Chapter 18

Sensing systems for smart building occupant-centric operation

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1 Introduction

As sensors and sensor systems grow in their availability, sophistication, and capabilities, they are increasingly being used throughout urban areas to collect data on many different aspects of the built environment. Combined with internet connectivity and data storage, sensors have enabled the growth of "smart cities" that take advantage of this combined hardware and software interconnectivity to intelligently monitor, manage, control, and coordinate various assets, resources, and services more effectively and efficiently.

Buildings represent a significant component of the urban environment, where many people work and live, as well as where businesses and industries operate. They are critical to all aspects and many of the functions of a city. These buildings include many interconnected systems that must work in parallel or together, to support the specific operations and the uses of each one. These systems can be classified into different groups, but generally include civil, electrical, mechanical, electrical/energy, plumbing, structural, and technology systems, among others. Each of these systems is complex, and many of them require energy to operate. Because of this, buildings account for nearly 40% of energy consumption and 74% of electricity use in the United States (EIA, 2020). They thus also largely influence the load shapes on the electric grid, which is a vital component to enable a smart city to run and function. As a result, buildings are also responsible for approximately 36% of CO_2 emissions (EIA, 2020) in the United States.

As climate change concerns continue, the efforts to address these concerns are also mounting. In an effort to reduce emissions and energy use overall, it is important to develop energy- and demand-saving approaches to help reduce

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energy impacts from buildings. The idea of a "smart building" was introduced to respond to external (e.g., climate and grid electricity prices) and internal (e.g., user patterns) boundary conditions to target nearly zero energy buildings (nZEBs) (Al Dakheel, Del Pero, Aste, & Leonforte, 2020). nZEB has been proposed to retrofit existing buildings to improve building energy efficiency and facilitate decarbonization, integrated with renewable energy sources. Such a concept supports the flexibility to adjust energy-consuming loads for demand-side management by using real-time interaction and monitoring.

For buildings that are primarily used for people-based functions, such as office buildings and residential buildings, building energy consumption is highly dependent on occupants, particularly their energy use patterns and comfort requirement. Sensor-enabled interactive connections between occupants and buildings support the ability of buildings and their systems to respond to users' needs while minimizing energy needs, and thus also help to achieve nZEB targets.

Currently, occupancy sensors are more commonly used for lighting control and security system applications in buildings. For example, van De Meugheuvel, Pandharipande, Caicedo, and Van Den Hof (2014) proposed a distributed lighting system to provide daylight and occupancy adaptive illumination based on information attained from light sensors and occupancy sensors. Park, Dougherty, Fritz, and Nagy (2019) developed "LightLearn," an occupant-centered controller for lighting control based on reinforcement learning, which was shown to reduce energy consumption as well as maintain occupant comfort. Brackney, Florita, Swindler, Polese, and Brunemann (2012) developed a novel image-processing occupancy sensor, providing output signals that can be integrated with the building security systems. However, there has been recent interest and efforts for these sensor systems to also be used for heating, ventilation, and air conditioning (HVAC) control applications. Given that HVAC systems represent a substantial portion of the energy consumption in buildings (Vakiloroaya, Samali, Fakhar, & Pishghadam, 2014), the use of advanced sensor systems for more intelligent HVAC controls represents a significant opportunity for energy performance improvements.

In residential buildings, smart thermostats with built-in occupancy sensors have been increasing available and used (Moon & Han, 2011). These thermostats often include a "home" and "away" mode, depending on whether or not the sensor detects the presence of occupants. In "away" mode, occupants are considered to not be present in the home and thus the setpoint temperature is adjusted for the HVAC system to be in unoccupied mode, to reduce operation time and thus energy consumption. Many thermostats, however, do not yet have these occupancy sensors integrated into them. In addition, many homes do not have programmable thermostats. Based on the Residential Energy Consumption Survey (RECS) (US EIA, 2015), there are 26.8 million housing units (23%) that do not have programmable thermostats, thus using manual controls only. There are, however, significant efforts by various stakeholders and utility companies, in particular, to encourage the adoption of smart thermostats. This has resulted in an adoption rate increase in recent years (Sanguinetti, Karlin, & Ford, 2018).

In commercial buildings, HVAC systems are generally more complex than residential buildings since they typically include multiple thermal zones with a variety of space types. In addition, commercial buildings require mechanical ventilation per energy code requirements, thus outdoor air is required to maintain acceptable levels of indoor air quality. The energy consumption associated with ventilation accounts for approximately 50% of the total HVAC energy use in commercial buildings in United States (CBECS, 2018). Based on ASHRAE Standard 62.1-2019 (ASHRAE, 2019), the outdoor airflow depends on the number of occupants, thus adjusting outdoor air intake based on real-time detection of the number of occupants has the possibility of significantly improving energy saving. In addition, GPC 36 (High-Performance Sequences of Operation for HVAC Systems) within ASHRAE (ASHRAE, 2018) has also included consideration for occupancy sensing technologies in recent years, including guidance on the use of both ventilation and setpoint adjustments based on occupancy data. However, similar to residential buildings, many existing buildings are older and do not have HVAC systems and/or building management systems (BMS) that can use sensor system input to adjust operations (Manjarres, Mera, Perea, Lejarazu, & Gil-Lopez, 2017). In addition, similar to residential buildings, there has been a greater push for improved intelligent operations of buildings, including the collection and use of occupancy data (ARPA-E, 2017).

The intelligent operation of buildings systems based on sensor-collected data and information requires that these systems collect useful and accurate information. In the case of occupancy data, this includes either occupant presence and/or counts, which is provided as input into occupant-based controls. Inaccurate sensor readings are not desirable. For occupancy presence sensors, a failure can be either a false positive reading (i.e., the sensor system indicates there is an occupant when there is not) or false negative (i.e., the sensor system does not register an occupant when there is one present). For occupancy counting, the failure would be to incorrectly count the number of occupants in a space. A false positive would result in systems being on that do not need to be; a false negative would result in a potentially thermally or visually uncomfortable space. For occupancy counting, an incorrect reading of the number of occupants would result in ventilation rates that could be too high or low for the number of occupants present. In summary, while challenging to detect, occupancy is of significant importance if the goal of a building is to be both energy efficient and comfortable for the occupants that use it.

