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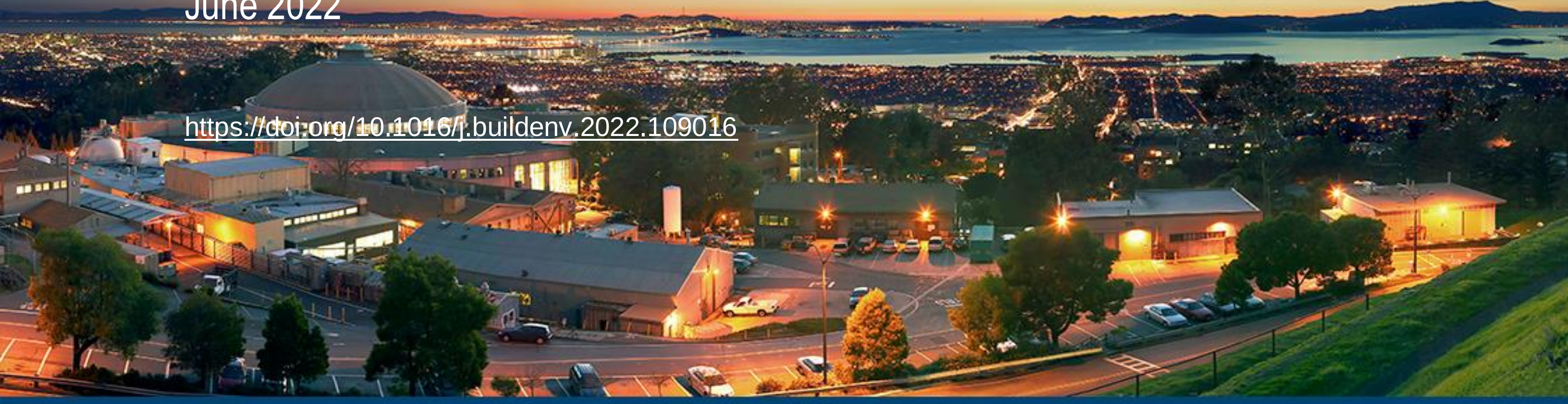

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Ten questions concerning agent-based modeling of occupant behavior for energy and environmental performance of buildings

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Abstract

The complexity of occupant behavior is one of the major contributors to uncertainty in building performance simulation. Agent-based modeling (ABM), a computational simulation technique, has gained attention in the occupant modeling field due to its capability and flexibility to capture the heterogeneity and dynamics of human behavior and the emergent effects. While multiple efforts in the past decade have demonstrated the usefulness of the ABM approach for simulating occupants and their impacts on building performance, several crucial matters in the ABM research still remain unexplored. This paper presents ten questions that highlight the most important issues regarding ABM research and applications for occupant behavior in the context of building performance simulation. The questions and answers aim to provide insights into current and future ABM research, and more importantly to inspire new significant questions from young researchers in the field. This research is part of the IEA EBC Annex 79 project, occupant-centric building design and operation.

Keywords: agent-based modeling, occupant behavior, human–building interaction, built environment, building performance simulation.

1. Introduction

Modelers desiring more realistic representations of human behavior in an increasingly complex world are turning frequently to agent-based models. Agent-based modeling (ABM) is a powerful technique that offers a bottom-up understanding of how agents interact with one another and with their external environments, thereby enabling examination of complexities in human decision-making and problem-solving processes [1]. Agent-based models are essentially computational simulation models that consist of dynamically interacting discrete agents or autonomous decision-making entities [2]. Such models can provide significant benefits when simulating human behavior by considering the behavior of individual agents, their heterogeneity, their ability to learn and adapt, the interactions among agents, and any resultant emergent effects. ABMs have been employed in a variety of disciplines to solve complex problems by simulating dynamic human behavior; for example, in economics for testing the effectiveness of labor market policies [3], in transport planning for designing public transport networks [4], in public health research for forecasting emerging infectious diseases [5], and in the built environment for examining walkability, evacuation management or building energy performance [6]–[9]. The ABM applications within the indoor built environment, concerning single or a group of buildings in urban settings are the focus of this study. This paper specifically pertains to the occupant representation and modeling and simulation techniques for energy and environmental performance of buildings.

The agent-based paradigm has become increasingly popular as an occupant modeling approach in buildings because of its potential to cope with the formally complex and dynamic aspects of occupant-related processes [10]. However, the limited and fragmented knowledge of the ABM procedures in building performance simulation (BPS) poses a challenge for collective learning and providing guidance to researchers. Berger and Mahdavi point out that the existing ABM applications in BPS motivated to capture human–building interactions are insufficiently grounded in an empirically based understanding of occupant behavior [11]. They argue that the extant literature rarely discusses the necessary computational loads, data sources for developing occupant agents, or decisions regarding the resolution of agents' behavioral repertoire [12]. Other ABM researchers have also acknowledged the challenges related to domain knowledge, validation methods, and scalable coupling approaches [13], [14] . Furthermore, there are several other crucial matters that remain unexplored in ABM research, such as the suitable behavioral theories for semantic representation of OB (or structured information about occupant behavior processes such as learning or sensing), required advancements in computational formalism for integrating the human dimension within BPS, and the modeling heuristics necessary to guide researchers and practitioners for practical applications. Hence, it is timely to formulate and discuss 10 questions highlighting the potential of agent-based approaches for the representation of human dimension in BPS and to raise the most important issues confronted by researchers and practitioners in ABM applications for building performance.

The main purpose of this paper is to improve the understanding of ABM in occupant behavior (OB) research and to motivate young researchers to create innovative applications in BPS. This research is part of the International Energy Agency's Energy in Buildings and Communities' (IEA EBC) Annex 79 project, occupant-centric building design and operation [15]. The paper poses the most pertinent 10 questions related to ABM of occupants that will be of interest to the architects, engineers and other stakeholders of the building simulation community and can guide future research. The answers offered to the questions are not intended to be conclusive or complete. Rather, they are meant to stimulate further debate and reflections on this subject. Figure 1 presents a thematic overview of the 10 questions in this paper. The first two capture the fundamentals that address the potential of ABM in representing human behavior (Question 1) and the need for such an approach in the building performance domain (Question 2). Question 3 offers an overview of the existing behavioral theories and how they can inform ABM of occupants. Question 4 explores diverse use cases across building life cycle phases that the ABM can support, while Question 5 deals with the required level of detail needed to represent occupants in such applications. The next two questions provide insights on how ABM can be implemented for simulating energy and environmental performance of the buildings. Question 6 discusses the existing ABM tools to capture the human–building interactions, while Question 7 covers the available co-simulation approaches for integrating ABM with BPS tools. Questions 8 and 9 elucidate the issues related to data availability for programming occupant behavior and validation or verification methods for ABM, respectively. Question 10 identifies key challenges and future perspectives of ABM research in the building simulation community.

