires are collected for each experiment to create data-driven comfort models. The results show that the framework separately enhances overall occupant comfort performance at the group and individual levels. However, combining group and personal models may lead to a potential loss in performance improvement. Differently, Crosby and Rysanek [47] propose a hierarchical Bayesian model to predict thermal satisfaction, incorporating not only thermal data but also $CO_2$ levels. The integrated model within the building uses data on thermal conditions and ventilation rates to enhance prediction accuracy.

Table 3: Summary of the Occupant Comfort and Health Applications

| Application | Ref | Built Environment | Raw Data Input | *Pre-processing* **Data Analysis Methods** | Data Results |
|---|---|---|---|---|---|
| Indoor Air Quality | [42] | Indoor Environment: sensor deployed in university building | $CO_2$ | ARIMA model(*Stabilisation* The autocorrelation function, the partial autocorrelation function of the sequence) Akaike information criterion | Prediction $CO_2$ concentration value after three hours |
| | [43] | Indoor environment: sensors deployed in offices of Microsoft campuses in China and use a web crawler to collect outdoor data | Indoor and Outdoor Air Quality Index, Temperature, Humidity, Pressure, Wind Speed | Back-propagation algorithm, PTI based on ANN | PTI with a minor decrease in accuracy, but infer a shorter purification time than default statution |
| Thermal Comfort | [44] | Indoor environment: Building | Temperature, Humidity, $CO_2$, Questionnaire for thermal perception vote | *Average, Standard Deviation* Ordinal Logistic Regression, Akaike Information Criterion | Due to the small size of samples, the regression model is poor for thermal comfort level |
| | [45] | Indoor environment: Building | ASHRAE RP-884 Database including eight variables | Extreme Gradient Boosting Algorithm | 33.36% improvement of thermal preference, 51.49% improvement of thermal sensation |
| | [46] | Indoor environment with HVAC control: the research deployed in National University of Singapore office building | Personal Comfort Model, Group Comfort Profile, Questionnaire for thermal comfort | *Normal distribution of questionnaire and standard effective temperature* Bayesian Network | Thermal cvomfort performance increase from 77% to 80.7%(Group) and 89%(Personal) |
| | [47] | Indoor environment: building | Temperature, $CO_2$, Thermal Statisfaction | Normal *distribution for thermal satisfaction* Monte Carlo sampling process for the thermal satisfaction after normal distribution, Hierarchical Bayesian modelling | Prediction accuracy has improved, reduce performance gap between prediction and observation of thermal comfort |
| Visual Comfort | [48] | Indoor environment: building | Minimum and maximum the brightness of lamps, Attenuation coefficient of lamps, Desired brightness of occupant at location | Lighting control algorithm, Branch and bound alogrithm in CPLEX | Achieve 98.85% occupant detection accuracy |
| | [49] | Indoor environment: building | Target illumination level, Daylight component, Dimming levels | *From DC electrical signal to dimmable luminaire* Visible light communication network lighting system | For daylight estimation, it is close to the ground truth with stable light monitoring |
| | [50] | Indoor environment | Preferred light level from user, Previous offered light levels | *Mean and variance of preferred light levels from the user* Bayesian learning algorithm | Most preferred light level of user is 640lx |

Visual comfort, the third significant factor influencing occupant comfort and health, is similar to thermal comfort in its subjective nature, as it varies based on individual preferences and is influenced by different room locations. Therefore, lighting systems pose even greater complexity than thermal systems, and achieving the ideal lighting system in real-life settings is challenging. There are two approaches to achieving visual comfort. The first approach involves real-time adjustments of artificial brightness levels to accommodate occupants' visual comfort preferences. One such system is WinLight, an occupant-driven lighting control system. The WinLight smartphone app allows occupants to customise their preferences and adjust the nearby smart lamps' brightness [48]. Another study by Werff et al. [55] investigates a lighting system that allows individual control through a smartphone app in office spaces and tablet control in meeting rooms. The second approach involves autonomous systems controlling the lighting. For instance, Warmerdam et al. [49] implement a stable light monitoring system based on visible-light communication. Light sensors collect natural light data, then adjust artificial light levels according to design parameters and achieve target illumination levels. Some lighting systems learn user preferences over time, reducing explicit user interactions. Wang et al. [50] collect user feedback through options like "insufficient," "satisfactory," and "excessive" illumination levels to study user preferences. Bayesian learning algorithms with Thompson Sampling are employed to learn user illumination preferences, and the system updates the information accordingly. Lastly, a new optimal light sensor placement method is proposed by Wagiman et al. [56]. This method aims to minimise the placement cost and enhance visual comfort.

### 3.3 Energy Efficiency

Energy consumption in buildings is a major aspect, with HVAC systems playing a central role. Efforts have been made to enhance HVAC systems to achieve energy efficiency [57].Table 4 show some examples of the energy efficiency in the building and presents an overview of the data processing techniques employed in the energy efficiency discussed earlier. It includes information on built environment, raw data collection, pre-processing methods, data analysis techniques, and the corresponding results obtained for each system.

Table 4: Summary of the Energy Efficiency Applications

| **Application** | **Ref** | **Built Environment** | **Raw Data Input** | ***Pre-processing*** **Data Analysis Methods** | **Results** |
|---|---|---|---|---|---|
| For HVAC System | [57] | Indoor environment: Building | Outdoor and Indoor air temperature, Outdoor and indoor air relative humidity, Diffuse solar radiation, Direct solar radiation, Solar incident angle, Wind speed, Wind direction, Average PMW, Heating and cooling setpoint, Dimming the level of lights, Window open percentage, Blind open angle | *Normalization* Lagrangian multiple function, Dueling Double Deep Q-Network | Saving 14.26% of energy with rule-based control methods and 8.1% energy with dulling Double Deep Q-Network |
| | [58] | Indoor environment: Research deployed in a kindergarden | $CO_2$, PM2.5, PM10, Temperature, Relative Humidity, Operation status | *Cleaning and Synchronization* Double Q learning couple with XGBoost algorithms, Random Forest, DNN or Long short time memory | XGBoost algorithm have best performance with balance energy efficiency and $CO_2$ concentration |
| Lighting System | [59] | Indoor environment: Building | Capture real-time images, Pixel intensities | *Mean pixel intensities* YOLOv3 for detect human, K-NN based patch classifier for LUX estimation | During daylight, 100% of occupant felt comfortable. During only LED-provided illumination, 86.6% of occupants felt perfect. |

As early as 2010, using sensors to collect user information for more efficient HVAC system operation was proposed. Agarwal et al. [60] presented a low-cost and deployable occupancy detection system using a PIR sensor with a battery. This system aimed to optimise HVAC system schedules in existing buildings by studying occupants' habits. Through simulations, the building's energy consumption for HVAC was reduced by 10% to 15%. However, HVAC systems may not control all factors impacting energy consumption and occupant comfort. Striking a balance between energy efficiency and occupant comfort can be challenging, often involving trade-offs. To address this, Ding et al. [57] introduced the OCTOPUS system, which employs a deep reinforcement learning framework and data-driven approach to find optimal control sequences for building subsystems. It considers trade-offs between three human comfort requirements and energy savings management. Moreover, the system also considers the trade-off between energy efficiency and occupant health parameters. Without considering energy efficiency, the $CO_2$ concentrations could be reduced by providing sufficient equipment with large energy consumption. To achieve energy efficiency, deep reinforcement learning was employed to control $CO_2$ concentration levels while using minimal energy consumption. Additionally, supervised learning-driven virtual sensors served as a feedback platform to further enhance deep reinforcement learning control [58]. The system ensures $CO_2$ levels are maintained within specific thresholds to optimise energy efficiency.

In addition to HVAC, lighting systems are also major energy consumers. Smart lighting systems aim to strike a balance between occupant comfort and energy efficiency [49]. Various smart lighting systems have been designed to enhance occupant comfort and health while incorporating energy-efficient features [56, 48]. Different approaches have been explored for the objective of energy-saving lighting systems. Ravi et al. [59] introduced CS-Light, an intelligent lighting control system that utilises surveillance cameras to gather data. An unsupervised machine learning approach classifies image pixels into light or dark regions, enabling the system to estimate the illuminance level (LUX) with statistical aggregation. The energy consumption can be optimised based on the time of day and occupancy status, leading to substantial energy savings, such as 79% when no occupants are present. Guedey and Uckelmann [61] developed a smart building system for public institutions without the need for building retrofitting. The system integrates various sensors to monitor the indoor environment, including temperature, humidity, motion, light, and window sensors. It uses thermostats and smart plugs to control actuators and achieve energy efficiency. Different from the other systems based on the data analysis, Chew et al. [62] proposed an energy-saving controller for a smart lighting system. The controller incorporates an optimised smart algorithm that utilises sensor feedback and automatically adjusts brightness through pulse width modulation. The controller can adapt to different usage patterns, resulting in significant energy savings.

### 3.4 Human Activity Recognition

Human activity recognition is important in various applications within smart building systems, including ambient assisted living, health management, medical diagnosis, elderly care, rehabilitation, entertainment, and surveillance [63]. The primary approach for human activity recognition is classification, which involves identifying and categorising different individual activities. Three main types of systems are commonly used to collect human activity data: multi-sensor systems, image processing systems, and WiFi-based systems. Table 5 shows some examples of human activity recognition and presents an overview of the data processing techniques for human activity recognition. It includes information on built environment, raw data collection, pre-processing methods, data analysis techniques, and the corresponding results obtained for each system.

For a multi-sensor system, ambient data is collected and analysed to recognise various activities. For instance, Luo et al. [64] employed two low-power radar-enabled sensors in the kitchen to identify 15 activities, which include walking, eating, drinking, sitting, standing, washing, opening and closing doors, cabinets, and ovens, as well as periods of no activity. The sensor signals are combined into a spectrogram, and a deep convolutional neural network (DCNN) is used for activity classification. Another example by Pereira et al. [65] provided a methodology for an indoor environment monitoring system to detect occupant actions, including window opening, showering, heating, and cooking. A new action detection algorithm involves distinct phases of creation and validation in the training process, which then assesses the impact of these activities on various environmental parameters.

In an image processing system, images are the input data. One approach for detection involves extracting the human skeleton from the image [66, 67]. Ramirez et al. [66] employed four classification methods - random forest, Support Vector Machine (SVM), multilayer Perceptron, and K-NN - to detect human falls with five different poses, comparing their accuracy. Nadeem et al. [67] used the maximum entropy Markov model classification method to identify twelve fitness activities based on a 12-point skeletal model, comparing their results with common machine learning methods. Some methods work with images without detecting the skeleton. For instance, Gul et al. [68] used YOLO, a common computer vision technique, along with backbone convolutional network (CNN) to classify eight abnormal activities from patients, such as chest pain, coughing, fainting, and others. To reduce labelling time, Luo et al. [69] introduced unsupervised learning using spectral clustering to group similar activities. Hidden Markov Models (HMMs) are employed to model normal activities with clusters and generate feature vectors. One-class SVMs are leveraged to distinguish between normal and abnormal activities, enabling the detection of anomalies even without specific abnormal activity data.

