Sensing within Smart Buildings: a Survey

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Increasingly, buildings are being fitted with sensors for the needs of different sectors, such as education, industry and business. Using Internet of Things (IoT) devices combined with analysis of data being generated by these devices, it is possible to infer a number of metrics, e.g. building occupancy and activities of occupants. The information thus gathered can be used to develop software applications to support energy management, occupant comfort, and space utilization. This survey explores the use of sensors in smart building environments, identifying different approaches to employ sensors in buildings. The most commonly used data-driven approaches for activity recognition in such buildings is also investigated, concluding by highlighting current research challenges and future research directions in this area.

CCS Concepts: • **General and reference → Surveys and overviews**; • **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

Additional Key Words and Phrases: Sensors, Smart buildings, Occupancy, Activity recognition.

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1 INTRODUCTION

Smart buildings are intelligent buildings that use technology to optimize energy efficiency, cost savings, operational performance, and occupant comfort and safety. They are equipped with sensors/ devices and generate data that allows them to control and measure the environment, such as temperature and humidity, lighting, energy use, and more. Smart building systems can also connect with other smart devices such as smartphones and smart home appliances, to provide a seamless user experience. By integrating advanced automation, analytics, and Machine Learning (ML) technologies, smart buildings can offer improved quality of life in terms of air quality, occupants comfort, and energy consumption. Smart buildings can include offices, homes, hospitals and libraries, all of which provide targeted automated services.

To understand the size of the global smart building market and its potential for development in the coming years, a recent report from Maximize Market Research [3] offers some key data; this report shows that the number of smart buildings globally is accelerating annually. In 2016, the market for smart buildings was approximately US $5.92B. By 2024, it is expected to reach US $47.8B. The report thus emphasizes the importance of this sector and the expected increase in demand and scientific research in this field in coming years.

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Smart building make use of Internet of Things (IoT) technology combined with Machine Learning and data analytics to achieve a range of services. These IoT devices are deployed in multiple locations around a building for different purposes; for example, a sensor might be deployed in a building elevator to send data to a maintenance team in case of an emergency or where malfunction/ deterioration is detected. Communication is achieved through various wireless communications protocols, yet the sensor data alone are meaningless. Such data must be processed using, for instance, single-board computers (SBCs), servers, or cloud systems, to extract meaningful information. Valuable insights can be obtained to support numerous applications in a building, such as lighting and environmental control systems.

The research method included search across the ACM Digital Library, BuildSys, SIGCHI, SenSys, IEEE Xplore, and Google Scholar. During the research process, keywords and phrases used included "smart buildings," "occupancy sensing," "occupancy estimation," "activity detection," "activity recognition," "sensing in smart buildings," "occupancy estimation in smart buildings," "activity detection in smart buildings," "behavior monitoring in smart buildings," "analytics used in smart buildings," and "sensing as services within smart buildings." The Boolean operators "and" and "or" were used to obtain better results, in addition, the word "sensors" was added to all previous keyword searches, as the target research field is the sensing domain in smart buildings.

In total, 137 research papers on sensing and activity recognition in smart building environments were reviewed. These papers were classified according to identified activities, data analysis algorithms used, number of sensors, sensor types, deployed locations and smart building types. Some research papers did not specifically mention where the identified activity occurred inside or outside the building. However, most were categorized into two indoor and/ or outdoor environments, which facilitated classification. The outdoor environment referenced activities such as swimming for instance (i.e. activities outside the building), and were eliminated based on this paper's focus on indoor environments and activities within smart buildings. Other research papers which did not mention the sensor type used in the relevant study were also removed from our survey.

1.1 Existing Reviews

Although many research papers have been published on sensing within smart buildings, many areas have not yet been explored in depth. This paper aims to review sensing technology used in different types of buildings, including identifying the IoT sensors used and their types, their deployed locations, and the activities identified. We explore how people use sensors to understand different types of building usage. Table 1 compares the relevant review studies in more detail.

Other research has focused more on buildings themselves: Pan et al. [114] concentrated on energy efficiency developments in buildings and microgrids, while Saha et al. [131] focused on data analytics approaches in smart buildings, and Liu et al. [92] concentrated on the integration of Building Information Modelling (BIM) and sensors. However, none of these papers focused on how sensors are used in smart buildings in terms of their types, deployment locations, and identified activities. In addition, more attention needs to be paid to recognizing how sensors can be used to understand various activities inside buildings.

1.2 Contributions and Article Organization

The research contribution of this paper can be summarized in three main points:

- Review existing research to identify what types of sensors are being used in smart buildings, where they were deployed, and activities they were able to identify.
- Explore how different types of sensors and data analytics are being combined to better discover activities within smart buildings.

Table 1. Existing survey papers

Reference	Sensor types	Deployed locations	Activities identified	Analytics used	Purpose	Focus
Kazmi et al. [65]				✓	Review Wireless Sensor Network (WSNs) enabled Building Energy Management Systems (BEMS)	The paper focused on energy management systems
Djenouri et al. [33]			✓	✓	Review data analytics used in smart building applications. Considering various types of ML tools and applications	The paper's main focus was on ML approaches used in smart building applications
Alam et al. [4]	✓		✓	✓	Review Smart Home (SH) projects, security, comfort, and healthcare. It describes used sensors, protocols, algorithms, and systems used widely in SH	The paper focused on the SH environment. It classified sensors, communication protocols, and technologies used inside SH
Verma et al. [156]	✓				Review infrastructure, controlling, and sensing in smart buildings. The review was based on IoT sensor-actuator automation in smart buildings	The paper reviews IoT infrastructure in smart buidings, sensing and control
Qolomany et al. [123]		✓		✓	Review big data and ML analytics in smart buildings.	The paper focused on big data and ML use in smart buildings
De Paola et al. [32]	✓	✓			Review intelligent systems for energy management. Focusing on existing architectures and methodologies	The paper focused on energy-aware intelligent management systems in smart buildings
Kumar et al. [75]	✓			✓	Review monitoring technologies in smart buildings. The review focuses on sensor-actuator-based applications	The paper reviews smart building monitoring sensing technologies
Dong et al. [34]	✓			✓	Review indoor sensing systems in smart buildings. It discussed types and applications of sensors regarding energy-saving and occupant comfort	The paper focused on sensing systems in smart buildings. It focused more on HVAC control systems
Jia et al. [62]	✓		✓		Review IoT technologies in buildings focusing on cases from academia and industry with future implementation recommendations in building construction and operation phases	The paper focused on investigating the adoption of IoT for developing smart buildings
Nguyen and Aiello [109]	✓		✓	✓	Review energy intelligent buildings based on user activities and determine activity and their impact on energy savings in three subsystems: lighting, HVAC, and plug loads	The paper focus specifies valuable activities and behaviors and their impact on energy saving

- Review how sensing systems are being used to monitor and meassure the most common smart building objectives.
- Highlight current research challenges and discussing future research directions for sensing within smart buildings.

The paper is organized as follows. Section 2 presents a review of sensing systems within buildings, and Section 3 discusses activity recognition in buildings. Section 4 presents key objectives that can be achieved using smart building capabilities. In section 5, challenges and future research directions emerging from this work are highlighted. Finally, concluding remarks are provided in Section 6.

2 SENSING WITHIN BUILDINGS

Sensing technology plays a crucial role in implementing various applications inside buildings, such as medical, agriculture and more. A variety of sensor types exist depending on their use within a smart building. Each group of sensors may represent a sensing system used to accomplish a specific task, such as recognizing human presence.

2.1 Sensors

Smart building sensing technology can collect data about the physical aspects of a building, such as temperature, humidity and ambient light. The data is then interpreted to deduce activities and exchanged through various transmission media. The data are then received and processed by more powerful processing devices, such as microcontrollers and single-board computers, to extract the required information. Sensors can measure various activities in a building and provide helpful information that can provide recommendations to reduce the cost of everyday activities, such as energy consumption, and detect abnormal events like falling of a person on the floor. The most commonly employed sensing technologies for occupancy sensing are infrared, ultrasonic and microwave sensors which give higher accuracy reading about occupancy. Combining other sensors, such as temperature and humidity, could improve the overall occupancy sensing accuracy. A study reached a detection accuracy of up to 99.79% in an office building using infrared and CO2 sensors [64]. Activity recognition can be achieved using a number of different types of sensors – the most used include wearable motion, vision, and embedded sensors.

Other sensors also help recognize activities, such as infrared and pressure sensors. A study used a tri-axial accelerometer and pressure sensor to differentiate normal action and violent attacks, and reached a 98.8% classification accuracy [126]. Another study reaches 98.3% recognition accuracy for activities such as sitting, standing and walking by using a low-resolution infrared array sensor [173]. One of the most used sensors in improving energy efficiency in smart buildings is occupancy sensors, as they can be utilized to control various electricity loads in the building, such as switching lights off when space is not occupied. Combining sensors gives higher accuracy most of the time. However, other factors, such as environmental conditions, could affect the sensors accuracy.

Sensing in buildings aims to maximize the use and efficiency of the building based on monitoring and understanding of the activities in the building. The sensor types and numbers used within buildings depend on the needs of a specific application. However, other factors, such as cost, processing time, and accuracy, should also influence the selection of suitable sensors. Aziz et al. Aziz et al. [9] proposed using a single sensor to recognize person activity, reducing costs and facilitating data processing. In contrast, Liang et al. Liang et al. [86] suggested using more sensors to achieve higher accuracy and collect more data. A multipurpose sensor is recommended by Wagner et al. Wagner et al. [159], which may be more convenient and easier to install.

The classification of existing sensors can be confusing, as this depends on several factors, such as sensor specification, sensor output signal type, and field of application. Elhoushi et al. [37] and Dong et al. [34] classified sensors in a more coordinated way, and this work thus combines their classification methods, as illustrated in Figure 1, some of the most commonly used sensors in smart buildings are therefore defined as follows:

- **Temperature Sensors**. These are among the most widely used sensors, and their primary function is to measure temperature changes. As the ambient temperature changes in temperature, some of the sensor's physical properties, such as resistance or voltage change. Further, there are many different temperature sensors, such as the LM35 sensor, thermal resistance sensors, and thermocouple switches. These sensors have been used in various studies for occupancy sensing [108], occupancy prediction [161], and occupancy behavior [63].