The challenge with occupants and occupancy data, however, is that occupants are inherently unpredictable, varying both from person to person, and from building type to building type. Factors such as interior building layout and geometry, lighting levels, and other physical parameters, depending on the type of sensor(s) used, can significantly impact the ability of a system to detect occupants (Gennarelli, Ludeno, & Soldovieri, 2016; Labeodan, Maaijen, & Zeiler, 2013; Wang, Chen, Huang, & Lu, 2017; Wang, Chen, & Song, 2017; Wang, Xiong, Jiang, Chen, & Fang, 2017; Yun & Lee, 2014). This impact varies depending on the type of sensor system used and its corresponding algorithms. Similarly, occupant characteristics, including their physical features and movements, their preferences, and their occupant-building interactions with energy-consuming appliances and systems in buildings, make the accurate detection of occupants challenging due to limited predictability (Yan et al., 2017; Yoshino, Hong, & Nord, 2017). The relative importance of these occupant characteristics, similar to physical building characteristics, is also dependent on the sensor system considered.

The objective of this chapter is to provide a comprehensive review of the types of occupancy sensor systems used for buildings, sensing modalities, and corresponding variables found to impact sensor performance. The performance methods and metrics that are used for the evaluation of reliability, the ability of the sensor system to be installed and commissioned, and the evaluation of energy savings potential are also summarized.

2 Occupant presence and counting sensing technologies

Human-sensing technologies can be divided into five main categories: presence, counting, location, tracking, and identification (Teixeira, Dublon, & Savvides, 2010). From the perspective of energy performance, whether or not there are people and how many are in each thermal zone of a building is significant for controlling lighting and the HVAC system in residential and commercial buildings. The specific location, the tracking of occupants, and their identification have a more limited impact on the energy use of a building and the controls informed by occupancy data. Thus, in this chapter, the main focus among these categories is occupant presence and counting.

Existing technologies for occupancy information extraction in buildings can generally be classified into two categories, including those that use a single sensor modality (single sensor systems), and those that use multiple (sensor fusion technologies). Single sensor systems utilize one or multiple sensors of the same type to infer occupancy information, while sensor fusion methods combine more than one type of occupancy sensor to help compensate for the disadvantages of each type of sensor system. A total of 120 recent papers published between 2003 and 2020, focusing on occupancy sensor system studies, have been identified by using keywords search in Google Scholar, Scopus, and Web of Science, including "occupancy sensor," "occupancy detection," and "occupancy counting." Among these papers, 80 concentrates on either occupancy detection or occupancy counting, which were used in this review. Fig. 1 summarizes the number of papers where each of the occupancy sensor technologies is considered.

In the following section, the literature review is discussed by sensor type. Table 1 shows the top five most commonly used sensor categories discussed herein, including radiofrequency-, soundwave-, infrared-, vision-based sensors,

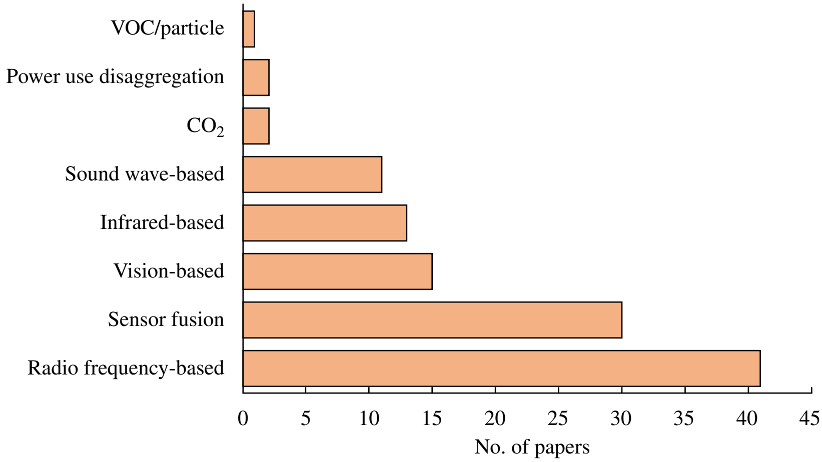
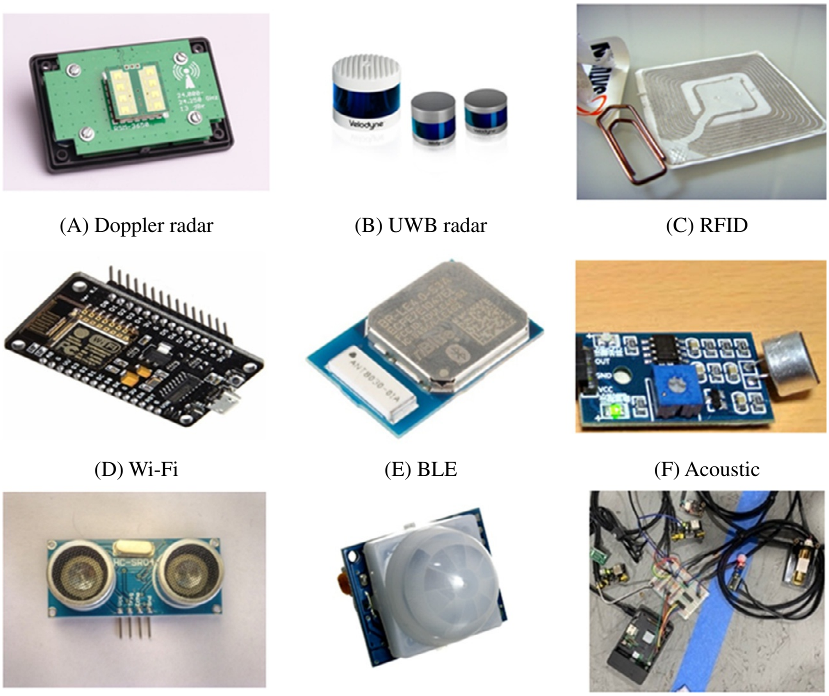


FIG. 1 Frequency of occupancy sensor modalities used in the recent literature from 2003 to 2020, including occupancy detection and occupancy counting.