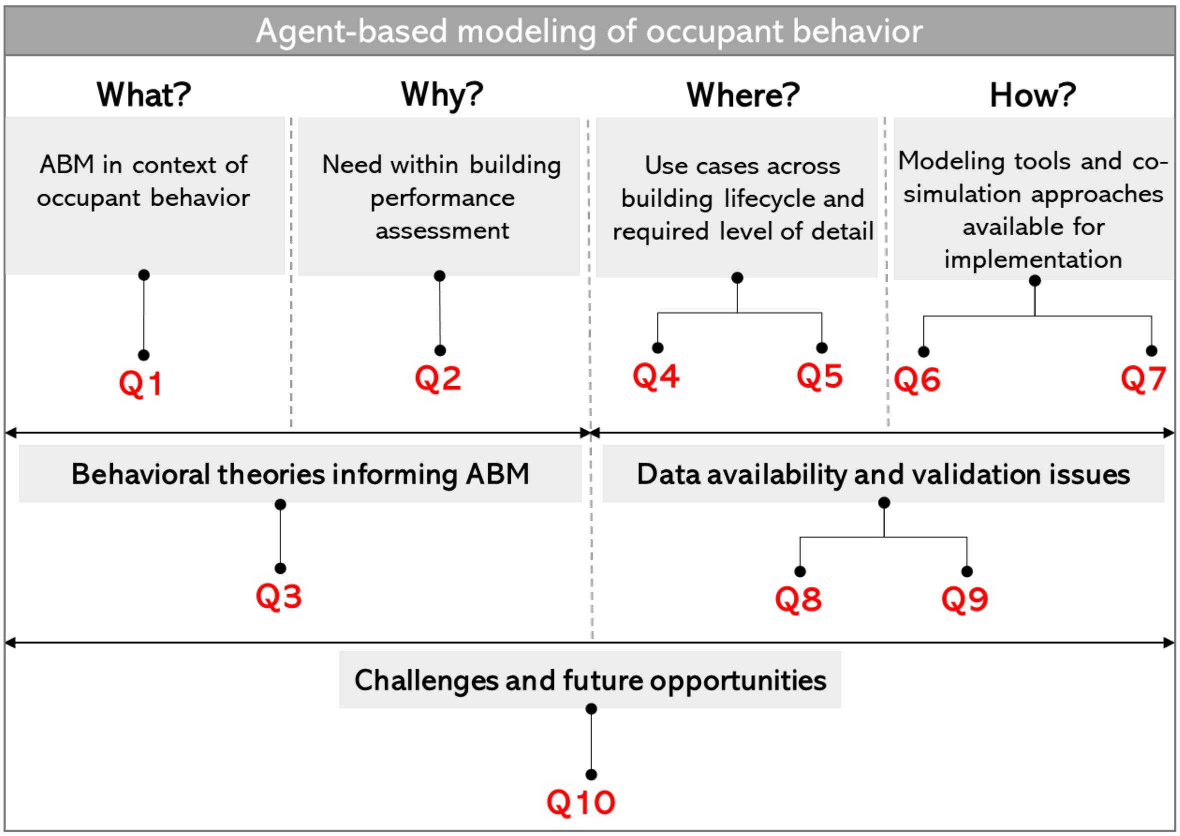

Figure 1. Overview of the thematic research questions

2. Ten questions (and answers) concerning agent-based modeling of occupant behavior

2.1. What is agent-based modeling (ABM) in the context of occupant activities and behavior in the indoor built environment?

Occupant behavior is one of the major factors contributing to the uncertainty in building performance, and its accurate representation is crucial for improving simulation results [16]–[18]. ABM is a computational simulation technique suitable for representing dynamic occupant actions and decision-making processes to capture realistic occupant behavior. The agent-based approach, having its roots in the human social and organizational behavior and individual decision-making domains, considers occupants as autonomous interacting agents [19]. Each agent can be an individual occupant or a group of occupants having identical or distinct characteristics. The agent-based approach allows modeling the behavior of occupant agents; characterizing their attributes and interactions among themselves as well as with their environment.

An agent-based model of occupants consists of three key elements: *agents, environment*, and *agent-environment relationships* [20], [21] which are interlinked through systematic specification of interdependencies and feedback [22]. An *agent* or a set of agents (or occupants) is an individual entity with certain attributes and rules that govern its behaviors and decision-making processes. An agent's attributes can either be static (such as gender that does not change during the simulation) or dynamic (for example, an agent's location within the building that may vary at each time step based on an agent's actions). The behavior of an occupant agent can be represented through various methods such as simple rules involving if-then actions, a set of logical rules, empirically grounded behavioral models, or sophisticated neural networks and genetic algorithms. Typically, an occupant agent can interact with other agents through agent-agent relationships. These connections essentially deal with the processes of socially relevant occupant exchanges and specify when, how, and with whom the occupants interact. For example, an ABM within a shared office setting can be programmed to specify the temporal and spatial features of occupant-occupant interactions, such as mealtimes and/or when the occupants are present in common spaces such as conference rooms. Occupant agents may exhibit attributes of influencing and being influenced by others, learning from the experiences, responding to changes in the environment, and adapting their behaviors to meet desired objectives. Moreover, agents may be programmed to represent other human behavior properties, such as heterogeneity or stochasticity to account for spatial, temporal, and inter-occupant variability. The second component is an agent's *environment,* which depicts the specific external context, often including a spatial position, within which agents exist and/or interact. The *environment* offers opportunities for the occupant agents to interact and could be the building or a location within the building (such as floor, room or zone), a building component (such as operable window, adjustable thermostat) or a building system (such as cooling and heating system, lighting system). The spatial attribute or agent's location is also determined by the environment. The third component in the ABM is a set of *agent-environment relationships* that describes the interactions among occupant agent and their surrounding environment, i.e., human-building interactions. Some examples of *agent-environment relationships* in context of ABM of occupants could be adjusting thermostat setting, opening windows, adjusting blinds, or operating electronic devices.

Some of the common modeling techniques to simulate the stochasticity in OB include Bernoulli process, discrete-time Markov chain and survival analysis [23]. The Bernoulli process simulates the probabilities of events that are independent of previous ones, for instance occupancy. The Markov chain models, on the contrary, depend on the previous state to predict the probability of an event occurring and are useful for representing individual occupant actions and the motivations for those actions. Survival processes evaluate the expected time duration of an event before a change occurs, such as the time duration until a window will remain closed. These techniques often fall short of modeling multiple OB at the same time, interactions within multi-occupant spaces and representing the inter-occupant diversity. The agent-based occupant models, which are an extension of Markovian models, can be advantageous to overcome these drawbacks because of their ability to specify multiple inter-occupant and occupant-environment interactions or model the sequence of OB. Furthermore, there are three central properties of the agent-based approach that set them apart from other occupant modeling techniques. First, because ABM is a bottom-up approach, it is capable of producing the effects of collective behavior that emerge from individual-level occupant interactions. This feature is particularly useful in the BPS domain to study the impact of emergent effects that arise from social dynamics or cultural influences on occupant behavior [24]. Second, ABM has the potential to effectively account for multidisciplinary drivers of OB and simulate their cumulative impacts. [25]. For example, an ABM can link the social and psychological aspects of occupants' thermal perception with physics-based thermal comfort models to produce spillover effects and simulate realistic comfort-related behavior. Furthermore, ABM allows the choice of modeling OB at any desired level of spatial and temporal resolution or semantic richness. For example, occupants and their activities can be defined at varied granularities, such as for a group of occupants at the whole building level or for an individual occupant within a single zone, to suit the specific use case. To summarize, ABM creates a flexible abstraction of the real world to simulate realistic OB [26].

2.2. Why is ABM needed in the occupant behavior domain?

As an advanced and high-resolution technique, agent-based modeling is argued to be a versatile and powerful approach for computational emulation of people's inherently complex patterns of movement and behavior [12]. But to what extent and in which cases is the application of this technique in the BPS domain necessary, justified, or even critical? To answer this question, we need to start with the fact that BPS can be used for diverse purposes [27]. Application instances include, among others, building component analysis, whole building design support, building systems sizing and configuration, building operation optimization, and urban-scale energy and environmental performance assessment. A significant portion of such application cases require the consideration of occupants' presence and actions in buildings [28]. It is thus supposed that the representation resolution of occupants in simulation studies should match the purpose of their employment [29]. The task-dependent selection process of a simulation model's proper level of detail can be informed by the nature of the targeted output, which is typically expressed in terms of the values of relevant building performance indicators (BPIs). Consequently, to select a suitable simulation model and its embedded occupant model, the specifics of the building performance indicators must be taken into consideration. Detailed classifications of BPIs have been expanded upon elsewhere [30], [31]. It suffices here to mention three key attributes of BPIs: topical, spatial, and temporal. The *topical* attribute simply specifies the domain of the inquiry (e.g., thermal, visual, air quality). The *spatial* attribute denotes the physical object of the query (e.g., room, floor, whole building, urban neighborhood). Finally, the *temporal* attribute denotes a specific instance of time, or a time period for which the BPI value is obtained.