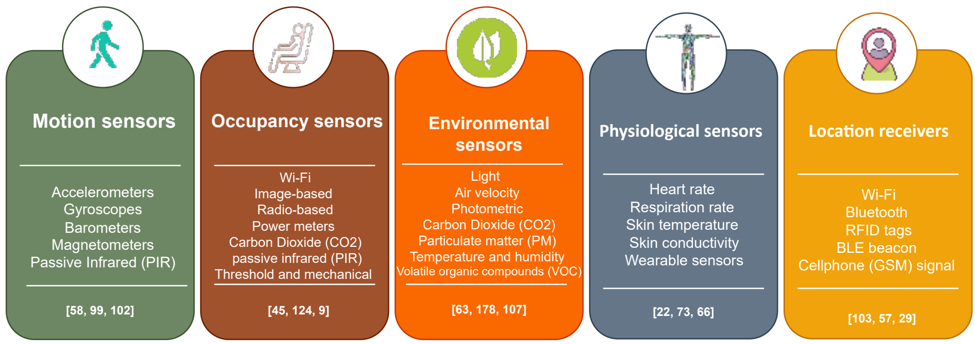

Fig. 1. Different types of sensors commonly used within smart buildings.

- **Humidity Sensors**. These devices accurately sense and assess the amount of water vapor in the atmosphere. Accordingly, they can measure the relative humidity and the degree of condensation in a room to achieve occupancy sensing and identify occupants' behaviors in smart buildings [63, 108].
- **Carbon Dioxide (CO2) Sensors**. These are used to measure the proportion of carbon dioxide in the air, thus assessing the emission levels of CO2 inside the building. These are widely used in occupancy sensing, and counting applications in smart buildings [64, 127].
- **Proximity Sensors**. These do not require physical contact to detect the presence of surrounding items, based on remotely assessing physical quantities related to distance and place. They can be divided into optical, inductive, and capacitive. They have been used in applications within smart buildings, such as indoor localization [93] and occupancy estimation [127].
- **Pressure Sensors**. Pressure is defined as the force perpendicular to a unit area, and pressure sensors thus monitor this force. A pressure sensor responds to pressure as a physical quantity. These are used in various areas, such as in military operations, water-lifting engines at certain pressure levels, and similar engineering applications. They are used in buildings mainly to detect human body postures [98] and activities [60, 126].
- **Infrared Sensors**. Infrared sensors are based on the principle of light detection and are usually used to estimate distances, as in most modern smartphones. There are two types of infrared sensors: transmissive and reflective sensors.
- **Motion Sensors**. These sensors are employed to monitor the motion of a person into or across a specific area. These sensors are often used in security alarm systems or lighting systems that automatically turn on when someone moves within a specified area. Although cameras may also be used in buildings to detect human presence, motion sensors have advantages of privacy and cost over cameras. They are thus often used in buildings to detect human activities [66, 80, 126].
- **Millimeter-wave radio sensors**. It uses radio waves in the millimeter wave range to detect and measure objects. It is used in various building applications, such as for security, occupant identification and detection [49], and indoor localization [71]. Table 2 shows some commonly used sensors within smart buildings and their uses.

2.2 Sensors Deployed Locations

Choosing the correct location is not always easy for sensors deployed in various locations inside buildings, as the sensor location must take into account a range of different factors, including sensor coverage area, distance from the measured object, and the relevant external conditions.

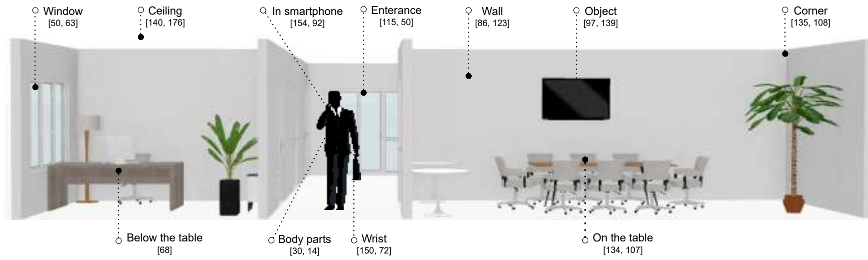

Fig. 2. Common sensor deployment locations within smart buildings.

The type of task to be completed must be considered when deciding on sensor deployment locations. For example, when monitoring the heartbeat every few minutes, sensors must be deployed on the wrist or other pulse point or body parts close to the heart. Figure 2 shows some common sensor deployment locations within smart buildings.

Laidi and Djenouri [76] proposed a means of dividing buildings into zones based on their occupancy and occupants' behaviors using PIR motion sensors. The building zones are divided into high and low-occupation zones, and a graph model is produced using a clustering algorithm. This solution was compared with two other studies, showing better accuracy and scalability. It could also be applied to different sensors, such as ultrasound. Sembroiz et al. [134] conducted a study on optimizing energy consumption in buildings that proposed a novel model to allocate optimal location to sensors and gateways. This was predicted to work with various sensor types, reducing the number of sensors and gateways required and optimizing energy consumption while maintaining sensing coverage and protection.

Studies conducted by Laidi and Djenouri [76] and Sembroiz et al. [134] proposed different solutions to effectively deploy sensors in smart buildings. Deploying sensors optimally helps optimize energy consumption [134] and sensing coverage [76] while minimizing the risk of privacy breaches and economic costs. However, other factors should also be considered, such as scalability and applicability. Further, occupation or use of different areas by people in smart buildings are not always evenly distributed; some areas are fully equipped and heavily utilized, thus requiring more sensors to cover more activities. At the same time, some other areas are underutilized. These areas should be identified to minimize the total cost and optimize building energy consumption because each assigned sensor directly or indirectly costs money, time, and resources, during the installation and maintenance phases.

Cost is an essential factor to consider when selecting and deploying sensors. There is a variety of sensing technology that can be used; some of them are more expensive. Sensing technology high in cost typically has a more range of features and capabilities, such as cameras, radar, and multi-spectral imaging sensors, when compared to fewer cost sensing technologies, such as motion and light sensors. Dong et al. [34] summarizes most of the used commercial occupancy sensing technologies used in smart buildings and finds that infrared cameras and RFID technologies are one of the most costly technologies, while reed switch, motion, and infrared technologies are the least expensive.

Privacy concerns are another important factor, as they often revolve around using sensors and other technologies that collect information about an individual's activities. Developing robust technologies is essential to ensure user privacy is maintained. Sensors should be regularly monitored for any suspicious activity. They should use various privacy-enhancing technologies to protect user data, such as data minimization methods that can reduce the amount of personal data.

Table 2. Commonly used sensors within smart buildings

Sensor type	Sensor location	Number of sensors	Building type*	Objective	Reference
CO_2	Two feets above the floor	4	Indoor environment - classroom	Occupancy estimation IoT model for Indoor environments	[127]
	On return ducting, supply ducting, and middle of the room	5	Office environment - room	Occupancy estimation at low-scale level in office environment	[125]
	On ceiling	Different numbers	Office environment - floor	Occupancy count estimation in office environment	[52]
	On table	2	Office environment - room	Occupancy detection in office environment	[64]
	Inside and outside the room	2	Smart home environment - room	Occupancy detection in smart home environment	[179]
	On wall around 1.5m height	6	Office environment - room	Occupancy modeling for cross spaces in office environment	[170]
Infrared	Placed on ceiling and wall	2	Indoor environment - meeting room	Activity detection include: walking, standing, sitting, lying, falling, and action change	[106]
	Placed on a flat acrylic plate	5	Smart home environment - room	Activity recognition for five different activities in 4 house rooms	[103]
	On ceiling	Hundreds	Indoor environment - building	Anomaly detection to improve building energy efficiency	[132]
	Facing the door	2	Indoor environment - room	Occupancy estimation to find number of people in the room	[44]
	On ceiling	3	Indoor environment - room	Anomalous occupancy behavior detection	[158]
	In off-the-shelf earpiece	3	Indoor environment - laboratory	Detecting eating activities include: talking, silent, eating, and walking	[11]
Radar	On ceiling	4	Office environment - room	Office occupancy activities include: walking at different speeds, and desk work	[115]
	Placed at ceiling level	1	Educational environment - classroom	Occupancy count estimation in an indoor environment	[172]
	Placed opposite of the corners	2	Indoor environment - kitchen	Kitchen activity detection with 15 activities include: walking, eating, drinking, sitting, etc.	[95]
	Mounted on a tripod stand	1	Indoor environment - room	Human activity recognition include: walking, jumping, jumping jacks, squats, and boxing	[140]
	On hand wrist	4	Indoor environment - laboratory	Recognition 10 daily human activities includes: walk, walk while carrying an object, sitting, standing, pick up an object, tie shoelaces, drinking water, answer a phone call, fall, and crouch and stand back up	[80]
	-	3	Office environment - room	Human activities classification include: walking, walking and carrying an object, sitting, standing, bending and coming back, etc.	[81]
	On table	2	Office environment - room	Detect and locate the presence of multiple people	[49]
	-	12 Wi-Fi Access Point (AP)	Office environment - room	Office occupancy detection	[120]
Wi-Fi	-	2 APs	Office environment - room	Occupancy estimation in an office environment	[8]
	-	7 and 9 APs in two floors	Office environment - floor	Occupants count estimation in an office environment	[163]
	-	4 APs	Office environment - personal and shared space	Occupancy sensing-based HVAC actuation in an office environment	[10]
	-	32 AP	Office environment - floor	Occupancy detection in an office environment	[47]
	On the arm, leg, and neck	3	Indoor environment - Multivariate time-series dataset	Recognition of different activities from three datasets including downstairs, jogging, going upstairs, sitting, walking, and standing.	[58]

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Table 2 – *Continued from previous page*

