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Towards integrating occupant behaviour modelling in simulation-aided building design: Reasons, challenges and solutions

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A B S T R A C T

Occupant behaviour is an important source of uncertainty in building energy performance simulations. This has led to the development and integration of different modelling approaches that represent the complex, stochastic nature of human-building interaction. Yet, several barriers prevent their wide use in simulation-aided building design. The procedures and practical solutions for integrating occupant behaviour models are segmented through the literature. Accordingly, this paper examines the state-of-the-art in the application of occupant behaviour models. Based on the PRISMA methodology, the literature is critically analysed to: i) identify and map the barriers between theory and application; ii) propose a simulation framework establishing the steps for integrating occupant behaviour models into building performance simulations; iii) synthetise practical solutions and highlight remaining challenges towards a simulation framework adequately integrating occupant behaviour. The paper stresses the added value within the decision-making process at different building design stages. Furthermore, key elements for identifying the appropriated modelling approach for each occupant behaviour aspect are presented considering factors such as type of behaviour, building type, and spatial and temporal scale. Ultimately, this critical review establishes guidelines for the integration of occupant behaviour into building design practice and defines a research pathway for bridging the gap between the OB research field and the simulation-aided building design practice.

Contents

Abbreviations: ABM, Agent-based model; BPS, Building performance simulation; DNAS, Drivers – Needs – Actions – Systems; EBC, Energy in Buildings and Communities; ECM, Energy conservation measures; EMS, Energy management system; FMU, Functional mock-up interface; HVAC, Heating, ventilation, and air conditioning; IAQ, Indoor air quality; ICT, Information and communication technology; IEA, International Energy Agency; IEQ, Indoor environmental quality; NPV, Net present value; NZEB, Nearly zero-energy buildings; OB, Occupant behaviour; OBM, Occupant behaviour model; OPA, Occupant́s presence and actions; PCA, Principal component analysis; PDF, Probability density function; PI, Performance indicator; PV, Photo-voltaic; SA, Sensitivity analysis; TUS, Time use survey; UA, Uncertainty analysis.

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1. Introduction

1.1. Motivation

Building Performance Simulation (BPS) tools are extensively used to support the decision-making process in the building design practice. Yet, a disagreement between predicted and actual building energy performance is often observed, the so-called performance gap [1]. As reviewed by Shi et al. [2] this gap could vary by a factor between 0.2 and 4, where in most cases measured energy consumption is higher. Assumptions related to occupant behaviour (OB), weather deviations, and discrepancies between design vs. as-built are acknowledged as main causes [2]. Regarding OB, its representation – comprising both occupants' presence and actions (OPA) – in BPS in terms of static schedules and occupant-related power densities is oversimplified. Occupants are typically described as homogeneous and passive agents although they are diverse and actively interacting with the building and building systems [3].

To overcome this challenge, in the last four decades several methods for modelling OPA have been developed [4] aiming at capturing the stochastic nature of the behaviour, the diversity of the occupants, and the two-way interaction between the occupants and their built environment [5]. Notably, IEA-EBC Annex 66 [6] and its follow up, Annex 79 [7] have motivated an international effort for advancing on the OB research. As a result, over 310 OPA models have been produced to better describe actions such as window, shading, and lighting operation, thermostat adjustment, appliance use, and clothing adjustment [4].

Despite these efforts, advanced OPA modelling approaches are still mainly applied by researchers and developers as several barriers prevent their widespread application [8]. Indeed, an international survey on current OB modelling approaches revealed that most interviewed practitioners consider OB the most important uncertainty source in BPS. However, BPS typically relies on deterministic schedules or rule-based models [9].

1.2. Existing reviews

Several review articles assessed crucial aspects of the OB modelling research field. For instance, Berger et al. [10] examined studies claiming OB as mainly responsible of the performance gap and assessed their evidence. Harputlugil et al. [11] focused on describing different categories of occupants, understanding occupant́s attributes, and exploring the interaction between humans and buildings. Similarly, Wu et al. [12] presented formal definitions for OB, drivers motivating OB, and the impact of OB on building energy analysis. They also started exploring BPS tools representing common OB. Stazi et al. [13] deepened the understanding of OB drivers and the influence of environmental and time-related factors. They reviewed how this information is translated into OB model variables. Different studies focused on the formalisms and application of OB modelling approaches [14–18], describing modelling requirements for different applications and related modelling approaches identifying their strengths and disadvantages, or giving a broad view of the field and the OB impact on energy-saving potential. Osman et al. [19] focused on the exploitation of Time Use Survey (TUS) data for developing OB models and their application on building energy use. Furthermore, while some researchers focused on OB modelling applied to specific contexts such as residential buildings [20], offices [3], and urban scale [21,22], Carlucci et al. [4] performed a systematic review on the modelling approaches and models developed for a wide range of building types, climates, and occupant actions.

Regarding the integration and application of OB models in the building design process, Yu et al. [23] focused on the main criteria for comparing and selecting modelling approaches, as well as improving the performance of OB models. Hong et al. [1] reviewed integration approaches of OB models into BPS, their advantages and shortcomings, how to choose them depending on the OB model, and related commercial software capabilities. Finally, Azar et al. [5] investigated simulation-aided occupant-centric design. They established and highlighted fundamental concepts and definitions for occupant-centric design, supporting mechanisms, and design methodologies.

Despite these efforts, most of the articles are focused on the OB research field and few on its application within simulation-aided building design. The reasons, challenges, and solutions for applying OB models are segmented across the literature.

1.3. This review: Objectives and methodology

This review aims at establishing a research pathway for bridging the gap between the OB research field and its application in simulation-aided building design. To the knowledge of the authors, this is the first review discussing in detail proposed and practical solutions to overcome the barriers preventing extensive use of advanced OB modelling approaches. This information is segmented throughout the literature without a clear proposition of the options and steps users need to address, from problem definition to informing the design decision, when implementing advanced OB modelling approaches. To this end, this critical review aims at answering:

i. What is the added value of considering more advanced OB models in the simulation-aided building design process?
ii. How to choose the most appropriate OB modelling approach and model depending on the design purpose?
iii. How can advanced OB models be integrated into BPS accessible and useful for supporting the decision-making process?

To clarify, in this paper and as stated by Becker and Parker [24] "a simulation enacts, or implements, or instantiates, a model. A model is a description of some system that is to be simulated, and that model is often a mathematical one. A system contains objects of some sort that interact with each other. A model describes the system in such a way that it can be understood by anyone who can read the description and it describes a system at a particular level of abstraction to be used".

This critical review is divided into two parts. In the first part, a literature survey was performed to draw a general view of the simulation-aided building design field and OB research field, thus identifying the barriers. Exploring key words such as *occupant behaviour*, *building design*, *energy*, *performance*, *practice*, *application*, and *industry*, 18 review articles published after 2015 focusing on the OB field and 12 articles focusing on simulation-aided building design processes were identified and included in Section 2.

As for the second part, a more exhaustive literature survey was performed to: i) identify novel and practical solutions to the challenges BPS users need to address for applying advanced OB representations within the building design process; ii) identify most urgent matters that would transform the current complex steps faced by an end-user into a streamlined simulation process seamlessly integrating OB (see Section 3). Using the search engine Scopus, combination of the keywords occupant, behavio*, building, model*, simulation, energy, and performance, and based on the methodology PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [25], four steps were performed, namely identification, screening, eligibility, and inclusion of studies (see Fig. 1).

The asterisk was used to simultaneously capture word variants (singular and plural as well as differences between British and American English) such as in behavio* for including 'behaviour' and 'behavior'. Besides, additional articles known to the authors, and articles citing or being cited by the articles were manually added to the collection.

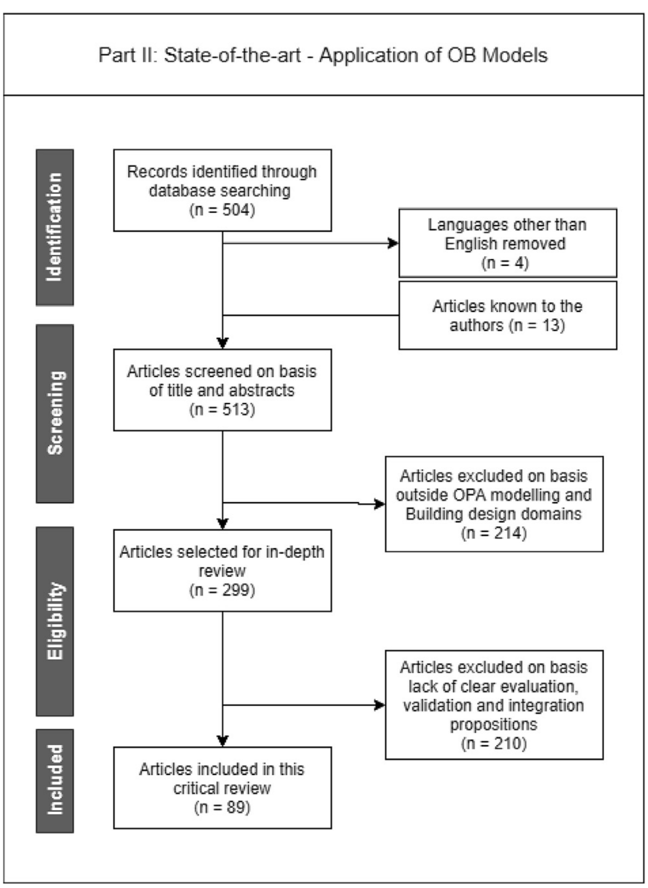


Fig. 1. PRISMA workflow - State-of-the-art on the application of OB models.

The selected articles included in this review go beyond the proposition of models but compare different modelling approaches, apply models from the literature in different contexts, or present clear model evaluation, validation, or integration methodologies. Special attention was given to studies demonstrating the application of advanced OPA models in simulation-aided design practice.

Accordingly, the rest of the article is structured as follows: Section 2 presents a general view of the simulation-aided building design field, the OB research field and maps the research gap between them; Section 3 presents solutions for bridging this gap; Section 4 synthetises the findings and highlights urgent matters requiring further research; Section 5 gives the main conclusions.

2. Simulation-aided building design & OB research field

2.1. On simulation-aided building design practice

BPS is the use of computational models to represent physical characteristics, operation and control strategies of a building and its energy systems [26]. It is adopted by building design practitioners i.e. architects, energy modelers, engineers, etc. [27] to reduce uncertainty in the performance of the building and thus assist the building design decision-making process [26]. Its application covers a range of purposes such as performing load calculations to select and size HVAC systems; demonstrating code compliance; evaluating design scenarios [28]. To better understand the different simulation requirements, input and output data, and simulation aims, Table 1 (adapted from [29]) presents different building design stages and possible simulation scenarios. This information is necessary to understand the current simulation-aided building design practice and hence the needs of the practitioners.

Different disciplines play a role in the building design process (e.g., architects, energy modelers, HVAC engineers). Practitioners can work under different collaborative approaches, for example, the engineer can assist the architect, the practitioner can be both engineer and architect, or they can be partners [30]. As a result, there is a synergy between practitioners with different skills, knowledge, and expertise levels [29], where not necessarily all of them are familiar with the resources and limitations of BPS tools and how to interpret their outputs [31]. Furthermore, modelling requirements are different depending on the design stage and type of simulation to be performed [32]. Thus, BPS tools need to produce initial results from a rough building representation and limited input data at early design phases as well as allow for detailing building components in more advanced design phases [30].

