Applied Energy 239 (2019) 1471–1508

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions

Wooyoung Jung[a], Farrokh Jazizadeh[b,*]

[a] 315B Patton Hall, 750 Drillfield Drive, Blacksburg, VA 24061, United States
[b] 200 Patton Hall, 750 Drillfield Drive, Blacksburg, VA 24061, United States

HIGHLIGHTS

- A review taxonomy for human-in-the-loop HVAC operations has been proposed.
- Human-in-the-loop HVAC operations have been reviewed using the proposed taxonomy.
- Methods for occupancy and comfort characterization were systematically reviewed.
- Methods for integration of human dynamics in the control of HAVC were reviewed.
- Presented quantitative and qualitative performance assessment on different methods.

ARTICLE INFO

Keywords:
Occupancy
Thermal comfort
User-centric
Human-centered
Human-in-the-loop
HVAC system
Energy efficiency
Data requirements

ABSTRACT

Heating, ventilation, and air-conditioning (HVAC) systems account for almost half of the energy consumption in buildings. By benefiting from advancements in information and communication technology, human-in-the-loop HVAC operations have drawn considerable attention in the last decade with the aim of curtailing unnecessary energy use and providing user-specific comfort zones with reduced user dedication. Future progress in thie field calls for an in-depth understanding of the current state and challenges of the human-in-the-loop HVAC systems. Therefore, using a structured literature review approach, we have investigated this field according to two parameters of human dynamics that drive user-centric operations of HVAC systems, namely, occupancy and comfort. In this review and assessment study, by proposing a five-tier hierarchical taxonomy, we have classified the studies based on their contributions to occupancy- and comfort-driven human-in-the-loop HVAC operations (e.g., occupancy detection or comfort profiling) and have presented categorization for techniques and their quantitative performance assessment. In doing so, we have accounted for the context of the studies as they relate to developments in residential and office buildings given that distinct circumstances in each context (e.g., accessibility to thermostats) have resulted in different methodologies, especially in adopting the sensing techniques and HVAC operations. Moreover, we have distinguished simulations from field evaluations to assess the actual viability and challenges in achieving desirable results in practice. Lastly, the Hype cycle model was utilized to qualitatively evaluate the developments of different technologies for human-in-the-loop HVAC operations from a research perspective.

1. Introduction

The efficient operation of Heating, Ventilation, and Air-Conditioning (HVAC) systems is of critical importance considering that people spend more than 80% of their time indoors [1], and HVAC systems account for 47.7% and 51.0% of energy use in residential and office buildings, respectively [2,3]. Given their substantial impacts on energy use and occupants' quality of life, the main objectives of research efforts on HVAC systems operation include (1) the minimization of energy use without compromising thermal comfort or (2) the optimization of occupants' thermal comfort.

Throughout studies in the field of HVAC systems, it has been demonstrated that current HVAC system operations have a number of major shortcomings: conditioning unoccupied spaces [4], assuming maximum occupancy in spaces [5], and over-conditioning in buildings regardless of occupants' perspectives [6]. These suboptimal circumstances are primarily due to the fact that HVAC systems in their conventional operating modes do not account for occupants' dynamics.

* Corresponding author.
E-mail addresses: jwyoungs@vt.edu (W. Jung), jazizade@vt.edu (F. Jazizadeh).

https://doi.org/10.1016/j.apenergy.2019.01.070
Received 8 September 2018; Received in revised form 5 January 2019; Accepted 11 January 2019
Available online 01 March 2019

These modes include (1) fixed operating schedules with full occupancy (e.g., standard working hours [7]) and (2) a single-point temperature measurement of a space or a thermal zone (i.e., a collection of spaces conditioned by means of one air-handling unit) [8]. In other words, there has been a lack of context-aware information delivery and means of interaction between occupants and HVAC systems. Specifically, it has been shown that in office buildings, thermostats are generally inaccessible for occupant intervention [9] and the temperature set points are often set by facility managers without consideration of occupants' thermal feedback [10]. Furthermore, post-occupancy evaluations, as an opportunity for integrating occupants' feedback, have been occasionally performed [11]. These limitations in office buildings resulted in higher thermal dissatisfaction compared with that in residential buildings [12]. On the other hand, in residential buildings, occupants have better access to thermostats and can configure temperature set points, since manually-configured thermostats are still widely utilized (41.2%) [13]. That is, operations rely on human intervention without considering energy-use efficiency. Even in the case of residential buildings with programmable thermostats (capable of scheduled operations with a setback that relaxes the temperature set point during vacancy), it has been reported that only 19.4% of occupants actively utilize this function [13]. It has been observed that dynamic occupancy patterns often do not match with user-defined setback schedules, which results in occupants' discomfort at their arrivals [14]. Furthermore, given that most residential buildings are composed of a single thermal zone [15], unnecessary conditioning for unoccupied spaces, as well as conflicts in thermal preferences, are deemed inevitable.

In the past decade, studies have sought to tackle the aforementioned limitations by leveraging cutting-edge Information and Communication Technologies (ICT). Advancements in ICT provided opportunities for ubiquitous data collection and communication and for application of data-driven pattern recognition and control algorithms. Accordingly, studies have moved towards Human-In-The-Loop (HITL) operations, which rely on information from human interactions, that is, accounting for the dynamics of occupants in indoor environments (e.g., occupancy-related features [i.e., presence, count, and position] and thermal comfort). These efforts have been sought under the constraints of energy efficiency and the need for user interaction. As a general trend, HVAC systems are envisioned to be aware of actual occupancy schedule, to prepare the desired conditions prior to occupant arrival, to maintain them during occupancy, and to adjust operations once the vacancy is confirmed to curtail energy waste. In this study, this approach is referred to as HITL HVAC operations.

Despite the remarkable progress of research and development in HVAC systems' operation and attention from the HVAC research community regarding HITL HVAC operations, little effort has been made to *comprehensively* review previous studies and to *synthesize* them *quantitatively and qualitatively*. Although there have been a number of high-quality review studies in this field (as details are presented in Section 2.1), these studies either were conducted in earlier years, when HITL HVAC operations had been in early stages of development (e.g., Guo and Zhou [15]), or focused on a specific aspect of human-centered operations by presenting the contribution of each individual study. An example of a recent review article, with a specific focus, is the study by Mirakhorli and Dong [16] on occupancy-based HVAC operation (one of the modalities in HITL HVAC operations), which concentrated on the control aspect (rule-based and model-predictive) by presenting each study's results. In this study, in order to facilitate the identification of the trends, we have presented a holistic comparative review through synthesis assessments. Enabling HITL HVAC operations depends on the interconnected processes of data acquisition and processing, occupancy and comfort inference/prediction, as well as control strategies for system operation. Therefore, given the performance interdependency of these processes, it is important to review the contribution of each study in the context of each individual process. Furthermore, in-depth understanding of the takeaways, limitations, and discovered difficulties of the state-of-the-art research efforts is imperative for the community in order to move towards more efficient HVAC operations. Thus, the goal of this study is to present an in-depth review and performance-based assessment of HITL HVAC operations by addressing the following research questions:

(1) What are the modalities for HITL HAVC systems? What technologies have been proposed for each modality? What are the proposed configurations for these technologies?
(2) How effectively does each technology perform? How reliably/robustly does each technology operate? What are the limitations of each technology?
(3) How has each technology/modality been integrated within the HVAC operational algorithms?
(4) What is the efficacy of each technology in improving energy efficiency? How has the efficiency been quantified?
(5) Do HITL-based systems improve occupants' thermal comfort? How has their performance for thermal comfort improvement been quantified?
(6) Are performances across the studies comparable? How could the studies move towards benchmarking?
(7) What is the level of maturity/development for each technology?
(8) What could be the potential future research needs within the scope of the identified modalities?

With the aim of addressing these questions in a systematic and comprehensive way, we proposed a five-tier taxonomy to classify and analyze each study: HITL HVAC modality, building type, measurement techniques, sensing performance, and performance of HVAC operations. The first two tiers are used for high-level contextual categorization of the collected studies, and the remaining tiers are used for quantitative assessment of the reported performance on the technology itself and the use for the HVAC system operation. Moreover, we employed a technology implementation evaluation approach (i.e., the Hype cycle model) to qualitatively assess the current state of HITL HVAC operations. Accordingly, the this study contributes by:

- Comprehensively covering the studies that have introduced human-related context-aware intelligence for HVAC system operation to improve performance in terms of energy efficiency and occupant comfort.
- Proposing a hierarchical taxonomy for systematic review of the literature and benchmarking efforts.
- Formalizing modalities for HITL HVAC operations including subclasses and parameters of interest.
- Presenting HITL HVAC operational strategies in the form of process maps as a holistic perspective of the state-of-the-art techniques.
- Organizing the technology use distribution based on building types (residential vs. office).
- Quantitatively assessing the performance of sensing and pattern recognition technologies with respect to their contextual information (i.e., occupancy and comfort sub-modalities, residential vs. office, simulation vs. field study, temporal and spatial scales of the studies) by categorizing the efforts according to their contexts.
- Identifying the data requirements for objective and quantified comparison between different studies.
- Quantitatively assessing the performance of HITL HVAC operations with respect to their contextual information (similar to the process for sensing technologies).
- Qualitatively evaluating the technology implementation state using a Hype cycle model.

This paper is structured as follows. In Section 2, we have presented the methodology for the structured literature review. We compared our review article with previous review articles in this field in Section 2.1 to articulate the novelty and contributions of our study. To answer the aforementioned questions, we adopted a structured literature review approach (as elaborated in Sections 2.2 and 2.3) through which we have extensively collected, carefully selected, and rigorously classified the relevant literature associated with HITL HVAC operations. Sections 3 and 4 present the systematic review and performance assessment of the major modalities for HITL HVAC operation, namely, occupancy-driven and comfort-aware, by leveraging our proposed taxonomy. In the first subsections of Sections 3 and 4, we have provided the major research directions and overall processes of each modality, and then presented the details and research gaps for each component (data acquisition and modeling methods as well as HVAC operational strategies) in the following subsections. In Section 5, we presented a qualitative evaluation of the research efforts and further comment on future research needs. To this end, we followed the logic, used by the Hype cycle model [17], which describes the maturity of technology adoption in five stages: (1) early adoption due to the potential, (2) growing high expectations, (3) revealing difficulties, (4) proposing remedies, and (5) assessing actual viability. Section 6 concludes by summarizing the contributions and findings of this study.

2. Structured literature review methodology

2.1. Previous review articles

We compiled the existing review articles (elaborated in Table 1), which presented reviews on occupant-related features that could facilitate the advanced operations of HVAC systems. Although these studies have presented reviews on concepts that could be used as building blocks for enabling HITL HVAC operations, none of the studies have presented a systematic review that covers the entire properties of HITL HVAC operations. Specifically, the performance assessment of the HVAC systems, improved by the HITL integration, has not been assessed comprehensively despite the fact that it is a major goal in the HVAC research community. Moreover, a comparative and quantitative performance assessment on both sensing/inference systems and the HVAC operations, specifically by comparing the reported performance in consideration of contexts, has not been presented in these previous studies.

As examples, Chen et al. [28] and Mulia et al. [24] have performed review studies on occupancy detection and counting (part of the required functionalities for HITL HVAC operations). Although the topic appears to have some overlaps with part of the content in our study, our assessment differentiates itself by focusing on (1) evaluating sensing technologies in consideration of context, represented by building type, application, etc., (2) quantifying performance variations with respect to sensing technology and experimental setup, (3) interdependence of occupancy characterization methods and HVAC system performance, and (4) characterization of data requirements for benchmarking and cross-study comparison. Moreover, some of these review studies have solely focused on the thermal comfort dimension in buildings, which is not at the intersection of ICT and HITL-based operations. As examples, Antoniadou and Papadopoulos [25] reviewed different aspects of comfort in the indoor environment, including thermal, visual, acoustic, and air quality, as well as methods for qualitative and quantitative evaluations of thermal comfort. Similarly, Rupp et al. [21] have presented a comprehensive literature review on different dimensions of thermal comfort standards by looking at the experimental and field studies of thermal comfort in diverse built environment settings (e.g., schools, kindergartens, etc.), by accounting for different human attributes.

By relying on the existing review articles, which have covered topics that are related to HITL HAVC operations, one needs additional processing to identify comparative performance benchmarking with respect to the context of individual studies. In this review article, thereby, with the objective of paving the way for improved benchmarking, we have adopted an approach to account for different dimensions (i.e., sensing and data acquisition, human dynamics inference and quantification, and HVAC control integration), required for realization of HITL HVAC operations. Moreover, in this study, we have proposed a structured method for reviewing the studies in this field so that it could enable the research/development communities to move towards formalization of benchmarking.

2.2. Literature compilation and selection process

We focused our efforts on academic publications in HITL HVAC operations. Many articles have not used the term “human-in-the-loop” directly, and thus, we have used various search keywords to ensure that the studies covered herein represent the breadth of HITL HAVC systems. The compiltaion process was as follows:

- The articles were compiled through an extensive search of literature databases/libraries using search engines and journal web pages in Elsevier, American Society of Civil Engineers (ASCE), Institute of Electrical and Electronics Engineers (IEEE), Association for Computing Machinery (ACM), and Google Scholar.
- The following search terms were used in our search:
  - o “HVAC system” (in conjunction with other terms like “human- or “user-centered,” “smart,” “decentralized,” “distributed,” “occupancy-based” or “–driven,” “user-” or “demand-driven,” “comfort-aware,” or “energy efficient”),
  - o “occupancy” (standalone or in conjunction with other terms such as “detection,” “recognition,” “counting,” “pattern,” “profile,” “density,” “monitoring,” “prediction,” and “model”),
  - o “thermal comfort” (standalone or in conjunction with other terms such as “personalized,” “individual,” “profile,” “model,” “response,” “sensation,” “perception,” “preference,” “satisfaction,” “sensitivity,” and “feedback”),
  - o “thermoregulation” or “physiological response” (as a reflection of heat exchange between the human body and environment; e.g., “skin temperature,” “heart rate,” or “respiration”),
  - o “the predicted mean vote (PMV) model,” “the predicted percentage of dissatisfied (PPD)”
  - o “sensor” (standalone or in conjunction with “wireless,” “network,” “distributed,” “wearable,” “non-intrusive or –obtrusive,” “environment,” “occupancy,” and “vision”),
  - o “energy” (standalone or in conjunction with “consumption,” “performance,” “use,” “efficiency,” “savings”),
  - o “management,” “optimization,” “thermostats” (standalone or in conjunction with “smart,” “adaptive,” “intelligent,” and “programmable”),
  - o “human activity recognition,” “clothing insulation,” “indoor positioning” (standalone or in conjunction with “localization,” “location”),
  - o “smart home” or “smart buildings.”
- We also compiled studies, cited by collected papers, as the second step in keeping track of previous studies and further explored the authors’ Google scholar pages to ensure that all relevant papers are included in this study.
- We concentrated on studies, published in the last decade (mostly from 2008) since we observed that extensive utilization of “ICT” for “HVAC” operations began around that time. Where necessary, we have included studies that define the milestones in this field (e.g., the studies related to PMV-PPD model).

After compilation, we filtered the studies using the following exclusion/inclusion criteria:

- Included any study with the objective of improving HVAC system performance by implementing the dynamics of occupants even if the study did not cover HVAC operation in its analysis.
- Excluded any study that used ICT and sensing technologies for other

Table 1
State-of-the-art review articles covering the topics (or subtopics) that are related to human-in-the-loop HVAC systems.

Ref.	Year	Subject Coverage
Guo and Zhou [15]	2009	Advanced HVAC system operations using neural networks, fuzzy rules, and wireless sensor networks that enable thermal comfort-aware and energy-efficient HVAC operations Office and residential buildings
Chua et al. [18]	2013	HVAC systems' efficient energy consumption derived from innovative cooling systems and operational strategies Office and residential buildings
Yang et al. [19]	2014	Occupant thermal comfort (primarily focused on the predicted-mean-vote (PMV) and adaptive models including their extensions) and its implications for energy saving Office, residential buildings, school, university, etc.
Kwong et al. [20]	2014	Energy saving potentials in regions with tropical climates by considering occupants thermal comfort Office and residential buildings
Mirakhorli and Dong [16]	2015	Occupancy-based rule-based and model predictive control for HVAC operations Office buildings and laboratory
Rupp et al. [21]	2015	A comprehensive review paper on different dimensions of thermal comfort standards; this paper has presented a review of the papers by looking at the experimental and field studies of thermal comfort in diverse built environment settings (e.g., schools, kindergartens, etc.), as well as different human attributes Office, residential buildings, school, university, kindergarten, etc.
Yan et al. [22]	2015	Occupant behavior modeling for building energy simulation including monitoring, data collection, modeling, evaluation, and implementation Office and residential buildings
Ortiz et al. [23]	2017	Occupant comfort (e.g., thermal, acoustic, visual, and air quality) across different disciplines (e.g., healthcare, and ergonomics) and their association with energy use in buildings Residential buildings
Mulia et al. [24]	2017	Occupancy detection and occupant counting Office and residential buildings
Antoniadou and Papadopoulos [25]	2017	Occupant comfort (visual, thermal, acoustic, and indoor air quality), as well as quantitative and qualitative methods for characterization of occupants' comfort Office buildings
D'Oca et al. [26]	2018	Human dimensions in energy use: the needs (research gaps)/advancements from the perspective of each stakeholder in the built environment (e.g., architects, engineers, etc.) Office and residential buildings
Balvedi et al. [27]	2018	Development of energy-related occupant behavior models (e.g., occupancy, window and blind control, and heating and cooling system control) and the use of such models for simulating building energy performance. Residential buildings
Chen et al. [28]	2018	Occupancy detection and occupant counting (including the description of the sensing technologies) Office and residential buildings
Happle et al. [29]	2018	Occupant behavior modeling (e.g., presence, lighting control, and appliance use) in consideration of urban-scale building energy models by covering, for example, multi-districts (residential and office at the same time) or several buildings. Office and residential buildings
Zhang et al. [30]	2018	Energy-saving potentials associated with occupant behavior (e.g., interaction with door and windows, thermostats, etc.) | They focus on energy as a whole not specifically HVAC system energy consumption Office and residential buildings
Guyot et al. [31]	2018	Demand-driven ventilation system based on occupancy and ambient conditions. Residential buildings

building systems' operations (e.g., lighting).

- Excluded any study that did not address occupants' aspects for enhanced HVAC performance (e.g., suggesting a new HVAC operational strategy that does not account for occupants).
- Excluded any study considering occupants' behavior that is not relevant to occupancy and comfort, ahich are the primary interests of this study (e.g., occupants' energy-use patterns).

Using the aforementioned criteria, we narrowed down the articles to 221 out of 411 compiled articles.

2.3. Taxonomy development

Upon review of the selected literature, we developed a five-tier hierarchical taxonomy, as presented in Fig. 1, to explore the selected literature and to classify them for further assessments, including classification and performance assessments. As this figure shows, we have accounted for the modality (i.e., type) of the HITL operations, building type, measurement techniques, sensing performance, and performance of HVAC operation.

For the first criterion in classifying the reviewed studies, we have categorized two high-level HITL HVAC modalities as presented in Fig. 2: occupancy and thermal comfort. We will simply call them "occupancy" and "comfort" modalities hereinafter. The former refers to an operational strategy that leverages occupancy-related features, such as presence, and the latter aims to provide occupant-specific indoor environments. We then identified the subclasses for each modality: (1) presence, count, and position for occupnacy and (2) personalized and collective conditioning strategies for comfort. As the next step, we have identified the parameters of interest in each modality. In the previous classifications (by Melfi et al. [32], Labeodan et al. [33], and Feng et al. [34]), occupancy modalities cover presence, count, identity, activity, location, and tracking. We merged location and tracking into position,

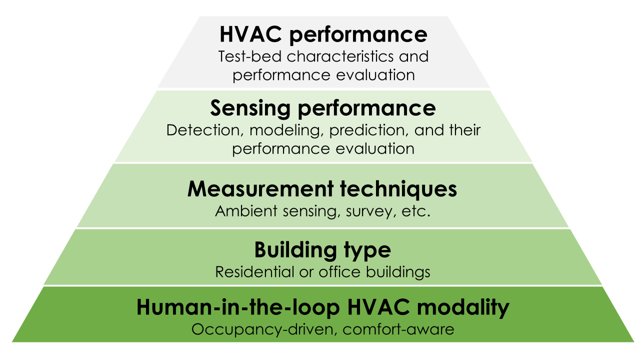

Fig. 1. Hierarchical taxonomy for this study.

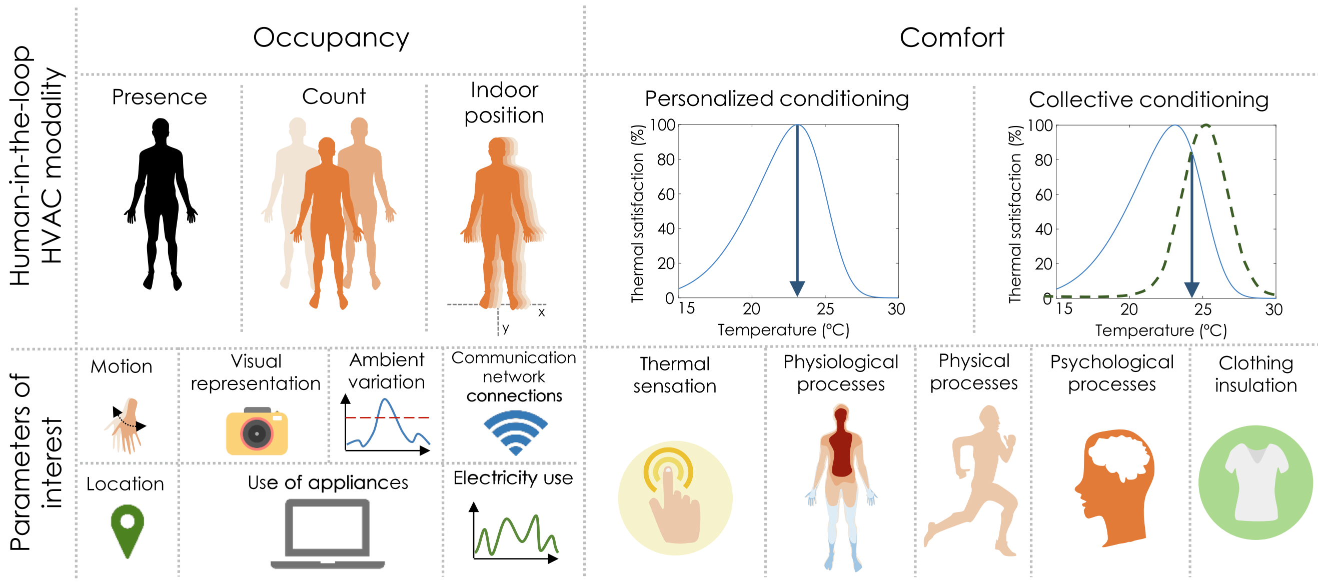

Fig. 2. Human-in-the-loop HVAC modalities of occupancy and comfort along with their parameters of interest.

given that tracking can be derived from indoor localization techniques. In addition, we considered occupants' activity as a parameter of interest under comfort modality (i.e., physical processes). It is worth noting that parameters of interest directly relate to the adopted sensing and data acquisition technologies under the third tier in our taxonomy. The remaining tiers of the proposed taxonomy are as follows:

- In the second tier, we identified building type as the higher-level context for each study. There are studies that were conducted in unique environments, such as laboratories, educational buildings, and banks [11,35–37]. However, the majority of these studies were conducted in residential and office building environments.
- The third tier supports the assessment of the measurement techniques to elaborate on their operational mechanisms and limitations (research question #2).
- The fourth tier is used in the assessment of the inference and modeling techniques and their performance with respect to occupancy or comfort. Using this rationale, we have assessed the performance of each method in the context of the experimental setup (e.g., sensor deployment strategy). In doing so, we have relied on the reported performance indicators (e.g., accuracy) and have discussed the takeaways.
- Lastly, by using the fifth tier, we have organized the proposed HITL HVAC control strategies and assessed the reported HVAC performances with respect to their (1) evaluation setting (simulation, experimental, or field studies) and (2) scale of the testbeds. We distinguished simulation-based performance analyses from the others to shed light on the actual viability of each HVAC modality/technology. Moreover, since the complexity of occupants' dynamics increases in larger testbeds [38], we assessed the studies according to the characteristics of the testbeds.

In the following sections, and for each modality, we presented *major research directions* to provide a holistic picture before getting into the details of technology description and performance assessment for each major direction.

3. Occupancy-driven human-in-the-loop HVAC modality

3.1. Major research directions

Occupancy is a key parameter in driving demands in building operations [39], and the occupancy-driven HVAC operation modality has gained extensive attention in the last decade, mainly inspired by successes in occupancy-based energy management of lighting systems. As a result, the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) Standard 90.1 [40] and European Standards [41] currently call for occupancy-sensing control of lighting systems. However, occupancy-driven HVAC operation has not been formalized in standards except for specific cases such as guest rooms in hotels. Given that HVAC energy consumption surpasses that of lighting [2] and that legacy HVAC systems do not account for occupancy states of a given environment, studies have explored the potentials of occupancy-driven HVAC operations.

Upon review and categorization of the selected studies, we have developed a holistic process map of the occupancy-driven HVAC operations, as presented in Fig. 3. Some of these studies have solely focused on occupancy inference and occupancy modeling with the potential for integration into HVAC systems, while the rest have also explored the performance of occupancy-driven HVAC operations.

This process map includes three components. The components (from left to right) correspond to the third, fourth, and fifth tiers of our proposed taxonomy, respectively. The first component represents occupancy data acquisition that could be either directly used for occupancy inference (presence, count, and position) or buffered for spatiotemporal occupancy pattern modeling in a given space. In this direction, we have synthesized the type of sensing technologies implemented for occupancy-driven HVAC operation. By doing so, we sought to answer (1) which measurement techniques have been investigated as a single-sensing method and (2) what combinations in the form of multi-sensor nodes (i.e., sensor fusion) or sensor network have been implemented. We also reflected on the distribution of studies in different building types.

The second component focuses on methods used for inference and spatiotemporal pattern modeling of occupant presence, number, or position (i.e., sub-modalities for occupancy-driven HVAC operations). Information in each sub-modality could be used for different operational strategies:

- Occupant presence
  - Adjusting setpoint and setback temperatures based on occupancy of spaces or thermal zones (i.e., contextual heating/cooling operation)
  - Space preconditioning before occupant arrival

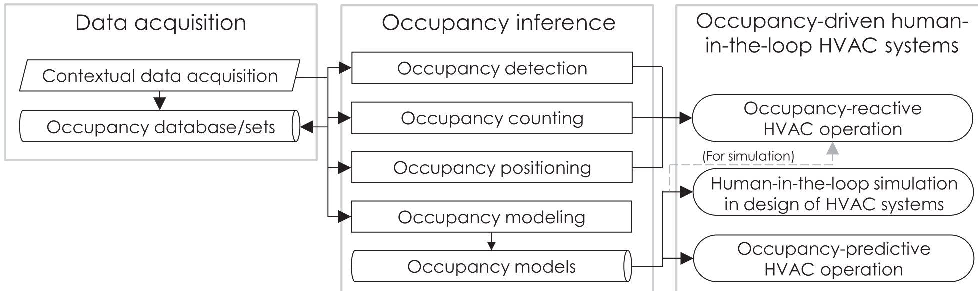

Fig. 3. Process map of occupancy-driven HVAC operations.

- Occupant counting
  - Adjusting ventilation load (i.e., contextual ventilation operation)
  - Optimizing setpoint temperature based on occupant thermal preferences
- Occupant positioning
  - Activating local HVAC units in a large space
  - Creating localized indoor conditions
  - Providing personalized comfort zones across different spaces

Various machine-learning and inference methodologies have been used in conjunction with different sensing technologies. We have evaluated the performance of these approaches in the context of sensing (i.e., sensor type (e.g., Co_2 sensors) and sensor use mode (e.g., single-sensing or multi-sensing)) and contextual information (e.g., single-occupancy spaces vs. multi-occupancy spaces). It is worth stating that, as illustrated in Fig. 3, some studies introduced occupancy models with the aim of enhancing building energy simulations (e.g., Page et al. [42] and Duarte et al. [43]). Given the fact that our review article addresses the operation aspect of HVAC systems, we excluded such studies in presenting the results.

