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From occupants to occupants: A review of the occupant information understanding for building HVAC occupant-centric control

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Review Article

Abstract

Occupants are the core of the built environment. Traditional heating, ventilation, and air-conditioning (HVAC) systems operate with predefined schedules and maximum occupancy assumptions with no consideration of specific occupant information. These generalized assumptions usually do not align with the actual demand and result in over-conditioning and occupant discomfort. In recent years, with the aid of Information & Communication Technology (ICT) and Computer Science (CS), it is possible to acquire real-time and accurate occupant information to satisfy the exact thermal requirement through specific HVAC control in one particular built environment. This mechanism is called HVAC "Occupant-centric Control (OCC)." HVAC OCC strategy starts with collecting the occupant's information (e.g., presence/absence) and then applies it to meet the occupant's requirement (e.g., thermal comfort). However, even though some research studies and field pilot demonstrations have been devoted to the field of OCC, there is a lack of systematic knowledge about occupant data, which is the principal component of OCC for HVAC researchers and practitioners. To fill this gap, this review paper discusses OCC with a particular emphasis on occupant information and investigates how this information can assist HVAC operation in providing an acceptable built environment in required spaces during the required time. We provide a fine-grained, comprehensive picture of occupant information, discuss its features, the modalities of information feed-in into the HVAC control, and the application of commonly utilized occupant information for OCC.

Keywords

occupant information;
occupant-centric control;
smart building;
HVAC;
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1 Introduction

Occupants have always been the center of indoor environment control. From 40,000 years ago, when Neanderthals began to dig caves to protect themselves from the cold (Janssen 1999), to 1947, when engineer Henry Galson developed a compact and inexpensive window air-conditioner (AC) and introduced modern ACs into hundreds of thousands of homes (DOE 2015), human beings have been contriving to build a safe and comfortable man-made space and satisfy their needs. Although the early phase of the modern heating, ventilation, and air conditioning (HVAC) system offered occupants the ability to individually control the indoor environment (for example, by turning on/off the AC or adjusting the thermostat setpoint), problems like low thermal comfort level, high energy consumption, and inconvenient control mechanisms were pertinent (Park et al. 2019). These issues occurred because ordinary people lacked the professional knowledge required to achieve stable thermal comfort manually, and HVAC industries had technical and cost limitations in automating these processes.

Automatic HVAC control allows the maintenance of an acceptable indoor environment with minimal human labor and involvement. The logic behind the control mechanism is either based on maintaining a predefined temperature and humidity range or pre-established metrics like the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) indices (Fanger 1970). However, due

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to a lack of real-time measurement application, traditional HVAC control focuses on providing thermal comfort to the statistically averaged occupant with a pre-assumed occupancy, and thus, has several problematic attributes: individual occupants' discomfort, conditioning unoccupied spaces (Erickson et al. 2009), predefined operating schedule that assumes maximum occupancy (Agarwal et al. 2011), etc. These issues cause significant occupant discomfort and energy wastage.

To achieve optimizing automatic HVAC control, the fundamental principle is ensuring that building services are delivered only when and where they are required for providing a suitable built environment for the occupant, and in the amount that they are required (Salimi and Hammad 2019). Two essential elements required to realize this goal are actual occupant information and comprehensive context-aware information from target buildings. Occupant characteristic is then recognized and fed into the control network to make an appropriate decision. HVAC occupant-centric control (OCC) exactly follows this process.

A concise summary and timeline of the aforementioned developments are demonstrated in Figure 1. We list major HVAC OCC advancements from the 1970s to the present, which illustrates how advances in interdisciplinary fields, like the ICT and CS, have been integral in driving HVAC control to be more specific (rather than general) by utilizing occupant information, thereby making HVAC OCC possible.

1.1 Definition of HVAC OCC

While the importance of occupant influence in the built environment is widely accepted by researchers and practitioners, there is a lack of consensus regarding how HVAC OCC should be defined. In the following subsections, we first discuss the definitions of occupant information and HVAC occupant-centric control used in this review paper.

1.1.1 Occupant information

Many studies have been conducted to develop various approaches to investigate the data associated with building occupants. Research in this spectrum started by detecting occupant presence/absence status in a particular space within certain time periods (Hagras et al. 2004; Harris and Cahill 2005; Dodier et al. 2006) and then progressed further into quantifying the number of occupants (Lam et al. 2009; Erickson and Cerpa 2010; Dong and Lam 2011). With the development of communication technology, the occupant's indoor position started playing a role in occupant research (Woo et al. 2011; Maaijen et al. 2012; Moreno-Cano et al. 2013). A combination of these concepts is commonly referred to as "occupancy" and can be regarded to be the primary level of occupant information (Melfi et al. 2011). Utilizing these pieces of occupancy information could improve HVAC control for more occupant-centric. However, the information was not enough to comprehensively reflect the status or activity of occupants in buildings. "Occupant behavior" was then introduced to describe occupants'

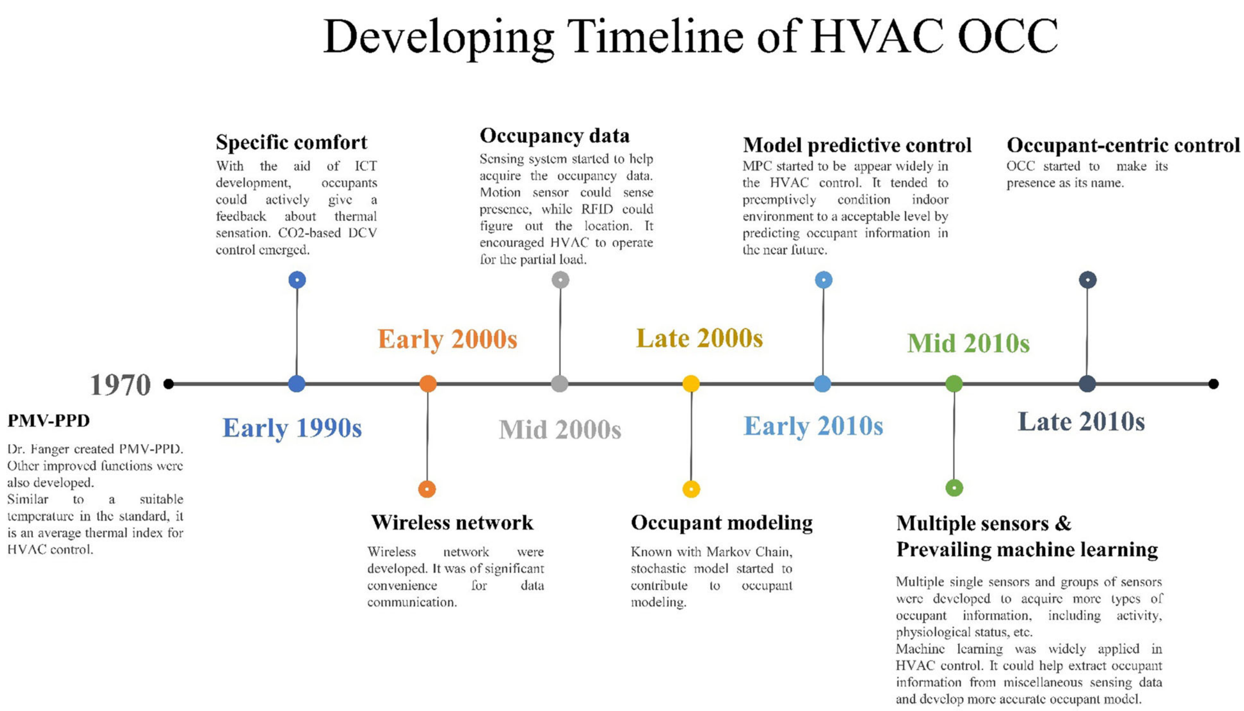


Fig. 1 Developing timeline of HVAC OCC

interactions with physical building components (e.g., windows, lights, thermostats, etc.). Each of these actions affects building energy consumption significantly and is a leading source of uncertainties in predicting building energy use (Yan et al. 2015).