Regarding OB, its related uncertainty is recognised as a major challenge within the building design field. Practitioners may tend to base their assumptions on building energy codes and standards which rely on outdated and simple OB representations not suitable for every case [26]. As observed by O'Brien et al. [9], despite practitioners often acknowledge this problem, they may not implement advanced OB modelling approaches due to barriers such as time constraints, the substantial effort required, and lack of understanding and education on the topic. As a result, they favour increasing OB modelling requirements by standards together with modelling capabilities in BPS tools. Consequently, building designers need data, models, tools, case studies and standards that support their practice including the human dimensions of energy use [33].

Finally, it has been stressed that more attention should be paid to BPS outputs. Practitioners prefer clear, concise, readable, and

Table 1
Aim, inputs and outputs of BPS at different design stages. . Adapted from [29]

	Conceptual Design	Preliminary Design	Detailed Design	Code Compliance
General aim	Examine alternative strategies and its impact on:• Achieving the required indoor environment• Investment and life-cycle cost• Energy consumption• Space requirements for HVAC systems	Specify technical solutions that fulfil the indoor air quality and cost targets of the project:• Definition of main HVAC zones• HVAC central plantSpecific shading systems	Definition of technical details and detailed building design and its systems.	Demonstrating the building design is compliant with requirements defined by energy codes or green building certifications
Purpose of	simulations	• Impact of building orientation and envelope configuration on energy economy and life-cycle;• Evaluation of architectural concepts involving alternative methods of energy savings;• Day lighting and electrical lighting;• Air flows in open areas of office buildings;• Natural ventilation air flows.	• Computation of the cooling requirements of systems and rooms;• Comparison of shading alternatives• Comparison of HVAC system alternatives;• Analysis of the zoning of HVAC systems;• Sizing of the central HVAC plant;• Daylighting and electrical lighting design;• Air infiltration;• Achievement of satisfactory indoor climate.	• Detailed sizing of air handling and cooling equipment;• Detailed dimensioning of piping and ductwork;• Acoustic analysis of ductwork;• Calibration and balancing of the piping and ductwork;• Simulation of control strategies;• Sizing of special systems;• Special evaluation of comfort.
Calculation of key	performance indicators:• Energy related;• Comfort related.			

well documented information presented in a visual format [29]. This is necessary to promote an effective communication with the different groups of stakeholders involved in the building design decision-making process [31].

Summarizing, to promote the integration of OB modelling in the simulation-aided building design field, practitioners need the proper motivation, knowledge, and tools. In this view, it is needed to:

i. Understand the added value of including OB models in the design process
ii. Have policies, regulations, and building standards that promote and guide in the use of OB models within the building design process
iii. Be educated and guided on when and how to use the OB models considering different simulation purposes and design stages (Table 1)
iv. Develop BPS tools that facilitate the integration and application of OB models whose outputs effectively communicate the results.

2.2. Progress in the OB research field

The OB research field can be described using the occupant-building interaction energy behaviour loop (see Fig. 2) consisting of the three, possibly iterated, steps *investigate, understand, improve* [17]. This schema describes a first stage of *investigation* where data collection techniques are used to gather information about the occupants and how they interact with the building as defined by their presence and actions. The latter include on the one hand adaptive behaviours such as window, light, blind and thermostat operation, intended to adapt the indoor environment, and on the other hand non-adaptive actions such as appliances use, which are not driven by physical discomfort but by contextual factors (non-physical factors affecting the behaviour, habits and attitudes of the occupants) [3]. Different studies have focused on sensing technologies [15,34,35], highlighting the link between energy consumption data and occupancy monitoring as opportunity for indirectly identifying behaviours such as appliance use [34]; proposing a categorization framework for OPA-sensing technologies [35]; emphasising the importance of sensor selection and placement arguing that not only environmental variables (e.g., CO_2 concentration and temperature) should be considered but also factors such as room orientation to exclude interferences [15]. Likewise, in-situ monitoring methods such as *sensor-based* (i.e., to detect occupant presence, measure environmental variables, and capture occupant actions on building systems), *model-based* (e.g., estimating occupant presence from CO_2 measurements), and *surveys* have been explored. As a result, the significance of conducting a monitoring campaign and a documentation process of meaningful information has been pointed out [36]. Further, surveys are recognised to have potential of revealing the role of socio-economic, cultural and psychological factors in the human-building interaction [37,38]. Finally, developments in immersive virtual reality [39] and the evolution of the Internet of Things (IoT) and Information and Communication Technology (ICT) [33] have made available an increasing amount of data to understand the energy-related behaviour of occupants.

In the *understanding* stage, the data collected is analysed and modelled to identify influential factors motivating OB and quantifying its impact on building performance [17]. Here, an important milestone was the establishment of the DNAS (drivers – needs – actions – systems) ontology to describe energy-related OB where: the *drivers* identify the motivation behind a behaviour; the *needs* specify what occupants look to fulfil; *actions* are carried out by the occupants; the building *systems* are acted upon by the occupants [40]. Recently, this ontology has been extended to include socio-economic characteristics, geographical location, subjective values, occupant activities, and collective and individual adaptive actions [41]. Accordingly, several reviews focused on the drivers behind occupants' actions exploring: fan use in different types of buildings [42]; light-switching behaviour in office buildings [43]; how climatic factors, social and personal attributes, architecture and interior design features, energy regulations and economic parameters affect the energy-related OB [12]. As a result, complex interactions have been noticed requiring the combination of multidisciplinary approaches, cognitive behavioural methods, and cognitive complex theory to provide a better understanding. This is because OB is influenced by: environmental, time-related, contextual, physiological, psychological, social, and random factors (i.e., uncertain, not quantifiable factors) [13].

The increasing knowledge on drivers of energy-related OB has led to the production of a myriad of modelling approaches and models thus, a large body of literature has focused on classifying them and identifying their limitations and opportunities. Based on the research goal OB models are classified as: *agent-based modelling* where agents are simulated to assess the interaction with each other and the external environment; *statistical analysis* performed to discover a numerical relationship between OB and for example indoor/outdoor environmental factors; *data mining approaches* used to learn behavioural patterns from information such as appliance energy consumption; *stochastic process modelling* developed to estimate occupancy state (e.g., whether an occupant is present or not) and related energy consumption [15]. Further, depending on the action modelled, they are differentiated between occupancy, adaptive, and non-adaptive models [3]. OB models can be also classified depending on their level of complexity (listed from the lowest to the highest level): fixed schedules, data-based (non-probabilistic) models, stochastic (probabilistic) models, and agent-based models (ABM) [8]. Ultimately, more than 300 models have been developed and included in dynamic open-access database [4].

In the *improving* stage (see Fig. 2), simulations are performed to quantify the impact of the occupants on energy-saving strategies, low energy building, or robust building design [17]. In this context, OB models can be integrated to the BPS program using a *direct input* or *control* method, a *built-in OB model*, a *user function* or *custom code*, or a *co-simulation* scheme [1] (see Section 3.5 for details). On a higher-level perspective, the simulation-aided occupant-centric building design process has been explored [5]. In this context, occupant-centric refers to considering the occupants and their well-being as the main priority throughout the building life cycle. Accordingly, occupant-centric metrics of building performance are defined covering aspects such as thermal comfort, indoor air quality (IAQ), well-being (i.e., physical, mental, emotional, and social health of a person), space planning, and energy use [5]. Finally, design strategies such as parametric design, optimization, and probabilistic design have been explored towards promoting an evolution from simple parametric design – where best/worst scenarios are employed – to probabilistic design in which stochastic models can quantify the likelihood of extreme results [5].

2.3. The gap between OB research and OB models application

This section presents the main research gaps reported in the literature that need to be addressed towards promoting the integration of OB models in the simulation-aided building design process. To this end, three knowledge domains are defined: the fundamental knowledge domain i.e., fundamental knowledge required for completely understanding the different aspects of the human-building interaction; the integrated knowledge domain i.e., the knowledge require for integrating the models within the design process; supporting tools i.e., the OB capabilities of BPS tools and post-processing modules. Table 2 presents the research gaps, their corresponding knowledge domain and related BPS user's need. Some gaps are not directly associated with a user's need, nevertheless they are presented in Table 2 since they need to be addressed to resolve other research gaps.

Starting in the fundamental knowledge domain of the three components of the human-building interaction research loop (Fig. 2) an urgent need for standardized protocols is required. Notably, in the data collection area monitoring campaigns require standardized procedures for their design, execution, and documentation. This would allow to properly compare the findings from different studies. As a result, a deeper understanding of the energy, comfort, and wellbeing-related OB would be achieved, assessing the influence of contextual factors on the behaviour. Further, more data and from other domains than the ones widely covered in the literature (i.e., geographically from developed countries in the northern hemisphere; according to the building use, residential and commercial buildings; regarding occupant actions, window, lighting, shading, HVAC systems operation) [4], is required

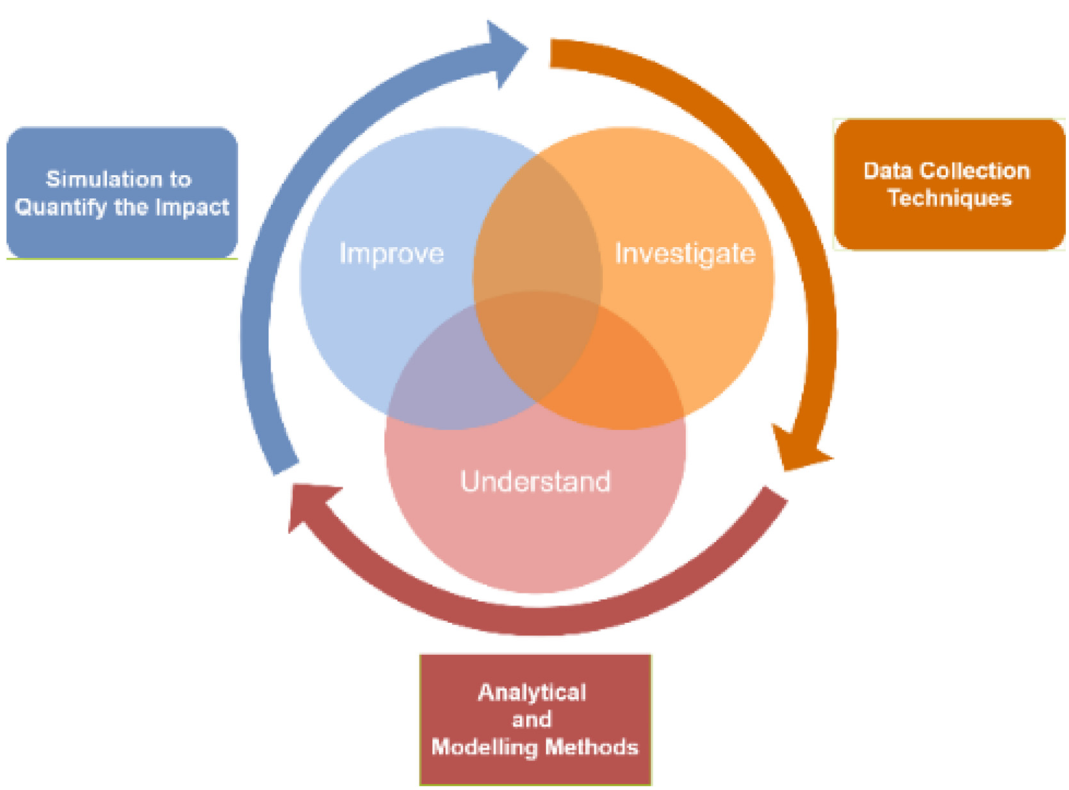


Fig. 2. Occupant-building interaction energy behaviour loop. . Adapted from [17]

to allow developing models for missing contexts, testing the scalability of developed models and defining a hierarchy of actions. The last aspect is fundamental for the integration of OB models into the design practice [17] (see Section 3.5).