The third component focuses on leveraging occupancy information for the occupancy-driven HVAC operation. Two main operational strategies exist: (1) the reactive operation is the mode, in which HVAC systems respond to an occupancy event in a given space, e.g., changes in the presence of occupants, the number of occupants, or the location of occupants; (2) the predictive operation is the mode, in which HVAC systems employ a proactive strategy for space-preconditioning to prepare setpoint temperatures at the time of occupant arrival or flagging vacancy as temporary for continuous conditioning.

Using the structure of this process map as a guideline, the following subsections present the results of our syntheses and performance assessments. We organized the details of all reviewed studies in the following sections as supplementary material in Tables 1–3.

3.2. Occupancy data acquisition

Data acquisition for occupancy characterization: A variety of sensing technologies has been investigated for occupancy identification/quantification in two modes of operation: (1) single-sensing mode, in which one sensor is used per space for measurement, and (2) multi-sensing (i.e., sensor fusion) mode, in which either multiple sensing technologies are combined in one sensing node or in a network of sensors. Conventionally, as a single-sensing mode for occupancy detection, passive infrared (PIR) or ultrasonic motion sensors are the most commonly used technologies [44]. However, this method has shown a number of limitations:

- PIR sensors require a direct line of sight and sufficiently detectable movements from occupants for detection [41].
- Ultrasonic motion sensors often result in false triggers due to their high sensitivity [41].
- Due to the discrete nature of motion, uncertainty is associated with occupancy state detection by PIR and motion sensors. A widely implemented mitigating strategy to address this uncertainty is to apply a 20–30-minute delay before turning off a system after the last motion is detected, which often results in a waste of energy [41].
- This sensing method cannot be used for occupant counting or positioning [41].

To address these limitations, the studies leveraged diverse types of sensing technologies and other data sources, as summarized in Table 2. In the first column of Table 2, we categorized the sensing technologies into methods that (1) rely on occupants' movements, (2) benefit from occupants' visual (RGB, depth, or infrared thermal) representations, (3) measure variations in ambient conditions triggered by the presence of occupants, (4) monitor communication between occupants' portable devices and local communication networks, and (5) rely on occupant-environment interactions, such as door openings or use of office appliances. In the second column, specific sensing technologies were provided. Further, we have described the measurement mechanisms (third column) and limitations (fourth column) for each method using a synthesis of discussions in the literature. In the fifth column, we organized the application fields that each sensing technology has been implemented for in the context of occupancy modality.

The combined sensing technologies have been used to compensate the drawbacks in the single sensing mode. Fig. 4 illustrates the use of sensors/data sources for occupancy characterization either in the single-sensing (left column) or multi-sensing (right column) mode. To improve the performance of occupancy detection or to enable occupant counting, numerous studies have utilized alternative and supplementary technologies in the multi-sensing (sensor fusion) mode. A majority of the studies have used sensor fusion or multi-sensing mode in occupancy characterization. However, they have also reported the inference of different occupancy features on the data from each individual sensor. Therefore, we have interpreted those scenarios as single sensing mode. By using arrows in Fig. 4, we show how and how frequent sensors were used in the fused mode. Most studies do not specify motion sensor type (either infrared, ultrasonic, or microwave), so we use the term "motion sensors" hereinafter to indicate both.

For **occupancy detection**, various sensors/data sources have been investigated in the *single-sensing mode*. PIRs [32,43,58,64–66], motion sensors (not specified) [42,67,68], and Doppler radar sensors [69,70] were used for motion sensing; sensors for measuring variations in air temperature, CO_2, particulate matter, sound, and light [58,64,71–75] were used for ambient condition monitoring; RGB cameras [66] were used for vision-based sensing; appliance use monitoring (e.g., keyboard and mouse) [32], door counter sensors [35], chair sensors [63], and electricity load monitoring [61,62] were used for contextual condition monitoring; and Wi-Fi networks [52,76], RFID transmitters and receivers [77], and GPS-enabled devices [55,78,79] were used as communication-network-based methods.

In the *multi-sensing mode*, to augment the performance of PIR and motion sensors, these sensors were either used in the form of a sensor network [43,60,80,81] or supplemented with other technologies such

Table 2
Measurement mechanisms and limitations of representative sensors used for occupancy-driven HVAC operations.

Category	Data source	Measurement mechanism	Limitation(s)	Application(s)
Movements (Motion)	Passive Infrared (PIR) sensors	Measure change in infrared energy received from the human body (passive) [33]	- Requires occupant motion [41] - Requires line of sight [41]	Detection, counting
	Ultrasonic or microwave motion sensors	Transmit ultrasonic or microwaves and measure variations in returned waves [33]	False triggers due to high sensitivity [41]	
Vision	RGB cameras	Use object-detection algorithms to identify occupants in a scene [4]	- Privacy concerns [7]	Detection, counting, positioning
	Depth sensors	Use object-detection algorithms to identify occupants in a scene [48]	- Cost [44]	
	Infrared thermal cameras	Background elimination, image feature extraction (e.g., number of active pixels and connected components, and classification) [49]	- Fixed focus of view [45,46] - Difficult to process an occluded scene- Cumulative counting errors [47]	
Ambient condition	CO_2 sensors	Measure variation in CO_2 concentration due to the presence of occupants [33]	Slow variations of physical parameters [50]	Detection, counting
	Temperature/humidity sensors	Measure variation in ambient temperature/humidity due to the presence of occupants [51]		
	Sound sensors	Measure variation in sound waves as occupants interact with space [33]	Responding to non-human triggers (e.g., natural light) [41]	
	Light intensity sensors	Measure variation of ambient light intensity as occupants interact with an environment [51]		
Communi-cation network activity monitoring	Wi-Fi networks	Monitor packet transfer from a device in the vicinity of an access point [52]	- Occupants need to carry a device [52]	Detection, counting, positioning
	Global Positioning System (GPS)	Monitor GPS signal as an indicator for occupant(s) absence from an indoor environment [55]	- Time-intensive annotation process for some methods (e.g., some methods that rely on RFID) [53]	
	Bluetooth Low Energy (BLE)	Monitor packet transfer from a device in the vicinity of an access point (beacon) [56]	- Privacy issue [54] - Inconsistent connection [54]	
	Radio Frequency IDentification (RFID)	Monitor communications between transmitters and receivers [57]		
Contextual condition	Door reed switches	Use magnetic switches to detect a door's state of being closed and open [44]	*Not reported in the literature*	Detection, counting
	Door counter sensors	Attached on a door frame to transmit infrared (or laser) beams and to monitor interruption by occupants [33]	Cumulative counting errors [58] Incapable of counting two people passing through a door at the same time [59]	
	Office appliance use	Tracks use of a computer or its accessories [60]	Requires users' use of the devices	
	Electricity loads	Monitor change in electricity load due to occupant interaction with a space [61,62]	Requires threshold tuning [61]	
	Chair sensors	Monitor chair usage by occupants in a given space using micro-switches [33] or vibration and strain sensors [63]	- False positives as occupants change position in a chair [33] - Requires use of chair [33]	

Table 3
Use of sensors for occupancy inference in residential and office buildings.

Category	Application / Sensors/Data Source	Detection		Counting		Positioning	
		Residential	Office	Residential	Office	Residential	Office
Motion	PIR	5	14		10		
	Motion (unspecified type)	4	7		3		
Ambient condition monitoring	Ambient condition**	7	9	1	10		
Vision	RGB or gray-scale camera		3		6		
	Depth camera				3		1
	Infrared thermal camera				3		
	PTZ camera						2
Com. network monitoring	**Wi-Fi*** **	1	6		1		1
	BLE	1				1	2
	RFID	1	1		1	1	1
	Ultra-wideband						1
	GPS-enabled devices	4	2				
	iBeacon		1				
Contextual condition monitoring	Electricity load	2	1		1		
	Door reed switches	1	8		3		
	Door counter		1		5	2	1
	Office appliance use		4				
	Chair		2				
	Total	26	59	1	44	4	9

*** Boldface shows the use of occupant-appliance interactions for occupancy inference
**Ambient condition represents the sensors that measure air temperature, relative humidity, CO_2, CO, particulate matters, sound, dew point, and light.
Background colors differentiate the representative sensing technologies that are most commonly used in each category as identified in the first column.
Com.: Communication

as contextual condition sensing (door reed switches [7,14,71,82], appliance use [60], or BLE-based methods [83,84]). Ambient condition sensing (measuring CO_2, light, sound, temperature, humidity) has often been used in the multi-sensing mode [71,74] and was integrated with motion-sensing techniques [38,64,71,85–89], door sensors [71], and contextual-sensing techniques [51,71,88,90–92]. Other attempts have used the combination of RGB cameras and contextual condition sensing (use of keyboard and mouse) [65], and communication network (Wi-Fi) and contextual condition-sensing (personal computer activity and user calendar checking) [76].

For **occupancy counting**, the multi-sensing mode comprises the majority of efforts. In contrast to occupancy detection, PIR sensors were used in a supporting role such as (1) occupancy confirmation [47] (this study looks at transition across sub-spaces by using a camera sensor network, which could suffer from a cumulative counting error) or (2) a power trigger for vision-based techniques (e.g., through thermal arrays and cameras) to save sensing energy demand [93,94].

Vision-based techniques (e.g., gray-scale cameras) were often deployed at a corridor and identified transitions of occupants [4,5,95,96]. In other efforts, the following combinations were commonly explored: (1) motion and ambient condition sensors [71,97–100], (2) ambient (temperature, humidity, CO_2, light, sound) and contextual condition-sensing techniques (door reed switch and door counter) [71], and (3) motion, ambient, and contextual condition-sensing techniques [71].

As a single-sensing mode, CO_2 sensors were the most frequently used sensors [33,71,73,101,102]. However, the efficiency of other ambient conditioning sensors, such as light, temperature, and humidity, in isolation have been also investigated [71]. Depth sensors [45,103,104], RFIDs [57], chair sensors [33], door counter sensors [59], and Wi-Fi activities [32] are among the single-sensing sources that have been used for occupancy counting.

In the case of **occupancy positioning**, the main focuses have been on the techniques that use communications between access points in network communications and devices carried by occupants. Indoor location sensing is a mature field of research, and numerous research and development efforts in this field were not presented in our study. The focus in this article is on efforts that used positioning to control HVAC operations. Wi-Fi [52,76], RFID, BLE, and Ultra-wideband are the communication technologies that have been used as a single data source in this domain. On the other hand, depth sensors and pan-tilt-zoom (PTZ) cameras have been used in the form of sensor networks.

Sensor use and building types: Table 3 presents the use of sensing technologies in offices versus residential buildings to provide insight on their distribution. In this table, each row represents one sensor/data source even if one study has used a multi-sensing mode. This means that the sum of the numbers, presented in this table is higher than the total number of studies in this domain. According to Table 3, investigating occupancy characterization in office buildings comprises the majority of studies compared to those in residential buildings. The ease of access to office buildings for sensor installation, mainly on university campuses, could be a major driving factor for this tendency. However, the dire need for automation in office buildings (due to inaccessibility to control systems and lack of motivation for building occupants for optimal control) could also play a part in this tendency. In other words, the studies demonstrated more interest in implementing occupancy-driven HVAC operations in office buildings. In case of occupancy counting, almost all studies have focused on office buildings with the exception of one.

As this synthesis shows, using sensors for detecting movements/motions (highlighted by yellow), monitoring ambient/contextual conditions (highlighted by green), vision-based techniques (highlighted by orange), and detecting activities on Wi-Fi networks (highlighted by blue) comprised the most commonly used methods for occupancy characterization. Therefore, observations in the selected studies could

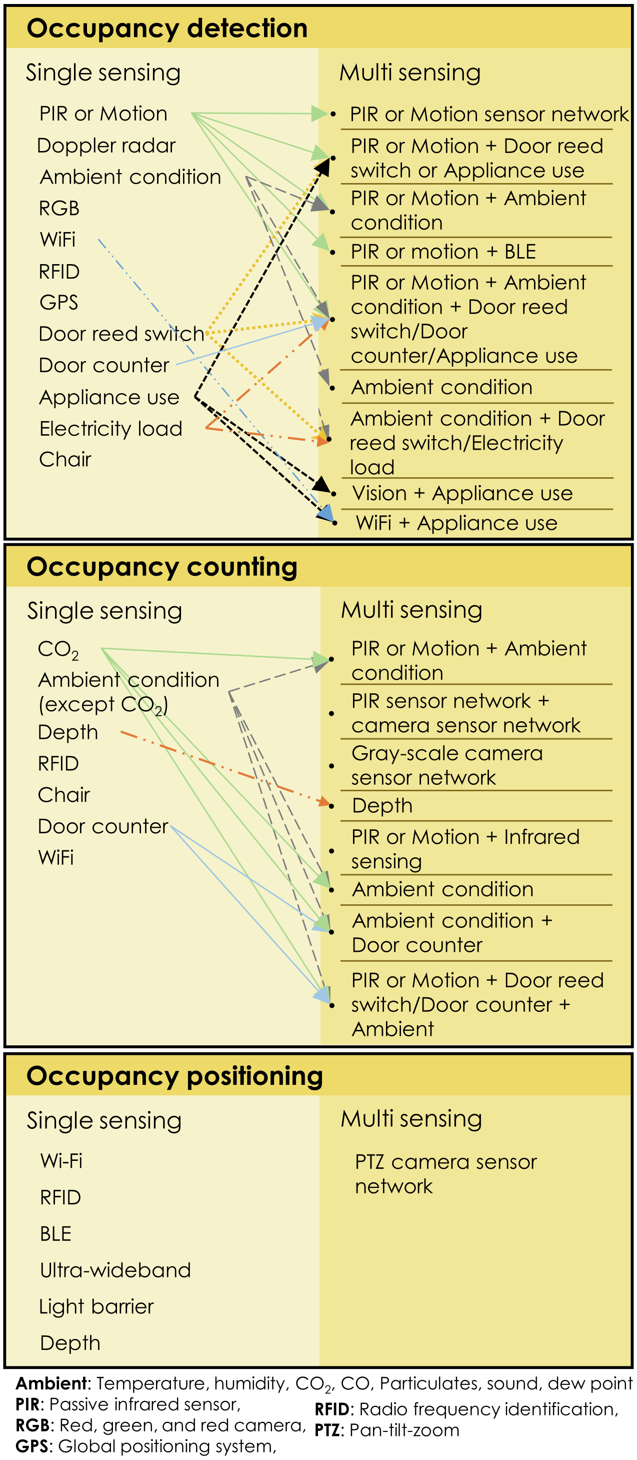

Fig. 4. Use of sensors for occupancy modality.

give us a relatively comprehensive/collective understanding of the performance of these monitoring methods. Although RGB cameras have been used in office environments for occupancy characterization purposes, associated privacy concerns with these sensors render them as the least popular approach unless they are used in areas, where surveillance cameras are used by default. Other vision-based techniques (i.e., the use of thermal cameras or depth sensors) have not been explored in residential buildings despite the fact that they raise fewer privacy concerns. Another direction of efforts has focused on the use of furniture/computer accessories (keyboards and mouse as well as chairs) as indicators for occupancy detection and counting in office environments and conference rooms [60,63,65,76,105].

Need for new sensing infrastructure: A large number of buildings/facilities have not been equipped with the infrastructure for monitoring occupancy dynamics. The need for new infrastructure (and the challenges associated with it) has raised the question of whether we could use existing infrastructure for enabling occupancy-driven HVAC operations. To this end, some studies have investigated the potential of using implicit/opportunistic sensing (i.e., using existing building infrastructure systems). As Table 3 shows in boldface, the use of occupant-appliance interactions (e.g., computer accessories such as keyboard or mouse) and the changes in data packets over Wi-Fi networks [32] have been explored as opportunistic sensing methods to characterize occupancy. However, the implementation of specialized inference methods is a requirement [52,60,65,106,107], and some studies stated the difficulties of utilizing existing ICT infrastructures due to hidden capital and labor cost [65,108]. Therefore, exploring the possibility of opportunistic sensing, and devising robust and reliable algorithmic techniques for using such methods, is an open direction of research that could alleviate the need for additional infrastructure. It is worth noting that, as shown by the majority of the studies, additional sensing systems would be required even for detecting occupants' presence (the simplest functionality in occupancy modality). Although retrofitting for occupancy-driven lighting control has gained attention in recent years, adding new sensing infrastructure to existing buildings for occupancy-driven HVAC operations is subject to the owner's will and sufficient maturity of the technologies.

Future Research Directions: Although research studies have explored various sensing systems for occupancy detection, the majority of the efforts appear to be focused on technologies that call for specialized infrastructure for occupancy detection. As the performance assessment reviews (in the following sub-sections) show, the use of motion and ambient sensing with high resolution could improve the performance. However, the trade-off between cost and performance is an important factor that needs to be considered. By reviewing the frequency quantifications in Table 3, we could pinpoint the gaps in the use of sensing technologies for HITL HVAC operations. The use of opportunistic sensing (e.g., interaction between user-carried devices with communication networks, the human-appliance interaction, etc.) is among the areas that have been less explored. Moreover, the research community needs to combine efforts towards formalization of sensor placement that enable effective sensing for different geometrical conditions (e.g., open areas versus close rooms).

As Table 3 shows, despite the potentials of occupant counting in the control of HVAC systems (mainly by adjusting the ventilation loads), it is a topic that is less explored, compared to occupancy detection. It could also be seen that occupant counting has not been explored in residential buildings. This observation could stem from the following facts: (1) the occupancy count has been considered a more predictable parameter in residential buildings, and (2) the need for more advanced control and specialized equipment for airflow control could be considered as a barrier. However, with single thermal zone configurations (the most common in the residential buildings [15]), ventilation load adjustment as a contextual/adaptive operation strategy could potentially result in high energy efficiency given that not all the areas in residential units are always fully occupied.

Although occupant positioning is a well-studied research area, as Table 3 shows, its application in the context of HVAC operations is in the early stages of technology implementation. The use of occupant positioning in this area calls for more flexible and localized air conditioning. Therefore, it is an area that has the potential for future explorations. In this category, the methods based on communication networks' activity monitoring are among the more explored topics, compared to vision-based systems and contextual condition monitoring. However, the trade-off among fidelity, privacy, and cost of implementation are the factors that should be considered in future explorations.

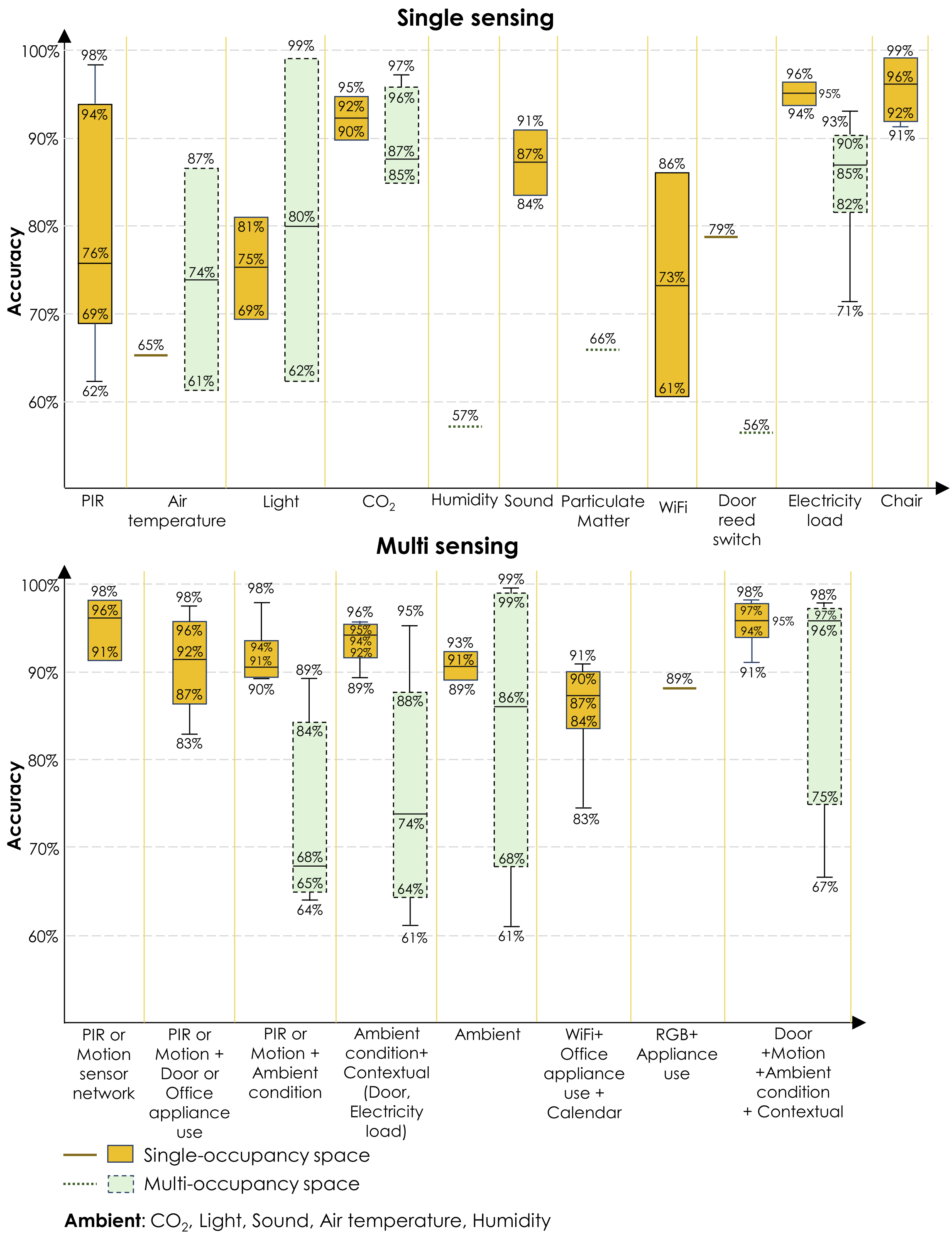

Fig. 5. Synthesized reported performances of occupancy detection for single- (upper) and multi-sensing (lower) modes.

Moreover, considering the necessity of new ICT infrastructure, life-cycle cost analyses of the HILT HVAC operations can shed light on the economic impact on the built environment. Specifically, cost-benefit analyses to compare implementation/operational costs and economic benefits from HITL HVAC operations could potentially bring about a positive perspective on adopting new ICT infrastructure.

3.3. Occupancy inference and modeling

Pattern recognition for inferring occupancy either as an occupancy state or occupancy profile has led to a wide variety of research efforts on the use of machine learning and probabilistic modeling for pattern recognition. These models have used data from single- or multi-sensing modes, and efforts have been more focused on feature analysis given that a wide range of standard classifiers has been used for the analysis. We have organized the findings according to different application domains, namely, sub-modalities (detection, counting, and positioning), as well as occupancy pattern modeling. In presenting the results, we have delved into the details of studies and looked into individual experimental scenarios rather than reflecting on an entire article as one data point. Note that we have not presented the details and specifics of algorithms for feature analysis and pattern recognition to emphasize the focus on sensing and contextual attributes. More specific criteria of our review process are given in each subsection.

3.3.1. Occupancy inference

<u>*Occupancy detection:*</u>

Synthesis Criteria: In synthesizing performance, we have classified the studies according to:

- Mode: single- vs. multi-sensing
- Sensing category and type as elaborated in Table 2
- Occupancy mode: single-occupancy space vs. multi-occupancy space (it has been shown that this factor affects the performance of occupancy inference systems [71])

A number of studies, which did not sufficiently specify sensing category and type (e.g., [32,66,72,92]) or did not associate the reported performance with single- or multi-occupancy rooms [7], were excluded from the visualizations. In addition to the aforementioned criteria, the following considerations were used in assessing the performance of different efforts:

- We have used the accuracy as the main performance indicator since it is the commonly reported factor across all studies. Some studies [60,64,71,74,77] have not reported the other metrics such as false-positive rate (incorrectly recognized as occupied – energy waste) or false-negative rate (incorrectly recognized as unoccupied - discomfort) and their relevant derived metrics such as precision, recall, and F-Measure.
- Studies have used different time intervals for occupancy measurement/quantification that has a significant influence on performance assessment (i.e., the shorter the time interval, the more difficult to get a high performance). Fifteen [7,52,62,77], 10 [109], 5 [14], 3 [51], and 1 minute(s) [61,74,76,92,110], 20 [60], and 1 second(s) [66,80] are the time intervals that have been used in different studies. We synthesized the performances without accounting for such differences so that we could provide a comprehensive comparison.
- Unless it was necessary, we have not accounted for different feature extraction methods and inference algorithms, but rather have focused on the type of sensors in pursuit of simplicity. Some studies used a number of features from the same type of sensors (e.g., the average and root mean square values from sensors [64] or the count features that indicate the number of times that a sensor is triggered in the last minute [71]), and several studies have employed several inference algorithms (i.e., machine-learning and statistical methods) to obtain the best performance from their datasets [71,74,97,98,111].
- Several studies (e.g., [60,74,76,81,109]) have included time-related features (e.g., weekday/weekend or time of day) as part of their features, but we did not use those attributes in categorizing performance assessments in pursuit of simplicity.

Using these criteria and considerations, we have processed the reported performances across different studies into box-plot visualizations as presented in Fig. 5. As a reference for the readers, Table 4 presents references that have been used in creating Fig. 5. The x-axis indicates the sensing technology category and type, and the y-axis represents accuracy. To provide the context for the range of observations in this graph, we have elaborated on the circumstances for each range.

Single-sensing Mode: *as noted, in some of the studies, although multi-sensing mode was the main focus, the performance of individual sensors has been reported. The following discussions reflect those cases as well.*

- *PIR motion sensor*: It has been noted that the performance of the PIR sensor is highly dependent on the (1) deployment arrangement (i.e., the line of sight), (2) sensitivity, and (3) time interval of measurements. Hailemariam et al. [64] have used a PIR sensor at the front of an occupant and achieved 98% accuracy using the decision tree algorithm with a time interval of one minute. However, Zikos et al. [58] and Newsham et al. [65] experienced line-of-sight problems, which resulted in lower performances (74–76%). Zhao et al. [60] stated that the PIR sensors are not capable of catching occupants' subtle motions (reported an accuracy of 62% for a time interval of 20 s), but the accuracy can be increased by 95% with a large time interval (15 min) at a risk of having a false positive rate. Yang et al. [71] used two features from the motion data (binary motion values and count values) and reported accuracies of 67% (using binary motion values) and 76% (using count values). They have discussed that, in multi-occupancy spaces, the information, gained from motion sensors, drops due to artifacts from occupants' movements.
- *Ambient conditions sensing (air temperature, light, CO_2, humidity, sound, and particulate matter)*: Reported performances from single ambient sensors show a considerable variance across different studies [64,71,74,75]. Overall, the CO_2 and sound sensors demonstrated a more robust performance throughout the studies [64,71,73]. CO_2 sensors appear to perform better in a multi-occupancy space. This observation could be associated with the pace of CO_2 concentration build-up in crowded spaces.
  - o Temperature/humidity sensors, in isolation, appear not to be a reliable source of occupancy detection for both single- and multi-occupancy conditions given the performances reported by Yang et al. [71]. The temperature sensor showed 65% accuracy in a single-occupancy space and 61% in a multi-occupancy space, and the humidity sensor had 57% accuracy in a multi-occupancy space. Even though the effect of both sensors was reported to be significant in multi-occupancy spaces [71], they could not reflect the varied dynamics as a single data source.
  - o Light sensors, in isolation, have been investigated in a number of studies. Hailemariam et al. [64] demonstrated a maximum accuracy of 81% with a light sensor for a single-person detection. In contrast, in a multi-occupancy space, Candanedo and Feldheim [74] have reported a maximum accuracy of 99% with a light sensor. These gaps could be associated with different sensor deployment strategies (although it is difficult to compare them due to the limited descriptions) and occupant behavior. It can be presumed that the participants in the study of Candanedo and Feldheim [74] were highly responsible in control of the lighting system at arrival and departure. In this stduy, a 99% of accuracy

Table 4
Contributing studies in generating the visualization in Fig. 5.