TABLE 1 Most common types of occupancy sensor types used in single sensor and sensor fusion applications in residential and commercial buildings.

Sensor category		Sensor type
Single sensor systems	Radio frequency based	Normal doppler radar
		Ultrawide band (UWB) radar
		Radio-frequency identification (RFID)
		Wi-Fi
		Bluetooth low energy (BLE)
	Sound wave based	Acoustic
		Ultrasonic
	Infrared based	Active infrared (IR)/passive infrared (PIR)
	Vision based	Video/camera
Sensor fusion		Single sensor systems (above) + environmental sensors (e.g., temperature, relative humidity, CO_2, VOCs)



(A) Doppler radar (B) UWB radar (C) RFID
(D) Wi-Fi (E) BLE (F) Acoustic
(G) Ultrasonic (H) IR/PIR (I) Sensor fusion

FIG. 2 Example of each type of occupancy sensor system.

and sensor fusion. For the single sensor systems, sensor failures are unique to each type of sensor modality. For sensor fusion technologies, which are typically a combination of one or more of the single sensor system sensing modalities and environmental sensors, the potential sensor failures will include failures caused by not only the above single sensor modality but also the environmental sensors, as well as the system's interpretation and use of this information. Table 1 shows each of the types of sensors for each sensor category. Fig. 2 shows an example of each type of sensor system from Table 1. This section focuses on the description of how each type of occupancy sensing technologies is used to infer occupancy and some advantages and disadvantages of each modality.

2.1 Radio frequency (RF)-based sensors

2.1.1 *Normal Doppler radar*

Doppler-shift sensors detect waves that are reflected from a person when the person is moving. The frequency of the Doppler signal shifts based on the velocity of occupants. Generally, this type of occupancy sensor can recognize people if they are moving. There are different motion levels for occupants, categorized as major motion, minor motion, and fine motion based on the National Electrical Manufacturers (NEMA) WD 7 Occupancy Motion Sensors Standard (2011, with revisions published in 2016). When people make movements categorized as fine motion or no motion, it can be more difficult for this sensor type to detect them (Yavari, Jou, Lubecke, & Boric-Lubecke, 2013).

2.1.2 UWB (ultrawide band) Doppler radar

One challenge with Doppler radar sensors is that they can easily be impacted by other parallel signatures, such as generating electromagnetic interference from a nearby system under the same frequency range. This is an issue for occupant counting (Diraco, Leone, & Siciliano, 2017). To address this, the ultrawide band is a radio signal with a fractional bandwidth equal to or greater than 0.20 or at a frequency greater than 500 MHz (Wood, 2006). It operates using a larger bandwidth with a wider range of frequencies, resulting in submillimeter range resolution as well as high penetration power. This supports the detection of small objects, including through obstacles and walls at a relatively low power consumption (Diraco et al., 2017; Kim & Rabaey, 2016). The high frequency also allows for this sensor type to continuously scan the entire space and track an object, and the wide bandwidth also helps to avoid interference with other radio signals with the same frequency.

2.1.3 RFID (radio-frequency identification)

RFID identifies and tracks tags attached to objects, or in this case, occupants. An RFID tag receives signals from a nearby RFID reader device and then transmits digital data back to the reader. The reader receives the information from each of the tags which are used to determine the location of the occupant(s), and thus whether they are in the targeted space. One advantage of this technology is that it does not require line of sight conditions for detection. Challenges in the use of RFIDs include that the anisotropic antennas are sensitive to signal interference, since the radio waves can be impacted by the proximity of metals and liquids existing in the environment, which can lower the transmission rate of the RFID system (Li, Li, Becerik-Gerber, & Calis, 2011). The sensor network density is also higher than other technologies because of the multiple beacon nodes needed, and that the person being detected must have a tag on them in order to be detected. This can be cumbersome to install and manage (Wang, Chen, Huang, & Lu, 2017; Wang, Chen, & Song, 2017; Wang, Xiong, Jiang, et al., 2017).

2.1.4 Wi-Fi

Wi-Fi is a local wireless network that uses radio waves to communicate data, typically from the internet. To be considered as Wi-Fi, the radio signal uses the IEEE 802.11 standard (2016) to communicate. Multiple versions of Wi-Fi are defined in the IEEE specifications, including common ones such as 2.4 and 5 GHz frequency radio waves. Given how common Wi-Fi is, it can be used as an efficient, affordable, and convenient to detect occupancy, where the Wi-Fi connections and disconnections can be utilized to infer building occupancy without requiring additional devices to be used beyond those that occupants already carry with them (e.g., computers, cell phones). However, unknowns include the number of Wi-Fi-connected devices per person, as some people may not have a Wi-Fi connected device, whereas others may have multiple. There may also be devices connected to Wi-Fi that are not occupant specific.

2.1.5 Bluetooth

Bluetooth is another wireless technology that uses short-wavelength radio transmissions in the range of 2400–2480 MHz, standardized in IEEE 802.15.1, to exchange data within short ranges from fixed and mobile devices. Using Bluetooth, smart devices need to be in discoverable mode (i.e., ready for pairing) for an initial connection to be made between devices. As long as the Bluetooth capability is enabled, there are no subsequent actions needed to change Bluetooth settings. iBeacon is an example of this technology, which uses Bluetooth Low Energy (BLE) wireless technology. This has also been studied to infer occupancy information in buildings (Conte, De Marchi, Nacci, Rana, & Sciuto, 2014). There are three main components: the beacon transmitters, which send uniquely identified packets with a Universally Unique Identifier (UUID), receivers which install a client mobile application on their smartphones to periodically scan signals to detect beacons in the building, and finally, building remote servers which gather and implement algorithms to identify occupancy information based on the detected packet information. Similar to Wi-Fi, if an occupant has a Bluetooth- or BLE-enabled device on them, such as a cell phone, this can be a cost-effective way to determine occupancy. However, similar to Wi-Fi, unknowns include the number of Bluetooth-/BLE-enabled devices per person, and whether or not all occupants have such devices.