Developments in the data collection field go in parallel with the evolution of the modelling front where it is urgent to establish standardized guidelines and systematic procedures for developing new models and documenting them [13,45]. Similarly, standardized and methodical model evaluation and validation protocols are required [4,14,17,34,45]. Most of the models are developed splitting a single dataset into two parts for model development (training) and *internal* validation, respectively, and are therefore presented without proper *external* validation (including data from different contexts). Additionally, developed models must be tested in different building types, locations, seasons, etc. All in all, the robustness, scalability and transferability of OB models is not well understood [5,13,14,20,34].

In the simulation field three main aspects need to be addressed [5,44]. First, it is essential to develop occupant-centric metrics with corresponding guidelines for their implementation. Currently, the scope of the metrics used is limited to energy and comfort aspects, which are normalised by building features instead of occupant-related factors. Second, the development and demonstration of design methodologies using advanced OB modelling approaches need further investigation. Third, the advances in the OB field need to be demonstrated in real scenarios and building design applications. Filling these gaps will allow designing buildings that are robust to OB while reducing the energy consumption and promoting occupants' wellbeing.

Regarding the integrated knowledge, several aspects emerge. First, guidelines for model integration need to be formulated together with the model documentation [13,15,34,45]. The lack of such guidelines results in researchers using different integration strategies, presenting the models without a simulation framework, and increasing the difficulty of making models interchangeable. Second, the most suitable modelling approach depends on the simulation aim and context, thus requiring the definition of qualitative and quantitative selection criteria [5,8]. Equally important, new OB modules need to be developed to include advanced modelling approaches in current BPS software [33].

Finally, based on the information presented in this section, a conceptual map of the main issues that need to be addressed for integrating OB modelling into the simulation-aided building design practice is presented in Fig. 3.

3. Integrating occupant behaviour in BPS

Following a logical workflow with the steps a user would need to address with the knowledge and tools available today, the literature is analysed to identify the propositions for facing each of the steps (Sections 3.2 - 3.6) and to draw a research pathway towards a full integration of advanced OB modelling approaches into the simulation-aided building design process. Yet, the discussion starts in Section 3.1 highlighting the added value of including OB models and supporting design practices.

3.1. Value proposition

It is necessary to explicitly review the advantages of OB models since the different stakeholders related to the building design practice are often not well informed about the added-value of this approach, the contractors are typically not adding resources, neither budget nor time, to the projects for this, and codes, standards, and green certifications do not yet require or guide the application of advance OB models [9,46–48].

Current standard schedules and nominal densities conventionally used to represent OB oversimplify human-building interaction [4]. As a result, buildings do not achieve the desired performance; building systems are over- or undersized; payback periods are wrongly estimated and investment decisions misled [32,49]. With Advanced OB modelling techniques modellers would have the ability to explore different occupant-related scenarios, assess building resilience, and quantify the potential for adaptive behaviour to achieve comfort in extreme situations [46]. A summary of studies highlighting the added value of using OB models in the building design practice is presented in Table 3.

As shown in Table 3, the benefits of OB models pertain different stages of the building life cycle. In *early architectural design or conceptual design stages*, it has been shown [50–52] that advanced OB modelling can help decide over factors such as aspect ratio and orientation of the building, roof type, glazing fraction, position of the windows, shading type and configuration towards reducing energy consumption, enhancing comfort, or promoting the benefits of natural ventilation. In other words, dynamic OB models allow the designer to assess how design alternatives influence adaptive behaviours to maximise comfort while reducing energy consumption. Concerning a more *advanced design* stage, mathematical and statistical techniques (e.g., factorial design) can be used together with advanced OB modelling approaches to find the most relevant

Table 2
Research gaps reported in the literature (Cont.)

Ref.	Research Gap	Objective	Knowledge Domain	Practitioners need
[4]	OB research in more contexts: Climates zones, building types, OB aspects, countries	Allowing the understanding and modelling of OB for meeting specific needs in different contexts.	Fundamental	Available models
[34]	Understanding influence of building size on occupants' energy behaviour			
[14]	Lack of new models that meet the specific needs for the application			
[14]	Challenge of training and validation of the developed model	Understanding accuracy and performance of OB models.	Fundamental	Models' strengths and limitations
[4]	Lack of standard model testing framework			
[4]	Lack of evaluation and validation protocols of OB Models			
[34]	Simulation research is recommended to test and verify the assumptions used to develop the models			
[17]	Lack of standardization of OB model development			
[17]	Lack of verification of behaviour models			
[8]	Lack of model validation			
[13]	Lack of standardized methods for modelling OB and validating OB models			
[15]	Improving validation of OB models			

parameters affecting specific performance indicators (PIs), e.g., heating and cooling demand. By accounting for the occupant-related uncertainty and describing PIs with probability distributions or expected ranges, it is possible to achieve more robust (i.e., the variability of the PI against OB is reduced) and resilient designs [32,53]. Concerning *building systems*, OB should be considered in their selection and sizing process. Occupants' preferences in terms of the indoor environment, occupancy, appliance use levels, and the control flexibility the occupants have with each system influence system performance. An advanced OB representation gives designers the opportunity of accounting for the occupants' diversity and their interaction with the building systems. Modellers are better informed to find more comprehensive and optimised solutions within an expected range of OB than if they use a single, averaged or conservative deterministic schedule [54,55].

The evaluation of IEQ is another important front that can profit from advanced OB modelling approaches. For example, with stochastic models capturing the occupant interaction with shading systems, daylight levels and glare can be realistically predicted for proper visual comfort assessment. This information can be used to inform interior designers regarding the best desk layout and seated positions [56]. By including realistic lighting and blinds use in the design of lighting and shading systems, appropriate design decisions can be taken improving

visual comfort [62]. Knowing the occupants' diverse needs and preferences regarding indoor air quality and thermal comfort, the most suitable ventilation strategy can be determined [63].

Energy-related OB has a high relative impact on the energy performance of nearly zero-energy buildings (NZEBs) [49,57], plus-energy buildings etc., making the use of advanced OB models particularly important in this context. To ensure that the designs achieve desired performance targets and that they are code-compliant, the uncertainty added by the occupants needs to be minimised and the design robustness to the OB maximised [58]. To this end, multiple OB patterns can be used to generate PI probability distributions, and stochastic models can capture the influence of design alternatives over the occupants and vice versa, hence, the building performance and its potential variation can be realistically predicted [57–59]. Furthermore, the electricity demand can be better estimated so that on-site electricity generation (i.e. using PV panels) can be properly designed [49]. Finally, energy conservation measures (ECM) and retrofit strategies can be better designed and evaluated using advanced OB modelling approaches. It has been demonstrated that energy savings associated to ECMs could be significantly overestimated using traditional modelling approaches. This in turn misleads the economic assessment, i.e., Net Present Value (NPV) is overestimated [60,61,64] and the ECM prioritization process wrongly executed [65].

To summarize, there are three main characteristics of the OB models that add value to the building design process over standard representations (see Table 4).

3.2. Identifying influential occupant behaviour

The BPS process integrates aspects of building design, weather and environmental information, and OB to estimate building performance. The complex and dynamic interaction between these elements and the non-linear nature of involved physical phenomena make the BPS process challenging [66]. Additional complexity from advanced OB models can enhance the accuracy and robustness of BPS [4], yet a balance between accuracy and complexity is required to avoid the so-called curse of dimensionality, i.e., introducing too many parameters with respect to available data. This is an issue that leads to further difficulty when identifying the most significant parameters within the model, so that calibrating or using BPS models become demanding tasks [8,66]. Consequently, it is essential to identify the elements of OB to which the BPS process is more sensitive, so that each element can be determined with the appropriate level of accuracy. Nonetheless, it has been demonstrated that the impact of the OB is case- and context-specific and that defining general guidelines is impossible [32] thus, identifying the most relevant aspects of the OB needs to be an integral step of the BPS procedure.

Sensitivity analysis (SA) and uncertainty analysis (UA) are used to reduce model complexity associated with BPS [23]: simplifying

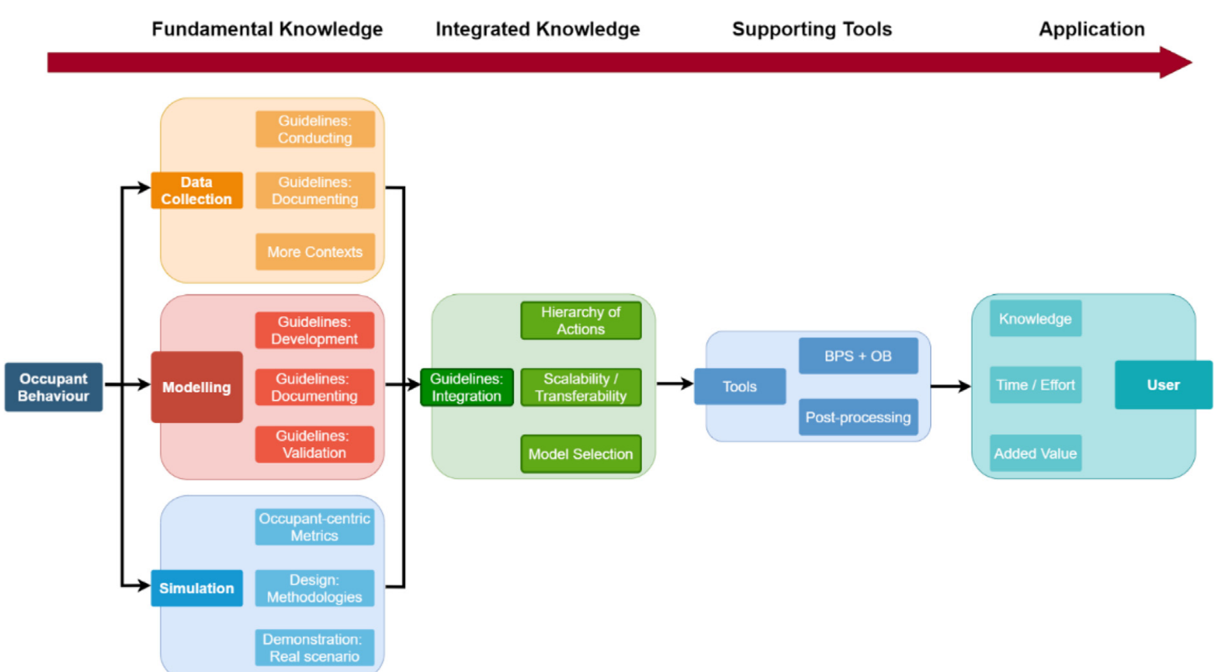


Fig. 3. Conceptual map - OB research gap.

Table 3
Summary of studies showing added-value from OB models.

