Building Technologies & Urban Systems Division
Energy Technologies Area
Lawrence Berkeley National Laboratory

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Energy Technologies Area
October 2020

DOI: 10.1016/j.enbuild.2020.110292

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Abstract

Occupants are active participants in their built environment, affecting its performance while simultaneously being affected by its design and indoor environmental conditions. With recent advances in computer modeling, simulation tools, and analysis techniques, topics such as human-building interactions and occupant behavior have gained significant interest in the literature given their premise of improving building design processes and operating strategies. In practice, the focus of occupant-centric literature has been mostly geared towards the latter (i.e., operation), leaving the implications on building design practices underexplored. This paper fills the gap by providing a critical review of existing studies applying computer-based modeling and simulation to guide occupant-centric building design. The reviewed papers are organized along four main themes, namely occupant-centric: (i) metrics of building performance, (ii) modeling and simulation approaches, (iii) design methods and applications, and (iv) supporting practices and mechanisms. Important barriers are identified for a more effective application of occupant-centric building design practices including the limited consideration of metrics beyond energy efficiency (e.g., occupant well-being and space planning), the limited implementation and validation of the proposed methods, and the lack of integration of occupant behavior modeling in existing building performance simulation tools. Future research directions include the need for large-scale international data collection efforts to move from generic assumptions about occupant behavior to specific/localized knowledge, the need for improved metrics of measuring building performance, as well as the need for industry practices, such as building codes, to promote an occupant-in-the-loop approach to the building design process.

Keywords: building design; occupant-centric; building performance simulation; occupant behavior; human-building interaction; performance metrics.

1. Introduction

1.1. Background

Beyond their energy, economic, and environmental footprints, buildings also have a significant impact on their occupants, as people are estimated to spend 87% of their time in enclosed buildings [1]. Numerous research efforts confirm the significant impact of indoor environmental conditions on the comfort, well-being, health, and productivity of occupants. Commonly-studied indoor environmental metrics include temperature, humidity, lighting, noise, and air quality levels [2–6].

In parallel to the effects of building conditions on occupants, occupants, in turn, exhibit a significant influence on building performance. As highlighted by de Dear and Brager [7], occupants are active – rather than passive – recipients of the indoor environments assigned to them. Through their presence and control of various building systems such as lighting, plug-loads, and space heating, ventilation, and air conditioning (HVAC) systems, occupants can significantly affect the thermal/energy performance of a building [8]. The stated impact is even applicable to buildings equipped with automated systems as occupants can look for adaptive actions to mitigate any thermal discomfort they experience (e.g., operating windows and shades), in addition to maintaining control over end-uses such as office equipment [9,10].

Acknowledging the two-way interaction between occupants and their built environment, researchers have turned to research methods and approaches that help evaluate building performance while accounting for its human dimensions [11]. A notable recent effort to advance the state-of-of-the-art in occupant behavior (OB) research is the Annex 66 project of the International Energy Agency Energy in Buildings and Communities Programme (IEA EBC): Definition and simulation of OB in buildings [12]. The project successfully advanced important aspects of OB research, such as data collection, behavior model representation, and evaluation approaches. However, it typically fell short of effectively integrating most developed tools and methods in the design process of actual occupant-centric buildings.

In this paper, the term occupant-centric refers to the notion of placing occupants and their well-being as a top priority throughout the building life-cycle. Rather than providing comfortable conditions in buildings, occupant-centrism means to provide comfort and well-being to occupants. Rather than the highly-implicit schedules as a basis to characterize occupants, occupant-centric approaches use an explicit presentation of occupants that recognizes the two-way interaction between occupants and building design. More broadly, occupant-centric design, in this paper, also refers to space utilization by occupants and the impact of a building's physical layout on its occupants.

In general, occupant-centric building research encompasses various disciplines covering both the design and operation phases of buildings. The former investigates design features and strategies that maximize one of more occupant-centric metrics (e.g., visual comfort, space utilization), while the latter focuses on operation strategies (i.e., post-construction) to achieve similar or other occupant-centric goals [13]. Such occupant-centric approaches to building research are in line with global efforts to develop and promote green or sustainable buildings that minimize resource consumption while ensuring high levels of occupants' comfort, well-being, health, and productivity [14].

Computer-based modeling/simulation is a promising tool that can be used to support occupant-centric decision-making during design and operation. It allows designers, engineers, and researchers to experiment with various design and/or operation-focused strategies and predict their impact on building performance. As detailed later in this paper, building performance simulation (BPS) models are commonly used to predict the performance of buildings in terms of energy consumption, carbon emissions, or occupant comfort-related metrics [15–17]. However, such tools tend to treat occupants in simplistic ways that fail to recognize their stochastic, diverse, and reactive nature, affecting the quality of their estimates [18]. For example, the Advanced Energy Design Guide of ASHRAE [19] summarizes the complex energy interactions between building systems but shows occupants as merely an internal heat gain rather than an agent that can affect the energy use of virtually every system. In contrast, the relationship between occupants, indoor environmental quality (IEQ), and energy is far more complex. For instance, building design and operations affect IEQ, which can result in adaptive behaviors that in turn affect IEQ (refer to Figure 1).

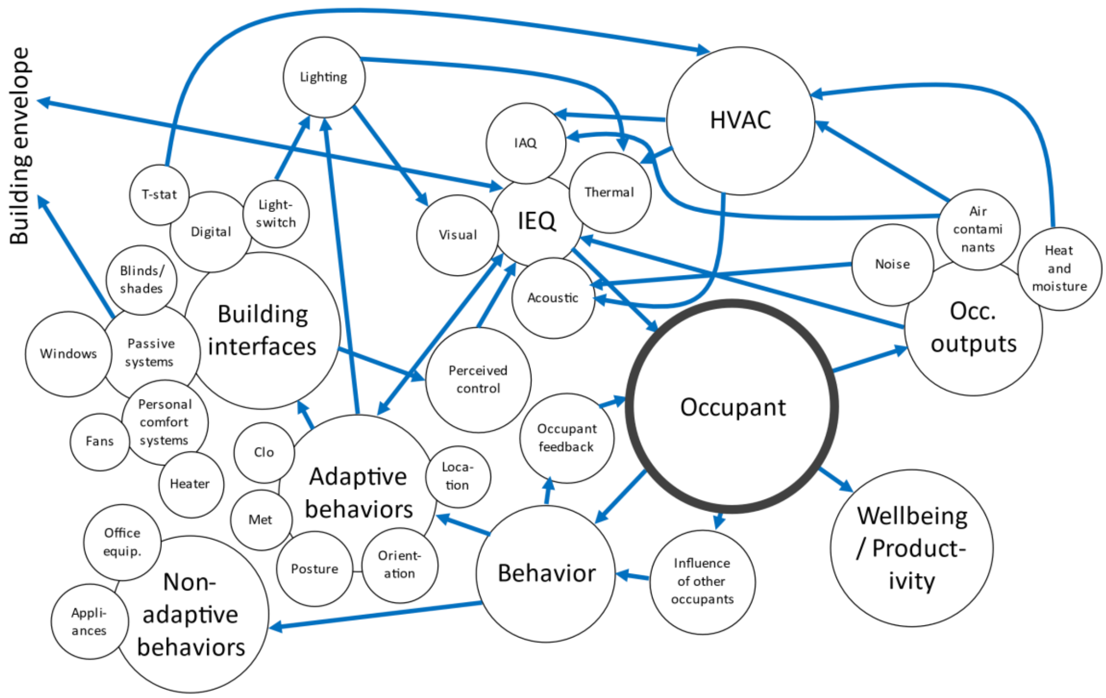

Figure 1: A conceptual figure showing the IEQ- and energy-related role of occupants in buildings.

The recognition of the above shortcomings to modeling approaches has contributed to the emergence of OB modeling tools and approaches that aim to overcome some of the gaps of BPS [11,20]. Integration efforts can also be found where BPS and OB capabilities are combined in holistic modeling frameworks [20,21]. In parallel, analytical methods are developed to leverage the power of the modeling tools and extract efficient design and operation strategies. These include – but are not limited to – parametric variations, uncertainty analyses, optimization algorithms, and robust/resilient design practices [22–24]. Finally, research efforts can also be found on mechanisms and practices that support the development and adoption of occupant-centric design approaches such as building codes, green building rating systems, and integrated project delivery methods that promote stakeholder communications from the early stages of building design [20,25].

1.2. Previous reviews and gaps in the literature

The literature lacks a comprehensive assessment of occupant-centric building design covering its multifaceted aspects, including occupant-centric metrics, simulation tools, analytical methods, and external mechanisms to apply research findings in actual buildings. Nonetheless, previous review articles covered topics related to occupant-centric buildings. The studies are summarized in Table 1 and discussed in the following paragraphs.

Table 1: Summary of previous review articles and their limitations pertaining to the current review.

Source	Year	Scope	Main gaps		
			Limited focus on the design phase	Limited coverage of multivariable metrics	Limited emphasis on simulation tools
D'Oca et al. [26]	2018	Review of energy-related behaviors of key stakeholders that affect energy use over the building life cycle	X		X
Zhang et al. [27]	2018	Review of the role of OB in building energy performance	X	X	
D'Oca et al. [28]	2019	Review and illustrative examples of office occupant modeling formalisms	X	X	
Gaetani et al. [11]	2016	Proposing a fit-for-purpose modeling approach for occupant behavior models	X		
Hong et al. [29]	2015	Proposing the DNAs 'Drivers-Needs-Actions-Systems' framework providing an ontology to represent energy-related OB in buildings	X	X	X
Hong et al. [30]	2015	Implementation of the DNAS framework proposed in [X] using an XML schema	X	X	
Østergård et al. [32]	2016	Review of building simulations supporting decision making in the early design stage		X	
Ouf et al. [31]	2018	Review and comparison of occupant-related features between common BPS tools	X		
Hong et al. [17]	2018	Review of implementation and representation approaches of OB models in BPS programs	X		
Lindner et al. [33]	2017	Determination of requirements on occupant behavior models for the use in building performance simulations	X	X	
Gunay et al. [40]	2016	Implementation and comparison of existing OB models in EnergyPlus	X	X	
O'Brien et al. [35]	2017	Review, discussion, and guidance for developing and applying of occupant-centric building performance metrics	X		X
Ouf et al. [38]	2019	Proposing an approach and metrics to quantify building performance adaptability to variable occupancy	X	X	X
Machairas et al. [22]	2014	Review of algorithms for optimization of building design	X	X	
Tian et al. [15]	2018	Review and survey of building energy simulation and optimization applications to sustainable building design	X	X	
Kheiri et al. [39]	2018	Review on optimization methods applied in energy-efficient building geometry and envelope design	X	X	
Shi et al. [13]	2016	Review on building energy-efficient design optimization from the perspective of architects		X	
Dong et al. [11]	2018	Review on modeling occupancy and behavior for better building design and operation		X	

D'Oca et al. [26] and Zhang et al. [27] reviewed and categorized the "human dimensions" of building performance and the need to integrate them into the operation and design processes. More specific reviews on various OB modeling approaches classified them into distinct formalisms [28], proposed a "fit-for-purpose" modeling strategy [11], or introduced an ontology to represent energy-related behaviors of building occupants [29,30]. Other papers focused on performing comparative reviews of occupant-related features and inputs in common BPS tools [31,32], or presented different approaches to implement OB models in BPS tools (e.g., [17,33,34]). On the other hand, O'Brien et al. [35] assessed occupant-centric building performance metrics and proposed new ones to quantify the impact of occupants on building performance, while Ouf et al. [36] introduced metrics to quantify building adaptability to variable occupancy. Other researchers have focused on applying a specific analytical technique to guide design choices such as optimization, which is used in various contexts such as overall building design [22], passive designs [37], building geometry and envelope design [38], and efficient designs from the perspective of architects [39]. Finally, Dong et al. [13] reviewed modeling efforts of OB with applications covering operation patterns and specific design features. However, the scope of that study was limited to two specific design areas: crowd circulation and HVAC sizing. Additional occupant-centric performance metrics such as thermal comfort, well-being, productivity, or space planning are not covered in that review.

In summary, the review articles described in the previous paragraph present three main gaps that motivated the need for the current work. The first and most important gap is that the vast majority of studies evaluating OB in buildings focus on its implications on building operation – rather than design – strategies. Limited insights are presented on how OB modeling can be leveraged to improve or guide the design stages of buildings. The second gap in existing reviews of occupant-centric simulation studies is the dominant focus on energy efficiency/conservation as the primary target or objective of the modeling process. Additional occupant-centric performance considerations such as occupant thermal comfort, well-being, productivity, or space planning are not thoroughly and systematically covered in review studies. Finally, existing reviews on occupant-centric performance metrics often fail to connect their results to state-of-the-art simulation tools and methods that can be used to guide design decisions.

1.3. Current review objectives and methodology

The aim of this paper is to provide a comprehensive and critical review of existing studies that apply computer-based modeling/simulation to guide occupant-centric building design. The review is inclusive in its coverage of metrics, tools, methods, and supporting mechanisms to guide the design of occupant-centric buildings. It provides readers with a holistic understanding of the field's state-of-the-art, its gaps, and future perspectives.

While the main scope of study is on occupant-centric design applications, it is essential to first review how studies in the literature define occupant-centric designs and the computer-based tools they use to experiment with and guide such designs. Therefore, Section 2 starts by covering the main occupant-centric metrics that can be used to guide the design of buildings (e.g., thermal and visual comfort, well-being, productivity, energy, and space planning). Section 3 then summarizes the main modeling/simulation tools and approaches currently used in the literature, including BPS, OB models, and efforts to integrate the two in comprehensive modeling schemes. Sections 2 and 3 serve as a foundation for Section 4, which reviews key research on simulation-aided occupant-centric design methods and applications such as parametric analysis, optimization, and robust/resilient design practices. In Section 5, practices that are currently supporting, or can be used to support, occupant-centric design applications are discussed, such as building codes and standards, as well as mechanisms to involve stakeholders (e.g., occupants) in integrated design processes. A synthesis of the results is then presented in Section 6, followed by concluding remarks and future perspectives in Section 7.

As for the data collection process, it consisted of the following steps: (i) collection of articles known to authors; (ii) collection of articles citing or being cited by the articles; (iii) initial screening and elimination of irrelevant articles (e.g., out of scope, content duplicated in multiple documents, non-English documents); (iv) final screening for inclusion and assignment to a specific section; (v) inclusion in the article. It is important to note that the above process provided the needed flexibility to cover the diverse topics reviewed, particularly in Sections 2 to 5, without limiting the search space to a predefined set of keywords. A total of 253 articles passed the initial screening stage, out of which 213 passed the final screening stage and were included in the paper.

2. Occupant-centric metrics of building performance

Building performance is a complex and evolving concept that allows stakeholders to quantify how well a building fulfills its functions [41]. For benchmarking purposes, building performance is commonly normalized using building-centric quantities such as the building's gross volume, the net, gross or treated floor areas, or the façade surface. Building users – who are the final recipients of the services offered by a building – are often not directly accounted for the performance evaluation [42]. The purpose of this section is to synopsize the main aspects and features of occupant-related building performance metrics that are commonly used in building performance estimation. Examples of such metrics covered in the next sections include occupant comfort (thermal, visual, and acoustic), indoor air quality (IAQ), well-being and productivity, space planning, and energy. These metrics are useful tools for the operational assessment of the performance of an existing building or for guiding the optimization of the design of the building envelope and systems, and related control strategies.