Given these premises, we could systematically discuss the suitability of ABM toward the representation of occupants in BPS. Consider the case of thermal performance simulation and the associated data for respective occupant models. Such data pertains to occupants' presence, their metabolism, their clothing, their passive effects (e.g., heat gain, carbon dioxide, water vapor emissions), and their interactions with the building's control devices (e.g., thermostats, windows, shades, lights). Broadly speaking, occupant models can be categorized in view of their position in three-dimensional conceptual space involving the domain, the spatial dimension, and the temporal dimension. For example, in case of thermal simulations, a low-resolution model can be spatially single-zone and temporally annual. Furthermore, in a low-resolution representational approach, occupants may be represented as a single entity (e.g., the entire population of a building) that follows uniform and synchronized schedules and rules. In a high-resolution agent-based model, on the other hand, occupants would be represented as individuals, that can display very different preferences, habits, and independent patterns of presence and action in buildings. In this case, the occupants' influence on the resulting high-resolution values of the relevant BPIs (energy use, indoor environment) is typically modeled probabilistically and dynamically. Therefore, not only individual parameters (e.g., an individual occupant's thermal comfort preferences) but also socially relevant factors (and their influence on occupants' disposition to specific behavioral attitudes) can be taken into consideration. As such, we suggest that ABM could be applied especially advantageously in those cases where the BPI values must be obtained at a very high level of temporal and spatial resolution. Moreover, ABM application appears to be particularly beneficial if the intention is to generate a realistic emulation of the presence and behavior of occupants in buildings via probabilistic formalisms that take functional, physiological, psychological, and social parameters into account. A detailed description of the ABM applications supporting various use cases and the level of detail required for representing OB is presented later in sections 2.4 and 2.5 respectively.

The significant impact of OB on the energy and environmental analysis of buildings necessitates the adoption of the agent-based approach by stakeholders such as architects, engineers, energy modelers, facility managers and researchers. The architects can take advantage of the agent-based approach to incorporate OB and occupant needs in designing or retrofitting buildings while the energy modelers and researchers can improve the predictive performance of building simulation models by incorporating realistic OB through ABMs. Moreover, by capturing the inter-occupant diversity or inter-occupant interactions, ABM can support the engineers and facility managers to design, optimize and improve the operations of building systems.

2.3. To which extent can behavioral theories inform ABM approaches to building performance simulation?

A crucial aspect in representation of agents is the underlying behavioral framework that defines the specific attributes and set of rules. As such, ABM applications concerning occupants' presence and behavior in buildings could presumably benefit from knowledge and insights entailed in relevant behavioral theories. The question is, however, if given their state of development and coverage, the state of existing behavioral theories could directly inform practically oriented ABM applications. To explore this point, findings of recent review efforts in this area [33], [34] may be useful. Specifically, application of behavioral theories to explain energy-related occupants' behavior may be suggested to be of direct relevance to agent-based modeling utility in the building domain. A few instances of behavioral theories (and their explanatory applications) identified in these reviews are briefly described in the following:

- An extended version of the Theory of Planned Behavior (TPB) [35]–[37] which entails perceived habit as an additional construct, was used by Lo et al. [38]. The subject was the study of energy-saving behaviors in offices of four organizations in the Netherlands. Therefore, the premise was that repeated actions can evolve into habits. Specifically, office workers' actions regarding operation of lights and shades, as well as the use of appliances and electronics, were observed and surveys regarding energy use were conducted. According to TPB, behavior results from the interplay of a number of constructs pertaining to attitudes (informed by previous experience), perceived norm (subject to individuals' social environments and their moral principles), and perceived control. Lo et al. [38] combined the TPB constructs with habits and physical context to appraise participants' survey data. They identified physical context, infrastructure, and organization as key influencing factors regarding occupants' energy-saving behavior. Others find empirical support for distinguishing between reasoned and unplanned or habitual behaviors, where only the former can be explained by values, beliefs, and norms [39].
- Social Practice Theory and Neoclassical Economic Theory [40]–[43] were adopted by DellaValle et al. [44] in their effort to explain the energy performance gap in the context of social housing. The underlying objective was to explore the potential for increasing the building retrofit effectiveness via behavioral and social levers. Collected data via a pre-retrofit survey among occupants were analyzed. Neoclassical Economic Theory considers rational decision making, as well as biases resulting from monetary context responsible for individuals' choices. In contexts where price signals are visible, such as owner-occupied buildings and tenanted buildings that pass energy costs through to occupants, both energy consumption and some energy end-use technology choices show price sensitivity [45]. However, according to the Social Practice Theory, the cultural context and the long-term socialization processes also play a role in the state and modifiability of individuals' energy-relevant behavior. The study implies that the comprehension of occupants' comfort- and satisfaction-seeking activities can guide the process of identifying more effective retrofit solutions.
- The Self-Determination Theory and the Maslow's Hierarchical Theory of Needs [46], [47] were referred to by Al-Marri et al. [48] in their analysis of the Qatari households'

energy consumption behavior and the residents' views concerning energy and sustainability. The former theory suggests that mechanisms such as rewards or penalties can encourage individuals toward certain types of behavior. The latter theory implies that short-term comfort may override long-term impact considerations of individuals. Both quantitative data (occupants' survey, reporting also on operation of buildings' control devices) and qualitative data (interviews with energy experts) were collected for this analysis. Results were discussed in the context of the observation that according to both theories, occupants' environmentally relevant behavior (including energy saving disposition) can be influenced by social encouragement, motivation, awareness, and education.

- The Norm Activation Model (NAM) [49], [50] informed a study and interventional experiment by Matthies et al. [51] involving staff in 15 public university buildings in Germany. The implementation of the intervention program led to the observation of behavioral changes with regard to energy use. Collected data for the study concerned energy use as well as both self-reported and observed occupant behavior. To explain the formation of a behavior, the NAM differentiates the four stages, namely: (1) attention (an individual's needs, behavioral consequences awareness, perceived behavior control); (2) motivation (an individual's personal norms, established social norms, and moral values); (3) evaluation (an individual's view of a behavior's outcome); and (4) commitment to or denial of a behavior. As such, the NAM focuses on activating and influencing personal norms. In the Matthies et al. [51] experiment, both information provision (regarding environmental behavior and its impact) and rewarding techniques were considered. The NAM's explanatory stance concerning the conflict between personal norms and the social context could help to explain, in this case, how conformance to the expectations from colleagues and superiors could result in behavioral changes.
- A contribution by D'Oca et al. [52] aimed at the synthesis of a number of theoretical approaches toward an "interdisciplinary framework for context and occupant behavior in office buildings." In this case, the proposed framework does not emerge from a fundamental reasoning concerning the choice of the theories or the explicit explanation of the logic behind their synthesis. Rather, the framework acted as the jumping-off point for a questionnaire-based assessment of an extensive number of variables that are suspected to potentially influence occupants' adaptive actions. As such, the conceptual and terminological inhomogeneities of the underlying original theories can be suggested to persist in the synthesized framework. The framework was nonetheless used as the basis for the DNAS (Drivers, Needs, Actions, and Systems) ontology proposed to "represent energy-related occupant behavior in buildings" [53], [54]. The subsequent occupant behavior eXtensible Markup Language (obXML) schema was developed under the IEA EBC Annex 66 [16] project to represent agent behavior and interactions for modeling and simulation.
- A high-level theory of control-oriented human behavior in buildings was recently proposed by Mahdavi et al. [34]. This human-ecologically oriented theory [55], [56] is

> referred to as pragmatic, so as to distinguish it from theories of human behavior proposed in more specialized domains (e.g., psychology, neuroscience). The proposed theory is suggested to be specifically relevant to the development of occupant models in computational tools for building performance assessment in view of criteria such as energy efficiency and indoor environmental quality. Meeting occupants' expectations and requirements implies specific indoor environmental conditions. On the other hand, occupants' actions influence these conditions. The proposed theory facilitates the formalization of the perception and evaluation processes that precede occupants' disposition to—and actual engagement in—behavioral manifestation [57]. Moreover, the theory is meant to facilitate the systematic formulation of a versatile ontology for occupant behavior and the instantiation of this ontology in computational applications.