Human activity recognition mainly relies on multi-sensor systems and image processing methods. With the progress of Wi-Fi technology, it has become feasible to gather activity data without the need for additional sensors. The WiFi-based system enables activity determination without requiring supplementary sensors. WiFi-based human activity recognition systems utilise channel state information (CSI) because the physical surroundings, including reflection, diffraction, and scattering, influence wireless communication signals. CSI captures amplitude and phase details from received WiFi

Table 5: Summary of the Human Activity Recognition Applications

| **Application** | **Ref** | **Built Environment** | **Raw Data Input** | ***Pre-processing*** **Data Analysis Methods** | **Result** |
|---|---|---|---|---|---|
| Multi-sensor Systen | [64] | Indoor environment: Home. Research deployed in Kitchen | Spectrogram of human activities from two radars | *Fused spectrogram* DCNN, SVM+PCA | Achieve 92.81% accuracy for classify 15 activities with DCNN, 91.71% with SVM+PCA |
| | [65] | Indoor environment: Residential building | Temperature, Relative humidity, $CO_2$ | *Aggregate data information* Action detection algorithm | Accuracy of the true positive more than 99.5% for five activities |
| Image Processing System | [66] | The method is not limited with environment. The research is deployed in indoor environment. | Image from a standard video camera | *Cleaning, labelling the ground truth action* AlphaPose to recognise body keypoint and joints. Random Forest, SVM, Multilayer Perceptron, and K-NN for classification | Best result is 99.34% with random forest. Average accuracy is 98.58% for five different falling poses. |
| | [67] | The method is not limited with environment | Raw video data from video sensors (UCF sports action, UCD Youtube action and an IM-DailyRGBEvents datasets) | *Combine extraction methods to achieve accurate silhouettes* 12-point skeletal model and multidimensional feature for pose estimation, quadratic discriminant analysis and for maximum entropy Markov model for classification | The proposed method outperforms typical machine learning algorithms achieving 90.91% overall accuracy by using skeleton structure with 12 points |
| | [68] | The method is not limited with environment. | Video | *Labeling* Backbone CNN base on the YOLO model for image classification | 94.8% accuracy for classify eight abnormal activities from the patients |
| | [69] | Indoor environment | PIR-based sensing system to capture spotio-temporal feature of human motion | Spectral clustering to profile the normal activities, One-class SVM for classification | The methods reduce labelling time and allow to detect the abnormal activities with only normal activities data |
| Wi-Fi Detection System | [70] | Indoor environment | CSI | *Normalisation, Median Absolute Deviation* One-Class SVM and Random Forest with singular value decomposition(SVD) for classification | Random forest with the SVD achieve higher accuracy for detect fall, sit and stand states |
| | [71] | Indoor environment: Experiment set in lab and meeting room | CSI | *Denoising by a Butterworth low-pass filter* AACA | Overall accuracy 94.20% with detection of ten activities |
| | [72] | Indoor environment: Building | CSI | Autpemcpder, CNN, LSTM | Achieves an average accuracy of 97.6% with two Wi-Fi route to detect run, sit, lit, walk, empty, and stand activities |
| | [73] | Indoor environment | RSSI | *Remove abnormal data, calculate mean value, use Gaussian filter* A fusion algorithm combines K-NN and classification tree | Fusion algorithms perform better than NaiveBayers, bagging and K-NN with detect activities |

signals. Human activity is detected through CSI, and various algorithms are applied to classify specific activities. As an illustration, Wang et al. [70] employ a one-class SVM classifier to detect users' fall, sit, and stand states. However, the one-class SVM's performance diminishes as more activities are introduced. They subsequently incorporate the random forests algorithm to enhance accuracy across various scenarios. Yan et al. [71] design an adaptive activity cutting algorithm (AACA)that involves variance processing, data smoothing, automatic threshold setting, and activity detection. Zou et al. [72] construct a network architecture comprising an autoencoder, CNN, and long-term recurrent convolutional network (LSTM) to identify various human activities, such as entering a room or sitting down. Additionally, received signal strength indicator (RSSI) data is collected from WiFi signals to detect diverse activities. Compared with CSI, RSSI provides less information, conveying signal strength levels to differentiate activities. Gu et al. [73] combine RSSI with a fusion algorithm involving K-NN and an empty classification tree to identify activities like empty, sleeping, sitting, standing, walking, falling, and running.

## 4 Mobile Sensing System

The mobile sensing system collects data in a smart environment to achieve flexibility, various data collection scenarios, attributes, and principles, and reduce the number of sensors. The concept of mobile sensing systems is integrating fixed sensors with a movable carrier to allow the sensors to expand data collection possibilities. This survey categorises existing research on mobile sensing systems into four categories based on the carriers: user-carried sensing systems, mobile stations and mobile robots carried sensing systems, drones-based sensing systems, and vehicle-based sensing systems. Each subsection offers comprehensive insights into the existing applications within these categories of mobile sensing systems.

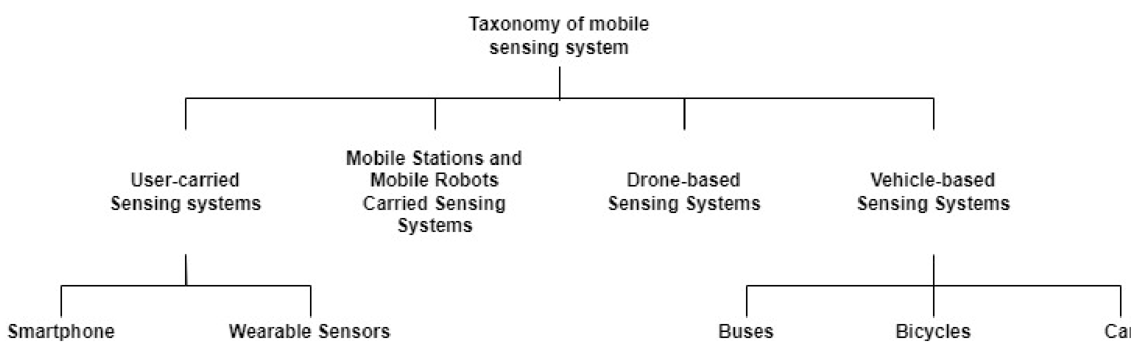


Figure 3: Taxonomy of mobile sensing system

### 4.1 User-carried Sensing System

A common type of user-carried mobile sensing system includes smartphones and wearable sensors, which achieve mobility by being personally carried. This mobility is constrained by the individual's proximity and doesn't extend far from the user. However, it facilitates personalised data collection, enhancing insights into the user's health and surroundings. The primary application of smartphone and wearable sensor systems is focused on human activity recognition and health monitoring. Smart buildings focus on people and their needs. Therefore, when a sufficient amount of data related to people in the building is collected, it becomes information about the building. Furthermore, understanding and collecting individual data helps to understand the needs of different populations. This mobile sensing system can assist smart buildings in collecting data from external sources, which are then utilised within smart buildings. When this data is combined with smart buildings, the buildings can better meet the needs of these populations.

Smartphone sensing systems serve various purposes, from gathering personal data within a residential setting to larger smart environments, like human localisation via GPS. Depending on the smartphone's available sensors, applications can be categorised into three main functions: dashboard display, user interaction, and inertial sensor-driven sensing. The operation of mobile sensing in smartphones necessitates user engagement for accessing internal sensor data or transmitting external sensor data to the network [8]. Moreover, smartphones feature built-in communication protocols for seamless wireless data transfer and real-time responsiveness.

Wearable sensors, similarly, collect data focused on individual activities, often on a smaller scale through devices worn by users [74, 75]. Wearable sensors offer scalability benefits compared to smartphone sensing. The constraints of smartphone sensors stem from device hardware limitations, which hinder their utility without additional external sensors. Conversely, wearable sensors can be tailored to specific applications without hardware constraints, offering a broader spectrum of options for collecting various data types. This adaptability in sensor choice facilitates a more nuanced and individualised assessment of users' health. Some wearable sensors establish connections with smartphones and employ smartphone apps to visualise the accumulated data.

### 4.1.1 Smartphone Sensing System

Smartphones are convenience devices in smart environments. Their versatility allows for the collection of data without the need for additional devices. Leveraging the built-in sensors of smartphones, this system captures valuable data related to user activities and overall well-being for subsequent analysis and monitoring objectives. The primary utilisation of the smartphone sensing system revolves around human activity recognition and health monitoring. Table 6 provides an overview of the data analysis techniques utilised in smartphone sensing systems discussed in this section. The table outlines the built environment and process of raw data input, pre-processing, data analysis methods employed, and the results across various applications.

Table 6: Summary of Smartphone Sensing Systems

| Application | Ref | Built Environment | Raw Data Input | *Pre-processing*<br>Data Analysis Methods | Result |
|---|---|---|---|---|---|
| Human Activity Recognition | [76] | Not limited with indoor or outdoor | Acceleration, Angular Velocity, Orientation from users (Smartphone position on the right, left, and front pocket) | *Labeling, Mean, Standard deviation, Principle compound analysis*<br>Decision tree, Discriminant analysis, SVM, Nearest Neighbour classifier for comparing with classification | The best result is 99% accuracy through Gaussian SVM with falling, sitting, standing, walking, lying, walking upstairs, and downstairs |
| | [77] | The dataset include both indoor and outdoor image | UCI HAR dataset with three-axis linear acceleration, Three-axis angular velocity, Own weakly labelled dataset | *Weakly labeled*<br>Reinforcement learning to optimise network parameters, and train agents to emphasise significant local segments, CNN for extracting coarse feature vector, Recurrent attention learning framework for reward strategy | The model employs recurrent attention learning to allow weakly labeled activities classification and detect four types of weakly labelled activities and six labelled activities with 94.6% accuracy. |
| | [78] | Not limited with indoor or outdoor, the experiment is in the indoor research lab. | Three-axis acceleration, Gyroscope signal | *Feature selection*<br>Multiclass SVM for classification | The average accuracy by hybrid feature selection is 98.13% with single and combined activities. |
| | [74] | Not limited with indoor or outdoor | Triaxial angular velocity, linear acceleration | *Feature extraction*<br>Deep belief network, SVM, ANN for classification | The deep belief network have the highest accuracy with 98.85% of single and combine activities |
| | [79] | Not limited with indoor or outdoor | Three-axis acceleration (Smartphone on trouser pockets) | *Feature selection*<br>SVM, Naive Bayes, K-NN, ANN, k-star | K-NN and k-star have the highest accuracy with 99.01% of classify standing, walking, sitting, jogging, and lying |
| Health Monitoring | [80] | Not limited with indoor or outdoor, the system focus on chronic disease. | Location data, Sound data, Physical activities | *Feature extraction*<br>SVM | Utilise three sensor data achieve the best prediction result with 10 different health metrics |
| | [81] | Not limited with indoor or outdoor, the experiment in university. | Self-reported emotional state, Sound data, Acceleration, Compass, Gyroscope data, Illumination | *Feature extraction, Feature selection*<br>Decision tree, SVM, Logistic regression for classification | The MoodExplorer can exact match average of 76% with detection user compound emotion. |

Smartphones employ inertial sensors, such as gyroscopes and accelerometers, to detect human activities. Human activity recognition often uses supervised learning methods for classification. Hakim et al. [76] classify activities including falling, sitting, standing, walking, laying, walking upstairs, and walking downstairs. Data is collected by smartphones embedded with IMU, positioned in the right, left, and front pockets. They employ SVM, decision tree, nearest neighbour classifiers, and discriminant analysis for classification and subsequently compare the results. Wannenburg and Malekian [79] enhance the feature selection process through a filter method to reduce system complexity and improve accuracy. They compare seven classifiers across various activities. Specifically, K-NN exhibits robust performance in jogging, sitting, and walking, while ANN excels in accurately classifying laying and standing activities. In addition to a single activity, Ahmed et al. [78]detect six combined activities: stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand. Their approach combines a hybrid feature selection model, which merges sequential floating forward search filter and SVM wrapper methods. These selected features are then utilised within a multi-SVM framework machine learning algorithm. Similarly, Hassan et al. [74] propose a novel human activity recognition system process, including feature selection using kernel principal component analysis and linear discriminant analysis, training via deep belief network, and classifying twelve activities, including single and combined activities. Meanwhile, to address computational complexity and memory demands, He et al. [77] propose a novel weakly supervised approach to human activity recognition. Their method integrates recurrent attention learning and two reward strategies, thus bypassing the need for traditional manual labelling.