Ref.	Simulation aim	Design stage	OB Models	Highlights
[32]	Best performing shading strategy	Preliminary / Detailed Design	Dynamic and stochastic models for lighting and blind operation	Without the OB models suboptimal strategies would be chosen. Dynamic models captured the influence of the design alternatives on OB. Therefore, the design decision-making process was better informed.
[50]	Optimize façade design and fenestration geometry considering energy use	Conceptual design	Stochastic models for: Occupancy, lighting and equipment use, thermostat adjustment and blinds operation	Building's design alternatives could lead to changes in the indoor environment. Occupants are encouraged to use building components (e.g., blinds) towards reducing energy use. Optimal configuration calculated using dynamic OB (two-way human building interaction).
[51]	Evaluating thermal comfort	Conceptual design	Stochastic models for window operation	Stochastic models can in principle better capture the dynamic nature of occupants' actions, the study showed that a standard model can over-predict comfort.
[52]	Optimize façade design and fenestration geometry for thermal comfort	Conceptual design	Stochastic models for window operation	The deterministic model likely overpredicted thermal comfort and underestimated the need for cooling measures. The stochastic approach seemed to better model the dynamic nature of occupants' actions and optimal solutions resulted in more shading elements.
[53]	Identifying the most influential aspects of energy needs	Conceptual design	Stochastic models for presence; windows, shading, and lighting use; heating set-point temperature adjustment.	Parameters identify for further optimisation: for example, intensive opening of windows and the temperature set-point had a more significant effect on heating needs than the orientation or the performance of the building.
[54]	Defining HVAC systems and evaluating performance of ground source heat pumps	Detailed design	Probabilistic model for Air conditioning operation	This study investigated thermal imbalance, building load, and heat pump performance. Information that can be used to inform design of HVAC systems and heat pumps considering the occupant behaviour, in this case the operation of the air conditioning units.
[55]	Sizing HVAC systems	Detailed design	Stochastic model for generating lighting, plug-load, and occupancy profiles	The standard schedules used in practice are reason- able, though conservative compared to measured values for predicting peak internal gains, relative to stochastic synthetic schedules.
[56]	Identifying optimal occupant's seating position and orientation considering visual comfort	Interior design	Blinds operation model	Performance prediction based on simulation using simple assumptions may deviate from actual performance and lead to a wrong decision in selecting appropriate furniture layout.

a model by screening parameters; performing robustness analysis; validating a model; and evaluating the model's sensitivity to errors [67]. SA is a method that quantifies how the uncertainty of the inputs is propagated to the uncertainty of the output. It focuses on ranking the input parameters regarding their contribution to the output uncertainty. On the other hand, UA analyses the response of the simulation output considering, along with input variations, the lack of knowledge and errors of the model. Together, they quantify uncertainties in the inputs and outputs of the BPS process [23,66]. In this view, ÓNeill et al. [66] aimed at establishing systematic guidelines for the application of SA discussing: *input categories*, such as urban-level and building-level design parameters, building envelope characteristics, ventilation and infiltration parameters, HVAC and other mechanical systems, OB aspects, economic factors, weather information, control strategies; *output categories*, namely building load and energy consumption, occupant thermal and visual comfort, indoor environmental factors, outdoor environmental factors, economic factors, equipment performance; *probability density functions* (PDFs) associated to uncertainties; *sampling methods* to propagate the uncertainty of the inputs through the whole model; *SA methodologies*, such as screening, local, and global approaches; *available tools* for performing such SA studies (readers are referred to [66] for details).

As stressed by Yu et al. [23] there is a limited cover of SA and UA studies dealing with OB parameters. They showed that the main focus of SA and UA studies on OB is understanding the impact of internal gains and presence while adaptive behaviours are assumed to be fixed scenarios. These studies assume occupancy scenarios and probability distributions for occupant-related inputs or use synthetic profiles from OB models. Further, ÓNeill et al. showed that OB is mostly considered together with building envelope and mechanical systems parameters to understand its impact on building load and energy consumption as well as occupants' thermal and visual comfort.

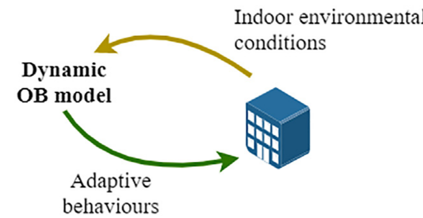
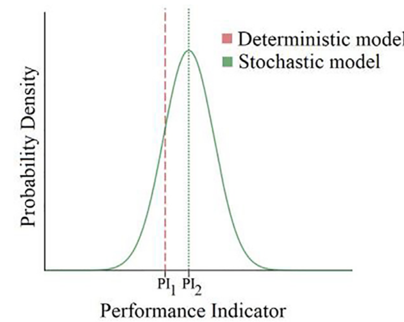
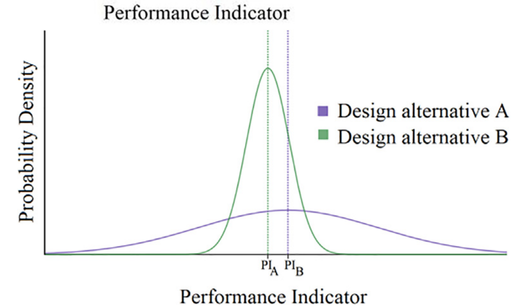
SA and UA studies might be infeasible within the simulation-aided building design practice because of the computational cost and time required i.e., large amount of runs required to evaluate all the parameter variations. Alternatively, a fast screening method was proposed for identifying the most relevant OB aspects as part of the fit-for-purpose strategy developed by Gaetani et al. [32] for choosing the most suitable modelling approach (for details see Section 3.3). It quantifies in one simulation the influence of OB aspects. Instead of using different OB scenarios, it calculates impact indices for each aspect of the OB, which are expressed in terms of ratios extracted from the building energy balance.

3.3. Choosing the most suitable OB modelling approach

For the most influential aspects of the BPS, the practitioner have the option of improving the estimations to reduce epistemic uncertainty or improving their representation to better account for their uncertainty [32,46]. As illustrated in Section 2.3, guidelines for choosing the most suitable model are still missing. To this end, this section discusses the findings reported in the literature regarding the application of advanced OB models considering: *type of behaviour* (e.g., adaptive behaviours) [3,4,32,68–71]; *building design stage* [3,18,23,55,65,72–77]; *spatial scale* of the study, i.e., whether it is at room or building level [3,9,23,65,78]. This is because the aforementioned dimensions dictate the modelling requirements in terms of resolution, complexity, and accuracy [23,32,79].

Advanced OB modelling can be static or dynamic regarding the interaction with the BPS tool. The former approach generates inputs for the building energy model at the beginning of the simulation, while the latter has continuous and two-way interaction

Table 4
Potential of OB models.

Two-way human-building interaction	Assessing how design alternatives influence adaptive behaviours to maximise comfort while reducing energy consumption	
Uncertainty in PI	Estimating what is the range or expected value of the building performance considering occupants diversity - e.g., Probability distribution of PI	
Robustness against OB	Assessing what is the impact of the OB on the performance of different design alternatives	

with the simulation, i.e., at each time step the output of a dynamic OB model affects the simulation, which in turn generates inputs for the OB model [65]. Therefore, presence and non-adaptive behaviours, which are mainly driven by contextual factors (e.g., occupanťs routines), are better represented by static models. Instead, depending on the degree of accuracy required, adaptive behaviours can be characterized either by static or dynamic models. For example, when estimating the total annual energy consumption of a building stock, the averaging effects of OB at large scales may allow the use of static models. In contrast, if the aim of the study is estimating the distribution of the peak load of a building, the interactions of the occupants with building systems such as thermostats and windows become highly relevant requiring dynamic models [3,9,23,65,78].

Presence and non-adaptive behaviours are typically modelled by schedules, discrete-time Markov models, and survival models [3]. Schedules can be fixed corresponding to *standards* (e.g., ASHRAE Standard 90.1), according to *monitoring data*, or considering different *types of occupants* (e.g., high/low occupancy scenarios) [3,68]. Markov-chain models predict the likelihood of a state to happen depending on the state of the previous time step together with state transition probabilities. The states can be defined as *arrivals*, *departures*, and *breaks* for office buildings [3] while in residential buildings they can be defined, for instance, as *at home and active*, *at home and sleeping*, *not at home* [69]. Survival models estimate the time until an event happens, such as considering the arrival time, when the occupant will leave, or how much time passes until the TV is turned off after turning it on [70,71]. Adaptive behaviours can be modelled using schedules, rule-based models (i.e., deterministic models), stochastic models such as Bernoulli models, discrete-time or discrete-event Markov models, and data-driven models based on machine learning techniques such as artificial neural networks, deep learning algorithms, and decision trees [3,4,32]. Furthermore, it has been highlighted that despite survival models are better suited for presence and non-adaptive behaviours, they can be modified for adaptive behaviours. However, they are only recommended for infrequently executed actions such as shading systems use. This is because the survival curves are given at particular environmental conditions that can be significantly influenced by the adaptive behaviours [3].

Concerning building life cycle stages, some suggestions are proposed for specific modelling approaches. For example, Bernoulli models (i.e., low complexity stochastic models) predict the likelihood of the state of a building system given defined predicting parameters [73]. Since they are computationally efficient and do not require much information, they are suitable for estimating the performance at the whole building level during early design [74]. However, they should not be used for comparing design alternatives or quantifying occupant comfort metrics. This is because generally Bernoulli models do not use indoor environmental conditions as predicting variables. Therefore, the impact of design alternatives on the behaviour cannot be captured [3]. Moreover, these models predict the state of the building rather than the occupant action (e.g., having a window open vs. an occupant opening a window). Thus, they cannot predict the number of interactions between the occupant and the building systems as a proxy for occupant comfort [23]. An ABM represents the occupants as individual agents capable of interacting with other agents and their surrounding environment. The agents are characterized by personal attributes and preferences along with rules that define their interactions [18,72]. In this way, this modelling approach can be used to represent with a great level of detail the OB and its relationship with the building performance considering not only environmental factors but psychological, social, cultural, and economic characteristics of the occupants. Therefore, an ABM can be used to reduce the occupant-related uncertainty when sizing building equipment, designing NZEBs, or assessing occupant comfort [75–77]. Nevertheless, ABMs have limited scalability. At small spatial scales (e.g., room level) few occupants can be modelled using an ABM, but at larger scales (e.g., building level) the number of occupants makes this approach impractical [15,16,55,72]. As an alternative, static-stochastic OB models can be used to generate profiles that account for occupant diversity. These models can be developed from monitored data to generate heat gains and electricity profiles for OB such as occupancy, equipment use, and lighting use. Using these synthetic profiles as inputs of BPS, peak loads and total energy use estimations can be more reliable for properly sizing, for example, HVAC and PV systems [55,65].

An important milestone was the fit-for-purpose strategy developed by Gaetani et al. [32] that aims at defining the most suitable level of complexity required for representing each OB aspect within the BPS study. Thus, their approach is specifically developed for supporting the building design practice in the decision-making process as well as in the selection of the most suitable modelling approach. The core of the strategy comprises three sequential steps: the impact indices method [80] (presented in Section 3.2), the diversity patterns method [79], and the Mann-Whitney *U* test [79]. First, the impact indices method is performed, and the lowest level of complexity (i.e., schedules and rule-based models) should be imposed for the OB aspects that show low influence on the PIs [32,80]. For the ones with a high impact, the diversity patterns method should be applied by using schedules or rule-based models to define low/high variations. Then, simulations are run to calculate the PI. This approach is applied to test the sensitivity of the results to the variations. Thus, the definition of the diversity patterns becomes crucial [32,79]. In other words, while the impact indices method extracts the contribution of each OB aspect using a single schedule, the diversity patterns method tests the sensitivity against the variation produced by schedules representing low/high OB scenarios. Finally, if the diversity patterns method is not conclusive, the Mann-Whitney *U* test would be performed. It assesses if the results from the low OB level and the high OB level simulations (i.e., from the diversity patterns) are significantly different, and ultimately which aspects of the OB are causing the spread in the results and are therefore worth focusing on [32,79].

In summary, systematic, and general guidelines for supporting the building design practitioner in selecting the most suitable modelling approach do not exist. Furthermore, the suggestions presented are not definitive since they are drawn from a limited number of studies that compare and apply advanced OB modelling approaches. These suggestions might be conditional to the context of each study. Despite them being a good starting point, a systematic methodology for selecting the modelling approach is an urgent matter in the field [5]. The fit-for-purpose methodology developed by Gaetani et al. [32] is the only quantitative method proposed. Still, its demonstration is limited to office buildings, heating, and cooling demand estimation, and using virtual experiments instead of real case studies. Further, like any approach, its effectiveness is conditional to the validity of the specific models a practitioner chooses.