Sensing mode	Sensing technology	References
Single-sensing mode	PIR	[58,64,65,71]
	Air temperature	[71,74]
	Light	[64,71,74]
	CO_2	[64,71,73,74],
	Humidity	[71]
	Sound	[58,64,71,74],
	Particulate matter	[75]
	Wi-Fi	[76,52]
	Door reed switch	[71]
	Electricity load	[61,62,64,105]
	Chair	[33]
Multi-sensing mode	PIR or motion sensor network	[60,80,81,109]
	PIR or motion + door or office appliance use	[14,60]
	PIR or motion + ambient condition	[58,64,71]
	Ambient condition + contextual	[64,71]
	Ambient condition	[71,74]
	Wi-Fi + office appliance use + calendar	[76]
	RGB + office appliance use	[65]
	Door + motion + ambient condition	[71,64]

was achieved by using the light sensor for occupancy detection even with a window close to the sensor. The experiment was conducted in an office space with two participants. As the exmaple implies, the experimental procedures and the behavior of human subjects, who participate in these experiments, could affect the performance of light sensors significantly. Moreover, the presence of natural light could mask the artificial light during the day. Jazizadeh et al. [112] and Jazizadeh and Becerik-Gerber [113] have addressed this challenge in a number of studies by proposing feature extraction [114] in both time and spectral domain to isolate artificial light operations.

- o Weekly et al. [75] attempted to use particulate matter measurements at a corridor (a multi-occupancy space) for occupancy detection, and the performance was not promising (66%). The adopted thresholding method in their study could be an obstacle to demonstrating the actual viability of this approach. Moreover, the approach needs to be also evaluated in a more confined environment (like a private office) to evaluate its feasibility.

- *Wi-Fi communications*: As noted, the Wi-Fi-based occupancy-detection methods primarily used packet traffic of an access point. Since an access point has a range that normally covers several rooms or thermal zones [52], the detection of room-level location could be challenging. These challenges have been reflected in the results (a 61% accuracy) reported by Ghai et al. [76]. Balaji et al. [52] augmented the approach with rule-based methods to overcome part of the challenges in occupancy inference. As an example, they assumed that a private office is occupied if the packet from the specific office occupant is observed. This rule might fail in the case that he/she is in an adjacent space covered by the same access point. Accordingly, they achieved 86% of accuracy in the private offices. The use of such augmentations has resulted in the observed wide range of accuracies across different studies.
- *Door reed switches*: Yang et al. [71] have explored the use of these sensors in isolation for both single-occupancy (79% accuracy) and multi-occupancy (56% accuracy). The main shortcoming in this direction will be in the cases that the door is not operated (closed/opened) while occupants pass through the door. Door counter sensors could address this shortcoming.
- *Electricity load:* By leveraging the occupants' interactions with appliances, it has been hypothesized that the electricity load could be used to infer the presence of occupants. In a small-scale examination, by installing appliance-level sensors, Hailemariam et al. [64] and Akbar et al. [105] monitored the electricity use of office appliances from specific participants and reported 94–96% accuracies for occupnacy detection. In residential buildings with multiple occupants, the aggregate electricity load data from smart meters has been used to monitor occupancy, and a median accuracy of 85% was observed [61,62]. The context of experiments plays an important role in interpreting the reported performances. Inferring the interactions of occupants and appliances from aggregate loads could be a challenging task as the contribution of individual loads is not known. Non-intrusive load-monitoring techniques have been explored in the past few decades to disaggregate the whole-house/-building power time series (e.g., obtained from smart meters) into appliances' contributions [115,116]. However, the need for training the algorithms [117,118,119] has remained a challenging aspect of these class of techniques.
- *Chair sensor*: Leveraging the specific patterns of occupants-environment interactions in office buildings, the use of chair sensors has been proposed. Labeodan et al. [63] implemented (1) vibration, (2) strain, and (3) mechanical-switch sensors on a chair to identify the better option and reported that the use of mechanical-switch sensors has resulted in 87 – 99% accuracy. The movements of occupants while they are sitting on a chair could be the main source of artifact in inference.

Multi-sensing Mode: Looking at the general trends presented in Fig. 5 (the lower graph), it is observed that multi-sensing methods manifest a more robust performance for single-occupancy rooms compared to the considerable variations in multi-occupancy rooms. Although the context of these investigations is important, these general trends represent the general challenges that we could observe in realistic scenarios. As noted, we have looked at contexts across the studies and combined similar experimental contexts to reflect the performances of the sensing technology groupings.

- *PIR sensor network:* To compensate for challenges associated with the line of sight, Dodier et al. [80] and Zhao et al. [60] explored the potentials of using multiple PIR sensors, coupled with stochastic models (the Bayesian belief networks and expectation-maximization algorithm), in a number of private offices and achieved 98% and 91% accuracies, respectively. In these experiments, each room was equipped with multiple PIR sensors, three on the north, south, and east walls [80] and two on the ceiling and front wall [60]. In other words, the sensor network covered a larger area and addressed the challenges associated with line of sight limitations, hence, the reported performance improvement.
- *Motion sensor network*: Soltanaghaei and Whitehouse [81] utilized a number of motion sensors in the hallways of each unit in a residential building and inferred occupants' sleeping or vacancy. The thresholding method and hidden Markov models were used with 95 – 96% accuracy with a time interval of 10 min.
- *PIR in conjunction with contextual data*: PIR sensors have been combined with contextual data sources to compensate for their limitations:
  - o Zhao et al. [60] demonstrated that the performance of occupancy detection can be improved by fusing data from the PIR sensors and interactions with keyboard and mouse to account for the moments when occupant motions are not detected by PIR sensors.
  - o Zikos et al. [58] deployed a PIR and sound sensor and reported that the combination of both sensors outperformed an individual sensor's performance (when the sound sensor does not recognize silent occupants and when the PIR sensor misclassifies the occupants who passed by the testbed). This combination of technologies is commonly used in practice as a dual-technology sensor.
- *PIR in conjunction with ambient and contextual condition data:* In these methods, PIRs are coupled with the ambient/contextual condition sensing to augment their performance:
  - o Yang et al. [71] used the data from a sensor box that includes ambient condition sensors (light, sound, CO2, relative humidity, and temperature), motion, door reed switch, and door counter sensors in single-/multi-occupancy spaces and reported the accuracy of the individual sensors and the combinations of them. They mentioned that the best performances were observed when the data from all sensors were used. The authors have stated that differences in occupant behavior in single and multi-occupancy spaces influence the sensor readings (e.g., states of operable building components such as doors show higher irregularity).
  - o Hailemariam et al. [64] used the combinations of PIR, CO_2, light, and sound sensors, as well as power meters on occupants' personal office appliances such as computers in cubicles, and demonstrated that the combination of PIR, CO_2, and sound sensors had the best performance (98%) among multi-sensing methods. They used multiple features from a single PIR sensor to achieve that performance. It is worth noting that the physical configuration, provided in the article, indicates that these sensors were in close vicinity (in the cubicles) of the human subjects.
  - o Newsham et al. [65] combined two PIRs, one radar motion, sonar, infrared thermal, four ambient condition sensors (light, sound, temperature, humidity), as well as one webcam. They also monitored the use of keyboard and mouse and indicated that the combination of features from webcam and the computer accessory

use had the best performance (accuracy of 92%). The experiments were conducted on human subjects in either private offices or cubicles.

- *Wi-Fi and contextual data*: Ghai et al. [76] demonstrated that the Wi-Fi-based occupancy detection (with a 61% accuracy in their study) could be improved by combining contextual information (occupants' laptop activity, instant messaging client, and calendar) to 90%. It has been stated that such features confirmed the presence of occupants. However, the practical use of such combinations calls for access to these data sources, which could be challenging.
- *Ambient condition sensors*: Candanedo and Feldheim [74] recorded the best performance (up to 99%) among all studies with only ambient condition sensors (light, sound, air temperature, CO_2, and humidity). They underlined the importance of the sensors' locations and associated their outstanding performance with this factor. Another important factor is the way that occupants interact with an environment. The experimental procedures could create a bias in conducting the studies specifically in experiments with a short period of data collection.

Occupancy counting:

Synthesis Criteria: In synthesizing the performance, we have classified the studies according to:

- Mode: single- vs. multi-sensing
- Sensing category and type in Table 2
- Number of occupants: spaces with up to five occupants vs. spaces with more than five occupants; this threshold was heuristically identified based on challenges associated with identifying the number of occupants in high-capacity multi-occupancy spaces [58].

Similarly, we used accuracy as the primary metric for comparison because it has been the most widely used throughout all the studies. The root-mean-square deviation (RMSE) has also been often employed [71,90,111], but some of those studies did not specify the maximum number of occupants in their testbeds [32,93]; thereby, it is infeasible to compare their performances against those of others. Hence, we excluded the studies that used occupancy density or level (e.g., empty: 0%, low: 0–25%, medium: 25–50%, high: 50–75%, full: 75–100%) instead of using actual number of occupants to calculate accuracy [58,120]. Moreover, we also excluded efforts that used a tolerance in their calculations (e.g., considering an error of two occupants as acceptable [102,121]). Nonetheless, it has been discussed that considering a tolerance in occupancy counting could be an acceptable rationale given that the exact numbers might not be necessary for adjusting the operational settings of HVAC systems [90,121].

Fig. 6 presents the reported performances of occupancy counting for different sensing and contextual conditions. The x-axis represents different sensing categories, and the y-axis shows accuracy. To provide the context for the range of observations in this graph, we have elaborated the circumstances for each range. Table 5 presents the references that have been used in creating Fig. 6 so that the reader can see how many studies contributed to identifying the ranges of the observations.

Single-sensing mode: *Similarly , in this case, the performance assessment of individual sensors in multi-sensor boxes was presented in this category:*

- *CO_2 sensor*: carbon dioxide sensors could be considered as one of the most well-known ambient sensing technologies for occupancy counting. Synthesis of the findings in different studies could provide an insight into the efficacy and potential causes for varied observations:
  - o Studies have shown a considerable variance in the performance of CO_2 sensors in inferring the number of occupants (accuracies from 46% to 81% [33,73]).
  - o Calì et al. [73] demonstrated that in spaces with 2–3 occupants, the performance of the CO_2 sensor is highly dependent on the deployment strategy (optimal vs. non-optimal) and use of additional contextual features (e.g., the states of doors and windows as well as infiltration rate). The importance of contextual features was also highlighted by Gruber et al. [124], who used mass balance equations for occupancy inference. An important attribute of optimality is the distance between sensors and occupants.
  - o The need for optimal sensor location has been highlighted in different studies. Several articles have stated the slow detection for CO_2 sensor as a limitation (e.g., [33,123]), which could be interpreted as the problem of location and challenges associated with air mixture when doors or windows were open during measurement. Evidence of these challenges has been reported in some studies. Gruber et al. [124] stated that placing a CO_2 sensor inside a room could lead to inconsistent performances. They have reported improved performance by locating the sensor in the exhaust air duct. Jiang et al. [102] used the feature-scaled extreme-machine-learning algorithm with a single CO_2 sensor at the center of an open office space with a maximum of 35 occupants and a time interval of one minute and demonstrated 50% accuracy. Open spaces could be a challenging case for the use of CO_2 sensors. Moreover, this performance could be also related to general challenges associated with detecting more than five occupants in an environment (see Fig. 6).
- *RFID technology:* Li et al. [57] evaluated the potentials of using RFID for occupant counting and performed five experimental scenarios with six subjects. As indicated in Fig. 6, a large variation in performances was observed, which was reported as occasional systematic malfunctions by the authors of the study. It was also reported that detecting mobile occupants (62% accuracy) was more challenging than detecting stationary occupants (88%). Given that the use of RFID requires readers, antennae, as well as tracking and reference tags, the practical use of this method could be challenging.
- *Depth sensor:* The application of depth sensors has been twofold: (1) capturing transitions of occupants from outside of a space (97–100%) [45,103] and (2) extracting the number of occupants from the view (95%) [104]. As mentioned in Table 2, a transition-based counting method causes a cumulative error problem, but the studies that used depth sensors for capturing transitions did not address such a problems [45,103].
- *Chair sensors*: The excellent performance of 100% accuracy was reported by using switch-sensor-equipped chairs in a conference room (for one day with up to 13 people) where occupants are highly likely to sit on chairs [33]. The testbed context is an important factor in such studies.
- *Door counter sensors:* As reported by Urgessa et al. [59], the door counter sensors could result in a good performance for detecting transitions (96%) from one space to another. However, the challenges of cumulative errors should be considered. Similarly, testbed context and experimental scenarios are important.

Multi-sensing mode: To address limitations and challenges associated with occupancy counting, multi-sensing methods have been used either as sensor networks or as multi-sensing technologies. The following points describe the results of our synthesis:

- *Gray-scale camera sensor network*: The use of a 64 × 64 pixel gray-scale camera sensor network (16 sensor nodes), on the ceiling in corridors of an office building, has shown an accuracy of 80% in inferring the transitions of occupants between different spaces [95,122]. The authors of these studies have mentioned that this system utilizes hardware with limited computational power, so accuracy could be improved with more powerful gadgets [95].
- *PIR coupled with ambient and contextual data sensing*: As Fig. 6 shows, the coupling of data from motion sensors with ambient and contextual sensing methods was investigated for occupant counting

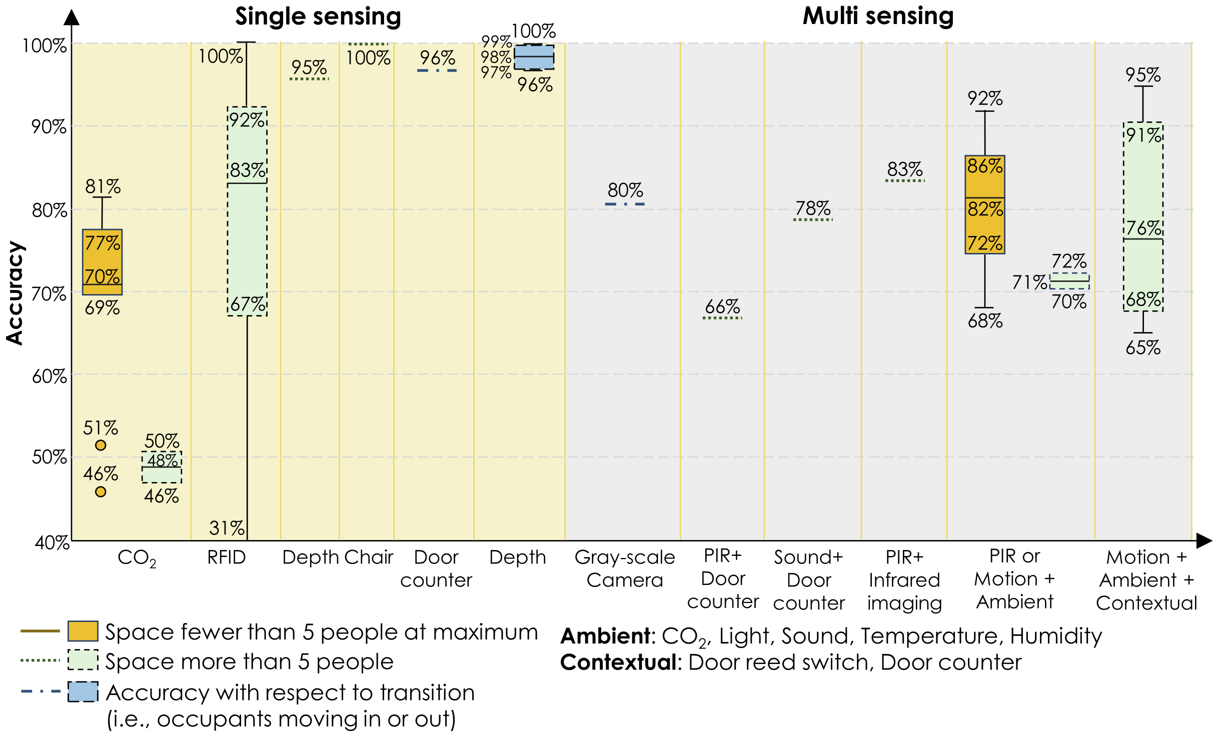

Fig. 6. Synthesized reported performances of occupancy counting for single- and multi-sensing modes.

Table 5
Contributing studies in generating the visualization in Fig. 6.

Sensing mode	Sensing technology	References
Single-sensing mode	CO_2	[33,73,102]
	RFID	[57]
	Depth	[104]
	Chair	[33]
	Door counter (transition)	[59]
	Depth (transition)	[45,103]
Multi-sensing mode	Gray-scale camera	[4,95,122]
	PIR + door counter	[58]
	Sound + door counter	[58]
	PIR + infrared imaging	[49]
	PIR or motion + ambient condition	[89,97,98,99,100,123]
	Motion + ambient condition + contextual	[111,58]

with improved performance compared to the use of CO_2 in isolation. Again, it is important to consider the context of the experiments for exact comparison. However, the addition of sensors shows improved performances, specifically for spaces with more than five occupants. Nonetheless, the robustness of these methods for different scenarios is still a remaining challenge.

o Ekwevugbe et al. [89] deployed six sensing platforms (each contained CO_2, air temperature, light, relative humidity, and motion) in an open-plan office, collected data for 7 days, and developed an occupant-counting estimation model which had a 70–72% accuracy on weekdays (11 occupants at maximum) and 68–85% on weekends (one occupant at maximum). This study also shows a drop in the performance when occupancy inference technology is applied in multi-occupancy spaces.

o Zikos et al. [58] placed PIR, door counter, sound, and CO_2 sensors in a space that could accommodate up to 16 people. They have reported that the combination of door counter and sound sensors had the highest accuracy (77.9%) and that having a CO_2 sensor as part of a multi-sensing system did not improve performance due to slow response.

o Three studies (Yang et al. [90], Yang et al. [71], and Mamidi et al. [111]) used the same sensing system, including light, sound, CO_2, air temperature, humidity, PIR, motion, door reed, switch, and door counter sensors in the same testbeds (two office spaces with up to 10 occupants). Using different features and algorithms (decision tree, ANN, regression, Gaussian process, and SVM), they have shown a range of accuracies with 98% reported as the highest using a decision tree [71]. In general, they have demonstrated that by integrating data from more sensors and features, the performance could be improved.

- *PIR and infrared imaging*: An experimental study was performed with three human subjects using a PIR sensor and an infrared camera [49]. This sensing system uses the PIR sensor to trigger the infrared camera to infer the number of occupants within the range, which demonstrated 83% accuracy.

Occupant-positioning:

Unlike occupancy detection and counting, a limited number of efforts on the use of occupant positioning for HVAC operations has been made. Indoor location sensing is a mature field of study, and readers are referred to the specialized review papers (e.g., [125;126]). As some efforts have described, the position of occupants could be used to create local climates [127]. Pursuing this concept, iBeacons have been used in three studies [56,128,129] with different resolutions to find the location of occupants using a grid of patches (sub-area units of the entire area).

Discussion on the occupancy inference:

Challenges in performance assessment: The inconsistency of data/information representation throughout the reviewed studies resulted in difficulties for the performance assessment. To tackle these challenges during our assessments and synthesis studies of different sub-modalities (presence, number, and positioning), we carefully developed a number of criteria for inclusion/exclusion of the reviewed studies (with the aim of minimizing the information loss from the reviewed articles). However, the following factors constrained the

Table 6
Required attributes for occupancy data representation in addition to primary data.

Attribute	Data
	Contextual data
Sensor metadata	● Type (e.g., PIR sensor) ● Specifications (including accuracy, resolution, range, field of view, power consumption)
Temporal information	● Time of measurement (e.g., time of day) ● Measurement frequency (including sampling rates for raw data) (e.g., a 15-min interval) ● Time of study (e.g., weekdays versus weekends or holidays versus working days) ● Duration of study
Spatial information	● Testbed dimensions (length, width, height) ● Testbed type (e.g., private versus multi-occupancy spaces) ● Sensor deployment information (sensor density) or plan (floor plan and cross-section views)
Occupants' characterization	● General information of participants ● Total number of participants ● Participants' normal activities (e.g., sitting, standing, sleeping, etc.) ● Experimental instructions for participants ● Participants' habits in interaction with the environment
	Modality-specific data (occupancy)
Occupancy (presence)	● Actual occupied versus unoccupied state (i.e., ground truth) ● Predicted occupied versus unoccupied
Occupancy (count)	● Actual number of occupants (i.e., ground truth) ● Predicted number of occupants
Occupancy (position)	● Actual position of occupants (i.e., ground truth) ● Predicted position of occupants ● Specifications for measuring actual positions
	Data analysis
Feature extraction method(s)	● Time domain versus spectral domain features ● Feature extraction algorithms ● Feature representations (e.g., instantaneous versus cumulative measures)
Pattern recognition algorithms	● Model type (e.g., support vector machine or Markov model) and characteristics (e.g., limitations) ● Model training requirements (e.g., number of data points) ● Important hyperparameters of models ● Training requirements
Performance metrics	● Confusion matrix (true positive/negative rates, false positive/negative rates, accuracy, precision, recall, F-measure) [Detection, Counting, Positioning] ● Normalized root-mean-square-deviation (NRMSD) [Counting] ● Average distance from the ground truth [Positioning]

performance assessment of the reviewed articles:

As noted, we adopted the use of accuracy as the core performance indicator in our assessments as it was the only metric, which most of the reviewed studies in this field had commonly used. Nonetheless, other performance indicators like precision, recall, and F-Measure that provide more in-depth information on the performance are critical in implementing the occupancy-driven HVAC operation. The use of accuracy for unbalanced datasets could result in biased and unrealistic results in occupancy studies (e.g., if the unoccupied time is 18 h and the algorithm predicts the space as unoccupied for the entire day, a 75% of accuracy is reported even though this is an entirely undesirable performance). The use of a confusion matrix for occupancy characterization will help drive several other measures, i.e., true positive/negative rates, false positive/negative rates, accuracy, precision, recall, and F-measure. Similarly, establishing a standardized resolution (e.g., a grid of points located one meter by one meter) for occupant positioning will help formalize the performance comparisons across different studies. Given the difference in the maximum number of occupants in different experiments, in case of occupancy counting, the use of normalized root-mean-square deviation (NRMSD) is also recommended:

$$NRMSD = \frac{\sqrt{\frac{\sum_{t=1}^{T}(\widehat{n_t} - n_t)^2}{T}}}{n_{max} - n_{min}} \tag{1}$$

where $\widehat{n_t}$ is the predicted number of occupants at a time t, n_t is the actual number of occupants at a time t, andn_{max} and n_{min} are the maximum and minimum number of occupants during the whole experiment, respectively. We tried to calculate NRMSE using the data from the reviewed studies, but the absence of required information for such calculations was a barrier.

Regardless of the evaluation metric, a comparison between the efficacy of sensing methods calls for a close understanding of the evaluation contexts. The importance of the contextual information could be observed in the results presented by Yang et al. [71] and Candanedo and Feldheim [74]. Both studies have measured ambient condition variations from multiple sensors in multi-occupancy spaces, but up to 40% of the difference in the reported accuracies is observed while they both have utilized common machine-learning algorithms. Despite the importance of contextual information, it was noticed that most studies did not describe the physical configuration of their testbeds in detail. The spaces were mostly described by the occupant-related terms (e.g., private offices or multi-occupancy spaces) without elaborating on the physical dimensions and the sensor deployment strategies. For example, the location of sensors, a core attribute for performance evaluation, is often approximately presented (e.g., on the front wall [60]), which limits the understanding of challenges (e.g., which angle was having a line of sight problem [58,65]).

The impact of the context on the sensing performance could be derived from (**i**) building type, (**ii**) space characteristics (e.g., dimensions and type (e.g., private vs. multi-occupancy spaces)), (**iii**) building system type (e.g., naturally ventilated vs. a mechanically conditioned or mixed mode) and its influence on measurement techniques (e.g., the use of CO_2 sensors in buildings with mixed natural and mechanical ventilation systems), (**iv**) time of the data collection (e.g., holidays vs. working days or weekdays versus weekends), and (**v**) occupants' behavioral characteristics (e.g., level of irregularity in occupancy, energy use behaviors, etc.). Accordingly, when it comes to performance evaluation through field studies, an elaborated description of testbeds and occupants could lead to a better understanding of the actual viability of the sensing mode and provide the ground for formalized benchmarking.

Occupancy data representation: Given the importance of benchmarking, by evaluating the breadth of the information, presented in the selected articles, we have proposed the outline of a schema for reporting the findings of a study, as well as creating databases/sets for occupancy characterization to facilitate the benchmarking in assessment of the studies. This schema is composed of three information categories: contextual, occupancy, and analysis as characterized in Table 6. The ***contextual data*** elaborates on experimental setup specifications, which include sensing system metadata, temporal and spatial attributes of the data collection, and occupants' information. The ***occupancy data*** includes the predicted and ground truth data. In this category, a critical factor is the reliability of the ground truth data collection [104], which is a time-consuming process and could be a barrier in investigating occupancy characterization methods in reality [60]. Three methods have been used for this objective: using RGB or infrared cameras for visual labeling by human users [4,35,51,66,74,75,80,89,92,123], relying on participants to document their occupancy [62,76,77], or monitoring and documenting occupancy patterns by an experimenter [7,52,80]. Identifying the most effective approach is yet to be determined and will depend on experimental setup and logistics. Utilizing cameras entails privacy concerns [44], using participants' data logs raises reliability concerns [51], and relying on experimenters to collect ground truth data is time-/cost-intensive and raises privacy concerns as well. The ***data analysis*** information elaborates the details of feature extraction methods, the characteristics of the pattern recognition algorithms, and the adopted performance metrics.

Future research directions: As the quantitative assessments in Fig. 5 show, the best performances of occupant detection were demonstrated in case of using the PIR/motion sensors in a network set-up and PIR/motion in conjunction with ambient condition sensing. However, high variations in performance have been reported for multi-occupancy spaces. The high variations are also observed in occupancy counting, specifically, when the number of occupants increases. In real-world scenarios, accounting for the higher number of occupants is an important factor for effective energy conservation. Therefore, further research is required to improve the robustness of occupancy detection and counting in multi-occupancy spaces. Innovative feature extraction and inference methods should be explored in close linkage with innovative sensing methodologies. Leveraging the interaction between the occupants and indoor environments could provide opportunities to increase the robustness of sensing methods. Similar to investigations on sensing methods, exploring the formalization of the inference methods with respect to the contextual information is an important direction of research. As an example of such efforts, Zikos et al. [58] have presented a matrix format to enumerate the factors of critical importance, which include (1) space type, (2) sensor combination, (3) occupancy type (e.g., presence or number), (4) cost efficiency, (5) privacy efficiency, (6) obtrusiveness, and (7) performance efficiency. Researchers in this field should combine efforts to explore further formalization.

Compared to occupancy detection research efforts, studies on occupant counting have been rather limited. Regardless of the parameter of interest, understanding the actual viability of a technology requires experimentations under different conditions and different experimental/field study setups. Therefore, further studies with current sensing technologies and inference methodologies under different conditions are important to provide a better understanding of the limitations. Under a formalized method of assessment, such studies will provide insight towards improvement in robustness and reliability.

Another important aspect in this line of research is the assessment of generalized models or at least methods that are less dependent on in-situ configuration. As pointed out by Yang et al. [90], developing generalized (or universal) occupancy characterization models is a non-trivial task due to the diversity in the characteristics of different spaces. Generalized models are trained according to the data in a selected number of spaces and are used in new environments. In a later study [130], they have noted three influential factors that drive the performance of occupancy detection models: (1) the level of real-time occupancy variation, (2) the degree of long-term occupancy differences between rooms, and (3) the difference between indoor and outdoor temperature. Given that these observations were based on a specific setup, they could be used as a point of departure for further investigations in this direction.

As a generic theme in the aforementioned future research directions, the context of the measurements plays a critical role in driving the performance of the methodologies. Therefore, moving towards formalizing the characteristics of the context by introducing a standardized representation of the context is of critical importance in this domain.

3.3.2. Occupancy pattern modeling

Occupancy modeling refers to the generation of models of spatio-temporal occupancy patterns (i.e., the state of occupancy in different spaces at different times (daily, weekly, monthly, or seasonal)) for either real-time HITL HVAC operations [108] or more representative energy simulations [55]. Studies [131,132] have shown that reflecting realistic (i.e., contextual) occupancy patterns, compared to ASHRAE-recommend deterministic models [133] could potentially bring about a considerable difference between the predicted and actual energy use. Occupancy modeling has been explored through different research efforts to address challenges associated with operational strategies. A synthesis of the methodologies for model generation and performance assessment used in these efforts have been presented in Table 7. A majority of these efforts (71%) have focused on office buildings, in which the HVAC operates according to a fixed schedule.