2.1. Thermal comfort

Thermal comfort is the "condition of mind that expresses satisfaction with the thermal environment" [43]; as such, it is a highly subjective phenomenon influenced by a range of factors. Quantifying thermal comfort has been the subject of studies for many decades due to its role in determining acceptable indoor design conditions and HVAC system requirements in buildings. While thermal comfort is primarily assessed by subjective evaluation (e.g., occupant surveys), in practice, empirical models are typically used, in lieu of subjective evaluation, to predict the human perception of thermal comfort based on physically observable qualities. The most widely accepted model is the Fanger's model of thermal comfort that expresses human thermal sensation in terms of environmental (air temperature, radiant temperature, airspeed, humidity) and personal (metabolic rate, clothing insulation) factors based on the steady-state heat balance principle [44]. It is expressed through two indexes: the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD). The PMV/PPD model provides a global estimation of thermal sensation and acceptability of indoor environmental conditions by a large group of people, and typically has to be accompanied by the verification of possible local discomfort conditions that can affect individual occupants. It associates comfort with neutral sensation, which can lead to narrow temperature prescriptions that are energy-intensive to maintain [45].

Adaptive comfort models present an alternative approach that expresses acceptable indoor temperatures in terms of prevailing outdoor temperatures [46,47]. Such an approach accounts for the human's ability to adapt to variable environmental conditions in naturally-conditioned buildings. Hence, it is often used to support passive design strategies or mixed-mode operation that allow a wider range of temperatures than can be explained by the PMV/PPD model. The adaptive comfort models assume that occupants have direct control on buildings devices to restore thermal comfort (often called adaptive opportunities), hence there exists the complex challenge of modeling the actual occupants' behavior in building simulation tasks. In an effort to overcome trivial and simplistic rule-based control strategies, research efforts in the last decades aimed to describe occupants' presence and their interaction with building devices using stochastic models and data-driven methods.

Another issue is that both the PMV/PPD model and the adaptive comfort models are often accompanied with right-here and right-now metrics (e.g., PPD, Nicol et al.'s overheating risk) [48], which result in time series that are difficult to be processed in automated design procedures. In this regard, several long-term thermal discomfort indices have been proposed to estimate the thermal stimuli accumulated by people into a building over a period. Such long-term thermal discomfort metrics differ by the type of thermal comfort model adopted for the right-here and right-now assessment of the thermal environment, the use of comfort categories or classes for weighting the estimation of thermal stress, whether considering symmetrical overshoots of acceptable conditions, and whether considering the non-linear relationship between the comfort temperature and acceptability of the indoor environmental conditions [49,50]. Despite their successful adoption into international standards (e.g., [43,51,52]), both types of models (PMV/PPD and adaptive) have displayed challenges in describing the thermal comfort of individuals in a particular field setting due to their one-size-fits-all approach [53]. To address this issue, a more recent approach called personal comfort models focuses on learning individuals' thermal comfort based on relevant data (e.g., behavior, biomarkers) collected via various sensors and devices in their everyday environment [54–56]. This new approach is gaining attention among researchers and practitioners whose goal is to create a personalized comfort experience in occupant-centric buildings.

2.2. Visual comfort

The European standard EN 12665 defines visual comfort as "a subjective condition of visual well-being induced by the visual environment" [52]. It is a complex state that depends on several intertwined aspects like the physiology of the human eye, the physical quantities describing the amount of light and its distribution in space, and the spectral emission of artificial light sources. Visual comfort has been commonly studied through the assessment of some coexisting factors characterizing the relationship between the human needs and the light environment, such as (i) the amount of light, (ii) the uniformity of light, (iii) the prediction of the risk of glare for occupants, and (iv) the quality of light in rendering colors. Numerous metrics have been proposed to assess such factors and used to inform the simulation process of buildings, for example [57]. However, although these factors are possibly correlated with each other, indexes usually only focus on one of them and fail to represent the full complexity of a luminous environment in particular from a human-centric perspective.

Furthermore, light, by stimulating the intrinsically-photosensitive retinal ganglion cells (ipRGCs), produces non-visual responses in humans. These responses have direct effects on human physiology (e.g., sleep-wake cycles, secretion of hormones like melatonin, core body temperature, and heart rate) [58] and psychology, for instance altering mood [59]. To this regard, the International Commission on Illumination (CIE) developed the International Standard CIE S 026/E:2018 [60] that addresses non-visual effects of light in humans. The standard defines spectral sensitivity functions, quantities, and metrics related to quantifying retinal photoreceptor stimulation of the five types of photoreceptors while also considering the effects of age and field of view. Nevertheless, it does not provide any indications of lighting applications or quantitative prediction of non-visual light responses or ipRGC-influenced light (ILL) responses [60]. Further details on non-visual effects of light are available in dedicated reviews (e.g., [61,62]).

For simulation, the amount and uniformity of light can be estimated in a reasonably good manner, at the room level, with illuminance-based metrics such as the Unified Glare Rating (UGR) [63] or the

Illuminance Uniformity (U_0) [64] even if no harmonized threshold levels are common among such types of metrics. These metrics are built upon the assessment/estimation of the illuminance at a point on a surface (the work plane or floor), but they do not explicitly take into account occupants' presence, activity, location, or orientation into the space. Glare depends on the location of an observer into space and on his/her relative position with respect to both natural (e.g., windows) and artificial (luminaires) light sources. This geometrical complexity makes it very impractical to estimate the glare risk for an individual person located in a built environment and requests a number of assumptions on use scenarios for testing the visual performance of space during the design phase. One of the most commonly used glare metrics is the Discomfort Glare Probability (DGP) [65]. However, it requires the knowledge of the exact location and orientation of the occupant into a space; but if the ambition of the glare risk assessment at each occupant in a built space is reduced, simplified metrics such as the Wienold's Simplified Discomfort Glare Probability [66], which are based on the vertical illuminance measured at the observer's eye, provide a good correlation with DGP. Regarding the quality of light in rendering colors, it has shown to affect the psychological reaction of occupants to a luminous environment but has not been linked to any energy-related performance of a building so far. Consequently, it has not been used in the whole building simulation, and its application remains mostly limited to the optimization of artificial light sources, such as light-emitting diodes (LEDs).

In general, the vast majority of light and daylight metrics do not account for the actual artificial lighting use and do not reflect the energy use for lighting. To overcome this limitation, O'Brien et al [35]. proposed the light utilization ratio (LUR) that simultaneously considers daylight availability, the lighting control scheme, and OB. This is an attempt to explicitly account for occupant impact on a building energy performance and link together more than one of the aforementioned aspects. Finally, lighting practices and regulations address visual and energy efficiency aspects of light while little interest is dedicated yet to non-visual light responses [60].

2.3. Acoustic comfort

Acoustic comfort is the perceived state of well-being and satisfaction with the acoustical conditions in an environment [67,68]. It can be affected by two main types of noise in buildings: (i) structure-borne (impact) noise that is created by physical impact or vibration against a building element, and (ii) airborne noise that is transmitted through the air [69]. The sound pressure level is one of the main acoustical factors that affect comfort. Maximum sound pressure level (L_{max}) is typically used when predicting comfort with impact noise, whereas equivalent sound pressure level over a given period of time (L_{eq}) is used for airborne noise [70,71]. Other acoustical factors that impact acoustic comfort are: (i) frequency of the noise, (ii) noise source, (iii) duration of noise, and (iv) its variation with time [72,73]. Acoustic comfort is, however, highly subjective, and noise sources with the same physical characteristics can be perceived differently by different people. Personal and societal characteristics, such as sensitivity to noise and attitude towards a noise source, are thus essential when quantifying acoustic comfort [71,72]

Due to the physical and psychological effects associated with acoustic discomfort, some regional and international standards provide guidelines on noise level limits and other acoustic performance evaluation metrics. These metrics vary based on the purpose of the space and the type of effect noise will have on occupants. For instance, in residences, the main effects of noise exposure are annoyance, activity interference, and sleep disturbance, while in offices, effects on communication, work performance, and speech privacy are more important [74]. Standards and guidelines thus provide different background noise level limits for different spaces to ensure minimum interference with the activities performed in the spaces. The World Health Organization (WHO) [74], for instance, identifies different noise level limits for several indoor spaces including residences, hospitals and schools. In open-plan offices, additional metrics, such as speech transmission index, distraction distance, and privacy distance are typically used to quantify the performance of an office with respect to speech privacy as well as effects of speech on occupants' work performance [75].

Despite the available standards and guidelines, acoustic discomfort remains one of the most important comfort issues even in spaces that meet requirements set by standards. One reason for this is the lack of consideration of individual differences, such as noise sensitivity. In addition, many guidelines fail to consider the effects of variable noise levels over time as well as variable noise sources [76]. For example, the focus of most guidelines for residential spaces is outdoor noise sources such as traffic noise, and outdoor community noise, and do not include indoor sources. In addition, some guidelines group all noise sources together. The U.S. Environmental Protection Agency (US EPA), for instance, provides one L_{eq} limit for all environmental noise sources to prevent annoyance and interference with activities disregarding the effects of specific noise sources and frequency on acoustic comfort [77]. Other guidelines, for instance, the WHO [74] and the Ontario Ministry of the Environment and Climate Change (MOECC) Noise Guideline [78], try to overcome this issue by providing different limits for different noise sources such as road traffic, rail traffic, and aircraft noise.

2.4. Indoor air quality

The term Indoor Air Quality (IAQ) includes all physical, chemical, and biological pollutants to which we are exposed via indoor air [79]. IAQ is an important determinant of two high-performance goals that are closely related to building occupants: (i) population health and well-being, and (ii) energy-efficient ventilation for indoor hygiene and comfort [80]. The time-weighted concentration thresholds of air contaminants are the key information to convert IAQ design to an engineering problem of achieving the two aforementioned goals. Among the different indoor air pollutants, eight groups of substances including carbon dioxide (CO_2), nitrogen dioxide (NO_2), formaldehyde (HCHO), carbon monoxide (CO), sulfur dioxide (SO_2), particulate matter in sizes up to 2.5 and 10 μm ($PM_{2.5}$ and PM_{10}, respectively), total volatile organic compounds (TVOCs), and Ozone (O_3), are the most frequently addressed contaminants. Abdul-Wahab et al. [81] and NRC [82] summarized the concentration limits published by a broad range of regional and international guidelines. It is worth noting that the acceptable values for the same substance could vary between guidelines because of the differences in the derivation approach and base data [83]. Some organizations, for instance, the WHO [84] and the German Federal Environment Agency [85], identified the requirements of certain VOC species that can be commonly found in building material emissions and synthetic products for household use. Some examples of those VOC agents are benzene, naphthalene, benzopyrene, trichloroethylene, and tetrachloroethylene. A few non-mandatory standards extended the IAQ metrics to include indoor bioaerosol contaminants. Singapore's SPRING [86] specified the recommended limit of microbial pollutants in indoor air, but its application in modeling and design could be a challenge due to limited knowledge on the emission-to-response model of bioaerosols. More guidelines (e.g., WHO [87]) address this issue from the source control perspective, through managing the indoor dampness and removing the microbial-contaminated material.

In response to the time-weighted concentration thresholds specified by legislations, numerical models have been developed to predict the indoor concentrations of various air contaminants as functions of outdoor air pollutant concentrations, indoor-outdoor air exchange rates, and indoor sources and sinks. The mechanistic nature of those indoor air pollution models ranges from single- to multi-compartment representations, from steady- to transient-state approaches. For example, the first-order differential approach representing mass balance in one compartment model consolidated by Batterman [88] can be applied to calculate CO_2 concentrations in both stable and unstable conditions. Earnest and Corsi [89] used a two-compartment model to predict concentration variations of two VOC agents owing to the use of cleaning products. The EnergyPlus generic contaminant model and CONTAM was employed to estimate indoor concentrations of NO_2, $PM_{2.5}$, and CO for the dwelling [90] and school spaces [91]. The indoor air simulation is based on many input parameters, and three of them are closely related to OB. The three parameters are (i) ventilation rate, which obviously depends on the operation of windows and doors, (ii) indoor source strength, which is under the influence of daily activities, such as cooking, the use of synthetic chemical products for cleaning, the burning of fossil fuels for heating, among others, and (iii) transient modifier, which relates to the location and duration of occupant activity.

The health impact of indoor air quality ushered in the paradigm transformation towards preserving occupants' health beyond the traditional performance goal on energy and resource reduction. To that point, the WHO issued a report in 2000, declaring the human right to healthy indoor air [92]. As summarized in a recent review work [93], the associations between adverse health outcomes and exposure to air contaminants commonly present in indoor spaces have been evidenced by toxicological testing, epidemiology association, and self-rated health assessment. In general, there is a clear link to the increased risk of developing lung cancer, respiratory infections, immune system diseases, skin and mucous membrane irritations, and other building-related illnesses. However, having a consensus on their quantitative relationships with indoor air exposure would be a great challenge because site-specific and contextual factors differ between studies.

Acknowledging the importance of indoor air to public health, many human health risk assessment models have extended their inhalation pathway developed for urban air quality research to include indoor media. Some examples are the indoor microenvironmental scenes incorporated in the APEX [94], USEtox [95], and SHAPE [96] models. The health risk assessment integrates three parameters in indoor air setting: (i) the time spent in the interior spaces (exposure time), (ii) the pollutant concentrations that the occupant is exposed to (exposure concentration), and (iii) the risk factors of different air pollutants. Occupants behavior greatly affects the first two parameters: the relationship between exposure time and occupant presence is obvious; the exposure concentration is built upon the indoor concentration, which is in turn affected by the location and behavior of occupants in the space.

2.5. Well-being and productivity

The built environment has a direct impact on how occupants sense and perceive a given space, and it has significant consequences on their well-being and productivity. Research shows ample evidence about the impact of office design on workers' health, well-being, and productivity. Despite that, occupant well-being and productivity have not been a priority in traditional building design and construction. This is changing in recent years as more companies recognize the business case for healthy and productive offices and third-party building rating systems begin to incorporate wellness and productivity into their requirements.

Well-being is a broad term that encompasses the physical, mental, emotional, and social health of a person, and is generally measured based on the level of happiness, satisfaction with life, and fulfillment [97]. Productivity is an economic term that measures the efficiency of production, expressed in terms of a ratio of outputs (e.g., goods and services) to inputs (e.g., labors and materials) [98]. Since both well-being and productivity are not architectural terms, a key role of research communities has been to establish the criteria and metrics that can describe the impact of the built environment on occupant well-being and productivity. Studies have identified the following criteria for the assessment of well-being and productivity in office environments: indoor environmental quality, office layout, biophilia, look and feel, and location and amenities [99,100]. The evaluation metrics are largely categorized into three groups: (i) financial metrics such as absenteeism, staff turnover, revenue breakdown (by department or per building), medical costs and complaints; (ii) perceptual metrics based on self-reported attitudes about health, well-being and productivity in the workplace; and (iii) physical metrics that are direct measures of IEQ (e.g., temperature, illuminance, pollutants) or an evaluation of design features (e.g., views outside, quality of amenities) [101].