In health monitoring, smartphone sensing has emerged as a novel technique for individual health assessment. Compared with the current health state measurement tools, the data from the smartphone is more reliable and accurate. Kelly et al. [80] present a multimodal approach using smartphone data, including location, sound, and motion, to gauge behaviours and health status. SVM is employed to predict diverse health indices. Mental health is an important part of health. Zhang et al. [81] find a strong correlation between emotional state and smartphone usage patterns. They collect composite emotional data through a smartphone app, utilising self-reporting. The app records content, microphone audio, illumination, and location data for predicting compound emotions. Raw data undergo pre-processing, with features such as sound data being classified as noise if the volume exceeds 85 dBA, location data identifying outdoor activity, and content revealing social interactions. Braund et al. [82] explore the link between circadian rhythm derived from smartphone GPS data and symptoms of major depressive disorder and bipolar disorder. A consistent change in location each day indicates a higher circadian rhythm in participants.

In contrast to other sensing systems, smartphones also possess the capability to function as actuators' controllers. Guo et al. [83] have designed a cost-effective and reliable door lock system on the Android platform, utilising Bluetooth communication to secure homes. Zaidi et al. [84] have proposed an IoT-enabled smart lighting system, leveraging smartphones as wireless interfaces for lighting control. The article highlights smartphones' potential to provide an optimal user interface for smart lighting systems. This architecture incorporates lighting control actuators, ambience sensors, smartphones, and room networks. Based on the IoT-empower smart lighting system, Karapetyan et al. [85] have enhanced the system's energy efficiency through adaptive lighting control algorithms that cater to user preferences. The smart's LIFX programmable bulbs and light sensing units test adaptive control algorithms and modelling.

#### 4.1.2 Wearable Sensor System

As previously mentioned, wearable sensor systems primarily emphasise personalised sensing. The smartwatch is the most prevalent appearance of wearable sensors; nevertheless, it can perform in diverse forms, including smart T-shirts or other body-worn configurations. Similar to smartphone sensing systems, wearable sensors possess the capability to detect human activities and monitor individuals' mental states through mood estimation. In contrast to smartphone sensing systems, wearable sensor systems offer augmented flexibility regarding sensor selection. This flexibility translates to enhanced data acquisition concerning physical well-being and environmental contexts, particularly essential for chronic illnesses necessitating diverse data collection. Consequently, wearable sensor systems are adept at amassing comprehensive data to monitor and manage an individual's health status effectively. Table 7 furnishes some examples of wearable sensor in all kinds of application. The table shows the information on raw data input and pre-processing to the employed data analysis techniques and their results.

Due to the removal of sensor constraints, wearable sensor systems are now capable of obtaining human activity recognition data not only from inertial measurement units but also from various other sensor types. For instance, Bianchi et al. [63] design a human activity recognition method integrating an inertial measurement unit and Wi-Fi connectivity. This approach facilitated wireless data transmission for monitoring the long-term activities of the elderly, detecting abnormal behaviour indicative of unhealthy conditions and emergencies. Activities such as walking, climbing stairs, sitting, standing up, and lying down were classified using a CNN-based architecture. Paraschiakos et al. [86] introduced an innovative approach for human activity recognition that focused on the elderly population. Data collection encompassed a range of parameters, including heart rate, breath rate, ECG, skin temperature, three-axis acceleration, and energy expenditure. This data was acquired using six wearable sensors strategically positioned on different body parts like the chest, face, right wrist, right ankle, and upper leg. The study encompassed the classification of sixteen distinct activities, and a confusion matrix was employed to analyse the correlation between sensor locations and activities. Ponce et al. [87] presented an inventive machine learning approach termed artificial hydrocarbon networks.

Table 7: Summary of Wearable Sensing Systems

| Application | Ref | Built Environment | Raw Data Input | *Pre-processing* Data Analysis Methods | Result |
|---|---|---|---|---|---|
| Human Activity Recognition | [63] | Indoor environment: Home | UserID, Counter Three-axis linear acceleration, Three-axis angular rate, Three-axis magnetic | *Random split/Repetition* RNNs with LSTM gates compared to CNNs | Global accuracy achieve 97% of detecting the abnormal behaviour for nine long-term elderly activities |
| | [86] | Indoor environment: Home | Heart rate, Breath rate, ECG, Skin temperature, Three-axis acceleration, Energy expenditure information (on the ankle, wrist and chest) | *Labelled, Compare intuitive feature extraction with combining accordion* Decision trees and Random forest as two classifiers, LARA algorithm to compare the classification power | Accuracy above 93% for 12-class classification. The random forest model combine with ankle and wirst accelerometer produce the best results. |
| | [87] | Not limited with built environment | Three-axis acceleration, Temperature (sensor on wrist, chest, and ankle) | *Random selection* Cross-validation, 15 different supervised classifiers methods are compared. | The artificial hydrocarbon network achieved the highest accuracy for all kinds of noisy datasets. |
| | [88] | Not limited with built environment | Three-axis acceleration | *Noise removal, Signal segmentation, resampling, feature extraction, feature selection* Gradient boosting decision tree, K-NN, SVM, Random forest for classification | Gradient boosting decision tree have the highest accuracy with 93% to classification human daily activities with new definitions |
| Health Monitoring | [89] | Not limited with built environment | Ozone, TVOCs, Temperature, Humidity, Activity level | *Normalization* Explicit regression for predicting ozone, Person's correlations calculated correlation between different calibration data | Temperature and humidity have good correlation with oxide resitance. Ozone cannot be ignored. |
| | [90] | Hospital | Pima Indians Diabetes datasets including age, gender, BMI, Heart rate, Sysrolic blood pressure, Diastolic blood pressure, Activities, Blood sugar, and Family history | *Cleaning, Standard value Stop word removal, Tokenisation, PoS tagging, Stemming, Lemmatisation, Character conversion, Feature extraction* Bi-LSTM-based classifier network | Compare with different classification methods, LSTM have the highest accuracy with 75% to efficient the healthcare monitoring with patient data |

Demonstrating noise tolerance for corrupted data and robustness in the face of diverse sensor-related challenges. The network utilised wearable sensors on the chest, wrist, and ankle. This enabled data collection and the classification of eighteen activities. In a different vein, RFID-equipped wearable sensors have been deployed to ensure the safety and security of children on school campuses, aiding in tracking the movements of students and staff. Each student and staff member has wearable sensor nodes that communicate via Bluetooth, facilitating location tracking and ensuring their presence in the classroom [91]. Lu et al. [88] classify human daily activities into countable and uncountable types. They achieve this by leveraging global and local features, thereby enhancing classification accuracy and understanding the nature of these activities.

To ensure health monitoring, wearable sensor systems have evolved to incorporate multiple sensors that collectively monitor the ambient environment, physiological data, and mood indicators. This integrated system gathers and analyses data concerning the user's health and environmental conditions by combining various sensors, such as measuring air quality, temperature, and humidity. Mallires et al. [89] has developed a wearable wrist sensor tailored for asthma research to identify asthma triggers. This wrist-worn sensor captures parameters like ozone levels, total volatile organic compounds (TVOCs), temperature, humidity, and user activity, monitoring indoor and outdoor chemical exposure. Considering the extent of data generated in continuous health monitoring scenarios, Ali et al. [90] proposed a framework based on data mining techniques, ontologies, and bidirectional long short-term memory (Bi-LSTM) to improve the classification accuracy for extensive data volumes. In terms of physiological data, wearable biosensors are swiftly advancing. These sensors are designed to integrate with single biosensors catering to specific health parameters such as sweat [92], glucose [93], and even the nutrition data [94]. The data collected from these biosensors is cross-referenced with precision instruments to establish correlations. Some systems are designed to combine multiple biosensors within a single device. For instance, Leu et al. [95] collect data through a smart shirt integrated with a temperature, heart rate, oximetry, an ECG, blood pressure and a blood glucose sensor. In ambient environment detection, Deng et al. [96] design a new portable wireless quartz tuning fork (QTF) sensors-based VOCs wearable sensor system for monitoring air quality data. QTF allows CO monitor to achieve a smaller, lighter, and more user-friendly than a photo ionisation detector or gas chromatography/mass spectrometry (GC-MS). Rodrigues et al. [97] has designed a smart t-shirt embedded with ECG sensors, 3-axis accelerometers, and an event button, which targets the detection of stress in public bus drivers. The data collected from these sensors is analysed using Kendall's Tau rank correlation test.

Due to the limited end-user application of wearable sensors, certain research endeavours leverage existing wearable sensor platforms. EMBR Labs, for instance, utilises wearable thermal technology through their platform, EMBR Wave™, tailored for occupants in both vehicles and buildings. This innovation merges wearable thermal technology with smart buildings and self-driving electric vehicles to monitor passengers' heating and cooling sensations, enhancing occupant comfort and specificity [75]. Xu et al. [98] have devised a sensor-sharing platform named SenseWear, which empowers smartphones with the capabilities of mobile sensing systems with minimal additional developer effort. Six enabled wearable sensor apps on this platform have been developed for smartphones, allowing users to manage their sensor data via a dedicated smartphone application. Tsuchiya et al. [99] has developed a web-based mobile application-driven smart home control system for the elderly. This system aims to enhance the independence of elderly individuals by employing images and videos to elucidate information and interactions, minimising confusion. It also assists in identifying the location of elements within the household, providing tailored support for the elderly.

#### 4.1.3 Fusion of Wearable Sensor and Smartphone System

The fusion of wearable and smartphone systems for human activity recognition could detect complex activities, such as smoking or missing a meal. Shoaib et al. [100] integrated the smartphone and smartwatch sensors. The smartphone is in the pocket, and the smartwatch is in the wrist. Based on this research, seven common physical activities include walking, jogging, sitting, standing, walking upstairs, walking downstairs, and biking, and six additional activities, including smoking, eating, drinking coffee, giving a talk, typing and writing. The result shows the fusion system is highly accurate in the additional activities. Although physical activities do not significantly improve, the fusion system is more reliable.

### 4.2 Mobile Station and Robot Carried Sensing Systems

Mobile stations and robots encompass a broader data collection scope than smartphones and wearable sensors. These systems possess the capability to navigate and operate within diverse ambient settings where occupants are situated. The principal application scenarios for deploying mobile stations and robots are smart homes and buildings. Within this context, enhancing occupant health, safety, and comfort constitutes the primary objective for refining the built environment of mobile stations and robot systems. Table 8 summarises the built environment and data analysis methods of the mobile station and robot systems applications for occupant safety, comfort, and health.

Mobile sensing systems possess the versatility to relocate to various positions, enabling data collection in locations inaccessible to static sensing systems. This adaptability renders mobile sensing systems particularly advantageous for gas and flame origin localisation tasks. Such systems are crucial for safeguarding occupant safety, as identifying the source of gas leaks is pivotal to averting hazards and minimising waste [110]. Rahmaniar and Wicaksono [111] have devised a mobile robot system for gas detection at ground stations. This system detects temperature and CO gas leaks; when an abnormal CO gas level is detected, the robot warns human operators. Hutchinson et al. [101] have integrated Bayesian estimation and path planning algorithms to enhance the accuracy and efficiency of mobile robots collecting CO data, considering uncertainties and gas dispersion. To improve accuracy and efficiency, Palacin et al. [102] propose a low-cost gas sensor array using Metal-Oxide (MOX) semiconductor sensors on a mobile assistant personal robot. This array, consisting of 16 individual gas measurements, is capable of detecting various gases at an early stage in enclosed spaces. Wind speed, an influential factor, is also considered for gas leak detection. A novel gas sensor, reduced graphene oxide (RGO) sensor, is introduced by Norzam et al. [103]. Compared to MOX, RGO sensors exhibit advantages such as low power consumption, lower operating temperatures, and faster recovery times. The detection accuracy is further enhanced by considering wind speed as an influencing factor. However, anemometer sensors are relatively expensive. Sanchez-Sosa et al. [110] use a Gaussian plume model for gas leak detection to replace the anemometer to achieve a low-cost detection system. Another common use is fire source detection. The robot aims to find the location of the fire before it becomes uncontrollable or help find injured victims. Diwanji et al. [112] design a robot with flame sensors on both sides. When no flame is detected, the robot proceeds forward; if a flame is detected on either side, it moves towards the detected flame. AlHaza et al. [113] is used to find the victims. This robot can ascend stairs and withstand temperatures up to 700°C for 60 minutes. It can establish communication with victims and relay information to a central unit upon locating victims.