We discussed a number of behavioral theories and their explanatory applications in (mostly energy-related) applications pertaining to the indoor built environment. The discussion reveals both the potential and the limitations of the current state of these theories. Many instances of such theories were not intended for explicit incorporation in building performance simulation. Rather, their applications targeted toward explanation or interpretation of specific – and frequently limited – behavioral circumstances. As a consequence, a direct operationalization of the theories in terms of semantic engines for ABM routines faces a number of formidable challenges [10], [57]. One key challenge thereby pertains to the observation, that the specific behavioral scenarios addressed in these theoretical investigations do not lend themselves readily for generalization. Moreover, the deployed constructs across various theories are not entirely consistent. This generated obstacles that hamper interoperability and scalability. Some theory-driven studies lack sufficiently rich repertoire of behavioral patterns. Others have not gone through robust operationalization tests. However, the most significant impediment faced by all theory development efforts may be the lack of extensive repositories of empirical (observational) data on occupants' behavior in specific, well-characterized environmental and social contexts. The availability of such data repositories represents a necessary and critical condition for the proper evolution, advancement, and verification of behavioral theories in view of coverage and robustness [10]. The rapid progress in the development and computational implementation of formal ABM methods is hoped to encourage and accelerate international data collection activities to realize and calibrate the semantic representations of OB in ABM applications.

2.4. What are the use cases of ABM of occupants?

This section offers common knowledge on the potential use cases of building performance assessment that can benefit from an agent-based occupant modeling approach. Though Section 2.2 presented a broad overview of this matter, here we elucidate the diverse ABM applications across different building life cycle stages, spatial scale, and specific settings. We selected building life cycle stages relevant to OB applications and therefore do not consider the construction phase applications of ABM.

Building life cycle stages: ABM can be useful at the schematic design stage to capture the influence of OB on building design parameters and thereby assist in the performance-based design process. Optimization of design components such as windows or shades, or evaluation of technological measures such as lighting sensors or personalized controls, may also be possible through the agent-based occupant models. For code compliance modeling, ABM can prevent the suboptimal design decisions made through conventional static OB assumptions that are known to yield inaccurate building performance simulation results [58]. Use cases concerning load calculations and estimating cooling or heating system sizing can also adopt the agent-based occupant representation to model movement and behavior for improving the prediction accuracy. Building operation and control applications can utilize the ABM technique for energy demand analysis, identifying optimal heating, ventilation, and air conditioning (HVAC) operation strategies [59], or designing model predictive controls (MPC) [60]. ABM is particularly useful for cases involving high temporal and/or spatial resolution such as forecasting peak hourly demand to arrive at effective demand management strategies or load shape analysis at the disaggregated zone level. Within measurement and verification applications, ABM may be advantageous in improving the prediction accuracy of energy savings measures by developing individual-level models that can simulate the heterogeneity and stochasticity of human behavior [61]. Similarly, use cases concerning the effectiveness of energy efficiency measures for thermal resilience during extreme weather events such as heat waves or cold snaps may also benefit from the ABM application. In the case of building stock renovation, comparing the efficacy of retrofit options by incorporating dynamic OB through ABM can help designers make informed choices. Evaluating the technological acceptance of different retrofit techniques is also possible by developing agent-based models that reflect the underlying behavioral processes and motivations that drive occupants' preferences.

Spatial scale: Use cases concerning energy and environmental performance of buildings at higher spatial extents such as urban or district level can take particular advantage of the ABM approach. For instance, developing household level agent-based occupant models to assess the macro effects of dynamic OB on residential district energy demand [62]. Additionally, ABM can also be employed for simulating bottom-up emerging OB; for example, the rebound effect of household energy use arising out of residential policy measures such as tiered utility rates or subsidized photovoltaics. Use cases at an urban scale that can be supported by ABM may include energy performance of city building stock to support efficiency programs, testing policy scenarios for creation of sustainable buildings in urban settings, and optimization of energy infrastructure such as smart building systems [63].

Specific settings: Apart from the different building life cycle stages and spatial extent, the agent-based approach is also valuable for several context-specific use cases. Within environments with greater human–building interaction, such as naturally ventilated buildings, ABM can be advantageous in determining comfort levels by realistically simulating occupants' perception of and behavior in the indoor environment [8]. Agent-based approach is also helpful in examining the efficacy of energy-saving policies in shared environments, such as university classrooms or office spaces, where interactions and peer effects have significant influences on OB [9], [64], [65]. For occupancy-driven analysis, such as evaluating performance of lighting sensors [66] or HVAC demand in airport terminal buildings [67], agent-based occupant modeling approaches are useful to simulate the stochasticity in occupancy patterns. Other potential application of ABM could be within net-zero energy communities, where occupants' acceptance of technological solutions is central to achieving the desired energy savings, or for cases where occupant-centric BPIs such as occupant hours and peak load per occupant hour are of interest. Interdisciplinary studies exploring psychological, social or cultural influence on energy use behavior can also implement ABMs to capture the underlying processes to reflect upon the OB insights. Use cases involving special groups of the population, such as elderly, poorly educated, or resource-constrained individuals having distinct patterns of behavior that cannot be predicted through the traditional OB models may also take advantage of the ABMs. For example, while assessing the thermal or visual performance in senior living housing, the agent-based approach will be able to account for the specific thermal and visual comfort needs of the elderly. Figure 2 summarizes the potential use cases of ABM of occupants for energy and environmental performance of buildings.

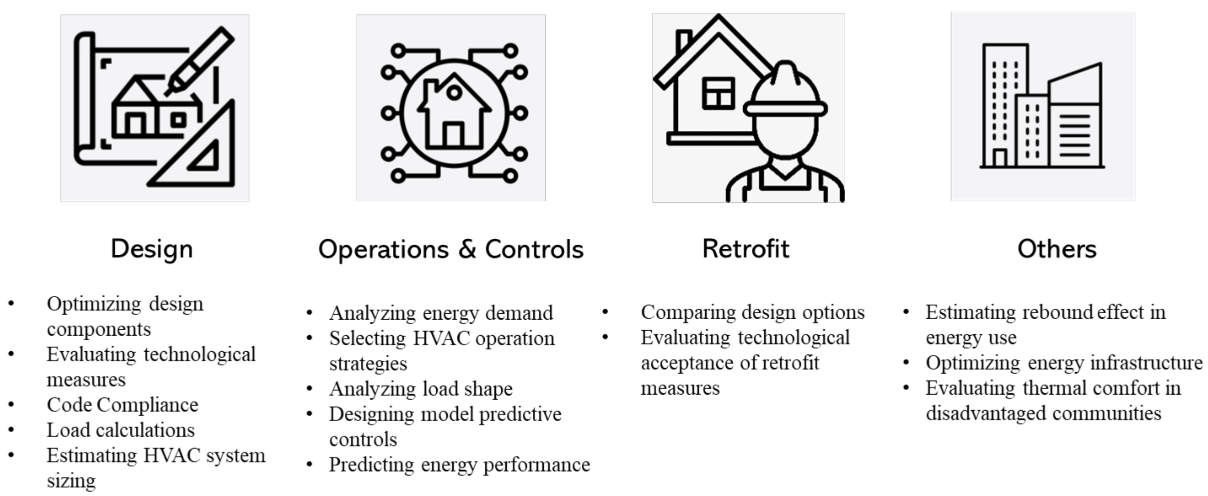

Figure 2. Use cases of ABM for energy and environmental performance of buildings.