Finding optimal ambient temperatures for office productivity is one of the most frequently studied topics. Amongst the best-known studies were the ones carried out by Seppanen and Fisk [102], showing an optimal temperature point for cognitive performance in an inverted-U relationship, which was later adopted by ASHRAE's Handbook of Fundamentals [103] and REHVA Guidebook No. 6 [104]. However, this approach has been criticized for oversimplifying human response to environmental stimuli, justifying tight and energy-intensive indoor temperature control practices worldwide [105]. Recognizing this, studies (e.g., [106,107]) have looked into the interactions between the environment, occupant comfort (thermal, visual), and behavior through building simulations to optimize energy consumption and office productivity.

Other research efforts (e.g., [105,108,109]) have adopted multidisciplinary approaches to provide a more holistic understanding of the relationship between physical environments and human well-being and productivity. For instance, Nayak et al. [109] study and predict work performance due to changes in indoor room temperatures using human brain signals recorded using electroencephalography (EEG). The proposed method achieved a performance prediction accuracy 17 times higher than that of traditional models using skin temperature, heat-rate, and thermal survey votes.

In parallel to the mentioned research efforts, studies have also investigated the positive link between passive/low-energy design strategies and occupant satisfaction, health, and performance, including natural lighting [110], occupant controls [111], and view of nature and plants [112]. Green building rating systems such as Leadership in Energy and Environmental Design (LEED), the WELL Building Standard, and Fitwel have adopted many of these design strategies to promote more natural and energy-conscious design solutions that can improve the indoor environment quality and the overall well-being of the occupants.

2.6. Space planning and organizational metrics

Beyond the individual aspects of occupant-centric metrics (e.g., comfort, IAQ), interactions among occupants can also be used to measure the success of a building from the perspective of the occupant and organization. This focus on group-level metrics can be particularly important in commercial buildings, where enabling the success and productivity of the occupants and organization in a building is a fundamental design goal of any commercial facility. Based on a review of the literature, we define two key categories for these kinds of organizational metrics: efficiency of space utilization and organizational performance.

Analysis of the utilization of spaces enables metrics that describe how appropriately spaces are serving their intended function; in other words, the ability of a building to enable occupants to carry out their intended activities. Spaces can be defined as under-utilized (which is both cost and energy-inefficient), properly utilized, or over-utilized (in which case occupants are inhibited from performing their activities) [113]. Metrics such as the percentage of desks occupied in a workspace can be used to determine the overall spatial efficiency [114]. With new methods enabling real-time, detailed inference of occupants' space utilization [115–117], researchers have defined metrics that explore the potential to improve overall space utilization rates by moving to a scenario in which occupants share desks [35].

Ultimately, organizations in commercial buildings care most deeply about the productivity of their workforce as the cost of people is typically an order of magnitude higher than the cost of building operation [118]. Recently, researchers have noted that the physical design of buildings can have large impacts on different metrics related to productivity, such as communication, collaboration, and innovation. Using the language of space syntax [119], researchers have defined metrics based on the physical layout and correlated them with occupant outcomes. For instance, Congdon et al. [120] found that higher levels of a single desk's spatial integration correlated with more central positions in the organizational network for the individual occupying that workstation. Kabo et al. [121,122] found that higher path overlap among occupants correlated with more successful collaborations. Generally, research has found that closer spatial relationships (e.g., proximity) improve the way individuals communicate and collaborate with one another in a building [123–126]. Conversely, recent research has also shown that certain *open-plan* office layouts – in which spatial relationships are harder to define due to a lack of spatial boundaries – are actually associated with a decrease in face-to-face communication [127]. This unique interface between spatial boundaries and communication patterns points up the need for further research relating building design to organizational performance.

2.7. Energy

Energy is a physical quantity that measures the capacity of a system to perform work or transfer heat to or from another (thermodynamic) system. It is an extensive property meaning that it is proportional to the extension of the system and is additive for independent and non-interacting subsystems [128]. In buildings, it is used to quantify the performance of any building services and mechanical systems to provide end-uses required by occupants. Focusing in the current work only on HVAC systems, renewable energy generation systems, artificial lighting, and electric appliances, energy is typically used to assess the performance of a building in providing space heating and cooling, humidification and dehumidification, ventilation and pumping, (domestic hot) water heating, (artificial) lighting, and electric appliances.

Several energy performance indicators (EPIs) are used to express a building performance, differing by the boundary at which they are measured or the contributions considered for their calculation. The international standard ISO 52000-1 [129] sets a systematic and comprehensive framework for the holistic evaluation of the energy performance of new and existing buildings, also by defining several EPIs, such as primary energy, delivered energy, energy uses, and energy needs. Furthermore, for benchmarking purposes, the building energy performance is commonly normalized with respect to other extensive properties that (i) describe the building geometry such as the net or gross/treated floor area, the net or gross volume, or (ii) quantify the number of users, generating energy intensity quantities that do not depend on building size. In occupant-centric design applications, the use of geometrical properties is more commonly used than occupancy despite the target being people using or living in a building. Such an approach may lead to misrepresentation of phenomena [42] because building geometry is assumed to be time-invariant with epistemic uncertainty that can be, at least in theory, nullified, while the count of occupants in a building is variable and typically affected by aleatory uncertainty that cannot be reduced.

2.8. Observations and gaps

The aim of this section was to present the most common occupant-related metrics of building performance prior to reviewing the tools and methods used to assess that performance in the upcoming sections. The following observations can be made. Firstly, there is an imbalance in the breadth and depth of information on the different metrics that were covered. For instance, thermal comfort is very well covered in the literature with clearly defined metrics and standards. Well-being or productivity, on the other hand, are more difficult to categorize, assess, and quantity. Secondly, while all metrics are directly related to and affected by occupants, there is a tendency to normalize metrics at the building level. A common example is the normalization of building energy performance per unit of floor area, which contributes to the categorization of energy as a building-focused, rather than an occupant-focused, metric. Such an aggregation of information contributes to the diluting of the personal and societal characteristics of the occupants, which have shown to contribute to the way they perceive and interact with their built environment. Thirdly, the reviewed sources of information mostly define what the different metrics are and how they are measured; less is presented on how to use such information to guide decision-making. Such a process is highly complex and depends on the characteristics of the building under study (e.g., typology, size, age, location) as well as the objectives of the different stakeholders involved (e.g., owner, facility manager, occupants). Moreover, possible conflicts may exist between metrics and should be accounted for (e.g., space utilization and acoustic comfort). While a holistic approach to assessing building performance is needed, most metrics are mostly defined and modeled in isolation, as further discussed in the following sections.

3. Occupant-centric building performance simulation

Following the review of occupant-centric building performance metrics, the current section covers common computer-based modeling and simulation approaches that are used to assess such metrics, as well as opportunities and challenges of adopting such approaches and tools to support building design. The section includes: (i) common BPS software tools and their core functions, (ii) their ability to account for occupant-related features as inputs to the models, and (iii) OB-focused modeling tools and their interoperability in BPS environments.

3.1. Building performance simulation overview

Building performance simulation – also known as building energy modeling, energy simulation, or building simulation – is a physics-based software simulation of building systems and their performance [16]. A BPS program takes as inputs the characteristics of the building, such as its geometry, construction materials, electro-mechanical systems (e.g., HVAC and lighting), water heating configurations, and renewable energy generation systems. Inputs also include occupancy schedules and the operation patterns of plug-loads, lighting, and HVAC systems (e.g., thermostat settings) [130]. A BPS program then combines the physics equations of the building systems with outdoor weather conditions to predict one or more of the following metrics: building energy flows, energy consumption, peak loads, carbon emissions, air quality, daylighting availability, thermal comfort (e.g., PMV and PPD), and visual comfort (e.g., DGP) [15,16].

Figure 2 provides a summary of common BPS software tools adapted from the work of Østergård et al. [32]. The figure classifies the tools according to two main characteristics. The first is the software's main functionality, which varies between BPS software with internal engine (right side), BPS software with external engine (bottom-left side), and plugin to existing BPS software (upper-left side). The interoperability between specific software is shown using arrows. The second characteristic is related to the available output metrics of the BPS engines, including useful metrics for occupant-centric design such as daylighting, thermal comfort, and air quality. It is clear that the outputs of these models are mostly focused on energy performance, followed by thermal, daylighting, and air quality related metrics. Other occupant-related metrics, such as acoustic comfort, well-being, productivity, or space planning, are not covered. Even when comfort outputs, such as PMV and PPD, are considered, they are often calculated at the building level, overlooking differences between occupants. Additional details are provided in the upcoming sections, which cover the ability of BPS tools to account for occupant-centric characteristics and behaviors, as discussed in the next subsection.

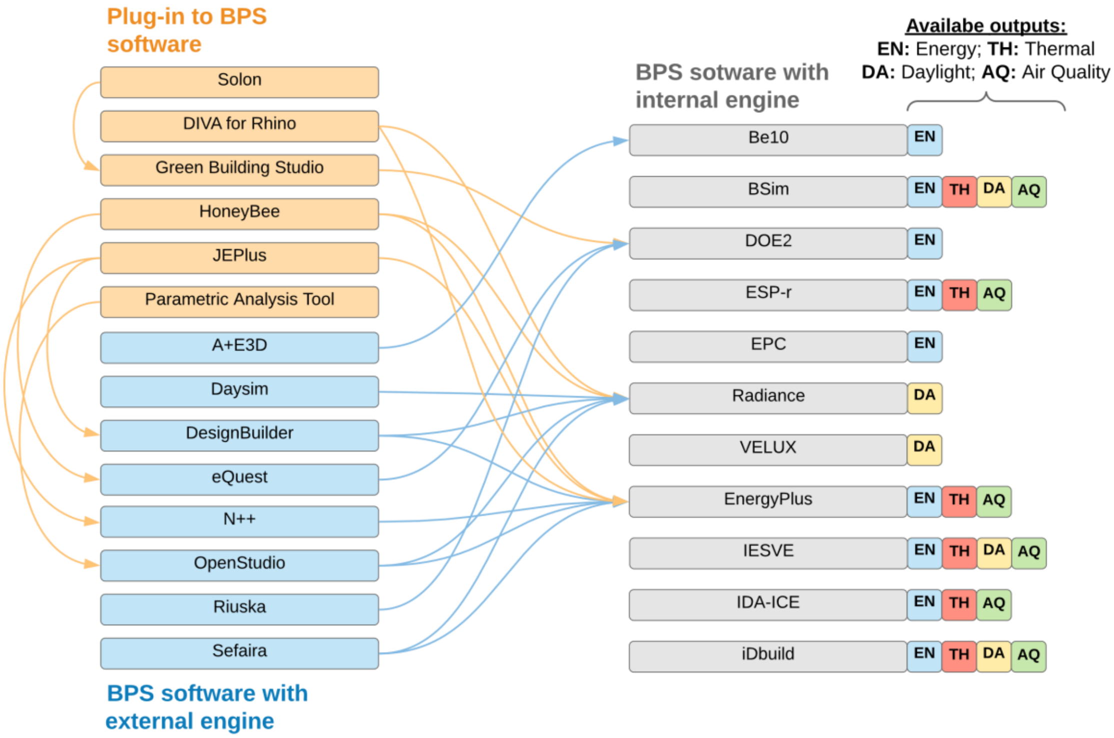

Figure 2: BPS software classification, adapted from Ostergard et al. [32].

3.2. Occupant behavior modeling overview

OB is a complex phenomenon that is driven by the response of occupants to multidisciplinary factors including the physical properties of the building (e.g., orientation), indoor and outdoor environmental conditions (e.g., temperature and humidity), state of building systems (e.g., an open window), personal characteristics (e.g., gender and age), and time of day [29,30]. However, one of the main limitations of current BPS tools is the simplistic representation of OB and its effect on simulation outputs. A recent survey of 274 building simulation practitioners in 36 countries confirmed this limitation, especially as most respondents (> 75%) indicated that common BPS tools should have more features for OB modeling [131]. Commonly-studied behaviors in OB models include – but are not limited to – occupancy presence/absence, lighting and blind control, windows opening, plug-load usage, and other user behaviors [132]. The same study classifies the models in three main categories or levels. Type 0 includes non-probabilistic models that mostly derive schedules (i.e., diversity profiles) from data monitoring and mining data (e.g., [133]). Type 1, covers stochastic or probabilistic models of behaviors using methods such as Poisson processes, Markov chain processes, Logit, Probit, or survival analyses (e.g., [11]). This type exhibits higher resolution and level of complexity compared to the previous ones. Finally, Type 2 includes object-oriented and agent-based models and is considered the largest among the three types in terms of modeling size, resolution, and especially complexity (e.g., [134]).

3.3. Occupant-related features in building performance simulation tools

While BPS programs may include built-in stochastic OB modeling capabilities, this functionality is far from consistent across the different programs and generally lacks flexibility for user customization [135]. This finding was confirmed by Ouf et al. [31], who evaluated and compared the direct occupant-related BPS inputs of five major BPS software. The first category consists of schedules that specify the operation patterns of various systems such as HVAC, lighting, and plug-in equipment, as well as the presence of occupants in the building. A schedule, also referred to as a diversity profile, determines the fraction of the loads that are operating at a specific hour of the day. The second category of inputs is densities, which can include the density of occupants and other building systems (e.g., plug load equipment, lighting, and water fixtures), in addition to the corresponding sensible and latent heat gains they generate. The last category consists of user-defined rules that represent operation patterns based on specific environmental conditions and thresholds (e.g., outdoor/indoor temperatures, daylight illuminance/glare). Overall, the authors argue that the vast majority of inputs used in BPS software to capture occupancy presence and actions are static or homogeneous rather than probabilistic that can better represent the diversity and stochastic nature of OB. The software also typically fails to capture the relationships between occupants' presence and their actions (e.g., operating lighting or equipment), as those are typically modeled with separate schedules. Finally, the limitations extend to the outputs of the software, which are commonly calculated at the building level; this complicates the process of using that output for detailed modeling of OB.

The limitations covered in this section have motivated the need to develop and integrate dedicated OB models in BPS as a step to generate more realistic models [11]. The next subsection presents common OB modeling approaches and integration efforts with existing BPS software tools.

3.4. Occupant behavior modeling and building performance simulation: toward integrated approaches

A study by Hong et al. [20] provided a thorough overview of OB implementation approaches in the current BPS tools, which are: (i) direct input or control – refers to the case when occupant-related inputs are defined using the semantics of BPS programs – just as other model inputs are defined (building geometry, construction, internal heat gains, and HVAC systems); (ii) built-in OB models – users can choose deterministic or stochastic models already implemented in the BPS program, which are initially data-driven and use functions and models such as linear or logit regression functions. These models typically include occupant movement models, window operation models, and lights switching on/off models; (iii) user function or custom – users can write functions or custom code to implement new or overwrite existing or default building operation and supervisory controls; and (iv) co-simulation approach – allows simulations to be carried out in an integrated manner, running modules developed by different programming languages or in different physical computers. The following paragraphs summarize key research efforts and tools on OB modeling and integration in BPS tools.

