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Review

A Review of Approaches for Sensing, Understanding, and Improving Occupancy-Related Energy-Use Behaviors in Commercial Buildings

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Abstract: Buildings currently account for 30–40 percent of total global energy consumption. In particular, commercial buildings are responsible for about 12 percent of global energy use and 21 percent of the United States' energy use, and the energy demand of this sector continues to grow faster than other sectors. This increasing rate therefore raises a critical concern about improving the energy performance of commercial buildings. Recently, researchers have investigated ways in which understanding and improving occupants' energy-consuming behaviors could function as a cost-effective approach to decreasing commercial buildings' energy demands. The objective of this paper is to present a detailed, up-to-date review of various algorithms, models, and techniques employed in the pursuit of understanding and improving occupants' energy-use behaviors in commercial buildings. Previous related studies are introduced and three main approaches are identified: (1) monitoring occupant-specific energy consumption; (2) Simulating occupant energy consumption behavior; and (3) improving occupant energy consumption behavior. The first approach employs intrusive and non-intrusive load-monitoring techniques to estimate the energy use of individual occupants. The second approach models diverse characteristics related to occupants' energy-consuming behaviors in order to assess and predict such characteristics' impacts on the energy performance of commercial buildings; this approach mostly utilizes agent-based modeling techniques to simulate actions and interactions between occupants and their built environment. The third approach employs occupancy-focused interventions to change occupants' energy-use characteristics. Based on the detailed review of each approach, critical issues and current gaps in knowledge in the existing literature are discussed, and directions for future research opportunities in this field are provided.

Keywords: commercial building; energy consumption; occupant energy use behavior; occupancy related approaches; review

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1. Introduction

The world's growing energy use raises concerns about energy consumption and its impacts, particularly in terms of resource consumption and environmental degradation. In the last two decades, global energy use has increased by 50 percent, and current predictions show an increasing trend of 2 percent in annual global energy consumption [1,2]. Currently, residential and commercial buildings share 40 percent of this total global energy consumption [3] and are responsible for a similar percentage of CO_2 emissions [4,5]. Such facts are particularly visible in the United States and European Union, where total energy-use in built environments is more pronounced than in other major energy end-use sectors—e.g., industry and transportation [2,3]. Contributing to this rising building energy use are population growth, increasing demand for maintaining a comfortable environment, and increasing time spent inside of buildings [2]. These factors point to the significance of residential and commercial building sectors in energy consumption [6,7]. The commercial building sector currently consumes about 12 percent of global energy use and 21 percent of United States' total energy use [3]. Its energy use intensity (energy per unit floor area per year) increased by 12 percent [8], and it has the greatest intensity rate when compared to residential or industrial sectors [9]. In addition, the energy demands of the commercial sector currently has an increasing rate of 2.9 percent and continues to grow faster than other major sectors: industry, residential buildings, and transportation [3,10]. Such energy use intensity and its increasing rate raise a critical concern about improving the energy performance of commercial buildings, which has brought about a greater emphasis on the importance of maximizing energy savings during the operational phase.

The need for improved operational efficiency has attracted attention from industry, research, and government to address energy saving approaches. Overall energy consumption in buildings during the operational phase generally depends on four main characteristics [2,11–17]: (1) climate characteristics (2) the building's physical characteristics; (3) appliances' and systems' characteristics and; (4) occupants' energy behavior characteristics. Improving climate characteristics is not possible at a given location. Enhancing the building's characteristics (building envelope) and appliance and system approaches require large capital investments and sometimes are infeasible for existing commercial buildings [13]. This leaves occupants' energy behavior characteristics as a prime target for energy conservation [18–20].

The commercial built environment's energy use is highly connected to the energy-use behavior of its occupants [21–23]. This behavior includes individual occupant's presence in a building and such occupants' actions and interactions that influence the energy-use of the building [24]. These occupancy actions and interactions use up to 70 percent of the United States' total electricity of built environments [25]. A single occupancy-driven energy parameter—e.g., heating, ventilation, and air conditioning (HVAC) set-points—can impact building energy performance up to 40 percent [26,27], and uncertainties in occupancy energy-use behaviors can significantly impact total annual energy use on the order of 150 percent for the commercial sector [8]. Occupant actions can also lead to excessive and unnecessary energy consumption [28]. In the United States' commercial built environment, less than half of most buildings' appliances and systems are turned off by occupants after operational hours [29]. Due to the fact that there are more non-working hours in a week than working hours, such behaviors can lead to more energy wasted during non-working hours than energy used during working hours [30]. In this context, therefore, a growing number of recent studies emphasize the importance of improving occupant energy-use behaviors as a cost-effective approach for saving energy in commercial buildings; such work spans various research communities, including psychology and economics [31]. It is of interest to explore how these studies address occupants' behaviors.

A glance at the current literature shows that a considerable number of approaches of varying complexity have been proposed to address problems related to occupants' energy-use behaviors in commercial buildings. These approaches in the current literature can be grouped into the following three categories:

1. Monitoring occupant-specific energy consumption: This approach provides individual occupant energy-use information in order to understand the energy behavior of individual occupants.
2. Simulating occupant energy-consuming behaviors: This approach simulates realistic occupancy energy-use behaviors in order to capture and predict how such behaviors influence energy consumption in built environments and how such behaviors impact change over time.
3. Improving occupant energy-consuming behaviors: This approach aims to adjust energy-consuming behaviors among occupants in order to achieve the most ideal energy-saving potential in buildings.

These three categories share the ultimate goal of improving occupant energy-use behaviors, and advances in one area are expected to lead to advances in another area. However, despite the clear attention given to research in each category, there has been no attempt to comprehensively review these three areas in order to identify the gaps between them and the potential areas for further research. Motivated by this lack in knowledge, the objective of this paper is to present a detailed, up-to-date review of various algorithms, models, and techniques employed in each area and to provide in-depth understanding on how the current literature in each area can be connected.

In the subsequent sections, we will review the literature of each main approach, discuss the gaps within and between each area, and conclude with directions for future research.

2. Monitoring Occupant-Specific Energy Consumption

Generally, commercial buildings contain a large number of end-users (*i.e.*, occupants and appliances). In buildings with a single tenant, a single meter is installed at the main electrical service to measure the total aggregate energy consumption of all end-users. In buildings with multiple tenants, a meter is installed to measure each tenant's aggregate consumption. In either case, the fact that the monitored energy consumption is an aggregate of all the users' and building's appliance (mechanical load, lighting, *etc.*) load significantly complicates the breakdown of observed energy loads to individual appliances or occupants [32,33].

In order to estimate electrical consumption information for individual appliances, intrusive and non-intrusive load monitoring techniques have been widely employed in the related literature [34–41]. Intrusive load monitoring techniques require a meter to be installed at each point of interest (*i.e.*, at a specific appliance, in a specific office, at a specific receptacle and so forth). However, non-intrusive load monitoring (NILM) techniques rely on the existing available data from the building's electrical meter and employ techniques that identify specific signatures in order to associate energy use with the appliances in operation. In this context, NILM is considered a cost-effective tool to monitor appliance-specific energy consumption, and the current prevalence of NILM indicates its success and feasibility [34,41–43]. It is worth mentioning that the effectiveness of NILM in commercial buildings is quite limited due to the number and abundance of similar appliances in use simultaneously (e.g., personal computers).