1.1.2 *Definition of HVAC OCC*

Since OCC is a relatively new concept and studied by researchers and practitioners around the world, there is no widely acknowledged definition for it at this time. To partially alleviate this issue, IEA-EBC Annex 79 (O'Brien et al. 2020) brought together international researchers from diverse disciplines. They defined OCC as "an approach for indoor climate control in which occupancy and/or occupants' comfort and preferences are directly measured or indirectly inferred from a variety of sensors, occupant feedback from control interfaces or mobile and wearable devices. This information is then used to train models to adapt to actual context-related conditions and occupants' needs."

Technically, HVAC systems have always been designed to be occupant-centric due to their primary function of serving occupants in buildings in order to ensure an acceptable built environment for health and productivity. Traditional HVAC control theory of temperature-humidity comfort range, PMV-PPD evaluation, or predefined schedule are all rooted in occupant information. So, while not an entirely new idea, why did this term "OCC" only become popular in recent years? The critical difference between modern occupant-centric control and traditional control stems from the specific time taken to acquire occupant information and particular subjects involved in a certain HVAC control. Instead of leveraging the predefined average data, modern OCC focuses on the requirements of actual occupants in the built environment. With the advancement in industrial technologies and the onset of the digital revolution, we believe it is the right time to prioritize the needs of individuals and respect their actual requirements for the built environment. This is the basic philosophy behind OCC development and serves as the primary motivation for this review paper.

In summary, we simplify the definition from IEA-EBC Annex 79 mentioned above and rephrase HVAC OCC as any kind of HVAC control that takes into consideration specific occupant information. Figure 2 illustrates its

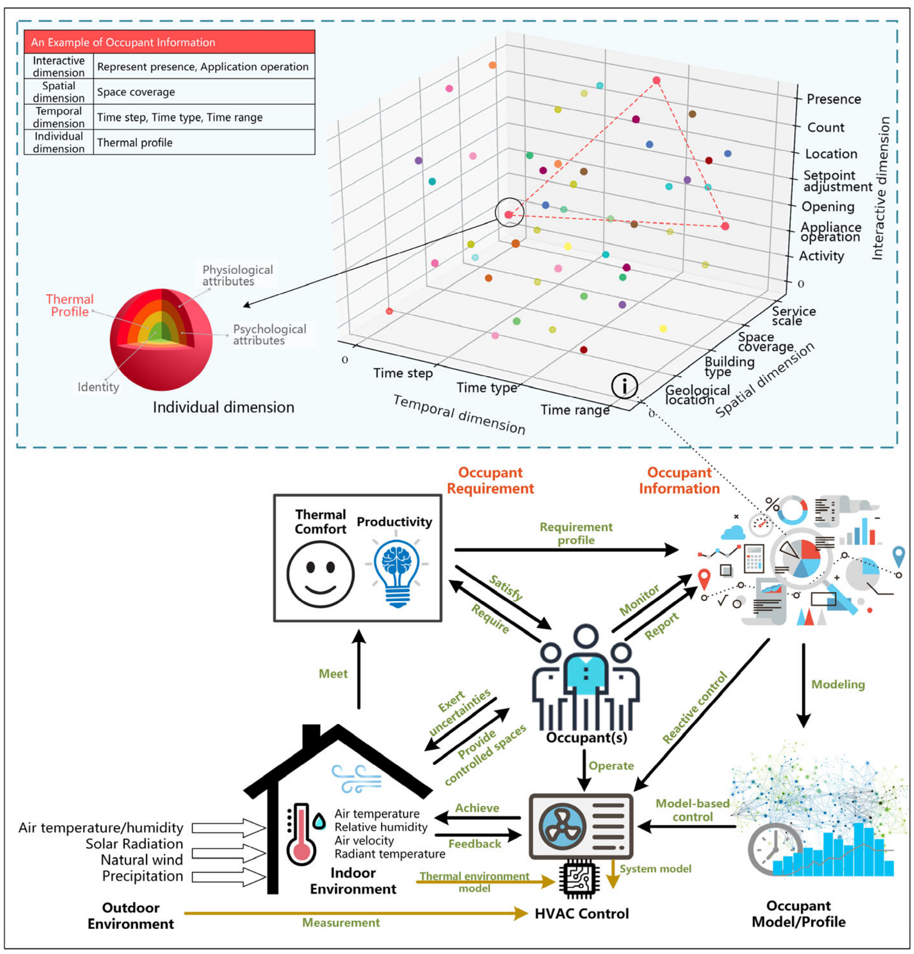


Fig. 2 Workflow of HVAC OCC—"From Occupants to Occupants"

concept of "from occupants to occupants"—OCC starts with collecting occupant information and comfort preferences, goes through occupant information transformation, and ends with requirements. Occupants are always at the center of the control cycle since the indoor environment is supposed to be controlled to satisfy occupants' needs. From a control system's perspectives, occupants are the sources of the information needed for control and they interact with the HVAC system (such as adjusting a thermostat), hence exerting uncertainties on the system that is being controlled. Occupant related information, such as occupancy, occupant behavior, occupant comfort, etc., are provided to the HVAC control directly for reactive control or indirectly through occupant model/profile for model-based control.

Four-dimensional occupant information datasets are demonstrated at the top of Figure 2. The z-axis of the coordinate grid is occupant information of interactive dimension, while the x-axis and y-axis denote temporal dimension and spatial dimension respectively. The tick marks correspond to different resolutions. Groups of small balls with the same color are sets of occupant information for different cases. The individual dimension is illustrated in the enlarged pink ball, where different layers denote different resolutions. Linked with red dashed lines, an example set of occupant information includes three small pink balls, which represent presence and application operation in the interactive dimension, space coverage in the spatial dimension, time step, time type, and time range in the temporal dimension, and thermal profile in the individual dimension.

1.2 Existing relevant review articles

Table 1 presents a list of existing review papers that focus on OCC for HVAC equipment and systems in buildings. Even though a widely used definition for OCC does not exist, the three essential elements of OCC—sensing systems, occupant modeling systems, and control systems—are commonly recognized. The review papers curated here comprise a systematic review of the properties and key elements of OCC in HVAC operations.

Observing existing review studies, there is a lack of systematic and comprehensive review of OCC with a strong emphasis on the characteristics and application of occupant information. Compared to other reviews that emphasize the different components of OCC (Eulerian perspective—similar to "specific locations" in a flow field), we will focus on occupant information in HVAC OCC (Lagrangian point of view—similar to the individual particles in a flow field) (Durst et al. 1984). This paper attempts to contribute to the existing literature by addressing the following five questions listed in Table 2.

These five questions originate from the application of occupant information in the HVAC operation by researchers and practitioners (i.e., what we should obtain and know if we want to implement effective occupant-centric control in

Table 1 State-of-the-art review articles related to the occupant-centric control

Reference	Year	Specific contributions
Mirakhorli and Dong 2016	2016	• The first review paper related to occupant-centric HVAC control • Expatiated the application of occupant information in model predictive control (MPC)
Shen et al. 2017	2017	• Analyzed the resolution and accuracy of building occupancy • Focused on sensing approaches
Naylor et al. 2018	2018	• Presented the collection of occupant data categorized as presence/number, location, activity, and energy behavior • Explained occupant-centric control strategies: real-time response to occupancy, control based on individual occupant preference and behaviors/activity types, control through occupancy/behavior prediction
Salimi and Hammad 2019	2019	• Explained a variety of HVAC control systems: set-point-based occupancy detection control, MPC, local control • Created a roadmap regarding the advances in different dimensions of the building management system (BMS)
Park et al. 2019	2019	• Focusing on field-implementation case studies in actual buildings • Analyzed OCC research trends by text-mining the identified publications • Classified HVAC OCC as occupancy-centric control (presence and count) and occupant behavior-centric control (thermal comfort)
Jung and Jazizadeh 2019	2019	• Explored literature from the perspective of human-in-the-loop HVAC systems • Presented holistic process maps in two modalities: occupancy-based and comfort-aware control
O'Brien et al. 2020	2020	• Highlighted the challenges and priorities in occupant-centric building design and operation
Xie et al. 2020	2020	• Concentrated on comfort-driven environmental control
Stopps et al. 2021	2021	• Focused on discussion of residential applications of OCC • Explored the historical advancement of residential OCC
Harputlugil and de Wilde 2021	2021	• Investigated the influence of occupant behavior in the HVAC control network