Table 8: Summary of Mobile Station and Robot Systems

| Application | Ref | Built Environment | Raw Data Input | *Pre-processing* Data Analysis Methods | Results |
|---|---|---|---|---|---|
| Occupant Safety | [101] | Indoor environment | Voltage reading | *Standard Deviation of noise* Bayes' theorem to update posterior density estimation of source parameters and uncertain dispersion variable. An information-based reward to choose the next position. | To robot located source with an uncertainty of approximately 0.01m within around 200s. |
| | [102] | Indoor environment: The experiment performed on the second floor in University of Lleida | Five acetone, Three air, Four ethanol | PLS-DA classifier for classifying the raw data from the gas sensor array | Gas leakage is detected at large distance from source indoor. |
| | [103] | Indoor environment | Response for 100 and 300 ppm ethanol from MOX and RGO | Kernel Gaussian function | RGO is 54% and 56% faster response time, 33% and 57% recovery time than MOX. |
| Occupant Comfort and Health | [2] [104] | Indoor environment: The experiment performed in a climate chamber in the center | $CO_2$ | *Spatial-temporal interpolation algorithm* The global and local trend estimation to capture the global variation. K-NN, Lasso regression, Support vector regression, Adaptive boosting, Random forest and extra tree for estimating age of air | Based on age of air, the influence of robot movement is negligible for $CO_2$ , compared with static sensing system |
| | [105] | Indoor environment: | Temperature | *Spatial-temporal interpolation algorithm* Linear regression, Lasso regression, K-NN, SVM, Decision tree and Random forest to predict performance in the next period | Velocity between 0.25-0.45 m/s have the best result. Decision tree and random forest is relatively consistent with ground truth. |
| | [106] | Indoor environment | FER+, RAF, and QIDER dataset for emotional recognition, 298 image for object detection | *Normalisation* CNN with stochastic gradient descent and standard backprop to classify face, CNN with inception and MobileNet for emotional recognition, Three meta-architecture with single-shot multi-box detector, faster region-based CNN, and region-based fully CNN for object detection | The face recognition achieve 92.6% accuracy, for both methods of emotional recognition achieve about 80% accuracy |
| | [107] | Indoor environment: Home | RGB image | *Labelling* Single-shot multi-box detectors, Regions with CNN, Region-based fully CNN for object detection | The robot used to find misplaced items in smart home environment |
| | [108] | Indoor environment: Home | RGB image | YOLOv1 based on CNN for object detection | The propose methods can find the misplaced item around 85s. |
| | [109] | Indoor environment: Home | RGB image, Laser range data, Thermal image | *Feature extraction* AdaBoost algorithm for detecting legs from laser range data, Bayesian tracker for detecting the position of people, SVM for recognised people, Fourier analysis for physiological data | The system can detect mobile items and wallets. However, it cannot detect key rings and has a detection accuracy of 46.3% for glasses. |

Mobile stations and robot systems are also used to gather indoor ambient environmental data. To fill in data gaps in spatial and temporal domains, the spatial-temporal interpolation algorithm is employed, enhancing the collected data's granularity and providing solutions [104, 2, 105]. Jin et al. [2] deployed a mobile station to collect the $CO_2$ data integrated into spatial-temporal methods and compared it with static sensing systems. This approach demonstrated the effectiveness of air change on a mobile platform. The result shows that mobile sensing systems with spatial-temporal methods can improve accuracy and granularity in the short term. To achieve long-term accuracy, Geng et al. [105] provide two situations involving the presence or absence of mobile sensing. Mobile sensing is employed initially to attain a high-resolution understanding of the environment, while static sensing is employed in the absence of mobile sensing. Additionally, mobile sensing systems can reduce building operational, maintenance, and diagnostic costs. This is accomplished by employing a mobile sensing system to collect data across extensive areas without necessitating building retrofitting, for instance, in rooms or floors. These mobile sensing systems integrate parameters such as temperature, humidity, light intensity, PM2.5 levels, $CO_2$, and VOCs [104].

The domain of assistive robotics aimed at health monitoring and aiding the elderly is garnering significant attention within mobile stations and robotic systems. Ranieri et al. [106] proposed the LARa framework, incorporating a software library and a robot for object detection. This LARa library encompasses six modules: robot facial features, speech interaction, face recognition, emotion recognition, object detection, and robot navigation. It aims to be the starting point for other research about using mobile sensing systems in the indoor environment. Wilson et al. [107] developed a robot support system that employs an RGB-D camera to detect objects, capture their images and assist in addressing activity errors that may occur in the daily lives of the elderly. CNNs were utilised for item classification. Wang et al. [108] a mobile robot intended to aid elderly individuals in locating misplaced items within a smart home environment. The robot relies on human historical trajectories and wearable sensor data to detect and retrieve the items in real-time. A convolutional neural network detects the misplaced item in real-time. Coşar et al. [109] introduced an assistive robot featuring health monitoring, complementary care, and social support modules. This robot assists seniors in locating items using an RFID antenna, with essential items equipped with RFID tags. Additionally, the robot employs a thermal camera to measure physiological data such as temperature, respiration, and heartbeat rate.

To reduce the complexity of the smart building system, a combination of robots and smart devices is necessary. Palacin et al. [114] employed a highly capable assistant personal robot to autonomously regulate environmental parameters like temperature, humidity, and luminance in areas frequently visited by humans. The robot enables a multi-agent control system capable of accomplishing various tasks. When the robot processes the main task, it simultaneously collects and updates the data. The acquired data is transformed into information maps for visualisation. This robot can interact with the primary smart building system, contributing to reducing system complexity. Bacciu et al. [115] propose using a self-adapting mobile robot with employing preparation and pre-programing to reduce the complexity of a smart building system. The robot reduces the calculation in a smart environment by distributed learning. The system employs incremental learning, unsupervised feature selection, and a model selection mechanism with integrated supervised feature selection to enable the self-adaptation and self-configuration of the learning system. However, it is worth noting that this robot may encounter challenges when handling multiple tasks simultaneously.

### 4.3 Drone

The drone, an autonomous aircraft integrated with various devices, finds applications in transportation, traffic control, and data collection across diverse fields [116]. Its most common usage is observed in outdoor and challenging environments.

Drones play a vital role in ensuring human safety by acquiring data from hazardous or hard-to-reach locations [117]. Vanesa Gallego et al. [118] designed an autonomous mobile gas detection system with micro drones equipped with gas sensors to provide adaptive and high-resolution data for harsh environments. This drone is embedded with a GPS module to provide location information on emission sources.

Furthermore, drones are employed for traffic monitoring. They are invaluable for capturing images or videos of street conditions and aiding traffic analysis. Masouleh and Shah-Hosseini [119] have designed a drone to collect thermal infrared images, normal pictures, or video for the system t to enable vehicle segmentation and assess road conditions. An advanced approach integrates the Gaussian-Bernoulli Restricted Boltzmann Machine with deep learning image segmentation architecture to enhance training processes. Zhu et al. [120] employ deep neural networks to analyse ultrahigh-resolution traffic videos captured by drones. These videos, recorded from five busy roads, are processed by a deep neural network (DNN) to identify vehicle types, count vehicles, and determine their locations. The ultrahigh-resolution video drone capture offers comprehensive information, enhancing traffic analysis capabilities.

### 4.4 Vehicle-based Sensing System

To expand the area of data collection, fixed sensor boxes are strategically deployed within public transport systems, allowing these sensors to collect urban data. These systems are predominantly applicable to air pollution monitoring and gas leakage detection within urban areas.

For an air monitoring system, an air pollution monitoring framework called EcoSensors is an exemplary illustration of such a system. Deployable on public transport or bicycles, this sensor captures air quality data that can be transmitted to the cloud. Employing spatial interpolation techniques, the collected data is then used to analyse pollution distribution within the city [121]. Furthermore, Velasco et al. [122] have adopted only a bicycle-based approach to collect air quality data for urban areas. This mobile sensing air quality system, equipped with PM10 and O3 sensors, is characterised by its portability, cost-effectiveness, and ability to offer better spatial distribution due to its mobility. By mounting these sensors on bicycles, data is acquired at street level, enhancing spatial granularity.

For gas leakage, extensive mobile sensing involves the integration of sensors with vehicles, where a mobile wireless sensor network is integrated with vehicles. Originally developed as stationary sensor terminals, these sensors are now mounted on vehicles to enable large-scale leakage detection. This innovative approach addresses power supply challenges by utilising the vehicle's power source. Guo et al. [123] has developed a gas leakage monitoring system that integrates sensors with mobile vehicles. This system comprises a sensor terminal and a central server, facilitating data transmission, cleaning, and storage. A GPS system provides positional data, enhancing the precision of gas leakage monitoring.

## 5 Discussion

### 5.1 Comparison between the Static Sensing Systems and Mobile Sensing Systems

In this section, a comparison between static sensing systems and mobile sensing systems is presented. Due to the energy efficiency evaluation in mobile sensing systems, there are limited research studies available. The comparison only includes three key aspects: occupant safety, occupant health and comfort, and human activity recognition. Table 9 and 10 show details of the comparison based on different objectives.

Table 9: Summary of Advantages of the Static Sensing System and Mobile Sensing System

| Objectives | Advantage of static sensing system | Advantage of mobile sensing systems |
|---|---|---|
| Occupant Safety | 1. Already have lots of existing solutions.<br>2. The system could connect with the local service. | 1. Allow finding origin localisation.<br>2. Ensures consistent sensitivity across monitoring points and enables faster detection of early gas leakage. |
| Occupant Comfort and Health | 1.More stable within the detected range.<br>2. Pre-processing is simple.<br>3. More safety without moving devices. | 1. Reduce the total number of sensors to reduce the complexity and cost of the building system[114, 124].<br>2. Collect the data for a large area without retrofitting a building[104].<br>3. Achieves high granularity data [125].<br>4. Allow close contact with the occupant and have more accurate data. |
| Human Activities Recognition | 1. Wi-Fi-based systems do not need extra devices and sensors. | 1. The primary use of inertial sensors ensures a higher level of privacy compared to image data.<br>2. Complex activity could be classified.<br>3. Wearable sensor close contact with humans has high sensitivity. |

Most of the existing smart building sensing systems are static sensing systems. Compared to mobile sensing systems, static setups do not require additional data collection devices, such as people or drones. In addition, since static systems have a much longer history of development, there are now many applications and the existing data is collected more comprehensively. static sensing systems are also more stable because the sensor is always connected to a power source, so the data is more consistent and stable.

Mobile sensing systems offer the advantage of not requiring retrofitting for older buildings, thereby achieving accurate data collection with a reduced sensor count, consequently cutting down on installation and maintenance expenses

Table 10: Summary of Disadvantages of the Static Sensing System and Mobile Sensing System

| Objectives | Disadvantage of static sensing system | Disadvantage of mobile sensing systems |
|---|---|---|
| Occupant Safety | 1. High coverage of the sensing will be expensive. | 1. Extra equipment is needed.<br>2. Moving devices cause some risks. |
| Occupant Comfort and Health | 1. High installation and maintenance cost, especially for large-scale and long-term data collection.<br>2. Low granularity problem of the non-detection zone.<br>3. some research uses the low-cost real-time sensor with low maintenance, and the system's reliability is compromised [126, 127]. | 1. Data gaps may occur in the mobile sensing systems during charging or when unexpected obstacles are encountered.<br>2. Extra equipment and technologies are needed.<br>3. Mobile stations and robots are typically limited to deployment on the same floor in open areas, as vertical movement poses challenges. |
| Human Activities Recognition | 1. Except for the Wi-Fi-based systems, the image data are collected with less privacy. | 1. Extra devices are needed. |

[2, 128]. Furthermore, establishing wired connections poses challenges, and the costs of installation and maintenance are notably high, especially for large-scale and long-term data collection [125, 129, 83] In some instances, older buildings lack the infrastructure necessary for retrofitting in compliance with static sensing systems. Additionally, mobile sensing systems exhibit a greater capacity for collecting finer data granularity than static sensing systems. This capability simplifies the system by using fewer sensors and permits more functional designs. The inherent flexibility of mobile sensing systems enables them to undertake tasks that static sensing systems are unable to perform, such as localisation of the gas leakage source.