Though NILM techniques work at an aggregate scale, there is still a need for effective tools to obtain detailed energy information regarding the consumption behaviors of individual occupants [44]. Using individual plug-in level meters in order to find the energy consumption of each occupant at his or her workspace has been used to address this challenge [45,46]. One criticism of this approach, though, is that this method is not reasonable in practice as it requires a large initial investment on the part of the business, which thereby decreases the likelihood that companies will adopt the approach. For this reason, researchers have begun looking for alternative means of tracking individual energy use. In their foundational work on this topic, Chen and Ahn [13] attempted to link energy-consuming data with occupancy-sensing data in order to track occupant-specific energy use without the need for capital-intensive plug-in meters. They proposed a coupled system that uses occupants' wireless devices' Wi-Fi connection/disconnection events to collect occupancy-sensing data and then correlates energy-load variations with these events to track occupant-specific energy use. This system confirmed that Wi-Fi connection information could be an effective indicator of energy load variations in commercial buildings. Therefore, this research capitalized on the breadth of research available regarding occupant detection in commercial buildings.

Detection technologies typically include cameras [47], CO_2 sensors [48], cellular phone control-channel traffic sensors [49], humidity sensors [50], infrared (IR) sensors [51], light sensors [52], motion sensors [53], radio frequency identification (RFID) [54], sound sensors [55], switch door sensors [56], telephone sensors [57], temperature sensors [50], ultra-wideband (UWB) [58], wireless sensor networks (WSN) [59], and Wi-Fi infrastructures [60]. These detection technologies can be divided to two main groups [61]: (1) precise technologies with incomplete coverage (e.g., cameras); and (2) imprecise technologies with full coverage (e.g., Wi-Fi infrastructures). Cost efficiency, resolution, accuracy, non-intrusiveness, and occupants' privacy are criteria that must be evaluated for occupancy-detection techniques. For instance, some researchers point out that since there are usually multiple overlapping Wi-Fi access points in commercial buildings, Wi-Fi-based occupancy sensing could act as a cost-effective option [13].

In addition, the occupant resolution level of occupancy-sensing is significant for distinguishing the energy-load of a single occupant from a large group of people since the process of coupling occupancy with energy-load data aggregates energy-consumption for all persons within a specified location. There are four levels of occupant resolution (see Figure 1) [62]: (1) occupancy: a zone has at least one occupant in it; (2) count: the number of occupants in a zone; (3) identity: who they are; and (4) activity: what they are doing. Considering all of these levels of occupancy resolution in conjunction with temporal and spatial resolution leads to correct and successful occupancy sensing.

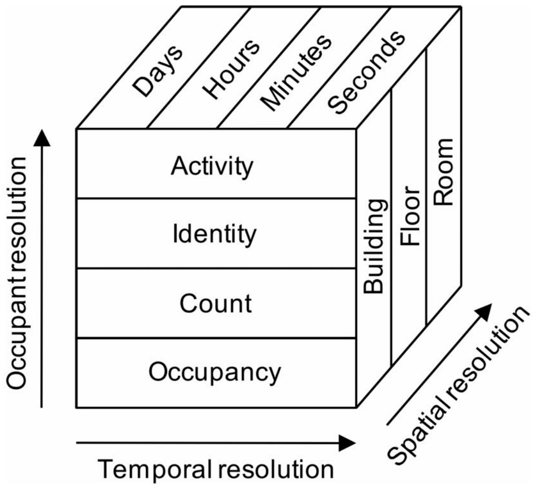

Figure 1. Dimensions of occupancy sensing resolution [62].

In commercial buildings, building management systems typically dedicate operational settings of main end-users—such as HVAC—according to assumed occupied and unoccupied periods during a day [63]. However, it has been found that average building occupancy for commercial buildings is at most a third of its maximum designed-for occupancy, even among office spaces at their peak working hours [64]. In this regards, occupancy-sensing data provides significant information for building management systems to adapt their system—e.g., HVAC and lighting—according to the exact number of occupants in a building at a given time [65–67]. The current status of sensing technologies therefore provides opportunities to economically monitor individual occupants and their energy consumption [68,69].

Concerning the linkage between aggregated energy data and occupancy-sensing data in commercial buildings, in order to find the energy use of individual occupants, Kavulya and Becerik-Gerber [70] linked the results of occupants' observations with NILM to study individual occupant's energy-consuming behaviors in an office environment. They employed visual observation in order to collect occupancy-sensing data. Their research was conducted for five weeks in an office space containing five occupants, and their results identified the energy consumption and potential waste of each occupant. The outcome of their research indicated the ability of the linkage concept to monitor occupant-specific energy consumption. Although visual observation is not an effective method for collecting occupancy-sensing data, this research revealed opportunities for further research into the concept of coupling NILM with occupancy-sensing technologies to track the energy consumption of individual occupants.

3. Simulating Occupant Energy-Consuming Behaviors

Nowadays, simulation approaches are widely used in various branches of science in order to model a real process over time. In built environments, a number of simulation models and software exist to predict energy consumption during the operational phase. These common, traditional energy software (e.g., BLAST, DOE-2.2, eQUEST, EnergyPlus, and ENERGY-10) are typically employed during the construction phase of buildings to simulate and predict the energy use within the operational phase.

However, these software have some limitations for simulating occupant energy-use behavior. The main limitation is that they assume the same energy use pattern for all occupants in a building, and this pattern is constant over time [18,24,28,71–73]. In fact, they are not able to account for dynamic aspects of occupancy. Due to these limitation, the energy use estimated by these software normally deviates from the real levels by up to 30 percent [5,28,74]. Furthermore, in addition to traditional software, traditional building management systems also have limitations with real-time inputs of occupancy-related dynamic factors, such as the number of occupants and their preferences, actions, and decisions [63]. This limitation is problematic since the inputs of real-time occupancy information can reduce HVAC and lighting energy consumption by up to 20 and 30 percent, respectively [56,66,67,75]. In response to these limitations in modeling occupants' energy-use behaviors, a number of studies have recently worked on various simulation techniques to attempt to overcome these particular limitations.

It is noteworthy that the developed energy-modeling and simulation tools for modeling occupants' energy-related characteristics and behaviors (discussed below) are mainly used during the early phase (*i.e.*, design phase) of buildings [73,76–78]. Such tools could help users to choose the correct size and most energy-efficient building systems and the appliances that are proportionate to the number of occupants. These tools, therefore, help to improve overall building simulation capabilities. However, to achieve the best results, the application of these tools should be very sensitive to occupants' input parameters to accurately represent occupants' actions [73,79]. In fact, these tools could be used to analyze the specific dynamics for all individual occupants, and could be calibrated to ensure that they can be used for all sizes of commercial buildings with different numbers of occupants. Researchers might also set the simulations to consider the decreased occupancy of after-hours and non-working days. To maximize the benefits of such software, the systems should be flexible enough to consider all possible occupant actions as well as all of the common practices of occupants.

In addition to simulating the design phase of the buildings, simulation tools could also be used during other phases such as the construction and operation phases [28,63,75,80–83]. For instance, within the renovation phase of buildings, such tools could help decision makers choose the most efficient appliances/systems when making a purchase. In addition, the use of such simulation techniques would help avoid the real resource-intensive process of testing which appliances and systems work well for a building. Time of a run, accuracy, and versatility (*i.e.*, solving different occupancy problems in any commercial building) are the main criteria that must be evaluated for occupancy simulation tools [50]. Many effective options are discussed below.

3.1. Agent-Based Modeling

Simulation research has indicated that occupants' dynamic energy use patterns can result in significant variations in energy consumption in the commercial sector [28]. In particular, a significant number of simulations employed Agent-Based Modeling (ABM) techniques to overcome software limitations in order to simulate actions and interactions between occupants and their built environment. These simulations sought to better predict building operational energy performance during the design phase. ABM is a kind of computational model that simulates the actions and interactions of agents with each other and their environments [84]; in ABM, building occupants are agents in the built environment. Unlike most mathematical models, ABM agents have heterogeneous features and abilities [85].