2.2 Sound wave-based sensors

2.2.1 Acoustic

These sensors detect acoustic waves based on the piezoelectric material. For people detection, they can target human audible sounds with a frequency of 20 Hz–20 kHz (Launer, 2017). The main applications are microphones which can detect human sounds to infer occupancy presence through analysis of the collected acoustical data. First, the recorded audio stream needs to be segmented into a uniform duration, i.e., a basic audio processing unit. Next, features which could be used to represent the human sound are extracted from the audio segments, such as frequency (Khan, Hossain, & Roy, 2015), pitch

(Xu et al., 2013), and Mel Frequency Cepstral Coefficient (MFCC) (Lu, Pan, Lane, Choudhury, & Campbell, 2009; Xu et al., 2013). These are considered among the most important features for audio signal processing. The advantage of the use of this sensing modality is that microphones are inexpensive as a standalone sensor and are integrated into common items such as smartphones. This enables easier data collection using commonly available devices. However, this recorded data must be preprocessed to extract the targeted features before analysis. In addition, privacy can also be a concern.

2.2.2 Ultrasonic

Ultrasonic sensors measure distances based on transmitting and receiving ultrasonic signals, which detect sounds greater than 20 kHz (inaudible to humans). Ultrasonic sensors are generally made up of piezoelectric material, where the ultrasonic transmitter transmits the ultrasonic wave which travels through the air until it reaches an object or person, then the wave is reflected back and received by the ultrasonic receiver. By analyzing the time and distance that the reflected ultrasonic wave is received and how these changes over time, it can infer whether there is an object or person in the space. However, the sensor itself may not be able to distinguish between people and other objects.

2.3 Infrared-based sensors

This type of sensor system includes both passive and active infrared sensors. PIR (passive infrared) sensors do not generate or radiate energy for detection purposes. Rather, they detect infrared radiation heat that is emitted by or reflected from objects, which in this case, are occupants. When a person enters the sensing area of a PIR sensor, the sensor receives an increased IR signal; when the person leaves the sensing area, the sensor receives a decreased IR signal. An active IR sensor requires both an emitter and receiver, however, this sensing method is simpler than its passive counterpart. The IR emitter sends out a beam of light, facing a receiver. If there is nothing in between, the receiver sends the signal back. If there is a person or other nonstationary object standing in between the emitter and the receiver, the receiver fails to detect the IR beam, therefore present in the monitored space. Low-resolution IR arrays are based on thermopile technology, where the thermopile element is sensitive to a motionless object. PIR technology is one of the most used off-the-shelf occupancy sensor types since it is relatively easy to implement and low in cost. However, it is not as easily able to detect low motion level of occupants because it depends on movement to generate the IR changes for the sensor to sense.

2.4 Vision-based sensors

Vision-based sensors include camera and video technologies. These sensors are used to collect video and/or camera frame data to infer occupancy information.

Methods include background subtraction, where the foreground elements are separated from the background by generating a foreground mask to be used for differentiating frames before and after a person appears, and pattern matching approaches, where the Adaptive Boosting algorithm is used to establish the Haar-like features and a cascade of classifiers (Zhu & Chen, 2015). Other methods include histogram of oriented gradients (Lee & Mokji, 2014), support vector machine (Liu et al., 2016), and scale-invariant feature transform (SIFT)-inspired features (Cruz-Mota, Bogdanova, Paquier, Bierlaire, & Thiran, 2012), to detect and locate occupants in a video frame, and frame-differencing which subtracts consecutive frames pixel by pixel and optical flow, which measures the motion gradient of each pixel over a range of frames (Sengar & Mukhopadhyay, 2017). The advantage of vision-based sensors is that video is considered the most accurate occupancy sensing technology and thus is usually used as a ground truth method. A disadvantage is that when using some of the abovementioned algorithms to process vision-based data, people can "disappear" when they stop moving, meaning there is no difference in the image frame if occupants stand static before and after.

2.5 Sensor fusion

Sensor fusion methods usually combine the use of environmental sensors, such as temperature, relative humidity, lighting, and CO_2, with other types of sensors, including those discussed in the previous sections, to determine occupancy. Compared to sensor systems that only use one sensing modality, sensor fusion methods have the advantage of multiple sensing modalities. With the appropriately developed data processing algorithms, sensor fusion methods can help to reduce the occurrence of false positives and negatives by checking the agreement among sensor data output. However, a limitation of sensor fusion is that the data-processing models can differ significantly in terms of their predictive accuracy (Hobson, Lowcay, Gunay, Ashouri, & Newsham, 2019).

3 Reliability evaluation

3.1 Influential variables

This section provides a brief literature review and summary of the influential variables that may impact the performance of occupant presence and counting sensing technologies (Table 2). These potentially influential variables are classified into five categories: building-related, environment-related, occupant-related, sensor-related, and others. For building-related and environment-related variables, factors such as interior building layout and geometry, and lighting levels can significantly impact the ability of a system to detect occupants (Gennarelli et al., 2016; Labeodan et al., 2013; Wang, Chen, Huang, & Lu, 2017; Wang, Chen, & Song, 2017; Wang, Xiong, Jiang,

TABLE 2 Influential variables evaluated in recent literature using occupant presence and counting sensing technology.

Sensor type	Reference	Influential variables mentioned/tested				
		Building-related	Environment-related	Occupant-related	Sensor-related	Others
Doppler radar	Yavari et al. (2013), Yavari, Lee, Pang, McCabe, and Boric-Lubecke (2014), Yavari, Song, Lubecke, and Boric-Lubecke (2014), and Sekine, Maeno, and Kamakura (2012)	Presence of large objects (fan, microwave, oven, washing machines)	Environmental noise	Motion level of occupant(s) Multiple occupants walking at similar speeds	Number of sensors Direction of arrival of received signal of the sensor	Nonhuman periodic motion
UWB doppler radar	Kilic, Wymeersch, Meijerink, Bentum, and Scanlon (2013), Yarovoy, Ligthart, Matuzas, and Levitas (2006), Ossberger, Buchegger, Schimback, Stelzer, and Weigel (2004), Rane, Gaurav, Sarkar, Clement, and Sardana (2016), Mabrouk et al. (2014), Rane et al. (2016), Singh, Liang, Chen, and Sheng (2011), and Yavari, Gao, and Boric-Lubecke (2018)	Occlusion Wall type (e.g., drywall, wooden door, brick wall) Presence of large objects Size/shape of the test space	–	Motion level of occupant(s) Location of occupant(s) (Occupants behind walls) Body shape of occupant(s) Number of occupant(s) Posture of occupant(s) Motion level of occupant(s) Clustering of occupants	Range of sensor system Location of sensors	Measurement duration Distance between the sensor and occupant(s)