Table 2 Five questions concerning OCC for the HVAC operation in buildings

No.	Questions	Relevant sections
1	What is the comprehensive understanding of occupant information in relation to HVAC control in buildings?	Sections 2–4
2	What form of occupant information is required for the HVAC system?	Section 3
3	How is occupant information involved in HVAC control?	Section 4
4	What methodologies are currently used for occupant-centric HVAC control?	Section 4.2
5	How can researchers and practitioners choose particular occupant information and OCC control strategies?	Section 5

the indoor environment), while also following the essential elements of the basic human cognitive process (what it is, why it matters, and how it is applied) (Kamijo et al. 2007). Thus, this paper aims to primarily define and clarify what kind of occupant information is required, without delving into how it is acquired (which is the work of researchers and practitioners in other fields). We collect OCC-related papers and categorize them into these predefined questions to evaluate if these questions are sufficient to cover most of the research objects and answered well.

1.3 Objective, scope, and organization of the article

The objective of this review paper is to present an in-depth understanding of the different features of occupant information and its application in OCC, as well as explore how this information passes from the sensing module to the building control module, with special emphasis on analyzing linkages between these modules.

The scope of this article is on HVAC systems for occupant-centric control. Mature lighting-associated OCC techniques are not discussed in this paper except for the purpose of making a comparison. The rest of this paper is organized as follows. Section 2 presents a fine-grained, comprehensive picture of occupant information, while Section 3 focuses on the representation, acquisition, and transformation of occupant information in OCC. Section 4 explains how this information is applied in HVAC OCC. Finally, the cost-efficiency, interdisciplinarity, and humanistic consideration of OCC are explored in Section 5, where answers to the five questions raised in the introduction section are also summarized.

2 Occupant information database for HVAC OCC

2.1 Paper collection for reviews

We focused our efforts on curating relevant academic publications on occupant-centric control of HVAC systems. Since several papers did not use the terms "occupant-centric control" or "OCC" directly, we used a variety of search keywords like "occupant-centric control," "human-in-the-loop control," "demand-driven control," "occupancy-based control," "human-building interaction," etc. in Google Scholar and Scopus to ensure that the collected studies represent the wide range of existing literature. Additionally, we scanned the bibliographies of the collected papers and investigated the authors' Google Scholar pages to track any relevant studies we might have missed. A detailed flowchart of the article curation process can be observed in Figure 3.

Some of the collected papers were not suitable to be included in our review article for the following reasons:

- Implementation of OCC in the building lighting system;
- Relates to only one of three elements (i.e., sensing, occupant modeling, and controlling) of OCC; and
- Multiple papers from the same authors covering similar concepts and narratives (e.g., different versions of an article published first as a conference paper and then as a journal article).

Finally, we obtained a total of 77 papers that aligned with the goals of this review study.

2.2 Occupant information database

Occupant information is the data generated by occupants and their interactions with the buildings that they live in. In this paper, we propose to systematically classify occupant information using the two metrics, "dimension" and "resolution." "Dimension" refers to a cluster of information with similar attributes, while "resolution" is the specific definition for a piece of information belonging to a particular dimension.

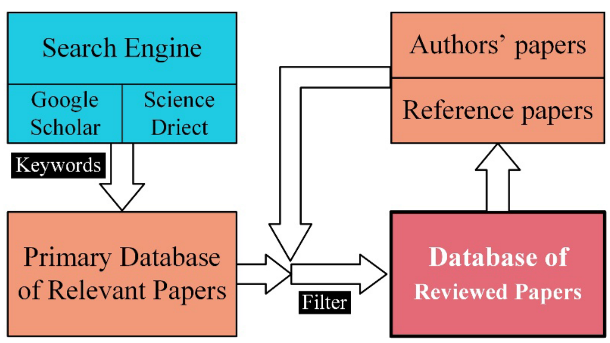


Fig. 3 Paper collection process

We categorize occupant information into the following four dimensions:

1) Interactive dimension: Information that is generated when occupants interact with the building, such as presence, location, etc.
2) Individual dimension: Information that belongs to the inherent characteristics of individual occupants, such as identity, thermal preference, etc.
3) Temporal dimension: Information that refers to the time, such as weekday and weekend, the time step of 15 minutes, etc.
4) Spatial dimension: Information that refers to space, such as building types (offices vs. residences), room types (private vs. shared), etc.

All dimensions and resolutions are explained in Table 3 with their respective definitions, examples, and applications. It should be noted that for this study, we only consider occupant information related to the indoor environment that is controlled by building HVAC systems. In the following subsections, we will discuss the four dimensions and their resolutions in detail.

2.2.1 *Interactive dimension*

The interactive dimension includes all occupant information generated when people interact with the buildings that they live or work in. When an occupant stays in a building, he/she creates a relationship with this space and influences the energy consumption patterns of the building HVAC system. The built indoor environment also affects occupant behavior, thereby creating the interactive dimension. Examples of this dimension include passive occupant information like occupant presence, number of the occupant, and location, as well as active occupant behavior such as opening windows, adjusting thermostat setpoint, and operating electrical appliances (Chen et al. 2015; Hu et al. 2020).

1) Presence

Presence is a binary parameter (i.e., 0 or 1) that represents whether any occupants exist in a particular space (Naylor et al. 2018). This parameter supports HVAC operation by negating the need for an all-time-on or predefined on/off operation schedule. Once the presence information (occupied or unoccupied) is available, the control strategy involves turning off or throttling back the HVAC system—an operation that has significant energy-saving potential. Due to the ease of recording this information, presence is the occupant information that was first applied in OCC and is mostly applied to date (Mirakhorli and Dong 2016). Rosiek and Batlles (2013) used this parameter to optimize the operating sequence of the solar-assist air-conditioning system. The cooling process started only when employees were detected to be present in the office. The results show that up to 42% energy saving could be achieved in the cooling season.

2) People count

People count refers to the number of occupants in a given space (Wang et al. 2017). It helps to quantify the real load instead of the maximum load schedule that is assumed in the design process. A typical application of this parameter in HVAC operation is DCV that adjusts the outdoor air supply rate based on the count information (Li et al. 2012). Two light beam sensors and three camera sensors were used in the study by Kuutti et al. (2014) study to detect the number of people and an energy consumption saving of people counting sensor-based DCV over the constant air volume ventilation (CAV) was demonstrated with an averaged 46% of the daily airflow reduction.

3) Location

Location refers to the spatial coordinates of an occupant in a room (Liu et al. 2016). It makes it possible to adjust the HAVC control to achieve zonal or individual level with personal comfort systems (PCSs) (Nagarathinam et al. 2017; Magni et al. 2019). Nagarathinam et al. (2017) utilized the spatial location of each occupant with desk tagging information in open-plan offices and optimized local temperature setpoints, which resulted in up to 12% energy savings. It implies that such a system can create a local environment required by a specific person without affecting others in the same space, as well as save energy with temperature setpoints setback (Jung and Jazizadeh 2019).

4) Thermostat setpoint adjustment

Setpoint refers to the indoor air temperature expected by an occupant or a group of occupants (Zhao et al. 2015). It is presumed that comfortable conditions are achieved when the thermostat is observed to be maintaining the required setpoint (Lu et al. 2010; Pritoni et al. 2016). Thus, Barbato et al. (2009) estimated the thermal comfort range of occupants from their interactions with thermostats. Some other researchers, in contrast, treated the action of adjusting the thermostat as an indicator of discomfort and then recorded these dissatisfactions to investigate a comfort principle for HVAC control (Tse and Chan 2008).