Gunay et al. [34] developed *EMS (Energy Management System)* scripts to implement 20 existing OB models for use with EnergyPlus. The EnergyPlus EMS feature allows users to write custom code in a runtime language that overwrites the EnergyPlus calculations without requiring the recompilation of EnergyPlus. Using Ruby scripts, O'Brien et al. [136] developed an OpenStudio library of measures representing typical OB models that can be directly applied to EnergyPlus simulation models. Although the EMS scripts and OpenStudio measures provide more flexibility than the direct inputs method to model OB in BPS tools, they lack interoperability due to the need for customization for different applications.

To address the interoperability issue of OB modeling in BPS tools, various approaches to coupling OB modeling and BPS have been explored. Plessis et al. [137] developed a co-simulation approach using a *Functional Mockup Interface (FMI)* that couples the *SMACH OB* simulator using agent-based modeling with a building energy model built with the *BuildSysPro Modelica library*. Gunay et al. [138] investigated the viability of employing the discrete event system specification (DEVS) formalism to represent OB using an adaptive time advancement scheme, which permits realistic patterns of decision-making while facilitating the coupling of stochastic occupant models with BPS tools. Menassa et al. [139] proposed a *High-Level Architecture (HLA)* framework coupling a BPS engine (DOE-2) with an ABM software (Anylogic). The authors illustrate their approach through a simulation of OB in an office building followed by an energy feedback mechanism that promotes energy conservation actions among occupants.

Two additional OB modeling tools, *obXML and obFMU*, were recently developed under IEA EBC Annex 66 [12] to (i) standardize the input structures for OB models, (ii) enable the collaborative development of a shared library of OB models, and (iii) allow for rapid and widespread integration of OB models in various BPS programs using the FMU-based co-simulation approach. *obXML* [29,30] is an XML schema that standardizes the representation and exchange of OB models for BPS. *obXML* builds upon the Drivers–Needs–Actions–Systems (DNAS) ontology to represent energy-related OB in buildings. Drivers represent the environmental and other contextual factors that stimulate occupants to fulfill a physical, physiological, or psychological need. Needs represent the physical and non-physical requirements of occupants that must be met to ensure satisfaction with their environment. Actions are the interactions with systems or activities that occupants can perform to achieve environmental comfort. Systems refer to the equipment or mechanisms within the building that occupants may interact with to restore or maintain environmental comfort. A library of *obXML* files, representing typical OB in buildings, was developed from the literature [140]. These *obXML* files can be exchanged between different BPS programs, different applications, and different users.

obFMU [141] is a modular software component represented in the form of functional mockup units (FMUs), enabling its application via co-simulation with BPS programs using the standard functional mockup interface (FMI). FMU is a file (with an extension fmu) that contains a simulation model that adheres to the FMI standard. *obFMU* reads the OB models represented in *obXML* and functions as a solver. A variety of OB models are supported by *obFMU*, including (i) lighting control based on occupants' visual comfort needs and availability of daylight, (ii) comfort temperature set-points, (iii) HVAC system control based on occupants' thermal comfort needs, (iv) plug load control based on occupancy, and (v) window opening and closing based on indoor and outdoor environmental parameters. *obFMU* has been used with EnergyPlus (Figure 3) and ESP-r via co-simulation to improve the modeling of OB.

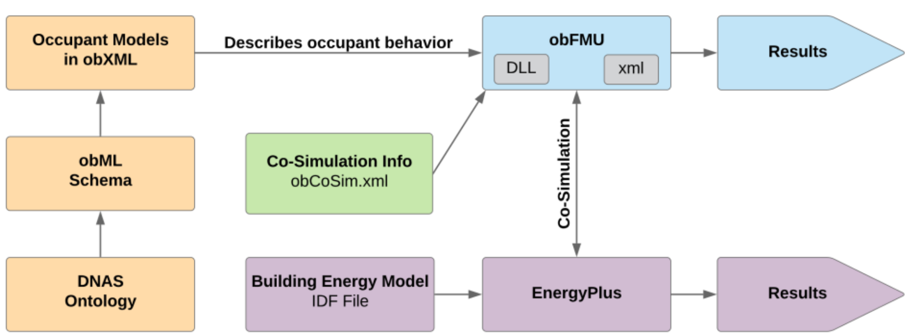

Figure 3: Co-simulation workflow of obFMU with EnergyPlus.

For Modelica users, *Buildings.Occupants* [142] is an OB model package that can be used to simulate the continuous and dynamic interaction between occupants and building systems. The *Buildings.Occupants* package is part of the Modelica Buildings Library [143]. The first release of the package includes 34 OB models, reported and clearly described in the literature, for office and residential buildings. The office building models include eight models on windows operation, six models on window blind operation, four models on lighting operation, and one occupancy model. These models vary by their region of origin, driving factors of actions (e.g., indoor air temperature, and/or outdoor air temperature for windows opening or closing), and other contextual factors such as types of windows.

Occupancy Simulator [144,145] is a web-based application running on multiple platforms to simulate occupant presence and movement in buildings. The application can generate sub-hourly or hourly occupant schedules for each space and individual occupants in the form of CSV files and EnergyPlus IDF files for building performance simulations. *Occupancy Simulator* uses a homogeneous Markov chain model [146,147] and performs agent-based simulations for each occupant. A hierarchical input structure is adopted, building upon the input blocks of building type, space type, and occupant type to simplify the input process while allowing flexibility for detailed information capturing the diversity of space use and individual OB. Users can choose a single space or the whole building to see the simulated occupancy results.

3.5. Observations and gaps

The aim of this section was to cover computer-based modeling and simulation approaches that can support decision-making toward occupant-centric building designs. Several main observations can be made. Firstly, the review of BPS tools highlights a plethora of available BPS engines, software, and plug-ins. However, as shown in Figure 2 and discussed earlier, the outputs of these models mostly focus on energy/thermal performance, with a tendency to normalize results at the building level. This finding highlights an important gap between the diversity of occupant-centric metrics covered in Section 2 of this paper and the capabilities of the BPS tools, mainly EnergyPlus, highlighted in the current section.

Secondly, the review of OB models and research efforts on their integration with BPS tools show promising potential to better account for occupant characteristics and interactions with their environment. However, it should be noted that the current available OB models were developed for specific purposes considering contextual factors (e.g., building type, location, season, and activity type) and with limited measurement data. Users should be cautious about using OB models for extended purposes [148]. Improving the interoperability between OB and BPS models is essential to leverage the power of advanced OB modeling methods without significantly increasing the complexity of the BPS process. Some of the tools covered in the previous section, such as *obXML* [29,30], *obFMU* [141], or the *Occupancy Simulator* [144,149], are important steps in that direction. In parallel, there remains a strong need to design and collect large-scale measured data of occupants, building operation and performance, to support OB model development, evaluation, validation, and application.

Thirdly, common challenges are contributing to the limited adoption of stochastic OB modeling to support building design, from the designers, engineers or modelers' perspectives, include: (i) not knowing what types of occupants and behavior patterns will be in the new building under design; (ii) lack of knowledge in using advanced OB modeling tools; (iii) complexity of OB modeling tools and steep learning curve for new users; and (iv) lack of clear value proposition for using advanced OB modeling.

Also to be noted is that stochastic models of occupant activities and behavior are not always necessarily needed or better than the use of static profiles or settings; fit-for-purpose modeling should be adopted to balance the needs, resources, and expertise [150]. Such an adaptive modeling approach also offers alternatives to the purely static (i.e., overly simple) and purely dynamic (i.e., overly complex) modeling schemes. For instance, “static-stochastic” is a hybrid modeling method where static BPS inputs (e.g., schedules) are multiplied by randomly-selected coefficients, hence introducing stochasticity in the modeling process while still managing its complexity [151].

4. Occupant-centric design methods and applications

The vast majority of research on occupant modeling and simulation has been focused on two topics: occupant model development (e.g., [34,152–154]) and quantification of the impact of occupants on energy and/or comfort (e.g., [155–161])Both these topics, along with papers focused on the implementation of occupant modeling (e.g., [40,133,145,162–164]), are clearly a necessary building block for simulation-aided occupant-centric design. However, far fewer papers have examined methods to apply occupant modeling to inform design, despite the fact that this -along with the so-called performance gap- is cited as a leading reason for improving occupant modeling.

This section is entirely focused on reviewing papers that applied occupant modeling to inform design processes. It is comprised of four main subsections. Section 4.1 provides a summary of frameworks and workflows for simulation-aided occupant-centric design. The remaining sections focus on the development and/or application of specific techniques. Section 4.2 is focused on papers where authors performed a systematic assessment of one or more design variables in the context of informing design (not merely for scientific purposes). Section 4.3 is focused on papers where authors performed design optimization using simulation paired with an optimization script. Finally, Section 4.4 is focused on robust and probabilistic design, whereby papers exploit the stochasticity of occupant models to consider both the uncertainty and mean predicted performance to inform design.

In brief, the papers fitting the topics of this section are few in numbers. They tend to focus on providing a proof-of-concept but generally required using one or more modeling or simulation tools in advanced ways. Accordingly, the developed methods are generally not readily available for deployment to design practice.

4.1. Simulation-aided occupant-centric design strategies

There are several noteworthy pieces of work whereby researchers outlined and/or demonstrated occupant-centric design workflows. Gaetani [150] developed a so-called “fit-for-purpose” approach to occupant modeling, whereby they proposed a systematic approach to assessing the optimal occupant modeling method for a particular situation, balancing model complexity and validity. Gilani and O’Brien [151] developed a best practices guidebook for occupant modeling to support design. The document provides a background on theory, recommendations for techniques on applying occupant modeling to building design, and guidelines for selecting the most appropriate occupant model. Both of the above works explain the importance of strategically choosing the most appropriate occupant modeling strategy as a function of modeling purpose, building model scale, and design phase (Figure 4). Roetzel [165] proposed a method to simulate occupants in early-stage design. She argues that there is significant uncertainty about occupants in early-stage design, yet simulation has the potential to be most influential at that time. Therefore, the recommendation is to use a best and worst-case scenario to assess the magnitude of the impact of occupants. Finally, recognizing that occupant modeling results remain relatively intangible and difficult to visualize, Chen et al. [145] developed a tool to visualize occupants and their energy impacts in a simulation environment.

The following sections review the literature on parametric design, design optimization, and probabilistic design methods - all with aspects of occupant-centric simulation-aided design. The vast majority of papers occupy a narrow zone within Figure 4, namely schematic design for rooms (or buildings) for the purpose of general design. The focus tends to be on architectural design or lighting/daylighting - perhaps because they are simpler to model and also directly relevant to occupants.

The authors argue that with the progression towards more accurate and precise occupant models (e.g., based on long-term field data collection), the research and practitioner community should evolve from simple parametric design (Section 4.2) to probabilistic design (Section 4.4). That is, the uncertainty analysis that is often performed in conjunction with a parametric design is normally approached from the standpoint that the uncertainty from occupants is high (e.g., passive and active occupants; best- and worst-case scenarios). However, a more refined approach is to acknowledge uncertainty but apply data-driven models that can quantify the likelihood of extreme results.

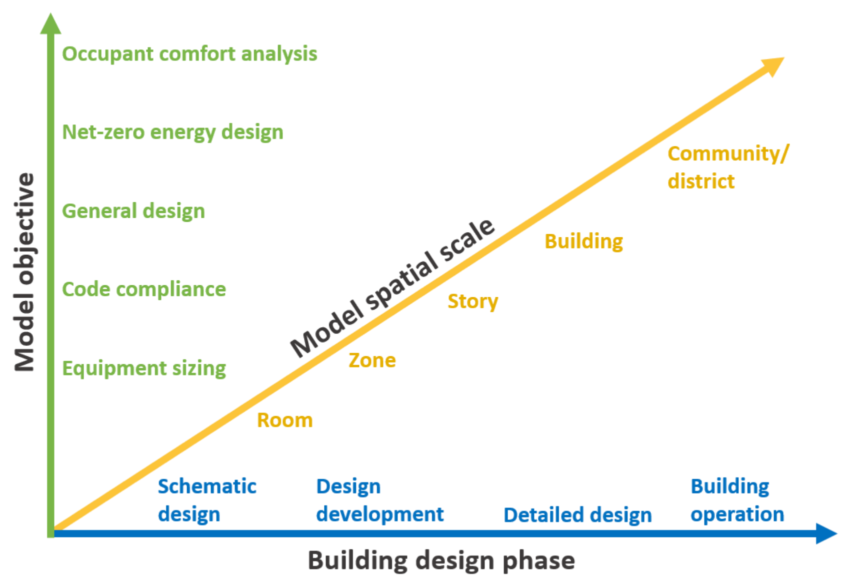

Figure 4: A conceptual design space indicating key considerations for the most appropriate occupant model section and modeling strategy.

4.2. Parametric design

Given the widely accepted uncertainty during building design that originates from occupants, a popular method to assess the impact of occupants in design is simultaneously varying occupant assumptions (i.e., uncertainty analysis) and design or control parameters (i.e., parametric analysis). A common approach is to model two or more extreme conditions either via personas (e.g., passive and active occupants) (e.g., [23,166]) or extreme schedule values or densities (e.g., [157]). Other papers simulated occupants according to a range of assumptions or compared simple and advanced models (e.g., [164,167]). Finally, some researchers have simulated the effects of spatial layouts and locations of occupants on metrics designed to capture the building's performance from a social perspective (e.g., [122]).

Reinhart et al. [168] provided an early example of simulation-aided design based on a relatively detailed occupant model. Starting with his Lightswitch-2002 stochastic occupant model, he demonstrated how a designer could use simulation to assess the impact of various lighting and blind control strategies for different occupant types. Even for a given occupant type and lighting/shade control configuration, Reinhart et al. [168] showed that the annual lighting energy could vary by a factor of four or more. Bourgeois et al. [163] implemented the Lightswitch-2002 lighting and blind use model in ESP-r to support decision-making for automated versus manual lighting. This work built upon Reinhart et al. [168] in that it included heating and cooling results in the simulation, though the primary modeled behavior was still focused on lighting and shades. They showed automation does not necessarily save energy if the occupants actively seek daylight. Compared to the previous studies, Parys et al. [169] performed a more comprehensive assessment than the above studies, which was enabled by occupant models that were developed in the meantime. They included models covering occupancy, window shades, operable windows, lighting, internal gains from equipment, heating, and cooling setpoints. Upon applying the models using a Monte Carlo approach to an office building with 20 private offices, the standard deviation of annual energy was approximately 10%. This level, which is typically lower than those reported by other papers (e.g., [159,168]), is due to the fact that Parys et al. [23] studied a whole building rather than a single office. Thus, the impact of individual occupants largely canceled out. This scaling effect was formally studied by Gilani et al. [170]. Sarwono et al. [171] evaluated the impact of cubicle geometry and materials on speech privacy in an open-plan office using the CATT-Acoustic software. Unsurprisingly, they found that higher cubicle walls improved acoustic performance.