3.4. Choosing and adapting the OB model

Carlucci et al. [4] have made available a comprehensive database containing more than 300 OB models published in the literature. They cover OB aspects such as presence, window operation, lighting operation, thermostat adjustment, shading operation, appliance use, and clothing adjustment. Further, these aspects were developed from data for 17 countries, 14 climate zones based on the Köppen-Geiger classification, and various building uses (offices, commercial, residential, educational, hotels). Identifying the most suitable OB model and transferring it to a given deployment space requires analysing the motivation, drivers, and actions that characterise the OB, and the different dimensions of the deployment space (for a detailed definition refer to [78]); the evaluation and validation of OB models; procedures to transfer a model from the development space to the deployment space. On the one hand, the OB in buildings is influenced by environmental, time-related, contextual, psychological, physiological, social, and economic factors. On the other hand, OB models are mainly developed using environmental and time-related factors as predictive variables [13]. Accordingly, these models have hidden information and imprinted characteristics of the occupants that go beyond the predictive variables [20]. Therefore, the extrapolation from a development space to a deployment space must be carefully evaluated [14].

In the view of drivers and factors affecting OB, deep reviews have been conducted to understand the influential factors for different actions across different building types [13,81]. While definitive and general conclusions have not been reached yet, the results presented provide an idea of the differences that might exist between different contexts. For example, indoor and outdoor temperatures are the main drivers of window operation in both residential and office buildings. However, indoor air quality seems to be a relevant factor only for residential buildings. Additionally, while in office buildings arrival and departure times influence the frequency of the interactions with windows, in residential buildings this frequency is related to the different types of activities (e.g., cooking) [13,44]. Lighting and shading system uses are commonly studied simultaneously in office or commercial buildings [13]. This is because of their high correlation and their combined effect on visual comfort. The interactions of the occupants with these systems are mainly driven by time-related factors (e.g., arrival and departure events, absence duration) and visual, comfort-related factors (e.g., work plane illuminance and glare) [62]. Instead, turning off the lights is mainly driven by departure times rather than illuminance levels [82]. In residential buildings the research on shading systems use is limited. However, it is observed to be noticeably infrequent (e.g., once shadings are open, they remain in this state for long periods) and not only driven by time-related and environmental factors but sometimes also privacy issues. Further, lighting use is mainly driven by time-related factors, type of activities, and illuminance levels [20]. Furthermore, aspects related to the building orientation can have an impact on OB. For example, drivers and frequency of shading operation could be different whether shading systems are located in a north or south façade [64]. Concerning air-conditioning, thermostats, fans, and doors, the indoor and outdoor temperatures are the main factors influencing their operation [13]. Additionally, in office buildings, the spatial scale has a big impact on OB such as lighting, shading, and window operation. For instance, in single offices the occupant is more autonomous to decide what to do, whereas in open-space office floors these behaviours are constrained by social interactions [83]. Finally, diversity, preferences, and lifestyles of the occupants have a greater impact in residential buildings, where occupants usually have complete control on the building systems, rather than in office buildings, where OBs could be limited by the building design aspects (e.g., the impossibility to open windows) and centrally controlled systems (e.g., central HVAC units).

A second aspect to be considered when choosing a specific OB model is the model development and quality evaluation processes. Notably, Mahdavi and Tahmasebi [84] discussed several necessary conditions for a systematic assessment of the models: the model validation should be performed with a dataset different from the one used for model development; models from a single behavioural study should not be extrapolated to all deployment spaces; measures need to be taken to reduce bias in the evaluation process, i.e., not only an internal validation process should be performed but an external evaluation, double-blind studies, and round-robin tests as well [23,70,84]. In consequence, models with insufficient documentation or simple evaluation tests, and models developed using short monitoring periods or small sample sizes (e.g., one apartment) cannot be generalized and should be used with caution [23].

A third aspect to consider when using an OB model developed for a different context are the mechanisms for transferring the model. Again, studies undertaking this kind of procedures are limited. In general, models are developed and used in the same context, or they are selected without exhaustive criteria and further adaptations. However, an alternative is to obtain calibration data from the context of interest and use it for fitting probability curves of the models to obtain specific model coefficients [62,84,85]. Since existing data is not always available, the development of factors to transfer the models from one context to another would be beneficial to the design practice [86]. For example, in the residential sector, scaling factors have been proposed to adapt an occupancy model developed for the UK to the Canadian context [87]. To do so, the time occupants usually spend in different activities is compared to scale the models accordingly (e.g., from an aggregated point of view, in Canada people spend about 35 min less at home and awake than people in the UK). This methodology is only suitable assuming that both countries have a similar lifestyle [87].

3.5. Implementing the OB models into the BPS

Advanced OB models are not readily available in most of the commercial BPS tools [5]. Therefore, dedicated integration approaches are required. Hong et al. [5] thoroughly reviewed and classified those approaches in: (a) *direct input* where the user defines temporal schedules for thermostat settings, occupancy, lighting, plug loads, and the HVAC system. Here, the user precalculates the schedules, so there is no runtime communication between the pre-calculation module and the BPS software; (b) *built-in OB models* in which a dedicated OB module is already implemented within the BPS software. Yet, this type of modules is found in a reduced number of BPS programs [1] and the implemented OB models lack of conclusive evidence of their generalizability [84]; (c) *user functions* that allow the user to write custom functions or codes to incorporate or overwrite supervisory controls without the need for recompiling the BPS engine. Deterministic and stochastic OB models can be included using this methodology; (d) *co-simulation* allowing the use of different simulation tools to be integrated and run simultaneously in a coupled runtime routine. In this latter case, BPS tools specialised on different aspects can be combined to achieve a consistent analysis [5]. For example, an OB module written in Python can be used along with EnergyPlus under a two-way interaction between these components. As a result, dynamic stochastic OB models can be included in the estimation of building performance metrics [88,89]. Nevertheless, OB models have been integrated into BPS software (for a comprehensive list of key integration efforts refer to [5]). For example, Gunay et al. [90] implemented 20 OB models using Energy Management System (EMS) scripts in a user function approach for EnergyPlus. Since this approach lacks interoperability and exchangeability between OB models and BPS tools, the co-simulation approach has gained significant attention [91]. For instance, using Functional Mockup Units (FMU) different simulation tools can be compiled into units, which are then interconnected by the Functional Mockup Interface (FMI) using a combination of XML files, binaries, and C code zipped into a single file [92]. Hong et al. [93] developed the obXML and obFMU tools. The former standardizes the representation and exchange of OB models, while the latter is a software component module working as the engine to compute the OB models. Together they can be used for co-simulation with different BPS software equipped with FMI compatibility.

The previous paragraph discussed possibilities for the integration of OB models into the BPS simulation from a technical point of view. Equally important, the hierarchy of OB actions needs to be discussed. It refers to the priority each occupant action has among different options to fulfil the same occupant's need. For example, occupants could either decide to adjust their clothing or to change their thermostat setpoint to achieve thermal comfort. This hierarchy of actions needs to be defined to implement suitable logics within the simulation framework when considering multiple models. This concept becomes relevant when developing ABMs that integrate different behavioural actions, as well as when considering multiple models for representing different behaviours in a BPS study [74]. As highlighted by Stazi et al. [13], few studies have addressed this problem. Some observations indicate that this hierarchy is conditional to the context of the study so that general conclusions cannot be defined [94]. For instance, Langevin et al. [95] noticed that clothing adjustment is preferred in both naturally ventilated and air-conditioned buildings. However, in naturally ventilated buildings window operation is chosen over fan operation whereas in air-conditioned buildings this sequence is reversed. Moreover, Kwak et al. [96] analysed the impact of implementing window and AC operation models, as well as interchanging their order of execution, in the energy consumption of a residential building. As a result, the prediction of the energy consumption has a variation of 7.5%. Considering that different actions have a different impact on occupant comfort and energy consumption, taking into account the behavioural hierarchy and assessing its influence in the BPS simulations is essential [76].

3.6. Performing the simulation and post-processing results

The inclusion of advanced OB models makes it necessary to review and discuss technical issues such as methods for conducting the simulations, the number of runs required, and methods for analysing the results. From the practitioner perspective, the whole BPS process must minimise model preparation and computational requirements to be feasible within the building design practice [46].

Azar et al. [5] exhaustively reviewed studies applying OB modelling formalisms to inform design decisions. They stressed the reduced number of works on this topic despite advances in the modelling field as well as a general focus on providing a proof-of-concept rather than effectively applying the proposed methodologies in actual building design applications. They categorised the research in four main areas: (a) *proposed workflows* such as the fit-for-purpose strategy developed by Gaetani et al. [32] and the best practices book for selecting the most appropriate modelling approach by Gilani and ÓBrien [65] (covered in Section 3.3); (b) *parametric design* propositions where the impact of extreme occupant-related conditions are evaluated using the concept of personas [5], i.e., the building performance is evaluated by implementing schedules, densities, or OB models that represent a different type of occupants such as active and passive [97–99], or austerity, normal, and wasteful [100]; (c) *design optimization* studies [5] in which geometric design alternatives and spatial layouts are evaluated using advanced OB models along with optimization algorithms (e.g., genetic algorithms, ant colony algorithm). Remarkably, not only energy-related performance indicators are used as optimization objectives but also organizational and productivity metrics; (d) *probabilistic design* methods that exploit the use of advanced OB modelling approaches and minimise the variance of non-deterministic outputs. In other words, this methodology aims to support designs that are robust to the impact of OB [5].

Another key point emerges when using stochastic OB models in BPS. Contrary to deterministic studies, a stochastic simulation will calculate a different output each time it is run [65]. Therefore, a criterion must be established for determining the minimum number of simulations required. Researchers often choose the number of simulations based on other references or perform simulations until certain convergence criteria are fulfilled. Different recommendations can be found varying from 10 to 100 simulations [23,32,56,62,64,101]. A common approach for defining the number of simulations is to calculate the mean value and variance of the performance indicators while the number of simulations increases. When the change in those parameters is small, the simulation process can be stopped [102]. Graphically, the cumulative mean of the outputs is plotted, and the simulation process stopped when the curve becomes flat without an upward or downward trend. Quantitatively, the percentage variation of the cumulative outputś mean and variance is calculated and when it is smaller than a threshold (i.e., a tolerance) the simulation process is stopped [61].

Finally, BPS tools do not post-process the aggregate results from multiple simulation neither visually nor quantitatively. This means the practitioner will be left with a set of results for each design configuration multiplied by the number of design alternatives or scenarios studied. For the latter, the postprocessing and visualization process needs to be performed manually [46]. As a result, researchers follow different strategies for analysing and communicating the results, such as: a) box plots of the outputs [32]; b) fitting the outputs to probability distribution functions such as the normal distribution and reporting the output mean value and a confidence interval at a defined significance level [64]; c) data mining of stochastic BPS, which has recently emerged as an alternative for analysing simultaneously all the simulation results to identify the influential aspects of the BPS model. Here, correlation matrices, Pearson correlation coefficients, and Principal Component Analysis (PCA) can be exploited to understand the role of each model parameter in the estimation of the performance indicators [53].

4. Discussion

This article critically reviewed the efforts aiming at transferring the knowledge developed within the OB research field to the simulation-aided building design process. While involuntary exclusion of relevant articles can be a limitation of this work, the PRISMA methodology was followed to minimise this risk. In line with the research questions in Section 1.3, this review covers findings related to the building design process. Building operation and control were considered out of scope.