Li *et al.* [86] employed ABM to simulate occupant load in HVAC design in order to optimize HVAC system size. By simulating the correct occupancy behavior characteristics, the model estimated a more accurate load and effectively designed an HVAC system that saved up to 43 percent of total energy. The number of occupants in each specific space at a given time became the main parameter of their proposed model. Erickson *et al.* [75] also used ABM to optimize HVAC loading and showed a total energy reduction of 14 percent at the room level of commercial buildings. They used wireless camera sensor networks to find occupants' mobility patterns in buildings. Then, they employed ABM to simulate the mobility patterns for various control strategies of HVAC. Li *et al.*'s [86] and Erickson *et al.*'s [75] approaches feed various dynamic occupants' information into the ABM simulation tools in order to directly calculate the HVAC loads. HVAC controls the indoor comfort; however, in their models, they did not clearly respond to the ventilation requirement that decreases CO_2 levels inside the building. Lee and Malkawi [81] developed an ABM tool that simulates multiple occupant behaviors (*i.e.*, adjusted clothing levels, adjusted activity levels, window use, blind use, and space heater/personal fan use) in order to predict such behavior changes due to changes in climate and buildings topologies. Their proposed tool is an open architecture program that can adapt to different building functions and climate topologies, and that provides opportunities for an occupant to make decisions based on his/her thermal comfort level. However, this tool cannot track the thermal comfort conditions of individual occupants to fully understand whether they are satisfied with the thermal comfort level. Azar and Menassa [28,80] proposed an ABM technique to simulate the diverse and dynamic energy-use patterns of occupants and their behavior changes over time. This technique also considers various interactions among occupants. Compared to common energy software, their proposed model showed a 25 percent reduction in energy use at a small office due to the correct modeling of occupant behavior. However, this technique is limited to interactions of occupants within a room, and could not account for occupants' interactions in different rooms of a building. Such interactions may be considered to achieve more realistic results.

Furthermore, social network type and structure can affect occupants' energy-use behaviors. The commercial sector frequently has complex social structures due to presence of multiple independent entities within the same building [87]. In most commercial buildings in the United States, at least two companies (*i.e.*, entities) work in the same building [88]. Some researchers recently employed ABM to simulate interactions of occupants in different entities within a commercial building. ABM can also differentiate the impact of various dynamic interactions of occupants from different social structures/networks [89], which greatly affect occupants' energy use behaviors [32,90]. Anderson *et al.* [78] applied ABM to simulate the interactions of heterogeneous building occupants in their social networks to examine how social network type and structure can affect occupants' energy use behaviors. They considered four social network types: random graph, scale-free network, small-world network, and regular ring lattice. The results from their case study of a commercial building with different social network structures and connectivity levels proved that network type and structure hold significant influence over an occupant's energy-use behavior. Anderson and Lee [91] employed ABM to evaluate the effect of static and dynamic social networks on occupants' energy-use behavior. Their results indicated that dynamic networks increase the uncertainties of energy behavior and therefore have more influence on occupant energy behavior than static networks. However, Anderson *et al.* [78] and Anderson and Lee [91] did not mention at what rate occupants' energy-use behaviors can be affected. Finding a rate for behavioral change would better indicate how different social networks affect occupants' behaviors. Such studies would also improve if they could find which types of networks are most common in commercial buildings. In addition, they could find whether there is any relationship between the building type and network type.

Azar and Menassa [12,87] used ABM to model occupancy-related behaviors in social sub-networks to show how occupants' interactions impact the energy-use of buildings. They tested various numbers of sub-networks in a typical United States' commercial building, and concluded that traditional modeling techniques (such as single-network modeling and bounded confidence models) are not applicable to simulate social networks and sub-networks in commercial buildings. However, in their studies, they did not considered the four main social network types studied by Anderson *et al.* [78]. In fact, they only considered the small-world and scale-free network. Studying all social network types could be more effective to show the limitations of traditional modeling techniques.

3.2. Multi Agent Systems

Compared to ABM, Multi Agent Systems (MAS) provide the opportunity for agents (*i.e.*, occupants) to communicate more with each other as well as with their built environment. MAS divides a complex problem into sub-problems solved by representative agents [63]; for this reason, this approach is employed to model complex problems with multiple cyber agents. ABM is related to, but clearly distinct from, the MAS concept [92]. A MAS can contain combined ABM, and in cases where the problem of energy saving is a multi-dimensional problem, MAS is an appropriate application [92,93]. MAS may balance between occupants' preferences and energy saving; ABM fails to achieve this aim. In fact, concerning the commercial sector, MAS typically helps make tradeoffs between both building demands and occupant comfort [94,95].

Qiao *et al.* [96] introduced some prospects to indicate how MAS can simulate occupant behaviors to adjust device control in commercial buildings. Dounis and Caraiscos [93] presented MAS architecture for energy efficiency and comfort in built environments. They indicated that various advanced techniques (e.g., Fuzzy Logic, Markov Chain Model, and Neural Networks) are implementing methods used in order to develop a MAS tool for improving the efficiency of building control systems. In addition, their simulation results from implementing MAS on a building showed that this model can manage occupants' preferences for thermal and luminance comfort, indoor air quality, and energy conservation. However, they did not clearly respond to the balance between thermal comfort and energy conversation. In some cases, achieving a level of thermal comfort could lead to an increase in energy consumption. They proposed MAS architecture for managing both energy efficiency and occupant comfort, and conducted a tradeoff between these two parties is needed. Klein *et al.* [63] proposed a MAS tool to model the management and control of appliances and occupants in a building. Their model could simulate and predict how changes to the building, occupant behavior (*i.e.*, preferences and schedule), and operational policies affect energy use and occupant comfort. In fact, their model simulated occupancy behavior as well as building operational policies. Based on their results from employing the model on a case study of a three-story university building, an improvement in occupants' comfort level and a reduction in energy consumption were realized. For this model, some data needed to be manually input. However, since such models need a large group of input data to simulate and predict energy use and occupant comfort in a commercial building, the process of inputting the data into these tools needs to be totally automated in order to facilitate the tool's operation.

3.3. Other Techniques

In addition to ABM and MAS, some researchers have proposed other models and techniques aimed at simulating occupants' energy-related characteristics. Yamada *et al.* [97] developed a system that combines neural networks, fuzzy systems, and predictive control in order to control air-condition systems. Their system can predict the number of occupants in order to estimate building performance to achieve energy savings and high comfort levels for indoor conditions. However, neural network- and fuzzy system-based models typically need a training process, and for Yamada *et al.*'s [97] developed tool, this training process needs a considerable amount of time. Their proposed system therefore needs to be improved in its training level. Yamada *et al.* [97] also considered only the temperature as an indicator for comfort level. Such works on comfort level may consider other aspects of indoor comfort, such as humidity and air speed. Wang *et al.* [98] proposed a Markov chain-based model for building-occupancy simulations in commercial buildings; the model can simulate occupants' stochastic movements in order to predict each occupant's location. It can also produce nonsynchronous occupants' location-changes according to the time and distribution of occupants in space; such predictions become inputs for building management processes for energy savings. However, they validated the model by single offices, which is problematic since for such studies, more cases—especially multiple offices—need to be considered to study occupants' stochastic movements. Jazizadeh *et al.* [82,83] developed a framework that models occupants' thermal preference profiles into HVAC control logic in order to set room conditions at occupants' desired temperatures. They employed a fuzzy based model to put occupants' comfort profiles into the framework. The results from their test bed of a university building showed up to a 40 percent reduction in HVAC daily average airflow. However, similar to Dounis and Caraiscos [93], they did not clearly respond to the balance between thermal comfort and energy conversation, which is important since achieving a level of thermal comfort might lead to increasing total energy consumption of a building. Zhao *et al.* [99] developed a practical data-mining approach that collects the energy consumption data of various systems and appliances within office spaces to find occupants' passive energy behaviors. The proposed data-mining approach is based on nominal classification (*i.e.*, C4.5 decision tree, locally weighted naïve bayes, and support vector machine) and numeric regression algorithms (*i.e.*, linear regression and support vector regression). The approach has the capability to separately find the behaviors of individual occupants and the schedule of an occupant groups and use this information to set various office appliances and systems in order to reduce the energy consumption. However, the validity of their proposed data-mining approach was limited to data that may have included some incorrect outcomes; such data-mining models require a considerable sample of validated data to test the models and show their effectiveness. Hong *et al.* [18] presented a framework, DNAs, to observe and simulate occupant energy use behaviors in built environments. This framework is developed based on four key components: (a) drivers of occupants' energy-related behaviors; (b) needs of occupants, (c) actions carried out by occupants; and (d) building's systems acted on by occupants. Such occupancy components directly and indirectly influence building's energy consumption, and therefore DNAs provide the opportunities to incorporate more energy-related behaviors into simulation tools. In addition, this framework has the capability to evolve into BIM.