Gilani et al. [167] used both typical (e.g., blinds all open or all closed) and stochastic lighting and blind use models from the literature in a parametric analysis to assess the impact of window size and shade transmittance on energy use in an office. They found that the case with blinds always open tends to lead to a larger optimal window size than if the stochastic models are used. This is because the stochastic window shade use model recognizes that a larger window leads to more frequent glare conditions (based on the work plane illuminance proxy), and thus, the window shade is closed more often, at the cost of greater reliance on electric lighting. Thus, this paper provided anecdotal evidence that the choice of occupant modeling approach can influence design decisions.

Sun and Hong [172] applied three different occupant scenarios – austerity, normal, and wasteful – against a wide range of energy-conservation measures (ECMs) for an office building. They found that except for natural ventilation, the wasteful occupant generally yields greater absolute predicted energy savings from ECMs; however, the relative energy savings are similar in magnitude between all occupancy scenarios for each ECM. Following a similar approach, Abuimara et al. [173] used parametric analysis to assess an office building under three different occupant-related scenarios and a list of 20 building upgrades. They found some significant differences in the rank of the upgrades' effectiveness at saving energy. For example, insulation was more beneficial for cases with lower occupant-related internal heat gains compared to cases with high heat gains. O'Brien and Gunay [174] used stochastic occupancy simulation in an open-plan office to quantify the relationship between lighting control zone size and energy use on an annual basis.

Reinhart and Wienold [164] developed a design workflow that involves modeling energy use and daylighting against several different extreme and simplistic and detailed occupant modeling methods. They provided a number of recommendations for extending their workflow into practice given the significant effort and computational time required. These include: automating the process (e.g., starting with a building information model), cloud computing, optimizing designs with expert systems to keep the designer in the loop at each design iteration, and providing the designers with a dashboard for comparison between designs and consideration of multiple performance criteria.

Researchers have also parameterized spatial layouts of buildings – explicitly connected to occupants' locations – and simulated their effects on metrics of organizational performance. This body of the literature connects design (typically discussed retrospectively) to workplace metrics using the language of space syntax, often describing spaces within a building according to their integration, or connectedness to the other spaces [119]. Congdon et al. [120] compared two different real building designs occupied by the same organization using metrics from space syntax and found that the more integrated layout enabled better communication and was correlated with increased productivity. Jeong and Ban [175] similarly compared multiple design options using space syntax and demonstrated the ability to compare integration – associated with how "public" that part of the building feels – among designs. These design simulations enable evaluation of organizational outcomes, as researchers have noted that spatial design decisions impact both the formation of social relationships in workplaces [126,176] as well as the frequency and success of collaborations [122]. This research shows that parameterizing spaces by measures of their connectedness to the rest of the building can enable the simulation of the organizational performance.

4.3. Design optimization

In contrast to the previous section on parametric analysis, very few papers have formally optimized building designs that use advanced occupant modeling. The papers below discuss both the impact of geometric design alternatives on energy performance as well as the impact of spatial and occupant layouts on energy and organizational outcomes.

Ouf et al. [150] used a genetic algorithm to optimize 10 facade-related design parameters for a private south-facing office. Using annual energy use as the cost function, they optimized the design using both standard occupant assumptions and the state-of-the-art in stochastic occupant models. Because the stochastic models yield a different annual performance level every time they are run, the mean energy use of 50 simulations was used to evaluate each design. The conclusions showed similar energy predictions for the optimal designs, but somewhat different optimal parameters. For example, the optimization with stochastic occupant modeling favored significant solar shading (side fin and overhang) to prevent the shade from being closed early in the day and reducing daylight potential for the remainder of the day. In a follow-up study, Ouf et al. [177] optimized both the mean and standard deviation of sets of 30 stochastic simulations. The intent was to show the potential trade-off between certainty and mean predicted performance.

To enhance thermal comfort in a housing design across different climates, Marschall and Burry [178] subjected building aspect ratio, orientation, roof type, window-to-wall ratio, and shading type to optimization. Thereby two types of window operation models were considered: a deterministic model based on a single indoor temperature setpoint (namely 23.9 °C) and a specific data-driven stochastic model based on another study [179]. In particular, the optimization results showed a considerable variation in shading design solutions depending on the choice of window operation models, which was more noticeable in warmer climates.

Based on metrics describing the organizational operation of buildings, research also suggests that optimization can be used to create building layouts and designs that improve space-use metrics as well as notions of organizational performance (e.g., productivity). Lee et al. [180] simulated occupants' walking behavior and used ant colony optimization to reduce cumulative walking time in a hospital building, thus improving its operating efficiency from a space-use perspective. Yang et al. [181] and Sonta et al. [115] connected this notion of optimally laying out a building based on space-use data to a building's energy performance. By hierarchically clustering occupants based on their overall patterns of presence and absence and then virtually re-assigning them to different building zones through an iterative process, this work demonstrates that physically co-locating individuals with similar occupancy patterns can reduce zone-level building energy consumption. As researchers discuss the importance of simulating the organizational performance of a building based on its design, the opportunity to optimize such designs for these organizational metrics emerges. Nascent work by Housman and Minor [125] shows that the spatial colocation of different types of workers can have differing effects on productivity. They show that a simple exploration of the design space can lead to spatial layouts that are optimized for productivity.

4.4. Probabilistic design methods

A widely-recognized trait of occupant modeling is the stochasticity of inputs and the corresponding uncertainty of simulation outputs. A growing number of papers that have treated non-deterministic simulation outputs (e.g., annual energy use) as an opportunity rather than a burden by focusing on minimizing both the mean and variance of the output(s) of interest. In practical terms, this means designing buildings to be less sensitive to occupants and less dependent on occupants' energy-saving behaviors. While robust design approaches have been developed and applied in engineering design since the 1960s [182] and have been applied to building design in general since then (e.g., [183]), they have only been applied to occupant modeling more recently.

The papers that applied robust design to occupant-centric building design fall into two categories, as shown in Figure 5. Either they use the classical approach, whereby occupants are treated primarily as heat gains via schedules, or an advanced approach whereby the two-way interaction between occupants and buildings is recognized. In the latter case, building design can affect the way people behave and their energy-related actions.

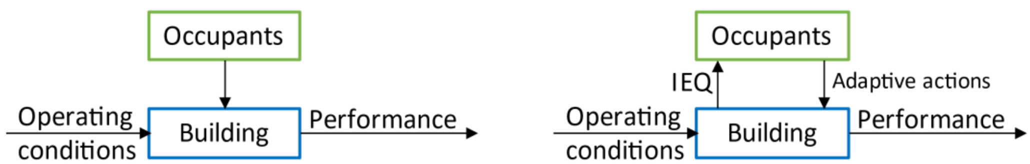

Figure 5: The classic P-diagram of robust design theory applied to occupant modeling [148]: assuming occupants can be treated as a source of noise to the building (left) and recognizing the two-way interaction between buildings and occupants (right).

The literature has generally pursued two ways to assess the robustness of building designs: in the formal sense by adding random noise to a building and by scenario analysis. The latter is more common. For example, Palme et al. [24] are the first known authors to explicitly tie robust design to occupant modeling. They defined robust design as designing buildings to such that it is "[...] difficult for users to make inappropriate decisions". They used a simplified modeling approach to demonstrate the impact of occupants, with a focus on windows opening. Hoes et al. [184] are considered to have spurred advances in the application of occupant modeling. They were pioneers in developing robust design in the context of occupant modeling and building design. They showed how the coefficient of variation caused by OB could be significantly reduced through passive design decisions such as thermal mass and window area. In a follow-up paper, Hoes et al. [185] applied a genetic algorithm to design a building to be robust against uncertainty from basic occupant parameters (i.e., setpoints and internal heat gains). In contrast to Palme et al. [24], Karjalainen [186] cautioned that robust design does not necessarily mean removing adaptive opportunities (e.g., operable windows and controllable thermostats) from buildings; such adaptive opportunities are known to allow occupants to tolerate a wider range of conditions (e.g., [46]). Karjalainen

[186] set out with a similar motivation as the previous papers but used occupant types (careless, normal, conscious) and TRNSYS to assess the robustness of a building design. He demonstrated that the ‘careless’ occupant used 75 to 79% less energy in the robust office (which consisted of occupancy-controlled and efficient lighting, an overhang, and a low-power computer) as opposed to the normal design. Similarly, Abuimara et al. [173] assessed the robustness of various building upgrades against a wide range of possible occupant-related scenarios.

Buso et al. [187] modeled 15 different design options for an office building in three different climates. Stochastic window shade and operable window use models were implemented in IDA ICE. They ran parametric simulations and reported the standard deviation among the simulations, as a measure for robustness. They concluded that the design options with high thermal mass and smaller windows resulted in the greatest robustness against OB. In a more targeted fashion, O’Brien and Gunay [148] set out to demonstrate that improving comfort can reduce energy by reducing the number of adaptive actions. They used a formal robust design method to show that fixed exterior shading to reduce the frequency of daylight glare can prevent the occupants from closing blinds, which in turn improves daylight availability and reduces dependence on electric lighting. However, in this paper and a follow-up paper [188], it was concluded that current occupant model development approaches do not lend themselves to robust design because they suppress diversity by aggregating all occupant data. In the meantime, this has generally been resolved in the literature by using several extreme occupant types (similar to Section 4.2).

On probabilistic occupant-centric design, O’Brien et al. [189] developed a plug and lighting use model for the building scale based on measured data. They implemented a stochastic schedule model for the lighting, plug load, and occupancy domains in a whole building simulation tool to perform HVAC-sizing. The paper showed several advantages to stochastic occupant modeling and a probabilistic approach to HVAC sizing. First, the trade-off between the probability of under-sizing and HVAC component sizing can be quantified. This allows designers to take calculated risks, whereby the comfort risk associated with under-sizing (relative to traditional design methods) can be quantified. For example, ASHRAE recommends 25% safety factors for heating equipment, whereas the new method showed that there is only a 1% risk of having the true heating load being 21% lower than the result of ASHRAE’s safety factor. Secondly, the results showed that larger buildings greatly benefit from diversity between tenants and that the building-scale plant size can be safely reduced on a per unit floor area compared to smaller buildings. Using the same tenant models (for occupancy, lighting, and plug loads), Abdelalim et al. [190] developed and demonstrated a probabilistic method to size a photovoltaic (PV) array for a net-zero energy office building. They showed that uncertainty from occupants is costly and that each percentage point of improved likelihood of reaching net-zero energy is more costly than the one before. For example, the PV array required to be 99.9% certain about achieving net-zero energy is 50% more expensive than a PV array that yields 90% certainty. This is a result of the long tails on the cumulative probability distribution for annual energy consumption (i.e., it is unlikely, but not impossible, to have extremely high values).

4.5. Observations and gaps

The aim of this section was to review articles that applied simulation/modeling to guide occupant-centric designs. The following observations can be made. Firstly, the number of studies fitting in this section is relatively small. Such a small number confirms what was observed earlier in Section 1.2 that most studies evaluating OB in buildings focus on building operation rather than building design strategies.

Moreover, most studies have a specific or narrow scope of coverage of occupant-centric building performance (e.g., simulation tools or behavioral classifications). They lack a comprehensive assessment of occupant-centric building design that covers its multifaceted aspects, including occupant-centric metrics, simulation tools, analytical methods, and external mechanisms to apply research findings in actual buildings.

Another gap is the lack of papers on design considering multiple aspects of IEQ simultaneously or on the domains of IAQ and acoustic comfort. This is thought to be a combination of fewer researchers in these areas and the relatively less emphasis on these domains in BPS tools. Moreover, IAQ and acoustic comfort have generally not been included as predictors in OB models.

Finally, most of the studies are limited to proofs-of-concept of occupant-centric designs using advanced modeling or analysis techniques. They typically fall short of effectively scaling or deploying the design practices in actual buildings, indicating an important gap remaining between OB research and actual design applications.

5. Supporting practices for occupant-centric methods/applications

Following the review of existing occupant-centric modeling tools and methods, the current section discusses two main practices or media that can promote further applications and implementations of occupant-centric designs in actual buildings. The first subsection discusses the premise of using building codes as a mechanism to promote occupant-centric design practices. The second subsection reviews common construction project delivery methods and their potential of engaging stakeholders - building occupants in particular - in the early building design stages.

5.1. Building codes and standards

Today's society may aspire for occupant-centric high-performance buildings, but, arguably, the majority of new buildings aim to comply and not exceed local codes pertinent to building performance and occupant comfort. Therefore, building codes play a critical role to tailor the future built environment for occupants and to achieve the global emissions reduction targets. In this context, as discussed in Section 2, building codes set a variety of building performance metrics to regulate different aspects of occupant requirements in the built environment with efficient use of resources. The authors, however, argue that while the building codes have been commonly trying to address occupant needs in terms of indoor environmental conditions, OB (i.e., occupants' adaptive actions to adjust the environmental conditions) and the controllability of building indoor environment by occupants (arguably as another occupant need) have not been sufficiently addressed in these efforts.

To clarify the aforementioned point, one can focus on building energy codes, which are meant to provide determinant regulatory requirements for the realization of occupant-centric high-performance buildings. In spite of the consensus on the substantial inter-influence of occupants and building performance, the current building energy codes often treat occupants in simplistic and often inadequate ways. On the lower end of the spectrum, a building energy code, which is based on steady-state heat balance calculations, may only rely on a single value for overall internal heat gains along with monthly hours of use (see, for example, the Austrian code for thermal protection in building construction [191]). On the higher end of the spectrum, the codes that benefit from dynamic building simulation represent OB with values of occupancy, lighting, and equipment power density along with associated schedules for weekdays and weekends (see, for example, the building energy codes used in England [192], United States [193] and Canada [194]). For instance, ASHRAE Standard 90.1 mandates that eligible BPS tools used for compliance "shall explicitly model hourly variations in occupancy, lighting and equipment power, as well as thermostat setpoints” [193]. In general, building codes, at best, only implicitly acknowledge the interactions between occupants and buildings and do not value building affordance in terms of indoor environmental control possibilities. Such a limitation is believed to contribute to the common use of deterministic input parameters in BPS tools when representing occupants’ presence and actions in buildings [135].

On the other hand, the aforementioned simplistic occupant representation can be considered beneficial for verification of modeling assumptions and validation of simulation results. It also, in principle, suffices for those building performance enhancement efforts that are not tightly intertwined with OB. However, as many aspects of building performance and OB are closely linked, overlooking the interactions between building performance and OB can undermine the use of building codes in occupant-centric design efforts. In this regard, while the new generation of data-driven OB models aims to capture the interactive nature of OB, the building codes and standards (e.g., LEED) are yet to benefit from the state-of-the-art research in this area. Of course, reliable modeling of the OB and measuring the controllability of indoor environment pose challenges for compliance checking applications. Nonetheless, the authors believe that building codes can further contribute to occupant-centric building performance optimization efforts by addressing the interactive relation between occupants and buildings in a more explicit manner. Moreover, standards and building rating systems that are specifically focused on occupant health and well-being (e.g., WELL) have the potential to drive the market towards simulation-aided occupant-centric design. While requirements in WELL are mostly verifiable without the use of simulation, a performance path in such standards could lead the industry in this direction. Another interesting line of inquiry is whether normalizing building performance by occupancy rather than floor area can address the uncertainty caused by space utilization and occupancy. To this end, efforts such as IEA EBC Annex 79 [195] and the present paper aim to pave the way for the preparation of guidelines and standards to form the future building codes and rating systems with a more holistic approach to occupant needs and behavior in buildings.