One of the most important points addressed by this review is why advanced OB models should be included into BPS (see Section 3.1). The advantages and potential of using advanced OB models over standard representations such as fixed, periodic schedules go beyond having an exact description of the OB. This is especially important since, as stressed in Section 3.4, OB is influenced not only by environmental and time-related factors but economic, socio-cultural, psychological, and physiological ones as well. Thus, developing generalized models entirely replacing standard schedules will be virtually impossible. Instead, the use of OB models gives the practitioner the possibility of a) understanding how the diversity of the occupants influences the building performance and b) predicting the probability distribution of PIs, i.e., the likelihood of a PI falling within a certain range. Second, dynamic OB models allow considering the two-way interaction between the occupants and the building and its systems. While the occupants affect the building performance passively (e.g., through OPA-related heat gains) and actively (e.g., adjusting the thermostat), the building design can influence the OB (e.g., the location and size of the windows could encourage occupants to adopt natural over mechanical ventilation modes). Including this interaction gives the designer the possibility to design a building that promotes energy-efficient behaviours and is more robust to the impact of the OPA. Accounting for the occupant-related uncertainty allows the designer to make better-informed decisions, e.g., avoiding overestimation of energy savings from ECMs.

It was also highlighted that it is not always necessary to use advanced OB models (See Section 3.3). Each case has specific requirements in terms of OB and energy model complexity and accuracy depending on the deployment space (i.e., climate, location, building type, use, and systems, occupant characteristics, spatial and temporal scale). As a result, identifying the OB aspects that significantly impact the PIs needs to be an integral part of the BPS process. To this end, a fit-for-purpose strategy is required so that the most adequate level of complexity can be imposed for each of them. General methodologies using a screening method are recommended, so that subsequent analysis focuses only on a small set of parameters reducing computational cost without compromising reliability. Furthermore, since OB models are not always the answer, standard schedules should be reviewed and updated to improve the OB representation. Similarly, proposing a variety of standard schedules that represent different OB scenarios tailored to different building life cycle stages and simulation purposes can be beneficial for the practitioner to better assess the building performance.

Further, the literature has shown preliminary observations regarding which modelling approaches should be used or avoided for the different dimensions of the deployment space. Regarding occupancy (i.e., presence) and non-adaptive behaviours (e.g., use of appliances) static models are recommended, while for adaptive behaviours the approach could be static or dynamic. The latter is especially recommended if different design alternatives are explored or if the PIs are related to occupant comfort. In these cases, the two-way interaction between the occupants and the building becomes highly relevant. Further, at large spatial scales (e.g., whole high-rise building) or when considering aggregated PIs (e.g., annual energy use), averaging effects are responsible for a reduced impact of the occupant diversity compared to small spatial scales (e.g., room level) or disaggregated PIs (e.g., peak load). Consequently, while in the first scenario low complexity models can be used, in the second one higher complexity is recommended. Further research is yet required to define systematic and fit-for-purpose guidelines for selecting the most suitable modelling approach.

This critical review also identifies two main points that required attention for promoting the use of OB models. On the one hand, it is urgent to define systematic guidelines for evaluating and documenting the models including not only an internal but also an external and double-blind process; conduct systematic monitoring campaigns to compare the differences in OB in different contexts; perform comparative studies to assess the generalizability and applicability of the models. These efforts will potentially help to define coefficients for transferring the models from one context to another, hence enhancing the generalizability of OB models. On the other hand, understanding and defining behavioural hierarchies are required to specify which logic should be used to execute multiple OB models.

Regarding the automation of the BPS process, this is an important aspect to be considered in each of the steps so that practitionerś time and effort is minimised. For example, a pre-processing engine can generate a set of synthetic schedules identifying diverse scenarios depending on the application (e.g., equipment sizing, robust design), possibly along with an estimated

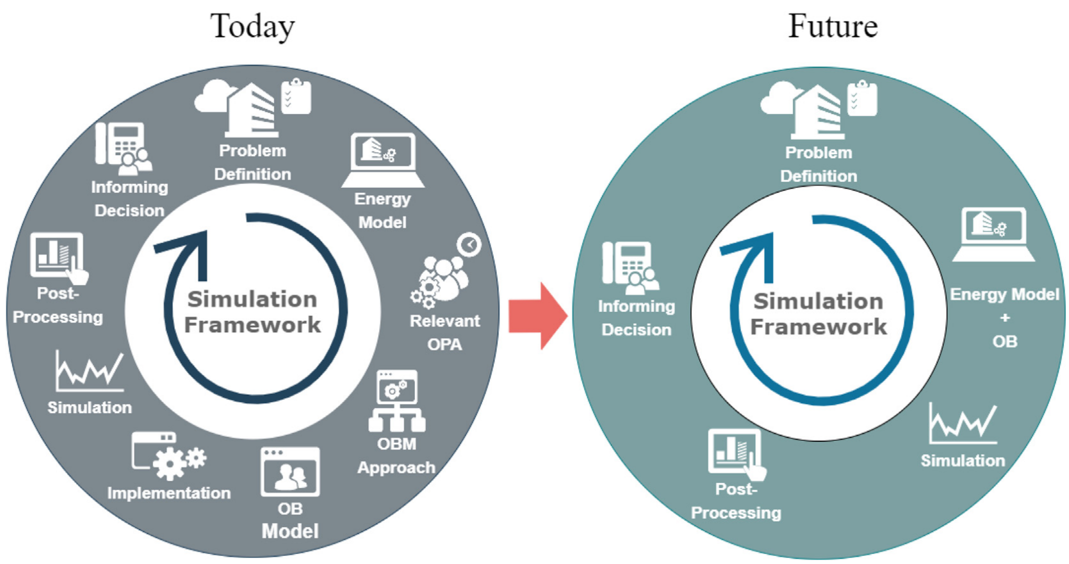


Fig. 5. Simulation framework.

probability measure on how often a scenario is expected to occur. This would allow designers giving appropriate weight to extreme OBs with a high potential impact on PIs but happening rarely. Then, the user could decide which subset of scenarios is worth investigating further. For stochastic OB models, a default tolerance threshold can be defined together with a maximum number of runs. The simulation would stop when one of these criteria is met. Finally, the outputs can be automatically visualized, and representative statistics computed.

Finally, the reviewed articles show the possibility of exploiting the potential of advanced OB models by performing parametric studies, design optimization, and probabilistic design. Yet, few studies have demonstrated these strategies using OB models. Further, the stochastic nature of the models introduces a level of difficulty that can be overcome by automating processes (e.g., running the simulations, calculating convergence parameters) and by applying statistical and data-mining techniques for analysing the outputs to, in the end, inform the design decision.

All in all, with the knowledge and tools available today, the integration of OB modelling into simulation-building design practice is a complex process, almost completely manual, without proper guidance. As shown in Fig. 5 (left – Today simulation framework), on top of the traditional steps problem definition, development of the energy model and informing the decision of a BPS study, the user needs to identify relevant OPA, choose the OB modelling approaches, choose an OB model, and implement the model. Furthermore, performing the simulation and post-processing the results gain additional complexity due to the stochastic nature of OB models and increased numbers of simulations required. This paper presented solutions towards guiding and simplifying this process but more importantly, highlighted the challenges that need to be addressed for answering to the BPS user needs and fully integrating the OB models into a BPS framework as in Fig. 5 (Right – Future simulation framework).

5. Conclusions

Among other endeavours, the research community is aiming at improving the representation of the energy-related OB and, at the same time, better accounting for the occupant-related uncertainty for bridging the energy performance gap. However, as illustrated in Section 2.3, several barriers are preventing the use of advanced OB modelling approaches in the simulation-aided building design field. To this aim, a simulation framework was proposed to establish a clear path for integrating the OB model in the building design practice. The literature on this topic was critically analysed for synthesising the practical solutions developed in each step.

First, it was highlighted the added value of better representing the stochastic and dynamic nature of the OB through advanced modelling approaches. Across the different building design stages, advanced OB models contribute to desired building performance, sizing building systems, estimating payback periods, and informing investment decisions. Ultimately, it will be possible to achieve the targets imposed by the different policies for mitigating environmental problems by improving the building robustness and resilience. Second, the strategies and solutions for identifying the most influential OB aspects, the most suitable modelling approach, and the most adequate model were reviewed. It is stressed that these steps are case specific and thus require a fit-for-purpose strategy fully integrated within the simulation framework. To reach this point, it is urgent to define the scalability and applicability OB models to different contexts. In parallel, simulation software needs to evolve for automatically integrating the OB models, performing multiple simulations resulting from the application of stochastic models, and post-processing the aggregated results. This will reduce the time and effort a user needs to invest for performing the BPS.