In residential buildings, a common approach for occupancy modeling relies on predicting occupants' time of departure from and arrival at their homes. In pursuing this objective, studies have either used publicly available datasets [134] as well as real-world travel data captured through GPS devices in participants' vehicles. Studies have used different timeframes including 1–2 weeks [14,55], 1–2 months [77,135], and 4 months [55]. Deterministic and probabilistic modeling were both used for pattern recognition.

The most commonly used frameworks for modeling occupancy patterns [5,47,51,93,95,96,104,137,138] have employed a variant of Markov models, which infer changes in occupancy states (e.g., occupied or unoccupied) at discrete steps under the assumption of Markov property. In these models, the future state of occupancy for a given space is inferred from its current state. The historical occupancy data is used to create transition probability matrices used in inferring the future states of occupancy. Lu et al. [14] have explored the use of Hidden Markov Models (HMM) for predicting the occupancy of subspaces (e.g., front door, bedroom, kitchen, etc.) in eight residential units by using data from door and motion sensors, augmented with time of day and achieved an accuracy of 88%. On the other hand, a diverse set of Markov models have been explored in office buildings. In doing so, studies have explored such modeling by using the ground truth occupancy data (captured by cameras and processed manually) [5,95,96], depth sensor data [104], as well as the outcome of occupancy detection from contextual and ambient sensing [51,137]. These efforts have been implemented on a number of rooms in educational buildings for different durations of data collection. Erickson et al. [4] used the occupancy data over 5 days. Longer-term studies have been explored for a limited number of rooms, for example, a conference room for 3 months [137] and three rooms over 6 months [51]. Given the challenges of labeling the data, the latter has used the outcome of the occupancy-detection models, and thus the performance reflects the errors of occupancy detection as well. Considering that these studies have used different methods for presenting the performance of the proposed models (see Table 7 for the diversity of the metrics), an objective reporting and comparison of the performances was not feasible. This is another aspect that needs to be formalized by the research community to enable benchmarking. Erickson and Cerpa [5] and Chen et al. [138] stated the limitations of employing the Markov models for occupant modeling. Specifically, when modeling at a building scale that includes

Table 7
Occupancy models' categories, modeling method, performance indicators, building type, and objective.

Building type	Operational objective	Modeling technique	Performance indicator	Reference
Residential	Predictive operation	Optimization between unconditioned and miss time based on historical departure/arrival time data		[134]
		Use of traveling time (e.g., minimum or average)		[55,136,136]
		Use of probabilistic schedule (e.g., thresholding)		[135,136]
		Use of historical arrival time (e.g., minimum or average)		[14,136]
		kNN	Accuracy	[77]
	Reactive operation	Hidden Markov model		[14]
Office	Predictive operation	Blended Markov models	Occupancy variability and flow, and JSD	[95,96]
		Markov and semi-Markov models	NRMSE	[104]
	Reactive operation	Semi-Markov model (occupancy duration)		[137]
		Moving window Markov models	Accuracy	[5]
		Blended Markov models	Occupancy variability and flow, and JSD	[47,93,95,96]
		Inhomogeneous Markov model	NRMSE, KLD	[138]
		Non-homogeneous Poisson process model		[139]
		Multivariate Gaussian model, agent-based model	RMSE, NRMSE	[4]
		Agent-based model, covariance graph model	Mean and SD of error, NRMSE, KLD	[140,141]
		Genetic programming	Accuracy	[67]
		ARMA Time-series model, ANN, Markov chain	Accuracy	[51]
		K-means and classification and regression tree		[142]

SD: Standard deviation
JSD: Jensen-Shannon divergence
KLD: Kullback-Leibler divergence
ANN: Artificial neural network
RMSE: Root mean square error
NRMSE: Normalized root mean square error
kNN: k-nearest neighbor
ARMA: Auto regressive-moving-average

several spaces with multi-occupancy, the number of states in the Markov model increases exponentially. Another problem derives from the conditions, not represented in the historical data (e.g., a transition from occupancy to vacancy at 3:00 pm in room #1). Studies have proposed different remedies for these conditions, including the use of a moving window, blended, and closest distance Markov models [5,95].

Stochastic process modeling (e.g., by using a non-homogeneous Poisson process [139] or an auto regressive-moving average modeling [51]), agent-based modeling [4], and other machine-learning algorithms (e.g., an artificial neural network (ANN) [51] or genetic learning (with an accuracy of 80–83%) [67]) are among other methods that have been explored in occupancy modeling for office buildings. Despite achieving a best performance of 95–97%, Yang and Becerik-Gerber [51] described the drawbacks of ANN and ARMA models, including the difficulty of interpreting the outcome and model variations depending on the initial states (for ANN), as well as assuming a linear relationship between the occupancy and contextual (or ambient) data (for ARMA). The improved performance of ANN compared to genetic learning could be associated with the fact that abnormal occupancy patterns were eliminated in [51]. In general, the variation in occupancy behavior, which results in abnormal behavior, could dramatically affect the performance of occupancy models [84].

Agent-based modeling (ABM) refers to the class of techniques that use the simulation of actions and interactions between autonomous agents. Using raw occupancy data [4] or occupancy probability profiles [140,141], agent-based simulations have been adopted to create occupancy pattern models, in which human agent behavior is defined to infer the profiles of space use. Using the data over 5 days, the overall RSME of 10.4 (3.8 and 7.6 in two office spaces, respectively) has been reported for ABM occupancy modeling [4].

Future research directions: Similar to occupancy status inference studies, in the field of occupancy pattern modeling, accounting for the context and benchmarking are important directions of research that should be further explored. As an example of such need in Table 7, one could see that studies tend to use different metrics of measuring performance (e.g., Kullback-Leibler divergence (KLD) and Jensen-Shannon divergence (JSD), and Normalized Root Mean Square Error (KRMSE)), which does not provide a common ground for enhancing the algorithms and comparison across different studies. The study of the cascading error impact on the accuracy of the prediction model is another direction that is worth exploring. In another observation, even though residential buildings play a major role in driving the energy demand, occupancy pattern modeling has been less explored in residential buildings. In addition to modeling the departure from or arrival to a residential unit, given the single thermal zone model of residential buildings, exploring occupancy pattern modeling between subspaces of a residential unit is another direction of research that is worth exploring. As the content of the next section shows, such information, coupled with innovative flexible control strategies, such as the use of smart vents, could provide more potentials for energy conservations.

3.4. Occupancy-driven HVAC operation (occupancy modality)

Occupancy modality utilizes occupancy characterization (i.e., detection and counting) for context-aware HVAC system operation as follows:

- *Context-aware heating and cooling operations*: Adjusting setpoint and setback temperatures in response to the presence and absence of occupants.
- *Context-aware ventilation operations*: Adjusting ventilation loads based on the number of occupants in a thermal zone.

Compared to conventional prescheduled operations (e.g., during official work hours) that assign a predefined temperature setpoint with the maximum ventilation rate, these contextual operations offer opportunities to conserve energy when (1) the actual occupancy time is shorter than the prescheduled time and (2) the number of occupants is fewer than the maximum capacity. Fig. 7 shows how different sources of information could play a role in achieving occupancy-driven HVAC operations.

The most intuitive operational strategy is the **occupancy-reactive operation**, which adjusts the operational settings of an HVAC system when a change in the occupancy state of a space is observed. Compared to the prescheduled operation, it is an adaptive strategy which follows occupants' dynamics. However, this strategy could result in occupants' discomfort at the time of arrival due to the recovery time (or ramping time) needed to adjust the temperature from a setback to a setpoint

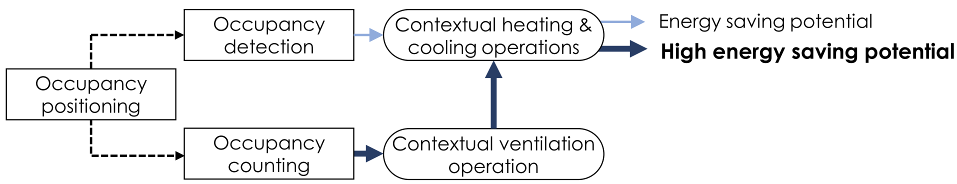

Fig. 7. Occupancy-driven HVAC operations for energy efficiency.

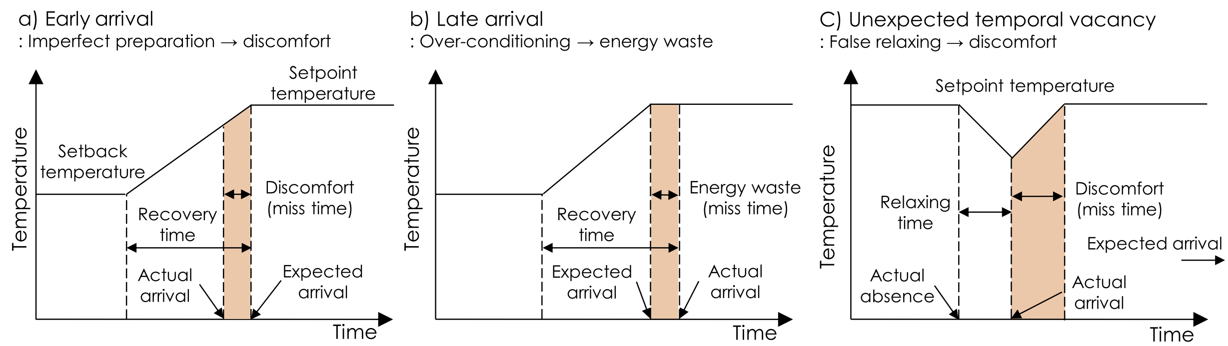

Fig. 8. Undesirable circumstances due to inaccurate occupancy prediction: (a) early arrival → discomfort, (b) late arrival → energy waste, and (c) unexpected arrival (e.g., due to false positives) → discomfort.

during occupancy. Accordingly, the **occupancy-predictive operation** has been introduced to prevent this initial discomfort by leveraging the knowledge of the expected arrival time as a trigger to preconditioning. Depending on real-world events in buildings, a number of scenarios could affect the trade-off between comfort and energy consumption. Fig. 8 illustrates the potential scenarios that could occur in case of errors in the prediction of the actual arrival time. Due to these observed potential challenges, a number of predictive operational strategies have been proposed in the literature:

- The basic predictive operational strategy uses a relaxing and recovery time for moving from a setpoint to a setback and vice versa (Fig. 9-a). This strategy has a high potential for the occurrence of miss time (illustrated in Fig. 8). Miss time refers to the mismatches between the time of arrival and the time needed for recovery, which could result in discomfort (i.e., late recovery) or energy waste (i.e., early recovery) [134]. A miss time could also occur when a temporal vacancy is inferred as a prolonged one due to false positives.
- A second approach is to use an adaptive strategy for the temperature setback depending on the expected length of vacancy. For example, Gupta et al. [55] made use of occupants' commuting time to decide the level of setback temperature (Fig. 9-b). In an alternative approach, Lu et al. [14] utilized two setback temperatures, namely, shallow and deep. This strategy deeply relaxes the setpoint temperature at the beginning of the vacancy and then recovers to a shallow setback temperature at the earliest expected arrival to minimize discomfort (Fig. 9-c).

Energy-saving potential: To provide an insight into how effective these strategies are in reducing the energy consumption of buildings, we have synthesized the literature using the following criteria:

- Occupancy sub-modality: detection, counting, and positioning,
- Operational strategy: reactive vs. predictive,
- Baseline operation: all-time-on vs. a predefined schedule,
- Spatial scale of the testbed, and
- Type of analysis: simulation vs. field study.

The categories and distribution of studies in this field have been presented in Table 8. In doing so, a number of studies were excluded: (1) when spatial [44,45,93,100,106] or temporal scale [101] of the experiments were not clearly presented (e.g., when the description was ambiguous due to the use of terms like "several offices"), (2) when non-conventional strategies were used, e.g., the room-based zoning control [143], user decision-support system (i.e., providing eco-feedback) [83,84,144], room reassignment based on personalized occupancy patterns [91], or adjustable airflow operation [127], (3) when energy-saving potentials are presented as a combination of both field and simulation results [145], (4) if a study is a demo [94,146], and (5) when the baseline (or control) scenarios have not been clearly described [82]. In Table 8, and the following figures (Figs. 10 and 11), we have counted every individual case/scenario in each study. As Table 8 shows, studies almost equally employed simulation and field study for energy implications of operations (simulation 48% and field study 52%), but simulations enabled more diverse scenario analyses (91.7%). Furthermore, the all-time-on baseline was only used in the simulation analyses as it is not a common strategy in real-world scenarios.

Occupancy detection: Fig. 10 summarizes the reported energy-saving

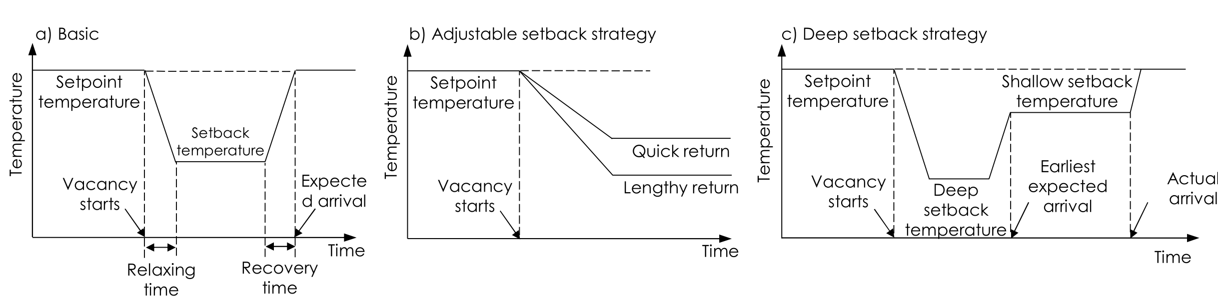

Fig. 9. The occupancy-predictive HVAC operation strategies in [14,55,134].

Table 8
Number of reported performances (and papers) of occupancy-reactive and -predictive operations.

Building type	Baseline		Occupancy-reactive operation			Occupancy-predictive operation		
			Detection	Counting	Positioning	Detection	Counting	Positioning
Residential	All-time-on	S	40 (1)*			229 (1)		
		F						
	Pre-scheduled	S		2 (2)				
		F		1 (1)		21 (5)		1 (1)
Office	All-time-on	S						
		F						
	Pre-scheduled	S	46 (3)			56 (2)	67 (3)	2 (2)
		F	16 (3)			23 (5)		

* The number in parentheses indicates the number of papers, **S**: Simulation, **F**: Field study.

potentials by using occupancy detection for HVAC system control, and Table 9 shows the references used in creating Fig. 10. This graph illustrates the general trend of energy-saving potentials for different contextual conditions.

In the **reactive operation mode**, most studies demonstrated promising energy-saving potentials. However, as the scale of the testbed in real-world studies increases, negative energy savings (−5.4 and −0.2%) have been also reported (these observations are from a field study based on 37 rooms in an office building during March in Southern California reported by [92]). Li et al. [92] have associated these results with the relationship between the setpoint and outdoor temperatures – the smaller the gap, the less conditioning load required. On the other hand, Newsham et al. [65] have shown the highest energy-saving potentials by using a reactive strategy for one single room, which was up to 64% (the first column in the field study category). These authors justified the reported high performance with occupancy patterns of the selected testbed. Goyal et al. [147] also showed high-energy-saving potentials (39–40%) for a single office. That is, in general, when a testbed scale is small (e.g., one thermal zone) and the occupancy period is shorter than predefined schedules, high energy saving potentials have been reported.

Yang and Becerik-Gerber [91], Erickson et al. [95], and Erickson et al. [47] conducted simulations of relatively large office environments. Table 10 describes the context of these simulations. According to annual analyses from Erickson et al. [95] and Erickson et al. [47], it has been demonstrated that in general spring and winter (November – April) have higher potentials for energy savings through occupancy-driven operations. Although Yang and Becerik-Gerber [91] have used the same season in their analysis, lower energy savings have been reported (the median of 9%; 5th column in Fig. 10). This could be associated with the insignificant difference between baseline and actual occupancy, as well as the short baseline operation time compared to the cases in Erickson et al. [47] (Table 10). Furthermore, it is often observed that among the studies based on simulation, the occupancy data, collected in a short period, is applied to an energy analysis of a long period, which might be infeasible to demonstrate actual viability in real-world scenarios. It appears that a normalization of energy consumption (or savings) based on occupancy time is required for an objective comparison between results. The larger real-world testbeds (e.g., the cases from Li et al. [92]) represent a more realistic scenario, as they represent scenarios closer to actual occupant interactions with the environment.

If compared in similar contexts, the **predictive operation mode** results in less energy savings compared to the reactive operation. Specifically, by looking at the cases in the first two columns in Fig. 10, reported by [136], the median values dropped to 9% from 13% for the apartment and to 8% from 13% for the house. However, higher energy savings by the predictive strategy have been reported by Erickson et al. [47] and Erickson et al. [95] (third and fourth columns in the reactive and predictive operation categories in Fig. 10, respectively). Although these studies have reported that the predictive operation had a longer conditioning time on average (1.2 h longer), they have associated the

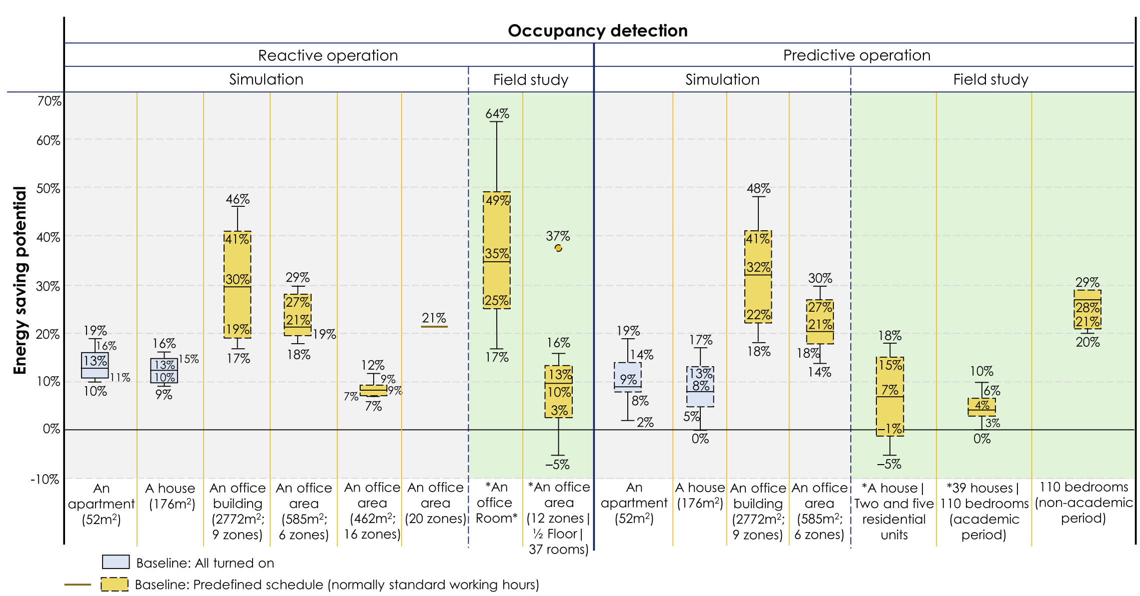

Fig. 10. Energy-saving potentials reported by studies using occupancy detection to control HVAC systems.

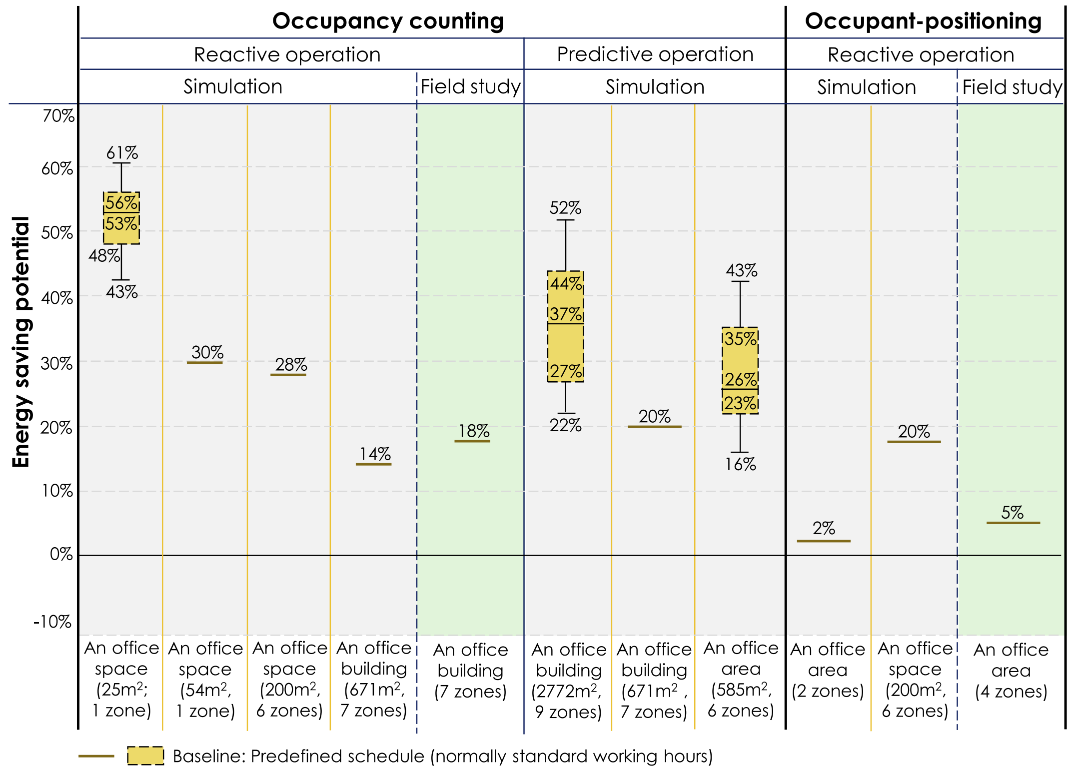

Fig. 11. Energy-saving potentials reported by studies using occupancy counting and positioning HVAC sub-modality.

increase in savings with small differences between the setback and setpoint temperatures in predictive mode. Reported by Woolley et al. [87] from their field study, the energy-saving potential diminishes when a short period of relaxing time is provided (i.e., when the system does not completely get to the setback temperature). Therefore, evaluating the energy saving potential of the predictive operation mode requires further validation by field studies. This is specifically important given the absence of important parameters in simulation-based analyses. Li et al. [92] have pointed out that in simulations the delay time that HVAC systems need to switch from the occupied mode to the vacant mode is not often considered and is reflected in energy-saving potentials.

Kleiminger et al. [136] investigated the impact of insulation and weather conditions with respect to the occupancy-predictive operations through simulation and reported that (1) weather conditions highly impact energy-saving potentials and (2) poorly-insulated buildings can better benefit from occupancy-driven operations. The lower saving potentials (the first two columns of Fig. 10) were observed in their studies compared to other simulation efforts and can be associated with higher occupancy duration (17 h and 40 min on average).

The last two columns of Fig. 10 represent a large-scale field study in a student housing building with 110 rooms [38,87], with a median accuracy of 4% in [38,87] and 28% in [38]. The predictive operation was used during the academic year (high-rate of occupancy) and summer (low-rate of occupancy). The results revealed higher energy-saving potentials by using the predictive operation during the summer period with lower occupancy rates. During the academic year, they reported cases in which no energy savings from predictive operation was observed [38,87]. As another example of insignificant energy savings from the predictive operation, Scott et al. [77] showed negative

Table 9
References used in creating the visualization in Fig. 10.

Occupancy sub-modality	Operation mode	Simulation/field study	Scale	Reference
Occupancy detection	Reactive	Simulation	An apartment (52 m^2)	[136]
			A house (176 m^2)	[136]
			An office building (2772 m^2; nine zones)	[95]
			An office area (585 m^2; six zones)	[47]
			An office area (462 m^2; 16 zones)	[91]
			An office area (20 zones; 30 rooms)	[71]
		Field study	An office room	[65,147]
			An office area (12 zones | a half floor | 37 rooms)	[148,7,92]
	Predictive	Simulation	An apartment (52 m^2)	[136]
			A house (176 m^2)	[136]
			An office building (2772 m^2; nine zones)	[95]
			An office area (585 m^2; six zones)	[47]
			An office building (910 m^2; nine zones)	[149]
			An office building (4,982 m^2; 15 zones)	[149]
			An office building (46,320 m^2; 61 zones)	[149]
		Field study	A house | Two and five residential units	[77,86]
			39 houses, 110 bedrooms (academic-period)	[87,38]
			110 bedrooms (non-academic period)	[38]

Table 10
Contextual information of three simulation studies on reactive occupancy-driven control of office buildings.

Ref.	Baseline time	Location	Energy analysis duration	Occupancy data collection time
[95]	7:00 am to 22:00 pm	Fresno, Miami, Chicago	1 year	5 days
[47]	6:00 am to 1:00 am	California (simulating a real building)	1 year	2 days
[91]	Weekdays: 6:30 am to 21:30 pm Weekends: 7:00 am to 21:00 pm	Southern California (simulating a real building)	4 months (from January to April)	28 days

energy savings (−5% and −1%) in a number of residential units (with predefined schedules) which they associated with having a single thermal zone in these units. It should be noted that this study used testbeds in the US and the UK, and that negative savings were observed in US residential units. In the UK, residential buildings had room-level thermal zones.

Learning from observations in these studies, we have synthesized the main insights from the reactive and predictive operational strategies in Table 11.

Occupant counting: Fig. 11 summarizes reported energy-saving potentials by using occupant counting for HVAC system operation, and Table 12 shows the references used in creating Fig. 11.

Energy-saving potentials by applying occupant counting have been mostly assessed by simulations with the exception of one single-field study [99]. According to our synthesis, the energy-saving potentials from the two operating modes are in the similar range: the medians of 14–30% for the reactive and 20–37% for the predictive with the exception of cases reported by Goyal et al. [150] and Goyal et al. [151] with a median of 56% (the first column in Fig. 11). As noted before, the use of a testbed of a sibgle office zone could be the reason for having such high potentials compared to other studies.

According to the simulation analyses by Erickson et al. [95] (2772 m^2 with 9 zones) and Erickson et al. [47] (585 m^2 with 6 zones), HVAC operation according to occupant counting has shown a higher energy-saving potential due to the context-aware ventilation operation, compared to results from operations based on occupancy detection. Specifically, their reported medians of energy savings have increased by 7% and 5% compared to results derived from the occupancy-detection-based reactive operation, respectively (Figs. 10 and 11). The only field study case with 18% of energy savings has not clearly specified the impact of the context-aware ventilation operation or practical challenges associated with real-world implementation [99].

Occupant-positioning: In our compiled literature, four studies proposed an approach for using occupant position instead of occupancy detection [127–129,152]. Wang et al. [128] and Liu et al. [152] explored the possibility of using occupant positions in open office spaces for energy savings using simulation studies. They have proposed controlling airflow according to occupant location. Wang et al. [128] reported a 20% energy savings by simulation of a real-world, large, open-office space with cubicles. On the other hand, Liu et al. [152] reported an energy savings of only 1.59% based on the simulation of a small office space.

Miscellaneous operational strategies: Some studies attempted alternative operational strategies to save more energy through occupancy-driven HVAC operation. One method proposes to accommodate occupants, with similar occupancy patterns, in the same thermal zones, hence, reducing the complexity of occupancy patterns and increasing the chances of having a vacancy at thermal zone level (an additional 8% energy savings was reported [91]). Another operational strategy aims to manage different occupancy states in a thermal zone with multiple rooms (e.g., two rooms, grouped as the same thermal zone, with unoccupied and occupied states, respectively) [154]. While maintaining the minimum supply-air flow in each room, this algorithm prioritizes occupied rooms for conditioning. Through a field study (three thermal zones for a week in February), this study demonstrated energy-saving potentials of 29–80%. As an attempt to decentralize a single thermal zone in residential buildings (as noted, the single thermal zone is widely applied in residential buildings [15]), Sookoor and Whitehouse [143] simulated a room-based conditioning to better adapt the dynamic nature of occupancy and indicated the energy-saving potentials of 15% could be achieved. Lastly, the user decision support system has been introduced [83,84,144]. This system suggests several setpoint schedules derived from users' occupancy patterns. Users can also select the mode that prioritizes energy use or comfort. Pisharoty et al. [83] showed that this system could reduce energy spending compared to the manual programmable and Nest thermostats (4.7% and 12.4%, respectively). Jia et al. [155] proposed a framework, which optimizes the privacy and performance losses. They have shown that a higher performance could be achieved by using personalized information.