5.2. Project delivery methods

One significant opportunity to support occupant-centric design applications revolves around innovations in project delivery methods. A project delivery method is a process by which various stakeholders (e.g., building owners, occupants, architects, engineers, constructors) work together to deliver a building; it is generally distinguished by two key characteristics: (i) the contractual relationships between project stakeholders; and (ii) their timing of engagement in the project [196].

The traditional Design-Bid-Build (DBB) delivery is one where the different project phases (e.g., design, construction, occupancy) are sequential and do not offer room for involving and aligning the various stakeholders. In DBB, the design is typically fully completed without engaging with the constructors who do not get a chance to offer insights on how the design could have been tweaked to save considerable amounts of time and resources in the construction phase of the project. Similarly, future building occupants, arguably the most important stakeholder group, are not part of the weekly or monthly decision-making process, where there is an opportunity to adapt the building design and construction to the future needs of its occupants [197].

In contrast, more progressive and integrated methods are on the rise, also referred to as Alternative Project Delivery Methods (APDM). APDM are designed to engage these critical building stakeholders as part of the design and construction process [198]. They offer the possibility of engaging the occupants and constructors much earlier in the process (e.g., before the design is complete) for occupants to test hands-on mock-ups of rooms, constructors to provide constructability advice, as well as to explore design strategies and their anticipated impact on construction performance metrics (e.g., cost and schedule) and occupant-centric metrics (e.g., comfort levels, efficiency of space utilization and organizational performance) [199,200].

The impact of this involvement has been considerable, leading to successive research efforts to study it further. In fact, this difference in performance has been measured over the past two decades, showing a significant improvement in project outcomes when the constructor in engaged in informing the design [201–204]. The average numbers from Sullivan et al. [205] meta-analysis are on the order of 2% to 4% improved cost control and 35% faster delivery. El Asmar et al. [25,206] show that the average building quality increases significantly, and stakeholder communication (through requests for information and change order processing times) can be up to four times faster; the authors then mapped the level of integration of major delivery methods versus overall project performance, showing that more integration in the process leads to increasingly higher project performance. There is new preliminary evidence that suggests the actual performance of the facility itself, over its lifecycle, may improve too [207,208].

The same tested concept of increasing communication and involvement between design and construction stakeholders can be pushed further upstream allowing the prospective occupants to participate in informing the design of the facility and provide the perspective of building users. Design charrettes with prospective occupants and successive iterations of the design and simulations that engage occupants are a good start in this direction. Contractual and process mapping elements to engage occupants through APDM have not yet been sufficiently explored yet, but the mountains of evidence linking stakeholder collaboration and integration to improved performance are hard to ignore. There is an exciting opportunity to use these proven frameworks to support occupant-centric design applications.

5.3. Observations and gaps

The aim of this section was to explore and discuss potential enablers for occupant-centric building designs, namely building codes and standards, in addition to project delivery methods. The main observation is that both approaches are promising and can contribute to addressing the challenges raised in the previous sections. However, currently, they are not successful in doing so.

Firstly, traditional buildings codes and rating systems (e.g., ASHRAE and LEED) account for occupants' needs mostly through indoor environmental specifications. They typically overlook occupant-building interactions and fail to leverage the advances in OB modeling and integration with BPS to provide a more realistic representation of occupants. Similarly, health- and well-being-focused standards, such as WELL, are not well integrated with the tools commonly used to guide the design process.

Secondly, project delivery methods, particularly APDMs, have shown to increase communication among stakeholders and better integrate the different phases of the construction process. However, it is important to note that no studies were found directly linking the capabilities of APDMs to occupant-centric design practices. Future research efforts can explore and quantify the potential contributions of APDMs towards more occupant-centric and integrated designs.

6. Synthesis

The in-depth reviews presented in the previous sections identified critical gaps in the literature on occupant-centric building design: (i) most occupant-centric simulation studies focus on energy efficiency and conservation as the main target or objective of the building modeling process. There is limited coverage and discussion of other occupant-centric performance metrics such as comfort (thermal, visual, and acoustic), IAQ, well-being, productivity, and space planning. Moreover, metrics are commonly measured and normalized at the building level, overlooking occupant-level characteristics and interactions with the built environment; (ii) the application of OB modeling and simulation tools in BPS is limited in the building design process. This can be attributed to multiple factors such as the lack of clear objective (i.e., why business-as-usual is not adequate), the lack of expertise of engineers, designers or energy modelers to effectively use the tools, the lack of readily available occupant models and data and easy to use BPS tools, or the lack of methods to communicate results or design considering the stochastic nature of OB; and (iii), while interdependent, there is a clear gap in the literature on occupant-centric metrics (Section 2), modeling tools (Section 3), applications (Section 4), and potential enabling mechanisms for occupant-centric building applications (Section 4).

A synthesizing framework is proposed in Figure 6 to connect the different themes covered in this paper and offer a more central role for occupants in the design process compared to the traditional approach, which deals with occupants in simplistic ways (e.g., conservative schedule values, passive tolerance to discomfort). At the core of the proposed framework below is the goal of achieving occupant-centric design, which is measured by the various occupant-centric metrics of performance covered in Section 2. There is a particular need to explore multi-domain drivers of occupants' perceptions and behaviors in buildings, which are still less studied in comparison to single-domain drivers [209]. As stated by ASHRAE [210], "current knowledge on interactions between and among factors that most affect occupants of indoor environments is limited". Recent efforts (e.g., [209,211,212]) are important steps in that direction and should be further developed into design guiding principles and processes. BPS, supported by OB modeling upon need, can provide the milieu to model these metrics. In parallel, various methods (e.g., uncertainty analysis and optimization) can be used to translate the generated knowledge into practical design decisions. Such decisions should also account for external factors, such as weather conditions, and internal factors, such as the needs of different stakeholders. The latter is particularly important as occupants, owners, facility managers, researchers, and practitioners might perceive and define "occupant-centric design" differently.

An important consequence of the agency problem stated above is that advances in research tools and methods developed in academic circles do not often translate to applications in the building industry. This was confirmed in the current review by the plethora of occupant-centric metrics, tools, and methods found in the academic literature on the one hand, and the minimal application to the design of actual buildings, on the other. Such disconnect is also present in academia, even in relatively close fields (e.g., studying various occupant comfort metrics). This was confirmed by the limited studies found in Section 4 that apply multivariable occupant-centric metrics of building performance to guide design. Further alignment is needed within academia, as well as between academics and practitioners. The latter can be enabled by case studies using real building projects to demonstrate how OB research and tools can effectively improve the design process, hence showing the added value to the practitioners. In parallel, building codes and regulations [213] can help translate the state-of-the-art of OB research to design guidelines and best practices.

Finally, the framework emphasizes the need to move from a linear top-down design process, where occupants are simply considered as end-consumers or passive recipients of building design, to a circular one, where occupants' needs and preferences are key guiding factors of the design. This approach is illustrated in Figure 6, with the dotted lines highlighting the iterative processes that are needed for effective occupant-centric modeling and design practices

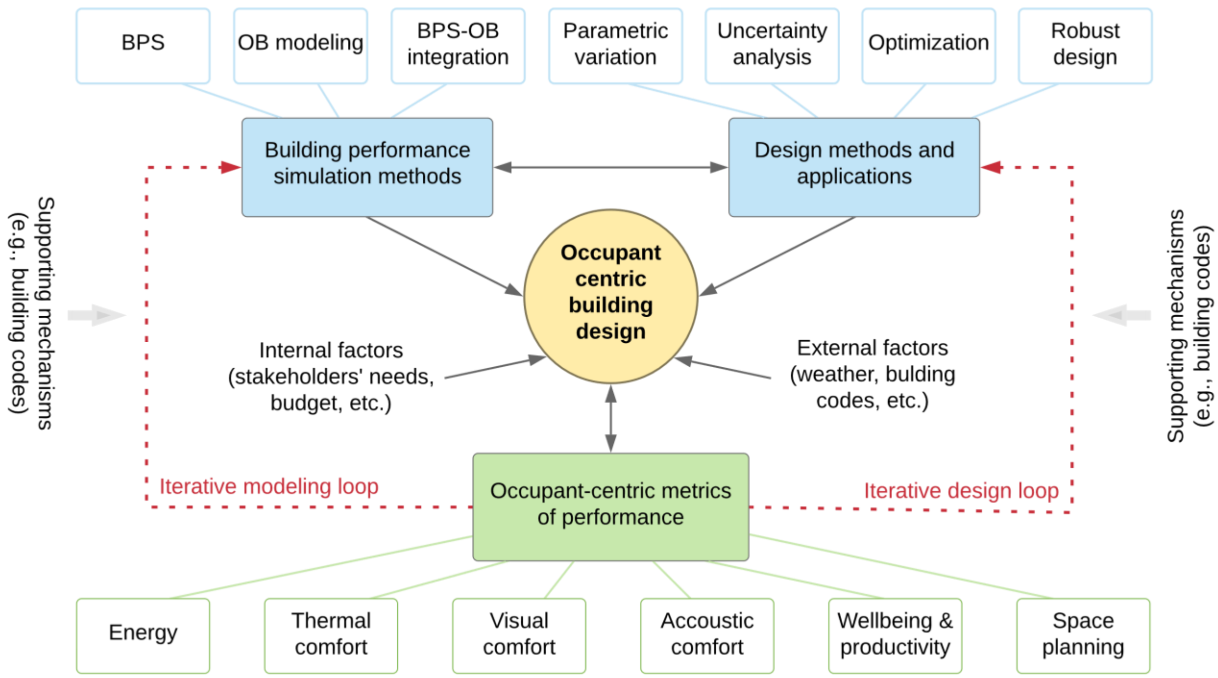

Figure 6: Proposed framework for occupant-centric building design research and applications.

7. Conclusion and Future Perspectives

In principle, most buildings are designed and operated to provide a comfortable and healthy environment for occupants; however, reality – particularly in simulation-aided design processes – is quite different. Understanding occupants' diverse needs are essential to optimize building energy use as well as to ensure occupants' comfort, well-being, and productivity. Occupants' activities and behaviors influence building operation and, thus, energy use; on the other hand, building design and operation patterns lead to adaptive behaviors of occupants. This two-way human-building interaction is crucial to achieving sustainable, zero-energy, or carbon-neutral buildings, which are targeted by more and more countries in the world.

In this paper, a comprehensive and critical review was conducted on existing studies that apply computational methods and tools to provide quantitative insights to inform occupant-centric building design. The reviews were organized into four cohesive themes covering occupant-centric metrics of building performance, modeling and simulation approaches, design methods and applications, as well as supporting practices and mechanisms. Key barriers were then identified for a more effective application of occupant-centric building design practices, including the limited consideration of metrics beyond energy efficiency (e.g., occupant well-being and space planning), the limited implementation and validation of the proposed methods, and the lack of integration of OB models in existing BPS tools.

Future research and applications are needed to address the gaps identified in this paper and support an integrated occupant-centric design approach, as proposed in Figure 6. These include: (i) developing a diverse collection of OB datasets based on large-scale monitoring or international surveys. Such effort can help improve the occupant data and assumptions that are used for building code compliance calculations, as well as define and quantify a suite of occupant-centric metrics (including occupants' thermal comfort, visual, acoustic, IAQ and well-being) to characterize building performance while considering their variability. The output of such activities can serve as an input to advanced OB models that can better capture the stochastic and dynamic nature of OB while accounting for the diversity and uniqueness of the individual users who are studied; (ii) integrating OB models in the building energy modeling process to support its multiple uses during building design (e.g., comfort and usability, space layout for productivity, peak load calculations, HVAC system type determination and sizing, code compliance, evaluation of design alternatives, and building performance rating). The studies reviewed in Section 4 can serve as a good start to the simulation-aided occupant-centric design, but additional efforts are needed both in terms of breadth of analysis (i.e., covering metrics beyond energy use and comfort) and depth (i.e., moving from proof-of-concept to implementation and validation); (iii) establishing an industry practice of engaging occupants and communicating occupant-centric building design among building owners, architects, engineers, energy modelers/consultants, and operators. Building codes and alternative project delivery methods can serve as media for such exchange, bringing users at the center of the different stages of a building's life-cycle: from early design to operation.

Acknowledgments

This work is part of the research activities of IEA EBC Annex 79; the paper greatly benefited from the expertise of its participants. Work at Khalifa University was supported by the Abu Dhabi Department of Education and Knowledge (ADEK), under Grant AARE18-063. LBNL's research was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Building Technologies of the United States Department of Energy, under Contract No. DE-AC02-05CH11231. Work at Stanford University was supported by a Stanford Graduate Fellowship, a Terman Faculty Fellowship, the Center for Integrated Facility Engineering, and the U.S. National Science Foundation under Grant 1461549 and Grant 1836995. Salvatore Carlucci would like to thank the European Union's Horizon 2020 Research and Innovation Programme under grant agreement 680529, acronym QUANTUM. Findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily represent those of the funding agencies.

References

[1] N.E. Klepeis, W.C. Nelson, W.R. Ott, J.P. Robinson, A.M. Tsang, P. Switzer, J. v. Behar, S.C. Hern, W.H. Engelmann, The National Human Activity Pattern Survey (NHAPS): A resource for assessing exposure to environmental pollutants, Journal of Exposure Analysis and Environmental Epidemiology. 11 (2001) 231–252. https://doi.org/10.1038/sj.jea.7500165.

[2] M.S. Andargie, E. Azar, An applied framework to evaluate the impact of indoor office environmental factors on occupants' comfort and working conditions, Sustainable Cities and Society. 46 (2019) 101447.

[3] S. D'Oca, H.B. Gunay, S. Gilani, W. O'Brien, Critical review and illustrative examples of office occupant modelling formalisms, Building Services Engineering Research and Technology. (2019) 014362441982746. https://doi.org/10.1177/0143624419827468.

[4] S. Carlucci, F. Causone, F. de Rosa, L. Pagliano, A review of indices for assessing visual comfort with a view to their use in optimization processes to support building integrated design, Renewable and Sustainable Energy Reviews. 47 (2015) 1016–1033. https://doi.org/10.1016/j.rser.2015.03.062.