5) Envelope operation

Envelope operation denotes the behavior of opening windows, curtains/blinds, or doors (Zhong and Ridley 2020; Zhou et al. 2021a). It is a way for occupants to satisfy their comfort needs by adjusting the air-exchange and solar-thermal transfer between the indoor and outdoor environment. Similar to setpoint adjustment, opening records also provide information to estimate one's comfort status and thermal preference. Andersen (2009) demonstrated a strong correlation between window opening behavior and temperature, while Dong et al. (2018) argued that the behavior patterns of window opening are not coupled with environmental factors in some cases, but simply a part of occupants' daily routines.

Table 3 List of dimensions and resolutions of occupant information

Dimension	Resolution	Definition	Example	Application
Interaction dimension (information that is generated when occupants interact with the building)	Presence [O]	A binary parameter indicating whether space is occupied	Occupied/unoccupied	Turning off or throttling back the HVAC system when unoccupied, instead of an all-time-on or predefined on/off schedule
	Count [O]	The number of occupants in the given space	0, 1, 2, etc.	Providing accurate real load, instead of the maximum load schedule that is assumed in the design process; Typical application in HVAC operation is demand controlled ventilation (DCV)
	Location [O]	The spatial coordinates of an occupant in the room	Places: at the desk, etc.; x and y coordinates	Tailoring building control to an individual level and tracking movement
	Thermostat setpoint adjustment [O]	The indoor air temperature expected by one occupant or group	24 °C, 26 °C, etc.	Assessing occupants' comfort by detecting whether thermostats setpoint temperatures are maintained or not
	Envelope operation [O]	A behavior of opening windows, curtains/blinds, or doors	Opening windows, etc.	Provides information to estimate occupant's comfort status and thermal preference; Provides information for energy consumption
	Appliance operation [O]	Use of electrical appliances	Computer desktop, printer, etc.	A reliable and cost-effective way to offer occupancy information
	Activity level (metabolic rate) [O]	A physical process that occupants conduct (not intended to adjust the indoor thermal environment)	Meeting, walking, etc.	Acts as a reference to maintain a suitable built environment since people with different activity levels likely have variable comfort preferences and CO_2 generations
Individual dimension (information that belongs to inherent characteristics of individual occupants)	Identity [Δ]	A unique ID for one person		Assists in conducting personalized and local indoor environment control by offering the predefined comfort profile for the given occupant.
	Thermal profile [Δ]	The occupants' preferred or acceptable thermal environment	24 °C & 75% RH, etc.	Consists of thermal preference and thermal acceptability; Classified into individual comfort and collective comfort; Meeting occupants' thermal comfort preference is one of the main objectives of HVAC control.
	Physiological/ physical demographics [OΔ]	The normal characteristics of living organisms and their body parts (including their clothing)	Age, gender, weight, shape, skin/ hair/ eye color, heart rate, blood pressure, skin temperature, clothes, etc.	Serve as influential factors to determine an occupant's thermal preference levels and act as an indicator for thermal comfort
	Psychological demographics [OΔ]	Mental and emotional states	Temperature expectation, etc.	Inconsistencies in thermal preference measurement may stem from the failure to account for psychological variation.
Temporal dimension (information that refers to the time)	Time step [Δ]	The minimum chosen unit of time	seconds, minutes, hours, days, etc.	The frequency to measure the occupant information or conduct the control strategy; Determines the information density.
	Time type [Δ]	The category of a day, week, or year	summer/winter, weekday/ weekend, etc.	Occupant information has different patterns corresponding to different time types
	Time range [Δ]	The duration of occupant information measured	X days/weeks/months/ seasons/years, etc.	Serves to describe the time duration when acquiring occupant data
Spatial dimension (information that refers to space)	Geological location [Δ]	Where the target building is situated on the earth	Climate zones	Occupants' energy use modes can be significantly different based on locations.
	Building type [Δ]	The category of the building	Commercial building, residential building	Different building types have different HVAC systems and operations
	Space coverage [Δ]	The thermal zone that is of interest in a particular building	Local, room, zone, floor, building	Different space coverages correspond to different levels of localized controls
	Service scale [Δ]	The space serving a single person or multiple persons	private space, shared space, etc.	Used as the basis to choose approaches for sensing, comfort control, and devising control strategies

[O] denotes dynamic data.
[Δ] denotes static data

6) Appliance operation

Appliance operation refers to the behavior of using electrical appliances and is the most influential variable in building energy performance (Fukuta et al. 2015). It includes turning on lights, working on laptops, etc. While the office equipment is not driven by the quality of the indoor environment (Parys et al. 2011), recording information regarding usage of appliances is usually a reliable and cost-effective way of gathering occupancy information (Maaijen et al. 2012). For example, Newsham et al. (2017) leveraged a combination of keyboard/mouse activity and pixel changes in a webcam image to effectively infer occupancy information in single-person offices.

7) Activity level

Unlike occupant behavior, which includes energy-related actions like opening the window or turning on the thermostat, activity level refers to a physical process that occupants conduct without the intention to adjust the indoor thermal environment (Zhou et al. 2021b). It can be classified either into the two simple categories of "active" and "quiet" or into different tasks like meeting, studying, exercising, cooking, etc. Comfort requirements usually depend on the activity levels of occupants (Li et al. 2017b). Further, different levels of activity generate various CO_2 levels and heat loads from occupants should be considered (ASHRAE 2019a). Thus, this information can act as a critical reference for DCV strategy (O'Neill et al. 2020).

2.2.2 Individual dimension

In contrast to the interactive dimension, the individual dimension refers to those intrinsic features of one person or one group that do not change with variations in the building conditions technically. This dimension is added to the occupant information database whenever a person is present, regardless of what he/she is doing (Teixeira et al. 2010). The individual dimension is usually used for personalized control of the built environment and adds a level of uncertainty and uniqueness to the occupant information.

1) Identity

Identity is a unique ID for one person (Teixeira et al. 2010). It can provide information about who the person is. For example, Balaji et al. (2013) detected occupancy by mapping WiFi logs to the owner's identity. Therefore identity-detection can aid in conducting personalized and local indoor environment control by offering the predefined comfort profile for the particular occupant.

2) Thermal profile

The thermal profile comprises thermal preference, which is used to describe the occupant's preferred thermal environment, and thermal acceptability, which indicates the thermal environment that the occupant can accept (Brager et al. 1993; Langevin et al. 2013). It is a subjective indication and a response to the combination of environmental parameters. Two significant features of thermal profile are uncertainty and fluctuation (both point towards inconsistency with the environment). This inconsistency exists not only for different persons but can also occur on different occasions for one person. As Jazizadeh et al. (Jazizadeh et al. 2014) found, one person reported different thermal preferences under the same thermal condition (e.g., reporting −20 (wanted to be cool) to 10 (wanted to be warm) at the same indoor air dry bulb temperature of 26 °C) and the same thermal preference at different temperatures (i.e., reporting 0, no need to be cooler or warmer, for any temperature between 22 °C and 26 °C).

3) Physiological attributes

ASHRAE 55 (ASHRAE 2017) defines "thermal comfort" as: "That condition of mind which expresses satisfaction with the thermal environment." This definition provides an open understanding of thermal satisfaction and emphasizes that comfort is a cognitive process affected by different factors, such as physical, physiological, and psychological attributes.

Physiological attributes are body-related factors (Teixeira et al. 2010), e.g., age, gender, weight, shape, skin/hair/eye colors, heart rate, blood pressure, skin temperature, etc.

People will feel thermal comfort when his/her body temperature keeps in a close range with less physiological effort for adjustment (ASHRAE 2019b). For example, when the temperature rises, sweat glands spring into action, making perspiration (Jung and Jazizadeh 2019). Likewise, Li and Chen (2021) operated an HVAC system with facial skin temperature measurement in a single-occupied office and achieved a 91% thermal neutrality.