### 5.2 Comparison between Four Types of Mobile Sensing System

Mobile sensing systems encompass four distinct categories of carriers, each characterised by unique attributes and roles. The sensing scale refers to the optimal distance the carrier can cover during movement. The different sensing scales decide the best fit smart building objective for each carrier. These mobile sensing systems exhibit variations in data collection scope and corresponding applications.

#### 5.2.1 From the Perspective of Smart Building Objectives

All four types of mobile systems share a common focus on enhancing occupant comfort and health with a different focus. An overview of sensing system applications aligned with smart building objectives is illustrated in Figure 4.

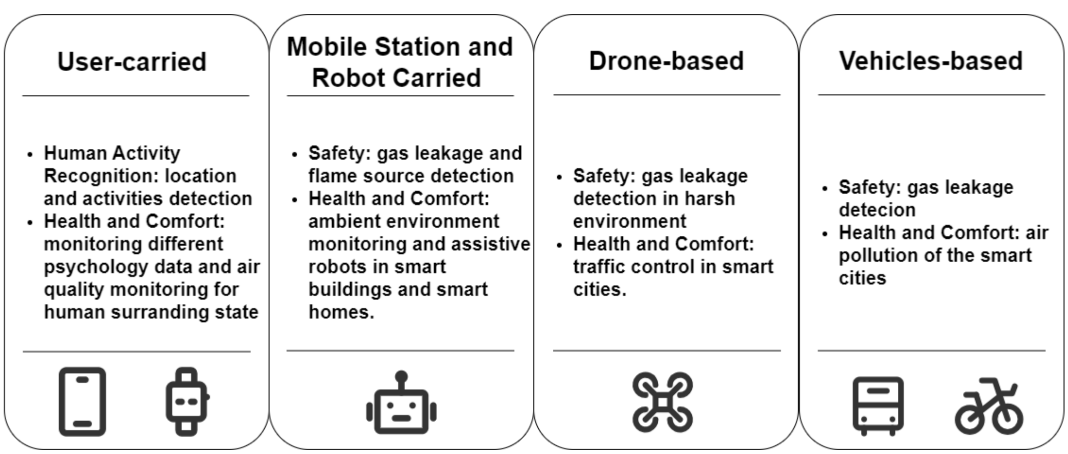


Figure 4: Summary of the Mobile Sensing System Application

Smartphones and wearable sensors concentrate on user health and emotional well-being. Mobile sensing systems are deployed to gather ambient environmental data for indoor environmental monitoring or to offer assistance in enhancing the quality of life for the elderly. Drones primarily target streets and urban areas and are employed for transportation-related tasks. Vehicles-based sensing systems focus on air pollution monitoring in the outdoor environment. Meanwhile, mobile stations and robots carried, and vehicles-based sensing systems contribute to occupant safety through gas detection. Among these, only smartphones and wearable sensors can deliver human activity recognition along with location detection, psychological data, temperature, and motion data, enabling the identification of activities and abnormal states.

### 5.2.2 From the Perspective of Sensing Scale Range

Smartphones and wearable sensors mainly capture user-centric data encompassing aspects like physical and mental health. The intimate contact with the user's body ensures higher precision of physiological data than other mobile sensing systems. They could recognise intricate occupant-specific information for a long time when users wear them, especially in environments relevant to chronic conditions. Nevertheless, their data collection is constrained to the user's immediate vicinity, making comprehensive data gathering across different locations challenging. They can also be used to collect information about the environment inside a building. However, because they depend on human movement, collecting information evenly from all points is difficult, and it is hard to predict the route of the sensor movement. Furthermore, they are tiny and portable with humans, have a weight limit, and cannot carry too many sensors simultaneously. Figure 5 shows the comparison of the limitation of the employment sensor with the mobile sensing and scale for different kinds of mobile sensing systems.

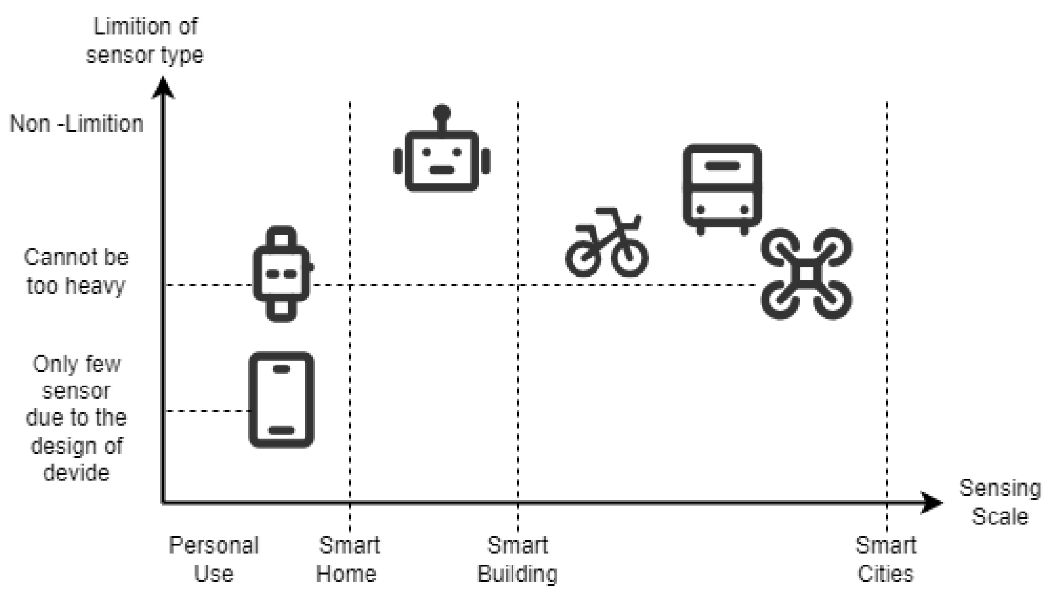


Figure 5: Comparison Limitation Level and Sensing Scale Comparison of the Mobile Sensing System

In contrast, mobile stations and robots exhibit a broader data collection range than smartphones and wearable sensors. The majority of these systems are employed within smart homes and smart buildings. They facilitate gathering indoor environmental data without human intervention, providing insights into the overall indoor environment. However, they still require development, especially in continuous user tracking, notably in navigating staircases, a feature currently lacking in most existing setups.

Drones offer the most extensive data collection range with minimal spatial restrictions. They can move freely between different floors within a building, collect data indoors, and capture the data in the air outdoors, which sets them apart from other mobile sensing systems. However, drones are limited by their payload capacity, making it challenging to carry heavy sensing systems.

Vehicles-based systems also allow the collection of data on a large scale. The air pollution in the cities could be monitored with them. However, the data collection area is limited to pre-designed public transport routes, and the speed of the vehicles may affect the accuracy of specific sensors.

### 5.3 Future Direction of Mobile Sensing System

As mentioned before, mobile sensing systems provide more application possibilities. Mobile sensing systems can replace static sensing systems in buildings that are difficult to retrofit—allowing all buildings to use smart buildings. In addition, mobile sensing systems can provide better performance for certain applications due to the flexibility of mobile sensing systems. For instance, mobile sensing systems provide more precise location information than static sensing systems in gas leak source detection. Similarly, mobile sensing systems allow more complex activity classification in human activity recognition. The flexibility of a mobile sensing system also allows it to have higher data granularity than a static sensing system [101], and a mobile sensing system can easily fill spatial data gaps. Furthermore, depending on the existing research, cooperation between mobile and static sensing systems addresses some of the challenges of smart buildings. It can be used for higher granularity cooperation between mobile and static sensing systems [125]. While increasing the number of static sensing systems is an applicable approach, a cooperation system provides an alternative that reduces the total number of sensors and minimises installation and maintenance costs. Currently, we can see the need for mobile systems. Based on the current application stage, there are five future research directions for mobile sensing systems.

#### 5.3.1 Analyse Building Pattern of Life through Sensing Systems

Patterns of life in the building help understand its regular and repetitive activities and provide insight into its behaviour. It impacts various aspects, such as safety, security, energy efficiency, experience of using the building, and even predictive maintenance and continuous improvement. Patterns of life and smart buildings are interdependent: understanding the normal building environment enables smart buildings to identify anomalies, allocate resources efficiently, and enhance occupant experience; smart buildings optimise the pattern of life to enhance quality, comfort, and health. However, there are currently limited applications for analysing the pattern of life within buildings. Most research focuses on short-term and one-time data, which is insufficient for studying regular and repetitive activities. More research is needed in this area to gain an understanding.

#### 5.3.2 Improve of Performance

Mobile sensing systems have a limited range of applications compared to static sensing systems. Smart buildings require different kinds of sensors as inputs. The basic requirements for most applications are carbon monoxide sensors, smoke sensors, temperature and humidity sensors. There are even some applications that combine indoor and outdoor for more accurate results [57]. However, mobile sensing systems deploy a limited variety of sensors. Besides smartphones with wearable sensors, other mobile sensing systems have not used multiple sensors to collect data simultaneously. Furthermore, according to the existing results, the speed and height of the sensors affect the collected data [105, 130]. Smartphones and wearable sensing systems are limited to data collection for comparative purposes in some research and often need more extensive data analysis, particularly about health detection. A more comprehensive understanding of different sensors that collect data under mobile conditions is needed. We can better understand how mobile sensing systems can replace static sensing systems in different scenarios.

#### 5.3.3 Ensure System Reliability

In large-scale and long-term sensing systems, a number of static sensing systems remain necessary. While mobile sensing systems offer flexibility and mobility, they may not fully replace static sensing systems in certain scenarios. Many mobile sensing systems have been assessed using limited data over a short time, depending on the battery. Mobile sensing systems need to be recharged at intervals, but static sensing systems are not needed. static sensing systems provide stable and continuous monitoring in fixed locations, allowing for consistent data collection over an extended period. They are beneficial for capturing detailed information in fixed areas or environments. Improving the stability and continuity of data collection in mobile sensing is essential. Depending on this situation, efforts have been made to enhance cooperation systems for thermal data detection over extended periods in a lecture room, with attempts to establish two operational modes, which are with mobile sensing systems or without [105]. However, extending the mobile sensing system on a large scale is still challenging.

#### 5.3.4 Strength the Stability of System

Human presence is unavoidable in buildings, and smart building research aims to enhance people's quality of life. Human activities can significantly impact environmental data. For instance, the concentration of $CO_2$ in a building varies based on the number of occupants. Additionally, human activity often affects mobile stations and robotic sensing systems used in buildings by slowing them down and enabling obstacle avoidance for safety purposes. However, despite being the most suitable mobile sensing systems for collecting environmental data in buildings, research involving mobile stations and robotic sensing systems is typically conducted in areas without humans. Further research is needed to consider the human factor when collecting data, develop methods to optimise data collection under limited conditions influenced by human presence and analyse collected data to achieve the best results.

#### 5.3.5 Implement Aggregation of Individual Data

Some mobile sensing systems target only individual-related data, especially smartphones and wearable sensing systems. It facilitates gathering information related to people because it relies on people to carry it and even physical contact with humans. But at the same time, its information is more dispersed for smart buildings. For this area, future research can be directed towards combining the information collected by multiple users in the building to obtain better data collection about the building. Furthermore, different mobile sensing systems can also work together. Drones and vehicle-based systems can collect outdoor environmental data to help more accurately predict the indoor conditions of a building.