Continued

TABLE 2 Influential variables evaluated in recent literature using occupant presence and counting sensing technology—cont'd

Sensor type	Reference	Influential variables mentioned/tested				
		Building-related	Environment-related	Occupant-related	Sensor-related	Others
RFID	Li et al. (2011), Li, Calis, and Becerik-Gerber (2012), Ranjan, Yao, Griffiths, and Whitehouse (2012), Wang, Chen, Huang, and Lu (2017), Wang, Chen, and Song (2017), and Wang, Xiong, Jiang, et al. (2017)	Size/shape of test space	Environmental noise	Number of occupants	Response time of the sensor	Awareness of occupant(s) wearing tags
				Motion level of occupant(s)	Configuration of antennas	
				Location of occupant(s) (occupants walk close to the boundary of thermal zones)	Locations of sensors (RFID tags attached to different parts of clothing; antennas placed on different appliances/ locations)	
				Motion level of occupant(s)		
				Number of occupants		

Wi-Fi-based	Ravichandran et al. (2015), Xi et al. (2014), Palipana, Agrawal, and Pesch (2016), Wang, Chen, Huang, and Lu (2017), Wang, Chen, and Song (2017), Wang, Xiong, Jiang, et al. (2017), Wang, Chen, and Hong (2018), Wang, Chen, Hong, and Zhu (2018), Ouf, Issa, Azzouz, and Sadick (2017), Balaji, Xu, Nwokafor, Gupta, and Agarwal (2013), Lu et al. (2016), Vasisht, Kumar, and Katabi (2016), Petrovic, Echigo, and Morikawa (2018), and Vattapparamban, Çiftler, Güvenç, Akkaya, and Kadri (2016)	Presence of large metal objects (refrigerator, computer monitor, large furniture, interior metal separations)	–	Motion level of occupant(s)	Orientation of the antennas	Distance between occupant(s) and sensors
				Posture of occupant(s)		Wi-Fi device not turned on by occupant(s)
				Number of occupants		Occupants' phone in sleep mode if not in use
				Clustering of occupants	Signal strength of sensors	Occupant(s) has multiple devices (phones, laptops, wireless printers)
				Walking speed of occupant(s)		Electromagnetic interference
		Size/shape of test area		Walking direction of occupants (toward the sensor, or move randomly)	Response time of sensor(s)	Occupant leaves space without carrying their phone
				Number of occupants		Data collection timestep

Continued

TABLE 2 Influential variables evaluated in recent literature using occupant presence and counting sensing technology—cont'd

Sensor type	Reference	Influential variables mentioned/tested				
		Building-related	Environment-related	Occupant-related	Sensor-related	Others
Bluetooth-based	Conte et al. (2014), Corna, Fontana, Nacci, and Sciuto (2015), Filippoupolitis, Oliff, and Loukas (2016), Shen and Newsham (2016), Park, Dougherty, and Nagy (2018), and Longo, Redondi, and Cesana (2019)	Size/shape of test area	Humidity	Number of occupants	Cyclic behavior of beacons	Occupant(s) have multiple devices
					Location of sensor(s)	Distance between occupant(s) and sensors
					Response time of sensor(s)	Occupant leaves space without carrying their phone
						Occupant(s) go beyond Bluetooth range
Acoustic	Khan et al. (2015), Xu et al. (2013), Yavari, Lee, et al. (2014), Yavari, Song, et al. (2014), Shih and Rowe (2015), Shih, Lazik, and Rowe (2016), Khalil, Benhaddou, Gnawali, and Subhlok (2018), Hnat, Griffiths, Dawson, and Whitehouse (2012)	Wall materials' absorption of sound waves	Environmental noise	Number of occupants	Location of sensors	Distance between occupant(s) and sensors
		Presence of reflective materials (glass, plastic)		Noise level of occupant(s)		Angle between occupant(s) and sensors
		Size/shape of test area		Motion levels of occupant(s)		Occupant(s) in a wheelchair

		Blind spots where sensor cannot see	Presence of non-occupant sounds	Body shape of occupant(s)	Performance over time of the sensor	Occupant(s) with a purse
		Location of the door frame (corner)		Number of occupants walking simultaneously		Occupant(s) wearing hat(s)
		Door size		Walking speed of occupant(s)		
		Movement of furniture over time	Characteristics of sound (utterance length of sound)	Height of occupant(s)	Number of sensors	Presence of household objects (bags, laundry baskets)
		Opening/ closing of doors and windows		Occupant(s) standing in doorways		
		Presence of large objects		Posture of occupant(s)		
Infrared-based sensor	Dodier, Henze, Tiller, and Guo (2006), Kuutti, Saarikko, and Sepponen (2014), Yun and Lee (2014), Zappi, Farella, and Benini (2007), Raykov, Ozer, Dasika, Boukouvalas, and Little (2016), Chowdhury, Ali, Boual, Hopper, and Udrea (2016), and Liu, Wang, Wang, and Lin (2017)	/	Presence of airflow/air movement	Location of occupant(s)	Differences among multiple individual sensors	Distance between occupant(s) and sensors
				Body shape of occupant(s)	Response time of sensor	
				Clustering of occupants	Height of sensor	
				Number of occupants	Number of sensors	Data collection frequency
				Different walking directions of occupant(s) (back and forth)		

Continued

TABLE 2 Influential variables evaluated in recent literature using occupant presence and counting sensing technology—cont'd

Sensor type	Reference	Influential variables mentioned/tested				
		Building-related	Environment-related	Occupant-related	Sensor-related	Others
				Motion level of occupant(s)	Location of sensors	
				Location of occupant(s)		
Vision based	Zou, Zhao, Yang, and Wang (2017), Teizer, Caldas, and Haas (2007), Tomastik, Lin, and Banaszuk (2008), Ahmad et al. (2018), and Yang et al. (2018)	Presence of interior lighting sources	Lighting levels	Age of occupant(s)	Presence of cobwebs on the camera	–
				Hairstyles of occupant(s)		
		Presence of large objects		Posture of occupant(s)		
			Presence of direct sunlight	Motion level of occupant(s)		
		Blind spots where sensor cannot see		Clustering of occupants		
				Objects located in the shadows		
		Door sizes (multiple entrances/exits)	Indoor air temperature	Number of occupants		
				Clustering of occupants		