Sensor type	Sensor location	Number of sensors	Building type	Objective	Reference
Accelerometers and gyroscopes	On hand wrist	4	Indoor environment - laboratory	Recognition 10 daily human activities includes: walk, walk while carrying an object, sitting, standing, pick up an object, tie shoelaces, drinking water, answer a phone call, fall, crouch and stand back up	[80]
	On hand wrist	2	Office environment - room	Recognizing six different activities in the office includes: sitting, standing, lying, walking, walking upstairs, and walking downstairs	[100]
	Attached to six body positions	3	Indoor environment - building	Recognizing set of twenty normal daily activities includes: kitchen work activities, household cleaning activities, office-work activities, etc.	[38]
	On door, fridge door, drawer, towel dispenser, and window	5	Indoor environment - building	Occupant Identification in smart home perform predefined activities: knock, opening/closing door, fridge, etc.	[50]
	In smartphone	2	Indoor environment - room	Human activity recognition system test 12 activities from dataset: standing, sitting, lying down, walking, etc.	[51]
Bluetooth Low Energy (BLE)	On ceiling	7	Indoor environment - room	Abnormal activities detection include: falling, sitting down, standing up from a chair, walking, and jogging.	[97]
	Three meters above the center of the detection area	1	Indoor environment - room	Human activity recognition of five states: lying, standing, sitting, walking, and empty	[173]
	On ceiling	-	Indoor environment - room	Group activity detection include: taking class, seminar, and discussion	[22]
	On ceiling	12	Office environment - shared, personal, and social space	Multi-Occupancy detection in an office environment	[120]
	Placed on the room corners and center	8	Office environment - room	Indoor positioning inside an office building	[124]
Pressure	On jacket	11	Controlled environment - laboratory	Human activity detection between normal motion and violent attack	[126]
	Attached on supporters at a height of 1.1m	2	Indoor environment - laboratory	Occupancy estimation in an indoor environment	[26]
	At the door way and in front of the room	2	Educational environment - classroom	Occupancy prediction in an indoor environment using IoT technology	[116]
	Cushion equipped with pressure sensors	12	Indoor environment - laboratory	Posture detection include: proper sitting, lean left, lean right, lean forward, and lean backward	[98]
Temperature	On ceiling	5	Indoor environment - building	Occupancy prediction to improving building energy efficiency	[161]
	Near the occupant	5	Office environment - building	Exploring occupant behaviors to improve office building energy. Include: window, door, and blinds status	[63]
	On table	4	Indoor environment - building	Occupancy sensing for smart buildings	[108]
	On wristband	-	Indoor and outdoor environment	Detection of migraine attacks	[74]

* Papers that do not mention the building type environment are classified as either indoor or outdoor environment based on the context of the paper.

In this review, the deployment locations are classified based on sensor location, sensor type, and measured activity type. Two different studies Muthukumar et al. [106] and Liang et al. [87] were found to use the same sensor type, an Infrared array sensor, to detect similar activities such as falling and movement. The sensors in each case were deployed in different locations. Another pair of studies, Papatsimpa and Linnartz [115] and Pratama et al. [120] detected similar activities and gathered data about office occupancy using sensors deployed in a similar location on the ceiling, yet used sensor types that were different, with Radar and BLE beacons used, respectively.

Another two studies, Luo et al. [97] and Samani et al. [132], used the same sensor type, a PIR motion detector, was deployed in a similar location on the ceiling to detect different activity types; one focused on the detection of abnormal activity, such as sudden falls, while the other concentrated on building anomaly detection to improve energy efficiency. This illustrates that each case has different requirements for determining the appropriate location to deploy sensors. Table 3 demonstrates some common sensor deployment locations within smart buildings.

Table 3. Common sensors deployment locations

Sensor location	Sensor type	Details	Reference
On ceiling	Radar	Detecting office occupancy by identifiying walking at different speeds and desk work	[115]
	Heat	Occupancy prediction in meeting room for smart offices	[141]
	Temperature, humidity, CO2	Occupancy prediction to improve building energy efficiency	[161]
	PIR motion	Abnormal activities detection include: falling, sitting down, standing up from a chair, walking, and jogging.	[97]
	Infrared Array	Object detection and tracking in commercial buildings	[48]
	PIR motion	Anomaly detection to improve building energy efficiency	[132]
	BLE beacons	Office occupancy detection	[120]
	BLE beacons	Group activity detection include: taking class, seminar, and discussion	[22]
	Camera, doppler motion, radio frequency RF	Occupancy sensing and activity recognition include: walking in a room, sitting in a chair, lying on a bed, and body turning on a bed	[177]
	RFID	Teamwork activity recognition includ: oxygen preparation, blood pressure, cardiac lead placement, temperature measurement, ear exam, and other activities	[84]
On wall or corner	Infrared array	Activity recognition include: quiescence, fall, and movement	[87]
	Camera	Occupancy sensing and activity recognition include: walking in a room, sitting in a chair, lying on a bed, and body turning on a bed	[177]
	Infrasound	Door opening and closing detection	[70]
	BLE beacons	Indoor positioning inside an office building	[124]
On/below table	Radar	Activities recognition include: walking, sitting and standing, bending to pick up a pen, drinking water, and frontal fall	[82]
	Temperature, humidity, light, CO2	Occupancy sensing in smart buildings	[108]
	PIR motion	Occupancy estimation for individual presence	[135]
	Millimeter-wave radio	Detect and locate the presence of multiple people	[49]
On the floor/ underfloor	Pressure mat	Smart floor monitoring system	[136]
	BLE beacons	Provides navigation aids for blind and visually impaired people	[27]
	Radon detector	Indoor radon gas concentration monitoring	[14]
	RFID	Navigation in indoor environment	[90]
On smartphone	Accelerometer, gyroscope, magnetometer	Activitiy detection include: walking, running, and standing	[155]
	Triaxial accelerometers and gyroscopes	Activity recognition include: standing, sitting, lying down, walking, walking-upstairs/downstairs, stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand to-lie, and lie-to-stand	[51]
	Magnetic	Indoor localization	[93]
On wrist	Accelerometer, gyroscope	Human activity sitting detection include: sitting, standing, lying, walking, walking upstairs, and walking downstairs	[100]
	Wrist-mounted inertial sensors	Eating detection and food intake gesture classification	[151]
	Empatica E4 device with sensors: accelerometer, photoplethysmography, temperature, electrodermal activity	Detection of migraine attacks using Empatica E4 wearable wristband	[74]
	3-axis accelerometer	Activity recognition include: draw, wash dishes, write, and brush	[73]
On body parts	Wearable device (accelerometer, gyroscope, magnetometer, and electrocardiogram)	Presence or the absence of the fall, static or dynamic movements including fall, recognizes the fall, and six other activities	[66]
	Accelerometer, proximity, 3D printed sensor	Detecting eating episodes	[29]

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Table 3 – *Continued from previous page*

Sensor location	Sensor type	Details	Reference
On body parts	Acceleration, gyroscope, magnetometer	Recognition of individual daily activities include: kitchen work activities, household cleaning activities, office-work activities, laundry activities, and watching TV activity	[38]
	Surface electromyography	Recognizing ADLs activities include: stand-to-squat, squat-to-stand, stand-to-sit, sit-to-stand, stair-ascending, stair-descending, and walking	[167]
	Acoustic, electromyography, microphone	Eating detection include: eating, talkings, silence, coughing, laughing, sniffling, deep breathing, and drinking	[13]
	Proximity, motion, sound	Detecting proximity, movement, and verbal interaction between people	[152]
	Infrared proximity	Detecting eating activities include: talking, silent, eating, and walking	[11]
On object	PIR motion	Activity recognition for five different activities in four house rooms	[103]
	Ballistocardiography (BCG)	Classification of sleep stages	[45]
	Radar	Human activity recognition include: walking, jumping, jumping jacks, squats, and boxing	[140]
	Smart plug	Recognizing ADLs activities include: dishwasher, hair dryer, iron, oven, and washing machine	[43]
	3-axis accelerometer, dual-axis gyroscope	Occupant identification include: knock, opening/closing door, fridge, cabinet drawer, window, pulling a towel from the towel dispenser	[50]
	Pressure	Posture detection include: proper sitting, lean left, lean right, lean forward, and lean backward	[98]
	Photosensor	Activity sensing for location differentiation, detecting open doors	[55]

2.3 Detecting Various Phenomena within Buildings

Sensors are being used to help facilitate the automation of various tasks, such as monitoring the energy use of a building, allowing for energy conservation. Studies conducted by Fiebig et al. [41] and Pratama et al. [120] used power meters, BLE beacons, and air quality sensors to detect occupancy in buildings. Occupancy is also predicted by [141] using very low-resolution heat sensor data to predict occupancy in smart office spaces. They have proposed two workflows one is based on computer vision, and the other on machine learning. Sensors are also used in health applications in smart buildings. It improves building occupants' safety and living conditions using various sensors such as temperature, humidity, and noise. For example, sensors can detect irregularities in the building, such as high levels of CO2 and dust particles. Also, detecting abnormal behavior, such as fall detection [66].

Managing smart buildings using sensors, IoT, and other technologies allows for recognizing potential risks and improving the overall building management experience. A study by Sembroiz et al. [134] optimized energy consumption within the building. They proposed a model that assigns the optimal location for sensors and gateways in the building while maintaining sensor coverage and protection within the building. Another study by Das et al. [31] in an educational building uses a 3D camera to recognize activities and space utilization. The testbed was a cafeteria hall, a shared space inside a university building, and the derived patterns were used to assist building managers in making informed judgments about space allocations that were properly matched with actual building use. Luo et al. [95] proposed a radar sensor network to recognize 15 human activities in the kitchen; they have collected the radar signals and they were able to reach 89% recognizing accuracy most of the time. Table 4 demonstrates different phenomena detected within buildings using sensors across various research studies.

2.4 IoT with AI in Smart Buildings

IoT and Artificial Intelligence (AI) are disruptive technologies that have revolutionized data use. IoT devices can include sensors, home appliances, and medical devices. Table 7 presents IoT and AI-based data analytics used for various smart building activities.

IoT Intelligence offers various functions for data processing and decision-making, using edge, fog, and cloud layers. Edge computing involves deploying computing resources closer to the source of data collection, allowing for faster data processing. This is particularly useful for instances such as autonomous vehicles, where latency can be critical. Fog computing is involves use of resources between the IoT devices and the cloud data center, often hosted on network components (such as routers and switches). The cloud layer can store and analyze large amounts of data, providing an additional layer of security and scalability for IoT devices. This is done through a network of connected IoT devices that can communicate with each other and remotely access powerful computing resources [112].