In summary, the findings of this work aim to serve as guidelines for researchers and practitioners pursuing the integration of OB models in the building design process and performance evaluation. Likewise, our study presented the most urgent matters that need to be addressed for encouraging the application of OB models in building design processes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] T. Hong, Y. Chen, Z. Belafi, S. D'Oca, Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs, Build Simul 11 (1) (2018) 1–14, https://doi.org/10.1007/s12273-017-0396-6.
[2] X. Shi, B. Si, J. Zhao, Z. Tian, C. Wang, X. Jin, X. Zhou, Magnitude, causes, and solutions of the performance gap of buildings: A review, Sustain 11 (3) (2019) 937, https://doi.org/10.3390/su11030937.
[3] S. D'Oca, H.B. Gunay, S. Gilani, W. O'Brien, Critical review and illustrative examples of office occupant modelling formalisms, Build Serv Eng Res Technol 40 (6) (2019) 732–757, https://doi.org/10.1177/0143624419827468.
[4] S. Carlucci, M. De Simone, S.K. Firth, M.B. Kjærgaard, R. Markovic, M.S. Rahaman, M.K. Annaqeeb, S. Biandrate, A. Das, J.W. Dziedzic, G. Fajilla, M. Favero, M. Ferrando, J. Hahn, M. Han, Y. Peng, F. Salim, A. Schlüter, C. van Treeck, Modeling occupant behavior in buildings, Build Environ 174 (2020) 106768, https://doi.org/10.1016/j.buildenv.2020.106768.
[5] E. Azar, W. O'Brien, S. Carlucci, T. Hong, A. Sonta, J. Kim, M.S. Andargie, T. Abuimara, M. El Asmar, R.K. Jain, M.M. Ouf, F. Tahmasebi, J. Zhou, Simulation-aided occupant-centric building design: A critical review of tools, methods, and applications, Energy Build 224 (2020) 110292, https://doi.org/10.1016/j.enbuild.2020.110292.
[6] D.a. Yan, T. Hong, B. Dong, A. Mahdavi, S. D'Oca, I. Gaetani, X. Feng, IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings, Energy Build 156 (2017) 258–270, https://doi.org/10.1016/j.enbuild.2017.09.084.
[7] Wagner A, O'Brien L. Occupant behaviour-centric building design and operation EBC Annex 79 October 2018 , updated after approval by IEA EBC Prepared by: 2018:2008–13.
[8] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy Build 121 (2016) 188–204, https://doi.org/10.1016/j.enbuild.2016.03.038.
[9] W. O'Brien, I. Gaetani, S. Gilani, S. Carlucci, P.-J. Hoes, J. Hensen, International survey on current occupant modelling approaches in building performance simulation†, J Build Perform Simul 10 (5-6) (2017) 653–671, https://doi.org/10.1080/19401493.2016.1243731.
[10] Mahdavi A, Berger C, Amin H, Ampatzi E, Andersen RK, Azar E, et al. The role of occupants in buildings' energy performance gap: Myth or reality? vol. 13. 2021. Doi: 10.3390/su13063146.
[11] T. Harputlugil, P. de Wilde, The interaction between humans and buildings for energy efficiency: A critical review, Energy Res Soc Sci 71 (2021) 101828, https://doi.org/10.1016/j.erss.2020.101828.
[12] E. Delzendeh, S. Wu, A. Lee, Y. Zhou, The impact of occupants' behaviours on building energy analysis: A research review, Renew Sustain Energy Rev 80 (2017) 1061–1071, https://doi.org/10.1016/j.rser.2017.05.264.
[13] F. Stazi, F. Naspi, M. D'Orazio, A literature review on driving factors and contextual events influencing occupants' behaviours in buildings, Build Environ 118 (2017) 40–66, https://doi.org/10.1016/j.buildenv.2017.03.021.
[14] B. Dong, D.a. Yan, Z. Li, Y. Jin, X. Feng, H. Fontenot, Modeling occupancy and behavior for better building design and operation—A critical review, Build Simul 11 (5) (2018) 899–921, https://doi.org/10.1007/s12273-018-0452-x.
[15] M. Jia, R.S. Srinivasan, A.A. Raheem, From occupancy to occupant behavior: An analytical survey of data acquisition technologies, modeling methodologies and simulation coupling mechanisms for building energy efficiency, Renew Sustain Energy Rev 68 (2017) 525–540, https://doi.org/10.1016/j.rser.2016.10.011.
[16] Y. Zhang, X. Bai, F.P. Mills, J.C.V. Pezzey, Rethinking the role of occupant behavior in building energy performance: A review, Energy Build 172 (2018) 279–294, https://doi.org/10.1016/j.enbuild.2018.05.017.
[17] T. Hong, S.C. Taylor-Lange, S. D'Oca, Y.D. Da, S.P. Corgnati, Advances in research and applications of energy-related occupant behavior in buildings, Energy Build 116 (2016) 694–702, https://doi.org/10.1016/j.enbuild.2015.11.052.
[18] M.N. Uddin, H.-H. Wei, H.L. Chi, M. Ni, Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach, Buildings 11 (2021) 41, https://doi.org/10.3390/buildings11020041.
[19] M. Osman, M. Ouf, A comprehensive review of time use surveys in modelling occupant presence and behavior: Data, methods, and applications, Build Environ 196 (2021) 107785, https://doi.org/10.1016/j.buildenv.2021.107785.
[20] B.F. Balvedi, E. Ghisi, R. Lamberts, A review of occupant behaviour in residential buildings, Energy Build 174 (2018) 495–505, https://doi.org/10.1016/j.enbuild.2018.06.049.
[21] G. Happle, J.A. Fonseca, A. Schlueter, A review on occupant behavior in urban building energy models, Energy Build 174 (2018) 276–292, https://doi.org/10.1016/j.enbuild.2018.06.030.
[22] B. Dong, Y. Liu, H. Fontenot, M. Ouf, M. Osman, A. Chong, S. Qin, F. Salim, H. Xue, D.a. Yan, Y. Jin, M. Han, X. Zhang, E. Azar, S. Carlucci, Occupant behavior modeling methods for resilient building design, operation and policy at urban scale: A review, Appl Energy 293 (2021) 116856, https://doi.org/10.1016/j.apenergy.2021.116856.
[23] Jun Li, Zhun (Jerry) Yu, Fariborz Haghighat, Guoqiang Zhang, Development and improvement of occupant behavior models towards realistic building performance simulation: A review, Sustain Cities Soc 50 (2019) 101685, https://doi.org/10.1016/j.scs.2019.101685.
[24] K. Becker, J.R. Parker, A simulation primer, Digit. Simulations Improv. Educ. Learn. Through Artif. Teach. Environ., IGI Global (2009) 1–24, https://doi.org/10.4018/978-1-60566-322-7.ch001.
[25] D. Denyer, D. Tranfield, Producing a Systematic Review, SAGE Handb. Organ Res. Methods (2009) 671–689.
[26] T. Abuimara, W. O'Brien, B. Gunay, J.S. Carrizo, Towards occupant-centric simulation-aided building design: a case study, Build Res. Inf. 47 (8) (2019) 866–882, https://doi.org/10.1080/09613218.2019.1652550.
[27] S. Alsaadani, C. Bleil De Souza, Architect–BPS consultant collaborations: Harmony or hardship?, J Build. Perform. Simul. 11 (4) (2018) 391–413, https://doi.org/10.1080/19401493.2017.1379092.
[28] Hong T, Langevin J, Sun K. Building simulation: Ten challenges. Build Simul 2018;11:871–98. Doi: 10.1007/s12273-018-0444-x.
[29] Warren P. Bringing Simulation to Application; 2002. Isbn: 0954267028;
[30] K. Negendahl, Building performance simulation in the early design stage: An introduction to integrated dynamic models, Autom Constr 54 (2015) 39–53, https://doi.org/10.1016/j.autcon.2015.03.002.
[31] R.C.G.M. Loonen, M.L. de Klijn-Chevalerias, J.L.M. Hensen, Opportunities and pitfalls of using building performance simulation in explorative R&D contexts, J Build Perform Simul 12 (3) (2019) 272–288, https://doi.org/10.1080/19401493.2018.1561754.
[32] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, A stepwise approach for assessing the appropriate occupant behaviour modelling in building performance simulation, J Build Perform Simul 13 (3) (2020) 362–377, https://doi.org/10.1080/19401493.2020.1734660.
[33] S. D'Oca, T. Hong, J. Langevin, The human dimensions of energy use in buildings: A review, Renew Sustain Energy Rev 81 (2018) 731–742, https://doi.org/10.1016/j.rser.2017.08.019.
[34] Rafsanjani HN, Ahn CR, Alahmad M. A review of approaches for sensing, understanding, and improving occupancy-related energy-use behaviors in commercial buildings. vol. 8. 2015. Doi: 10.3390/en81010996.
[35] M.B. Kjærgaard, F.C. Sangogboye, Categorization framework and survey of occupancy sensing systems, Pervasive Mob Comput 38 (2017) 1–13, https://doi.org/10.1016/j.pmcj.2016.09.019.
[36] S. Gilani, W. O'Brien, Review of current methods, opportunities, and challenges for in-situ monitoring to support occupant modelling in office spaces, J Build Perform Simul 10 (5-6) (2017) 444–470, https://doi.org/10.1080/19401493.2016.1255258.
[37] Z. Deme Belafi, T. Hong, A. Reith, A critical review on questionnaire surveys in the field of energy-related occupant behaviour, Energy Effic 11 (8) (2018) 2157–2177, https://doi.org/10.1007/s12053-018-9711-z.
[38] C. Carpino, D. Mora, M. De Simone, On the use of questionnaire in residential buildings. A review of collected data, methodologies and objectives, Energy Build 186 (2019) 297–318, https://doi.org/10.1016/j.enbuild.2018.12.021.
[39] Y. Zhu, S. Saeidi, T. Rizzuto, A. Roetzel, R. Kooima, Potential and challenges of immersive virtual environments for occupant energy behavior modeling and validation: A literature review, J Build Eng 19 (2018) 302–319, https://doi.org/10.1016/j.jobe.2018.05.017.
[40] T. Hong, S. D'Oca, W.J.N. Turner, S.C. Taylor-Lange, An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework, Build Environ 92 (2015) 764–777, https://doi.org/10.1016/j.buildenv.2015.02.019.
[41] H.C. Putra, T. Hong, C. Andrews, An ontology to represent synthetic building occupant characteristics and behavior, Autom Constr 125 (2021) 103621, https://doi.org/10.1016/j.autcon.2021.103621.
[42] Y. He, W. Chen, Z. Wang, H. Zhang, Review of fan-use rates in field studies and their effects on thermal comfort, energy conservation, and human productivity, Energy Build 194 (2019) 140–162, https://doi.org/10.1016/j.enbuild.2019.04.015.
[43] V. Fabi, R. Andersen, S. Corgnati, Accounting for the Uncertainty Related to Building Occupants with Regards to Visual Comfort: A Literature Survey on Drivers and Models, Buildings 6 (2016) 5, https://doi.org/10.3390/buildings6010005.
[44] X. Dai, J. Liu, X. Zhang, A review of studies applying machine learning models to predict occupancy and window-opening behaviours in smart buildings, Energy Build 223 (2020) 110159, https://doi.org/10.1016/j.enbuild.2020.110159.
[45] S. Chen, G. Zhang, X. Xia, S. Setunge, L. Shi, A review of internal and external influencing factors on energy efficiency design of buildings, Energy Build 216 (2020) 109944, https://doi.org/10.1016/j.enbuild.2020.109944.
[46] M.M. Ouf, W. O'Brien, H.B. Gunay, Improving occupant-related features in building performance simulation tools, Build Simul 11 (4) (2018) 803–817, https://doi.org/10.1007/s12273-018-0443-y.