## 6 Conclusion

This literature review provides an overview of current research into smart building systems. The review initiates by delving into existing surveys carried out within the domain of building systems. Then, it provides the various objectives of smart buildings, with a focus on the use of static sensing systems. Furthermore, the review dissects various categories of mobile sensing systems grounded in their sensing scope, categorising them into four distinct types. Finally, An investigation into the distinctions among the four categories of mobile sensing systems is undertaken, accompanied by a thorough analysis of the difference between mobile and static sensing systems. This analysis sheds light on their intrinsic advantages and limitations. The review involves a discussion of future directions and potential advances in mobile sensing systems. It highlights the need for further research and development to improve the capability and effectiveness of mobile sensing technologies in smart building environments.

## References


[1] Eleni Papadonikolaki, Ilias Krystallis, and Bethan Morgan. Digital Technologies in Built Environment Projects: Review and Future Directions. *Project Management Journal*, 53(5):501–519, 10 2022.

[2] Ming Jin, Shichao Liu, Stefano Schiavon, and Costas Spanos. Automated mobile sensing: Towards high-granularity agile indoor environmental quality monitoring. *Building and Environment*, 127:268–276, 1 2018.

[3] Neil E Klepeis, William C Nelson, Wayne R Ott, John P Robinson, Andy M Tsang, Paul Switzer, Joseph V Behar, Stephen C Hern, and William H Engelmann. The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. *Journal of exposure science & environmental epidemiology*, pages 231–252, 2001.

[4] D. P. Wyon. The effects of indoor air quality on performance and productivity. *International Centre for Indoor Environment and Energy*, pages 92–101, 2004.

[5] Bing Dong, Vishnu Prakash, Fan Feng, and Zheng O'Neill. A review of smart building sensing system for better indoor environment control, 9 2019.

[6] Keyur K Patel, Sunil M Patel, and P G Scholar. Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. Technical report, 2016.

[7] Ejaz Ahmed, Ibrar Yaqoob, Abdullah Gani, Muhammad Imran, and Mohsen Guizani. Internet-of-things-based smart environments: State of the art, taxonomy, and open research challenges. *IEEE Wireless Communications*, 23(5):10–16, 10 2016.

[8] Elsa Macias, Alvaro Suarez, and Jaime Lloret. Mobile sensing systems, 12 2013.

[9] Francisco Laport-López, Emilio Serrano, Javier Bajo, and Andrew T. Campbell. A review of mobile sensing systems, applications, and opportunities. *Knowledge and Information Systems*, 62(1):145–174, 1 2020.

[10] Bin Guo, Zhu Wang, Zhiwen Yu, Yu Wang, Neil Y. Yen, Runhe Huang, and Xingshe Zhou. Mobile Crowd Sensing and Computing: The review of an emerging human-powered sensing paradigm. *ACM Computing Surveys*, 48(1), 8 2015.

[11] Ferhat Attal, Samer Mohammed, Mariam Dedabrishvili, Faicel Chamroukhi, Latifa Oukhellou, and Yacine Amirat. Physical human activity recognition using wearable sensors, 12 2015.

[12] Muhammad Asghar Khan, Bilal Ahmad Alvi, Engr Alamgir Safi, Inam Ullah Khan, Bilal Ahmed Alvi, and Alamgir Safi. *Drones for Good in Smart Cities:A Review ICTIST'22: International Conference on Trends and Innovations in Smart Technologies View project UAVs assisted ad hoc network for Smart Cities. View project Drones for Good in Smart Cities:A Review*. 2018.

[13] Jayoung Kim, Alan S. Campbell, Berta Esteban Fernández de Ávila, and Joseph Wang. Wearable biosensors for healthcare monitoring, 4 2019.

[14] Anas Abou Allaban, Maozhen Wang, and Taşkin Padir. A systematic review of robotics research in support of in-home care for older adults, 2 2020.

[15] Juliane R. Sempionatto, Victor Ruiz Valdepeñas Montiel, Eva Vargas, Hazhir Teymourian, and Joseph Wang. Wearable and Mobile Sensors for Personalized Nutrition, 5 2021.

[16] Fatemeh Serpush, Mohammad Bagher Menhaj, Behrooz Masoumi, and Babak Karasfi. Wearable Sensor-Based Human Activity Recognition in the Smart Healthcare System, 2022.

[17] Wael Alsafery, Omer Rana, and Charith Perera. Sensing within Smart Buildings: a Survey. *ACM Computing Surveys*, 12 2023.

[18] Michael B. del Rosario, Stephen J. Redmond, and Nigel H. Lovell. Tracking the evolution of smartphone sensing for monitoring human movement, 7 2015.

[19] Alex Opoku. The Role of Culture in a Sustainable Built Environment. In Andrea Chiarini, editor, *Sustainable Operations Management: Advances in Strategy and Methodology*, pages 37–52. Springer International Publishing, Cham, 2015.

[20] Noa Pinter-Wollman, Andrea Jelic, and Nancy M. Wells. The impact of the built environment on health behaviours and disease transmission in social systems. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 373(1753), 8 2018.

[21] Mia A. Papas, Anthony J. Alberg, Reid Ewing, Kathy J. Helzlsouer, Tiffany L. Gary, and Ann C. Klassen. The built environment and obesity, 5 2007.

[22] Gary W Evans. The Built Environment and Mental Health. Technical Report 4, 2003.

[23] N. Soares, J. Bastos, L. Dias Pereira, A. Soares, A. R. Amaral, E. Asadi, E. Rodrigues, F. B. Lamas, H. Monteiro, M. A.R. Lopes, and A. R. Gaspar. A review on current advances in the energy and environmental performance of buildings towards a more sustainable built environment, 9 2017.

[24] Amy J. Lynch and Simon M. Mosbah. Improving local measures of sustainability: A study of built-environment indicators in the United States. *Cities*, 60:301–313, 2 2017.

[25] Yuting Hou, Winston Yap, Rochelle Chua, Siqi Song, and Belinda Yuen. The associations between older adults' daily travel pattern and objective and perceived built environment: A study of three neighbourhoods in Singapore. *Transport Policy*, 99:314–328, 12 2020.

[26] Lars Böcker, Patrick van Amen, and Marco Helbich. Elderly travel frequencies and transport mode choices in Greater Rotterdam, the Netherlands. *Transportation*, 44(4):831–852, 7 2017.

[27] Lawrence D Frank and Peter O Engelke. The Built Environment and Human Activity Patterns The Built Environment and Human Activity Patterns: Exploring the Impacts of Urban Form on Public Health. Technical Report 2, 2001.

[28] Angeliki Kylili, Paris A. Fokaides, and Petra Amparo Lopez Jimenez. Key Performance Indicators (KPIs) approach in buildings renovation for the sustainability of the built environment: A review, 4 2016.

[29] Ghezlane Halhoul Merabet, Mohamed Essaaidi, Mohamed Ben Haddou, Basheer Qolomany, Junaid Qadir, Muhammad Anan, Ala Al-Fuqaha, Mohamed Riduan Abid, and Driss Benhaddou. Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques, 7 2021.

[30] Samuel Tang, Vineetha Kalavally, Kok Yew Ng, and Jussi Parkkinen. Development of a prototype smart home intelligent lighting control architecture using sensors onboard a mobile computing system. *Energy and Buildings*, 138:368–376, 3 2017.

[31] Evangelos Maltezos, Konstantinos Petousakis, Aris Dadoukis, Lazaros Karagiannidis, Eleftherios Ouzounoglou, Maria Krommyda, George Hadjipavlis, and Angelos Amditis. A Smart Building Fire and Gas Leakage Alert System with Edge Computing and NG112 Emergency Call Capabilities. *Information (Switzerland)*, 13(4), 4 2022.

[32] Sourav Kumar Bhoi, Sanjaya Kumar Panda, Biranchi Narayan Padhi, Manash Kumar Swain, Balabhadrah Hembram, Debasish Mishra, Chittaranjan Mallick, Munesh Singh, and Pabitra Mohan Khilar. FireDS-IoT: A Fire Detection System for Smart Home Based on IoT Data Analytics. In *Proceedings - 2018 International Conference on Information Technology, ICIT 2018*, pages 161–165. Institute of Electrical and Electronics Engineers Inc., 12 2018.

[33] Lesong Wu, Lan Chen, and Xiaoran Hao. Multi-sensor data fusion algorithm for indoor fire early warning based on bp neural network. *Information (Switzerland)*, 12(2):1–13, 2 2021.

[34] Wajahat Khalid, Asma Sattar, Muhammad Ali Qureshi, Asjad Amin, Mobeen Ahmed Malik, and Kashif Hussain Memon. A smart wireless sensor network node for fire detection. *Turkish Journal of Electrical Engineering and Computer Sciences*, 27(4):2541–2556, 2019.

[35] Arpit Jadon, Mohd. Omama, Akshay Varshney, Mohammad Samar Ansari, and Rishabh Sharma. FireNet: A Specialized Lightweight Fire & Smoke Detection Model for Real-Time IoT Applications. 5 2019.

[36] Saydirasulov Norkobil Saydirasulovich, Akmalbek Abdusalomov, Muhammad Kafeel Jamil, Rashid Nasimov, Dinara Kozhamzharova, and Young-Im Cho. A YOLOv6-Based Improved Fire Detection Approach for Smart City Environments. *Sensors*, 23(6):3161, 3 2023.

[37] Ravi Kishore Kodali, Greeshma R.N.V, Kusuma Priya Nimmanapalli, and Yatish Krishna Yogi Borra. IOT Based Industrial Plant Safety Gas Leakage Detection System. In *2018 4th International Conference on Computing Communication and Automation(ICCCA)*, pages 1–5, 2018.

[38] Haythem Ahmad Bany Salameh, Mohammad Fozi Dhainat, and Elhadj Benkhelifa. An End-to-End Early Warning System Based on Wireless Sensor Network for Gas Leakage Detection in Industrial Facilities. *IEEE Systems Journal*, 15(4):5135–5143, 12 2021.

[39] Faisal Saeed, Anand Paul, Abdul Rehman, Won Hwa Hong, and Hyuncheol Seo. IoT-Based intelligent modeling of smart home environment for fire prevention and safety. *Journal of Sensor and Actuator Networks*, 7(1), 3 2018.

[40] A. I. Dounis and C. Caraiscos. Advanced control systems engineering for energy and comfort management in a building environment-A review, 8 2009.

[41] M. Frontczak, S. Schiavon, J. Goins, E. Arens, H. Zhang, and P. Wargocki. Quantitative relationships between occupant satisfaction and satisfaction aspects of indoor environmental quality and building design. *Indoor Air*, 22(2):119–131, 4 2012.

[42] Ruchao Xiahou, Jianjun Yi, Liang He, Wang He, and Tianhua Huang. Indoor air monitoring system based on internet of things and its prediction model. In *ACM International Conference Proceeding Series*, pages 58–63. Association for Computing Machinery, 3 2019.

[43] Xuxu Chen, Yu Zheng, Yubiao Chen, Qiwei Jin, Weiwei Sun, Eric Chang, and Wei Ying Ma. Indoor air quality monitoring system for smart buildings. In *UbiComp 2014 - Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 471–475. Association for Computing Machinery, Inc, 2014.

[44] Ghezlane Halhoul Merabet, Mohamed Essaaidi, Driss Benhaddou, Nacer Khalil, and Júlio Chilela. Measuring human comfort for smart building application: Experimental set-up using WSN. In *ACM International Conference Proceeding Series*, pages 56–63. Association for Computing Machinery, 10 2018.

[45] Liang Yang, Zimu Zheng, Jingting Sun, Dan Wang, and Xin Li. A domain-Assisted data driven model for thermal comfort prediction in buildings. In *e-Energy 2018 - Proceedings of the 9th ACM International Conference on Future Energy Systems*, pages 271–276. Association for Computing Machinery, Inc, 6 2018.

[46] Eikichi Ono, Yue Lei, Kuniaki Mihara, and Adrian Chong. The impact of resolution of occupancy data on personal comfort model-based HVAC control performance. In *BuildSys 2022 - Proceedings of the 2022 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, pages 254–257. Association for Computing Machinery, Inc, 11 2022.