AI can be used to interpret data in near-real time, allowing for more intelligent decision-making. Combining IoT with AI-based data analysis is further enhanced; autonomous vehicles, for example, can make decisions quickly and accurately based on information gathered from their sensors and the environment around them, allowing them to move safely through their surroundings. However, such integration also introduces additional challenges, e.g. smart building systems must be able to integrate with existing infrastructure, which can be a challenge due to the complexity of existing systems, which requires extensive testing and debugging to ensure that the system is functioning correctly. Scalability is another key factor, as AI algorithms must be able to process large amounts of data quickly and efficiently. Security is also a key requirement, so data must always be encrypted and securely shared and processed [33, 112].

Reducing computational costs is also essential, as data processing in smart buildings can vary greatly depending on system complexity. Computational costs and energy usage will increase significantly with more complex analytics, such as real-time energy optimization and predictive analytics. Therefore, more research is needed to optimize the computational cost, e.g. Ostadijafari et al. [113] proposed an optimization approach that can successfully optimize electricity costs in commercial buildings by using occupancy information. More details about challenges are in technical challenges section 5.1.

Table 4. Different phenomena to detect within buildings using sensors

To understand	Sensors used	Datasets used	Existing work
Occupancy (sensing, counting, estimation)	Heat, air quality sensors, temperature, humidity, light, CO2, Wi-Fi probe-sensing, camera, PIR, millimeter-wave radio, power meters, BLE beacons sensors	LBNL Building 59 [96], ROBOD [149], LANGEVIN [77]	[141],[161], [44],[120], [158],[135],[108],[41], [125],[170], [49]
Activity (sensing, recognition, detection)	Temperature, humidity, illumination, CO2, air quality, Wi-Fi probe-sensing, camera, radar, infrared array, fiber bragg grating, PIR, power meters, BLE beacons, geophone, electric field, 3-axis accelerometer sensor	HASC-PAC2016 [56], OPPORTUNITY [130], UT Smoking [138]	[115],[161],[48], [132], [120],[82],[158], [63], [135],[81],[108], [41]
Group activity (recognition, detection)	BLE beacons, web-cam, sound, WiFi-based indoor location, microphone, acceleration, smartphone sensors	PPS grouping [165], UT Smoking [138], ActivityNet [16]	[60],[22], [164]
Activities on a room-level within building	Infrared array, camera, 3D camera, doppler motion, millimeter-wave radio, infrasound, Radio Frequency Identification (RFID), CO2 sensor	OPPORTUNITY [130], PPS grouping [165], PAMAP2 [128]	[106],[105],[177], [49], [70], [7],[84]
Building energy consumption	PIR, temperature, humidity, illumination, CO2, accelerometer, gyroscope, magnetic, GPS, proximity, pressure sensor	KAG-energydata [17], LBNL Building 59 [96], CU-BEMS [118]	[132],[63],[166],[73]
Building indoor environmental quality	Temperature, humidity, illumination, sound, carbon monoxide (CO), CO2, formaldehyde, particulate matter 2.5 (PM2.5), particulate matter 10 (PM10), total volatile organic compounds (TVOC), pressure sensor	LANGEVIN [77], CU-BEMS [118], ROBOD [149]	[25],[122],[168]

2.5 Smart Building Use Cases

Smart buildings make use of IoT and AI to better manage their facilities, e.g. to monitor, control, and optimize the operations of a building. Berkeley Connected Campus is an example of a use case using technologies in smart buildings. It is an initiative by the University of California to connect different parts of the University using smart and IoT technologies to develop a connected campus environment These technologies are intended to improve student engagement and learning, improve pedestrian safety, and keep up with new advancements in transportation [1].

The *edge building* is an exemple of a sustainable office building in Amsterdam, focusing on being more efficient, comfortable and environmentally responsible for the occupants. The building, designed with a distributed system, uses sensors to monitor the environment and adjust settings accordingly. This system can modify parameters such as room temperature and air quality, consuming less energy while maintaining a comfortable environment. Occupants in the building can use a Mobile App to control their environment and access services [59].

A study was conducted to explore the role of sensor toolkits in current auditing by facilities managers (FMs) who often have limited access to the infrastructure and insufficient existing data sources. The toolkit can be repurposed and retrofitted. An online tool was developed to generate reports from sensor data. The study's findings demonstrate that the fine-grained data enabled FMs to understand building efficiency and generate actionable suggestions for improvement [42].

Sint-Maarten Hospital in Belgium enables automated building management, improved energy efficiency, and better security. The adopted approach has been used to adjust the temperature and lighting levels in response to the number of people in a given space. It allows for better security by detecting motion and informing security staff. The hospital also uses sensors to detect when lights are on in unused rooms to reduce consumed energy and carbon footprint. This allows patients to control various functions of their rooms and improve communication with staff [2].

3 ACTIVITIES WITHIN BUILDINGS

This section seeks to clarify the range of activities within buildings to allow a more effective analysis of activity recognition approaches. Figure 3 shows the hierarchy of activities within a building.

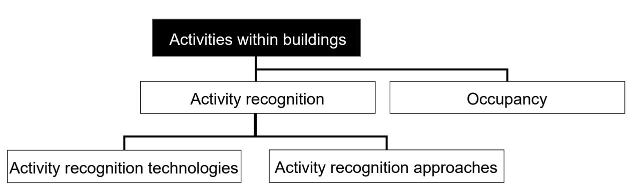

Fig. 3. Hierarchy of activities within buildings.

3.1 Occupancy

Building occupancy information is essential for several aspects of building management, including assessing energy consumption and indoor environmental quality. According to Iea [57], buildings and construction sector account for about a third of all global energy consumption and nearly 15% of CO_2 emissions; these numbers are anticipated to increase further in the next few years. This section examines the concept of occupancy sensing. Figure 4 shows the hierarchy of occupancy.

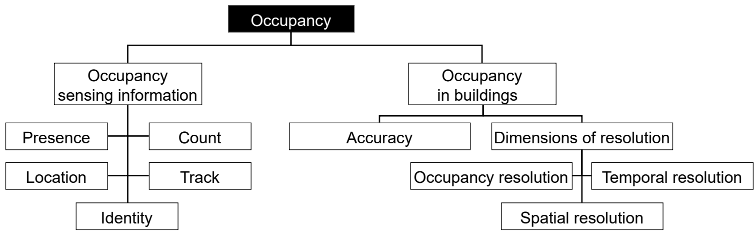

Fig. 4. Hierarchy of occupancy section.

3.1.1 Occupancy sensing information. This can be classified based on five key properties: presence, count, location, track, and identity [148].

- **Presence.** This provides information about occupants present or absent within a given area. Occupant presence detection is used widely across various applications, including lighting control and alarm systems.
- **Count.** This provides information about the number of people in a particular area. It is also used to count the number of individuals going into or out of the given area. It is thus used in applications requiring more details about occupancy status, such as adjusting energy consumption based on occupancy numbers, e.g. in shopping malls.
- **Location.** This provides information about the current location of occupants inside a given area. The location of occupants can be used across many different applications, including healthcare and energy management applications.
- **Track.** This provides information about occupant movements between different areas. It can be used in applications such as improving emergency evacuation processes and tracking and identifying intruders in monitored areas.
- **Identity.** This provides information about occupant identity to help distinguish between different occupants, using trained algorithms to identify specific features about occupants such as facial features or smartphone MAC address. The identity of occupants can be used in security applications such as occupant access control and surveillance. However, increasingly this introduces additional challenges associated with privacy of individuals.

3.1.2 Occupancy in buildings. This comprises two aspects: accuracy and dimensions of resolution. Accuracy relates to the distance between the measured value (data collected from sensors) and the ground truth data [101]. The greater the distance between the measured value and ground truth data, the lower the occupancy detection accuracy, and vice versa. The occupancy dimension focuses on three main features, which lead to different levels of resolution:

- **Occupancy resolution.** This indicates different occupancy levels, such as occupant presence or absence, calculating the number of occupants, identifying those occupants, and identifying occupant activities within the building.
- **Temporal resolution.** This represents the different frequencies over time (seconds, minutes, hours or days) of events taking place.
- **Spatial resolution.** This represents the building structure, including rooms, floors, ceilings and the building as a whole.

Table 5 shows occupancy information types with different spatial resolutions and the relevant sensors used within buildings.

Occupancy information can also be used in different applications inside the building. Lau et al. [79] conducted a study to analyze spatial and temporal urban space utilization using a specially designed Renewable Wireless Sensor Network (RWSN), highlighting a few interesting observations,

Table 5. Occupancy information types within smart buildings.

Occupancy resolution	Spatial resolution	Used sensors	References
Presence	Building	CO2, PIR, temperature, humidity, illuminance, VOC, pressure mat, light dependent resistor, sound	[35],[157],[85]
	Floor	CO2, PIR, double-beam, acoustic, pressure mat, Wi-Fi	[47],[178]
	Room	CO2, PIR, door switch sensor, temperature, humidity, pressure, double-beam, doppler sensor, camera, acoustic, pressure mat, light, sound, microphone, Wi-Fi	[177],[64],[179],[85],[178],[137],[170],[67],[10],[116]
	Zone	CO2, PIR, distance sensor, chair sensor, microphone, light, humidity, emperature, infrared camera, Wi-Fi	[8],[102],[67],[10],[137]
Count	Building	CO2, PIR, temperature, humidity, pressure	[19], [61]
	Floor	CO2, PIR, electricity load meters, double-beam, acoustic, pressure mat, lighting, gas detection sensor, Wi-Fi	[163],[52], [178]
	Room	CO2, PIR, heat sensor, camera, temperature, humidity, pressure, ultrasonic, infrared proximity, BLE beacons, power meter, doppler radar, thermal tripwire, chair sensor, light, sound, door switch sensor, RFID, Wi-Fi	[68],[127],[28],[120],[172],[26],[178],[153],[170],[67],[171]
	Zone	CO2, PIR, velocity, temperature, humidity, light, radio, sound, RFID, microphone, long-wave infrared thermal camera, 3D stereo vision camera, Wi-Fi	[125],[31],[28],[8],[102],[36],[67],[171]
Identity	Building	Wearable wrist sensor, passive RF sensors, load sensor	[89],[72]
	Floor	Wi-Fi	[47],[99]
	Room	BLE beacons, Wi-Fi	[10],[99]
	Zone	3D camera, Wi-Fi	[31],[10]

on hot days, morning and evening periods showed the highest space utilization, while on cloudy days, the afternoon and early evening had higher space utilization. Clear days also showed higher space utilization at night; overall, mornings demonstrated higher space usage rates than evenings. In addition, the weather was shown to have a considerable impact on how people utilise outdoor space. Moretti et al. [104] conducted a study to enhance maintenance operation tasks inside a building. Data of occupants were collected using ultrasonic sensors, which were then processed and connected to the building maintenance strategy. The system issued a maintenance notice to the contractor when a specified threshold was reached, telling the contractor to begin cleaning. Other studies, including Balaji et al. [10], Martani et al. [99], and Thanayankizil et al. [150], have focused on energy saving applications in various building environments.