Sensor fusion	Hailemariam, Goldstein, Attar, and Khan (2011), Ekwevugbe, Brown, Pakka, and Fan (2013), Yang, Li, Becerik-Gerber, and Orosz (2014), Chen, Masood, and Soh (2016), Zikos, Tsolakis, Meskos, Tryferidis, and Tzovaras (2016), Meyn et al. (2009)	Size/shape of test area	Indoor air temperature	Number of occupants	Number of sensors	Short term transition (person arrived/ left office)
				Noise level of occupant(s)	Location of sensors	Interrupted Wi-Fi connection
		Presence of large objects	Presence of direct sunlight		Response time of sensors	Loss of electricity
				Motion level of occupant(s)	Number of sensor types	Physical damage to sensors
		Door size			Response time of sensors	Data corruption

et al., 2017; Yun & Lee, 2014). This impact varies depending on the type of sensor system being evaluated, its corresponding algorithms, and how the sensor system is deployed in a particular location.

Similarly, occupant-related characteristics, including their physical features and movements, their preferences, and their occupant-building interactions with energy-consuming appliances and systems can make the accurate detection of occupants challenging (Yan et al., 2017; Yoshino et al., 2017). The relative importance of these occupant characteristics, similar to physical building characteristics, is also dependent on the sensor system considered. Regarding the sensor-related variables, factors such as the number of sensors utilized, and the placement of sensors can be significant. These factors are usually determined by the sensor system developers. Other variables include those that do not fit into the other four categories, such as the presence of pets.

Among the recent literature, while many of the sensor testing studies have considered multiple different factors in evaluating their influence on occupancy sensor system performance, all papers follow different methods and test different variables. The comprehensive literature review is included herein helps to determine what variables consistently impact occupancy sensor system performance (Table 2).

3.2 Reliability/performance metrics

Performance metrics, along with a standard methodology for the evaluation of the reliability of occupancy sensing technologies, are important to drive the development of new and more capable technologies, and to increase the adoption rate of these technologies in the US building stock and beyond. To determine reliability, a ground truth methodology is also important, which is expected to be sufficient to clearly validate the reliability of the technologies. In this section, both performance metrics and ground truth methods are summarized based on a literature review of 80 relevant peer-reviewed research articles.

Fig. 3 shows performance metrics that were used in the reviewed papers, as well as the number of appearances. Accuracy is the most widely used, which is the percentage of the correct number of occupancy predictions out of the total number of experimental scenarios, providing an indication of the overall performance of the system. Some of the failures were discussed using a confusion matrix, including true positive (TP), true negative (TN), false-positive (FP), and false-negative (FN) designations. However, generally, only an overall accuracy or estimation error percentage was provided. Each of the four items in the confusion matrix is not typically specified and analyzed, so in many cases, it does not clear what is the weightage of actual presence/nonpresence scenarios to the total scenarios and where the most errors (FP or FN) happen.

F-score is another method, calculated based on collected TP, TN, FP, and FN data. Based on the importance (self-determined) of TP, TN, FP, and FN, a weighted F-score can also be used to evaluate the overall performance of

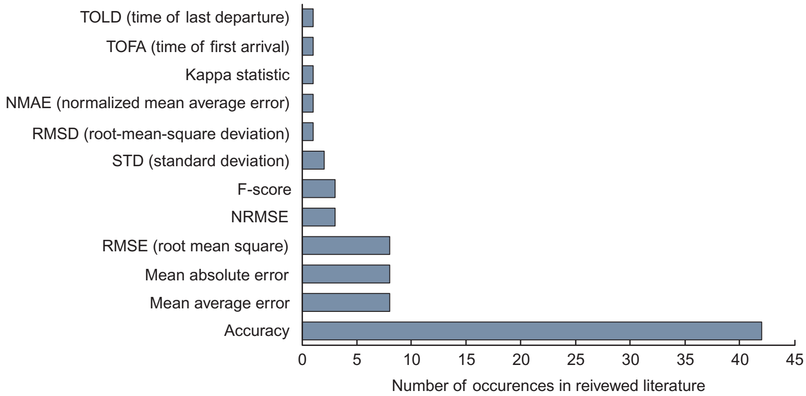


FIG. 3 Performance metrics for reliability evaluation and associated number of appearances from literature review.

the occupancy sensor system. Most of the other performance metrics use a variety of statistical methods. These include the mean average error, mean absolute error, root mean square error (RMSE), normalized root mean square error (NRMSE), standard deviation, root mean square deviation (RMSD), normalized mean average error, and Kappa statistic, among others. However, among these metrics, there is no industry-accepted standard which suggests which should be used, and what threshold error rate can be used to demonstrate that an occupancy sensor system is performing well enough for use in occupied buildings.

Along with the reliability evaluation, ground truth methods are also developed to provide the actual occupancy information as a basis of comparison to the tested sensor system. Fig. 4 presents the common ground truth methodologies,

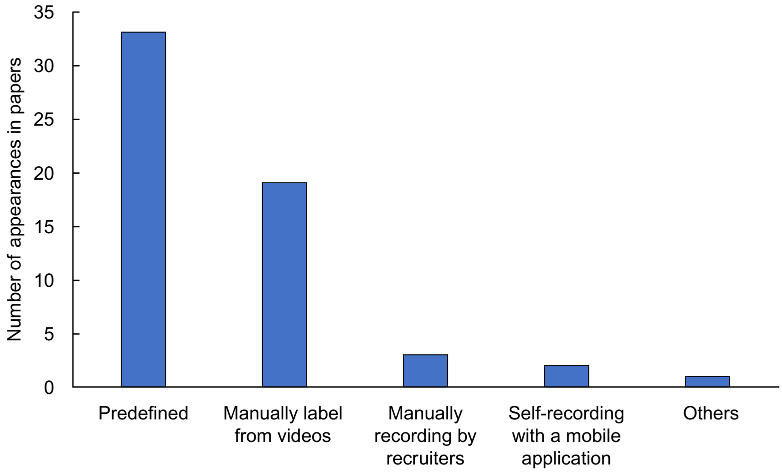


FIG. 4 Ground truth methodologies implemented with reliability evaluation and associated number of appearances from literature review.

