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Advances in research and applications of energy-related occupant behavior in buildings☆

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ABSTRACT

Occupant behavior is one of the major factors influencing building energy consumption and contributing to uncertainty in building energy use prediction and simulation. Currently the understanding of occupant behavior is insufficient both in building design, operation and retrofit, leading to incorrect simplifications in modeling and analysis. This paper introduced the most recent advances and current obstacles in modeling occupant behavior and quantifying its impact on building energy use. The major themes include advancements in data collection techniques, analytical and modeling methods, and simulation applications which provide insights into behavior energy savings potential and impact. There has been growing research and applications in this field, but significant challenges and opportunities still lie ahead.

Contents

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1. Introduction

An occupant's interaction with building systems attributes to the sizeable variation in building energy use. Therefore it becomes paramount that solutions in both energy efficient behavior and technology robustness collectively contribute toward achieving low energy buildings [1,2,3•]. Social scientists have been scrutinizing occupant behavior for decades, particularly in the areas of user behavior, attitudes, individual or household consumption patterns etc. [4]. Recently, the need to integrate social science aspects into energy research has brought more awareness to the role of occupants in buildings [4,5]. Energy related occupant behavior, in its simplest form, includes adjusting thermostat settings, opening/closing windows, dimming/switching lights, pulling up/down blinds, turning on/off HVAC systems, and movement between spaces. In addition, behavioral adaptations, such as clothing adjustments, the consumption of drinks and changes in the human metabolic rate, all directly affect individual comfort which in turn influences building energy consumption. In fact, direct and indirect drivers, at the individual, local, whole-space or zonal level each impact the building energy consumption differently. Langevin et al. [6] demonstrated that the use of personal heating/cooling devices could allow for an increase in the thermostat set point enhancing thermal comfort, while reducing the total energy use. An occupant's interaction with building systems and the available systems, play a significant role in influencing the total energy use of buildings. A study by Danny Parker of Florida Solar Energy Center [7] (Fig. 1) showed that the total energy use of 10 identical homes varied by a factor of three, even though they had the same floor area (102 m^2), were on the same street, built in same year and with similar efficiencies. This variation is even larger at the energy end use level (e.g. up to 10.6 times in space heating energy use).

Due to the uncertainty associated with occupant behavior model inputs, simulation results often vary widely from actual building energy consumption [8]. Eguaras-Martínez et al. [9] suggested that the inclusion or exclusion of occupant behavior in simulations, resulted in differences of up to 30%. A comparison between the simulated energy consumption in the design phase and the measured energy use for LEED (Leadership in Energy and Environmental Design) certified buildings in the U.S., shows a significant error (root mean square error of 18%) in a group of 62 buildings [10]. The prediction error is even larger for low energy buildings which use passive designs, such as natural ventilation, relying more on occupant interactions. Therefore, occupant behavior is a leading source of uncertainty in predicting energy use [11].

ASHRAE 90.1 Standard [12] Appendix G states that there are large discrepancies between measured and building design energy consumption. This limits the application and potential impact of building performance simulation (BPS) in industry. Thus, having a better understanding of occupant-building interactions will help bridge-the-gap between actual and predicted energy consumption [13•]. However, quantifying the impact of these behaviors proves challenging. The International Energy Agency Energy in the Buildings and Communities Program (IEA EBC) Annex 53: Total Energy Use in Buildings, indicated that there are six driving factors of energy use in buildings: (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) occupant behavior. While significant progress has been made in quantifying these primary drivers, there lacks scientific and robust methods to define and model energy related occupant behavior in buildings.