[5] A. Chokor, M. el Asmar, C. Tilton, I. Srour, Dual Assessment Framework to Evaluate LEED-Certified Facilities' Occupant Satisfaction and Energy Performance: Macro and Micro Approaches, Journal of Architectural Engineering. 22 (2015) A4015003. https://doi.org/10.1061/(asce)ae.1943-5568.0000186.
[6] S. Carlucci, L. Pagliano, A review of indices for the long-term evaluation of the general thermal comfort conditions in buildings, Energy and Buildings. 53 (2012). https://doi.org/10.1016/j.enbuild.2012.06.015.
[7] R. de Dear, Gail.S. Brager, Developing an adaptive model of thermal comfort and preference, ASHRAE Transactions. 104 (1998) 145–167.
[8] E. Azar, C.C. Menassa, A comprehensive framework to quantify energy savings potential from improved operations of commercial building stocks, Energy Policy. 67 (2014). https://doi.org/10.1016/j.enpol.2013.12.031.
[9] H.B. Gunay, W. Shen, G. Newsham, A. Ashouri, Modelling and analysis of unsolicited temperature setpoint change requests in office buildings, Building and Environment. 133 (2018) 203–212. https://doi.org/10.1016/j.buildenv.2018.02.025.
[10] E. Azar, C.C. Menassa, Optimizing the performance of energy-intensive commercial buildings: Occupancy-focused data collection and analysis approach, Journal of Computing in Civil Engineering. 30 (2016) 1–11. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000521.
[11] I. Gaetani, P.-J. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy, Energy and Buildings. 121 (2016) 188–204. https://doi.org/http://dx.doi.org/10.1016/j.enbuild.2016.03.038.
[12] D. 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 and Buildings. 156 (2017). https://doi.org/10.1016/j.enbuild.2017.09.084.
[13] B. Dong, D. Yan, Z. Li, Y. Jin, X. Feng, H. Fontenot, Modeling occupancy and behavior for better building design and operation—A critical review, Building Simulation. 11 (2018) 899–921. https://doi.org/10.1007/s12273-018-0452-x.
[14] D. Chwieduk, Towards sustainable-energy buildings, Applied Energy. 76 (2003) 211–217. https://doi.org/10.1016/S0306-2619(03)00059-X.
[15] T. Han, Q. Huang, A. Zhang, Q. Zhang, Simulation-based decision support tools in the early design stages of a green building-A review, Sustainability (Switzerland). 10 (2018). https://doi.org/10.3390/su10103696.
[16] T. Hong, J. Langevin, K. Sun, Building simulation: Ten challenges, Building Simulation. 11 (2018) 871–898. https://doi.org/10.1007/s12273-018-0444-x.
[17] 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, Building Simulation. 11 (2018) 1–14. https://doi.org/10.1007/s12273-017-0396-6.
[18] T. Hong, D. Yan, S. D'Oca, C. fei Chen, Ten questions concerning occupant behavior in buildings: The big picture, Building and Environment. 114 (2017) 518–530. https://doi.org/10.1016/j.buildenv.2016.12.006.
[19] ASHRAE, Advanced Energy Design Guide for Small to Medium Office Buildings, Atlanta, GA, 2011. www.ashrae.org.

[20] T. Hong, D. Yan, S. D'Oca, C. fei C.-F. Chen, Ten questions concerning occupant behavior in buildings: The big picture, Building and Environment. 114 (2017) 518–530. https://doi.org/10.1016/j.buildenv.2016.12.006.

[21] S. Papadopoulos, E. Azar, Integrating building performance simulation in agent-based modeling using regression surrogate models: A novel human-in-the-loop energy modeling approach, Energy and Buildings. 128 (2016). https://doi.org/10.1016/j.enbuild.2016.06.079.

[22] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design: A review, Renewable and Sustainable Energy Reviews. 31 (2014) 101–112. https://doi.org/10.1016/j.rser.2013.11.036.

[23] W. Parys, D. Saelens, H. Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices–a review-based integrated methodology, Journal of Building Performance Simulation. 4 (2011) 339–358.

[24] M. Palme, A. Isalgue, H. Coch, R. Serra, Robust design: A way to control energy use from human behavior in architectural spaces, in: Proceedings of the PLEA Conference, 2006.

[25] M. el Asmar, A.S. Hanna, W.Y. Loh, Quantifying performance for the integrated project delivery system as compared to established delivery systems, Journal of Construction Engineering and Management. 139 (2013) 1–14. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000744.

[26] S. D'Oca, T. Hong, J. Langevin, The human dimensions of energy use in buildings: A review, Renewable and Sustainable Energy Reviews. 81 (2018) 731–742. https://doi.org/10.1016/j.rser.2017.08.019.

[27] Y. Zhang, X. Bai, F.P. Mills, J.C.V. Pezzey, Rethinking the role of occupant behavior in building energy performance: A review, Energy and Buildings. 172 (2018) 279–294. https://doi.org/10.1016/j.enbuild.2018.05.017.

[28] S. D'Oca, H.B. Gunay, S. Gilani, W. O'Brien, Critical review and illustrative examples of office occupant modelling formalisms, Building Services Engineering Research and Technology. (2019) 014362441982746. https://doi.org/10.1177/0143624419827468.

[29] 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, Building and Environment. 92 (2015) 764–777. https://doi.org/10.1016/j.buildenv.2015.02.019.

[30] 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, Building and Environment. 94 (2015). https://doi.org/10.1016/j.buildenv.2015.08.006.

[31] M.M. Ouf, W. O'Brien, H.B. Gunay, Improving occupant-related features in building performance simulation tools, Building Simulation. 11 (2018) 803–817. https://doi.org/10.1007/s12273-018-0443-y.

[32] T. Østergård, R.L. Jensen, S.E. Maagaard, Building simulations supporting decision making in early design - A review, Renewable and Sustainable Energy Reviews. 61 (2016) 187–201. https://doi.org/10.1016/j.rser.2016.03.045.

[33] A.J.M. Lindner, S. Park, M. Mitterhofer, Determination of requirements on occupant behavior models for the use in building performance simulations, Building Simulation. (2017) 1–14. https://doi.org/10.1007/s12273-017-0394-8.

[34] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, S. Gilani, Modeling plug-in equipment load patterns in private office spaces, Energy and Buildings. 121 (2016) 234–249. https://doi.org/10.1016/j.enbuild.2016.03.001.
[35] W. O'Brien, I. Gaetani, S. Carlucci, P.J. Hoes, J.L.M. Hensen, On occupant-centric building performance metrics, Building and Environment. 122 (2017) 373–385. https://doi.org/10.1016/j.buildenv.2017.06.028.
[36] M.M. Ouf, W. O'Brien, B. Gunay, On quantifying building performance adaptability to variable occupancy, Building and Environment. 155 (2019) 257–267. https://doi.org/10.1016/j.buildenv.2019.03.048.
[37] Z. Tian, X. Zhang, X. Jin, X. Zhou, B. Si, X. Shi, Towards adoption of building energy simulation and optimization for passive building design: A survey and a review, Energy and Buildings. 158 (2018) 1306–1316. https://doi.org/10.1016/j.enbuild.2017.11.022.
[38] F. Kheiri, A review on optimization methods applied in energy-efficient building geometry and envelope design, Renewable and Sustainable Energy Reviews. 92 (2018) 897–920. https://doi.org/10.1016/j.rser.2018.04.080.
[39] X. Jin, B. Si, X. Shi, W. Chen, Z. Tian, A review on building energy efficient design optimization rom the perspective of architects, Renewable and Sustainable Energy Reviews. 65 (2016) 872–884. https://doi.org/10.1016/j.rser.2016.07.050.
[40] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, Implementation and comparison of existing occupant behavior models in EnergyPlus, Building Performance Simulation. 9 (2016) 567–588.
[41] P. de Wilde, Ten questions concerning building performance analysis, Building and Environment. 153 (2019) 110–117. https://doi.org/10.1016/j.buildenv.2019.02.019.
[42] W. Kampel, S. Carlucci, B. Aas, A. Bruland, A proposal of energy performance indicators for a reliable benchmark of swimming facilities, Energy and Buildings. 129 (2016). https://doi.org/10.1016/j.enbuild.2016.07.033.
[43] ISO, ISO 7730: Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria, International Standard Organization, Geneva, CH, 2005.
[44] P.O. Fanger, Thermal comfort. Analysis and applications in environmental engineering., Danish Technical Press, Copenhagen, 1970.
[45] E. Arens, M.A. Humphreys, R. de Dear, Are 'class A' temperature requirements realistic or desirable?, Building and Environment. 45 (2010) 4–10. https://doi.org/10.1016/J.BUILDENV.2009.03.014.
[46] R. de Dear, Gail.S. Brager, Developing an adaptive model of thermal comfort and preference, ASHRAE Transactions. 104 (1998) 145–167.
[47] J.F. Nicol, M.A. Humphreys, Adaptive thermal comfort and sustainable thermal standards for buildings, Energy and Buildings. 34 (2002) 563–572. https://doi.org/10.1016/S0378-7788(02)00006-3.
[48] J.F. Nicol, M. a. Humphreys, New standards for comfort and energy use in buildings, Building Research and Information. 37 (2009) 68–73.
[49] S. Carlucci, L. Pagliano, A review of indices for the long-term evaluation of the general thermal comfort conditions in buildings, Energy and Buildings. 53 (2012) 194–205. https://doi.org/10.1016/J.ENBUILD.2012.06.015.

[50] S. Carlucci, Thermal Comfort Assessment of Buildings, Springer Milan, Milano, 2013. https://doi.org/10.1007/978-88-470-5238-3.
[51] ASHRAE, ASHRAE 55: Thermal Environmental Conditions for Human Occupancy, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA, 2013.
[52] CEN, EN 15251: Criteria for the indoor environment including thermal, indoor air quality, light and noise, European Committee for Standardization, Brussels, BE, 2007.
[53] J. van Hoof, Forty years of Fanger's model of thermal comfort: comfort for all?, Indoor Air. 18 (2008) 182–201. https://doi.org/10.1111/j.1600-0668.2007.00516.x.
[54] J. Kim, S. Schiavon, G. Brager, Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control, Building and Environment. 132 (2018) 114–124. https://doi.org/10.1016/J.BUILDENV.2018.01.023.
[55] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, G. Brager, Personal comfort models: Predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning, Building and Environment. 129 (2018) 96–106. https://doi.org/10.1016/J.BUILDENV.2017.12.011.
[56] H.B. Gunay, W. O'Brien, I. Beausoleil-Morrison, J. Bursill, Development and implementation of a thermostat learning algorithm, Science and Technology for the Built Environment. 24 (2018) 43–56. https://doi.org/10.1080/23744731.2017.1328956.
[57] S. Carlucci, F. Causone, F. de Rosa, L. Pagliano, A review of indices for assessing visual comfort with a view to their use in optimization processes to support building integrated design, Renewable and Sustainable Energy Reviews. 47 (2015). https://doi.org/10.1016/j.rser.2015.03.062.
[58] T.L. Shanahan, C.A. Czeisler, Physiological effects of light on the human circadian pacemaker, Seminars in Perinatology. 24 (2000) 299–320. https://doi.org/10.1053/sper.2000.9123.
[59] N.E. Rosenthal, T.A. Wehr, Towards understanding the mechanism of action of light in seasonal affective disorder, in: Pharmacopsychiatry, 1992: pp. 56–60. https://doi.org/10.1055/s-2007-1014389.
[60] CIE, CIE 26–CIE System for Metrology of Optical Radiation for ipRGC-Influenced Responses to Light., Vienna, Austria, 2018.
[61] B. Fabio, B. Chiara, L.R. Ornella, B. Laura, F. Simonetta, Non visual effects of light: An overview and an Italian experience, in: Energy Procedia, Elsevier Ltd, 2015: pp. 723–728. https://doi.org/10.1016/j.egypro.2015.11.080.
[62] M. Figueiro, R. Nagare, L. Price, Non-visual effects of light: How to use light to promote circadian entrainment and elicit alertness, Lighting Research & Technology. 50 (2018) 38–62. https://doi.org/10.1177/1477153517721598.
[63] CIE, CIE 17–Discomfort glare in interior lighting, Vienna, Austria, 1995.
[64] DIN, DIN 5035–Innenraumbeleuchtung mit künstlichem licht, Berlin, Germany, 1979.
[65] J.. Wienold, J. Christoffersen, Towards a new daylight glare rating, Berlin, Germany, 2007.
[66] J. Wienold, Dynamic simulation of blind control strategies for visual comfort and energy balance analysis, in: Building Simulation, 2007: pp. 1197–1204.
[67] N.-G. Vardaxis, D. Bard, K. Persson Waye, Review of acoustic comfort evaluation in dwellings—part I: Associations of acoustic field data to subjective responses from building surveys, Building Acoustics. 25 (2018) 151–170. https://doi.org/10.1177/1351010x18762687.

[68] C. Wang, Y. Si, H. Abdul-Rahman, L.C. Wood, Noise annoyance and loudness: Acoustic performance of residential buildings in tropics, Building Services Engineering Research and Technology. 36 (2015) 680–700. https://doi.org/10.1177/0143624415580444.
[69] C. Hopkins, Sound insulation, Butterworth-Heinemann, Imprint of Elsevier, Oxford, 2007.
[70] J.Y. Jeon, J.K. Ryu, P.J. Lee, A quantification model of overall dissatisfaction with indoor noise environment in residential buildings, Applied Acoustics. 71 (2010) 914–921.
[71] D. Ouis, Annoyance caused by exposure to road traffic noise: An update, Noise and Health. 4 (2002) 69.
[72] R. Guski, Personal and social variables as co-determinants of noise annoyance, Noise and Health. 3 (1999) 45–56.
[73] William Burns, Noise and man, 2nd ed., William Clowes & Sons Limited, London, 1973.
[74] B. Berglund, T. Lindvall, D.H. Schwela, Guidelines for community noise, World Health Organization, 1999. https://www.who.int/docstore/peh/noise/guidelines2.html.
[75] S. Delle Macchie, S. Secchi, G. Cellai, Acoustic Issues in Open Plan Offices: A Typological Analysis, Buildings. 8 (2018) 161. https://doi.org/10.3390/buildings8110161.
[76] H.E. Laszlo, E.S. McRobie, S.A. Stansfeld, A.L. Hansell, Annoyance and other reaction measures to changes in noise exposure - A review, Science of the Total Environment. 435–436 (2012) 551–562. https://doi.org/10.1016/j.scitotenv.2012.06.112.
[77] U.S. Environmental Protection Agency (US EPA), Information on Levels of Environmental Noise Requisite to Protect Public Health and Welfare with an Adequate Margin of Safety, Washington, DC, 1974. http://www.nonoise.org/library/levels74/levels74.htm.
[78] The Ministry of the Environment and Climate Change (MOECC), Publication NPC-300: Environmental Noise Guideline, Stationary and Transportation Sources, MOECC, Ottawa, ON, Canada, 2013. https://www.ontario.ca/page/environmental-noise-guideline-stationary-and-transportation-sources-approval-and-planning.
[79] A. Steinemann, P. Wargocki, B. Rismanchi, Ten questions concerning green buildings and indoor air quality, Building and Environment. 112 (2017) 351–358. https://doi.org/10.1016/J.BUILDENV.2016.11.010.
[80] P. Spiru, P.L. Simona, A review on interactions between energy performance of the buildings, outdoor air pollution and the indoor air quality, Energy Procedia. 128 (2017) 179–186. https://doi.org/10.1016/J.EGYPRO.2017.09.039.
[81] S.A. Abdul-Wahab, S. Chin Fah En, A. Elkamel, L. Ahmadi, K. Yetilmezsoy, A review of standards and guidelines set by international bodies for the parameters of indoor air quality, Atmospheric Pollution Research. 6 (2015) 751–767. https://doi.org/10.5094/APR.2015.084.
[82] National Research Council (NRC), Indoor Pollutants, The National Academies Press, Washington, DC, 1981. https://doi.org/10.17226/1711.
[83] T. Salthammer, Critical evaluation of approaches in setting indoor air quality guidelines and reference values, Chemosphere. 82 (2011) 1507–1517. https://doi.org/10.1016/J.CHEMOSPHERE.2010.11.023.
[84] World Health Organization (WHO), WHO Guidelines for Indoor Air Quality: Selected Pollutants, WHO, 2010. https://books.google.com.au/books?id=St0a6djRU_cC.
[85] H. Fromme, M. Debiak, H. Sagunski, C. Röhl, M. Kraft, M. Kolossa-Gehring, The German approach to regulate indoor air contaminants, International Journal of Hygiene and Environmental Health. 222 (2019) 347–354. https://doi.org/10.1016/J.IJHEH.2018.12.012.