Another approach, Relative Agreement (RA) modeling, is an extension of a Bounded Confidence model [100] that can take into account different energy use characteristics of occupants, uncertainties about their opinion dynamics, and their interactions to each other. RA was defined and introduced by Deffuant *et al.* [101–103], and it can consider occupants as a population of agents that are selected randomly to interact with each other. In addition, each occupant (*i.e.*, agent) is characterized by two variables: its opinion, and its uncertainty [100,101]. These two variables change over time. The ABM model developed by Azar and Menassa [12,87] is based on an RA concept. Additionally, Verplanken and Wood [104] and Göckeritz *et al.* [105] employed RA concepts to simulate pre-environmental behaviors of occupants in order to understand occupants' responses to the new energy characteristics of their built environment. Their results shows that an occupant's energy-conserving behavior is highly connected to his/her belief regarding other occupants' energy-conserving behaviors.

Figure 2 shows the framework of current research. Although MAS tools have potential to simultaneously integrate ABM and other techniques for simulating occupancy related behavior [93], such MAS tools have not been directly addressed by literature. In this context, hybrid simulation approaches could be proposed.

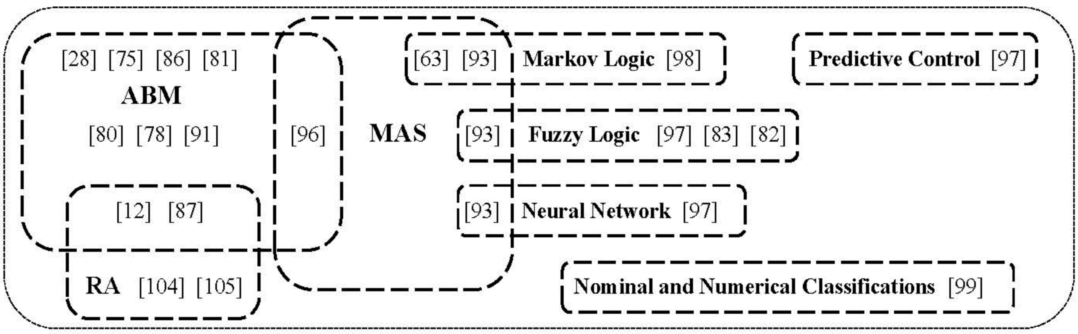

Figure 2. Framework of current research.

4. Improving Occupant Energy-Consuming Behaviors

Improving occupant energy-consuming behaviors is a more cost-effective technique for cutting energy consumption than improving building's physical properties [18–20]. Failure to improve occupant behaviors undermines the investment in retrofitting building envelopes and appliances since occupants define the success of such sustainable retrofitting projects [13,31]. Furthermore, if occupants learn appropriate energy-saving behaviors, they can practice such behaviors in all buildings. Therefore, adopting energy-saving behaviors among occupants would then provide an opportunity for general energy savings within all built environments.

Changing energy-use behaviors and motivating occupants to have sustainable behaviors are typically achieved by providing intervention tools for their behaviors and habits in order to improve the occupant's intentions and beliefs [45]. Such interventions have used several techniques (e.g., prompts, providing information and feedback, goal setting, and motivations) to attempt to improve occupant behavior, and each technique has had a level of success in reducing energy consumption [91,106–109]. Generally, there are two main occupancy-focused intervention approaches (see Figure 3) [12,79]: (1) continuous interventions; (2) discrete interventions. These approaches mainly provide occupants with the information about their consumption behaviors and associated impacts. The continuous intervention typically includes occupancy interactions (peer pressure and word-of-mouth) and continuous feedback techniques [110–112]. The discrete intervention mainly includes green community-based social marketing campaigns, energy efficiency education and training, and discrete feedback techniques [104,113–115]. Social marketing campaigns are some commercial marketing techniques for the purpose of social engagement to influence occupants to change their social behaviors in order to save energy in built environments [116,117].

Education and training are also important for improving occupants' knowledge regarding energy-saving behaviors. Verplanken and Wood [104] and Göckeritz *et al.* [105] discussed how improving occupants' energy behaviors first requires changing individuals' beliefs and intentions regarding energy use. In this context, periodically holding energy meetings and workshops for occupants in individual commercial buildings has shown to be effective in improving energy-saving knowledge of built environments. In particular, these discrete interventions educate occupants about how to conserve energy, and occupants can share their energy-saving knowledge with each other through continuous interventions. Some consider combining discrete and continuous interventions as the most ideal and effective intervention technique.

In addition to dividing interventions into continuous and discrete categories (see Figure 3), Archer *et al.* [118] divided the models motivating energy-saving behaviors into two groups: (1) rational-economic model; and (2) attitude model. In the rational-economic model, occupants are assumed to perform energy-saving behaviors that are economically advantageous. In the attitude model, occupant energy-saving behaviors result from promising and desirable attitudes about conservation. While occupancy-focused interventions assume the non-energy-saving behavior of occupants and work to improve occupants' behaviors, the rational-economic model assumes occupants have energy-saving behaviors. However, the attitude model needs occupancy-focused intervention to change the occupants' attitude to saving energy.

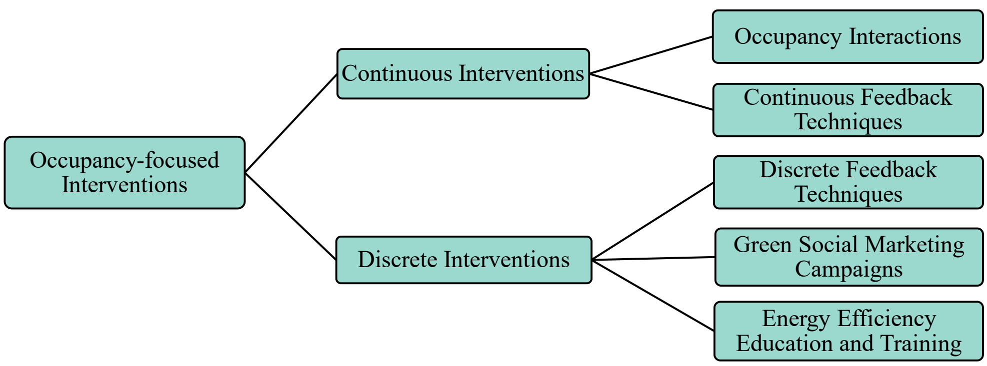

Figure 3. Occupancy-focused interventions for improving energy-use behaviors [12,79].

It is noteworthy that the influence of an intervention technique significantly depends on social structures/networks within the built environment [85,119]. In fact, organizational network and structure dynamics determine occupant engagement levels with an intervention technique, and therefore structures/networks could impact the results achieved by employing an intervention tool for improving energy-saving behaviors [68]. Misunderstanding the influence of social structures might change occupants' behaviors into bad habits, a concept known as the rebound effect [120]. Some intervention studies [121–123] show that ignoring the effects of social networks can change occupants' energy-saving behaviors into bad behaviors.