Recent advances, presented in journal articles from 2013 to 2015 (up to February), have shown significant improvements in the three thematic areas shown in the occupant-building interaction energy behavior loop (Fig. 2). On the *data collection* front, data driven techniques such as real-time remote sensing to investigate occupants' interaction with building technologies is at an all-time high, with more data on occupant actions collected than ever before. On the *analytical and modeling* front, advanced statistical, data mining, and stochastic modeling methods are being developed and applied to extract behavioral models from the experimental data. An ontology to standardize the representation of energy related occupant behavior in buildings has been proposed. The combination of observation and modeling aspects will subsequently help to improve *simulation* techniques to quantify the impacts of the energy-related occupant behavior and to provide insights toward energy saving behaviors and robust architectural design. The article is organized according to the three themes shown in Fig. 2. Additionally, this review covers both residential and commercial buildings at a higher level, with the understanding that specific differences exist between these unique building types. Some influential differences include: (i) behaviors in each building are usually different considering the different activities performed and who is responsible for paying the energy bill, (ii) negotiations and group behavior may be different between a commercial setting and home environment and, (iii) the system controls are often different [14]. These considerations, among others, are particularly important to keep in mind during the data collection and model input phases of occupant behavior research.

2. Advances in data collection techniques

Gathering data to change building operation and occupant behavior is the next frontier in sustainable design. Improvements to data collection techniques, the accuracy of individual sensors, and the information obtained, has led to progress in the areas of (i) occupant movement and presence, (ii) thermal comfort, (iii) windows, shades and blinds and, (iv) lighting and electrical equipment.

2.1. Occupant movement and presence

The use of sensors in wireless networks and wearable devices provides the unprecedented ability to easily capture occupant movement and presence, a preeminent factor that affects lighting, thermostat, plug loads, HVAC equipment, fresh air requirements and internal heat gains or losses within a building. Energy simulation programs often rely on homogenous and standardized occupant schedules, often unrepresentative of actual occupancy diversity. Data and analytics has enabled the active reforming of occupancy schedules to better capture the stochastic nature of occupants, with improved schedules demonstrating as much as 46% difference from the prescribed ASHRAE 90.1 Standard [12,15,16]. Individualized occupancy patterns facilitate more accurate modeling of occupant movement and presence and their implementation into BPS provides one method to assess the impact of occupant behavior on building energy consumption [17–19]. For example, Motuziene and Vilutiene [20] used four different occupancy profiles from homes in Lithuania in conjunction with BPS, to demonstrate up to 31% savings depending upon heating strategies. Moreover, excessive energy use during vacancy has proven to hold substantial energy savings potential [21,22]. For example, dormitories in South Korea use up to 31.5% of all energy while unoccupied [23].

2.2. Thermal comfort

Thermal comfort is defined as an occupant's gratification with their thermal environment [24]. Energy consumption can fluctuate subject to the HVAC control strategy, with the primary physical-behavioral forces including ventilation, thermostat set-point and indoor thermal environment [25,26]. Thermostat control is used by different users with varied privileges dependent upon the organizational policy of the building [17]. About 30% of programmable

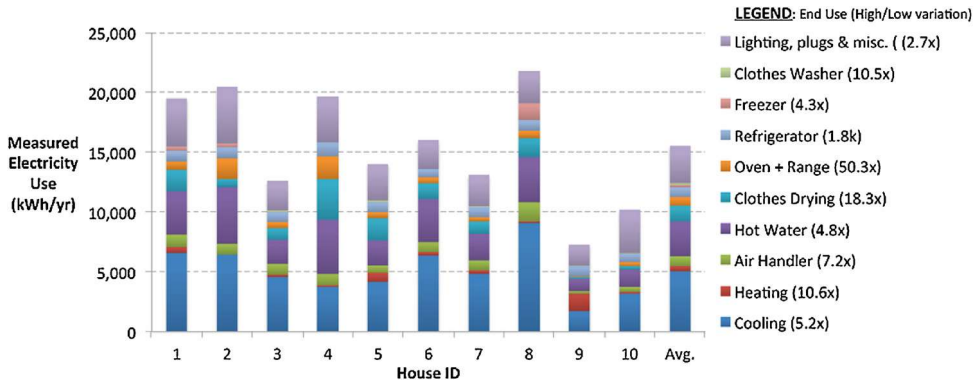

Fig. 1. The measured electricity use for ten nearly identical homes, showing considerable variations in energy use [7].