2.5. What are levels of detail for ABM to support various use cases?

An important matter that needs to be addressed in occupant modeling using the agent-based approach is at what level of detail (LoD) the occupants' presence, movement, decision-making processes, interactions, learning, and other behavioral features should be represented. The concept of level of detail in ABM for the built environment essentially deals with the amount of information or the degree of granularity adopted in representing OB [68]. For instance, occupants' presence and movement in BPS can be demonstrated through diverse modeling expressions and at various spatial resolutions such as at aggregated whole-building level through a set of rules, at floor level following a uniform distribution probabilistic expression, or even at individual zone level through a stochastic process. Apart from occupant actions, presence, or movement, behavioral capabilities such as sensing, learning, predicting, and inter-occupant interactions can also be described at different degrees of detail to model the dynamics of human behavior.

The degree of detail incorporated within the ABM can have a significant impact on the model outcomes, and thus the selection of an adequate LoD for OB representation is of utmost importance. Choosing a simple theoretical model may oversimplify multifaceted OB, leading to building simulation results apart from reality (i.e., the building performance gap). Alternatively, a complex empirically grounded model with individual-level specifics may unnecessarily overload the model and require additional computing time or resources. Moreover, striking a balance with a mid-level ABM [69], which is realistic enough to represent the dynamics of OB, but does not incorporate too many elements that make the model difficult to interpret, has its own challenges related to model evaluation and validation. To date, there is no consensus on the adequate LoD for occupant modeling within the OB community. However, the need to articulate a level of detail for occupant behavior and how it is influenced by the objective of simulation have been discussed by a few ABM researchers. Chen et al. highlighted the need for systematic definitions at different resolutions to describe occupant behavior for different research purposes [70]. They defined three levels of definition for OB modeling but included basic OB attributes related to occupancy, appliance operations, and actions with no consideration to occupants' perceptual and behavioral processes that are known to influence building simulation results. Berger and Mahdavi, in their review on ABM applications for the built environment, underlined the necessity to understand the extent to which decisions concerning granularity in OB modeling are influenced by the purpose of the simulation [12].

The modeling purpose or the desired outcomes of simulation must be adopted as the guiding heuristic for the selection of LoD. Additionally, the trade-offs between the BPIs and available resources must be considered. Explaining this in detail, there are three major rules that the modelers must ponder upon before arriving at the suitable LoD. First, the resolution of occupant representation should be able to capture substantial OB aspects that can influence the model outcomes. For instance, if the model objective is to investigate thermal comfort in a conditioned office building where occupants do not have control over HVAC operations, a coarse LoD would be sufficient. Conversely, if a naturally ventilated building is the object of simulation, the ABM would require a higher degree of detail to reflect the underlying behavioral processes and dynamics that govern occupants' control-oriented actions such as opening/closing windows or turning on/off ceiling fans. Second, the LoD must strike an appropriate balance between the desired accuracy of results and the required effort in terms of data, computational resources, and time for model development. Given the availability of big data and advanced computational resources, developing complex ABM incorporating a higher degree of detail may seem feasible. Nevertheless, the modelers must ensure that if a granular LoD is able to yield acceptable results that serve the model purpose, a finer LoD that requires more effort must only be selected if there is substantial improvement in model outcomes. In other words, Einstein's razor that states "Everything should be made as simple as possible, but not simpler" must be applied [71]. For instance, an ABM intended to compare the annual energy use of various retrofit design options for a residential district may adopt a simpler LoD. Incorporating complexities of occupant behavioral processes using a higher LoD may not have a considerable impact on the objective of simulation, i.e., relative performance, given the scale of model and the aggregated performance metric. And lastly, the data necessities to develop ABM must be carefully considered before selecting a certain LoD. Constructing a detailed ABM would require qualitative and quantitative data through measurement, surveys, or interviews. For process-driven environments, such as hospitals that provide a critical indoor environment for operations and patients, occupant-driven variable energy use may be limited, and therefore developing data-intensive ABM is not necessary. However, for residential or office buildings, developing ABM with a higher LoD may be feasible, given the larger representation of such building typologies in the existing literature and open-access OB databases, such as the ASHRAE Thermal Comfort Database [72] and the ASHRAE Global Occupant Behavior Database [73]. A detailed description of the OB data availability and requirements for ABM is addressed in Section 2.8.

2.6. What are the modeling and simulation tools used for ABM?

Building energy modelers usually rely on the available ABM toolkits and software platforms to develop their models. Some of these popular toolkits are AnyLogic, NetLogo, and Repast [12]. Researchers have also programmed ABM features by using general programming languages, such as MATLAB, Python, Java, or C++ [12], [74]–[77]. There are a few specific toolkits developed for occupant behavior modeling, such as the Occupancy Simulator app based on the obFMU, and the PMFserv platform [78]–[80]. This section offers an overview of the existing ABM tools and software platforms required to capture the human–building interaction realistically.

In selecting toolkits and software platforms, modelers usually have a set of criteria to meet their specific modeling goals. There should be (1) *a coupling mechanism between an ABM-based occupant model and other BPS models.* The building and occupant interaction model consists of exchanging information in a way where a representative agent perceives a building environment and takes adaptive adjustments, such as adjusting the thermostat setpoint, dimming the lighting, and closing the blinds. There are several methods for coupling the two models, such as via functional mock-up unit (FMU) and direct coupling [81], [82]. A detailed discussion on the coupling methods is presented in Section 2.7. (2) *An ABM software toolkit should be able to model real occupants with scalable attributes*. An occupant agent may have only thermal comfort; other models could have demographic and value characteristics attributed to the agents [39]. Using these attributes, agents perceive and perform adaptive actions in relation to their environment. In a real-world scenario, occupants' decisions of the same built environment are often influenced by other occupants' decisions. (3) *A toolkit should allow a multi-agent system*, in which each occupant-agent can interact with other occupant-agents [53], [83]. Finally, one motivation for using the ABM modeling approach is to explore agents' changing perceptions and behaviors over time. Most

ABM modeling toolkits allow the agents to perform actions at time *t* by learning from their decisions and impacts at time *t*-- -1. Therefore, the toolkit must also have (4) *the ability to observe evolutionary pathways of occupant behaviors and activities in simulation time*. The criteria mentioned above inform our selection of ABM toolkits to be discussed for their current and potential use in occupant behavior modeling work.