including predefined, manually labeling from videos, manually recording by volunteers, self-recording with a mobile application, and others. Among all these methodologies, approximately 57% are predefined, which means occupants follow what they are supposed to do during the experiments, and thus the occupancy information is already known before experiments are implemented. In these scenarios, no additional data collection is needed to determine the ground truth. Manually labeling videos is also common (~33%). For this method, the test space is monitored using cameras during experiments, then the video/camera data is used to manually check the presence/nonpresence or count of occupants. Manual recording by volunteers and self-recording with a mobile application account for approximately 3.5% and 1.7% of the literature, respectively.

4 Ease of commissioning evaluation

Another key component to occupancy sensor systems is that they need to be able to inform building operations, such as through lighting control, or heating, cooling, and ventilation controls. To be able to integrate with these systems in an occupied building, they (a) need to be installed and linked to the building's HVAC, lighting, or other control systems, as well as (b) need to operate overtime continuously and consistently. However, currently, there are no established and vetted methodologies or certification processes to assess the ease of commissioning and integration of occupancy sensor system technologies into buildings. A methodology that enables an accurate evaluation of occupancy sensor system technologies is needed. Newly developed and existing sensor systems would benefit from being tested using this methodology for ease of comparison.

In an effort to provide insights on the evaluation of integration and commissioning, the literature on what aspects people consider important when integrating sensor systems in buildings were reviewed. There are very limited research efforts focusing on this area. For residential buildings, particularly smart thermostats some of which use occupancy sensing systems, there is somewhat more literature. There is very little literature on commercial building applications of sensor systems and the associated commissioning needs.

Peffer, Pritoni, Meier, Aragon, and Perry (2011) discussed the architecture and features of smart thermostats, including user interface, communication, memory, and power supply. The user interface is a means to display information and to provide inputs. Communication to the HVAC system is generally through wired connections, which is important for HVAC controls. The programmable thermostats require memory to store data, which can be permanent or volatile. The power supply is normally from the electric power, and batteries can also be used in case of power outages. Among these features, interface and communication were found to be the more important factors. Koupaei, Song, Cetin, and Im (2020) collected 26,372 product reviews for five commercially available smart thermostats and used an opinion mining methodology to summarize and categorize customers' opinions into eight topics, including "Feelings," "Control/Occupancy," "Easy/Hard," "Connectivity/Application," "Installation," "Comfort/HVAC," "Costs," and "Energy." From these eight topics, connectivity and installation are the two main categories which fall into the ease of commissioning domain. Schäuble, Marian, and Cremonese (2020) also mentioned that one of the noneconomic barriers for the application of smart thermostats is the complexity of installation and operation and the interoperability of smart home components from different suppliers.

Based on the above discussion, common categories of commissioning and system integration that may be considered for occupancy sensor systems, include installation, connection, interface, and communication. These could be used to evaluate the ease of commissioning and integration. Installation evaluates the ease of installing the occupancy sensor system; connection evaluates the ease of connection of the sensor system to HVAC control system, and how consistent the connection is during operation; user interface assesses how easy it is to access and communicate with the occupancy sensor system; communication assess the accuracy of data transmission from the sensor systems to the HVAC system. However, it is noted that some of these may not apply to all sensor systems, such as the user interface, which may not be present for some systems.

To evaluate each of these categories a rubric could be used (e.g., Table 3). For doing this, several ASTM standards may be helpful, which is a similar rating system, including ASTM E2943-15 (2015), ASTM E3041-17 (2018), and ASTM F2008-00 (2018). Among these standards, ASTM E3041-17 proposes a Sensory Quality System (SQS) Scale with an Overall Quality Score for sensory evaluation: Reject (1–2), Unacceptable (3–5), Acceptable (6–8), and Match (9–10). Using a similar method, each category could be evaluated on a scale of 1–5, with 1 being the worst, and 5 being the best.

TABLE 3 Possible ease of commissioning rating system.

Metric	1	2	3	4	5
Not easy/ hard	Not easy/hard		Some-what easy	Easy	Very easy
Accept/reject	Unacceptable		Acceptable		Acceptable

5 Energy energy-saving evaluation

To evaluate the energy savings impact of the use of occupancy sensor systems in buildings, it is critical to first identify the targeted control strategies that are to be used and the type of building application in which the energy savings is to be evaluated. The most common applications currently are for commercial building lighting systems, however, there is growing literature and use for controls of other systems, as mentioned above. Similar to the other abovementioned performance metrics related to commissioning and reliability, there is also no established or standard method for evaluating the energy savings of occupancy sensor systems. To conduct any energy-saving evaluation, several items need to be known. This includes the targeted building characteristics and systems, the climate, the occupancy patterns, the control strategy, and the reliability (i.e., when the failure occurs such that the correct occupancy is not reflected in the controls).

To evaluate energy savings, both energy modeling methods can be used, or for specific buildings or scenarios, controlled laboratory or field testing can be used. For modeling, a common tool used to evaluate the impact of various technologies in commercial and residential buildings is to use prototype buildings, such as those developed and supported by the US Department of Energy (US DOE, 2018). These include single-family detached and multifamily low-rise apartment buildings, and 16 commercial building types (such as offices, retail, malls, and restaurants) in 19 climate locations. These represent the characteristics of a diversity of types of buildings in the United States by climate zone and by either age or energy code year.