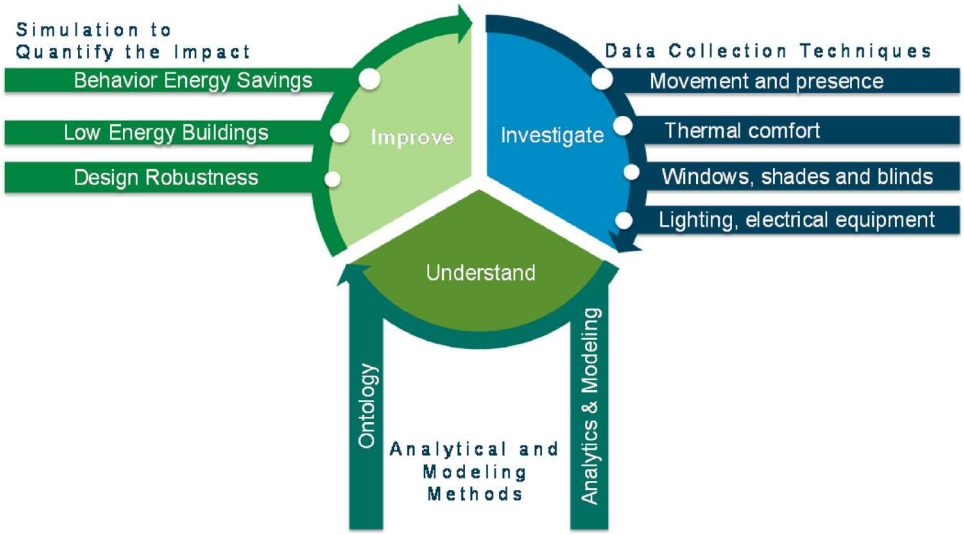

Fig. 2. Occupant-building interaction energy behavior loop.

thermostats are used as intended by the manufacturer, suggesting a large margin for improvement [27,28]. The drivers of space-heating behavior can be categorized as (i) environmental factors, (ii) building and system related factors, (iii) occupant related factors and, (iv) other factors (i.e. time of day, time of week) [29]. Some of the top influential factors impacting heating loads include occupant mode, thermostat set-point and heated area [30,31]. An alternative methodology is to classify the occupant, as an active, medium and passive user, linking occupant behavioral characteristics with heating set-point preferences which in turn impacts the indoor thermal environment and energy consumption [32,33]. Technical solutions which limit an occupants' interaction with technology may seemingly provide a robust solution to mitigate wasted energy. However, it is suggested that the perception of having thermal control results in greater occupant satisfaction, indicating a solution requiring occupant-building interactions [3•].

2.3. Windows, shades and blinds

Windows, shades and blinds allow building occupants to control and adjust thermal and visual comfort levels. Currently, there is great variability associated with the operation of windows, shades and blinds within buildings and these actions impact the thermal comfort, IAQ and building energy consumption [34•]. Studies have focused on the influence of opening combinations, open area [13•], seasonal transitions [35] or end-of-the-day positions [36]. Wei et al. [36] showed the end-of-the-day window position impacted the energy and thermal performance of the building, the following day. To better capture patterns within seemingly random data, advanced numerical methods, such as data mining, are being used [13•]. Using data mining, D'Oca and Hong [13•] classified the primary, behavioral-driven, categories for motivating window opening and closing, as (i) thermal driven patterns, (ii) time driven, opening duration patterns (iii) activity or inactivity patterns (iv) opening position patterns [13•]. Like windows, the position and the frequency of interaction with movable shading and blinds impacts the building energy use, peak loads, and visual and thermal comfort. O'Brien [34•] comprehensively reviewed advancements in the experimental practices and methodologies for manual shade operation. Proper activity with windows, shades and blinds offers an energy efficient strategy, but also easily lends the opportunity for misuse, leading to energy waste [8,35].

2.4. Lighting and electrical equipment

Lighting represents about 25.5% of the energy used in commercial buildings in the U.S., indicating an opportunity for more natural light and control systems [3•]. Control types such as occupancy detection techniques, passive infrared sensors and imaging occupancy detection allows for more consistent energy savings [37]. Traditionally, stochastic models are used to simulate lighting profiles and quantify and predict the impact of LEDs on lighting systems [37]. Models demonstrating future predictions indicate that a 65% reduction in energy consumption could be obtained with 80%

replacement of current lamps for LEDs, in Andalusia, Spain [38]. The use of real time monitoring of electrical equipment and providing occupants with systematic energy visualization, generated energy savings of more than 9% [39].