Comfort assessment in occupancy-driven HVAC operations: Most studies assessed occupants' comfort by monitoring whether thermostats maintained the required setpoint temperature during occupancy. In other words, it was presumed that comfortable conditions are achieved by having the setpoint temperature [14,38,47,55,71,77,78,86,87,95].

Energy performance data representation: Similar to the discussion for occupancy characterization methods, an objective comparison of studies that evaluate the potential for energy savings calls for a clear

Table 11
Factors that influence the energy-saving potentials of occupancy-driven operations and their associate rationales.

Feature	Rationales
Occupancy patterns	• Energy savings is highly correlated with occupancy patterns (the lower the occupancy, the higher the energy savings) [38,86,87,92,136]. • Impact of occupancy on energy savings between two groups (one with larger than 0.55 daily occupancy on average, i.e., more than 13.2 h per day and the other) was not statistically significant (unpaired right-tailed *t*-test) [92]. • Irregular occupancy patterns have less potential for energy savings [14]
Climate	• Relationship between outdoor temperature and setback or setpoint temperatures affects energy-saving potentials [14,87,92,95,136]. • Mild climates manifest less potential for energy savings [87]. • Cloudy days reduce energy-saving potentials [136].
Building feature	• Poor envelope insulation increases the potential for energy savings from the occupancy-driven operation [87,136]. • Having a larger number of thermal zones results in higher potentials for energy savings (i.e., efficient for adapting the dynamics of occupancy patterns) [38,87,134,143]. • Thermal interaction between adjacent zones reduces the chance to have a setback temperature [38]. • Individual rooms in a complex building cannot be considered independent [38].
Operation	• When setback temperature is not achieved, little energy savings can be realized [87]. • Energy savings from a short period of vacancy are neutralized by recovery conditioning loads [87].

Table 12
References used in Fig. 11.

HITL HVAC sub-modality	Operation mode	Simulation/field study	Scale	Ref.
Occupant counting	Reactive	Simulation	An office area (25 m^2; a single zone)	[150,151]
			An office area (54 m^2; a single zone)	[137]
			An office area (200 m^2; six zones)	[128]
			An office building (671 m^2; seven zones)	[5]
		Field study	An office building (seven zones)	[99]
	Predictive	Simulation	An office building (2772 m^2, nine zones)	[95]
			An office building (671 m^2; seven zones)	[5]
			An office area (585 m^2; six zones)	[47]
Occupant positioning	Reactive	Simulation	An office area (two zones)	[152]
			An office area (200 m^2; six zones)	[128]
			An office area (four zones)	[153]

understanding of the contexts in which the studies have been conducted. Therefore, similarly, in this case, we also have proposed in Table 13 the outline of a schema for contextual data representation for energy assessment studies. The importance of each attribute was clarified in the performance assessment of the existing literature. An important factor that is often ignored is the actual energy savings capitalized by using occupancy-driven operations. In most studies, relative changes according to the baseline energy consumption have been reported. Providing the absolute energy savings could also bring about a better understanding of the potentials.

Future research directions: Table 8 provides a map of unexplored areas. As this table shows, the majority of the efforts have been focused on methods based on occupancy detection. The number of case studies and scenarios using simulation far exceeds those in field studies. This is mainly due to the complexities of field studies specifically in active and operational buildings. Nonetheless, there are unexplored areas in both residential and office type buildings even through simulation studies. For example, reactive operations in residential buildings have not been sufficiently explored. As it could be seen, pre-scheduled operations, common methods of energy conservation in buildings, have not been compared to more advanced reactive operations. Furthermore, methods based on occupancy counting, in general, are less explored. Studies, including the studies by the Department of Energy, have shown that the control strategies that leverage occupancy counting has a higher potential for energy conservation although it is more challenging to be achieved. Similarly, operations based on occupant positioning (both reactive and predictive) is a topic that worth exploring although these directions require more innovative adaptive control strategies in the building operations.

Review of the literature shows the need for further assessment of these methodologies through field studies. Although simulation is a valuable and established tool in this field, the results from simulation might not reveal the challenges for real-world implementation. As elaborated in Table 11, diversity in testbeds at different geographical locations are required to evaluate the actual viability of different methodologies under diverse conditions. Moreover, the assessment through simulation studies might not reflect the realistic thermal comfort of occupants in practice – an important factor in building systems operations. Some studies have shown that 15–28% of occupants are often dissatisfied with the indoor conditions despite the fact that they determine the temperature setpoints [12,156]. Therefore, the aforementioned assumption in the assessment of energy saving potentials, by maintaining the standard-recommended temperature range, might need to be reconsidered.

Another direction for exploration is the standardization of the evaluation method when it comes to energy conservation. Proposed operational strategies should be evaluated by comparing them against a benchmark setup (e.g., the prescheduled operating hours from 8:00 am

Table 13
Required attributes for assessing energy saving potentials by occupancy-driven HVAC operations.

Attribute	Data
	Contextual data
Building attributes	• Location (e.g., Arlington, Virginia, USA)
	• Number of thermal zones and number of spaces included in the zones
	• Dimensions (height, width, length, area, and volume)
	• Age and physical attributes of the building (e.g., insulation, windows, etc.)
Regional attributes	• Climate
	• Outdoor conditions (temperature, humidity, etc.)
Temporal information	• Duration of operation (e.g., 3 months of reactive operation)
	• Time of experiments/assessments (i.e., which months or seasons)
	Occupant data
Occupancy	• Profile type used for energy analysis (e.g., presence (100%) vs. absence (0%) or partial occupancy (30% as in three occupants are present, but 10 is the maximum at a given time (9:00 am))
Comfort	• Occupants' thermal preference or thermal sensation
	Operation data
Evaluation method	• Simulation or field study
Operation strategy	• Occupancy detection, counting, or occupant-positioning
	• Occupancy-reactive or predictive operation (in the case of predictive, the strategy for setback/setpoint temperature adjustments)
	• Relaxing and recovery time
	• Setback and setpoint temperatures
Baseline operation	• All-time-on
	• Prescheduled with operation time (e.g., from 7:00 am to 5:00 pm)
Thermal condition	• Indoor thermal condition variations during operation
	Performance analysis
Energy use	• Absolute energy-use value of the baseline and occupancy-driven operation
	• Relative energy-saving values (e.g., 30% of saving)

to 5:00 pm). However, studies have used varied baselines, which makes the reporting of energy conservation inconsistent. Such formalizations will be more meaningful if they will be presented by accounting for the diversity of geographical locations and contextual conditions.

4. Comfort-aware human-in-the-loop HVAC modality

4.1. Major research directions

The main method for design configuration of legacy HVAC systems is to use the predicted mean vote (PMV) model to account for the occupants' perspective [39]. In addition to environmental factors, this model utilizes generalized human-related factors in the form of the met unit for metabolic rates (1 met unit: 58.1 W/m^2) and the clo unit for clothing insulations (1 clo unit: 0.155 $Km^2 W^{-1}$), which are assumed according to standards' recommendations. The required capability of HVAC systems is calculated based on this model during the design phase, when there is no information available about actual occupants. However, previous studies have enumerated a number of limitations for the use of the PMV model, including general interpretation of the neutral state as thermal comfort preference [157] and the use of generalized human factors, including metabolic rate values, which are based on average European males [158]. These limitations have resulted in reported discrepancies between the PMV-based and actual thermal sensations [159].

In the post-occupancy stage, human perspective in the operation of the HVAC systems is reflected in the temperature setpoints of the control loop. These setpoints are either controlled by occupants (in residential buildings) or set by building managers (in office buildings) based on generic ranges recommended by the standards. However, individuals have different thermal preferences [157] and respond to ambient thermal conditions differently [160]. Therefore, by accounting for contextual information (i.e., thermal comfort preferences of actual occupants in buildings [161]), studies have sought to enhance the thermal comfort representation for improved thermal satisfaction and efficient energy consumption. As a traditional method of contextual thermal comfort quantification, post-occupancy surveys have been used in office buildings [162] due to the virtue of direct quantification [163], although they have been used occasionally and usually in response to complaints from occupants in buildings [11]. However, by the increase in the prevalence of the ICT technologies, studies have shifted their efforts to enable continuous and dynamic sensing and quantification of thermal comfort in buildings [164].

The synthesis of the selected literature revealed three main objectives in the HITL comfort-aware HVAC operations: (1) facilitating post-occupancy evaluations, (2) personalized comfort quantification, and (3) HVAC operation based on personalized or collective thermal preferences. A holistic process map for comfort-aware HVAC operations has been presented in Fig. 12. Similar to the one in occupancy modality, this process map includes three main components that have been identified reflecting our proposed taxonomy (from left to right, the third, fourth, and fifth tiers, respectively).

The first component represents the measurement and data-processing techniques that have been used for the quantification of personalized thermal comfort. In doing so, we have synthesized the studies according to their parameter of interest (e.g., occupant feedback or thermophysiological response of the human body) to reflect on the research trends of (1) occupant voting systems (OVS) and (2) physiological sensing systems (PSS). The former uses ICT to facilitate occupant feedback data acquisition (e.g., through web-based or smartphone-based surveys), and the latter employs measurement of physiological responses from the occupants' bodies to infer their thermal sensation/perception.

The second component focuses on inference methods for (1) personalized thermal comfort prediction, (2) personalized thermal comfort profiling, and (3) collective thermal comfort profiling for multi-occupancy spaces. These methods have been proposed to identify and leverage distinct characteristics in individual thermal comfort considering the differences in individual thermal perceptions and preferences. The third component focuses on integrating the dynamic personalized/collective thermal comfort information (the outcome of the second component) in the control loop for comfort-aware HVAC operations. In the third component, we have also synthesized efforts on the large-scale comfort evaluation in buildings enabled though ICT-based surveys.

Following the structure of this process map, the rest of the subsections include a systematic presentation of the results for our syntheses and performance assessment. The details of all studies reviewed in the following sections were presented as supplementary material in Tables 4 and 5.

4.2. Comfort data acquisition

Occupant voting system (OVS): thermal comfort quantification is a challenging task given that various factors could affect individual thermal comfort perceptions. Therefore, in the early years of the 21st century, and by an increase in the use of personal computers, research studies explored the feasibility of electronic surveys (introduced in 2002 [11]) to directly collect individual thermal comfort perceptions. This trend was later augmented by context-aware participatory sensing through the application of smartphones [164]. These efforts comprised the foundation for OVS integration into HVAC operations and mainly rely on the ASHRAE definition of thermal comfort as "the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluations" [165]. As the description implies, the thermal comfort assessment relies on occupants' subjective input, which could be collected through a thermal sensation scale for comfort vote expression – a scale which associates occupants' votes into a numerical value. The most frequently used thermal sensation scale is the ASHRAE scale with seven degrees of hot (3), warm (2), slightly warm (1), neutral (0), slightly cool (−1), cool (−2), and cold (−3). A 5-degree scale without the votes for slightly warm and slightly cool has been also implemented in different studies. A variety of different thermal sensation scales have been introduced over the years, addressing the incorrect notion that having a thermal neutrality vote is associated with satisfaction [157], and have been adopted in data collection processes. Table 14 presents the formalized scales and a few examples of studies that combined scales for data collection.

OVS methods call for occupants' contribution to data collection, which has shown a number of limitations. One limitation includes the lack of consistency in the votes submitted by participating occupants. As an example, the challenges of quantification have been shown in Fig. 13, which were reported by Jazizadeh et al. [10]. Data presented in this figure was collected by the same user in the same season over a period of two months. However, this person manifested different thermal comfort preferences under the same thermal condition (e.g., −20 (wanting to be cool) to 10 (wanted to be warm) at 26 °C – with more emphasis on preference for a cooler environment) and showed the same thermal comfort preference at different temperatures (e.g., 0 from 22 to 26 °C). These inconsistencies could stem from different causes: (1) the insufficiency of thermal sensation scales in quantifying thermal lingual votes, (2) complexity of perceiving thermal comfort states by occupants, (3) failure in accounting for other contextual factors, such as variation in clothing insulation or other physiological/psychological variations, and (4) inaccurate quantification of indoor thermal conditions such as temperature values at the location of occupants due to unbalanced distribution of thermal condition. The diversity of the scales presented in Table 14 reflects the efforts in addressing the challenges observed in this process. Among these efforts, Jazizadeh et al. [171] have proposed a combined perception/preference scale through an experimental study with the objective of designing a sensation scale that increases the consistency of the occupants' votes under

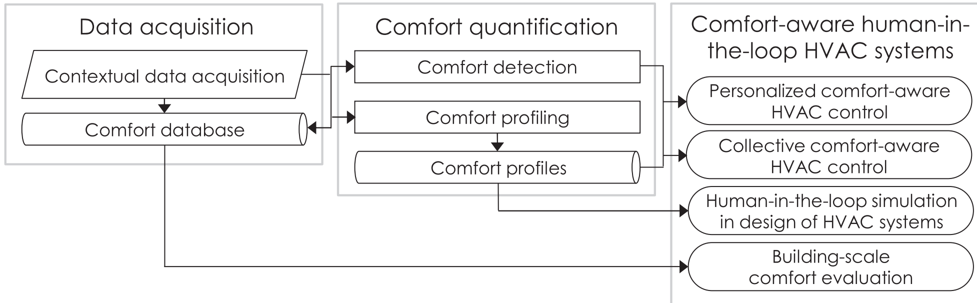

Fig. 12. Process map of the HITL comfort-driven HVAC operations.

similar thermal conditions.

Another reported limitation of OVS methods is the need for occupants' dedication to providing continuous input. The challenges of engaging occupants in the process of data collection have been documented in the literature: Jazizadeh and Becerik-Gerber [172] used a stratified sampling approach to engage only motivated participants to ensure the quality of the data collection; Kim et al. [173] and Jazizadeh et al. [10] also pointed out that users' participation was a challenging task while collecting data to create personalized comfort profiles; Fukuta et al. [174] proposed to reduce end-users' efforts by managing intervals between occupant input inquiries; Barbato et al. [175] proposed to benefit from occupants' interactions with thermostats, assuming that setpoint temperatures reflect the preferred conditions. The latter is the concept that the Nest thermostats [83] have adopted in learning the preferences of occupants over time in residential units.

Physiological sensing system (PSS): As an alternative and complementary method to OVS and as a result of the prevailing sensing technologies, the use of physiological response from the human body, through PSS, has gained momentum in recent years. These efforts have sought to identify generalized or personalized features from human bio-signals to reduce or obviate the need for occupants' interaction with OVS.

Investigations into the correlation between physiological processes and thermal comfort have been carried out for more than 5 decades by the indoor thermal comfort research community [176]. By definition, thermal comfort is a cognitive inference that depends on physical, physiological, and other human-related contextual factors (e.g., psychological) [170] and can be achieved when physiological efforts for thermoregulation are minimized and the core body temperature is kept within a close range [170]. These processes include an adjustment in the blood flow to the skin surface through vasodilation for warmer environments and vasoconstriction for cooler ones. As the temperature increases, other mechanisms, such as sweating and shivering, get triggered. Inspired by these features, the PSS-based methods have sought to use physiological measurements of the human body for real-time quantification of thermal comfort and as feedback to the HVAC control loop.

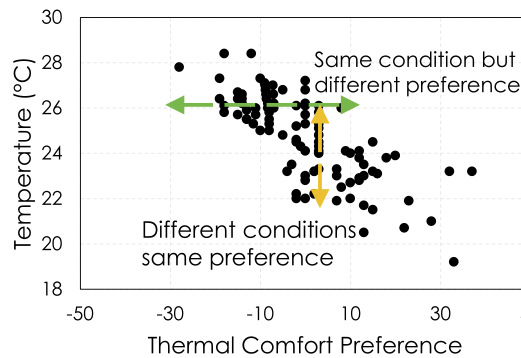

Fig. 13. The subjective nature of thermal comfort preference ([10]).

The literature in this domain can be categorized into two groups of (1) feature engineering and (2) comfort modeling. A majority of efforts focused on investigating correlations between physiological responses of the human body in reflection to the ambient thermal condition variations. As Table 15 shows, the majority of efforts have focused on establishing a correlation between skin temperature and thermal comfort perceptions (e.g., [176–181]). Heart activity, and specifically heart rate, also a driving factor for metabolic rate [183], has been investigated in a number of research efforts [184–186]. These studies have shown a rather moderate correlation between the variations in heart rate with respect to thermal sensations or ambient conditions. Specifically, heart rate appears to show correlations in identifying a three-class thermal comfort assessment [187] compared to more refined levels of thermal comfort perception. However, no statistically significant differences have been reported [177,188]. There have been

Table 14
Thermal comfort sensation/preference scales and their representations.

Thermal comfort measurement scale	Representation
ASHRAE thermal sensation scale [39]	[Hot, warm, slightly warm, neutral, slightly cool, cool, cold]
Bedford scale [166]	[Much too warm, too warm, comfortably warm, comfortable, comfortably cool, too cool, much too cool]
McIntyre preference scale [167]	[Cooler, no change, warmer]
Combined scales	
Becker and Paciuk [159]	• ASHRAE Scale • [much cooler, cooler, slightly cooler, no change, slightly warmer, warmer, much warmer] • [comfortable, slightly comfortable, uncomfortable, very uncomfortable, unbearable]
Zhang et al. [168]	• 9-point ASHRAE scale (added very hot and very cold) • [comfortable, slightly comfortable, uncomfortable, very uncomfortable] • [clearly acceptable, just acceptable, just unacceptable, clearly unacceptable)
Wong and Khoo [169]	• ASHRAE scale for temperature feeling • Bedford scale for comfort feeling • McIntyre scale for preferences • A binary question for overall acceptability
Jazizadeh et al. [170]	• A graduated sliding preference scale with snapping degrees for increased consistency of the votes

Table 15
Use of sensing technology for thermal comfort assessment or comfort-aware HVAC operations.

Parameter of interest	Feature	Sensing technology	Field study		Experimental study
			Residential	Office	
Occupant feedback	Thermal sensation/perception or preference	Electronic/web-based survey		10*	
		Smartphone-based survey	2	15*	
Physiological response	Skin temperature	Thermometer			14
		Wearable device - smartwatches	2	1	
		Infrared imaging		1	2
	Heart rate (heart activity)	Wearable fingertip/earlobe sensors (smartwatches)		2	
		ECG (Electrocardiography)			5
		PPG (Photoplethysmography) on webcam data			1
	Nerve conduction velocity	EMG (Electromyography)			1
	Brain activity	EEG (Electroencephalography)			1
	Blood perfusion	PPG on webcam data			3
	Respiration	DRS (Doppler Radar sensing)			2
Physical process	Activity	PIR			1
Clothing insulation	Insulation state	Infrared imaging			1

* Includes other types of buildings such as laboratories, banks, courthouses.

Table 16
Variation of contextual conditions and acclimation time considered in the studies – captured form [187].

Measured physiological response	Measurement technique	Temperature range	Acclimation time	Reference
Skin temperature, ECG, EEG	Thermometer, ECG	21–29 °C	60 min	[189]
Skin temperature, ECG	Thermometer, ECG	21–29 °C	40 min	[190]
Skin temperature	Thermometer	20–30 °C	30 min	[181]
Skin temperature	Thermometer	21–33 °C	15–20 min	[191]
Heart rate	RGB Webcams (PPG)	20–29 °C	20 min	[192]
Heart rate variability	ECG	21–29 °C	40 min	[184]
Skin temperature, heart rate, blood pressure	Thermometer	19–22 °C	30 min	[188]
Respiration	Doppler radar	20–29 °C	20 min	[193]

studies that used a more sophisticated feature of heart activity in the form of the ratio of high frequency (0.15–0.40 Hz) to low frequency (0.04–0.15 Hz) of the electrocardiographic (ECG) signal and showed an increasing trend once subjects felt discomfort [184,185,189]. In the majority of these efforts, conducted by the indoor thermal comfort research community, identifying correlations was the main objective, and, therefore, the feasibility of sensing has been less emphasized. In other words, wired sensor systems or cost-intensive thermal cameras have been used. Another important factor that the majority of these efforts have taken into account is the acclimation. Acclimation time refers to the time that is considered for the stabilization of the human subjects' thermoregulation processes. Table 16 presents the spectrum of the experimental conditions in the representative studies.

To account for the feasibility of using physiological attributes in the control of HVAC systems, PSS should account for the following factors [187,194]:

- **Applicability**: Inferring the correlation of at least one physiological parameter with the ambient thermal conditions so that thermoregulation states could be identified,
- **Sensitivity**: Recognizing subtle variations in physiological responses corresponding to thermal sensations in a timely manner so that the system can respond to the discomfort state promptly; the impact of acclimation time is an important parameter,
- **Non-intrusiveness**: Minimizing interruptions/interference with occupants' activities and being acceptable to occupants without raising privacy concerns, and
- **Ubiquity**: Being pervasively available to facilitate scalable data collection processes and enable distributed assessment of thermal sensations in an environment.

Applicability and sensitivity are interconnected and could be also interpreted as one factor. As a non-intrusivene method, the feasibility of the sensing systems should be evaluated under the constraints of (1) limited human-body parts that could be instrumented, as well as (2) in consideration of occupnats' normal daily activities.

Among the research efforts, conducted by the HVAC research community, the majority of the efforts [179,181,182,184,185,186,191,194–201] investigated the feasibility of using physiological features for thermal comfort assessment. Choi [203] has used bio-signals for HVAC operations by performing an experimental study, in which a thermometer was used to capture participants' wrist temperatures as feedback to HVAC systems and reported the potentials for comfort and energy management. In recent years, there have been other efforts, in which smartwatches were used in field studies for thermal comfort inference and HVAC operations. Infrared imaging, photoplethysmography (PPG), Doppler radar sensing (DRS), and smart wearable devices are the emerging methods that have been investigated for thermal comfort assessment. In Table 17, we have provided information on the studies that have used these emerging technologies for thermal comfort assessment as feedback to HVAC systems. As noted, there exist other studies that have investigated the correlation between thermal comfort and physiological attributes; however, their objectives did not include HVAC operations. To provide a better insight into the content of these papers, we have briefly described the use of PPG and DRS. PPG, a commonly used method in medical applications, leverages changes in image pixel values to estimate variations of blood flow to the skin, from which frequency and amplitude values are used to infer heart rate and states of blood vessels (i.e., vasodilation vs vasoconstriction), respectively. DRS systems use Doppler radar sensors to quantify variations of motions, within certain frequency bands, which can be used for respiration quantification.

Future research directions: Investigating innovative sensing and data acquisition systems for the integration of personalized thermal comfort should be conducted by considering different feasibility dimensions. This calls for further experimental and field studies, which

Table 17
Details of studies that used PSS for comfort-aware HVAC operations.

Sensing tech.	# of subjects	Region	Physiological attribute	Temperature setup	Objective	Ref.
Thermometer	18	Wrist	Skin temperature	Personalized setpoint temperatures assigned by participants	Performance of the comfort-aware operation (energy savings and comfort)	[203]
Infrared imaging	15	Facial area	Skin temperature	Two transient temperatures 1) from 20 to 30 °C and 2) from 30 to 20 °C	Classify the necessity of heating/cooling	[204]
	15	Facial area	Skin temperature	Three steady-still Temperatures (comfortable, 18, and 29 °C)	Distinguish comfort/discomfort	[205]
	12	Facial area	Skin temperature	One steady-still condition at 25 °C and two transient temperatures from 22 to 28 °C and from 28 to 22 °C	Classify thermal preferences (cooler, no change, warmer)	[206]
	30	Facial, neck, palm area	Skin temperature	Field study that participants can adjust setpoint temperature	Classify the necessity of heating/cooling	[207]
PPG	10	Facial area	Heart rate	Four steady-state temperatures (20, 23, 26, and 29 °C)	Applicability assessment	[192]
	4	Facial area	Blood perfusion	Two steady-state temperatures (20 and 29 °C)	Applicability assessment	[208]
	21	Facial area	Blood perfusion	Two steady-state temperatures (20 and 29 °C)	Applicability assessment	[209]
	15	Facial area	Blood perfusion	Transient temperatures (from 20 to 30 °C)	Applicability and sensitivity assessment	[187]
	16	Hands	Blood perfusion	Hands were immersed into 45 °C water for 10 min and the variations were measured	Applicability and sensitivity assessment	[210]
DRS	6	Chest & abdomen area	Respiration	Two steady-state temperatures (20 and 30 °C)	Applicability assessment	[193]
	4	Chest & abdomen area	Respiration	Transient temperatures (from 20 to 30 °C)	Applicability and sensitivity assessment	[194]
Smart-watch	4	Wrist	Skin temperature, heart rate, sweat	Not specified	Classifying thermal sensation	[211]
	3	Wrist	Skin temperature, heart rate	Field study	Classifying thermal sensation	[212]
	23	Wrist	Skin temperature, heart rate	Field study	Classifying thermal preference	[213]

will shed light on unexpected challenges (emerging from the field studies) to facilitate the improvement in technology development and technology adoption in practice. Given the increasing trend in the market penetration rate of wearable devices in recent years and the fact that users utilize physiological response measurement technologies for health management (e.g., PPG in smartwatches), research in this field has a promising perspective.

Furthermore, other dimensions could affect thermal comfort perception besides the aforementioned factors, which were the subject of the main body of research in this field. **Psychological factors** are among the parameters that remain to be explored. In an example study, Oseland [214] reported that subjects felt warmer in their homes in the same ambient thermal condition with the same clothing insulation level. The investigation of behavioral interventions and their impact on thermal comfort perception comprise another important research direction that has not been explored although human behavioral studies for energy management is a well-studied field. **Level of activity** is another factor that could impact the thermal comfort perception and need for air conditioning. In an example study, Kim et al. [215] used a PIR-based sensor network to identify occupants' locations and to infer their activities (e.g., occupants' movement) and developed an air-conditioning unit that regulated fan speed and operating mode accordingly. Through an experiment, this study has shown the potentials for using actual physical activity for human-centered operations. Several studies, which have investigated human activity recognition (HAR), also pointed out the potentials for energy management (e.g., [216–218]), but these articles do not provide details about how HAR can be utilized for operating HVAC systems. Human activity recognition is a mature field of study and out of the scope of this review study. In some studies, **higher-level human-related variables** such as *activity level, met unit,* or *clo unit* have been required to be provided by occupants through OVS-based techniques [164,212,213]. However, as noted, the use of such values provided by occupants might not represent actual values. Quantification of the exact impact of clothing insulation is not trivial as it is derived from several different factors such as fabric types, air layers, and posture [164,212]. However, there has been an effort [220] to quantify the impact of clothing insulation by using infrared imaging to estimate temperature inside the clothes without any further use in HVAC operations.

4.3. Thermal comfort inference and profiling

Using the personalized thermal comfort data to enhance real-time operational efficiency of the HVAC systems calls for pattern recognition models that infer personalized thermal comfort in a given thermal condition. Therefore, moving from generalized thermal comfort models (e.g., PMV model), studies have sought to create personalized thermal comfort models either for instantaneous thermal comfort prediction or thermal comfort profile generation. These models map an input data point $\boldsymbol{x} \in \mathbb{R}^d$, a d dimensional variable to either a class of thermal comfort perception (e.g., satisfied, feeling warm/hot, feeling cool/cold) or a thermal comfort satisfaction score (e.g., the probability of being satisfied). The latter corresponds to thermal comfort profiling techniques that map the thermal conditions to a thermal satisfaction probability. As Fig. 14 illustrates, due to the stochastic nature of the thermal comfort modeling and the subjective nature of occupant input, probabilistic inference methods, as well as fuzzy-rule-based modeling [10,218–220], have been commonly used. Examples of probabilistic modeling could be found in the work, presented by Daum et al. [161]. They used multinomial logistic models to create personalized thermal comfort profiles. They have also explored the possibility of using generalized models for inferring posterior models with minimal training in the field. Examples of fuzzy-rule-based modeling could be found in the work of Jazizadeh et al. [221], where they used a Wang-Mendel fuzzy-pattern recognition algorithm to create non-linear thermal comfort profiles without assuming an underlying model. The use of machine-

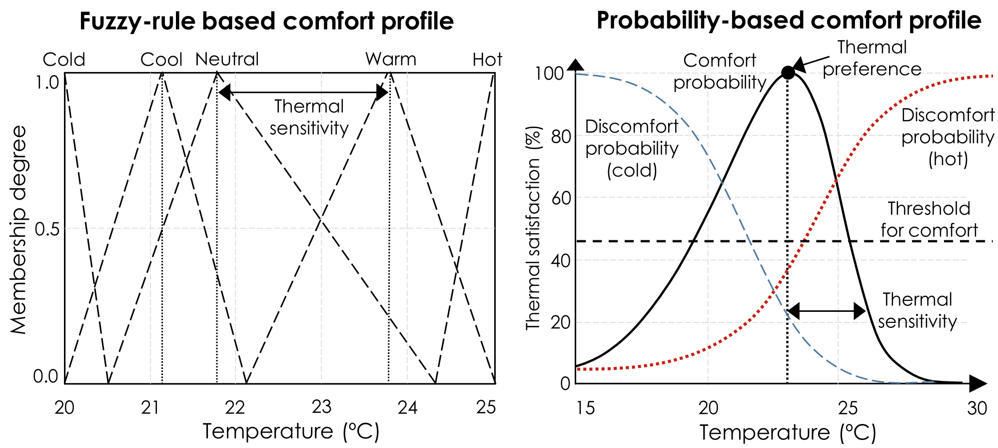

Fig. 14. Comfort profiling methods: (1) fuzzy-based and (2) probability-based comfort profiles (reproduced from Jazizadeh et al. [221] and Daum et al. [161]).

learning algorithms, specifically classifiers, have also been utilized to create thermal comfort inference models. A variety of classification models have been investigated using different combinations of features. Temperature has been the main feature in almost all analyses and has been augmented with additional features such as human-related parameters [173,206,212,224].