4) Psychological attributes

Psychological conditions can be difficult to sense (Jazizadeh and Becerik-Gerber 2012) and inconsistencies in thermal preference measurement partly stem from the failure to account for their variations (Jung and Jazizadeh 2019). Langevin et al. (2012) found that perceived control levels (the ability to control the indoor environment in line with their expectations) are statistically related to occupants' thermal satisfaction. Compared to those who perceived little or no control over the indoor environment, occupants with easier access to control were found to be more tolerant towards a wider temperature range (Brager et al. 2004; Toftum 2010). To utilize physiological and psychological attributes, factors that should be considered are applicability, sensitivity, non-intrusiveness, and ubiquity (Jung and Jazizadeh 2017, 2018, 2019).

2.2.3 Temporal dimension

The temporal dimension describes occupant information from the perspective of time and provides sequenced tags for occupant information recording. Each piece of occupant information in the temporal dimension is an indispensable component of the overall time slice of building operation information. Based on application type, we categorize the solutions in the temporal dimension as: 1) time step; 2) time type (e.g., summer/winter, weekday/weekend, etc.); and 3) time range (e.g., days, weeks, months, years, etc.).

1) Time step

Time step is the minimum chosen unit of time (Nagarathinam et al. 2017) and determines the information density. It is the frequency at which occupant information is measured or the control strategy is conducted. A time step can be chosen to be seconds (Erickson et al. 2009; Scott et al. 2011; Erickson et al. 2013), minutes (Nassif and Moujaes 2008; Widén and Wäckelgård 2010; Maaijen et al. 2012; Goyal et al. 2013; O'Brien et al. 2017; Gilani et al. 2018), hours (1 hour for heating control (Dong et al. 2011)), among which 5 minutes (Nassif and Moujaes 2008; Maaijen et al. 2012; O'Brien et al. 2017) are the most commonly used time step for data acquisition. The higher resolution of time steps can potentially capture the dynamic variation of occupant information, which in turn allows us to conduct a more detailed analysis if required. However, recording information at high resolution can require additional sensory energy, extra storage space, and more computational time to parse through (Melfi et al. 2011).

2) Time type

Time type is the category of time. Examples include daytime and nighttime for one day, workday and weekend for one week, summer and winter for one year. Occupant information can have different patterns corresponding to different time types (Lee et al. 2019). In a particular study, when occupant information is categorized into different time types, the control strategy is often simplified. Using this approach, Gunay et al. (2016) studied temperature setbacks during the night on weekends and on weekdays and finally found that a setback schedule could cover less than 55% of the year.

3) Time range

Time range is the duration of occupant information acquisition or OCC implementation (Erickson et al. 2009). It could be minutes, hours, days, weeks, or even months. The use of prediction horizon (the amount of time into the future for which predictions are made (Naylor et al. 2018)) in predictive optimal control (Nguyen and Aiello 2013) is an example of the utility of time range. The time range of OCC validation in literature can vary significantly from a few hours (Castilla et al. 2011) up to a year (Aghemo et al. 2014). Most studies focus on short-term occupant information to implement OCC in buildings.

2.2.4 Spatial dimension

The spatial dimension refers to the occupant information from the perspective of the space where this information is generated (Xie et al. 2019). Based on the application type, solutions in the spatial dimension can be categorized as 1) geological location, 2) building type, 3) space coverage, or 4) service scale.

1) Geological location

Geological location is the place where the target building is situated on the earth. Climate zones are often more meaningful when discussing geological locations. International Energy Conservation Code (IECC) (Suh et al. 2014) divides the US regions into eight temperature-oriented climate zones. Different climate zones not only have contrasting local weather patterns but also have distinct occupant energy use modes. Pang et al. (2020a) quantified the influence of group occupant schedules on HVAC energy performance in five locations by simulating a medium-sized office from the DOE Commercial Prototype Building Models. They found a higher rate of energy savings in heating-dominated climate zones as compared to that in cooling-dominated zones. For example, the energy-saving ratio in Chicago (Zone 5A) was 42.3%, while that in Houston (Zone 2A) was found to be only 18.5%.

2) Building type

For the purpose of this review article, buildings are classified as commercial building types and residential building types, as defined in Field et al. (2010). Commercial buildings include offices, hospitals, schools, etc. Among these building types, offices are most commonly studied (Jung and Jazizadeh 2019). Different types of buildings have significantly different HAVC operation schedules (Naylor et al. 2018).

3) Space coverage

Space coverage refers to the thermal space of interest in a building. It includes local, rooms, zones, floors, and buildings. The resolution of space coverage in a particular study depends on the purpose of research and the sensing ability. Different space coverages correspond to different levels of localized control. A majority of the existing literature detects coverage at the room or zone level (Shen et al. 2017).

4) Service scale

Service scale refers to a space serving a single person or multiple persons, i.e., a shared space or a private space. Thermal sensing usually has higher accuracy in a single-person space than in a multiple-person space. It is also easier to achieve satisfaction using thermal comfort control in a single-person room since comfort conflicts can cause problems in a multi-occupied space. However, in terms of control strategy, a private room is less suitable for predictive control than an open-plan room (Nagarathinam et al. 2017).

3 Representation, acquisition, and transformation of occupant information

3.1 Occupant information representation

Before the occupant information summarized in Section 2 can be utilized, the raw data needs to be processed and represented in a form that is applicable for occupant-centric control of HVAC systems. Single independent points of information can be directly used in real-time reactive control. However, for advanced control strategies (like predictive control), it is necessary to analyze a batch of points and develop corresponding occupant models.

3.1.1 Independent points

Independent points can contain any of the different types of occupant information described in Section 2. They are commonly used as an instantaneous "if-then" control strategy. For example, if space is "unoccupied," the temperature is adjusted as a setback. This is called reactive control or feedback control, which will be discussed in Section 4 in detail. An independent point can also act as the input of one occupant model for predictive control.

3.1.2 Grouped points

Grouped points are a series of independent points. Collectively, these points form an occupant model to either support predictive control directly or to indicate occupant information with ambient values. Occupant models can be classified as occupant schedules and occupant profiles. Occupant schedules represent groups of occupancy information (e.g., presence, number, setpoint, etc.) over time, while occupant profiles indicate occupant thermal profile and occupant behavior (e.g., adjust setpoint, open door/window, turn on/off the electrical appliances, etc.) related to building energy performance (Tang et al. 2021).

1) Occupant schedule

The occupant schedule is a traditional way of providing occupant information for HVAC design and operation. It is usually an hourly binary value or fraction of the presumed occupancy (having a value between 0 and 1) on weekdays/weekends/holidays (Chen et al. 2015). A typical occupancy schedule in an office is shown in Figure 4. The occupant schedule used by the current energy modeling is usually predefined based on the ASHRAE standards (Jia et al. 2017), so it cannot reflect the real occupancy variation. Simulations of different schedules and behaviors

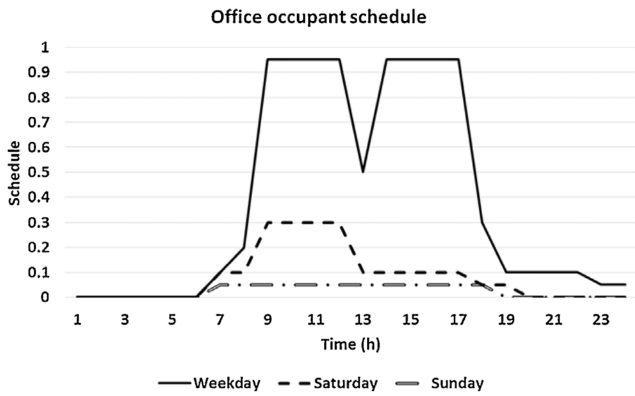


Fig. 4 Office occupant schedule in the DOE reference model for office buildings (Sun and Hong 2017)

in commercial buildings showed an occupant-dependent variation of 30%–150% of final energy use (Naylor et al. 2018). Thus, in OCC, the predefined schedule is upgraded by real-time occupancy information (Muroni et al. 2019; Kang et al. 2021). For example, Gunay et al. (2015) learned the occupancy patterns and parameters to dynamically adjust the setback temperature schedules.