[47] Sarah Crosby and Adam Rysanek. Towards improved thermal comfort predictions for building controls: Hierarchical bayesian modelling of indoor environmental design conditions. In *BuildSys 2021 - Proceedings of the 2021 ACM International Conference on Systems for Energy-Efficient Built Environments*, pages 286–289. Association for Computing Machinery, Inc, 11 2021.

[48] Han Zou, Yuxun Zhou, Hao Jiang, Szu Cheng Chien, Lihua Xie, and Costas J. Spanos. WinLight: A WiFi-based occupancy-driven lighting control system for smart building. *Energy and Buildings*, 158:924–938, 1 2018.

[49] Kevin Warmerdam, Ashish Pandharipande, David Caicedo, and Marco Zuniga. Visible Light Communications for Sensing and Lighting Control. *IEEE Sensors Journal*, 16(17):6718–6726, 9 2016.

[50] X. Wang, T. Tjalkens, and J. P. Linnartz. An Intelligent lighting System: Learn user preferences from inconsistent feedback. In *UbiComp 2016 Adjunct - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 1620–1626. Association for Computing Machinery, Inc, 9 2016.

[51] A. P. Jones. Indoor air quality and health. *Atmospheric Environment*, 33(28):4535–4564, 12 1999.

[52] Ali Majdi, Ali Jawad Alrubaie, Alia Haider Al-Wardy, Jamel Baili, and Hitesh Panchal. A novel method for Indoor Air Quality Control of Smart Homes using a Machine learning model. *Advances in Engineering Software*, 173, 11 2022.

[53] Mohieddine Benammar, Abderrazak Abdaoui, Sabbir H.M. Ahmad, Farid Touati, and Abdullah Kadri. A modular IoT platform for real-time indoor air quality monitoring. *Sensors (Switzerland)*, 18(2), 2 2018.

[54] Rui Oliveira, Jérôme Kämpf, Romeu Vicente, Ricardo Almeida, and António Figueiredo. CO2 experimental measurements towards the development of a predictive framework using user actions in smart buildings. In *Journal of Physics: Conference Series*, volume 1343. Institute of Physics Publishing, 11 2019.

[55] Thomas Van De Werff, Charlotte Van Lotringen, Harm Van Essen, and Berry Eggen. Design considerations for interactive office lighting interface characteristics, shared and hybrid control. In *Conference on Human Factors in Computing Systems - Proceedings*. Association for Computing Machinery, 5 2019.

[56] Khairul Rijal Wagiman, Mohd Noor Abdullah, Mohammad Yusri Hassan, and Nur Hanis Mohammad Radzi. A new optimal light sensor placement method of an indoor lighting control system for improving energy performance and visual comfort. *Journal of Building Engineering*, 30, 7 2020.

[57] Xianzhong Ding, Wan Du, and Alberto Cerpa. OCTOPUS: Deep reinforcement learning for holistic smart building control. In *BuildSys 2019 - Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*, pages 326–335. Association for Computing Machinery, Inc, 11 2019.

[58] Patrick Nzivugira Duhirwe, Jack Ngarambe, and Geun Young Yun. Energy-efficient virtual sensor-based deep reinforcement learning control of indoor CO2 in a kindergarten. *Frontiers of Architectural Research*, 12(2):394–409, 4 2023.

[59] Anuradha Ravi, Kasun Galmath, Siyan Hu, and Archan Misra. CS-light: Camera sensing based occupancy-aware robust smart building lighting control. In *BuildSys 2021 - Proceedings of the 2021 ACM International Conference on Systems for Energy-Efficient Built Environments*, pages 61–70. Association for Computing Machinery, Inc, 11 2021.

[60] Yuvraj Agarwal, Bharathan Balaji, Rajesh Gupta, Jacob Lyles, Michael Wei, and Thomas Weng. Occupancy-Driven Energy Management for Smart Building Automation. In *BuildSys*, page 86. Association for Computing Machinery, 2010.

[61] Paul Davidsson and Marc Langheinrich. Exploring Smart Home and Internet of Things Technologies for Smart Public Building, 10 2020.

[62] Ivan Chew, Vineetha Kalavally, Naing Win Oo, and Jussi Parkkinen. Design of an energy-saving controller for an intelligent LED lighting system. *Energy and Buildings*, 120:1–9, 5 2016.

[63] Valentina Bianchi, Marco Bassoli, Gianfranco Lombardo, Paolo Fornacciari, Monica Mordonini, and Ilaria De Munari. IoT Wearable Sensor and Deep Learning: An Integrated Approach for Personalized Human Activity Recognition in a Smart Home Environment. *IEEE Internet of Things Journal*, 6(5):8553–8562, 10 2019.

[64] Luo Fei, Poslad Stefan, and Eliance Bodanese. Kitchen Activity Detection for Healthcare using a low-power Radar-Enabled Sensor Network. 2019.

[65] Pedro F. Pereira, Nuno M.M. Ramos, Ricardo M.S.F. Almeida, and M. Lurdes Simões. Methodology for detection of occupant actions in residential buildings using indoor environment monitoring systems. *Building and Environment*, 146:107–118, 12 2018.

[66] Heilym Ramirez, Sergio A. Velastin, Ignacio Meza, Ernesto Fabregas, Dimitrios Makris, and Gonzalo Farias. Fall Detection and Activity Recognition Using Human Skeleton Features. *IEEE Access*, 9:33532–33542, 2021.

[67] Amir Nadeem, Ahmad Jalal, and Kibum Kim. Accurate physical activity recognition using multidimensional features and markov model for smart health fitness. *Symmetry*, 12(11):1–17, 11 2020.

[68] Malik Ali Gul, Muhammad Haroon Yousaf, Shah Nawaz, Zaka Ur Rehman, and Hyungwon Kim. Patient monitoring by abnormal human activity recognition based on CNN architecture. *Electronics (Switzerland)*, 9(12):1–14, 12 2020.

[69] Xiaomu Luo, Huoyuan Tan, Qiuju Guan, Tong Liu, Hankz Hankui Zhuo, and Baihua Shen. Abnormal activity detection using pyroelectric infrared sensors. *Sensors (Switzerland)*, 16(6), 6 2016.

[70] Yuxi Wang, Kaishun Wu, and Lionel M. Ni. WiFall: Device-Free Fall Detection by Wireless Networks. *IEEE Transactions on Mobile Computing*, 16(2):581–594, 2 2017.

[71] Huan Yan, Yong Zhang, Yujie Wang, and Kangle Xu. WiAct: A Passive WiFi-Based Human Activity Recognition System. *IEEE Sensors Journal*, 20(1):296–305, 1 2020.

[72] Han Zou, Yuxun Zhou, Jianfei Yang, and Costas J. Spanos. Towards occupant activity driven smart buildings via WiFi-enabled IoT devices and deep learning. *Energy and Buildings*, 177:12–22, 10 2018.

[73] Yu Gu, Fuji Ren, and Jie Li. PAWS: Passive Human Activity Recognition Based on WiFi Ambient Signals. *IEEE Internet of Things Journal*, 3(5):796–805, 10 2016.

[74] Mohammed Mehedi Hassan, Md Zia Uddin, Amr Mohamed, and Ahmad Almogren. A robust human activity recognition system using smartphone sensors and deep learning. *Future Generation Computer Systems*, 81:307–313, 4 2018.

[75] Matthew J. Smith, Kristen Warren, David Cohen-Tanugi, Sam Shames, Kelly Sprehn, Jana L. Schwartz, Hui Zhang, and Ed Arens. Augmenting smart buildings and autonomous vehicles with wearable thermal technology. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, volume 10272 LNCS, pages 550–561. Springer Verlag, 2017.

[76] Abdul Hakim, M. Saiful Huq, Shahnoor Shanta, and B. S.K.K. Ibrahim. Smartphone Based Data Mining for Fall Detection: Analysis and Design. In *Procedia Computer Science*, volume 105, pages 46–51. Elsevier B.V., 2017.

[77] Jun He, Qian Zhang, Liqun Wang, and Ling Pei. Weakly Supervised Human Activity Recognition from Wearable Sensors by Recurrent Attention Learning. *IEEE Sensors Journal*, 19(6):2287–2297, 3 2019.

[78] Nadeem Ahmed, Jahir Ibna Rafiq, and Md Rashedul Islam. Enhanced human activity recognition based on smartphone sensor data using hybrid feature selection model. *Sensors (Switzerland)*, 20(1), 1 2020.

[79] Johan Wannenburg and Reza Malekian. Physical Activity Recognition from Smartphone Accelerometer Data for User Context Awareness Sensing. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(12):3142–3149, 12 2017.

[80] Daniel Kelly, Joan Condell, Kevin Curran, and Brian Caulfield. A multimodal smartphone sensor system for behaviour measurement and health status inference. *Information Fusion*, 53:43–54, 1 2020.

[81] Xiao Zhang, Wenzhong Li, Xu Chen, and Sanglu Lu. MoodExplorer: Towards Compound Emotion Detection via Smartphone Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(4):1–30, 1 2018.

[82] Taylor A Braund, May The Zin, Tjeerd W Boonstra, Quincy J J Wong, Mark E Larsen, Helen Christensen, Gabriel Tillman, and Bridianne O'Dea. Smartphone Sensor Data for Identifying and Monitoring Symptoms of Mood Disorders: A Longitudinal Observational Study. *JMIR Mental Health*, 9(5):e35549, 5 2022.

[83] Hengyuan Guo, Qian Zeng, Zike Chen, and Ming Zhao. Bluetooth door lock system based on smart mobile device. In *ACM International Conference Proceeding Series*. Association for Computing Machinery, 10 2018.

[84] Syed Ali Raza Zaidi, Ali Imran, Des C. McLernon, and Mounir Ghogho. Enabling IoT empowered smart lighting solutions: A communication theoretic perspective. In *2014 IEEE Wireless Communications and Networking Conference Workshops, WCNCW 2014*, pages 140–144. Institute of Electrical and Electronics Engineers Inc., 10 2014.

[85] Areg Karapetyan, Sid Chi-Kin Chau, Khaled Elbassioni, Syafiq Kamarul Azman, and Majid Khonji. Multisensor adaptive control system for IoT-empowered smart lighting with oblivious mobile sensors. *ACM Transactions on Sensor Networks*, 16(1), 12 2019.

[86] Stylianos Paraschiakos, Ricardo Cachucho, Matthijs Moed, Diana van Heemst, Simon Mooijaart, Eline P. Slagboom, Arno Knobbe, and Marian Beekman. Activity recognition using wearable sensors for tracking the elderly. *User Modeling and User-Adapted Interaction*, 30(3):567–605, 7 2020.

[87] Hiram Ponce, María De Lourdes Martínez-Villaseñor, and Luis Miralles-Pechuán. A novel wearable sensor-based human activity recognition approach using artificial hydrocarbon networks. *Sensors (Switzerland)*, 16(7), 7 2016.

[88] Jianchao Lu, Xi Zheng, Michael Sheng, Jiong Jin, and Shui Yu. Efficient Human Activity Recognition Using a Single Wearable Sensor. *IEEE Internet of Things Journal*, 7(11):11137–11146, 11 2020.

[89] Kyle R. Mallires, Di Wang, Vishal Varun Tipparaju, and Nongjian Tao. Developing a Low-Cost Wearable Personal Exposure Monitor for Studying Respiratory Diseases Using Metal-Oxide Sensors. *IEEE Sensors Journal*, 19(18):8252–8261, 9 2019.

[90] Farman Ali, Shaker El-Sappagh, S. M.Riazul Islam, Amjad Ali, Muhammad Attique, Muhammad Imran, and Kyung Sup Kwak. An intelligent healthcare monitoring framework using wearable sensors and social networking data. *Future Generation Computer Systems*, 114:23–43, 1 2020.

[91] R. Kamalraj, E. S. Madhan, K. Ghamya, and V. Bhargavi. Enhance Safety and Security System for Children in School Campus by using Wearable Sensors. In *Proceedings of the 4th International Conference on Computing Methodologies and Communication, ICCMC 2020*, pages 986–990. Institute of Electrical and Electronics Engineers Inc., 3 2020.