In addition to the effects of social structures, the variability of individual occupants' energy intensity (e.g., kWh/ft^2/occupant/year) over time can also influence the success of intervention techniques [12,104]. Studies indicate that low variability in energy intensity demonstrate that an occupant has strong energy habits. Therefore, interventions seeking to influence such rigid occupants are much harder to accomplish than interventions targeting occupants with flexible habits [12,99,101,122,123]. Furthermore, in addition to rigid occupants, extremists can affect the performance of occupancy-intervention tools. Such occupants significantly affect their peers' opinions and therefore cloud the interventions' performance; even a small number of extremists could push their ideas onto a large number of occupants within a built environment [79,124–127]. Finding the number of extremists and studying how they may interrupt an intervention study can help researchers reduce such occupants' effects on occupancy-intervention techniques. Since organizational network and structure dynamics affect the occupants' communication within commercial buildings, studying the extremists' effects within different structures/networks could also help researchers understand how extremists influence overall energy consumption.

With these categories and concerns in mind, occupancy-focused intervention efforts in commercial sectors mainly focused on occupancy interactions and feedback techniques, described below.

4.1. Occupancy Interactions

Occupant behaviors are significantly influenced by peers in their built environment, especially when there are strong relationship ties among occupants. Peer pressure capitalizes on the fact that occupants influenced by interventions interact with other occupants to influence them to improve their energy-use behaviors [105,128–131]. In one case, an occupant could observe and adjust his or her own behavior to follow other occupants' energy-saving behaviors. In fact, peer pressure interactions engage occupants to help themselves. Azar and Menassa [12,87] modeled peer pressure interactions among occupants. Each occupant sent a message to other occupants, and the interaction occurred when the two occupants' energy-use characteristics paralleled each other. In fact, Azar and Menassa assumed that peer pressure is most effective when the energy-use characteristics of the two occupants are the same and is least effective otherwise. They employed their experiment on a case study of medium office buildings and achieved up to 24.7 percent energy-savings through peer-pressure intervention. However, the mentioned main assumption of these works could limit the achieved conclusions. For example, an extremist could significantly affect his/her peers—even those who have energy-saving behavior—and therefore, two occupants with different energy-behavior characteristics could significantly affect each other's behavior. Carrico and Riemer [132] also studied the effect of peer pressure during a case study of office buildings for a four-month period of time. In their study, they disseminated energy-saving information among occupants, and considered that each occupant would educate and encourage others to have energy-saving behaviors. Their results indicated a 4 percent reduction in total energy use. However, they did not clearly discuss how peer pressure affects occupants' behavior. Since the peer-pressure concept involves different kinds of interactions among occupants, such research might significantly discuss which kind of peer-pressure interaction influenced occupants' energy behavior.

Within the boundary of peer-pressure concept, Word-of-Mouth (WOM)—a type of informal, occupant-to-occupant, face-to-face communication [133]—is considered a very influential communication method to influence occupancy-related behaviors [110]. WOM includes relating pleasant information and recommendations to others [134]. In energy-related research, WOM is typically employed when occupants with various energy characteristics share a common space [28], and it can be significantly effective in improving occupant energy-use behaviors [135]. Azar and Menassa [28,80] studied WOM interactions among 10 students in a small graduate student office building in a 40-month period to understand how occupants from different groups with different energy use behaviors can influence others within their group and in other groups. In their research, they considered three groups of occupants: high-energy consumption, medium energy consumption, and low energy consumption. The results indicate the effectiveness of WOM to adopt energy saving behaviors among high and medium energy consumption categories and convert them to low energy consumption category. However, WOM is obviously connected to occupants' social structures/networks, and such WOM interactions need to be evaluated through medium or big office buildings since the structures/networks of small offices are completely different with other sizes of office buildings.

4.2. Feedback Techniques

Feedback techniques typically provide occupants with their energy-use information. A growing body of energy-saving literature has shown that feedback is a more prevalent and cost-effective intervention technique than occupancy interaction for bringing about reductions in energy use. The earliest studies in this field date back to the 1970s. For example, in 1977, Seligman and Darley [136] provided daily electrical energy use feedback to a group of households within a one-month period; they saw an 11 percent reduction in energy use. In 1980, a United States local T.V. channel in West Texas provided information about the amount of gasoline people used daily via a nightly news television program [137]. The results showed a reduction of up to 31.5 percent in fuel consumption.

Feedback techniques are generally divided into continuous and discrete techniques (see Figure 3). In continuous techniques, the energy-use related information is typically provided to occupants through bulletins and announcements installed on boards located in places where occupants have the opportunity to see the information every time they are nearby. However, discrete techniques provide information periodically. For example, occupants could be informed about their energy-use information via weekly e-mail.

There are certain characteristics that help a feedback technique to be more effective. The most important characteristic emphasizes giving positive comments to occupants rather than negative ones (e.g., using language such as "saved" instead of "wasted"). Comments on specifics energy behaviors are also more effective than general comments. Overloading on feedback tends to reduce occupant's ability to effectively use comments [138]; therefore, a well-timed plan regarding when to provide feedback to occupants is also important.

In particular, representative units significantly affect the success of feedback. There are three meaningful units for representing the energy-saving related feedback [139]: (1) Direct energy units (e.g., kWh); (2) Monetary units (e.g., $); and (3) Environmental externality units (e.g., greenhouse gas emission). The representative unit has a significant influence on occupants' behaviors as it effectively dictates comprehension, relevance, and importance of energy consumption to associated problems [140]. Since commercial occupants have no direct financial responsibility about their energy consumption in the commercial sector, financial incentives (*i.e.*, monetary units) do not efficiently motivate occupants. However, sharing energy-consumption information with direct energy and/or environmental externality units has been shown to improve energy saving behaviors in the commercial sector [28,117,132,141]. In fact, commercial building occupants who are aware of their ecological consequences are more likely to improve their behaviors [142,143].

A group of researchers [144] developed a site (StepGreen.org) that provides environmental externalities (e.g., the equivalent CO_2) of occupants' activities to them in order to motivate energy-saving behaviors. They deployed StepGreen on a case study of 32 students in a local community for a three-week period of time. Their findings indicate the effectiveness of the environmental externalities unit in changing behavior actions. However, such sites need to provide a motivation for occupants to use the data that is shared through the website. Conventional feedback delivers data to occupants; however, sharing data through a site may not actually deliver data since some occupants could forget to access the site. Matthies *et al.* [45] provided environmental externalities feedback over the whole period of November 2008 to January 2009 for 15 university buildings in the German state of North Rhine-Westphalia. They gave information on the reduction of CO_2 emission to all occupants through different methods such as posters, websites, e-mails, and brochures. Their results showed 8 percent reductions in electrical energy consumption, and therefore show how feedback using environmental externalities units is an effective strategy for improving occupant behavior. This research is a good case study for showing how a feedback study could be implemented within large-scale buildings. Further researcher might follow the methodology explored in this research to employ such feedback studies on large-scale buildings. However, in their work, the authors assumed that all objective data (e.g., meter reading) is highly reliable, and this assumption inevitably affected their results. Employing a data analysis method in order to verify the data at the early stage of such works could be helpful in yielding more reliable results and conclusions.