2) Occupant profile

Occupant profiles include occupant thermal profiles and behavior models that can be used for practical controls of building HVAC systems (Jia et al. 2017; Zhang et al. 2021). While occupant schedule is widely studied to replace conventional fixed- schedule operation of building systems, research involving occupant profiles is limited.

Quite a few data-driven techniques, including logistic regression, artificial neural networks, fuzzy predictive modeling, Gaussian process, are employed to learn occupant preference with diverse types of variables (Fan et al. 2021; Zhu et al. 2021a). Apply a smartphone application framework, Li et al. (2017a) achieved a thermal preference prediction accuracy of 0.68 and 0.62 separately, using a logistic regression and a linear regression with various input variables (e.g., indoor temperature/umidity, skin temperature, cloth level, etc.).

For occupant behavior models, one of the main objectives is to assist Model Predictive Control (MPC) in predicting the future evolution of the building system so that control actions can be generated in advance to meet the occupants' requirements to the extent possible (Oldewurtel et al. 2012). Since occupant behavior usually has a causal relationship with the surrounding environment, ambient data sensors are usually placed within the area of interest. Langevin et al. (2015, 2016) used agent-based modeling (ABM) approach to explore the interaction between occupants in a medium-sized, air-conditioned office building and built environment systems for adaptive behaviors, like turning fan, heater, and window on/off.

3.2 Occupant information acquisition and transformation

The acquisition of raw occupant information is the first step of OCC. Technological advances in the fields of electrical and computer engineering over the past decade have helped facilitate data collection and enhance data accuracy. Physical measurements and survey studies are the two different approaches to conduct occupant information acquisition (Awada et al. 2021). Various types of devices, such as sensors, cameras, or meters, are currently used (Jia et al. 2017).

A majority of sensed occupant information originates in the interactive dimension, especially presence and count resolutions. Reviews on occupant information acquisition are out of the scope of this paper. If readers are interested in the detailed descriptions of sensing system techniques as well as their accuracy, advantages, and limitations (which are beyond the scope of this paper), review papers from Jung and Jazizadeh (2019), Shen et al. (2017), and Dong et al. (2019) are recommended.

After the collection of selected data, occupant modeling is required to transform the data to the modes (Wang et al. 2011; Jin et al. 2020), as described in Section 3.1. Then, occupant profiles can be used for predictive control of the indoor environment (Jin et al. 2021a; Zhou et al. 2021c). The main techniques currently used to model occupant information can be categorized into "agent-based modeling (Lee and Malkawi 2014)," "statistical analysis (Langevin et al. 2012)," "data mining (D'Oca and Hong 2015)," and "stochastic modeling (Meyn et al. 2009)."

4 Application of occupant information in HVAC control

The ultimate goal of OCC is to satisfy the comfort requirement of occupants in required spaces throughout a preferred timeframe, while achieving other performance goals, such as saving energy. To achieve this goal, building operations should automatically respond to dynamic thermal load instead of relying on fixed schedules and maximum occupancy assumptions. This drives the need for the upgradation of traditional HVAC control with real-time occupant information, as shown in Figure 5.

In this section, we first introduce the commonly applied occupant information in OCC. Then, we introduce two control elements: the control strategy (i.e., reactive control and predictive control) and control objects (i.e., temperature and ventilation). These two types of elements are categorized from the perspectives of the required operation timing and the required indoor environment for HVAC control, respectively.

4.1 Occupant information applied in the OCC

While each piece of occupant information presented in Section 2 is useful in occupant-centric control, only a few of that information is utilized currently due to the complexity and cost. Figure 6 presents that presence, count, location, identity, thermal preference, and activity levels have all been utilized for HVAC OCC in the paper reviewed in this

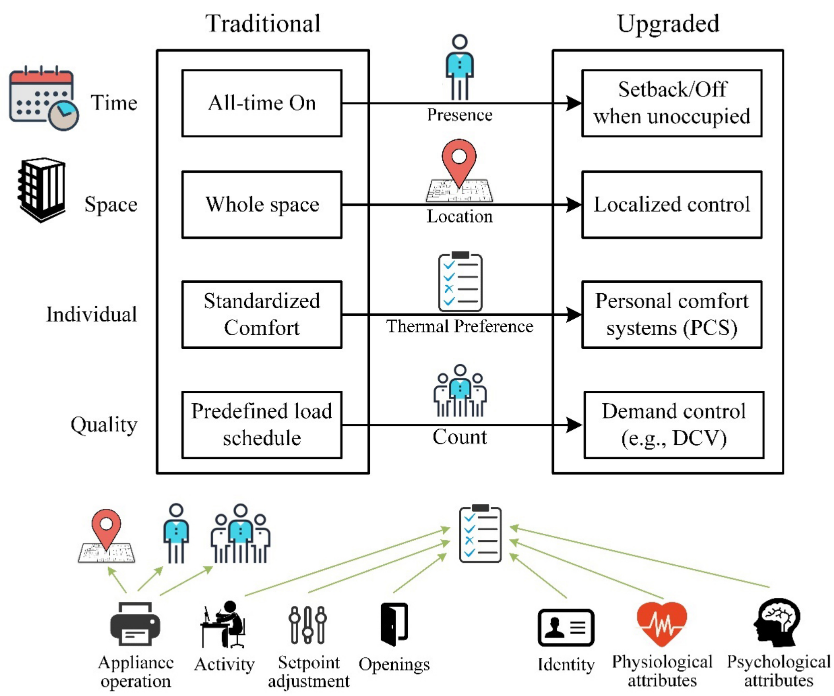
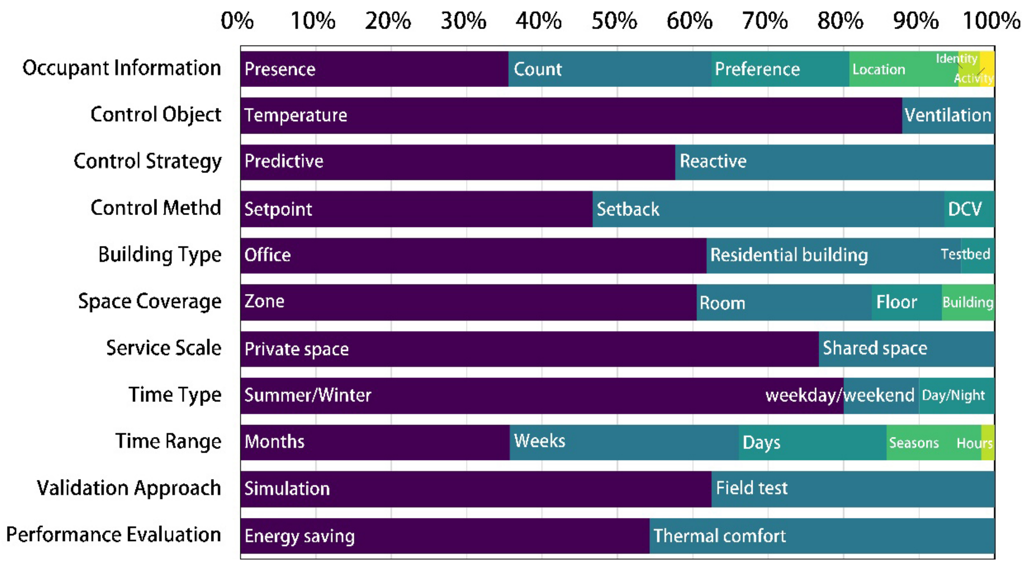


Fig. 5 Functions of occupant information in HVAC OCC (the green arrows represent the inference direction (e.g., occupant presence can be detected by printer operation), while the black arrows display the upgradation direction)



* Some of location/identity is used for counting calculation.