3.2 Activity Recognition

Activity recognition plays a significant role in smart buildings and represents a means for acquiring and collecting data about activities inside a building. This data helps control various applications and enhances the comfort levels inside the building, by controlling aspects such as energy consumption, temperature control, and safety. Further, single user activity refers to any activity undertaken by an individual user, such as working on a computer in an office. Prastika et al. [119] and Cui et al. [30] focused on single-user activity recognition. Multi-user activities are activities of more than one user in the same location, such as where employees work on different tasks in the same office. Tan et al. [145] and Alhamoud et al. [5] sought to recognize multi-user activities.

Group activities refer to the same task or related sets of tasks by more than one user at once, such as an employees meeting in a conference room. Tang et al.Tang et al. [147] and Tang et al. [146] performed activity recognition research specifically on group activity. Li et al. Li et al. [83] classifyhybrid activity as a combination of individual and group activities happening at the same location, such as two employees working on the same task while a third one is working on a different task in the same office. Other research studies [54, 107] have attempted hybrid activity recognition. Figure 5 illustrates various user activities classifications in a smart building.

Fig. 5. Various forms of human activity recognition inside a building, including single, multi- user, group, and hybrid activity recognition.

3.2.1 Activity Recognition Technologies. Approaches and technologies to identify activities in a building can also be classified, e.g. Chen et al. [24] classified activity recognition into two main approaches based on the sensor type used: vision-based activity recognition and sensor-based activity recognition. Each approach has various technologies supporting it and the purposes for which it is best used. This paper mainly focuses on sensor-based approaches to identifying human activities. Figure 6 shows a taxonomy of activity recognition technologies.

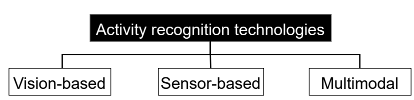

Fig. 6. Taxonomy of activity recognition technologies.

- **Vision-Based Activity Recognition.** Vision-based technology generally depends on visual devices other than sensors to identify activities, such as cameras. Most of its applications are thus related to computer vision-based approaches across areas such as virtual reality, video surveillance, human-computer interaction (HCI), home monitoring and security [133]. However, it faces some obstacles regarding human activity recognition, including privacy and security issues. Further, many cameras rely on specific lighting to identify and recognize human activities [53]. This research thus focuses on the other type of human activity recognition, sensor-based approaches, due to the increased availability of this data type in most smart buildings and the reasonable price of the used sensors.
- **Sensor-Based Activity Recognition.** This type of technology depends on using various sensors to recognize human activity. Data is collected from scattered sensors and then processed simultaneously to detect and recognize human activities. The sensors used are often very reasonably priced due to the extensive development of such technology, especially when linked with other technologies such as IoT. The sensor-based approach can also be applied across multiple different domains, and it has also been used in healthcare, security, object detection, and multiple other applications [91, 160].
  Table 6 shows sensor types activities identified within smart buildings, and activity recognition in the table can be defined as the ability to recognize what type of activity it is, e.g. whether a human is walking, standing, eating, etc., while activity detection is about determining whether something is there or not. Some sensors in the table can be applied to various activities, while others are most suitable for focusing on certain activities within a building.

The sensor-based approach can be classified into three groups: wearables-based sensing, embedded sensing, and dense sensing [24]. Wearable sensors are attached to a person to recognize their activities: several studies have been conducted on wearable sensors to recognize human activities. Jalal et al. [58] and Kerdjidj et al. [66] focused on healthcare and fall detection, while Koskimäki et al. [74] focused on detecting specific medical conditions such as migraine attacks and spasticity. Chun et al. [29] and Bi et al. [13] focused on detecting eating activities using data gathered from wearable sensors positioned on the body, including neck and ear.

The second type of sensor used is object sensing, which is based on objects with sensors, such as smartphones, that users operate daily, collecting data about users to facilitate recognition of their activities. Vaughn et al. [155], Hassan et al. [51], and Yin et al. [174] all used smartphone sensors recognising and detecting human activities such as walking, standing, running and similar movements. Other activities detected by using smartphone sensors include driving activities and group activities [22]. Further, sport-related activities, hand activities [78], stress [139], and sitting [100] are more commonly assessed using smartwatch sensors.

The third type is dense sensing, which differs from the other two types because it is not controlled or carried by a user. Instead, it relies on sensors placed around the user's location to recognize and detect user activities in that location. Various studies using this type of sensor includes studies on user activity detection [87, 173], occupancy sensing and prediction [115, 161], indoor positioning and localization [93, 124], recognizing collaborative [164] and group [60] activities, abnormal activities detection [60], and detecting location-based activities, such as activities happening in the kitchen [95] and sleep stages[45].

Wearable sensors and object/ embedded sensing methods have the drawback that they may not always be functional. For example, wearable sensors require users to wear them; some users may find them uncomfortable. Object sensing similarly requires the user to use specific objects to recognize activities. The dense sensing technique eliminates these obstacles and allows the user to carry out daily activities naturally; however, this technique still faces obstacles with data collection processes, as ground truth data intersecting with the environment may produce noise in data [53].

Another area for improvement when using sensors is reliability and availability. Sensor reliability can be improved by selecting the most appropriate sensor for a given application. Sensor availability can be improved by choosing a reliable power source and a backup source. Sensors should be regularly checked and maintained while maintaining sufficient communication range.

- **Multimodal Activity Recognition.** This type of detection uses a combination of vision and sensor-based techniques for activity recognition. Such combinations can improve activity recognition reliability, accuracy and robustness. They may also reduce the required cost and effort. Wearable cameras have been the subject of research recently, as these need not be set in a fixed place like regular cameras [40]. Combining wearable cameras and sensors can thus provide more valuable information than wearable sensors alone. However, this combination may cost more and be more complex than applying either technology separately [40].

  Various studies on multimodal activity recognition have combined vision and sensor technologies to improve recognition. Muthukumar et al. Muthukumar et al. [105] detected a range of human activities, such as walking, standing, falling, sitting, lying and action changes, using a camera in conjunction with a low-resolution infrared array sensor. Detection of eating activities was performed by Thomaz et al. Thomaz et al. [151], who classified food intake gestures using cameras and wrist-mounted commodity sensors.

Table 6. Sensor type activities identified within smart buildings

Sensor	Activities identified	References
PIR	Occupancy sensing, estimation, and counting	[44],[158],[135],[153],[52]
	Abnormal activities detection	[97],[132],[23]
	Recognizing activities of daily living	[103]
CO2	Occupancy sensing, counting and prediction	[161],[63],[108],[7]
Temperature	Occupancy sensing and prediction	[161],[63],[108]
Humidity	Occupancy sensing	[63],[108]
Light	Occupancy sensing	[108],[63]
Wi-Fi	Occupancy estimation, counting and prediction	[8],[163],[161]
Infrared array	Activity recognition and detection	[87],[173],[106]
	Occupancy estimation	[127]
	Object detection and tracking	[48]
Proximity	Activity detection	[152],[11]
Proximity	Detection of movement and verbal interaction	[152]
	Recognizing eating activities	[11]
Pressure	Human activity detection	[126]
	Human posture detection	[98]
	Occupancy estimation and prediction	[26],[116]
Sound	Recognizing collaborative activities	[164]
	Occupancy sensing and prediction	[36],[116]
Heat	Occupancy prediction	[141]
Radar	Occupancy estimation	[172]
	Activity recognition and detection	[115],[95],[82],[81]
Accelerometer/3-axis	Occupant identification	[50]
	Activity recognition and detection	[58],[81],[51],[174],[73]
Gyroscope/Dual-axis	Occupant identification	[50]
	Activity recognition and detection	[58],[51],[80], [100]
Magnetometer	Activity recognition and detection	[66],[154],[80], [38]
Electrocardiogram	Activity recognition and detection	[66],[154]
Electromyography	Activity recognition and detection	[167],[13]
BLE beacon	Activity recognition and detection	[120],[22]
	Occupancy detection	[120]
	Indoor positioning	[124]
RFID	Recognizing teamwork activities	[84]
Millimeter-wave radio	Occupant identification and detection	[49]
	Indoor positioning	[71]
Electric field	Activity recognition and detection	[110]

Chen et al. Chen [23] conducted research to detect suspicious activities in volatile areas using a camera, a motion sensor, an infrared sensor and an alarm module, while activity recognition and occupancy sensing using a camera and wireless sensors were performed by Zhao et al. Zhao et al. [177] to recognize activities such as walking into a room, sitting in a chair, lying on a bed, or turning over in bed. Occupant office counts were conducted by Arendt et al. Arendt et al. [7] using 3D stereo vision cameras and CO2 sensors. Further, occupancy prediction to improve building energy efficiency conducted by Wang et al. Wang et al. [161] employed a camera and a variety of sensors.

3.2.2 Activity Recognition Approaches. Human activity recognition has relied on data and knowledge driven approaches, including a hybrid approach [142]. Figure 7 shows the taxonomy of activity recognition approaches that may be used to create effective activity models. These models help with inferences around human activities, but each approach has benefits and drawbacks for creating an activity model. Before selecting an approach, it is thus important to understand what human activity recognition entails and what makes starting a model with high accuracy particularly challenging.

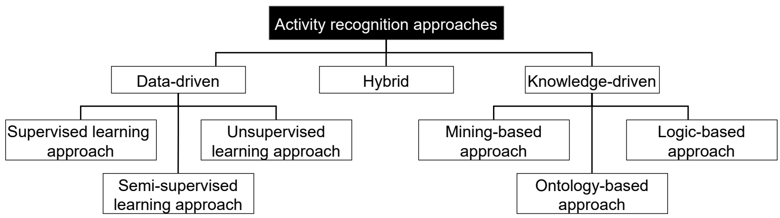

Fig. 7. Taxonomy of activity recognition approaches.