Plug loads generally refer to an equipment powered by an ordinary AC plug and excludes major end uses such as HVAC, lighting, electric car charging and water heating. Plug loads are generated by specific devises requiring power (e.g. computers, toasters, localized fans/heaters) and therefore are typically unique to the building. As the demand for charging technological devices becomes more prolific, the portion of demand associated with plug load draw also increases. User behavior is a major factor for the overall increase in plug load energy use. One of the simplest methods to reduce plug loads is to turn-off or unplug unused items. Webber et al. [40] observed, in offices in Washington DC and San Francisco, that only 44% of computers, 32% of monitors and 25% of printers were turned off at night. Presently, there is an opportunity to reduce the energy consumption from lighting and plug loads, especially during the design and operation phase of the building.

2.5. Data gathering

Gathering data to investigate (i) occupant movement and presence, (ii) thermal comfort, (iii) windows, shades and blinds and, (iv) lighting and electrical equipment, requires a host of information, from the utilization of custom sensors, weather stations, building, energy and lighting management systems (if applicable). Table 1 presents a general guideline highlighting the different variables within the building that need to be monitored to capture the necessary information to analyze different behavioral actions. The guideline uses a priority ranking of mandatory or optional dependent mostly upon the building type, experimental accessibility and experimental resources available. Generally, the more data collected for longer durations of time is preferred, however resource and time limitations often restrict data collection periods. Specific sensors for each variable are rapidly advancing with the opportunity to easily obtain the necessary information for monitoring. Generally, environmental, behavioral and personal data is collected and integrated across time to match particular drivers with actions.

3. Advances in analytical and modeling methods

3.1. Ontology and schema to represent occupant behavior

Advancements in the standardization of the quantitative descriptions and classification of occupant behavior on building performance has been initiated by programs such as the IEA EBC Annex 66: Definition and Simulation of Occupant Behavior in Buildings. An ontology to represent energy-related occupant behavior has been outlined in a DNAs (Drivers, Needs, Systems, Actions) framework, providing a systematic representation of energy-related occupant behavior in buildings [41••]. An XML (eXtensible Markup Language) schema is used for the exchange of occupant information modeling and to integrate with building simulation tools [41••] (Fig. 3).

3.2. Implicit and explicit behavioral models

Implicit models, based on a predictor variable, capture the driving forces behind occupant behavior or predict the state of a building system or the occurrence of an action [41••]. Simply, implicit models deal with rules associated with physical systems (e.g. windows, lights etc.) rather than the occupant directly. These models include linear and logistic regression [42], probability equations [43,44], statistical analysis of measured occupancy data [45], sub-hourly occupancy-based control models and Bayesian estimations [46].

Explicit models, based on monitored behavior, provide the state of a building system or the action of the occupant or agent [41••]. Simply, they deal with rules and logic associated directly with the occupant. The three major forms of stochastic occupant behavior models most commonly found are: (1) Markov chain [1,18,47,48] and agent-based modeling [49,50•], (2) the Bernoulli process [51] and, (3) survival analysis. The Bernoulli process, functions such that the probability of an event or state is independent (memoryless or not dependent on a previous state). Although simple and easily applied, it fails to capture individual comfort or to predict individual behaviors. In contrast, the discrete-time Markov chain depends on the previous state, becoming particularly useful for representing individual actions such as occupant movement. An extension of the Markovian model are agent-based modeling (ABM) that specify the interactions of occupants with their environment. ABM include individual attributes such as behavior rules, memory, resources and decision-making. One common framework used for ABM is Belief-Desire-Intention (BDI) model [52] that mimics the practical reasoning process of occupant decision making and gives structure to this process. Lastly, the survival process, a continuous time approach, is used to estimate the time duration until an event occurs (initially used to predict longevity). Other promising approaches include discrete event formulation, which only triggers when significant changes to model inputs occur [48].