In addition to representative units, the means of communicating information also play a role in audience response. Staats *et al.* [145] provided feedback about heating-related behaviors to 384 office spaces at a large office building over the course of two successive winters; each study was performed during a four-week period. Their feedback sought to reduce natural gas used for radiators, and they used posters, brochures, and individual feedback to provide energy information to occupants. They assessed the long-term effects of the first feedback during the 11-month-long gap between the two feedback periods. The work overall achieved a 6 percent reduction in total gas consumption during the duration of the study. Such studies can reveal how occupants with previous experience using a feedback tool will respond to a similar feedback study after a short-term or long-term passage of time. Carrico and Reimer [132] provided energy feedback for occupants at a mid-sized private university in the southern United States; the case study's 24 buildings were used primarily for office space, research, and teaching, and the monthly feedback was presented to the 2300 employees via e-mail over the course of a four-month duration. Their feedback showed an average reduction of 7 percent in total energy consumption. Similar to the research of Matthies *et al.* [45], this research is also a good case to show how a feedback study can be implemented within large-scale buildings. In such studies, a single feedback method applies to hundreds of occupants who work in various commercial buildings, which means that handling such studies is relatively hard work. Collecting data after each feedback to fully understand how the feedback influences occupant behavior over time would also be necessary, but Matthies *et al.*[45] and Carrico and Reimer [132] only looked at overall energy reduction. One likely reason for the limited examination is that separately analyzing the data from each feedback would be a highly time-consuming activity for their studies.

Research also shows that comparative feedback among different groups is more effective than individual feedback for changing behavior strategies [146]. Occupants in commercial buildings typically work in different groups, and information about the outcomes of other groups mostly leads to competitive feelings and the motivation for better performance. Therefore, comparative, group-based feedback yields more energy-saving actions than groups who only received feedback about their own actions [146]. In fact, providing individual occupants with access to the energy information of others in their organization can result in significant energy savings [68]. Siero *et al.* [147] studied the effect of environmental feedback on occupants of two units of a company over a four-month period. They chose two units with the same social structures and personal characteristics. The weekly feedback was presented through various energy bulletins and announcements. Occupants of the first group just received the feedback for their own behavior; however, the second unit received information both regarding their own energy-use behavior as well as comparative feedback about the first group. The results show the second unit saved more energy than the first unit. In addition, occupants in the second group reported being more competitive at the end of the study than the first group, and they also continued their energy-savings behaviors after completing the study. Similar to the Siero *et al.* [147], Gulbinas and Taylor [68] and Peschiera and Taylor [123] divided their occupant samples into two groups and provided a comparative feedback for one group. Their results also indicate the comparative method is more effective than individual feedback. They also discussed how occupants who receive energy-use feedback only for their own behavior may not have sufficient information to significantly improve their energy-use behaviors. However, although all of these comparative feedback research projects indicated that comparative feedback would encourage occupants to save energy; they do not provide any insight about the negative impact of comparative feedback. In such a case, occupants in a comparative feedback group could be negatively impacted by the information that shows that they consume more energy than other groups.

Understanding the individual energy-efficiency behavior of each occupant can lead to providing better energy-saving feedback to individual occupants. The energy consumption of appliances of individual occupants (e.g., personal computer, desk lamp) is typically less than 10 percent of overall energy use in commercial buildings [148,149], and a workdesk can offer the simplest environment in such buildings for understanding individual occupant's energy behaviors [45]. Murtagh *et al.* [46] investigated the influence of individual feedback on energy use in commercial buildings. They chose a case study of 83 office workers at a medium-sized university in the south of England and measured their energy consumption at the desk level within an 18-week period—each desk was under control of an individual occupant. Then, Murtagh *et al.* [46] provided an environmental externalities-based feedback named MyEcoFootprint to all individual occupants. Their results indicate a significant energy reduction. Similarly, Staats *et al.* [145] provided individual feedback to occupants once within the last two weeks of the second intervention period (*i.e.*, the second winter). They gave each occupant a separate personal letter that provided information about the particular windows and thermostats within his/her office space. This information, for example, could have revealed to an occupant that the window of his/her space was open in the winter on a specific day and therefore wasted a specific quantity of energy. What is most promising about such studies is that since they provide feedback to individual occupants by collecting data at the level of individual occupants, there is a potential for these studies to investigate how occupants with different energy behavior characteristics adopt energy-saving behaviors. In addition, these studies also can help researchers find extremists within a built environment and can reveal how extremists influence their peers.

Table 1 provides a summary of presented feedback techniques employed in commercial buildings. This summary shows that most researchers provide weekly feedback to occupants. In addition, the logical length for feedback studies seems to be between two to four months. Furthermore, as mentioned, these studies indicate that occupants typically control less than 10 percent of total energy use in commercial buildings [148,149]—Table 1 shows that feedback research has led to energy savings of less than 10 percent, which could confirm that occupants control less than 10 percent of overall energy consumption.

Table 1. Summary of feedback techniques.

Feedback features		References
Type	Individual	[46,145]
	Comparative	[68,123,147]
Frequency	Weekly	[45,123,145,147]
	Biweekly	[68]
	Monthly	[132]
Duration	Less than 2 Months	[123,145]
	2–4 Months	[45,68,132,147]
	More than 4 Months	[46]
Energy saving	Less than 10 percent	[45,46,68,123,132,145,147]
	More than 10 percent	NA

5. Discussion and Future Research Prospects

The recent evaluations of occupancy-related energy-use behaviors have grown in importance, and an increasing portion of research has focused on the variety of methods and techniques used to evaluate this topic in commercial buildings. In the previous sections, we have discussed exciting literature and have highlighted the main limitations of these works. The following sub-sections will discuss the overall challenges of the current literature to point out important research directions for future studies. We will first go through individual approaches and then argues connection between these approaches.

5.1. Overview of Current Approaches

Despite the attention given to the topic, there are still various limitations and issues that should to be addressed by future studies. The first point that the current literature failed to consider is the effect of ambient temperature and humidity on occupant behavior in commercial buildings. Occupancy energy-use behavior varies according to weather conditions [73,150]. Individual occupant's behaviors may have a larger impact on energy consumption in hot-dry climates than in mild-humid ones [8]. For instance, Paatero and Lund has shown that in sub-tropical countries, occupant energy behaviors are markedly different during different seasons [151]. Consequently, conducting occupant-related energy research during different seasons could foreseeably lead to dramatically different results. Further studies are therefore recommended to consider the effect of ambient temperature on built environments and their occupants' energy consumption activities. Such studies could, for example, examine two groups of occupants who are residents of the same commercial building and have similar energy behavior characteristics; the studies could evaluate the difference in these groups' behaviors during two different seasons. Such results would offer an appropriate mode for addressing temperature-related issues in this discussion.

Another area prime for analysis is the role of building size on occupant energy use. Occupant energy-use behaviors vary according to building size [73]. In a small building, occupants typically have more control over different appliances, and therefore they are more engaged in energy-saving behavior. However, in a large building, building management systems typically control more appliances. We found that current research mainly focused on small- and medium-sized offices; however, there are very few papers that examine large-sized office or other such large-scale cases. Therefore, we recommend that researchers next evaluate the influence of building size on occupants' energy behavior.

Another point that is well-represented in the literature is the role of permanent occupants in commercial buildings' energy consumption. However, temporary occupants have the potential to influence occupancy-related energy consumption. Permanent occupants are those who work full-time in buildings, whereas temporary occupants are less often in the buildings. For example, in a case study of a university building, Klein *et al.* [63] considered faculty and staff as permanent occupants and students as temporary occupants; what is particularly interesting about these designations in Klein *et al.*'s study is that the number of people in the temporary group was eight times as populous as that of the permanent group. This difference between the numbers of people in each group highlights the significant role temporary occupants have on the total occupant energy-use. Therefore, dividing occupants into permanent and temporary groups and finding the energy-related role of temporary groups is recommended for future research.

The process of planning occupant group activities according to the total energy efficiency of a building to save energy is a concept known as a green schedule. Future research into green schedules could provide energy-saving recommendations and policies for a series of commercial buildings' specific occupant-related activities. A case study that did address these options indicated that changing the time and location of meetings can save energy in commercial buildings [63]. Therefore, detecting the different kind of occupant group activities in a commercial building and suggesting green schedule options for such activities (*i.e.*, schedules targeting energy savings) would be a valuable topic for future research. Such studies could provide general policies to higher-level management in commercial buildings to save energy by green planning.