The activity recognition process involves creating models that can precisely and effectively recognize human activities. To achieve this, it is essential that the same actions are performed in the same order each time the activity is undertaken. For example, making a cup of coffee may require the user to put on a kettle, find a cup, add water and ground coffee to a cafeteria, and then brew the coffee before pouring it – comprising a set of sequential steps that make up the activity of making coffee. However, other aspects can affect the model recognition process, such as the order of actions or the amount of time it takes to perform each action. This may result in the necessity for multiple models to account for these changes effectively. Thus, it is important for the optimal model to work in a dynamic environment and recognize different human activities as they occur [142]. To do this, the model must be able to process various inputs and precisely provide accurate outputs.

Recognizing human activities begins with activity modeling, a process used in software and systems development to model the activities that take place during the design and engineering of a system. Activity modeling analyzes user needs, uncovers problems, and identifies potential solutions. It uses data from various sources like sensors and cameras to identify user activities and patterns [24]. The data is then used to recognize and predict future activity patterns, which can be done using a data drive, ML-based approach, or rule-based control technique. Further, challenges with activity recognition approaches such as scalability and re-usability will be mentioned in each approach separately below.

- **Data-Driven Activity Recognition Approach.** This approach follows the process of creating an activity model from a collected dataset of users, applying different ML and data mining techniques as required. Although these may adopt different processes such as training and learning, this classification process of human activities is based on using statistical and probabilistic methods to infer user activities [24].
  This approach can thus produce models that can handle time-variant and stochastic information, being the opposite of knowledge-driven approaches, which are inappropriate for such work. However, a data-driven approach has some drawbacks: it requires collection of data for training and learning processes, and it is thus subject to issues of data scarcity: when the data is limited, or there is not enough labeled data, training may fail. There is also a re-usability problem, as the model produced for one user may be difficult to reuse with another [24].
  Activity recognition approaches produce activity models using a data-driven approach, applying ML techniques. These ML techniques can be classified as supervised, unsupervised, and semi-supervised. The supervised learning approach is used chiefly for activity recognition. The supervised technique trains the model by using labelled data; the model should then be able to classify incoming unlabeled data by activity type using a generative, discriminative, or hybrid approach.

The generative approach uses probabilistic models, such as Naive Bayes and Gaussian Discriminant Analysis (GDA) algorithms, to categorize data after determining how those data were generated, while the discriminative approach categorizes given input data and then uses models such as Linear regression and Support Vector Machine (SVM) algorithms. Further, Deep neural networks (DNNs) are a powerful type of AI algorithm that can analyze complex data sets and recognize patterns. They are made up of multiple layers of neurons, with each layer responsible for a different processing task. DNNs have proven highly effective in face and object recognition.
Transfer learning is another ML technique where the model uses the knowledge it acquired from previous tasks to train for new tasks without spending much time and resources. It is used with applications such as natural language processing (NLP) and image recognition [129]. In addition, multimodal learning is an ML technique that uses multiple input modalities to process data. This is important due to the increase in unstructured data, such as images and videos, which are difficult to process with traditional models. It combines multiple data sources to produce a more detailed representation compared to what can be achieved with a single modality. For example, face recognition algorithms can use images and audio to better identify faces.
The one-shot learning technique allows the system to learn from a single example or experience. It can be helpful for tasks that involve recognizing or classifying new objects that the AI system has not seen before. Few-shot learning is similar to one-shot technique, where the models are trained using a few examples. It helps provide models that can quickly learn new tasks when large datasets are unavailable. It works by training models on meta-learning algorithms designed to learn from a few examples and apply them to new tasks. For example, a model can use an instance of a dog to learn how dogs are classified in other images [162]. Table 7 demonstrates the main analytics methods used to identify activities in smart building.

- **Knowledge-Driven Activity Recognition Approach.** This approach uses prior knowledge to make activity models based on various knowledge and management techniques. This process involves knowledge acquisition, representation, implementation, verification and validation. The approach is considered more robust to noise than data-driven approach semantically, logically straightforward, and easy to interpret. However, it is ineffective when handling time-varying or uncertain information, generating only static models [24]. The structure of knowledge in such models can be represented in different ways, such as networks, rules, or schemas. Overall, the approach may be classified into three main based types: mining, ontology, and logic-based.
  Mining activity knowledge from public data sources to create an activity model is a valuable approach that many organizations can benefit from. By leveraging public data sources, companies can gain insight into the context of their customer activities, the types of activities people engage in and identify associated trends. This can improve customer experience, marketing campaigns, and more effective product usage.
  Mining-based and data-driven approaches are similar in terms of using statistical and probabilistic models for activity recognition. However, a data-driven approach can still generate a personalized model, which a mining-based approach cannot. In contrast, mining-based approaches can determine a model's parameters to avoid the data scarcity problem seen in data-driven approaches [24].
  The ontology-based approach involves using a set of facts and tools to create an organized and logical conclusion model. This approach relies on using ontologies to represent the knowledge in a computational form. It helps with the reusing and sharing models and technologies.

Table 7. Activities identified, sensors, analytics used, and IoT roles in smart building environment

Activities identified	Sensor type	Analytics used	IoT roles	Reference
Activities recognition and detection	Pressure, stretch, and accelerometer	k-Nearest Neighbors (K-NN), Decision Tree (DT), and Support Vector Machine (SVM)	The sensor data was collected and stored on a Flora board and then processed in a PC to classify normal and violent human actions	[126]
	Thermopile imaging array	Connected domain extraction algorithm and Feature point localization	The sensors output sequential images are sent to a Raspberry Pi to analyze and detect three elderly activities: rest, fall, and movement	[87]
	Tri-axial inertial sensor	Genetic Algorithm(GA), DT, and SVM	The sensor data was collected and stored on Arduino Uno and then processed in a PC to detect physical activities from different datasets	[58]
Occupancy sensing	Temperature, humidity, CO2, and Wi-Fi probe	k-nearest neighbors (kNN), SVM, artificial neural network(ANN)	Sensor data is stored locally and WiFi data is sent to the cloud. The data is fused to predict occupancy and improve energy efficiency	[161]
	Accelerometer and gyroscope	SVM	The sensor data was fused and stored on Arduino Uno for different objects to identify different occupants in the smart home	[50]
	Plug-load meters and PIR	K-means clustering	The sensor data was collected and transmitted from Raspberry Pi to an external server to estimate individual occupancy in office spaces	[135]
Indoor positioning	Temperature, humidity, light, and pressure	xgboost, Random Forest (RF),DT, LightGBM, and Gradient Boosting Classifier (GBDT)	Sensors data was collected using an Arduino board, and the board uploaded the data to an external server for visualization and enable accurate indoor location	[46]
	BLE beacons	Trilateration algorithm	The Beacons sensors transmit the BLE signals to estimate the occupant's position, Arduino Mega and the smartphone are used to track the position, and then the data was sent to an external server for analysis	[18]
	Wearable wristband and smart phone	Fuzzy logic and genetic algorithm	Designed wristbands are used to receive the Received Signal Strength Index (RSSI) strength, and the corresponding MAC address is then sent to the cloud server, and then the server calculates and analyzes the received data for indoor positioning in an smart hospital environment	[21]
Building energy consumption	Temperature, light, PIR, and MQ-2 gas	Proposed lighting control algorithm	The sensor data was collected by the Arduino Mega board, the board controlled the lights in the house to reduce energy consumption	[20]
	CO2, temperature, and humidity	Model predictive control (MPC), and long short-term memory (LSTM)	Sensors data was collected and stored in a Raspberry pi. Then the data was sent to a remote ThingsBoard platform to control smart building ventilation predictively while enhancing energy efficiency	[69]
	Temperature, humidity, CO2, and Wi-Fi probe	k-nearest neighbors (kNN), SVM, artificial neural network(ANN)	Sensor data is stored locally and WiFi data is sent to the cloud. The data is fused to predict occupancy and improve energy efficiency	[161]
Building indoor environmental quality	CO2, temperature, and humidity	Model predictive control (MPC), and long short-term memory (LSTM)	Sensors data was collected and stored in a Raspberry pi. Then the data was sent to a remote ThingsBoard platform to control smart building ventilation predictively while enhancing energy efficiency	[69]
	Particulate matter (PM), temperature, and humidity	On-Off Control	The sensor data was collected by the Arduino Pro Mini board and sent to a Raspberry Pi server for processing, and then the data was sent to the ESP8266 board to monitor and control the air quality in the building	[169]
	Temperature, humidity, and gas sensor	Neural network (NN), NaïveBayesian (NB), KNN, SVM, and RF	Sensor data was collected using an Arduino board and then sent to a PC for monitoring and predictive characterization of air quality	[6]

Comparing this approach with the logic-based approach shows that both use the same techniques in terms of activity model recognition. However, the ontology-based approach has more access to rich resources, being supported by research in a semantic web, with resources such as APIs and advanced tools used to carry out tasks related to ontology-based approach activity recognition [24].

The Logic-based approach uses various logical forms, such as facts, rules, and expressions, to derive information regarding context. This approach is different from the data-driven approach in terms of less reliance on a large dataset to create an activity model. The activity models are thus more explicit semantically and can use low-level context to extract high-level information. This approach retains some weaknesses in representing uncertainty and fuzzy information. One way to reduce uncertainty in the model is to use sensors in the building to collect data about the environment and occupant activity.

The data collected can create a more accurate and reliable model. Another possibility is to use ML algorithms that can analyze the sensor data and predict the occupants' behavior. Another area for improvement is that the activity model is not adaptable to different occupants' behaviors. It thus lacks reusability and applicability due to minimal standardization [24, 117].

- **Hybrid Activity Recognition Approach.** Each of the previously mentioned approaches has its limitations. The knowledge-based approach produces activity models that cannot capture all user activities, and both approaches have other weaknesses. Thus, a hybrid approach may select key features from each approach to producing a better activity recognition model. Several such features were identified in research by Sukor et al. [142], who found that using a hybrid approach eliminated the data scarcity problem known as the "cold start" problem. As there is no need for a large dataset for training and learning, they could model activities initially by incorporating knowledge approach techniques, the model then moved on to a learning process using data-driven reasoning. Another important feature of a hybrid approach is scalability, which allows a model to be used in different environments without specific training. This approach automatically learns and adapts general activity models based on the previous knowledge context.