- **AnyLogic** is a Java-based modeling tool that allows several simulation approaches, such as discrete events, system dynamics, and agent-based [84] methods. The software toolkit has a proprietary license, but a free edition is available for noncommercial use.
- **NetLogo** is a multi-agent Java-based modeling tool that is known for its simple implementation [85]. NetLogo is an open-source toolkit that enables modelers to contribute to the core codes as well as develop code-modules. For example, BehaviorSpace is a useful module to run several models by using multiple available processors [85]. Other useful modules include various software wrappers for co-simulation purposes, such as PyNetLogo [86], RNetLogo [87] , and NetLogo-Matlab [88] .
- **MASON** is Java-based discrete-event multi-agent simulation tool. It is an open-source software toolkit for large custom models, yet it is fast and lightweight. The toolkit has never been used for simulating building occupant behaviors but has some potential.
- **Repast Suite** is a package of several ABM software toolkits. Java modelers may use *Repast Symphony* for simple ABM implementation across multiple computing clusters. *Repast for High Performance Computing* is a C++-based tool that is designed for use on large computing clusters. *Repast for Python* is the most recent addition to accommodate the Python community. The last tool has been widely accepted for various applications that require large-scale distributed ABM methods.
- **MATLAB** has been known to run discrete-event simulations. It has also been used in building occupant simulation [14]. Recently, they added the ABM capability into the Simulink environment [89].
- **SARL** is one of the most recent Java-based multi-agent programming languages. The toolkit is fully supported by a popular Eclipse IDE for the programming environment and is intended to develop an extensible multi-agent model [90].
- **obFMU** is a C++ -based occupant behavior modeling tool [53], [54] packaged as an FMU for simulating occupant presence and movement [91], as well as occupant adaptive behavior defined in the obXML schema [54]. obFMU can be used to co-simulate occupant behavior with BEM tools such as EnergyPlus that implements the functional mockup interface.
- **PMFserv** is another ABM-based occupant behavior modeling toolkit that co-simulates with EnergyPlus. The toolkit is a result of a 10-year development that was originally built for general social science and systems engineering purposes [78]–[80].
- Video game engine (e.g. **Unity 3D** and **Unreal**) is a cross-simulation platform that has been explored for multi-agent simulation in built environments. Some of the attractive features that come with the platforms are path-finding, collision avoidance, and other

related agent behaviors and interactions. The advanced visualization features of the platforms also help modelers to do detailed design evaluations and communicate their findings to relevant stakeholders [92]–[94].

2.7. What coupling simulation approaches are used for co-simulation of ABM with BPS?

Co-simulation has been an option to integrate ABM of occupant behaviors with BPS software programs (or simulators), such as EnergyPlus, IDA ICE, and Modelica Buildings Library. Three common co-simulation approaches are one-to-one, Functional Mock-up Interface (FMI), and middleware. In a *one-to-one* approach, the co-simulation is straightforward, by implementing the occupant behavior model within a BPS program or vice versa. (FMI) is an open-source standard that defines an interface that supports model exchange and co-simulation [95],[96]. Another popular approach is to use *middleware* that is a hub program to bridge the interactions between the BPS program and the occupant behavior model implemented in a different program. Building Control Virtual Testbed (BCVTB) is a software program developed for this purpose [98]. Multi-agent Environment for Complex-SYstem CO-simulation (MECSYCO) middleware is a lesser-known middleware for ABM co-simulation [99]. This section discusses the latter two co-simulation methods to integrate models built under different programming environments. This section also discusses the limitations of each technique with a few examples.

The FMI approach translates one or more simulators developed using various tools (e.g., Dymola, MATLAB/Simulink, and EnergyPlus) into an FMU format: a zipped file containing the program and an XML description file [97]. A non-FMI program is required to connect all interacting simulators. One example program using this approach is the occupant behavior Functional Mockup Unit (obFMU). The obFMU package comes with four main components: the co-simulation interface, an XML description file called obXML, a data model, and solvers. The obXML describes the occupant behavior as defined in the DNAS (drivers-needs-actions-systems) framework [53]. The obFMU is, then, directly connected with a BPS simulator, such as EnergyPlus. Figure 3a illustrates how EnergyPlus communicates with the obFMU. FMI may also be implemented within a hub program that connects both FMU-packages and non-FMU packages. One example is using PyFMI, a Python package, to implement the hub program for the Python environment (see Figure 3b).

In the middleware approach, one method is to use MECSYCO, a generic approach to integrate multiple simulators using the Discrete Event Specification (DEVS) [99]. DEVS works as a wrapper for participating discrete-event simulators. One advantage of using MECSYCO is its interoperability with FMU components generated using the FMI standard. MECSYCO has a lot of potential for BPS since it has been widely used to co-simulate with ABM models. Camus [99] uses the tool in smart heating application to integrate simulators that are built using OpenModelica and NS-3 [97].

A more popular middleware in BPS is BCVTB. BCVTB is built on Ptolemy II, a Java-based open-source software toolkit that supports the co-simulation of multiple simulation programs, such as EnergyPlus, Modelica, FMU, MATLAB, Radiance, ESP-r, TRNSYS, and BACnet stack (see Figure 3a). In the BCVTB environment, each simulator needs to implement interfaces to connect with BCVTB. In other words, BCVTB is a hub program that manages the data flow between the simulators (see Figure 3c). One early BCVTB implementation integrated EnergyPlus and Fluent [100]. Li and Wen [101] use MATLAB to transfer signals to EnergyPlus through BCVTB. Since then, BCVTB has been supporting tests of various MPC implementations, such as reducing demand and energy costs for buildings' HVAC systems [102]. Bernal et al. [103] developed MLE+ based on BCVTB to integrate EnergyPlus and MATLAB specifically. In OB research, BCVTB also integrates EnergyPlus with an ABM of occupant model written in MATLAB [14] and with NetLogo [9].

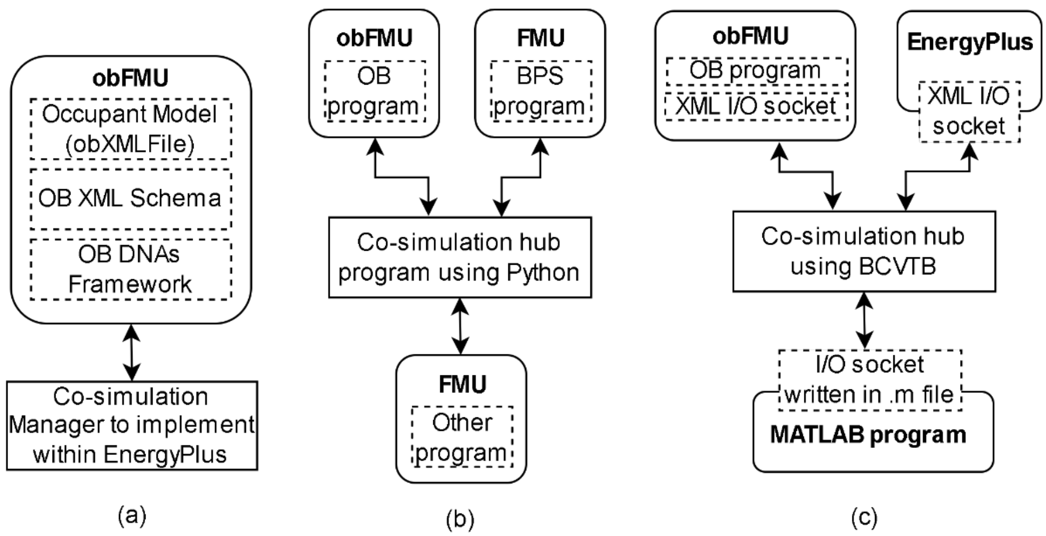

Figure 3. Diagrams of co-simulation methods between OB modeling program, BPS program, and auxiliary programs (inspired by Fathollahzadeh and Tabares-Velasco [104]). (a) shows an FMI approach to directly link EnergyPlus and an FMU-packaged OB model, obFMU, and (b) an FMI approach that connects the exportable FMU files containing all programs that is also via a Python-based hub program, and (c) a BCVTB program acting as a hub program to connect all interacting programs through interfaces.