Furthermore, future work should be undertaken to consider the effect different occupant characteristics have on energy consumption. Age, educational level, gender, and nationality are all occupant characteristics that influence energy behavior [28,152–154]. Such characteristics could greatly impact occupant energy-saving adoption and the relevant intervention methods. However, the current literature has generally failed to consider the significance of these kinds of characteristics. Conducting research specifically to examine the influence of such characteristics is therefore recommended for further studies.

While the research topics highlighted above provide new categorical options for future research, there are still several lingering gaps in knowledge relevant to the three approaches discussed in the previous sections. The following subsections discuss the issues and challenges of each approach separately.

5.1.1. Monitoring Occupant-Specific Energy Consumption

In regard to monitoring occupant-specific energy consumption in commercial buildings, load disaggregation among individual occupants is still a challenging issue. Although the literature has demonstrated a large variety of occupancy-sensing techniques, very little research has been conducted in the area of monitoring occupant-specific energy consumption. In fact, building management systems have been utilizing increasingly extensive sensor networks, but these networks often fail to correctly collect building occupancy data [155] and therefore do not effectively leverage total energy consumption data as a measurement of individual occupant's energy consumption. The fact that there are so few publications about approaches for monitoring occupant-specific energy use [156–159], gives evidence to the fact that less attention has been paid to this approach than to the other two main approaches (*i.e.*, simulation and improvement of occupants' energy consumption). However, the success of simulation and improvement approaches highly depends on detailed occupant-specific energy consumption. In fact, outputs of monitoring individual occupant's energy consumption can form the inputs for the second and third approaches.

Monitoring occupant-specific energy consumption also provides researchers with the ability to quantitatively classify occupants into different energy-related groups based on their specific energy-use behaviors. Such classifications could help improve occupant-driven energy-conserving behaviors. Furthermore, the outcomes of occupant-specific energy use would provide researchers with an opportunity to present explicit feedback to individual occupants about their own individual energy actions and decisions. Future research is therefore recommended to propose models and techniques that would monitor the energy load of individual occupants.

One option for future actions would be to extend the concept of existing non-intrusive load monitoring techniques. Such NILM techniques have been widely employed to disaggregate total energy consumption to identify specific loads and subsequently individual users. This concept would be helpful for developing related reliable methods for estimating the energy consumption of individual occupants. Chen and Ahn [13] indicated that Wi-Fi connection/disconnection events could be an effective indicator for occupancy energy load variation in commercial buildings. Developing such occupancy frameworks as well as occupancy-detection technologies could also be helpful in developing occupancy non-intrusive load monitoring techniques.

Furthermore, Gulbians *et al.* [160] recently proposed a three-stage clustering algorithm as a new set of metrics that classifies commercial building occupants according to their energy-use efficiency, entropy, and intensity. This algorithm segments building occupants' energy consumption data in order to understand individual occupant's energy-use characteristics. Further developing the concept of such algorithms in order to estimate energy-use information of individual occupants is recommended.

5.1.2. Simulating Occupant Energy-Consuming Behaviors

In simulation research, it is necessary to accept certain assumptions, and these assumptions greatly influence the results. In fact, the accuracy of a simulation technique significantly depends on the adequacy of its assumptions. However, the validation of a simulation technique mainly focuses on technical validation. Future simulation research is recommended to test and verify the assumptions used to develop the models.

In order to develop the practical aspect of occupancy-related models, future research should indicate how the developed models can be integrated into current energy simulation software or can be developed as new software. Such moves would be a step toward the practical application of models that shape the future of energy software in built environments. For this reason, future research is recommended to monitor and collect data from a large number of commercial buildings to better validate any proposed models and their corresponding software. Testing and validating the scalability of future models for different building types, different occupant social networks, and within multiple buildings are also recommended.

Although there are several studies in the literature that consider occupants' social networks, they simply represent the first step necessary for understanding how various social networks affect energy-use in commercial buildings. More comprehensive studies are still needed. In [123], it was shown that larger network degrees can play a positive role in inspiring occupants to use less electricity. However, the results of [12] indicate non-significant differences in energy savings between moderate and high levels of connection among sub-networks. Therefore a moderate level of connection might be enough to maximize energy savings. Further investigation is needed to determine at what network degree the ideal energy saving can be achieved. Furthermore, mediocre and poor relative networks should be studied in order to completely understand the influence of all network types on occupants' energy use.

Chen *et al.* [161] proposed a block configuration model as a novel agent-based simulation model in order to emulate occupant peer networks and their impact on building energy consumption. Compared with other models, their proposed model can generate a more accurate random network, and allow for a controlled network size and connectivity for occupants' energy use simulation. However, they just tested and validated their model for residential buildings. Future research is thus recommended to verify such models in commercial buildings.

5.1.3. Improving Occupant Energy-Consuming Behaviors

Different intervention techniques must be individually examined according to whether they are effective, comprehensible, inexpensive, and easy to implement on large-scale groups of occupants in commercial buildings. Furthermore, an intervention technique must be suitable to its target group. In order to find a suitable intervention technique and to adjust it for its targeted group, pre-surveys should be employed to find the energy-related characteristics of occupants in a studied group. Ignoring this step might lead to getting worse energy-consumption behaviors. In [162–164], the results indicate that the occupants had a limited understanding of the goal of the feedback studies and that some occupants had a hard time understanding the used representative units. In such cases, a pre-survey could help identify the general knowledge of the targeted occupants for the feedback study and could help reveal which representative units would work better for them. Therefore, conducting a pre-survey is critically needed for intervention studies, especially in order to find how the targeted occupants understand the terminology and what their preferences are. Pre-surveys also help researchers evaluate their audiences, select intervention techniques according to the audience's need, and provide tailored information that will reach participants—such tailored information seems to be more effective than non-tailored information for knowledge improvement and behavior change [165]. The pre-survey could also provide some general energy-saving information to initially motivate occupants to engage in energy-saving actions.

Section 4.2 indicates the importance of representative units. However, the methods for communicating the information to users are also important. In this regards, distributional graphs typically appear to be the most easily comprehended and preferred method of presenting energy-consumption information to occupants [166]. That said, future research in this area is needed to conduct various displaying methods to verify the most effective means.

The success of feedback depends mainly on its data resolution, and various levels of resolution might have different levels of success in improving energy behavior. In this regards, although high resolution feedback—which typically requires more time and capital investment—has a clear record of success in the literature, it is currently unclear whether a high level of resolution is always needed or whether a lower level can still be effective [68,119]. In fact, higher resolution data do not necessarily lead to more energy knowledge. Future research is therefore recommended to study the effects of different levels of resolution on energy behavior.

Future research is also needed to evaluate the frequency at which energy-related feedback should be provided to occupants to achieve the best possible behavior adaptation. Furthermore, researchers need to develop policies regarding how to avoid providing intrusive feedback to occupants. Intrusive feedback might lead to decreases in the quality of energy-saving behavior and may therefore increase the energy consumption. Deeper research into these concerns would be warranted.

In most corresponding studies [12,113,114,119,145,167,168], the promoted energy-saving behavior during the feedback experimental period were rarely remained over time by occupants in built environment. Therefore, the cost and time investment for conducting such studies have typically achieved short-term and temporary results but failed to lead to long-term or permanent energy-saving behaviors. Future research therefore needs to assess and evaluate the long-term effectiveness of feedback. In particular, an alternative long-term technique could be occupant-interaction techniques in which peers are able to influence their co-workers over a longer period of time to improve energy-saving behaviors. The long-term cost investment for such interactions is typically less than feedback techniques and should be examined.