[92] Jayoung Kim, Juliane R. Sempionatto, Somayeh Imani, Martin C. Hartel, Abbas Barfidokht, Guangda Tang, Alan S. Campbell, Patrick P. Mercier, and Joseph Wang. Simultaneous Monitoring of Sweat and Interstitial Fluid Using a Single Wearable Biosensor Platform. *Advanced Science*, 5(10), 10 2018.

[93] Yihao Chen, Siyuan Lu, Shasha Zhang, Yan Li, Zhe Qu, Ying Chen, Bingwei Lu, Xinyan Wang, and Xue Feng. Skin-like biosensor system via electrochemical channels for noninvasive blood glucose monitoring. Technical report, 2017.

[94] Juliane R. Sempionatto, Ahmed A. Khorshed, Aftab Ahmed, Andre N. De Loyola E Silva, Abbas Barfidokht, Lu Yin, K. Yugender Goud, Mona A. Mohamed, Eileen Bailey, Jennifer May, Claude Aebischer, Claire Chatelle, and Joseph Wang. Epidermal Enzymatic Biosensors for Sweat Vitamin C: Toward Personalized Nutrition. *ACS Sensors*, 5(6):1804–1813, 6 2020.

[95] Fang-Yie Leu, Chia-Yin Ko, Ilsun You, Kim-Kwang Raymond Choo, and Chi-Lun Ho. A smartphone-based wearable sensors for monitoring real-time physiological data. *Computers and Electrical Engineering*, 65:376–392, 1 2018.

[96] Yue Deng, Cheng Chen, Xiaojun Xian, Francis Tsow, Gaurav Verma, Rob McConnell, Scott Fruin, Nongjian Tao, and Erica S. Forzani. A novel wireless wearable volatile organic compound (VOC) monitoring device with disposable sensors. *Sensors (Switzerland)*, 16(12), 12 2016.

[97] João G.P. Rodrigues, Mariana Kaiseler, Ana Aguiar, João P.Silva Cunha, and João Barros. A mobile sensing approach to stress detection and memory activation for public bus drivers. *IEEE Transactions on Intelligent Transportation Systems*, 16(6):3294–3303, 12 2015.

[98] Jian Xu, Arani Bhattacharya, Aruna Balasubramanian, and Donald E. Porter. Sensor Virtualization for Efficient Sharing of Mobile and Wearable Sensors. In *SenSys 2021 - Proceedings of the 2021 19th ACM Conference on Embedded Networked Sensor Systems*, pages 460–466. Association for Computing Machinery, Inc, 11 2021.

[99] Letícia Diniz Tsuchiya, Lucas Fiorini Braga, Otávio de Faria Oliveira, Raphael Winckler de Bettio, Juliana Galvani Greghi, and André Pimenta Freire. Design and evaluation of a mobile smart home interactive system with elderly users in Brazil. *Personal and Ubiquitous Computing*, 25(2):281–295, 4 2021.

[100] Shoaib, Muhammad and Bosch, Stephan and Scholten, Hans and Havinga, Paul J. M. and Incel, and Ozlem Durmaz. Towards Detection of Bad Habits by Fusing Smartphone and Smartwatch Sensors. *2015 IEEE International Conference on Pervasive Computing and Communication Workshops*, pages 591–596, 2015.

[101] Michael Hutchinson, Cunjia Liu, and Wen Hua Chen. Information-Based Search for an Atmospheric Release Using a Mobile Robot: Algorithm and Experiments. *IEEE Transactions on Control Systems Technology*, 27(6):2388–2402, 11 2019.

[102] Jordi Palacín, David Martínez, Eduard Clotet, Tomàs Pallejà, Javier Burgués, Jordi Fonollosa, Antonio Pardo, and Santiago Marco. Application of an array of metal-oxide semiconductor gas sensors in an assistant personal robot for early gas leak detection. *Sensors (Switzerland)*, 19(9), 5 2019.

[103] H A S ; F ; Hawari, K ; Kamarudin, Z H M ; Juffry, N A A ; Hussein, and M ; Gupta. Mobile Robot Gas Source Localization Using SLAM-GDM with a Graphene-Based Gas Sensor. 2022.

[104] Ming Jin, Mingjian Lu, Shichao Liu, Stefano Schiavon, Yulun Tian, and Costas Spanos. Indoor environmental quality monitoring by autonomous mobile sensing. In *BuildSys 2017 - Proceedings of the 4th ACM International Conference on Systems for Energy-Efficient Built Environments*, volume 2017-January. Association for Computing Machinery, Inc, 11 2017.

[105] Yang Geng, Mufeng Yuan, Hao Tang, Ye Wang, Ziliang Wei, Borong Lin, and Weimin Zhuang. Robot-based mobile sensing system for high-resolution indoor temperature monitoring. *Automation in Construction*, 142, 10 2022.

[106] Caetano M. Ranieri, Guilherme Nardari, Adam H.M. Pinto, Daniel C. Tozadore, and Roseli A.F. Romero. LARa: A robotic framework for human-robot interaction on indoor environments. In *Proceedings - 15th Latin American Robotics Symposium, 6th Brazilian Robotics Symposium and 9th Workshop on Robotics in Education, LARS/SBR/WRE 2018*, pages 383–389. Institute of Electrical and Electronics Engineers Inc., 12 2018.

[107] Garrett Wilson, Christopher Pereyda, Nisha Raghunath, Gabriel de la Cruz, Shivam Goel, Sepehr Nesaei, Bryan Minor, Maureen Schmitter-Edgecombe, Matthew E. Taylor, and Diane J. Cook. Robot-enabled support of daily activities in smart home environments. *Cognitive Systems Research*, 54:258–272, 5 2019.

[108] Qi Wang, Zhen Fan, Wei hua Sheng, Sen lin Zhang, and Mei qin Liu. Finding misplaced items using a mobile robot in a smart home environment. *Frontiers of Information Technology and Electronic Engineering*, 20(8):1036–1048, 8 2019.

[109] Serhan Coşar, Manuel Fernandez-Carmona, Roxana Agrigoroaie, Jordi Pages, François Ferland, Feng Zhao, Shigang Yue, Nicola Bellotto, and Adriana Tapus. ENRICHME: Perception and Interaction of an Assistive Robot for the Elderly at Home. *International Journal of Social Robotics*, 12(3):779–805, 7 2020.

[110] Jorge Edwin Sánchez-Sosa, Juan Castillo-Mixcóatl, Georgina Beltrán-Pérez, and Severino Muñoz-Aguirre. An application of the Gaussian plume model to localization of an indoor gas source with a mobile robot. *Sensors (Switzerland)*, 18(12), 12 2018.

[111] Wahyu Rahmaniar and Ardhi Wicaksono. Design and implementation of a mobile robot for carbon monoxide monitoring. *Journal of Robotics and Control (JRC)*, 2(1):1–6, 1 2021.

[112] Mukul Diwanji, Saurabh Hisvankar, and Chhaya Khandelwal. Autonomous Fire Detecting and Extinguishing Robot. pages 327–329, 2019.

[113] T. AlHaza, A. Alsadoon, Z. Alhusinan, M. Jarwali, and K. Alsaif. New Concept for Indoor Fire Fighting Robot. *Procedia - Social and Behavioral Sciences*, 195:2343–2352, 7 2015.

[114] Jordi Palacín, Eduard Clotet, Dani Martínez, Javier Moreno, and Marcel Tresanchez. Automatic Supervision of Temperature, Humidity, and Luminance with an Assistant Personal Robot. *Journal of Sensors*, 2017, 2017.

[115] Davide Bacciu, Maurizio Di Rocco, Mauro Dragone, Claudio Gallicchio, Alessio Micheli, and Alessandro Saffiotti. An ambient intelligence approach for learning in smart robotic environments. *Computational Intelligence*, 35(4):1061–1088, 11 2019.

[116] Junhai Luo, Zhiyan Wang, Ming Xia, Linyong Wu, Yuxin Tian, and Yu Chen. Path Planning for UAV Communication Networks: Related Technologies, Solutions, and Opportunities. *ACM Computing Surveys*, 55(9), 1 2023.

[117] Sarmad Rashed and Mujdat Soyturk. Effects of UAV mobility patterns on data collection in wireless sensor networks. In *4th IEEE Conference on Communication, Networks and Satellite, COMNESTAT 2015 - Proceedings*, pages 74–79. Institute of Electrical and Electronics Engineers Inc., 3 2016.

[118] Vanesa Gallego, Maurizio Rossi, and Davide Brunelli. Unmanned aerial gas leakage localization and mapping using microdrones. In *SAS 2015 - 2015 IEEE Sensors Applications Symposium, Proceedings*. Institute of Electrical and Electronics Engineers Inc., 6 2015.

[119] M. Khoshboresh Masouleh and Reza Shah-Hosseini. Development and evaluation of a deep learning model for real-time ground vehicle semantic segmentation from UAV-based thermal infrared imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 155:172–186, 9 2019.

[120] Jiasong Zhu, Ke Sun, Sen Jia, Qingquan Li, Xianxu Hou, Weidong Lin, Bozhi Liu, and Guoping Qiu. Urban Traffic Density Estimation Based on Ultrahigh-Resolution UAV Video and Deep Neural Network. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11(12):4968–4981, 12 2018.

[121] Oscar Alvear, Willian Zamora, Carlos T. Calafate, Juan Carlos Cano, and Pietro Manzoni. EcoSensor: Monitoring environmental pollution using mobile sensors. In *WoWMoM 2016 - 17th International Symposium on a World of Wireless, Mobile and Multimedia Networks*. Institute of Electrical and Electronics Engineers Inc., 7 2016.

[122] Alejandro Velasco, Renato Ferrero, Filippo Gandino, Bartolomeo Montrucchio, and Maurizio Rebaudengo. A mobile and low-cost system for environmental monitoring: A case study. *Sensors (Switzerland)*, 16(5), 5 2016.

[123] Ke Guo, Pan Yang, Dan Huai Guo, and Yi Liu. Gas Leakage Monitoring with Mobile Wireless Sensor Networks. In *Procedia Computer Science*, volume 154, pages 430–438. Elsevier B.V., 2018.

[124] Bharadwaj R.K. Mantha, Carol C. Menassa, and Vineet R. Kamat. Robotic data collection and simulation for evaluation of building retrofit performance. *Automation in Construction*, 92:88–102, 8 2018.

[125] Yuan Yang, Jiang Liu, Wei Wang, Yu Cao, and Heng Li. Incorporating SLAM and mobile sensing for indoor CO2 monitoring and source position estimation. *Journal of Cleaner Production*, 291, 4 2021.

[126] H. Chojer, P. T.B.S. Branco, F. G. Martins, M. C.M. Alvim-Ferraz, and S. I.V. Sousa. Development of low-cost indoor air quality monitoring devices: Recent advancements, 7 2020.

[127] Prashant Kumar, Claudio Martani, Lidia Morawska, Leslie Norford, Ruchi Choudhary, Margaret Bell, and Matt Leach. Indoor air quality and energy management through real-time sensing in commercial buildings, 1 2016.

[128] Richard Ribón Fletcher, Nicolas M. Oreskovic, and Alyssa I. Robinson. Design and clinical feasibility of personal wearable monitor for measurement of activity and environmental exposure. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014*, pages 874–877. Institute of Electrical and Electronics Engineers Inc., 11 2014.

[129] Yang Geng, Borong Lin, Juan Yu, Hao Zhou, Wenjie Ji, Hongzhong Chen, Zhongchen Zhang, and Yingxin Zhu. Indoor environmental quality of green office buildings in China: Large-scale and long-term measurement. *Building and Environment*, 150:266–280, 3 2019.

[130] Yanan Zhao, Zihan Zang, Weirong Zhang, Shen Wei, and Yingli Xuan. Predicting indoor temperature distribution based on contribution ratio of indoor climate (Cri) and mobile sensors. *Buildings*, 11(10), 10 2021.