[47] W. O'Brien, F. Tahmasebi, R.K. Andersen, E. Azar, V. Barthelmes, Z.D. Belafi, C. Berger, D. Chen, M. De Simone, Simona d'Oca, T. Hong, Q. Jin, D. Khovalyg, R. Lamberts, V. Novakovic, J.Y. Park, M. Plagmann, V.S. Rajus, M. Vellei, S. Verbruggen, A. Wagner, E. Willems, D.a. Yan, J. Zhou, An international review of occupant-related aspects of building energy codes and standards, Build Environ 179 (2020) 106906, https://doi.org/10.1016/j.buildenv.2020.106906.
[48] J.Y. Park, M.M. Ouf, B. Gunay, Y. Peng, W. O'Brien, M.B. Kjærgaard, Z. Nagy, A critical review of field implementations of occupant-centric building controls, Build Environ 165 (2019) 106351, https://doi.org/10.1016/j.buildenv.2019.106351.
[49] O. Guerra-Santin, H. Bosch, P. Budde, T. Konstantinou, S. Boess, T. Klein, S. Silvester, Considering user profiles and occupants' behaviour on a zero energy renovation strategy for multi-family housing in the Netherlands, Energy Effic 11 (7) (2018) 1847–1870, https://doi.org/10.1007/s12053-018-9626-8.
[50] M. Ouf, W. O'Brien, H.B.B. Gunay, Optimizing building performance using stochastic occupant models, ASHRAE Trans. 125 (2019) 96–105.
[51] M. Marschall, F. Tahmasebi, J. Burry, Including occupant behavior in building simulation: Comparison of a deterministic vs. a stochastic approach, Simul. Ser. 51 (2019) 185–188.
[52] Marschall M, Burry J. Can the use of stochastic models of occupants' environmental control behavior influence architectural design outcomes? Intell. Inf. - Proc. 24th Int. Conf. Comput. Archit. Des. Res. Asia, CAADRIA 2019, vol. 1, 2019, p. 715–24.
[53] Q. Darakdjian, S. Billé, C. Inard, Data mining of building performance simulations comprising occupant behaviour modelling, Adv Build Energy Res 13 (2) (2019) 157–173, https://doi.org/10.1080/17512549.2017.1421099.
[54] M. Qian, D.a. Yan, J. An, T. Hong, J.D. Spitler, Evaluation of thermal imbalance of ground source heat pump systems in residential buildings in China, Build Simul 13 (3) (2020) 585–598, https://doi.org/10.1007/s12273-020-0606-5.
[55] W. O'Brien, A. Abdelalim, H.B. Gunay, Development of an office tenant electricity use model and its application for right-sizing HVAC equipment, J Build Perform Simul 12 (1) (2019) 37–55, https://doi.org/10.1080/19401493.2018.1463394.
[56] Yao J. IDENTIFYING OCCUPANTS' APPROPRIATE SEATING POSITION AND VIEW DIRECTION IN OFFICE BUILDINGS: A STOCHASTIC SHADE CONTROL BASED MULTIOBJECTIVE VISUAL COMFORT OPTIMIZATION. J Green Build 2020;15:15–36. Doi: 10.3992/1943-4618.15.1.15.
[57] T. Picard, T. Hong, N.a. Luo, S.H. Lee, K. Sun, Robustness of energy performance of Zero-Net-Energy (ZNE) homes, Energy Build 224 (2020) 110251, https://doi.org/10.1016/j.enbuild.2020.110251.
[58] J. Rouleau, L. Gosselin, P. Blanchet, Robustness of energy consumption and comfort in high-performance residential building with respect to occupant behavior, Energy 188 (2019) 115978, https://doi.org/10.1016/j.energy.2019.115978.
[59] S. Gilani, W. O'Brien, H.B. Gunay, J.S. Carrizo, W. O'Brien, Use of dynamic occupant behavior models in the building design and code compliance processes, Energy Build 117 (2016) 260–271, https://doi.org/10.1016/j.enbuild.2015.10.044.
[60] F. Ascione, N. Bianco, R.F. De Masi, M. Mastellone, G.M. Mauro, G.P. Vanoli, The role of the occupant behavior in affecting the feasibility of energy refurbishment of residential buildings: Typical effective retrofits compromised by typical wrong habits, Energy Build 223 (2020) 110217, https://doi.org/10.1016/j.enbuild.2020.110217.
[61] J. Yao, Building cooling energy uncertainty and life cycle economic performance: A stochastic air conditioning behavior model based comparative analysis, J Clean Prod 266 (2020) 121910, https://doi.org/10.1016/j.jclepro.2020.121910.
[62] Y. Ding, X. Ma, S. Wei, W. Chen, A prediction model coupling occupant lighting and shading behaviors in private offices, Energy Build 216 (2020) 109939, https://doi.org/10.1016/j.enbuild.2020.109939.
[63] L.O.O. Neves, A.P.P. Hopes, W.J.J. Chung, S. Natarajan, "Mind reading" building operation behaviour, Energy Sustain Dev 56 (2020) 1–18, https://doi.org/10.1016/j.esd.2020.02.003.
[64] J. Yao, R. Zheng, Uncertainty of Energy and Economic Performance of Manual Solar Shades in Hot Summer and Cold Winter Regions of China, Sustainability 11 (2019) 5711, https://doi.org/10.3390/su11205711.
[65] S. Gilani, W.O. Brien, Best Practices Guidebook on Advanced Occupant Modelling, Human Building Interaction Lab, Carleton University, Ottawa, Canada, 2018.
[66] Z. Pang, Z. O'Neill, Y. Li, F. Niu, The role of sensitivity analysis in the building performance analysis: A critical review, Energy Build 209 (2020) 109659, https://doi.org/10.1016/j.enbuild.2019.109659.
[67] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy Build 43 (10) (2011) 2798–2805, https://doi.org/10.1016/j.enbuild.2011.06.034.
[68] Zhang C, Jia Q-SS. A review of occupant behavior models in residential building: Sensing, modeling, and prediction. Proc. 28th Chinese Control Decis. Conf. CCDC 2016, IEEE; 2016, p. 2032–7. Doi: 10.1109/CCDC.2016.7531318.
[69] V. Fabi, R.V. Andersen, S. Corgnati, B.W. Olesen, Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models, Build Environ 58 (2012) 188–198, https://doi.org/10.1016/j.buildenv.2012.07.009.
[70] H.B.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices, Build Environ 70 (2013) 31–47, https://doi.org/10.1016/j.buildenv.2013.07.020.
[71] Abdallah M, Clevenger C, Golparvar-Fard M. Developing a Thermal Comfort Report Card for Building. In: Chong, WO and Chang, J and Parrish, K and Berardi, U, editor. Procedia Eng., vol. 118, 2015, p. 675–82. Doi: 10.1016/j.proeng.2015.08.502.
[72] J. Langevin, J. Wen, P.L. Gurian, Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors, Build Environ 88 (2015) 27–45, https://doi.org/10.1016/j.buildenv.2014.11.037.
[73] F. Haldi, D. Robinson, The impact of occupants' behaviour on building energy demand, J Build Perform Simul 4 (4) (2011) 323–338, https://doi.org/10.1080/19401493.2011.558213.
[74] D.a. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and future challenges, Energy Build 107 (2015) 264–278, https://doi.org/10.1016/j.enbuild.2015.08.032.
[75] C.J. Andrews, D. Yi, U. Krogmann, J.A. Senick, R.E. Wener, Designing buildings for real occupants: An agent-based approach, IEEE Trans Syst Man, Cybern Part ASystems Humans 41 (6) (2011) 1077–1091, https://doi.org/10.1109/TSMCA.2011.2116116.
[76] Y.S. Lee, A.M. Malkawi, Simulating multiple occupant behaviors in buildings: An agent-based modeling approach, Energy Build 69 (2014) 407–416, https://doi.org/10.1016/j.enbuild.2013.11.020.
[77] C. Berger, A. Mahdavi, Review of current trends in agent-based modeling of building occupants for energy and indoor-environmental performance analysis, Build Environ 173 (2020) 106726, https://doi.org/10.1016/j.buildenv.2020.106726.
[78] A. Mahdavi, F. Tahmasebi, The deployment-dependence of occupancy-related models in building performance simulation, Energy Build 117 (2016) 313–320, https://doi.org/10.1016/j.enbuild.2015.09.065.
[79] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, On the sensitivity to different aspects of occupant behaviour for selecting the appropriate modelling complexity in building performance predictions, J Build Perform Simul 10 (5-6) (2017) 601–611, https://doi.org/10.1080/19401493.2016.1260159.
[80] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, Estimating the influence of occupant behavior on building heating and cooling energy in one simulation run, Appl Energy 223 (2018) 159–171, https://doi.org/10.1016/j.apenergy.2018.03.108.
[81] Schweiker M, Carlucci S, Andersen RK, Dong B, O'Brien W. Occupancy and Occupants' Actions. Explor. Occupant Behav. Build., Cham: Springer International Publishing; 2018, p. 7–38. Doi: 10.1007/978-3-319-61464-9_2.
[82] P. Correia da Silva, V. Leal, M. Andersen, Occupants' behaviour in energy simulation tools: lessons from a field monitoring campaign regarding lighting and shading control, J Build Perform Simul 8 (5) (2015) 338–358, https://doi.org/10.1080/19401493.2014.953583.
[83] Y.D. Da, X. Feng, Y. Jin, C. Wang, The evaluation of stochastic occupant behavior models from an application-oriented perspective: Using the lighting behavior model as a case study, Energy Build 176 (2018) 151–162, https://doi.org/10.1016/j.enbuild.2018.07.037.
[84] A. Mahdavi, F. Tahmasebi, On the quality evaluation of behavioural models for building performance applications, J Build Perform Simul 10 (5-6) (2017) 554–564, https://doi.org/10.1080/19401493.2016.1230148.
[85] P. Zhu, M. Gilbride, D.a. Yan, H. Sun, C. Meek, Lighting energy consumption in ultra-low energy buildings: Using a simulation and measurement methodology to model occupant behavior and lighting controls, Build Simul 10 (6) (2017) 799–810, https://doi.org/10.1007/s12273-017-0408-6.
[86] M. Schweiker, F. Haldi, M. Shukuya, D. Robinson, Verification of stochastic models of window opening behaviour for residential buildings, J Build Perform Simul 5 (1) (2012) 55–74, https://doi.org/10.1080/19401493.2011.567422.
[87] J. Rouleau, A.P. Ramallo-González, L. Gosselin, P. Blanchet, S. Natarajan, A unified probabilistic model for predicting occupancy, domestic hot water use and electricity use in residential buildings, Energy Build 202 (2019) 109375, https://doi.org/10.1016/j.enbuild.2019.109375.
[88] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings, ENERGY Build 87 (2015) 348–359, https://doi.org/10.1016/j.enbuild.2014.11.067.
[89] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy Build 117 (2016) 272–281, https://doi.org/10.1016/j.enbuild.2015.10.033.
[90] H.B.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, W.O. Brien, I. Beausoleil-Morrison, H.B.B. Gunay, et al., Implementation and comparison of existing occupant behaviour models in EnergyPlus, J Build Perform Simul 9 (2016) 567–588, https://doi.org/10.1080/19401493.2015.1102969.
[91] A.J.M. Lindner, S. Park, M. Mitterhofer, Determination of requirements on occupant behavior models for the use in building performance simulations, Build Simul 10 (6) (2017) 861–874, https://doi.org/10.1007/s12273-017-0394-8.
[92] Blockwitz T, Otter M, Akesson J, Arnold M, Clauss C, Elmqvist H, et al. Functional Mockup Interface 2.0: The Standard for Tool independent Exchange of Simulation Models. Proc 9th Int Model Conf Sept 3-5, 2012, Munich, Ger 2012;76:173–84. Doi: 10.3384/ecp12076173.
[93] T. Hong, S. D'Oca, S.C. Taylor-Lange, W.J.N. Turner, Y. Chen, S.P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema, Build. Environ. 94 (2015) 196–205, https://doi.org/10.1016/j.buildenv.2015.08.006.
[94] Hom Bahadur Rijal, Paul Tuohy, Michael Alexander Humphreys, James Fergus Nicol, Aizaz Samuel, Considering the impact of situation-specific motivations and constraints in the design of naturally ventilated and hybrid buildings,

Archit. Sci. Rev. 55 (1) (2012) 35–48, https://doi.org/10.1080/00038628.2011.641734.
[95] J. Langevin, P.L. Gurian, J. Wen, Tracking the human-building interaction: A longitudinal field study of occupant behavior in air-conditioned offices, J. Environ. Psychol. 42 (2015) 94–115, https://doi.org/10.1016/j.jenvp.2015.01.007.
[96] S.H. Mun, Y. Kwak, J.H. Huh, Influence of complex occupant behavior models on cooling energy usage analysis, Sustain 13 (2021) 1–20, https://doi.org/10.3390/su13031243.
[97] S.T. Moghadam, F. Soncini, V. Fabi, S. Corgnati, Simulating Window Behaviour of Passive and Active Users, Energy Procedia 78 (2015) 621–626, https://doi.org/10.1016/j.egypro.2015.11.040.
[98] Wout Parys, Dirk Saelens, Hugo Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices – a review-based integrated methodology, J Build Perform Simul 4 (4) (2011) 339–358, https://doi.org/10.1080/19401493.2010.524711.
[99] W Belazi, S-E Ouldboukhitine, A Chateauneuf, A Bouchair, Experimental and numerical study to evaluate the effect of thermostat settings on building energetic demands during the heating and transition seasons, Appl Therm Eng 152 (2019) 35–51, https://doi.org/10.1016/j.applthermaleng.2019.02.020.
[100] K. Sun, T. Hong, A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures, Energy Build 146 (2017) 383–396, https://doi.org/10.1016/j.enbuild.2017.04.065.
[101] Fabi V, Buso T, Andersen RK, Corgnati SP, Olesen BW. Robustness of building design with respect to energy related occupant behaviour. Proc. BS 2013 13th Conf. Int. Build. Perform. Simul. Assoc., Chambery: 2013, p. 1999–2006.
[102] Geun Young Yun, Paul Tuohy, Koen Steemers, Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models, Energy Build 41 (5) (2009) 489–499, https://doi.org/10.1016/j.enbuild.2008.11.013.