Individual occupants also have their own strategies and intentions—known as personalized behavioral strategies—to change their behaviors to energy-saving behaviors. In [46,132,147], the authors studied the personalized behavioral strategies. For example, Murtagh *et al.* [46] provided individualized feedback to individual occupants and found that different occupants needed different motivations to adopt energy-efficient behaviors. Future research should investigate such strategies to better understand how personalized strategies affect behavior changing. Adjusting occupants' own strategies to energy-saving strategies could also provide an opportunity for occupants to continue their energy-savings for longer periods of time and therefore could be considered as a way of achieving long-term energy-saving behaviors.

Energy savings could be adopted suddenly during one part of a study or be adopted steadily throughout the whole duration of a study. In this context, identifying a rate for behavioral changes could potentially be considered a means of determining whether an intervention method can lead to energy-saving behaviors during specific amounts of time. In fact, the speed at which occupants adopt certain energy-saving behavior is valuable information. This rate could also be considered an indicator for comparing several intervention methods. For example, this rate could be defined as the amount of energy saved by an occupant per day. By dividing the total amount of energy saved by the total number of occupants and feedback durations, this rate could reveal which methods are the most effective at inspiring change. Considering this rate in further studies would provide even better opportunities for understanding which intervention techniques are most efficient.

One of the most effective feedback tools to motivate energy-saving behavior is historical comparison [169], which allows occupants to make a good comparison regarding their own energy consumption. In particular, historical comparisons could provide energy-use related information for individual occupants over a period of time to show them, for example, when they used less energy. Then, occupants can check their own behavior across time to understand their own energy-saving actions. However, there is a gap in the literature to study how historical comparison feedback works for commercial occupants. Further research needs to study the influence of historical comparison feedback on improving occupant energy-use behaviors.

5.2. Connections between Three Main Approaches

Apart from the importance of each individual research category, their connections are also very important in helping the ultimate goal of improving occupancy-related behaviors to bring about general energy savings within all built environments. We therefore argue that by understanding the connections between these areas, researchers can understand how efforts in each area bring about change in other areas, and researchers can identify which kinds of connections were missed; failure to achieve such connections can undermine the overall efforts of three areas for general energy saving.

Finding individual occupants' energy consumption, as happens in the first approach, could form the input data for the second and third approaches. The current status of simulation models shows the maturity of the second approach's ability to model the dynamic behaviors of individual occupants. Such models need as one of their input data the occupant-specific energy use to simulate the real process of occupants' energy use over time. However, the current status of this research indicates that the literature has failed to consider this link between the first and second approaches. The immaturity of the first approach as compared to second approach could be the main reason for missing this link. Failing to provide occupant-specific energy consumption might disturb the performance of a simulation tool.

In addition, in the field of improving occupant behavior, there is a need for researchers to know the energy consumption of individual occupants during the three phases of their research: before starting using the intervention tools, during the studies, and after finishing these studies. In particular, such energy knowledge about individual occupants not only helps to track changes in occupants' energy behaviors over time but also shows the performance of an intervention tool. The current status of the literature shows that researchers have used the overall energy consumption of all occupants for tracking occupants' changes in behavior and intervention tools' performance. However, in these cases, energy data of individual occupants would provide a much better opportunity for researchers for tracking process. In addition, Azar and Menassa [79] mentioned how an extremist could influence the energy consumption of his/her peers. In such a case, an intervention tool has to be adopted based on the presence or absence of extremists. In such cases, monitoring occupant-specific energy consumption would therefore help researchers find extremists before starting a research for improving energy behavior. Furthermore, in [28,80], researchers at the first step of their works divided the subject occupants to three groups: high energy-consuming occupants, medium energy-consuming occupants, and low energy-consuming occupants. Then, they studied how occupants' energy behaviors change with time and therefore how an occupant will move from one group to another group. In this research, based on different performance of individual occupants, they assigned occupants to three groups. For example, if an occupant turned off all of his/her appliances before leaving the work desk, this occupant will be assigned to group of low energy consumers. However, the amount of energy used by an occupant compared to other occupants is a better index to assign him/her to such groups of energy consumers. In such studies, therefore, finding occupant-specific energy consumption provides this opportunity to find this index for researchers.

In summary, there is a critical need for a link between the first and third approaches. However, the first approach has fairly ignored and therefore the literature failed to provide this link. Therefore, future research may propose tools to monitor occupant-specific energy consumption, which will lead to improvements in the whole topic of occupant-performance in commercial buildings' energy consumption.

In addition to the connections between the first approach and the two other approaches, there are mutual connections between the second and third approaches. Simulating occupants' behaviors could be a great help in understanding how an improving method performs over time. In [12,28,80,81,85], authors simulated occupants' behaviors to assess the performance of their intervention tools for improving behavior. The current literature therefore shows that there is a good link for a connection between the second and third approaches. On the other hand, correlating the real results of an intervention method for improving occupant behavior with the results achieved from a simulation tool could be helpful to find flaws of the simulation tool and would therefore provide an opportunity to adjust the tool to work better. In fact, this link between the third and second approaches is the most effective method to evaluate different simulation tools. However, the literature seems to fail to consider this link. Testing various simulation tools by using the results of an intervention method also could help to find the most appropriate simulation technique for an occupancy-related behavior-improving problem. It is worth highlighting that monitoring individual occupants' energy consumption, as happens in the first approach, also plays a key role for improving this connection between the third and second approaches. Tracking the individual occupants' energy use over time provides more accurate results of an improving study, and therefore could help to better understand the performance of simulation tools.

In summary, a broad discussion of the topic of occupancy-related energy use behaviors indicates that currently, a good link only exists between the second and third approaches, *i.e.*, using the results of simulation tools to test the performance of intervention models. Further research may therefore address the abovementioned links between all three approaches. In this context, a special attention to the first approach is critically needed.

6. Summary and Conclusions

Energy consumption in commercial built environments is highly correlated to occupants. However, the available research in this domain is insufficient and not proportional to the importance of the topic. This paper evaluated the current status of the topic and revealed many issues that are still open in this domain. One such consideration that appears to be critical is the need for tools to monitor the energy-consumption of individual occupants. To the best of our knowledge, there is no applicable, cost-effective technique for providing good-resolution energy use data regarding the energy-use behaviors of individual occupants. Failing to track occupant-specific energy consumption might lead to incorrect simulations and flawed approaches for improving occupant energy-use behavior.

In the field of simulating occupant behavior, ABM and MAS has a clear record of success for modeling occupant-related energy-use behaviors. Furthermore, other predictive techniques such as fuzzy modeling, neural networks, and Markov chains were also employed to model such behaviors, and the results from such studies indicated the success of the techniques. However, there is a critical need to show how theses developed techniques can be integrated into current energy-simulation software or developed as new software.

With regards to improving occupant behavior, the literature also indicates promising results. However, there is a need for better-defined policies, especially with regards to which type of occupant-focused interventions should or should not be applied to which type of occupants. In addition, there is a need for an occupant-focused intervention technique that can promote energy-saving behaviors for a long-term period. Identifying a rate for occupant behavioral change as well as for finding the most effective frequency of providing feedback is also needed.

The connections between three approaches are critically important to helping the main goal of general energy savings within all built environments. There is an ongoing need for such connections since most links are missed. In this case, the immaturity of techniques for monitoring occupant-specific energy consumption appears to be the main reason for the missed opportunities. As such, this area of research provides fertile ground for broader applications in the field.

Apart from the general themes manifested in the literature, green recommendations and policies for group activities (such as the coordination of meetings and working sessions according to the optimal energy-saving periods of the day) are almost completely absent in the literature and still need to be proposed in commercial built environments. As discussed in this paper, such literature gaps should be addressed in future studies.

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Author Contributions

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Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this article.

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