Fig. 6 Application percentage distribution of occupant information in reviewed papers

study. Among them, presence (~35.6%) and count (~26.9%) are the most common occupant information used in existing studies that are reviewed. Specific control of each occupant's information has been expatiated in Section 2 and is not repeated here.

4.2 Control strategy

From the perspective of the temporal dimension, several HVAC OCC strategies with occupant information can be implemented to optimize parameters (like temperature setpoints and airflow volumes) during the required timeframe (Li et al. 2012; Ouf et al. 2021). Alkhatib et al. (2021) reviewed a series of control methods (e.g., rule-based control, intelligent control, adaptive control, etc.) that can be used to handle occupant-like uncertainties in the control loop. Based on that, we introduce two strategies in the following subsections: reactive control and predictive control, classified by the time scale. Both strategies are significant improvements from the traditional fixed schedule.

4.2.1 Reactive control

Occupant-reactive operation (i.e., feedback control, real-time response, etc.) is an intuitive operational strategy. It involves adjusting the operational settings of an HVAC system in real-time when a change (presence/absence) in the occupant state of a particular space is observed (Jung and Jazizadeh 2019). Examples include turning off the system or letting the temperature/ventilation in a room drift away from comfortable conditions when the room is detected to be unoccupied. When space is occupied again, the HVAC system will be operated to recover the comfort levels. Pang et al. (2020b) applied this control strategy and used a heating setpoint of 21 °C and a cooling setpoint of 24 °C during occupied hours, and 1 °C (for offices)/2 °C (for conference rooms) for the setback in unoccupied hours. Simulation results showed a 19%–44% reduction in HVAC energy consumption nationwide, for the medium office using the ASHRAE Standard 90.1–2004 as the baseline.

Unlike lighting, the thermal ramp up or down of a room involves delay because of the thermal inertia of buildings. Thus, reactively conditioning a room will likely leave occupants uncomfortable until the target indoor environment is met. Because of its contribution to energy saving, it is suitable for the scenario where precise comfort control is not required. However, in some cases, it might be more energy efficient to maintain temperature than to ramp up temperatures from a very low level, as the reactive strategy has to work hard to ramp up the room temperatures between periods of occupancy (Erickson et al. 2013). These shortcomings of reactive control can partially be solved by using predictive control with forecasting occupant information.

4.2.2 Predictive control

Though towards a similar objective of utilizing real-time occupant information and adjusting the indoor environment based on occupant requirement, the main difference of predictive control from active control is the operation time, i.e., "predictive horizon.", which is strongly related to the occupancy and occupant behavior prediction (Alkhatib et al. 2021; Jin et al. 2021b). Utilizing the slower-response HVAC systems, predictive control aims to condition the space to acceptable levels in advance by predicting the attributes of occupant-based space in the near future. This preconditioning time helps relieve the discomfort of occupants at the beginning of HVAC operation and reduces energy waste by a setback when the space is unoccupied.

Predictive control that cooperates with occupant information can be categorized as rule-based control (RBC) and optimal control (Drgoňa et al. 2020). RBC constructs a set of predefined rules, which are defined as a function of preconditioning time, conditioning rate, or occupancy probability (Esrafilian-Najafabadi and Haghighat 2021), to achieve thermal comfort and energy saving, corresponding to the future occupancy status. Applying such an RBC strategy for OCC, Peng et al. (2018) reported 7%–52% energy savings in various room types of a real building.

More advanced and complex compared to the RBC, MPC, a dominant strategy in optimal control, employs optimization algorithms to support HVAC control decisions. MPC requires a model that is used for predicting some variables and figures out the optimal control actions in advance by taking into account the occupant comfort and technological constraints, and weather forecasts (Drgoňa et al. 2020). It can improve thermal comfort while achieving energy saving from 15% up to 50% in several simulations and field tests (Ma et al. 2012; Maasoumy et al. 2014; Dobbs and Hencey 2014).

4.3 Control objects

The goal of occupant-centric control is to provide an indoor built environment that satisfies the comfort and work efficiency requirements of occupants while maintaining other building performances. Temperature and ventilation are the main control variables (Janssen 1999). The temperature in a space, controlled according to the occupant's thermal preference, occupancy detection, occupant activity, and outside weather, directly affects the comfort of occupants. It is the most commonly used control object (Balaji et al. 2013; Gao and Keshav 2013; Jazizadeh et al. 2013). As shown in Figure 6, room temperature is the primary control object, accounting for 87.7% of the reviewed OCC papers.

Ventilation air is introduced into the zone to improve indoor air quality, of which the required minimum amount is dependent on the real-time number of occupants. Ventilation control is usually involved in the temperature setpoint regulation. O'Neill et al. (2020) conducted a simulation study of the CO_2 based DCV in typical single-duct variable air volume systems. This study reported 9%~33% HVAC energy savings compared to the baseline of a simplified ASHRAE 62.1 approach in four U.S. climate zones.

5 Discussion

5.1 Accuracy and errors of occupant information: Balance in HVAC OCC

A balance must be maintained between the accuracy level of occupant information and the financial or computational cost associated with collecting or predicting that information. High accuracy requirements with smaller time steps in the temporal dimension can lead to significant sensory equipment costs (Shen et al. 2017) and the computational burden of running complex algorithms (Dong et al. 2019). Therefore, it is beneficial to define a minimum acceptable accuracy limit for occupant data that will still satisfy the primary objective of maintaining thermal comfort.

The HVAC system is generally error-tolerant in HVAC OCC. Unlike lighting control, which has an immediate influence on occupants, HVAC control can endure prediction errors to a large extent (Bengea et al. 2015). Occupancy sensing errors can be categorized as false positive (sensing someone in the zone when, in fact, the zone is unoccupied) and false negative (sensing no one in the zone when, in fact, the zone is occupied) (Shen et al. 2017). A system with false positives will waste energy, while a system with false negatives will result in occupant inconvenience. Since in reality, in particular for office buildings, satisfying occupant comfort usually takes the relatively higher priority than reducing energy consumption, false negatives are generally more problematic than false positives.

5.2 Interdisciplinary efforts: Techniques fuel OCC

Technological advancements and scientific innovations require strong interdisciplinary efforts. information & communication technology (ICT) and computer science (CS) (e.g., artificial intelligence (AI)) are two significant interdisciplinary technologies that aid the collection, transportation, storage, and transformation of occupant information.

5.2.1 Information & communication technology

Many occupants have to endure thermal dissatisfaction (Huizenga et al. 2006) owing to inaccurate occupant information acquisition and consequent over-cooling/heating (Sanguinetti et al. 2016; Jung and Jazizadeh 2018). Over the past few decades, declining hardware costs and the availability of configurable software have made it possible for researchers to collect a huge amount of real-time data in different categories (e.g., presence, number of people, comfort feedback, etc.). This data has, in turn, fueled the rapid development of OCC.

As a result of the advancements in ICT, IoT (Internet of Things) now provides ample opportunities for ubiquitous occupant data collection and communication. For example, it can combine occupancy-related sensors and data sources to support building occupant detection with less cost (Shen et al. 2017) for the application of data-driven pattern recognition and occupant-centric control algorithms.

5.2.2 *Artificial intelligence*

Occupant model development with AI methods (e.g., machine learning) has been prevailing in recent years (Ryu and Moon 2016; Huchuk et al. 2019; Lu et al. 2021). AI approaches are especially suitable for modeling human patterns (e.g., activity routine, presence schedule, thermal preference, etc.) as these can successfully extract relevant information from information security measures datasets as well as handle human behavior randomness. The growing amalgamation of AI predictive analysis and smart BMSs makes building systems self-learning and intelligent by adapting to changes and uncertainties in the building (Salimi and Hammad 2019).

5.3 Information privacy: Humanity matters

Due to acquiring and storing occupant information in OCC implementations, privacy concerns emerge. There are mainly two privacy concerns in intelligent buildings (Namdeo and Pawar 2017; Cui et al. 2018). The first is identity privacy. One example is the concern of using the video camera to collect occupant information in public spaces (Wang et al. 2017). The second one is location privacy, since location information is sometimes required for personalized OCC implementation or people counting (Park et al. 2019). More information means more responsibility. For the OCC deployment, more information security measures should be considered in the future to protect occupant privacy.