Performance assessment of thermal comfort inference: Performance assessment in this section refers to the performance of classification models that sought to predict an instantaneous state of comfort. By reviewing the literature, we identified the following criteria for categorizing the efforts in presenting their performance: (i) number of classes, (ii) type of features, and (iii) type of inference algorithm.

For the first criterion, studies have used the following classifications: (1) thermal preference (warmer, no change, and cooler), (2) thermal sensation (cold, cool, neutral, warm, and hot), and (3) necessity of using more energy for comfort (binary representation). In the last category, researchers explored whether more energy consumption is required for comfort. For example, when a space is overcooled beyond occupants' comfort zone, it is classified as unnecessary energy use [167]. The second criterion focuses on what features have been used for mapping thermal condition to a comfort index. These features include environmental factors, commonly temperature in an environment, as well as human-related features, including either physiological (i.e., skin temperature or heart rate) or physical (i.e., clothing insulation and activity) [212]. We have categorized these features into environmental versus human-related to shed light on the impact of human-related features.

Fig. 15 summarizes the performance of machine-learning algorithms in inferring thermal comfort states according to the aforementioned three criteria, and Table 18 shows the references used in Fig. 15 in the order that they have been presented. As noted before, in these visualizations, we have presented different scenarios from a single study as different data points. The reported accuracy values, which were used as the primary performance indicator in all studies, have been presented in the form of a box plot.

Fig. 15A (the upper part of Fig. 15) represents the studies that mainly relied on environmental factors as the representative features. The results in this figure (Fig. 15A) represent the efforts of three separate studies [163,173,213], in which multiple experimental scenarios were evaluated. The only human-related factor that was used in some of these efforts is the level of clothing insulation. In general, by considering median values in the box plots, moderate performances have been demonstrated. The range is from 61% to 72% [163,173,213]. The horizontal axis shows the type of classification algorithms or generalized thermal comfort models (i.e., PMV [225] and Adaptive Thermal Comfort [226]). As this figure shows, the integration of clothing insulation attribute has helped slightly improve the performance of the models considering the median values for accuracy. More specifically, the case without clothing insulation attribute has shown a median accuracy of 63% [213] but when it is combined, the median accuracy increased to 72% with the same machine-learning algorithm [173]. It is worth noting that this study [163] has used 22 environmental factors as attributes for the model, including temperature adjustments on the chairs. Therefore, it is not trivial to identify the causality behind the observed improvements. Moreover, the use of PMV for inferring personalized thermal comfort has not been shown to be successful. To use the PMV model (with a 7-point output), a modified 3-point representation (too cold: from −3 to −0.5, comfortable: from −0.5 to 0.5, and too hot: from 0.5 to 3) has been used in studies [163,173].

Fig. 15B (the lower part of Fig. 15) represents the efforts that use parameters from the physiological response of the human body as a critical component of the features. All studies have relied on skin temperature and/or heart rate. Skin temperature has been the most commonly used feature in this category. In general, as more parameters, including skin temperature, heart rate, activity level, and clothing insulation are added, an improvement in performance is observed. Among these efforts, one study [213] has only used human-related attributes (including wrist skin temperature from a smartwatch, heart rate, clothing insulation, and activity) without any environmental attributes that resulted in a median accuracy of 60%. However, they have demonstrated that by, adding environmental parameters (i.e., indoor and outdoor temperatures and humidity, CO_2, and window state), an improved median performance of 79% was achieved. Even higher performances, median accuracies of 90% and 95%, have been observed when information on facial skin temperature has been employed [206,207]. However, an increased number of features (65 and 26 for the two-class [207] and three-class [206] classification problems, respectively) representing skin temperatures have been used in the latter analyses. These studies have used thermal imaging from the hands, neck, and facial skin areas. In the case of the five-class classification, six environmental (including indoor and outdoor temperatures, humidity, CO_2, and window state) and four human-related features (including wrist skin temperature from a smartwatch, heart rate, clothing insulation, and activity) have been used, and a median accuracy of 59% was observed [212].

Thermal comfort data representation: Similar to the studies in occupancy modality, comparative performance assessment of comfort-aware HVAC operations highly depends on understanding the context of the studies. The context description schema (or the outline for reporting the findings of a study, as well as for creating a dataset for personalized comfort characterization) shares many attributes with studies in occupancy modality. However, it further includes domain-specific attributes as follows. In the ***contextual data*** category, the specifications of data collection methods for thermal sensation/

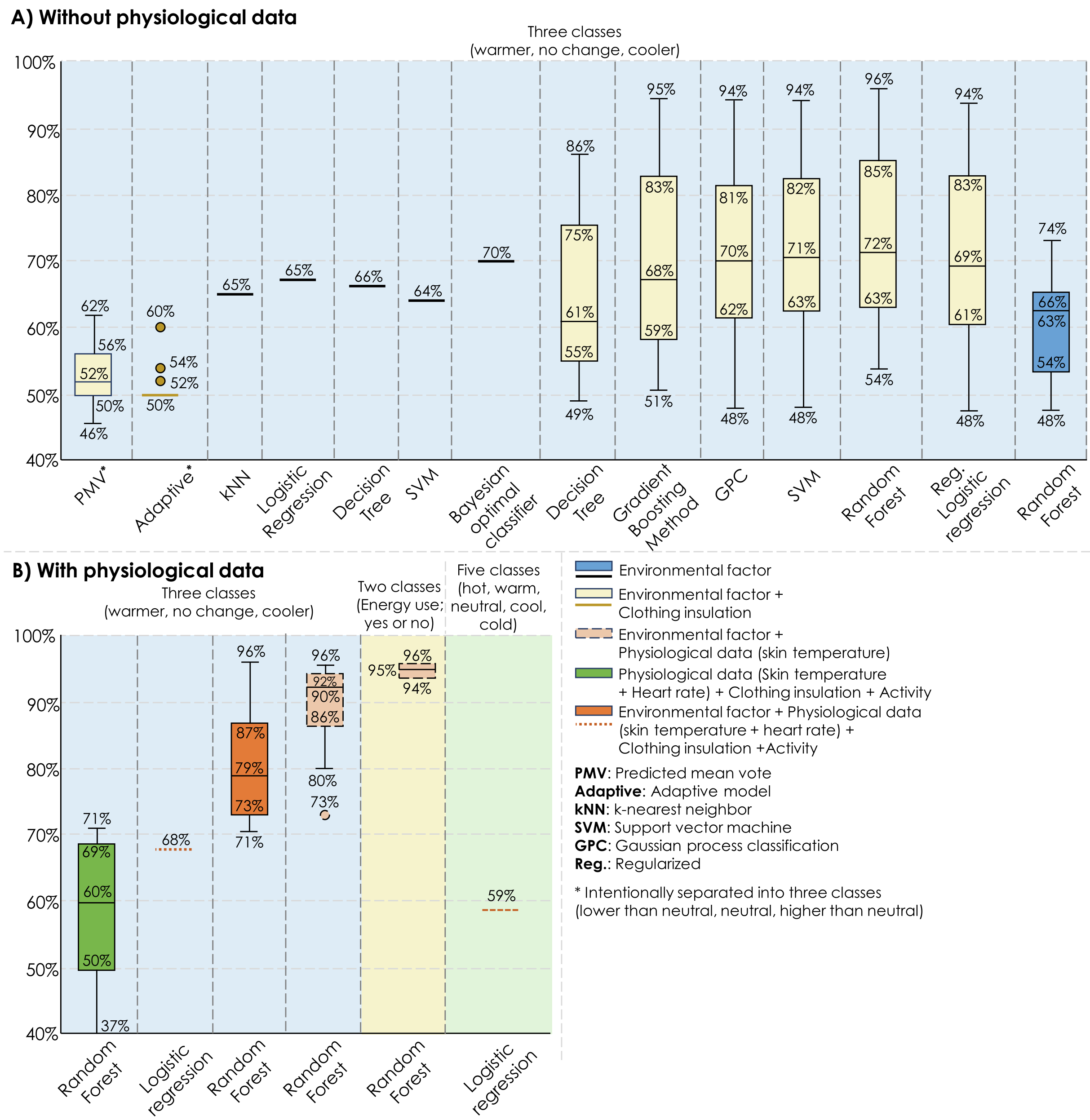

Fig. 15. Boxplot of the reported accuracy of comfort inference.

Table 18
References used in creating Fig. 15.

Figure	# of class	Parameter	Algorithm	# of participants	Reference
Fig. 15A	Three (warmer, no change, cooler)	Environmental + clothing insulation	PMV	67	[163,173]
			Adaptive comfort model	34	[173]
		Environmental	kNN, logistic regression, decision tree, SVM, Bayesian optimal classifier	33	[163]
		Environmental + clothing insulation	Decision tree, gradient boosting method, Gaussian process classifier, SVM, random forest, regularized logistic regression	33	[173]
		Environmental	Random forest	10	[213]
Fig. 15B	Three (warmer, no change, cooler)	Human	Random forest	10	[213]
		Environmental + human	Logistic regression	3	[212]
			Random forest	10	[213]
			Random forest	12	[206]
	Two (Energy use: yes or no)	Environmental + human	Random forest	24	[207]
	Five (thermal sensation)	Environmental + human	Logistic regression	3	[212]

preference/satisfaction are added. This information mainly includes the characteristics of the sensation scales used for collecting occupants' thermal comfort sensation. Moreover, the assessment of the comfort studies calls for information on the regional climate (demonstrated to have an impact [227]), thermal conditioning systems' specifications, thermal conditions in the testbed buildings, sensor set-up for human sensing, and more dimensions for contextual data on human subjects (e.g., weight, height, clothing insulation, gender, ethnicity, etc.). Characteristics of human participants [207] and how they experience the environment (mainly their location in the testbed) [214] could affect their perception of the thermal environment. In the ***modality-specific data*** category, data could include perception, preference, and/or satisfaction as predicted, as well as ground truth. In the ***data analysis*** category, given the nature of the thermal sensation measurements, the task of inference could be tackled as a classification problem, and therefore, a confusion matrix and its associated derived metrics will be required. In some cases of thermal comfort profiling, relative error and goodness of fit could be used as alternative metrics for assessment. Table 19 presents the description of attributes for the proposed comfort modality data schema.

Future research directions: As the nature of thermal comfort implies, comfort modeling and prediction is a challenging task that often calls for stochastic methods. This stems from the fact that several factors could affect thermal comfort perception, but those factors might not be trivial to measure or quantify. Therefore, one of the future research directions is investigating feature analysis and/or inference methods that account for those factors while considering the trade-off between the cost of sensing and efficacy. Although comfort profiles/models are often developed by using labeled data from the human subjects, fewer studies (see an example study by Jazizadeh et al. [222]) have investigated the validation of such profiles in the field. Instead, they rather focused on purely data-driven validation methods like cross-validation or similar methodologies. Field validation of these models could provide a more realistic assessment of comfort modeling performance on inferring the actual thermal preference/sensitivity. Another dimension to the knowledge gap is whether personalized comfort profiles can account for temporal and contextual variations induced by either seasonal variations or thermal history of human subjects. These are the areas that are critical in comfort modeling and profiling for integration into operational strategies.

Given that comfort votes from occupants act as ground truth in personalized comfort modeling/profiling, facilitating feedback data collection process is of dire importance. Therefore, research in the following directions appears to be necessary: (1) devising methods for incentivizing occupants, (2) developing data processing techniques that require minimal data points from occupants, and (3) moving towards generalizability by accounting for thermal comfort profiling for typical individuals, characterized by different attributes such as body dimensions, gender, age, etc.

4.4. Comfort-aware human-in-the-loop HVAC operations (comfort modality)

The thermal comfort perception/preferences of real occupants have been explored in different sub-modalities: (1) evaluating building energy management system performance, (2) adopting personalized comfort profiles in building energy simulation, (3) implementing comfort-aware HVAC operations with respect to collective perceptions/preferences, and (4) applying comfort-aware HVAC operations with respect to personalized perceptions/preferences.

Large-scale HVAC operation assessment in providing comfort: Access to computing devices, such as desktops, laptops, tablets, smartphones, and network connectivity, has provided the opportunity for large-scale performance assessment of HVAC operations during the

Table 19
Required attributes for personalized comfort data representation in addition to primary data.

Attribute	Data
	Contextual data
Data acquisition system metadata	• Sensor type (e.g., RGB sensor, infrared thermal camera, thermometer) • Sensor specifications (including accuracy, resolution, range, field of view, and power consumption) • Interface specifications (web-based, smartphone-based, or smartwatch-based) • Thermal sensation scale type (e.g., formalized scales or custom scales) • Thermal sensation scale specification (e.g., scale resolution, numeric vs non-numeric, mapping between lingual to numerical values)
Temporal information	• Measurement frequency (including raw sensing data temporal resolution) • Time of study (e.g., season and time of day) • Duration of study
Spatial (including environmental information)	• Testbed location climate • Testbed dimensions (length, width, height) • Testbed type (open versus closed space | residential versus office space) • Thermal conditioning system specifications (including (1) mode: natural | mechanical | mixed, (2) diffusor(s) and thermostat (s) locations and (3) thermal condition ranges) • Sensor deployment information (sensor location on the body, distance between sensors, and point of measurement) • Thermal conditions of testbed (including temperature, relative humidity, etc.)
Occupants' characterization	• General information of participants (e.g., weight and height for Body-Mass-Index, ethnicity, gender, etc.) • Total number of participants • Participants' normal activities (e.g., sitting, standing, sleeping, etc.) • Experimental instructions for participants • Level of clothing at time of experiment
	Modality-specific data (thermal comfort)
Thermal sensation | preference |satisfaction	• Actual values • Predicted values
	Data analysis
Feature extraction method(s)	• Time domain versus spectral domain features • Feature extraction algorithms • Feature representations (e.g., instantaneous versus cumulative measures)
Pattern recognition algorithms	• Model type (e.g., Support Vector Machine (SVM) or Markov model) and characteristics (e.g., limitations) • Model training requirements (e.g., number of data points) • Important hyperparameters of the models
Performance metrics	• Goodness of fit or relative error values • Confusion matrix (accuracy, precision, recall, F-measure)

occupancy stage. Leveraging such opportunities, a number of studies have focused on understanding the overall performance of HVAC systems with respect to providing comfort. In a comprehensive effort, starting with 22 buildings in an earlier study [11], Huizenga et al. [37] collected 34,169 responses over 4 years concerning 215 buildings located in the US, Canada, and Finland. Another example is the study of Sanguinetti et al. [228], in which they collected 10,315 responses (2,684 rooms in 183 buildings from 4,471 users) on a university campus over one year. In addition to demonstrating the feasibility of large-scale data collection for performance assessment, these studies have revealed a number of generalized facts about the performance state in buildings. Huizenga et al. [37] stated that only 11% of buildings out of 215 in three countries (US, Canada, and Finland) satisfied 80% or more of their occupants [37]. The 80 percent boundary is commonly used for measuring the performance of HVAC systems in buildings given the criterion indicated in ASHRAE standard 90 [39]. These studies have also reported that overcooling is a common problem [228] and that access to control interfaces and portable air-conditioning devices (e.g., thermostats, operable windows, and portable heaters and fans) plays a critical role in achieving occupants' thermal comfort. Another reported observation points to the configuration of HVAC systems in buildings, namely, the location of the air-distribution system. Under-floor air-distribution systems have rendered less satisfied occupants, compared to overhead air distribution [11].

Apart from understanding the general perceptions of thermal comfort in buildings, another contribution of such large-scale surveys is to make use of the results in other buildings as a benchmark [11,36]. In other words, such analysis, if accompanied by sufficient contextual metadata, could be used for establishing benchmarks for best practices. A rigorous investigation of buildings with a high number of comfort votes could shed light on the performance of their HVAC system management and design. As an example, Pritoni et al. [229] have reported an exceptionally high number of complaints (828 votes) from occupants in one classroom building who voiced their concerns about a serious and expensive mechanical problem with its HVAC systems.

Use of personalized comfort profiles in building energy simulation: The current state-of-the-practice in building energy simulations does not reflect the personalized thermal comfort preferences/profiles of occupants. As noted earlier, this mainly stems from the fact that occupant preferences are not known at the simulation stage. However, the impact of personalized preferences could bring about considerable differences in energy performance of the buildings. Although compared to occupancy-driven simulations, fewer studies have explored this research direction, these impacts have been demonstrated in a number of research explorations. Given the dynamic nature of the interactions between humans and the buildings, accounting for human thermal preferences has been commonly explored using multi-agent-based (MAB) simulation techniques [225,226,230]. By simulating a real-world building, Klein et al. [230] have shown that by accounting for occupants' preferences and schedules (collected from the real-world testbed), a 12% reduction in energy consumption and 5% improvement in occupant comfort has been observed compared to standard baselines. The importance of thermal comfort profiles was also reflected in a MAB simulation study by Jung and Jazizadeh [231], in which it has been shown that the thermal sensitivity of occupants could significantly change the thermostat settings of the HAVC systems during operations. Further explorations in this direction could result in design procedures for building systems. However, given the possibility of changes in the future occupancy of buildings, the integration of personalized comfort profiles during the design should be carried out by accounting for future scenarios and adaptive operational strategies.

Comfort-aware HVAC operations: We have evaluated the performance of the comfort-aware operations using five criteria: (i) submodality, (ii) operational strategy, (iii) operational baseline, (iv) spatial scale, and (v) simulation vs. field studies. As shown in Fig. 12, two types of comfort-aware HVAC operations have been demonstrated. The personalized conditioning method considers the thermal preference of a single occupant in a space (i.e., addressing a single personalized comfort profile). On the other hand, the collective conditioning method, which accounts formultiple personalized comfort profiles, more often occurs in buildings due to the use of thermal zones. In such cases, a strategy for resolving thermal conflicts [232] and the integration of personalized thermal comfort is imperative. Review of the literature shows that this integration has been carried out using four strategies:

i. using occupants' individual thermal preferences/profiles to calculate temperature setpoints that minimize overall discomfort [233–235],
ii. using personalized preferences/profiles along with additional temperature sensors at room level to calculate dynamic temperature setpoints that minimize overall discomfort in a thermal zone [10,213,221,222],
iii. creating a thermal-zone-scale discomfort or comfort profile to minimize discomfort in the thermal zone by minimum energy use [223], and
iv. calculating a context-aware PMV value to optimize setpoint temperature [236].

In the first strategy, the occupants' perspectives could be acquired either through continuous and direct votes from occupants or through personalized thermal comfort profiles. The temperature setpoint is therefore adjusted based on an objective function of discomfort. For example, Murakami et al. [234] used the majority vote from occupants (e.g., cooler) to adjust the temperature setpoint. An alternative to the first strategy, described as the drifting operational strategy [229,233,234], also has been adopted to save energy. This method was used along with control strategies, in which occupants can adjust the operation of the HVAC system by sending continuous feedback. Through this method, the setpoint is adjusted to gradually move towards matching the outdoor temperature and this adjustment is stopped/reversed upon receiving a discomfort vote from occupants. In these studies, thermal comfort profiles have not been used, and the system relies on the continuous engagement of the occupants in an environment. The concept of drifitng has been illustrated in Fig. 16.

The second strategy not only leverages personalized thermal comfort profiles to identify each occupant's preferred temperature, but also aims to demonstrate uneven temperature distribution in subspaces, being conditioned under one thermal zone with single thermostats (measuring a temperature at an arbitrary location). The third strategy focuses on multi-objective optimization, minimizing discomfort and energy use, using the thermal-zone-level discomfort profile, created from individual comfort profiles. In the fourth strategy, an adaptive PMV model that reflects real-time values in buildings is used to provide comfort to occupants.

By adopting the aforementioned strategies, energy consumption

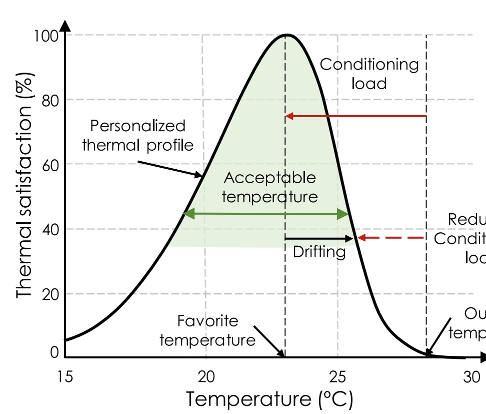

Fig. 16. Reduced conditioning load by the drifting operation method.

Table 20
Distribution of cases (and papers) that reported the performance of comfort-aware HVAC operations in residential and office buildings.

		Comfort-aware operation	
		Personalized conditioning	Collective conditioning
Office	Simulation		4 (2)
	Field study	3 (2)	10 (6)
Residential	Simulation		1 (1)*
	Field study		

* The number in parentheses shows the number of papers that reported the cases.

implications have been explored in a number of studies through either simulation or field studies. Given that thermal zones are configured for multi-occupancy by default, all studies have explored the use of personalized thermal comfort information for collective thermal conditioning, and no study explicitly investigated personalized thermal conditioning by solely relying on HVAC systems. However, some studies explore thermal zones with a single occupant. We have used those cases as a proxy to investigate energy implications of the strategies. Table 20 presents the number of cases that have reported on the performance of comfort-aware HVAC operations (one article could have more than one case). The majority of these studies focused on office spaces (94.4%), and the field studies were dominant (72.2%).

The reported energy-saving potentials of comfort-aware HVAC operations have been illustrated in Fig. 17, and Table 21 shows the references used in Fig. 17. It is worth noting that we excluded the cases from Barbato et al. [175] and Pritoni et al. [229], as the former calculated the energy-saving potentials (28%) derived from both occupancy-driven and comfort-aware operations, and the latter did not specify the number of occupants in their testbeds (20–30% of energy savings were reported).

As the box plots in Fig. 17 show, the majority of the investigated cases are related to thermal conditioning according to collective thermal comfort. We have considered the reported changes in energy-saving percentages regardless of the metric that was used in each study. This figure synthesizes performance improvements from different strategies, as described above, by considering the context of the experiments. According to the results reported in field studies, the integration of personalized thermal comfort in a number of thermal zones has shown an average savings of 20% [221–223,235]. However, given the dependency of the operations on the personal preferences of occupants in the testbeds, a negative percentage (i.e., increased energy consumption) has also been reported. Jazizadeh et al. [221] reported –17% of energy saving in a single thermal zone. As the cases derived from the single-occupancy thermal zones illustrate, personalized thermal preferences for some occupants resulted in higher energy consumption due to the higher needs for thermal conditioning loads [221]. As Jazizadeh et al. [222] stated, the observed energy savings in the field study stems from preventing over-conditioning. Research efforts that used discomfort/comfort profiles at thermal-zone-level [223], drifting [229,233,234], and contextual PMV data [236] have reported average energy savings of 50% (reflecting energy optimization as well), 21%, and 10%, respectively. Again, it is emphasized that these percentages reflect changes observed in different metrics for energy quantifications (e.g., average daily air flow and calculated energy consumption).

Most studies did not specify detailed information for testbed characteristics. In some studies, quantitative specifications (e.g., area) were provided, some provided floor plans, and in some, no detailed specifications were presented. Therefore, in the categorizations of Fig. 17, the general descriptions provided by each study were used for synthesis purposes. The challenges in normalizing the results with respect to the testbeds' specifications emphasize the importance of adopting a generalized schema, such as the one proposed in Table 19. Studies have used different metrics in quantifying the energy-saving potentials of the comfort-aware operations, including daily airflow [221–223,236], calculated energy based on airflow, as well as supply and discharge temperatures [236], and energy [235]. The baseline in all studies has been set as the energy consumption required for thermal conditioning when using predefined temperature setpoints. Information about the conditioning schedule (e.g., from 9:00 am to 6:00 pm) is often missing, which makes normalization challenging. Only a few studies clearly mentioned the conditioning time on both conventional (i.e., baseline operations), and comfort-aware HVAC operations [10,222,234].

Comfort assessment in comfort-aware HVAC operations: Another important factor in the performance assessment of the comfort-aware operations is the thermal comfort improvement. Through interviews with occupants, Jazizadeh et al. [221], Jazizadeh et al. [222], and Lam et al. [235] have demonstrated that the comfort-aware operations have resulted in considerable improvement in the thermal satisfaction of occupants. Murakami et al. [234] and Pritoni et al. [229] have mentioned that feedback from occupants remained similar after the comfort-aware HVAC operations were implemented, while energy consumption was reduced.

Future research directions: Understanding the potential of personalized thermal comfort integration calls for more diverse field studies. The reported energy saving potentials in the literature have been demonstrated by the studies, which were performed in a similar climate region and mostly in small-scale test beds. Hence, diverse analyses on different regions, scales, and building types (i.e., various contexts) are required to shed light on the actual viability of comfort-aware HVAC operation. Energy saving through comfort-driven strategies is based on the assumption (which has been validated in few studies) that commonly used operational settings of building systems are set to be conservative. Therefore, if we account for the contextual thermal preferences, we should be able to conserve energy. Further validation of this assumption under varied conditions is another direction of research that is critical in the realization of HITL HAV operations. Moreover, integrating diverse thermal comfort preferences from different individuals, who share the same thermal zone, is an ongoing research topic that requires further explorations. Research in these directions could be carried out by simulation-based studies first, and consistent and constructive field studies should be conducted for further viability evaluations. It is important to note that in this study, we did not include research efforts on personalized thermal conditioning (i.e., personal heaters or fans) by using distributed devices given the focus on HVAC systems. However, following the same rationale, moving towards enabling HVAC systems with higher flexibility for targeting individual preferences is another direction of research that worth exploring.

5. Qualitative evaluation

Upon reviewing and assessing the compiled studies, we have reflected on the research directions that could pave the way for further enhancements in the HITL domain. To this end, in an analogy to the concept of technology implementation stages of the Hype cycle model, we have provided a qualitative evaluation of the research in HITL HVAC operations and have discussed potential directions of explorations. This model describes the adoption cycles that a technology goes through until the practical viability of the technology is revealed. Table 22 states different stages of this model, and Fig. 18 graphically describes each stage.