  However, there are some limitations to the proposed hybrid approach mentioned. One limit is that it does not support real-world activity scenarios that happen concurrently or work for more than one activity simultaneously. It can thus only be used to investigate consecutive or singular activities. Further, the proposed approach cannot differentiate whether used objects are relevant, arbitrary, or meaningless [142].

4 SMART BUILDINGS OBJECTIVES

The previous section reviewed smart buildings' capabilities for recognizing occupants and human activities. In this section, several important objectives that can be achieved using these smart building capabilities are thus outlined. Figure 8 illustrates some key smart building objectives that can be achieved using IoT technology combined with advanced analytics capabilities.

4.1 Occupant Localization Enhancement

This process aims to identify the location of an occupant or a device within the building. Occupant localization data is used mainly to facilitate navigation inside the building to reach the desired location [175]. Several technologies are used to measure occupant localization, including Wi-Fi-based indoor location, BLE beacons, and RFID detecting motion. Determining where occupants are located inside the building at a given time helps minimize energy consumption and costs based on occupant behaviors. It also helps to understand occupants' behaviors inside the building, which helps improve building facility design. Applications that may benefit from occupant location

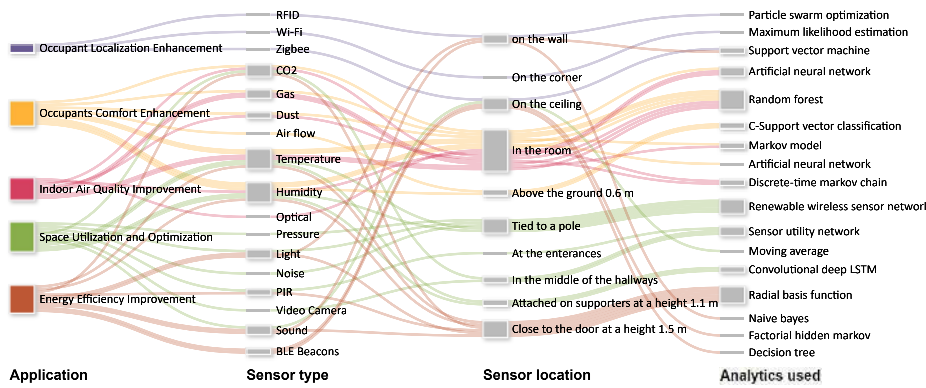

Fig. 8. Smart building objectives achieved by IoT technology combined with advanced analytics capabilities.

information within the building include energy consumption, improving safety, providing customer insights, and health systems.

The Global Positioning System (GPS) is the most common and popular location technology used in various applications. Despite its widespread use, GPS is limited in accurately locating occupants inside a building. To address this limitation, several other technologies have been developed and used for this purpose, such as Wi-Fi, Bluetooth, ZigBee, ultrasound, visible light, and Ultra-Wideband (UWB). Taking advantage of IoT technology and integrating it with such localization technologies may help enhance the accuracy of occupant localization and proximity detection within buildings [175]. A study that combined magnetic and visual sensors in the office building achieved 91% localization accuracy [124]. IoT technology can help by providing more precise information about the occupant's location using various sensors within the building, such as vision and pressure sensors. However, more research is needed on occupant localization applications due to the difficulties in their installation and maintenance.

4.2 Indoor Air Quality Improvement

Nearly 90% of people's time is spent inside of buildings [12]; maintaining indoor air quality is thus essential to improving people's daily lives. Indoor air pollution can affect productivity and work performance. Recent research conducted by Sun et al. [143] estimates that a yearly 5% reduction in work productivity could cost around 20 to 200 billion US dollars in loss across the global economy.

Indoor air quality can be measured using various sensors, such as CO2, temperature, humidity, and volatile organic compounds. Adopting IoT technology and advanced analysis can help monitor indoor air quality and improve work environments. Recognizing occupants' activities can also help in understanding different occupants' pollution activities that may affect indoor air quality. It is also essential to monitor indoor air pollutants to inform building occupants about critical or dangerous levels as required and to help facility managers make relevant decisions about improving air quality in the building. According to Qabbal et al. [121], such collected data could also be used to develop indoor air quality guidelines to support different aspects of improvement such as ventilation design and occupants satisfaction.

4.3 Space Utilization and Optimization

Modern building spaces are designed to allow various activities such as individual work, group work, meetings, and socializing. These modern designs help optimal use of the multiple spaces within a building, yet there is often a lack of follow-up processes to measure the actual use of these spaces once a building is completed. Space utilization is measured in buildings using various sensing technologies such as infrared, motion, microwave, and video processing technologies.

Finnigan et al. [49] explored the role of the sensor toolkit in enhancing energy auditing practices in buildings: that study's findings showed that the fine-grained insights thus produced enabled facility managers to develop better knowledge of building efficiency that let them provide practical recommendations for improvement. Using IoT technology with various deployed sensors should help enhance space utilization within buildings, combined with advanced analytics to help develop an understanding of occupants' behaviors in different spaces to produce valuable insights.

Further, during the COVID-19 pandemic, smart buildings are equipped with technologies that can be used to monitor and enforce maximum room capacity. Room occupancy sensors can detect how many people are in a given area, ensuring that social distancing protocols are being followed. Longo et al. [94] proposed a prototype called Smart Gate that monitors people's flow in the building and track their occupancy. The system was placed on one side of the entrances and primarily used a pair of time-of-flight sensors to detect people entering and exiting.

4.4 Occupants Comfort Enhancement

Occupants' comfort inside a building is one of the essential applications of smart buildings, as enhancing occupants' comfort helps to increase productivity performance and increases occupants' satisfaction levels. Various services can enhance occupants' comfort, mainly based on monitoring and controlling aspects of the indoor climate, including temperature, cooling, and noise levels. Occupant comfort can be affected by various variables, including air temperature, air quality, background noise, lighting, and other factors. Zhang et al. [176] sought to enhance building energy efficiency and occupants' thermal comfort by using a deep learning model in IoT-enabled buildings. The model proposed in their study achieved a high level of accuracy in a short period, based on finding the optimal value of the thermal comfort level for the occupants.

Different services can be monitored and controlled with the help of IoT devices and advanced analytics to be adjusted based on occupants' preferences and usage history. Acoustic sensors, for example, can detect particular types of noise, such as alarms or conversations, which can be useful for security and privacy purposes. Additionally, acoustic sensors can be used to detect the presence of people in a room, which can be used to trigger lights or other electronic systems.

4.5 Energy Efficiency Improvement

Building Information Modeling System (BIMS) is a powerful tool for improving energy efficiency in buildings by monitoring and controlling energy consumption. BIMS utilizes various sub-systems to collect, store and analyze data related to the energy consumption of the building, such as heating, cooling, lighting, and plumbing systems. This data can then be used to identify energy-saving opportunities, such as turning off unnecessary lights or systems when not in use. Traditional energy meters are used to collect information about energy consumption in each space. However, they provide only limited data. With BIMS, more detailed information can be collected, including data related to the number of occupants and their known comfort preferences.

Building sensor data can be analyzed to create an Energy Efficiency Index (EEI) that shows how much energy is used in different building areas and compares it with other buildings' consumption. Analyzed data can reveal energy consumption patterns and help make decisions about energy optimization in the building.

Occupant-centric control (OCC) and automated energy system strategies can improve buildings' energy efficiency by reducing energy consumption and environmental impact. OCC utilizes occupant behavior and preferences to optimize energy systems. Automated energy system uses sophisticated control algorithms to identify and implement energy-saving measures. The successful implementation of these technologies requires energy management systems, occupant sensing, and optimization software.

4.6 COVID-19 introduced applications

The COVID-19 pandemic has changed the way we live. To keep people safe, many businesses have had to implement measures to limit the capacity of their spaces and enforce social distancing. This has resulted in the development of new technologies, such as sensors, cameras, and software applications, which are used to monitor the number of people in a room and their distance from each other. Fazio et al. [39] propose scalable indoor navigation systems to navigate the user inside smart buildings using BLE beacons and smartphones. The smartphone detects the user's position over time and suggests the best route to the destination.

The proposed system can be further enhanced using AI technologies to predict user movement. For example, if a user regularly visits the same location each day, the system can use this information to suggest the quickest route to that location. The system can also provide helpful information during the user's journey, such as directions, alerts, and information about nearby points of interest.

Buildings are also being used to provide a safer environment for occupants by utilizing technologies like digital signage, automated temperature checks, and automated ventilation and air conditioning systems. Buildings are also used to create a more efficient way of working and living by enabling occupants to access their workspaces remotely.

Implementing AI and ML technologies is being used to improve the efficiency and accuracy of operational processes in buildings. In addition, developers created new applications built on top of existing smart building infrastructure to provide additional safety measures and improved efficiency. For example, smart buildings can now be used to provide automated contact tracing so that buildings can quickly respond to any potential virus outbreaks. Similarly, they can be used to provide automated temperature checks and access control to ensure the safety of occupants.

5 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

This section clarifies the previously discussed gaps in existing research and identifies some challenges that may direct future research directions. Section 5.1 discusses technical challenges, including privacy and security, selecting sensor types and dealing with data uncertainty, deploying sensors and computational power, and building heterogeneous data sources. In section 5.2, Human-Building interaction is discussed, identifying the challenges shared between humans and buildings, the difficulty of recognizing complex activities, the challenges in delivering the explanations needed by building facility managers, and the space utilization application challenges.

5.1 Technical Challenges

5.1.1 Privacy and Security. Smart buildings are becoming increasingly popular with the advent of IoT and AI technologies, bringing greater convenience and control to people. These technologies also raise significant privacy and security concerns. Privacy is a major concern for smart buildings and their devices, as the data collected can reveal a lot about occupants' behavior and interests. This data can be misused without proper protection, which can have serious privacy implications.

Security is another challenge for smart buildings; as many connected devices are installed in a building, the possibility of system hacks, data breaches, and other malicious activities increases. In addition, the consequences of such events in a smart building can be more severe since great physical damage can be caused if the security systems are compromised. Therefore, it is crucial to ensure that smart building systems have robust security measures to protect them from potential threats. This can be done using advanced authentication mechanisms, encryption technologies, firewalls, and other security protocols [155], [51]. Similarly, data protection policies should be adopted to ensure that personal data is not misused or abused.