5.4 Open-source occupant dataset: Making the best of collective intelligence and labor

The availability of occupant information data is critical for occupant-centric control as it facilitates the development of more accurate occupant models for specific HVAC OCCs. Therefore, an open-source dataset is valuable for the entire HVAC field and beneficial to improving the quality of OCC research. Without an open dataset, it is virtually impossible to conduct a peer review properly or reproduce studies effectively. A consequence is that academic peer reviews are often capable of checking methods, without ways to verify the models and data proposed in the research (Pfenninger et al. 2017).

Open-source data also helps to save the time and cost of researchers and practitioners in the HVAC field. The collection of occupant information is usually time-consuming and expensive. An open occupant dataset, especially generated by research supported by public funds (Kazmi et al. 2021), can help avoid unnecessary duplication in the sense of collaboration. The Horizon 2020 project by the European Commission is one such example (Spichtinger 2012). Recently, several programs, including Ecobee's "Donate Your Data" (Ecobee), the Pecan Street Datasets (https://www.pecanstreet.org), the REFIT Datasets (REFIT 2019), and the ASHRAE Global Occupant Behavior Database (ASHRAE 2021), have begun making their efforts to build the available open-source of laboratory data and field data.

One of the problems facing the open dataset for occupant information is the collection standards of different researchers who are willing to make contributions. To deal with this issue, the International Energy Agency's Energy in Buildings and Communities Programme (IEA EBC) Annex 79 (O'Brien et al. 2020) initiated a platform for sensing technologies and data sources on Occupant Presence and Action (OPA). They proposed to develop a metadata schema to support the consistent sharing and reuse of OPA data. Similarly, Balaji et al. (2016) proposed Brick Schema to promote a united naming convention by developing a concrete ontology to describe sensors, equipment, and control variables contained in the BAS.

5.5 Brief answers to the questions raised in Introduction Section

Question 1: What is the comprehensive understanding of occupant information in relation to HVAC control in buildings?
Answer: Occupant information is the data generated by occupants and their interactions with the buildings that they live or work in. It can be classified systematically using the two metrics, "dimension" and "resolution." With occupant information, building services are delivered only when and where they are required for providing a suitable built environment for the occupant, and in the amount that they are required.
Question 2: What form of occupant information is required for the HVAC system?
Answer: Single independent points and grouped points of occupant information are applied in HVAC control. Grouped points can collectively form occupant models, which are classified as occupant schedules and occupant

profiles. Occupant schedules represent groups of occupancy information (e.g., presence, number, setpoint, etc.) over time, while occupant profiles indicate occupant thermal profile and occupant behavior (e.g., adjust setpoint, open door/window, turn on/off the electrical appliances, etc.) related to building energy performance.

Question 3: How is occupant information involved in HVAC control?

Answer: Occupant information improves HVAC control by providing the required operation timeframe and required indoor environment. These elements are revealed in the control strategy (reactive/predictive control) and control objects (temperature and ventilation), respectively. Single independent points of information can be directly used in real-time reactive control. Grouped points collectively form an occupant model to either support predictive control directly or to indicate occupant information with ambient environment values.

Question 4: What control strategies are currently used for occupant-centric HVAC control?

Answer: Two OCC control strategies are reactive control and predictive control. With specific occupant information known, both strategies are significant improvements from the traditional fixed schedule for energy efficiency and occupant comfort. Reactive control involves adjusting the operational settings of an HVAC system in real-time when a change (e.g., presence/absence) in the occupant state of a particular space is observed. Predictive control that cooperates with forecasted occupant information can be categorized as rule-based control and optimal control. Predictive control aims to condition the space to acceptable levels in advance by predicting the attributes of occupant-based space in the near future.

Question 5: How can researchers and practitioners choose particular occupant information and OCC control strategies?

Answer: When conducting OCC in the HVAC system, for a given application, particular occupant information can be inferred in Table 3. Meanwhile, costs and benefits of utilizing occupant information, along with the interdisciplinary techniques and information privacy should also be considered.

6 Conclusion and future research directions

This paper aims to provide an in-depth understanding of occupant information in HVAC OCC and explore how the occupant information flows from the sensing module to the building control module with special emphasis on the linkages between these modules.

Firstly, we compared the existing OCC-related review papers and defined OCC as any kind of HVAC control that considers the specific occupant information.

Secondly, we presented a fine-grained, comprehensive picture of occupant information with "dimensions" and "resolutions." We categorized various occupant information into four dimensions: Interactive dimension, Individual dimension, Temporal dimension, and Spatial dimension.

Furthermore, to reiterate, the ultimate goal of HVAC OCC is to satisfy the comfort preferences of occupants in required spaces throughout a required timeframe. In this paper, we discussed the application of the following aspects of occupant information:

1) Occupant information applied in OCC, including presence, count, location, comfort preference, activity level;
2) Control strategies: reactive control and predictive control (for required operation timing);
3) Control objects: temperature and ventilation (for the indoor built environment).

Finally, we also explored the costs and benefits of applying occupant information, the interdisciplinary techniques, and information privacy that are integral to the utilization of occupant information in OCC. Answers to the five questions of occupant information understanding raised in the Introduction section are also elaborated.

The future research directions are summarized as follows:

1) Interdisciplinarity is the inherent nature and driving force of HVAC OCC. It is imperative to enhance the connection with a variety of other cutting-edge research fields and develop a commonly acceptable protocol to transfer data and techniques among different disciplines.
   - Information and Communications Technology (ICT) research, including IoT, 5G (5th generation of mobile networks), and cloud computing, can provide more sources, data storage and communication approaches for occupant information and real-time control. IoT makes it possible to interconnect objects in the building and facilities occupant information acquisition by data fusion (Zhu et al. 2021b). 5G provides real-time big data access and speeds up the data transmission for occupant information. Cloud computing offers a shared and dynamic infrastructure for running advanced control algorithms with a large number of occupant information. Application of these ICT techniques can potentially remove obstacles for acquisition, transmission, storage and computation of occupant information in the application of OCC.
   - Computer Science (CS) research can enrich occupant information by data mining technique, transform occupant information to models by neural network technique (e.g., deep learning), or generate HVAC control logics by reinforcement learning.

- Grid-Interactive Efficient Building (GEB) research can incorporate occupant information into operations with flexible demand.
- The combination of these state-of-the-art technologies can largely strengthen occupant information acquisition. The computer vision technique, which performs well in multiple occupant information types (e.g., detection, counting, localization, identification, etc.), is a typical example. It can enhance computation power by transmitting images to the cloud over 5G and extract accurate occupant information by utilizing advanced image recognition in cloud computing, and then realize high accuracy occupant-centric HVAC control.

2) An open-source occupant information dataset would facilitate the development of more accurate occupant models for specific HVAC OCC, and promote academic peer review and research reproducibility.
3) Occupant information privacy and security is the biggest concern that hinders the occupant information from being open and accessible. Blockchain would be a possible way to solve this problem.
4) The non-intrusive sensing system is required to minimize the interference to the occupant's normal daily activities. The virtual sensor is a potential solution to provide non-intrusive and cost-effective measurement to detect occupancy by utilizing existing energy-related systems.
5) The balance between individual and collective occupant thermal requirements, especially when conflicting, still needs further investigation.
6) Occupant information, including lifestyle and schedule, varies in some new events (Sánchez-García et al. 2020), for example, the COVID-19 period (Dai and Zhao 2020). Pre- and post-pandemic comparison and new operation schedule optimization are worth further study.
7) Besides the occupant presence, the number of people and occupant's thermal preference is commonly used in the current HVAC OCC control. Other occupant information such as location, psychological and psychological attributes could be integrated into the HVAC OCC.
8) More field tests are required to demonstrate practical HVAC OCC in real buildings.

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