3.3. Modeling challenges

A present challenge is dealing with the oversimplification of existing occupant behavior models [27]. Simply, the stochastic nature of the occupant is distilled into homogeneous and deterministic inputs, often ignoring the diversity and inter-dependency of various behavioral and seemingly stochastic actions. Model inputs are typically model specific, often selected based on the intent of the study and suffer from user input assumptions. The incorporation of qualitative models that can significantly improve the predictability of behavior, include: (1) clustering multiple contextual factors or inputs into a single equation or (2) treating the factors that influence model behavior independently [53]. At the most basic level, model inputs and model validation are based on real behaviors (actual data), using statistical methods (chi-square goodness-of-fit, R^2, variance) [46,54]. However no general scientific standard outlines appropriate model validation techniques, thus often model validation is not upheld.

Additionally, one greater challenge to model development is establishing common hierarchies of behavioral actions, such as how to deal with multiple decisions and multiple actions. When modeling sequences of behavior, the complexity of the model grows due to the necessity to capture all combined affects that influence different behaviors together [55]. Programming often uses a form of priority ranking or logic to represent multiple occupant decision making, with inherent error associated with this process. Perhaps future work will be able to determine behavioral action hierarchy from future data for advanced algorithm development.

4. Simulation to quantify the impact

4.1. Integration of occupant behavior models with building performance simulation programs

The integration of occupant behavior models with existing BPS programs enables researchers and practitioners to simulate energy-related occupant behavior in buildings, helping to match simulated results with the actual energy use. Observational

Table 1
A mapping of the data needed to complete basic occupant behavior studies in window opening/closing, occupancy, shading, lighting, thermal comfort, plug loads, and HVAC.

	Variables\behaviors	Units	Window opening	Occupancy	Shading	Lighting	Thermal comfort	Plug loads	HVAC	Occupancy survey	Device/system
Weather data	Outdoor air temperature	°C	√√				√√		√√		Weather station
	Outdoor air humidity	%	√√				√√		√√		Weather station
	Wind speed	m/s	√√				√√				Weather station
	Wind direction	N, E, S, W	√				√				Weather station
	Solar irradiance	W	√		√√	√√	√		√		Weather station
	Illuminance	Lux	√		√√	√√	√				LMS
	Rain (event)	Y, N	√				√		√		Weather station
Space data	Indoor air temperature	°C	√√		√√		√√	√	√√		BMS
	Indoor air humidity	%	√				√√	√	√√		BMS
	CO_2	ppm	√√	√√			√√		√√		BMS
	Occupancy	0–1	√√	√√	√√	√√	√√	√√	√√		BMS/custom sensor
	Light level	On-off, dimming		√	√√	√√	√	√			BMS/LMS
	Window state	Open, closed	√√	√	√		√√		√		BMS/LMS
	Shading state	Up-down, partial		√	√√	√√	√		√		EMS
	Plug loads	On-off		√		√		√√	√		EMS
	Thermostat settings (cooling & heating)	°C		√			√√	√	√√		BMS
	Heating/cooling state	On-off		√			√	√	√√		EMS
Energy data	Total energy use	kW h	√	√	√	√	√	√	√√	√√	EMS/survey
	Submetering (lighting, HVAC, plug-loads, etc)	kW h				√	√	√	√		EMS
	Energy production (renewable)	kW h				√	√	√	√		EMS
Occupants data	Age	Number	√	√	√	√	√	√	√	√√	Management/survey
	Gender	F, M	√	√	√	√	√	√	√	√√	Management/survey
	Working profiles	Working, non-working	√	√	√	√	√	√	√	√√	Management/survey

BMS = building management system
EMS = energy management system
LMS = lighting management system