Algorithmic bias is one of the biggest privacy concerns in AI technologies. Algorithms are only as good as the data they are trained on, and if that data is unbalanced or unevenly distributed, then the algorithms may produce biased results. Additionally, AI systems may not be transparent in their decision-making processes, making it difficult to determine why specific decisions were made and how they will affect people. It is also essential to limit access to the central AI systems that are used to control the building. AI systems often use sensitive data, such as user information, to make decisions. Therefore, access to these systems must be strictly controlled and monitored to prevent malicious activity. Further, it is essential to ensure the building itself is secure.

Buildings often combine different types of technology, such as facial recognition and motion sensors. This data must be securely stored and transmitted, and malicious actors must be prevented from accessing it [111]. IoT and AI in smart buildings offer numerous possibilities for creating energy-efficient, cost-effective, and comfortable living and working environments. With proper implementation, these technologies could revolutionize how people live and work in smart buildings.

5.1.2 Choosing Sensors and Dealing with Data Uncertainty. Smart buildings rely on the data collected by sensors to make decisions that increase efficiency and reduce costs. Choosing the right sensors is therefore crucial for a successful building system. When selecting sensors, such accuracy, reliability, and power requirements must be considered. Sensors should also be chosen based on the type of data they can collect.

Different sensors are required to measure various environmental conditions, such as temperature and light. It is important to ensure that the sensors selected are compatible with the system in which they will be used. After selecting sensors, the collected data could be unreliable. It is important to understand the sources of uncertainty in sensor data, which can be divided into measurement errors and environmental effects. The first arises from factors such as the device's accuracy and the second from external factors such as temperature and light.

In addition, optimizing the energy efficiency of sensors must also be considered. For example, a framework proposed by Liang et al. [88] could keep the energy consumption of IoT devices at almost half of what was previously consumed by optimizing the sampling frequency, communication, and the models used. Therefore, further research is needed to develop suitable sensors for use in different building areas, identify potential uncertainty sources in sensor data, and minimize their impact. In addition, research should focus on developing collaborative frameworks and advanced analytics tools to identify opportunities for energy savings and improved occupant comfort.

5.1.3 Deploying Sensors and Dealing with Computational Power. Once an appropriate combination of sensors is identified, those sensors must be used efficiently to obtain accurate information. Placing a sensor directly in the area of interest is the most commonly used means [106, 115], but this can be challenging since different sensors require different placement locations to offer accurate readings. For example, temperature sensors need to be placed away from windows and sunlight to provide accurate readings. Therefore, there is a trade-off between sensor locations within buildings.

Areas may have features that differentiate them from other areas in the building, so sensor placement and the number of sensors required based on those features must be considered. After deploying sensors, it is important to manage the computing power to run a building. The amount of power required depends on the complexity of the building, the number of connected devices, and the speed at which the data can be processed. IoT-enabled buildings require significant computing power and networking capabilities to manage data flows, analyze insights, and provide feedback.

Therefore, high-end servers, computers, and cloud computing solutions are required to run a smart building successfully. These solutions require high-speed networks, robust storage systems, and strong security to ensure data is not compromised. In addition, AI is needed to automate the processes and allow the building to respond quickly. It is important to carefully consider the project's specific needs and assess the existing infrastructure and technologies. This includes evaluating the performance of existing hardware, the type of cloud services needed, and the availability of AI solutions. Considering all of these elements makes it possible to create a reliable and efficient building for all its occupants.

5.1.4 Building Heterogeneous Data Sources. Data collected from buildings can be used to improve energy-saving opportunities, occupant comfort, and other systems in the building. However, the data collected can be heterogeneous and complex, making it difficult to analyze. Collecting and analyzing building data presents many challenges. For example, it can be difficult to identify different sources of energy use and their relationship to one another. The data may not be reliable or accurate, making it challenging to measure the energy used by the building and its occupants.

The data collected from buildings can be challenging to interpret. This is because the data is often collected from multiple sources, making it harder to identify patterns and relationships between different factors. It can contain a large amount of noise, making it difficult to identify patterns or trends accurately. It also may need to be completed or updated to draw meaningful conclusions. To overcome these challenges, developing systems that can effectively store, process, and manage the data collected from buildings is essential. It helps ensure that the data is up-to-date and can be easily accessed and analyzed. Using advanced analytics tools and techniques to identify patterns, trends, and relationships could help in the process of collecting data.

5.2 Human-Building Interaction

5.2.1 Sharing Information. Sharing the information is achieved through communication between the two parties, buildings and humans; the communication process remains challenging; many buildings are still not augmented with sensors due to the additional costs and lack of perceived value. Further, sensor data alone is insufficient for this purpose: it must be combined with advanced analytics to obtain valuable insights that can support rational decision-making. In a research study by Finnigan et al. [42], sensor data was used to generate actionable recommendations for facilities managers regarding energy auditing practices in different buildings. According to Das et al. [31], understanding occupants' behaviors and Human-Building interactions can help enhance energy consumption and minimize building costs in many circumstances.

Smart building systems typically use a variety of communication protocols, such as CAN bus, Zigbee, Bluetooth, LoRaWAN, and more. One of the most commonly used protocols for communication between devices in a smart building is Zigbee, explicitly designed for low-power, low-data-rate applications and is highly secure, reliable, and power-efficient. Low-Power Wide-Area Networks (LPWANs) provide a cost-effective way to connect low-power, low-data-rate devices over long distances. With LPWANs, smart buildings can communicate and report data back to their central systems, allowing for greater flexibility and automation while reducing energy consumption. It is best suited for buildings that do not require large amounts of data to be transmitted. For example, LPWANs can be used in buildings requiring real-time energy consumption monitoring and environmental conditions.

LPWANs often have less throughput and coverage than other networks, such as Wi-Fi or cellular, leading to poor performance in some applications. It is typically more expensive than other networks due to the additional cost of building the infrastructure required to support the network. Due to their low-power nature, they are prone to problems, and these networks require more maintenance. Further, LPWANs can be an excellent option for specific applications in smart buildings, but it is important to be aware of the potential drawbacks before implementing them [15].

Successful communication can increase understanding of various building phenomena, such as occupants' productivity and comfort. Improving communication allows facility managers to make better-informed decisions regarding different phenomena in a building. Further, featured models of Human-Building communication with optimal chosen sensors and analytics will improve the communication and desired end results.

5.2.2 Recognizing Complex Activities. Understanding occupant activity is achieved by collecting sensor data and training an ML model to recognize activities. Static activities such as standing and sitting or dynamic activities such as walking and running all have movement ranges and produce recognizable sounds or vibrations that certain sensors can detect. Other complex activities may be harder to detect using sensors, it may be difficult to determine whether an occupant is watching a lecture or reading an e-book on a laptop.

Some activities can be easily recognized by applying vision-based techniques to monitor an occupant's activities, but these techniques have many drawbacks, including processing demand and lack of privacy. Several sensors can also recognize different activities sufficiently in isolation yet may find it challenging to recognize them when several things happen simultaneously at the same location.

There is a trade-off between the complexity level of the activity and the accuracy of recognition, especially when the activity is more complicated. More research is thus needed to efficiently recognise complex activities happening within smart buildings, as improved ML models and external data sources could improve this recognition accuracy.

5.2.3 Supporting Facility Managers with Enhanced Data. Data from sensors can be variable and difficult to interpret due to noise and missing data; Some sensors even have manufacturing defects that can affect readings. Facility managers often look for high-level explanations for various phenomena in a building. They need information such as building occupancy rates for different spaces in the building with different designs that allow facility managers to renovate or improve spaces to maximize occupancy rates.

The nature of currently used sensors makes it challenging to deliver the range and types of data needed by facility managers. More reliable data cleaning frameworks and recognition solutions are thus needed to improve the final outputs. These should handle missing, incorrect and irrelevant data and prioritize the most critical data for required purposes.

5.2.4 Space Utilization. Smart building are designed based on basic information available at the time of the design; however, this is generally insufficient to determine how different spaces inside the building will be used in practice or whether occupants will utilize them efficiently as designed. There is now a tendency to work outside of standard office buildings, based on current technological advances and improved means of communication.

Proposed solutions to optimize space usage have been developed previously by firms employing observers to take notes about occupancy in the building across different spaces over time [144]. This technique is inefficient and does not support flexible working practices such as hot-desking, it only detects occupancy at specific times rather than continuously throughout working hours. Currently, solutions have emerged based on vision-based and sensor-based technologies. Vision-based approaches that use cameras suffer from privacy and security concerns. Some also rely on outside lighting sources to identify occupants, making them prone to error.

Other solutions based on sensors can tackle issues regarding continuous occupancy detection while maintaining privacy. However, gathering continuous readings from sensors and understanding the nature of various building spaces remains challenging. The collected data can be affected by external sources, and occupants may act in ways that deliver inaccurate data about space utilization, such as changing furniture locations, blocking sensors, or incorrect readings being generated by sensors due to their relative location to other objects.

More research is thus needed to understand how spaces are being used within buildings to help in reducing costs and to help designers and facility managers understand occupant's behavior when using these spaces [42]. The collected data can be transformed into insights that help designers and facility managers in making informed decisions.

6 CONCLUSION

Smart buildings are are designed to provide occupants with tailored services, applications, and improved energy efficiency. Using Internet of Things technology (IoT) and data analytics, smart buildings can now provide building occupants with insights about their activities and behaviors, making the environment more efficient and cost-effective. This work provides a survey of sensors used in different building environments, focusing on sensor types and how they can be deployed. A review of activities that can be identified in smart buildings with these sensors and the appropriate analytics for activity recognition is also provided. Table 4 outlines the various types of sensors used in smart buildings. Table 6 provides further information on the activities that can be detected by each type of sensor. Figure 8 illustrates some key smart building objectives that can be achieved using IoT and data analysis. Although recent advances have made the concept of smart buildings much more accessible, there remain several challenges that limit their usage, such as added costs and a perceived lack of value. This work also identifies research challenges that must be addressed for smart buildings to become widely adopted, suggesting potential future research directions.

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