There are several limitations to using each of the aforementioned methods, which have been recognized for their different uses. Fathollahzadeh and Tabares-Velasco [104] developed an evaluation metric to compare co-simulation procedures. The first key comparison point is based on the simulation runtime that the co-simulation model developed using the FMI standard typically runs 15% faster than BCVTB. Another important metric is to compare the methods mathematically. In either BCVTB or FMI-standard, the coupling follows two mathematical approaches, namely the Jacobi method that considers all participating simulators proceed and exchange data in parallel at time $t + 1$ (where t is the starting time). Another method is the Gauβ-Seidl that exchanges in a sequential process (where the generated values of one simulator are sent to another simulator at time t+1. The FMI-based co-simulation allows both Jacobi and Gauβ-Seidl methods, whilst BCVTB only uses the Jacobi method. In terms of user-friendliness, the FMI method is generally easier to implement than BCVTB, since the FMI method provides an open-source level of flexibility and is straightforward. BCVTB has a plus point for its GUI environment. Using BCVTB is relatively easier to connect multiple simulators by implementing the system command actor rather than making exportable FMUs for all the FMI methods. Perhaps, FMI is still a better approach for modelers since it has a more active development with the latest update being in January 2021 [97]. The latest update for BCVTB was for April 2016 [98].

2.8. What data are available to program the agents' behavior?

One of the major challenges in developing ABMs of occupant behavior is the availability of relevant data for programming and validating agents' behaviors. The type of data needed directly depends on the specific use case considered (see Section 2.4) and the modeling LoD adopted (see Section 2.5). The following paragraphs detail (1) common data collection approaches and acquisition technologies, (2) open-access occupant modeling libraries, and (3) relevant data-related challenges limiting ABM applications.

Starting with data collection, Yan et al. [23] identified three main approaches: observational studies, occupant surveys and interviews, and laboratory studies. *Observational studies* typically consist of passively monitoring occupants' behaviors and actions in their actual environment. In contrast, *occupant surveys and interviews* aim to better understand the behavioral characteristics of occupants and their drivers, going beyond their direct interactions with building systems. Laboratory studies often consist of controlled experiments to quantify occupants' environmental preferences and study the adaptive actions they may take to maximize their comfort. It is worth noting that controlled experiments also can be conducted in virtual environments (e.g., using head-mounted virtual reality devices), as documented in a recent review article by Alamirah et al. [105].

In terms of the data acquisition technologies used to collect occupant behavior data, Jia et al. [106] define four main types. The first type is *occupancy and occupant behavior,* which measures ground truth data about occupants through devices such as cameras and passive infrared (PIR) sensors. The second type is *indoor and outdoor environment,* which includes sensing environmental conditions often using a wireless sensor network (WSN) or weather stations. The third category is *energy consumption and usage pattern,* often using electricity or gas meters. The fourth category, *others,* covers additional self-developed sensors used to monitor specific occupancy behaviors (e.g., window opening state or shade position).

In practice, collecting high-quality and reliable occupant behavior data is often challenging for researchers due to privacy concerns and costs of sensing and data curation. Acknowledging this gap, researchers have created open-access databases that can support the development of ABMs of occupants. Such databases are also important to compare different OB modeling approaches, benchmark their results, and test different LoDs and scales. Examples of publicly available datasets that can support ABMs of occupant behavior are listed below:

- ASHRAE Global Comfort Database I [107] includes 52 field studies conducted between 1982 and 1997 in 160 buildings worldwide, resulting in approximately 21,000 sets of raw thermal comfort data.
- ASHRAE Global Comfort Database II [72] includes field studies conducted from 1995 and 2016 around the world, resulting in a total of 81,846 rows of raw data of monitored thermal environment parameters paired with subjective "right-here-right-now" comfort votes. The database is publicly available at http://www.comfortdatabase.com/.
- ASHRAE Global Occupant Behavior Database [73] includes 34 field-measured building occupant behavior datasets gathered from 39 institutions in 15 countries covering 10 climatic zones. The database is publicly available at https://ashraeobdatabase.com/.
- Library of occupant behavior models: Within the effort of IEA EBC Annex 66 [16] energy-related OB literature has been reviewed to identify and compile a list of 127 commonly used OB models in the field that cover the following categories: (1) *behavior types*—occupant movement and different types of occupant interactions with windows, doors, shading, blinds, lighting systems, thermostats, fans, HVAC systems, plug loads, taking hot/cold beverages, and adjusting clothing levels. (2) *building types*—office, residential, and school buildings. In this list, those models with clear documentation were considered for library inclusion, and were processed and implemented using the DNAS (Drivers, Needs, Actions, Systems) framework, presented in a standardized schema obXML [108]. In addition, a library of occupant behavior models in Modelica was developed [109], which can be more conveniently integrated into Modelica-based building system models.

Despite the advantages of large OB datasets, some data concerns exist and are worth noting. First, a well-calibrated stochastic model based on large empirical datasets may realistically emulate occupant-related processes and behaviors. However, as argued by [23], "this does not necessarily establish scalability toward anticipation of long-term future processes and events (predictive potency) or toward transportability to other buildings and other locations." The rich dimensionality and context-dependence of occupant behaviors are believed to complicate the development of synthetic—more "generalizable"—OB datasets [110], [111]. Another factor that complicates the generalization of existing datasets is that the temporal and spatial granularities needed to represent occupant behaviors depend on the use case at hand (see Section 2.4). For instance, an ABM for building control-related applications may require high temporal and/or spatial granularities that are not always reported in general OB datasets. Furthermore, data with such granularities may require high storage and computational costs that could limit the capabilities of the ABMs. Such costs could be detrimental to applications that require fast responses, such as real-time building control systems. A fit-for-purpose approach is recommended here to match the size and complexity of the data needed to the scale and LoD of the ABM. Finally, despite the promising data collection efforts and datasets described above, there is still a lack of available semantically rich datasets to support the development of agent-based models that are grounded in empirically based behavioral theories. The scope of data collection efforts should extend beyond observing existing occupant behaviors and aim to capture the multi-domain drivers (e.g., physical, contextual, social, psychological) behind these behaviors.

2.9. What methods and data can be used to validate the results from ABM?

An important step when developing an ABM is to ensure a correct and accurate representation of the real-world phenomenon studied. This section covers two distinct processes that contribute toward reliable and robust ABMs: (1) verification and (2) validation. Definitions and examples of verification and validation methods are presented by adapting and combining from various sources [112]–[116].

Verification is the process of determining that the implemented software correctly represents a model of a process. In other words, "are we building the model right"? Verification is a continual process that starts with the first basic version of the ABM and continues throughout the development process. In parallel to debugging, verification also includes looking for incorrect implementation of conceptual models and ensuring that any calculations or equations used are solved correctly.

Validation, on the other hand, is the process of determining how much the computer model accurately represents the real world studied phenomenon and whether the model is a reasonably accurate representation. Validation is also the process of determining that the equations and logic used are the correct ones. In other words, "are we building the right model"? A distinction is made between three types of validation, namely conceptual, operational/structural, and outcome/predictive validation.

Conceptual validation ensures that the concepts used to develop the ABM are sound and supported by empirical evidence. This is first achieved by using actual data to initialize the model's parameters (see Section 2.8 for common data types and sources). A common modeling practice is to fit collected data to known probability distributions and use them to stochastically initiate model parameters (e.g., agents' attributes and behavioral characteristics). In parallel, conceptual validation also entails basing the model, such as agents' decision-making rules, on existing theories and concepts. Examples of common behavioral theories were covered in Section 2.3.