√√ Mandatory
√ Optional

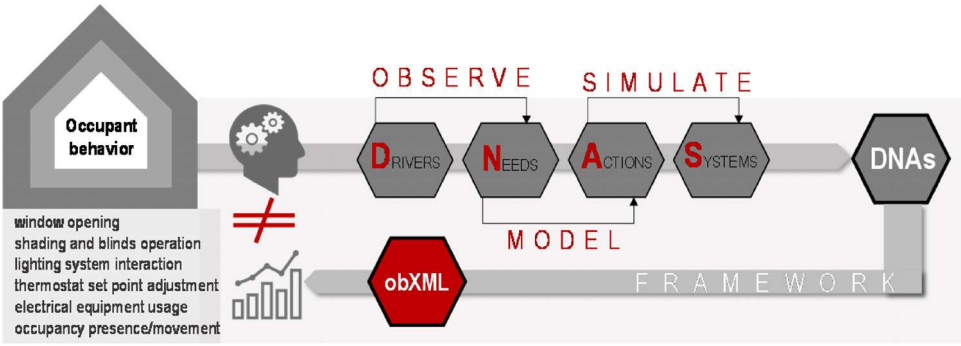

Fig. 3. A schematic showing the integration of advanced data collection techniques with the DNAs framework and integrated into the obXML for occupant information modeling [41••].

data, processed through derivative, descriptive or stochastic methods, can lead to predictive occupancy and activity models which can be integrated in BPS applications. Simulation engines allow researchers to assess the implications of different occupant behaviors within the context of the building environment and energy flow. The main approaches used to integrate occupant behavior into building simulation programs are shown in Table 2. There are on-going efforts to develop a stand-alone behavior module, as a functional mock-up unit, which can co-simulate with BPS programs. Such co-simulation approaches provide the maximum degree of flexibility in coupling behavior modeling with BPS program [56]. However work is needed for current BPS programs to fully support co-simulation features.

4.2. Behavior influence on energy savings

Quantifying the savings from occupant behavior remains a primary challenge. For behavior-related energy savings an estimated savings of 10% [57] to 20% [58] for residential and 5% to 30% [59] for commercial buildings (i.e. private offices) was achieved. More moderate savings was shown using a workplace behavior program, demonstrating only 5% in energy savings [60]. Hong et al. [59] compared work styles in a single story office building, suggesting an energy-saving work style consumed up to 50% less energy, while an energy-wasteful work style consumed up to 90% more energy, compared with a control. As can be demonstrated, the quantification of energy saving varies widely from study to study, retracting from the meaningfulness of such estimates and highlighting the fact that quantification of behavior energy savings is a current weakness in the field. Future work should strive to more clearly categorize behavior energy style and incorporate the associated uncertainties into simulated energy impacts.

4.3. Behavior influence on non-energy savings

A large portion of the energy spent in buildings is to maintain healthy and comfortable conditions, for the occupants' well-being and productivity. Therefore, occupant behavior also impacts comfort conditions, and indoor environmental quality (IEQ). Roughly 26% of the total primary energy consumed in the U.S. is used in an effort to maintain a healthy and comfortable indoor climate [61]. It has been shown that the utilization of technologies and designs, that strengthen the correlation between occupants' perceived control of building systems and thermal comfort, helps occupants to exhibit energy savings behavior without perceived loss of comfort [62]. In general, one of the greatest goals is to achieve indoor thermal comfort and premium indoor air quality, with the minimum possible energy cost and environmental impact.

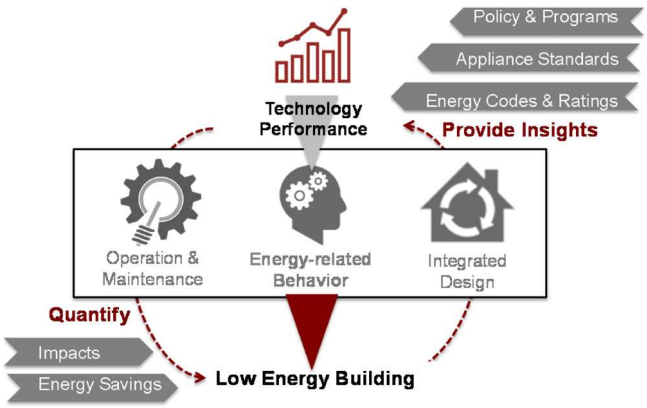

Fig. 4. Key strategies to low energy buildings.