As a steppingstone for HITL HVAC operations, in the first step, we have assessed the inference of human dynamics' attributes, namely, presence, count, and comfort. In doing so, we considered performance (i.e., the accuracy of inference). Occupant positioning is excluded in our qualitative evaluation given that it has not been actively adopted in HITL HVAC operations. Nonetheless, occupant-positioning techniques could potentially provide other dimensions of occupancy dynamics

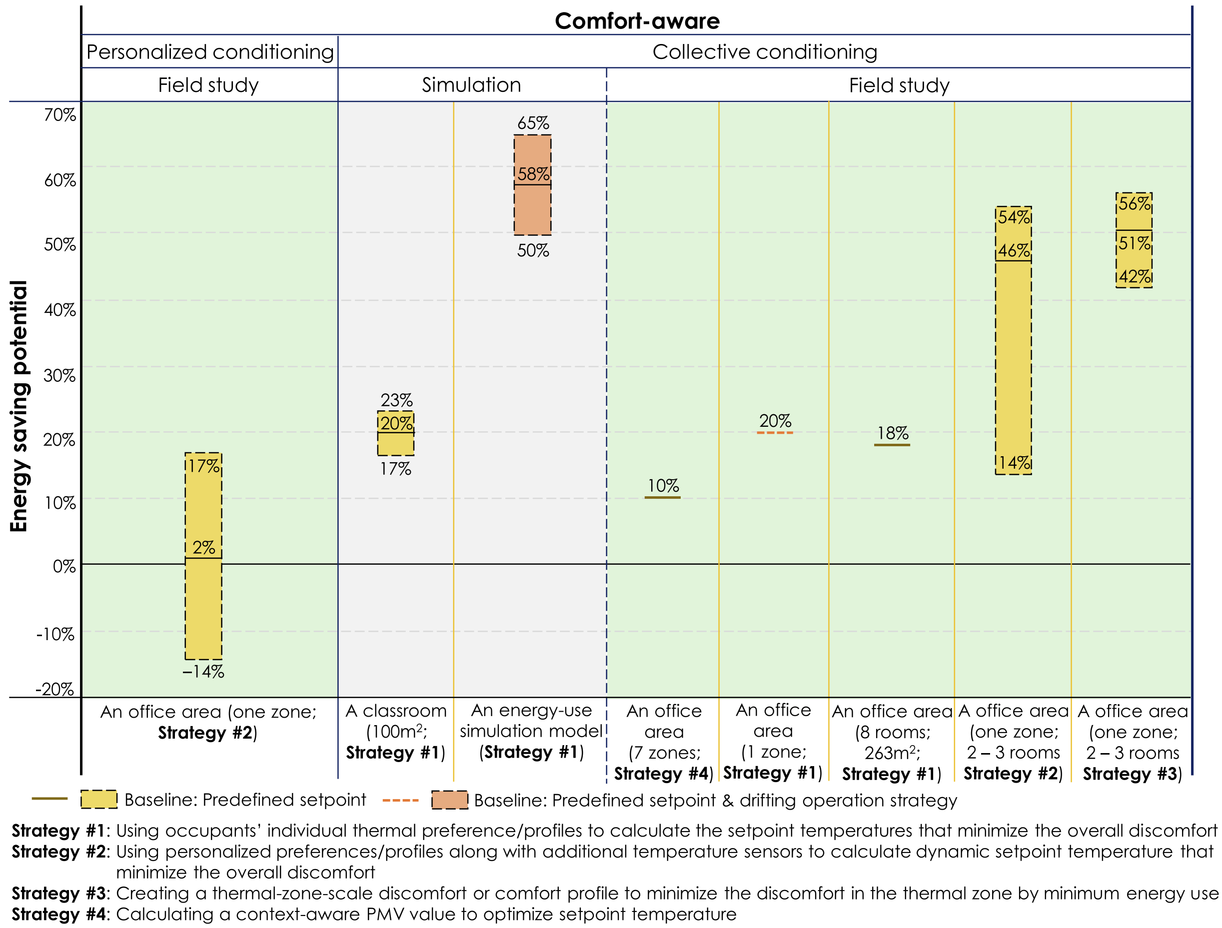

Fig. 17. Reported energy savings percentages from the comfort-aware operation.

(i.e., presence and count) and even could provide higher resolutions for more refined control strategies. However, benefiting from positioning calls for methods that could provide high accuracy. Therefore, research efforts could focus on specialized positioning for HITL HVAC operations.

- *Occupancy detection*: Based on the synthesized performance of the multi-sensing (i.e., sensor fusion) techniques presented in Fig. 5, although accuracy values higher than 90% have been reported, the studies have shown a considerable range of variations for different cases. This is specifically true for multi-occupancy rooms. Therefore, the conventional challenges, reported from the use of PIR/motion sensors, have not been completely addressed by the use of these complementary sensing methods, and further studies for achieving a robust performance are needed. Consequently, research on occupancy detection appears to be at the intersection of the third to fourth technology implementation stages. In this category, further research on alternative sensing technologies that could bring about improved and reliable performance by accounting for privacy concerns is needed. Moreover, investigations on effective sensor systems' configurations, including spatial placement and temporal resolution of data collection, could improve the current state-of-the-art sensing technology. This is specifically important for occupancy detection for multi-occupancy spaces that pose more challenges for detection.
- *Occupant counting*: Despite the high accuracy values (presented in Fig. 6), observed from the use of depth and door counter sensors in identifying transitions across sub-spaces, the challenges associated with error accumulation have not been sufficiently addressed. Moreover, the overall median accuracy, derived from multi-sensing systems, varied between 66 and 83%, which is lower than occupancy detection performance. These models also manifest performance variations across different cases, with reduced robustness for a higher number of occupants. Consequently, research on occupancy

Table 21
References used in creating Fig. 17.

Sub-modality	Simulation/field study	Scale	Operational strategy	Ref.
Personalized conditioning	Field study	An office area (one zone)	#2	[221]
Collective conditioning	Simulation	A classroom (100 m^2)	#1	[235]
		An energy-use simulation model	#1	[233]
	Field study	An office area (seven zones)	#4	[236]
		An office area (one zone)	#1	[234]
		An office area (eight rooms; 263 m^2)	#1	[235]
		An office area (one zone)	#2	[222]
		An office area (one zone)	#3	[223]

Table 22
Technology implementation stages in the hype cycle model [17].

Technology implementation stages (original terms)	Description
Stage #1: Technology adoption (innovation trigger)	Potential of a technology draws attention
Stage #2: Increased expectation (peak of inflated expectations)	A bandwagon comes into effect, so expectation exceeds the actual capability of the technology
Stage #3: Emerging difficulties (through disillusionment)	Less favorable results emerge, and the expectations drop
Stage #4: Overcoming difficulties (slope of enlightenment)	Tackling difficulties is explored, and best practices are reported
Stage #5: Stabilization (plateau of productivity)	Real-world benefits are accepted, and the risk of adopting the technology is acceptable to a growing number of users

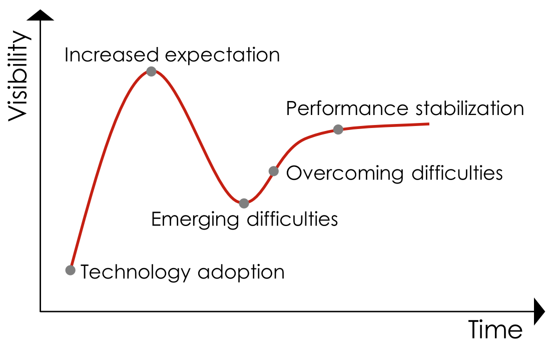

Fig. 18. Graphical representation of each stage in the Hype cycle model.

counting appears to be at the third technology implementation stage. More reliable sensing techniques in this category, similar to detection, are needed, and even more research challenges need to be overcome.

- *Comfort inference (based on comfort voting and physiological responses)*: The inference models, built solely on features derived from environmental factors, have resulted in median accuracies ranging from 70 to 80 percent. However, models tend to show a lack of reliability given the high variations in their performance. Adding physiological features appears to improve performance. However, labeling personalized thermal comfort data is a challenging task, which could be the source of the observed errors. Specifically, as the resolution in acquiring thermal votes increases (i.e., asking for more refined perception (warm vs. hot) votes), labeling errors increases. Based on these observations, personalized comfort modeling and inference could be interpreted at the third implementation stage. This category calls for more in-depth research on identifying feasible sensing solutions that provide a representative measure of personalized comfort under the constraints of non-intrusiveness, non-disruptiveness, and ubiquity. A feasible solution in this category should account for consistent inference of accurate thermal perception/preferences of occupants. An important aspect, which has not been the subject of research efforts, is the impact of psychological factors on thermal comfort perceptions. Activity levels are another less explored feature of human dynamics when it comes to context-aware operations of HVAC systems. The level of activity in indoor environments could affect the perception of occupants about thermal conditions. One challenge that thermal comfort inference studies encounter is the process of contextual data collection, which reflects the realistic scenarios that occupants might experience. Research on identifying the most effective methods of data collection that represent the actual experience of occupants will facilitate studies in this field.

Assessment of the aforementioned categories reveals that, in general, larger scale studies are necessary to (1) provide an insight on the viability of these methodologies for different scenarios, (2) formalize sensor setup configuration impact on performance, and (3) identify challenges for practical integration for different components, including sensing, feature analysis, and algorithm design. Research on developing generalized methods for inference, either for occupancy or comfort, is another direction that has encountered several challenges for practical implementation of HITL operations. Moreover, as elaborated for each category, the research community needs to combine its efforts to enable performance assessment benchmarking towards achieving accumulative contributions.

Similarly, operational strategies have been qualitatively evaluated according to the context of assessment:

- *Occupancy-detection-driven operation*: Although field studies on operational strategies based on occupants' presence have resulted in energy savings. In some studies, increases in energy consumption have also been observed. Large-scale studies have better revealed the challenges of implementation. Therefore, sharing the lessons learned across these projects could result in the formalization of best practices. Furthermore, contextual assessment of thermal comfort is required to ensure that energy savings are not achieved at the cost of thermal comfort. Accordingly, this operational strategy could be interpreted at the transition from third to fourth stages of implementation. Larger scale studies in more diverse climates are necessary for evaluating the real potentials for energy savings and exchanging lessons learned. The studies do not sufficiently reveal the efficacy of this strategy for different modes of operations (cooling vs. heating). Moreover, alternative operational strategies in lieu of the current binary setback-setpoint might result in higher energy saving potentials.
- *Occupant-counting-driven operation*: Most results in this category have been derived from simulation studies. Therefore, insufficient insights have been provided on implementing contextual ventilation operations for real-world scenarios. Therefore, it appears that this operational strategy is at the second stage of implementation.
- *Comfort-aware operation*: field studies that proposed operational strategies for integration of personalized thermal comfort in the control loop have shown promising results in improving energy efficiency in buildings. However, the assessments have been conducted in relatively smaller scales, and further explorations in larger scales and diverse climates are needed to identify better strategies and associated challenges. Moreover, most evaluations have used occupants' voting and profiling as the feedback source and physiological sensing has been less explored. Therefore, this operational strategy is interpreted to be at the second stage of implementation.

Similarly, an effective benchmarking approach that helps identify the contributions of each study and assess the causality of different parameters is deemed necessary.

6. Conclusion

In this study, we have systematically evaluated the current state of the research on the human-in-the-loop HVAC operations with an emphasis on quantitative performance assessment. In doing so, we have proposed and used a proposed hierarchical taxonomy not only to facilitate a systematic review of the research efforts, but also to formalize a benchmarking process. We have presented holistic process maps in each modality (occupancy-based and comfort-aware) and have synthesized the studies according to the operational modality (i.e., occupancy-driven and comfort-aware). These efforts shed light on the overall composition of the studies in the field of human-in-the-loop HVAC operations, which has not been presented in the prior review efforts.

Following the aforementioned taxonomy, we presented the state-of-the-art advancements in sensing/data acquisition as well as control strategies for enabling human-in-the-loop HVAC operations. In doing so, we sought to categorize different studies into a number of classifications according to their sensing, control, and evaluation contexts. Using these categorizations and treating individual scenarios in each study as separate data points, we have presented box-plot representations of the performance for proposed methodologies in different contexts. These graphs serve two purposes of demonstrating the median performance observed across these contexts, as well as the variation of performance measures for a given approach. The latter factor could be used as a proxy for assessing the robustness/reliability of the methodologies in different contexts. According to our assessments, the results from all field evaluation studies showed that occupancy reactive operations could result in a median of 15% energy savings while the occupancy predictive operations could bring about a median of 6% savings, which were lower than expectations from simulation studies (16% and 10%, respectively). Accounting for the number of occupants in operations has a higher potential for energy savings (median of 38%), mostly demonstrated through simulations. Occupant voting and profiling for comfort-aware HVAC operations mostly explored in office buildings, illustrated a promising median of 20% of energy savings across all field study evaluations. These values were statistically derived from previous studies and could be leveraged as performance indicators for future studies. We also discussed a new trend that leverages occupants' physiological responses as a new feature to infer occupant comfort due to commercially and ubiquitously available non-intrusive and wearable sensors. However, their integration for real-time HVAC operations has not been thoroughly explored.

Moreover, we presented the required data representation schema for the studies in this field to encourage constructive performance evaluations. In other words, we have initiated the discussion by formalizing the information need for such normalized objective comparison. This will contribute to the information compiling process with respect to HITL HVAC operation, which is emerging as a crucial process in the HVAC research community. Finally, based on these syntheses, we have also presented qualitative evaluations on technology adoption for each human-in-the-loop HVAC operation modality. These qualitative assessments were conducted based on our observations and analyses made during this study. Inquiring the perceived advancements and viability of different aspects of human-in-the-loop HVAC operations from both research and industry communities could be among the future directions of this study.

Acknowledgment

This material is based upon work supported by the National Science Foundation under grant #1663513. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2019.01.070.

References

[1] Itron I. California commercial end-use survey (CEUS); 2006.
[2] U.S. Energy Information Administration, 2012 commercial buildings energy consumption survey: energy usage summary; 2012.
[3] U.S. Energy Information Administration. Heating and cooling no longer majority of U.S. home energy use; 2013 [cited 2017 1.8.]; Available from: http://www.eia.gov/todayinenergy/detail.php?id=10271&src=%E2%80%B9%20Consumption%20%20%20%20%20%20Residential%20Energy%20Consumption%20Survey%20(RECS)-b1.
[4] Erickson VL, Lin Y, Kamthe A, Brahme R, Surana A, Cerpa AE, Sohn MD, Narayanan S. Energy efficient building environment control strategies using real-time occupancy measurements. Proceedings of the first ACM workshop on embedded sensing systems for energy-efficiency in buildings. Berkeley, California: ACM; 2009. p. 19–24.
[5] Erickson VL, Cerpa AE. Occupancy based demand response HVAC control strategy. Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building. Zurich, Switzerland: ACM; 2010. p. 7–12.
[6] Brager G, Zhang H, Arens E. Evolving opportunities for providing thermal comfort. Build Res Inf 2015;43(3):274–87.
[7] Agarwal Y, Balaji B, Dutta S, Gupta RK, Weng T. Duty-cycling buildings aggressively: The next frontier in HVAC control. Proceedings of the 10th ACM/IEEE international conference on information processing in sensor networks. 2011.
[8] Lin C, Federspiel CC, Auslander DM. Multi-sensor single-actuator control of HVAC systems. In: Proceedings of the international conference for enhanced building operations. Berkeley, CA; 2003.
[9] Karjalainen S, Koistinen O. User problems with individual temperature control in offices. Build Environ 2007;42(8):2880–7.
[10] Jazizadeh F, Ghahramani A, Becerik-Gerber B, Kichkaylo T, Orosz M. Human-building interaction framework for personalized thermal comfort-driven systems in office buildings. J Comput Civil Eng 2014;28(1):2–16.
[11] Huizenga C, Laeser K, Arens E. A web-based occupant satisfaction survey for benchmarking building quality. Indoor Air 2002:1–6.
[12] Karjalainen S. Thermal comfort and use of thermostats in Finnish homes and offices. Build Environ 2009;44(6):1237–45.
[13] U.S. Energy Information Administration. Residential energy consumption survey; 2015 [cited 2018 02/16]; Available from: https://www.eia.gov/consumption/residential/data/2015/hc/php/hc6.1.php.
[14] Lu J, Sookoor T, Srinivasan V, Gao G, Holben B, Stankovic J, et al. The smart thermostat: using occupancy sensors to save energy in homes. ACM; 2010.
[15] Guo W, Zhou M. Technologies toward thermal comfort-based and energy-efficient HVAC systems: A review. 2009 IEEE international conference on systems, man and cybernetics. 2009.
[16] Mirakhorli A, Dong B. Occupancy behavior based model predictive control for building indoor climate—A critical review. Energy Build 2016;129:499–513.
[17] Fenn J, Raskino M. Mastering the hype cycle: how to choose the right innovation at the right time. Boston, Mass: Harvard Business Press; 2008.
[18] Chua KJ, Chou SK, Yang WM, Yan J. Achieving better energy-efficient air conditioning – A review of technologies and strategies. Appl Energy 2013;104:87–104.
[19] Yang L, Yan H, Lam JC. Thermal comfort and building energy consumption implications – A review. Appl Energy 2014;115:164–73.
[20] Kwong QJ, Adam NM, Sahari BB. Thermal comfort assessment and potential for energy efficiency enhancement in modern tropical buildings: A review. Energy Build 2014;68:547–57.
[21] Rupp RF, Vásquez NG, Lamberts R. A review of human thermal comfort in the built environment. Energy Build 2015;105:178–205.
[22] Yan D, O'Brien W, Hong T, Feng X, Burak Gunay H, Tahmasebi F, et al. Occupant behavior modeling for building performance simulation: Current state and future challenges. Energy Build 2015;107:264–78.
[23] Ortiz MA, Kurvers SR, Bluyssen PM. A review of comfort, health, and energy use: Understanding daily energy use and wellbeing for the development of a new approach to study comfort. Energy Build 2017;152:323–35.
[24] Mulia MT, Supangkat SH, Hariyanto N. A review on building occupancy estimation methods. 2017 International conference on ICT for smart society (ICISS). 2017.
[25] Antoniadou P, Papadopoulos AM. Occupants' thermal comfort: State of the art and the prospects of personalized assessment in office buildings. Energy Build 2017;153:136–49.
[26] D'Oca S, Hong T, Langevin J. The human dimensions of energy use in buildings: A review. Renew Sustain Energy Rev 2018;81:731–42.
[27] Balvedi BF, Ghisi E, Lamberts R. A review of occupant behaviour in residential buildings. Energy Build 2018;174:495–505.
[28] Chen Z, Jiang C, Xie L. Building occupancy estimation and detection: A review. Energy Build 2018;169:260–70.
[29] Happle G, Fonseca JA, Schlueter A. A review on occupant behavior in urban building energy models. Energy Build 2018;174:276–92.
[30] Zhang Y, Bai X, Mills FP, Pezzey JCV. Rethinking the role of occupant behavior in building energy performance: A review. Energy Build 2018;172:279–94.
[31] Guyot G, Sherman MH, Walker IS. Smart ventilation energy and indoor air quality performance in residential buildings: A review. Energy Build 2018;165:416–30.
[32] Melfi R, Rosenblum B, Nordman B, Christensen K. Measuring building occupancy using existing network infrastructure. Green computing conference and workshops (IGCC), 2011 international. IEEE; 2011.
[33] Labeodan T, Zeiler W, Boxem G, Zhao Y. Occupancy measurement in commercial office buildings for demand-driven control applications—A survey and detection system evaluation. Energy Build 2015;93:303–14.
[34] Feng X, Yan D, Hong T. Simulation of occupancy in buildings. Energy Build 2015;87:348–59.
[35] Davis JA, Nutter DW. Occupancy diversity factors for common university building types. Energy Build 2010;42(9):1543–51.
[36] Huizenga C, Zagreus L, Arens E, Lehrer D. Measuring indoor environmental

quality: a web-based occupant satisfaction survey, Proceedings, Greenbuild. Pittsburgh, PA; 2003.

[37] Huizenga C, Abbaszadeh S, Zagreus L, Arens EA. Air quality and thermal comfort in office buildings: Results of a large indoor environmental quality survey, Proceedings, Healthy Buildings. Lisbon: Portugal; 2006. 393–397.

[38] Pritoni M, Woolley JM, Modera MP. Do occupancy-responsive learning thermostats save energy? A field study in university residence halls. Energy Build 2016;127:469–78.

[39] ASHRAE, thermal environmental conditions for human occupancy, ASHRAE: Atlanta, GA; 2017.

[40] ASHRAE, energy standard for buildings except low-rise residential buildings, ASHRAE: Altanta, GA; 2016.

[41] Guo X, Tiller D, Henze G, Waters C. The performance of occupancy-based lighting control systems: A review. Light Res Technol 2010;42(4):415–31.

[42] Page J, Robinson D, Morel N, Scartezzini JL. A generalised stochastic model for the simulation of occupant presence. Energy Build 2008;40(2):83–98.

[43] Duarte C, Van Den Wymelenberg K, Rieger C. Revealing occupancy patterns in an office building through the use of occupancy sensor data. Energy Build 2013;67:587–95.

[44] Agarwal Y, Balaji B, Gupta R, Lyles J, Wei M, Weng T. Occupancy-driven energy management for smart building automation. Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building. ACM; 2010.

[45] Diraco G, Leone A, Siciliano P. People occupancy detection and profiling with 3D depth sensors for building energy management. Energy Build 2015;92:246–66.

[46] Shih H-C. A robust occupancy detection and tracking algorithm for the automatic monitoring and commissioning of a building. Energy Build 2014;77:270–80.

[47] Erickson VL, Achleitner S, Cerpa AE. POEM: power-efficient occupancy-based energy management system. Proceedings of the 12th international conference on Information processing in sensor networks. Philadelphia, Pennsylvania: ACM; 2013. p. 203–16.

[48] Krinidis S, Stavropoulos G, Ioannidis D, Tzovaras D. A robust and real-time multi-space occupancy extraction system exploiting privacy-preserving sensors. 2014 6th international symposium on communications, control and signal processing (ISCCSP). 2014.

[49] Tyndall A, Cardell-Oliver R, Keating A. Occupancy estimation using a low-pixel count thermal imager. IEEE Sens J 2016;16(10):3784–91.

[50] Fisk WJ. A pilot study of the accuracy of CO2 sensors in commercial buildings, Indoor Environment Group, 2008 [cited 2017. 5.8]; Available from: https://indoor.lbl.gov/publications/accuracy-co2-sensors-commercial.

[51] Yang Z, Becerik-Gerber B. Modeling personalized occupancy profiles for representing long term patterns by using ambient context. Build Environ 2014;78:23–35.

[52] Balaji B, Xu J, Nwokafor A, Gupta R, Agarwal Y. Sentinel: occupancy based HVAC actuation using existing WiFi infrastructure within commercial buildings. Proceedings of the 11th ACM conference on embedded networked sensor systems. ACM; 2013.

[53] Jiang Y, Pan X, Li K, Lv Q, Dick RP, Hannigan M, et al. ARIEL: Automatic Wi-Fi based room fingerprinting for indoor localization. Proceedings of the 2012 ACM conference on ubiquitous computing. Pittsburg, PA. 2012.

[54] Yang J, Santamouris M, Lee SE. Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings. Energy Build 2016;121:344–9.

[55] Gupta M, Intille SS, Larson K. Adding gps-control to traditional thermostats: An exploration of potential energy savings and design challenges. Springer; 2009.

[56] Corna A, Fontana L, Nacci AA, Sciuto D. Occupancy detection via iBeacon on Android devices for smart building management. Proceedings of the 2015 design, automation & test in Europe conference & exhibition. Grenoble, France: EDA Consortium; 2015. p. 629–32.

[57] Li N, Calis G, Becerik-Gerber B. Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations. Autom Constr 2012;24:89–99.

[58] Zikos S, Tsolakis A, Meskos D, Tryferidis A, Tzovaras D. Conditional Random Fields - based approach for real-time building occupancy estimation with multi-sensory networks. Autom Constr 2016;68:128–45.

[59] Urgessa T, Maeng W, An KS, Lee JS. Prototyping sensor based people counting system. Proceedings of HCI Korea. Jeongseon, Republic of Korea: Hanbit Media, Inc.; 2016. p. 121–6.

[60] Zhao Y, Zeiler W, Boxem G, Labeodan T. Virtual occupancy sensors for real-time occupancy information in buildings. Build Environ 2015;93:9–20.

[61] Chen D, Barker S, Subbaswamy A, Irwin D, Shenoy P. Non-intrusive occupancy monitoring using smart meters. Proceedings of the 5th ACM workshop on embedded systems for energy-efficient buildings. Roma, Italy: ACM; 2013. p. 1–8.

[62] Kleiminger W, Beckel C, Staake T, Santini S. Occupancy detection from electricity consumption data. Proceedings of the 5th ACM workshop on embedded systems for energy-efficient buildings. Roma, Italy: ACM; 2013. p. 1–8.

[63] Labeodan T, Aduda K, Zeiler W, Hoving F. Experimental evaluation of the performance of chair sensors in an office space for occupancy detection and occupancy-driven control. Energy Build 2016;111:195–206.

[64] Hailemariam E, Goldstein R, Attar R, Khan A. Real-time occupancy detection using decision trees with multiple sensor types. Society for Computer Simulation International; 2011.

[65] Newsham GR, Xue H, Arsenault C, Valdes JJ, Burns GJ, Scarlett E, et al. Testing the accuracy of low-cost data streams for determining single-person office occupancy and their use for energy reduction of building services. Energy Build 2017;135:137–47.

[66] Brackney LJ, Florita AR, Swindler AC, Polese LG, Brunemann GA. Design and performance of an image processing occupancy sensor. Proceedings: The second international conference on building energy and environment 2012987 topic 10. Intelligent buildings and advanced control techniques. Citeseer; 2012.

[67] Yu T. Modeling occupancy behavior for energy efficiency and occupants comfort management in intelligent buildings. 2010 Ninth international conference on machine learning and applications. 2010.

[68] Mahdavi A, Tahmasebi F. Predicting people's presence in buildings: An empirically based model performance analysis. Energy Build 2015;86:349–55.

[69] Yavari E, Jou H, Lubecke V, Boric-Lubecke O. Doppler radar sensor for occupancy monitoring. 2013 IEEE radio and wireless symposium. 2013.

[70] Song C, Yazavi E, Lubecke V, Boric-Lubecke O. Smart occupancy sensors. 2014 Asia-Pacific microwave conference. 2014.

[71] Yang Z, Li N, Becerik-Gerber B, Orosz M. A systematic approach to occupancy modeling in ambient sensor-rich buildings. Simulation 2014;90(8):960–77.

[72] von Bomhard T, Wörner D, Röschlin M. Towards smart individual-room heating for residential buildings. Comput Sci-Res Dev 2016;31(3):127–34.

[73] Calì D, Matthes P, Huchtemann K, Streblow R, Müller D. CO2 based occupancy detection algorithm: Experimental analysis and validation for office and residential buildings. Build Environ 2015;86:39–49.

[74] Candanedo LM, Feldheim V. Accurate occupancy detection of an office room from light, temperature, humidity and CO2 measurements using statistical learning models. Energy Build 2016;112:28–39.

[75] Weekly K, Rim D, Zhang L, Bayen AM, Nazaroff WW, Spanos CJ. Low-cost coarse airborne particulate matter sensing for indoor occupancy detection. 2013 IEEE international conference on automation science and engineering (CASE). 2013.

[76] Ghai SK, Thanayankizil LV, Seetharam DP, Chakraborty D. Occupancy detection in commercial buildings using opportunistic context sources. 2012 IEEE international conference on pervasive computing and communications workshops. 2012.

[77] Scott J, Brush AJB, Krumm J, Meyers B, Hazas M, Hodges S, et al. PreHeat: controlling home heating using occupancy prediction. Proceedings of the 13th international conference on ubiquitous computing. Beijing, China: ACM; 2011. p. 281–90.

[78] Scott J, Krumm J, Meyers B, Brush AJ, Kapoor A. Home heating using gps-based arrival prediction, the Pervasive 2010 Workshop on Energy Awareness and Conservation; 2010.

[79] Koehler C, Ziebart BD, Mankoff J, Dey AK. TherML: occupancy prediction for thermostat control. Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing. Zurich, Switzerland: ACM; 2013. p. 103–12.

[80] Dodier RH, Henze GP, Tiller DK, Guo X. Building occupancy detection through sensor belief networks. Energy Build 2006;38(9):1033–43.

[81] Soltanaghaei E, Whitehouse K. WalkSense: Classifying home occupancy states using walkway sensing. Proceedings of the 3rd ACM international conference on systems for energy-efficient built environments. ACM; 2016.

[82] De Bock Y, Auquilla A, Kellens K, Vandevenne D, Nowé A, Duflou JR. User-adapting system design for improved energy efficiency during the use phase of products: case study of an occupancy-driven, self-learning thermostat. Sustainability through innovation in product life cycle design. Springer; 2017. p. 883–98.

[83] Pisharoty D, Yang R, Newman MW, Whitehouse K. ThermoCoach: reducing home energy consumption with personalized thermostat recommendations. Proceedings of the 2nd ACM international conference on embedded systems for energy-efficient built environments. Seoul, South Korea: ACM; 2015. p. 201–10.