Various efforts have used these buildings for technology-based energy savings evaluation. For example, Ye, Hinkelman, Zhang, Zuo, and Wang (2019) proposed a methodology to develop prototypical energy models to represent US religious worship buildings. The energy-saving potential was evaluated, with a maximum energy savings of approximately 30%. Ali and Al-Hashlamun (2019) used the prototypical governmental schools built before 2003 to evaluate the indoor thermal environments before and after the insulation was added. Specifically, for occupancy sensor systems, there have been some recent efforts to support improved accuracy of energy savings evaluation of HVAC-connected occupancy sensor systems. Pang et al. (2020) proposed occupant-based control strategies and quantified the nationwide energy savings potential by implementing the occupant-based control into HVAC systems in medium-size office buildings using energy simulation. Chu, Mitra, and Cetin (2021) developed typical academic building models and implemented occupant-based control in these models to evaluate the energy-saving potential. The benefit to this method of evaluation is that it can be used to evaluate nationwide savings and savings in a diversity of different scenarios. Some critiques of this method are that without laboratory or field validation (e.g., IPMVP, 2003; DOE M&V guidelines, 2015; ASHRAE Guideline 14, 2014), the models cannot be verified to be accurate in assessing energy savings.

For laboratory and field testing, various efforts have used real occupied buildings or controlled full-scale test spaces for evaluating the energy savings from occupancy sensor systems. Wang, Chen, Huang, and Lu (2017), Wang, Chen, and Song (2017), and Wang, Xiong, Jiang, et al. (2017) proposed a dynamic spatial occupancy distribution method to determine occupancy information, and a new control algorithm, then both the occupancy sensing system and control algorithm were conducted in a real office room at the City University of Hong Kong. It was found that the proposed method could achieve a 20% energy use reduction compared to a traditional control system. Han and Zhang (2020) integrated an occupancy sensing system into the HVAC controls in a typical office building with multiple zones testbed. Energy savings achieved was approximately 45% of fan electricity and 36.5% of room cooling/heating energy consumption. From these studies, it is seen that energy savings can be significantly different, even when using similar types of buildings. The challenge with these evaluation methods is that they do not often represent "typical" buildings and cannot necessarily be translated to energy savings evaluation estimates in other buildings.

In order to decrease the uncertainties due to different operation time periods, and in an attempt to have a strong and nearly identical baseline condition as a basis of comparison, one method proposed is the use of a parallel set of laboratories. PNNL Lab Homes (Cort et al., 2018) include two custom factory-built double-wide homes that built side-by-side, which are used for researchers to conduct energy-saving and peak load reduction research. Michigan State University also has similar facilities, including two typical homes placed side-by-side, located at Civil Infrastructure Laboratory. In such conditions, one of the two laboratories can be used as a baseline where typical building controls are applied without an occupancy sensor system, while the other could be used to test the implementation of occupant-based control with the integration of occupancy sensors with the building systems. The two laboratories then operate in parallel under identical weather conditions, building characteristics, and other conditions to minimize differential conditions that can occur if comparing performance from two different time periods.

Moving forward there may be some possibilities of combining the benefits of both sets of methods, such as full-scale laboratory facilities for controlled laboratory testing in buildings close to the characteristics of a prototypical building type, then using this data for energy model validation following M&V guidelines, and finally, using this validated model to estimate energy savings across a certain building type in diverse climate zones and occupancy scenarios.

6 Occupancy sensor applications in smart cities

With increasingly developed advanced occupancy sensor systems and improved reliability, occupancy sensors present an opportunity to be better integrated into the Internet of things (IoT) within smart buildings (Daissaoui, Boulmakoul, Karim, & Lbath, 2020). In such a scenario, a variety of sensors are connected, and data generated by these sensors are stored, which can accomplish real-time monitoring, control, and supervision to support the operation of building systems. There have been studies focusing on the integration of occupancy sensors into lighting (Park et al., 2019; van De Meugheuvel et al., 2014) and security systems (Brackney et al., 2012). Recently, there has also been interest and efforts to integrate occupancy sensors into heating, ventilation, and air conditioning (HVAC) control applications. Smart thermostats with built-in occupancy sensors have been increasingly available and used in residential buildings (Moon and Han, 2011). Recent studies have focused on theoretical potential energy-saving analysis with the integration of occupancy sensor systems using energy simulation (Manjarres et al., 2017). However, there are few studies that connect occupancy sensors to HVAC systems and apply controls to reduce energy consumption while also maintaining thermal comfort. Beyond HVAC systems, there are also other opportunities to integrate occupancy sensors, such as integration into smart plugs to cut off power to the equipment if the occupancy sensor detects no people. Others include smart window systems to control daylight differently depending on occupancy (King & Perry, 2017). In the future, it is likely that more equipment and/or appliances will be connected and automatically controlled with the implementation of occupancy sensors in smart buildings. Beyond buildings, recently, there have also been studies on the development of smart parking that utilize occupancy sensors to detect parking spot status (occupied or idle) and provide real-time updates (Grodi, Rawat, & Rios-Gutierrez, 2016), or predict car park occupancy rates (Baroffio, Bondi, Cesana, Redondi, & Tagliasacchi, 2015), to support smart cities goals.

7 Conclusions

In this chapter, a literature review was conducted on 80 relevant peer-reviewed research articles on occupancy sensor systems in buildings, focusing on occupancy detection and occupancy counting, which resulted in five types of sensor technologies that were most commonly used. Among the recent literature, while many of the sensor-testing studies have considered multiple different factors in evaluating their influence on occupancy sensor system performance, there has been no comprehensive assessment gauging the relative influence and importance of these diverse factors on the performance of occupancy sensor systems. Similarly, there are no standard methods to evaluate sensor system performance, including defining what influential factors to consider for evaluating reliability for typical and edge-case scenarios. The literature review provided helps to determine what variables can impact occupancy sensor system performance, what variables are likely to vary under normal and extreme scenarios, and the performance metrics used to evaluate reliability.

Along with reliability, ease of commissioning and integration with buildings systems are also important, as well as the level of energy savings that can be achieved using such systems. Minimal efforts have been made on this ease of commissioning and integration evaluation, despite various stakeholders suggesting this of significant importance to industry adoption of technologies. For energy savings, a diversity of efforts has focused on energy saving evaluation using either simulation tools or in real building scenarios. Moving forward utilizing methods that integrate the findings from both modeling and full-scale scenarios should help provide a better picture of energy savings. Moving forward, the opportunity to use occupancy sensor systems in buildings will continue to be one of interest, both within smart building applications, and beyond, to connect to the various other intelligent systems that support smart cities.

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