4.4. Low energy buildings and design robustness

To satisfy comfort needs, occupants use technologies which impact the building energy performance [63,64]. It is commonplace that low energy buildings, with substantial dependence on passive design and intricate technologies, do not meet design goals, in part due to operational behavior [3•,65]. Quantifiable performance metrics and appliance standards go into the performance strategy for achieving low energy buildings (Fig. 4). This

Table 2
Current approaches to include occupant behavior into building simulation programs.

Approach	Description	BPS program
User defined profiles	Users define and input temperature set points, schedules of lighting use, plug-loads and HVAC system operations	EnergyPlus, DeST, DOE-2, TRNSYS, IDA-ICE, ESP-r
User customized code	Users can write custom code or overwrite existing or default values without re-compiling the simulation tools	EnergyPlus, DOE-2
Embedded occupant behavior modules	Users directly employ the occupant behavior module of the simulation tools	DeST, IDA-ICE, ESP-r
User modified source code	Users add new code or change existing code requiring re-compiling the simulation tools	EnergyPlus, DeST, TRNSYS, IDA-ICE, ESP-r
Co-simulation	Occupant behavior tools and the simulation tools run simultaneously and exchange information in real-time	EnergyPlus

combined with advanced building technologies, energy-related behavior, integrated design, and active operation and maintenance, complete the strategy (Fig. 4). Recent, proposed solutions for technological advancement to bridge-the-gap between building design and actual energy consumption include (i) occupant-based energy retrofits [66], (ii) building performance simulations that capture the occupant dimension and passive design [67••] and (iii) operational improvement technologies built on guiding occupants toward energy savings.

5. Discussion

Occupant behavior in buildings is a multidisciplinary research topic crossing social and behavior science, building science, sensing and control technologies, computing science, and data science. One of the biggest challenges associated with data collection is the lack of standardized data and the regulation of privacy issues. Uncertainties beyond physical and user behavior [68], occur due to situational awareness, when occupants alter behavior due to heightened awareness, making data collection challenging. The current challenges in modeling and simulation include the lack of standardization within models, with developers using diverse semantics, the lack of support for co-simulation, the inflexibility of behavior software modules, and the accuracy of input assumptions.

The applicability and lack of verification for occupant behavior models begs the question as to the limits of research findings. In a broader context, one can argue the usefulness of occupancy behavior categorization in capturing the stochastic nature of individual occupants. Such that many believe that each occupant is unique and can't be lumped into a general category such as 'wasteful' or 'austerity.' Despite these challenges, real opportunities exists where big real-time data from sensors and IcT (Information and Communications Technology), data analytics and modeling provide valuable actionable information to guide occupants, building designers and operators in reducing energy consumption in buildings [69]. From the analysis of measured data, building energy simulation or sensitivity analysis, it is generally concluded that occupant behavior greatly impacts building system operation and energy consumption [70]. It is projected that the evaluation of technologies, technological design and robustness of design, will be guided by occupant interaction studies [71]. Therefore solutions in both energy efficient behavior and technology robustness will collectively contribute in achieving low energy buildings.

6. Conclusions

A growing interest emerged from the most updated literature on the role of occupant behavior in bridging the gap toward more energy efficient buildings. This review covered a combination of methods to measure and collect data on occupant behavior, new occupant behavior models, and the integration of these models with building simulation programs. The review also highlights case studies demonstrating the use of these tools to solve real world problems to improve building design, operation and retrofit.

Current challenges are: (1) collection of good and adequate data for behavior understanding and modeling, (2) an ontology specific and broad enough to represent occupant behavior in buildings, (3) evaluation of applicability of behavior models, (4) quantifying the impact of energy-related occupant behavior on building energy performance, and (5) providing metrics and insights to integrate sustainable behaviors into robust buildings and smart communities. Despite these challenges, understanding occupant behavior poses a new opportunity to mold the evolution of building technology, to improve energy efficiency and occupant comfort in buildings.

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- •• of outstanding interest

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