[84] Yang R, Pisharoty D, Montazeri S, Whitehouse K, Newman MW. How does eco-coaching help to save energy? Assessing a recommendation system for energy-efficient thermostat scheduling. Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing. ACM; 2016.

[85] Khan A, Nicholson J, Mellor S, Jackson D, Ladha K, Ladha C, Hand J, Clarke J, Olivier P, Plötz T. Occupancy monitoring using environmental & context sensors and a hierarchical analysis framework; 2014.

[86] Woolley J, Peffer T. Occupancy sensing adaptive thermostat controls–a market review and observations from multiple field installations in university residence halls. ACEEE summer study. Retrieved from http://www.aceee.org/files/proceedings/2012/data/papers/0193-000245.pdf; 2012.

[87] Woolley J, Pritoni M, Modera M, Center WCE. Why occupancy-responsive adaptive thermostats do not always save-and the limits for when they should. Proceedings of the 2014 ACEEE summer study on energy efficiency in buildings, Asilomar, CA. 2014.

[88] Pedersen TH, Nielsen KU, Petersen S. Method for room occupancy detection based on trajectory of indoor climate sensor data. Build Environ 2017;115:147–56.

[89] Ekwevugbe T, Brown N, Pakka V. Real-time building occupancy sensing for supporting demand driven hvac operations; 2013.

[90] Yang Z, Li N, Becerik-Gerber B, Orosz M. A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations. Proceedings of the 2012 symposium on simulation for architecture and urban design. Orlando, Florida: Society for Computer Simulation International; 2012. p. 1–8.

[91] Yang Z, Becerik-Gerber B. The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use. Energy Build 2014;78:113–22.

[92] Li N, Yang Z, Becerik-Gerber B, Orosz M. Towards energy savings from a bimodal occupancy driven HVAC controller in practice. 30th CIB W78 international conference. 2013.

[93] Beltran A, Erickson VL, Cerpa AE. ThermoSense: Occupancy thermal based sensing for HVAC control. Proceedings of the 5th ACM workshop on embedded systems for energy-efficient buildings. Roma, Italy: ACM; 2013. p. 1–8.

[94] Erickson VL, Beltran A, Winkler DA, Esfahani NP, Lusby JR, Cerpa AE. TOSS: thermal occupancy sensing system. Proceedings of the fifth ACM workshop on

embedded sensing systems for energy-efficient building (BuildSys 2013). Rome, Italy. 2013.
[95] Erickson VL, Carreira-Perpiñán MÁ, Cerpa AE. OBSERVE: Occupancy-based system for efficient reduction of HVAC energy. Proceedings of the 10th ACM/IEEE international conference on information processing in sensor networks. 2011.
[96] Erickson VL, Carreira-Perpinan MA, Cerpa AE. Occupancy modeling and prediction for building energy management. ACM Trans Sensor Networks (TOSN) 2014;103:29.
[97] Lam KP, Höynck M, Dong B, Andrews B, Chiou Y-S, Zhang R, et al. Occupancy detection through an extensive environmental sensor network in an open-plan office building. IBPSA Build Simul 2009;145:1452–9.
[98] Dong B, Andrews B, Lam KP, Höynck M, Zhang R, Chiou Y-S, et al. An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network. Energy Build 2010;42(7):1038–46.
[99] Dong B, Lam KP, Neuman C. Integrated building control based on occupant behavior pattern detection and local weather forecasting. Twelfth international IBPSA conference. Sydney: IBPSA Australia; 2011.
[100] Dong B, Lam KP. Building energy and comfort management through occupant behaviour pattern detection based on a large-scale environmental sensor network. J Build Perform Simul 2011;4(4):359–69.
[101] Jin M, Bekiaris-Liberis N, Weekly K, Spanos CJ, Bayen AM. Occupancy detection via environmental sensing. IEEE Trans Autom Sci Eng 2016;99:1–13.
[102] Jiang C, Masood MK, Soh YC, Li H. Indoor occupancy estimation from carbon dioxide concentration. Energy Build 2016;131:132–41.
[103] Petersen S, Pedersen TH, Nielsen KU, Knudsen MD. Establishing an image-based ground truth for validation of sensor data-based room occupancy detection. Energy Build 2016;130:787–93.
[104] Adamopoulou AA, Tryferidis AM, Tzovaras DK. A context-aware method for building occupancy prediction. Energy Build 2016;110:229–44.
[105] Akbar A, Nati M, Carrez F, Moessner K. Contextual occupancy detection for smart office by pattern recognition of electricity consumption data. 2015 IEEE international conference on communications (ICC). 2015.
[106] Lee S, Chon Y, Kim Y, Ha R, Cha H. Occupancy prediction algorithms for thermostat control systems using mobile devices. IEEE Trans Smart Grid 2013;4(3):1332–40.
[107] Trivedi A, Gummeson J, Irwin D, Ganesan D, Shenoy P. Ischedule: Campus-scale hvac scheduling via mobile wifi monitoring. ACM; 2017.
[108] Shen W, Newsham G, Gunay B. Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review. Adv Eng Inf 2017;33:230–42.
[109] Soltanaghaei E, Whitehouse K. Practical occupancy detection for programmable and smart thermostats. Appl Energy 2017.
[110] Ortega JLG, Han L, Bowring N. A novel dynamic hidden semi-markov model (D-HSMM) for occupancy pattern detection from sensor data stream. 2016 8th IFIP international conference on new technologies, mobility and security (NTMS). 2016.
[111] Mamidi S, Chang Y-H, Maheswaran R. Improving building energy efficiency with a network of sensing, learning and prediction agents. International Foundation for Autonomous Agents and Multiagent Systems; 2012.
[112] Jazizadeh F, Ahmadi-Karvigh S, Becerik-Gerber B, Soibelman L. Spatiotemporal lighting load disaggregation using light intensity signal. Energy Build 2014;69:572–83.
[113] Jazizadeh F, Becerik-Gerber B. A novel method for non intrusive load monitoring of lighting systems in commercial buildings. Computing civil engineering (2012). 2012. p. 523–30.
[114] Jazizadeh F, Wang J. Artificial versus natural light source identification with light intensity sensors for energy monitoring. Procedia Engineer 2016;145:956–63.
[115] Zeifman M, Roth K. Nonintrusive appliance load monitoring: Review and outlook. IEEE Trans Consumer Electron 2011:57(1).
[116] Jazizadeh Farrokh, Afzalan Milad, Becerik-Gerber Burcin, Soibelman Lucio. EMBED: A Dataset for Energy Monitoring through Building Electricity Disaggregation. Proceedings of the Ninth International Conference on Future Energy Systems (e-Energy '18) New York, NY, USA: ACM; 2018. p. 230–5. https://doi.org/10.1145/3208903.3208939.
[117] Jazizadeh F, Becerik-Gerber B, Berges M, Soibelman L. Unsupervised clustering of residential electricity consumption measurements for facilitated user-centric non-intrusive load monitoring. Comput Civ Build Eng 2014:1869–76.
[118] Jazizadeh F, Becerik-Gerber B, Berges M, Soibelman L. An unsupervised hierarchical clustering based heuristic algorithm for facilitated training of electricity consumption disaggregation systems. Adv Eng Inf 2014;28(4):311–26.
[119] Afzalan M, Jazizadeh F, Wang J. Self-Configuring Event Detection in Electricity Monitoring for Human-Building Interaction. Energ Buildings 2019;187:95–109. https://doi.org/10.1016/j.enbuild.2019.01.036. ISSN 0378-7788.
[120] Arora A, Amayri M, Badarla V, Ploix S, Bandyopadhyay S. Occupancy estimation using non-intrusive sensors in energy efficient buildings. Build Simul 2015.
[121] Wang W, Chen J, Hong T, Zhu N. Occupancy prediction through Markov based feedback recurrent neural network (M-FRNN) algorithm with WiFi probe technology. Build Environ 2018;138:160–70.
[122] Kamthe A, Jiang L, Dudys M, Cerpa A. SCOPES: Smart cameras object position estimation system. Proceedings of the 6th European conference on wireless sensor networks. Cork, Ireland: Springer-Verlag; 2009. p. 279–95.
[123] Ekwevugbe T, Brown N, Pakka V, Fan D. Improved occupancy monitoring in non-domestic buildings. Sustain Cities Soc 2017;30:97–107.
[124] Gruber M, Trüschel A, Dalenbäck J-O. CO2 sensors for occupancy estimations: Potential in building automation applications. Energy Build 2014;84:548–56.
[125] Mainetti L, Patrono L, Sergi I. A survey on indoor positioning systems. Software, telecommunications and computer networks (SoftCOM), 2014 22nd international conference on. IEEE; 2014.
[126] Zafari F, Gkelias A, Leung K. A survey of indoor localization systems and technologies. arXiv preprint arXiv:1709.01015; 2017.
[127] Abedi M, Jazizadeh F, Huang B, Battaglia F. Smart HVAC systems — adjustable airflow direction. Advanced computing strategies for engineering. Cham: Springer International Publishing; 2018.
[128] Wang W, Chen J, Huang G, Lu Y. Energy efficient HVAC control for an IPS-enabled large space in commercial buildings through dynamic spatial occupancy distribution. Appl Energy 2017;207:305–23.
[129] Wang W, Chen J, Hong T. Modeling occupancy distribution in large spaces with multi-feature classification algorithm. Build Environ 2018;137:108–17.
[130] Yang Z, Becerik-Gerber B. Cross-space building occupancy modeling by contextual information based learning. ACM; 2015.
[131] Turner C, Frankel M. Energy performance of LEED for new construction buildings. New Build Inst 2008;4:1–42.
[132] Akbas R, Clevenger C, Haymaker J. Temporal visualization of building occupancy phase. Comput Civil Eng (2007) 2007:208–15.
[133] ASHRAE Standard 90.1. Energy standard for buildings except low-rise residential buildings. ASHRAE: Altanta, GA; 2004.
[134] Gao G, Whitehouse K. The self-programming thermostat: optimizing setback schedules based on home occupancy patterns. ACM; 2009.
[135] Krumm J, Brush AJB. Learning time-based presence probabilities. Pervasive computing. Berlin, Heidelberg: Springer; 2011.
[136] Kleiminger W, Mattern F, Santini S. Predicting household occupancy for smart heating control: A comparative performance analysis of state-of-the-art approaches. Energy Build 2014;85:493–505.
[137] Dong B, Andrews B. Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings. 11th international building performance simulation association. Glasgow; 2009.
[138] Chen Z, Xu J, Soh YC. Modeling regular occupancy in commercial buildings using stochastic models. Energy Build 2015;103:216–23.
[139] Wang D, Federspiel CC, Rubinstein F. Modeling occupancy in single person offices. Energy Build 2005;37(2):121–6.
[140] Liao C, Barooah P. An integrated approach to occupancy modeling and estimation in commercial buildings. IEEE; 2010.
[141] Liao C, Lin Y, Barooah P. Agent-based and graphical modelling of building occupancy. J Build Perform Simul 2012;5(1):5–25.
[142] Capozzoli A, Piscitelli MS, Gorrino A, Ballarini I, Corrado V. Data analytics for occupancy pattern learning to reduce the energy consumption of HVAC systems in office buildings. Sustain Cities Soc 2017;35:191–208.
[143] Sookoor T, Whitehouse K. RoomZoner: occupancy-based room-level zoning of a centralized HVAC system. Proceedings of the ACM/IEEE 4th international conference on cyber-physical systems. ACM; 2013.
[144] Huang C-CJ, Liang S-Y, Wu B-H, Newman MW. Reef: Exploring the design opportunity of comfort-aware eco-coaching thermostats. ACM; 2017.
[145] Sun Z, Wang S, Ma Z. In-situ implementation and validation of a CO2-based adaptive demand-controlled ventilation strategy in a multi-zone office building. Build Environ 2011;46(1):124–33.
[146] Li D, Balaji B, Jiang Y, Singh K. A wi-fi based occupancy sensing approach to smart energy in commercial office buildings. Proceedings of the fourth ACM workshop on embedded sensing systems for energy-efficiency in buildings. ACM; 2012.
[147] Goyal S, Barooah P, Middelkoop T. Experimental study of occupancy-based control of HVAC zones. Appl Energy 2015;140:75–84.
[148] Brooks J, Goyal S, Subramany R, Lin Y, Liao C, Middelkoop T, et al. Experimental evaluation of occupancy-based energy-efficient climate control of VAV terminal units. Sci Technol Built Environ 2015;21(4):469–80.
[149] Ghofrani A, Jafari MA. Distributed air conditioning control in commercial buildings based on a physical-statistical approach. Energy Build 2017;148:106–18.
[150] Goyal S, Ingley HA, Barooah P. Zone-level control algorithms based on occupancy information for energy efficient buildings. IEEE; 2012.
[151] Goyal S, Ingley HA, Barooah P. Occupancy-based zone-climate control for energy-efficient buildings: Complexity vs. performance. Appl Energy 2013;106:209–21.
[152] Liu Z, Salimi S, Hammad A. Simulation of HVAC local control based on occupants locations and preferences. ISARC. Proceedings of the international symposium on automation and robotics in construction. Vilnius Gediminas Technical University, Department of Construction Economics & Property; 2016.
[153] Gupta SK, Atkinson S, O'Boyle I, Drogo J, Kar K, Mishra S, et al. BEES: Real-time occupant feedback and environmental learning framework for collaborative thermal management in multi-zone, multi-occupant buildings. Energy Build 2016;125:142–52.
[154] Brooks J, Kumar S, Goyal S, Subramany R, Barooah P. Energy-efficient control of under-actuated HVAC zones in commercial buildings. Energy Build 2015;93:160–8.
[155] Jia R, Dong R, Sastry SS, Sapnos CJ. Privacy-enhanced architecture for occupancy-based HVAC control. 2017 ACM/IEEE 8th international conference on cyber-physical systems (ICCPS). 2017.
[156] Amasyali K, El-Gohary NM. Energy-related values and satisfaction levels of residential and office building occupants. Build Environ 2016;95:251–63.
[157] Humphreys MA, Hancock M. Do people like to feel 'neutral'?: Exploring the variation of the desired thermal sensation on the ASHRAE scale. Energy Build 2007;39(7):867–74.
[158] ASHRAE, 2013 ASHRAE handbook: fundamentals - Chapter 09. Thermal comfort. Atlanta, Georgia: American Society of Heating, Refrigerating and Air-Conditioning Engineers; 2013.
[159] Becker R, Paciuk M. Thermal comfort in residential buildings – Failure to predict

by Standard model. Build Environ 2009;44(5):948–60.
[160] Zhao J, Lam KP, Loftness V, Ydstie BE. Occupant individual thermal comfort data analysis in an office, in sustainable human&#x2013. Build Ecosyst 2015.
[161] Daum D, Haldi F, Morel N. A personalized measure of thermal comfort for building controls. Build Environ 2011;46(1):3–11.
[162] Nicol F, Roaf S. Post-occupancy evaluation and field studies of thermal comfort. Build Res Inf 2005;33(4):338–46.
[163] Ghahramani A, Tang C, Becerik-Gerber B. An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling. Build Environ 2015;92:86–96.
[164] Jazizadeh F, Kavulya G, Klein L, Becerik-Gerber B. Continuous Sensing of Occupant Perception of Indoor Ambient Factors. Comput Civil Eng; 2011. p. 161–8. https://doi.org/10.1061/41182(416)20.
[165] American Society of Heating, R. and I. Air-Conditioning Engineers, 2017 ASHRAE® Handbook - Fundamentals (I-P Edition). American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc; 2017.
[166] Bedford T. The warmth factor in comfort at work. A physiological study of heating and ventilation. The Warmth Factor in Comfort at Work. A Physiological Study of Heating and Ventilation 1936;76.
[167] McIntyre DA. Seven point scales of warmth. Electricity Council; 1976.
[168] Zhang Y, Wang J, Chen H, Zhang J, Meng Q. Thermal comfort in naturally ventilated buildings in hot-humid area of China. Build Environ 2010;45(11):2562–70.
[169] Wong NH, Khoo SS. Thermal comfort in classrooms in the tropics. Energy Build 2003;35(4):337–51.
[170] American Society of Heating, R. and I. Air-Conditioning Engineers. 2017 ASHRAE® Handbook - Fundamentals (I-P Edition) - Chapter 9. Thermal comfort. 2017, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
[171] Jazizadeh F, Marin FM, Becerik-Gerber B. A thermal preference scale for personalized comfort profile identification via participatory sensing. Build Environ 2013;68:140–9.
[172] Jazizadeh F, Becerik-Gerber B. Toward adaptive comfort management in office buildings using participatory sensing for end user driven control. Proceedings of the fourth ACM workshop on embedded sensing systems for energy-efficiency in buildings. ACM; 2012.
[173] Kim J, Zhou Y, Schiavon S, Raftery P, Brager G. Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. Build Environ 2018;129:96–106.
[174] Fukuta M, Matsui K, Ito M, Nishi H. Proposal for home energy management system to survey individual thermal comfort range for HVAC control with little contribution from users. IEEE; 2015.
[175] Barbato A, Borsani L, Capone A, Melzi S. Home energy saving through a user profiling system based on wireless sensors. Proceedings of the first ACM workshop on embedded sensing systems for energy-efficiency in buildings. Berkeley, California: ACM; 2009. p. 49–54.
[176] Gagge AP, Stolwijk JAJ, Hardy JD. Comfort and thermal sensations and associated physiological responses at various ambient temperatures. Environ Res 1967;1(1):1–20.
[177] Hall JJF, Klemm FK. Thermal comfort in disparate thermal environments. J Appl Physiol 1969;27(5):601.
[178] Tanabe S, Arens EA, Bauman F, Zhang H, Madsen T. Evaluating thermal environments by using a thermal manikin with controlled skin surface temperature; 1994.
[179] Bulcao CF, Frank SM, Raja SN, Tran KM, Goldstein DS. Relative contribution of core and skin temperatures to thermal comfort in humans. J Therm Biol 2000;25(1–2):147–50.
[180] Arens EA, Zhang H. The skin's role in human thermoregulation and comfort. Center for the Built Environment 2006.
[181] Choi J-H, Loftness V. Investigation of human body skin temperatures as a biosignal to indicate overall thermal sensations. Build Environ 2012;58:258–69.
[182] Frank SM, Raja SN, Bulcao CF, Goldstein DS. Relative contribution of core and cutaneous temperatures to thermal comfort and autonomic responses in humans. J Appl Physiol 1999;86(5):1588–93.
[183] Parsons KC. Human thermal environments. Bristol, PA; London: Taylor & Francis; 1993.
[184] Liu W, Lian Z, Liu Y. Heart rate variability at different thermal comfort levels. Eur J Appl Physiol 2008;103(3):361–6.
[185] Yao Y, Lian Z, Liu W, Jiang C, Liu Y, Lu H. Heart rate variation and electroencephalograph – the potential physiological factors for thermal comfort study. Indoor Air 2009;19(2):93–101.
[186] Choi J-H, Loftness V, Lee D-W. Investigation of the possibility of the use of heart rate as a human factor for thermal sensation models. Build Environ 2012;50:165–75.
[187] Jung W, Jazizadeh F. Vision-based thermal comfort quantification for HVAC control. Build Environ 2018.
[188] Wang Z, Ning H, Ji Y, Hou J, He Y. Human thermal physiological and psychological responses under different heating environments. J Therm Biol 2015;52:177–86.
[189] Yao Y, Lian Z, Liu W, Shen Q. Experimental study on physiological responses and thermal comfort under various ambient temperatures. Physiol Behav 2008;93(1–2):310–21.
[190] Liu W, Lian Z, Deng Q, Liu Y. Evaluation of calculation methods of mean skin temperature for use in thermal comfort study. Build Environ 2011;46(2):478–88.
[191] Maiti R. Physiological and subjective thermal response from Indians. Build Environ 2013;70:306–17.
[192] Dabiri S, Jazizadeh F. Exploring video based thermal perception identification. 16th international conference on computing in civil and building engineering, ICCCBE2016. Osaka; 2016.
[193] Jung W, Jazizadeh F. Non-intrusive detection of respiration for smart control of HVAC system. Comput Civil Eng; 2017. https://doi.org/10.1061/9780784480847.039.
[194] Jung W, Jazizadeh F. Towards integration of doppler radar sensors into personalized thermoregulation-based control of HVAC. 4th ACM conference on systems for energy-efficient built environment (BuildSys' 17). Delft, The Netherlands: ACM; 2017.
[195] Huizenga C, Zhang H, Arens E, Wang D. Skin and core temperature response to partial- and whole-body heating and cooling. J Therm Biol 2004;29(7):549–58.
[196] Zheng J, Chen L, Li B-Z, Chen L. Indoor thermal comfort studies based on physiological parameter measurement and questionnaire investigation. J Central South Univ Technol 2006;13(4):404–7.
[197] Sakoi T, Tsuzuki K, Kato S, Ooka R, Song D, Zhu S. Thermal comfort, skin temperature distribution, and sensible heat loss distribution in the sitting posture in various asymmetric radiant fields. Build Environ 2007;42(12):3984–99.
[198] Oliveira FD, Moreau S, Gehin C, Dittmar A. Infrared imaging analysis for thermal comfort assessment. 2007 29th Annual international conference of the IEEE engineering in medicine and biology society. 2007.
[199] Yao Y, Lian Z, Liu W, Jiang C. Measurement methods of mean skin temperatures for the PMV model. HVAC&R Res 2008;14(2):161–74.
[200] Liu H, Liao J, Yang D, Du X, Hu P, Yang Y, et al. The response of human thermal perception and skin temperature to step-change transient thermal environments. Build Environ 2013;73:232.
[201] Sim SY, Koh MJ, Joo KM, Noh S, Park S, Kim YH, et al. Estimation of thermal sensation based on wrist skin temperatures. Sensors 2016;16(4):420.
[202] Xiong J, Zhou X, Lian Z, You J, Lin Y. Thermal perception and skin temperature in different transient thermal environments in summer. Energy Build 2016;128:155–63.
[203] Choi JH. CoBi: Bio-sensing building mechanical system controls for sustainably enhancing individual thermal comfort. Carnegie Mellon University; 2010.
[204] Yi B, Choi J-H. Facial skin temperature as a proactive variable in a building thermal comfort control. System 2015:117–25.
[205] Ghahramani A, Castro G, Becerik-Gerber B, Yu X. Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort. Build Environ 2016.
[206] Li D, Menassa CC, Kamat VR. Non-intrusive interpretation of human thermal comfort through analysis of facial infrared thermography. Energy Build 2018.
[207] Ranjan J, Scott J. ThermalSense: Determining dynamics thermal comfort preferences using thermographic imaging; 2016.
[208] Jazizadeh F, Pradeep S. Can computers visually quantify human thermal comfort? Proceedings of the 3rd ACM international conference on systems for energy-efficient built environments. ACM; 2016.
[209] Jazizadeh F, Jung W. Personalized thermal comfort through digital video images for energy-efficient HVAC control. Appl Energy 2018.
[210] Cheng X, Yang B, Olofsson T, Liu G, Li H. A pilot study of online non-invasive measuring technology based on video magnification to determine skin temperature. Build Environ 2017;121:1–10.
[211] Abdallah M, Clevenger C, Vu T, Nguyen A. Sensing occupant comfort using wearable technologies. Construction research congress 2016. 2016. p. 940–50.
[212] Li D, Menassa CC, Kamat VR. A personalized HVAC control smartphone application framework for improved human health and well-being, in computing in civil engineering 2017; 2017.
[213] Li D, Menassa CC, Kamat VR. Personalized human comfort in indoor building environments under diverse conditioning modes. Build Environ 2017;126:304–17.
[214] Oseland NA. Predicted and reported thermal sensation in climate chambers, offices and homes. Energy Build 1995;23(2):105–15.
[215] Kim H-H, Lee K-C, Lee S. Location-based human-adaptive air conditioning by measuring physical activity with a non-terminal-based indoor positioning system. Build Environ 2013;62:167–73.
[216] Ortega JLG, Han L, Whittacker N, Bowring N. A machine-learning based approach to model user occupancy and activity patterns for energy saving in buildings. 2015 Science and information conference (SAI). 2015.
[217] Ortega JLG, Han L, Bowring N. Modelling and detection of user activity patterns for energy saving in buildings. In: Chen L, Kapoor S, Bhatia R, editors. Emerging trends and advanced technologies for computational intelligence: extended and selected results from the science and information conference 2015. Cham: Springer International Publishing; 2016. p. 165–85.
[218] Benezeth Y, Laurent H, Emile B, Rosenberger C. Towards a sensor for detecting human presence and characterizing activity. Energy Build 2011;43(2):305–14.
[219] Nguyen TA, Raspitzu A, Aiello M. Ontology-based office activity recognition with applications for energy savings. J Ambient Intell Hum Comput 2014;5(5):667–81.
[220] Lee J-H, Kim Y-K, Kim K-S, Kim S. Estimating clothing thermal insulation using an infrared camera. Sensors (Basel, Switzerland) 2016;16(3):341.
[221] Jazizadeh F, Ghahramani A, Becerik-Gerber B, Kichkaylo T, Orosz M. Personalized thermal comfort driven control in HVAC operated office buildings. ASCE international workshop on computing in civil engineering (IWCCE) conference. 2013.
[222] Jazizadeh F, Ghahramani A, Becerik-Gerber B, Kichkaylo T, Orosz M. User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings. Energy Build 2014;70:398–410.
[223] Ghahramani A, Jazizadeh F, Becerik-Gerber B. A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points. Energy Build 2014;85:536–48.
[224] Kim J, Schiavon S, Brager G. Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control. Build Environ 2018.

[225] Kwak J-y, Varakantham P, Maheswaran R, Tambe M, Jazizadeh F, Kavulya G, Klein L, Becerik-Gerber B, Hayes T, Wood W. SAVES: a sustainable multiagent application to conserve building energy considering occupants. Proceedings of the 11th international conference on autonomous agents and multiagent systems - volume 1. Valencia, Spain: International Foundation for Autonomous Agents and Multiagent Systems; 2012. p. 21–8.
[226] Li N, Kwak J-y, Becerik-Gerber B, Tambe M. Predicting HVAC energy consumption in commercial buildings using multiagent systems. Vilnius: Vilnius Gediminas Technical University, Department of Construction Economics & Property; 2013.
[227] Huang K-T, Lin T-P, Lien H-C. Investigating thermal comfort and user behaviors in outdoor spaces: a seasonal and spatial perspective. Adv Meteorol 2015;2015:1–11.
[228] Sanguinetti A, Pritoni M, Slamon K, Morejohn J. TherMOOstat: occupant feedback to improve comfort and efficiency on a university campus. In: American council for an energy-efficient economy summer study on energy efficiency in buildings. Asilomar, CA: 2016.
[229] Pritoni M, Salmon K, Sanguinetti A, Morejohn J, Modera M. Occupant thermal feedback for improved efficiency in university buildings. Energy Build 2017;144:241–50.
[230] Klein L, Kwak J-Y, Kavulya G, Jazizadeh F, Becerik-Gerber B, Varakantham P, et al. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. Autom Constr 2012;22:525–36.
[231] Jung W, Jazizadeh F. Multi-occupancy Indoor Thermal Condition Optimization in Consideration of Thermal Sensitivity. In: Smith I, Domer B. editors. Advanced Computing Strategies for Engineering. EG-ICE 2018. Lecture Notes in Computer Science, vol.10864. Springer, Cham: 2018. https://doi.org/10.1007/978-3-319-91638-5_12.
[232] Lee J. Conflict resolution in multi-agent based intelligent environments. Build Environ 2010;45(3):574–85.
[233] Purdon S, Kusy B, Jurdak R, Challen G. Model-free HVAC control using occupant feedback. 38th annual IEEE conference on local computer networks - workshops. 2013.
[234] Murakami Y, Terano M, Mizutani K, Harada M, Kuno S. Field experiments on energy consumption and thermal comfort in the office environment controlled by occupants' requirements from PC terminal. Build Environ 2007;42(12):4022–7.
[235] Lam AH-Y, Yuan Y, Wang D. An occupant-participatory approach for thermal comfort enhancement and energy conservation in buildings. Proceedings of the 5th international conference on Future energy systems. United Kingdom, Cambridge: ACM; 2014. p. 133–43.
[236] Erickson VL, Cerpa AE. Thermovote: participatory sensing for efficient building HVAC conditioning. Proceedings of the fourth ACM workshop on embedded sensing systems for energy-efficiency in buildings. Ontario, Canada: ACM; 2012. p. 9–16.