Operational/structural validation consists of studying the model's input-output behavior to confirm that the model outcomes are realistic under different initial conditions. Parametric variations and sensitivity analyses are often employed to evaluate ABMs' operational/structural validity. On the one hand, they help confirm that the model is reacting well to changes in input parameters. On the other hand, they help identify the parameters with the highest influence on the model's outputs. In parallel, statistical methods (e.g., confidence intervals) can also be used to quantify the variability in the results of different model runs. Given the stochastic nature of ABMs, it is common to conduct multiple runs (e.g., 100 or 1,000) for each combination of inputs and use statistical metrics to capture the spread in the results. *Tracing* is another method that could be used to ensure that the logic of execution of the model is correct. This is typically done by following and analyzing the behavior of specific entities in the model (e.g., a single building occupant) to help detect any anomalies. Finally, when possible, the use of graphical animation can facilitate the analysis of the model's behavior and outcomes.

Outcome/predictive validation aims to confirm that the model and its outputs are a reasonably accurate representation of the real-world phenomenon that is being studied. Put differently, are the predictions of the model accurate enough to be considered valid? Data are often needed to answer the question above and quantify the accuracy of the predictions. The use of data that was unseen by the model during development (i.e., out-of-sample validation) is typically preferred to in-sample validation, in order to minimize overfitting issues and increase the generalizability of the model. A wide range of performance metrics can be used to quantify model accuracy (or errors), depending on the nature of the problem (i.e., type of predicted output). Examples of common performance metrics for regression, classification, and probabilistic problems are presented next. These were obtained from [117]:

- *Regression problem* (e.g., energy consumption or thermostat setpoint predictions): Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Root Mean Squared Logarithmic Error (RMSLE), Coefficient of Variation of Root Mean Squared Error (CVRMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), and Coefficient of determination R-Squared (R^2).
- *Classification problem* (e.g., occupant presence or shade position predictions): Accuracy, error rate, precision, recall, F1-Score, FBeta-Score, Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) curve, and confusion matrix.

- *Probabilistic problem* (e.g., probability of window opening prediction): Prediction Interval Coverage Probability (PICP), Coverage Width Criterion (CWC), and Continuous Ranked Probability Score (CRPS).

In summary, the stochastic nature of ABMs often makes their verification and validation challenging. Depending on the ABM's scope, scale, LoD, and availability of data, different verification and validation methods can be used. The methods presented in this section should not be considered as mutually exclusive but rather complementary. Modelers are advised to use combinations of the methods to help get as close as possible to a verified and valid model. George Box famously said that "All models are wrong, some are useful" [118], implying that modelers should focus on building models that are accurate enough to be useful rather than aiming for "perfect" representations of real-world phenomena.

2.10. What are the main challenges and future opportunities in ABM?

Despite the agent-based mindset being increasingly accepted to represent OB in the BPS, there remain significant challenges associated with the theoretical approaches and implementation techniques of ABM. One of the most significant issues is to identify which are the key processes of human behavior that should or should not be included in the model so as to balance the model complexity or the level of detail. Integrating systematic approaches such as pattern-oriented modeling [119] with ABM can help in identifying substantial OB patterns from empirical knowledge to develop or test ABMs. Pattern-oriented modeling offers a structured way to incorporate observed patterns of human behavior at different levels of hierarchy (such as individual or community level) that can then be used to develop a theoretical foundation for agent-based models. Though ABMs can effectively account for emergent effects arising out of multiple occupant interactions at the local level, the method falls short of representing top-down effects (such as that related to organizational hierarchy), collaborative task-based behaviors, or structured behavior sequences. Integrating approaches such as event-based narratives to combine planned and unplanned sequences of events [120] or personas to describe fictional individuals for behavior customization [121] within ABM may be advantageous to holistically simulate OB in semantically rich environments.

A second opportunity and challenge is associated with the adoption of "smart" features in the indoor built environment. Occupant responses to intelligent building controls and dynamically adaptable infrastructure systems are still poorly understood, and the empirical basis for modeling is thin. It is reasonable to hypothesize the emergence of destabilizing dynamics that might render system control ineffective. ABM is well suited to explore these dynamics even in the absence of complete data, because the modeling framework supports interactions among both stylized human and software agents. The agents' environment becomes another actor in the system, and the concern is now not just who, but *what* is acting, and how [122].

The next issue in ABM of occupants is related to the urban scale applications, where apart from the data availability concerns discussed in Section 2.8, there also exists a lack of scalable approaches to model OB at community scale. Developing methods to aggregate individual-level OB within the ABM while capturing the significant details and dynamics could benefit urban building energy modelers and researchers. Furthermore, one of the most pressing needs in the ABM for building performance assessment is a set of guidelines or the development and documentation tools that can enable efficient representation of OB. A modeling guideline describing best practices and step-wise approaches to implement OB will assist researchers and practitioners through the ABM simulation process.

The future perspective of ABM research, beyond the incremental improvements to the existing methods discussed earlier, could be geared towards improving their computational efficiency, advancing theoretical understanding or dealing with uncertainty. Exploring how different machine learning techniques such as Neural Networks or Bayesian Classification can be incorporated with

ABMs could be a potential area of interest to the BPS community. Such a hybrid approach can serve as a powerful tool for decision support during the design stage or to develop data-driven ABMs for operational stage applications. Generating synthetic datasets using machine learning predictive models to train ABMs [111], especially for the adaptation processes, can help users overcome challenges related to data availability. Issues pertaining to parameter space exploration and ABM calibration could be tackled through advanced methods such as surrogate modeling that combine machine learning and intelligent iterative sampling [123]. In parallel, transfer learning approaches [124], where knowledge about occupant behavior from one building is transferred to other buildings, could enhance the scalability and generalizability of ABMs. Another research avenue that could support the future development of ABMs for occupant representation is their integration with interdisciplinary fields such as psychology, sociology, economics, and anthropology. Adopting multimodal data collection approaches to gather occupant data can enable users to develop comprehensive ABMs that reflect empirical human behavior. Moreover, conducting virtual reality tests on occupant behaviors and adaptation within their indoor environment or adopting the narrative analytics to feed additional information to the traditional ABMs may also be useful. The next generation ABMs might also explore data assimilation techniques to minimize the uncertainties due to the dynamic and stochastic processes incorporated. Developing data assimilation algorithms to incorporate empirical data and dynamically adjust the simulation to improve prediction would be beneficial in real world applications of ABM.

3. Summary

Agent-based modeling is a powerful computational tool to represent and simulate occupant behavior and interactions with other occupants and the indoor built environment. With the global trend toward decarbonizing the building sector, an integrated array of technologies and strategies are applied. However, their adoption and effectiveness of use is significantly influenced by human behavior. The increasing research, development, and applications of ABM for occupant behavior are made possible due to: (1) more practical use cases and values for stakeholders, (2) more affordable computing, and (3) more available ABM modeling and simulation tools, as well as emerging datasets to support occupant agent programming.

This paper presents 10 questions and answers that highlight major issues in agent-based occupant behavior modeling for building performance simulation, hoping to inform building energy modelers on why, when, and how to apply ABM in order to provide insights into various stages of the building life cycle to achieve energy efficient, demand flexible, and climate resilient buildings.

Understanding and representing occupant behavior within a behavioral theory and ABM computing framework for the indoor built environment remains a challenge. Getting adequate real-world data to represent the diverse and heterogeneous occupants' realistic behaviors is another challenge. Lastly, integrating agent-based occupant modeling with building energy modeling and other domain models (e.g., transportation, power grid) for community and urban scale applications can be data and computing intensive. These topics deserve further research to accelerate the adoption of agent-based occupant modeling.

Declaration of competing interest

All co-authors declare there is no conflict of interest in the reported work.

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