[86] Standards Productivity and Innovation Board (SPRING) Singapore, SS 554:2016 - Code of Practice for Indoor Air Quality for Air-conditioned Buildings, (2016).
[87] World Health Organization (WHO), WHO Guidelines for Indoor Air Quality: Dampness and Mould, WHO, 2009. https://books.google.com.au/books?id=PxB8UUHihWgC.
[88] S. Batterman, Review and Extension of CO2-Based Methods to Determine Ventilation Rates with Application to School Classrooms, International Journal of Environmental Research and Public Health. 14 (2017) 145. https://doi.org/10.3390/ijerph14020145.
[89] C.M. Earnest, R.L. Corsi, Inhalation exposure to cleaning products: Application of a two-zone model, Journal of Occupational and Environmental Hygiene. 10 (2013) 328–335. https://doi.org/10.1080/15459624.2013.782198.
[90] J. Taylor, C. Shrubsole, P. Symonds, I. Mackenzie, M. Davies, Application of an indoor air pollution metamodel to a spatially-distributed housing stock, Science of the Total Environment. 667 (2019) 390–399. https://doi.org/10.1016/j.scitotenv.2019.02.341.
[91] S. Silva, A. Monteiro, M.A. Russo, J. Valente, C. Alves, T. Nunes, C. Pio, A.I. Miranda, Modelling indoor air quality: validation and sensitivity, Air Quality, Atmosphere and Health. 10 (2017) 643–652. https://doi.org/10.1007/s11869-016-0458-4.
[92] World Health Organization (WHO), The Right to Healthy Indoor Air, (2000). http://www.euro.who.int/__data/assets/pdf_file/0019/117316/E69828.pdf?ua=1.
[93] K.W. Tham, Indoor air quality and its effects on humans—A review of challenges and developments in the last 30 years, Energy and Buildings. 130 (2016) 637–650. https://doi.org/10.1016/J.ENBUILD.2016.08.071.
[94] T.R. Johnson, J.E. Langstaff, S. Graham, E.M. Fujita, D.E. Campbell, A multipollutant evaluation of APEX using microenvironmental ozone, carbon monoxide, and particulate matter (PM2.5) concentrations measured in Los Angeles by the exposure classification project, Cogent Environmental Science. 4 (2018). https://doi.org/10.1080/23311843.2018.1453022.
[95] S. Hellweg, E. Demou, R. Bruzzi, A. Meijer, R.K. Rosenbaum, M.A.J. Huijbregts, T.E. Mckone, Integrating human indoor air pollutant exposure within life cycle impact assessment, Environmental Science and Technology. 43 (2009) 1670–1679. https://doi.org/10.1021/es8018176.
[96] W.R. Ott, Concepts of human exposure to air pollution, Environment International. 7 (1982) 179–196. https://doi.org/10.1016/0160-4120(82)90104-0.
[97] K. Danna, R.W. Griffin, Health and well-being in the workplace: a review and synthesis of the literature, Journal of Management. 25 (1999) 357–384. https://doi.org/10.1016/S0149-2063(99)00006-9.
[98] D.P. Wyon, Indoor environmental effects on productivity, in: Proceedings of IAQ, Paths to Better Building Environments, Baltimore, MD, 1996.
[99] Y. al Horr, M. Arif, A. Kaushik, A. Mazroei, M. Katafygiotou, E. Elsarrag, Occupant productivity and office indoor environment quality: A review of the literature, Building and Environment. 105 (2016) 369–389. https://doi.org/10.1016/J.BUILDENV.2016.06.001.
[100] Y. al horr, M. Arif, M. Katafygiotou, A. Mazroei, A. Kaushik, E. Elsarrag, Impact of indoor environmental quality on occupant well-being and comfort: A review of the literature, International Journal of Sustainable Built Environment. 5 (2016) 1–11. https://doi.org/10.1016/J.IJSBE.2016.03.006.

[101] J. Aker, M. Malanca, C. Pottage, R. O'Brien, No Health, wellbeing & productivity in offices: The next chapter for green building, London, UK, 2014.

[102] O. Seppanen, W. Fisk, Some Quantitative Relations between Indoor Environmental Quality and Work Performance or Health, HVAC&R Research. 12 (2006) 957–973. https://doi.org/10.1080/10789669.2006.10391446.

[103] ASHRAE, 2013 ASHRAE handbook fundamentals., Atlanta, GA, 2013. https://www.worldcat.org/title/2013-ashrae-handbook-fundamentals/oclc/882088522 (accessed July 10, 2019).

[104] P. Wargocki, O. Seppänen, J. Andersson, A. Boerstra, D. Clements-Croome, K. Fitzner, S.O. Hanssen, REHVA Guidebook No. 6 - Indoor Climate and Productivity in Offices - How to Integrate Productivity in Life-Cycle Cost Analysis of Building Services, REHVA, 2006.

[105] F. Zhang, R. de Dear, P. Hancock, Effects of moderate thermal environments on cognitive performance: A multidisciplinary review, Applied Energy. 236 (2019) 760–777. https://doi.org/10.1016/J.APENERGY.2018.12.005.

[106] F. Mofidi, H. Akbari, An integrated model for position-based productivity and energy costs optimization in offices, Energy and Buildings. 183 (2019) 559–580. https://doi.org/10.1016/J.ENBUILD.2018.11.009.

[107] F. Haldi, D. Robinson, Adaptive actions on shading devices in response to local visual stimuli, Journal of Building Performance Simulation. 3 (2010) 135–153. https://doi.org/10.1080/19401490903580759.

[108] P.M. Bluyssen, S. Janssen, L.H. van den Brink, Y. de Kluizenaar, Assessment of wellbeing in an indoor office environment, Building and Environment. 46 (2011) 2632–2640. https://doi.org/10.1016/J.BUILDENV.2011.06.026.

[109] T. Nayak, T. Zhang, Z. Mao, X. Xu, L. Zhang, D. Pack, B. Dong, Y. Huang, Prediction of Human Performance Using Electroencephalography under Different Indoor Room Temperatures, Brain Sciences. 8 (2018) 74. https://doi.org/10.3390/brainsci8040074.

[110] M.B.C. Aries, J.A. Veitch, Guy.R. Newsham, Windows, view, and office characteristics predict physical and psychological discomfort, Journal of Environmental Psychology. 30 (2010) 533–541. https://doi.org/10.1016/J.JENVP.2009.12.004.

[111] F.S. Bauman, T.G. Carter, A. v. Baughman, E.A. Arens, Field study of the impact of a desktop task/ambient conditioning system in office buildings, ASHRAE Transactions. 104 (1998).

[112] J. Heerwagen, B. Hase, Building biophilia: Connecting people to nature in building design | By By, Environmental Design and Construction. 3 (2001) 30–36.

[113] T.W. Kim, R. Rajagopal, M. Fischer, C. Kam, A knowledge-based framework for automated space-use analysis, Automation in Construction. 32 (2013) 165–176. https://doi.org/10.1016/j.autcon.2012.08.002.

[114] K. Sailer, R. Pomeroy, R. Haslem, Data-driven design — Using data on human behaviour and spatial configuration to inform better workplace design, Corporate Real Estate. 4 (2015) 249–262. http://www.ingentaconnect.com/content/hsp/crej/2015/00000004/00000003/art00008 (accessed June 13, 2018).

[115] A.J. Sonta, P.E. Simmons, R.K. Jain, Understanding building occupant activities at scale: An integrated knowledge-based and data-driven approach, Advanced Engineering Informatics. 37 (2018) 1–13. https://doi.org/10.1016/j.aei.2018.04.009.

[116] T. Labeodan, W. Zeiler, G. Boxem, Y. Zhao, Occupancy measurement in commercial office buildings for demand-driven control applications - A survey and detection system evaluation, Energy and Buildings. 93 (2015) 303–314. https://doi.org/10.1016/j.enbuild.2015.02.028.
[117] A. Tomé, M. Kuipers, T. Pinheiro, M. Nunes, T. Heitor, Space-use analysis through computer vision, Automation in Construction. 57 (2015) 80–97. https://doi.org/10.1016/j.autcon.2015.04.013.
[118] University of California, Revenue and expense data, (2019). https://www.universityofcalifornia.edu/infocenter/revenue-and-expense-data (accessed August 26, 2019).
[119] S. Bafna, Space syntax: A brief introduction to its logic and analytical techniques, Environment and Behavior. 35 (2003) 17–29. https://doi.org/10.1177/0013916502238863.
[120] C. Congdon, Yan Zhang, M. Rashid, S. Bafna, S. Warmels, J. Bromberg, R. Bajaj, C. Zimring, J. Peponis, Designing Space to Support Knowledge Work, Environment and Behavior. 39 (2007) 815–840. https://doi.org/10.1177/0013916506297216.
[121] F.W. Kabo, N. Cotton-Nessler, Y. Hwang, M.C. Levenstein, J. Owen-Smith, Proximity effects on the dynamics and outcomes of scientific collaborations, Research Policy. 43 (2014) 1469–1485. https://doi.org/10.1016/J.RESPOL.2014.04.007.
[122] F. Kabo, Y. Hwang, M. Levenstein, J. Owen-Smith, Shared Paths to the Lab: A Sociospatial Network Analysis of Collaboration, Environment and Behavior. 47 (2015) 57–84. https://doi.org/10.1177/0013916513493909.
[123] F. Kabo, The architecture of network collective intelligence: Correlations between social network structure, spatial layout and prestige outcomes in an office, Philosophical Transactions of the Royal Society B: Biological Sciences. 373 (2018) 20170238. https://doi.org/10.1098/rstb.2017.0238.
[124] M. Claudel, E. Massaro, P. Santi, F. Murray, C. Ratti, An exploration of collaborative scientific production at MIT through spatial organization and institutional affiliation, PLoS ONE. 12 (2017). https://doi.org/10.1371/journal.pone.0179334.
[125] M. Housman, D. Minor, Workplace Design: The Good, the Bad, and the Productive, 2016. http://www.hbs.edu/faculty/Publication Files/16-147_c672567d-9ba2-45c1-9d72-ea7fa58252ab.pdf (accessed June 26, 2018).
[126] J.D. Wineman, F.W. Kabo, G.F. Davis, Spatial and Social Networks in Organizational Innovation, Environment and Behavior. 41 (2009) 427–442. https://doi.org/10.1177/0013916508314854.
[127] E.S. Bernstein, S. Turban, The impact of the 'open' workspace on human collaboration, Philosophical Transactions of the Royal Society B: Biological Sciences. 373 (2018) 20170239. https://doi.org/10.1098/rstb.2017.0239.
[128] E.R. Cohen, T. Cvitaö, J.G. Frey, B. Holmstrm, K. Kuchitzu, R. Marquardt, I. Mills, F. Pavese, M. Quack, J. Stohner, H.L. Strauss, M. Takami, A.J. Thor, Quantities, units and symbols in physical chemistry, 3rd ed., The Royal Society of Chemistry, Cambridge, UK, 2008.
[129] ISO, ISO 52000-1:2017: Energy performance of buildings – Overarching EPB assessment – Part 1: General framework and procedures., Geneva, Switzerland, 2017.
[130] A. Roth, Building Energy Modeling 101: What Is It and What Is DOE's Role?, (2017). https://energy.gov/eere/buildings/articles/building-energy-modeling-101-what-it-and-what-doe-s-role.
[131] O'Brien et al., International survey on current occupant modelling approaches in building performance simulation, Building Performance Simulation. (2016).

[132] S. D'Oca, V. Fabi, S.P. Corgnati, R.K. Andersen, Effect of thermostat and window opening occupant behavior models on energy use in homes, Building Simulation. 7 (2014) 683–694. https://doi.org/10.1007/s12273-014-0191-6.

[133] A. Mahdavi, F. Tahmasebi, Predicting people's presence in buildings: An empirically based model performance analysis, Energy and Buildings. 86 (2015) 349–355. https://doi.org/10.1016/j.enbuild.2014.10.027.

[134] E. Azar, C. Nikolopoulou, S. Papadopoulos, Integrating and optimizing metrics of sustainable building performance using human-focused agent-based modeling, Applied Energy. 183 (2016). https://doi.org/10.1016/j.apenergy.2016.09.022.

[135] A. Cowie, T. Hong, X. Feng, Q. Darakdjian, Usefulness of the obFMU module examined through a review of occupant modelling functionality in building performance simulation programs, in: IBPSA Building Simulation Conference, 2017.

[136] H.B. O'Brien, W., Gunay, Implementation of the Occupant Behavior and Presence Models in OpenStudio, 2016.

[137] Y. Plessis, G., Amouroux, E., Haradji, Coupling occupant behaviour with a building energy model - A FMI application, in: Proceedings of the 10th International Modelica Conference, March 10-12, Lund, Sweden., 2014.

[138] I. Gunay B.H., O'Brien, W., Beausoleil-Morrison, Coupling stochastic occupant models to building performance simulation using the discrete event system specification formalism, Building Performance Simulation. (2014).

[139] C.C. Menassa, V.R. Kamat, S. Lee, E. Azar, C. Feng, K. Anderson, Conceptual Framework to Optimize Building Energy Consumption by Coupling Distributed Energy Simulation and Occupancy Models, Journal of Computing in Civil Engineering. 28 (2014) 50–62. https://doi.org/10.1061/(asce)cp.1943-5487.0000299.

[140] Z. Deme Belafi, T. Hong, A. Reith, A library of building occupant behaviour models represented in a standardised schema, Energy Efficiency. 12 (2019) 637–651. https://doi.org/10.1007/s12053-018-9658-0.

[141] T. Hong, H. Sun, Y. Chen, S.C. Taylor-Lange, D. Yan, An occupant behavior modeling tool for co-simulation, Energy and Buildings. 117 (2016). https://doi.org/10.1016/j.enbuild.2015.10.033.

[142] Z. Wang, T. Hong, R. Jia, Buildings.Occupants: a Modelica package for modelling occupant behaviour in buildings, Journal of Building Performance Simulation. 12 (2019) 433–444. https://doi.org/10.1080/19401493.2018.1543352.

[143] M. Wetter, W. Zuo, T.S. Nouidui, X. Pang, Modelica Buildings library, Journal of Building Performance Simulation. 7 (2014) 253–270. https://doi.org/10.1080/19401493.2013.765506.

[144] X. Luo, K.P. Lam, Y. Chen, T. Hong, Performance evaluation of an agent-based occupancy simulation model, Building and Environment. 115 (2017). https://doi.org/10.1016/j.buildenv.2017.01.015.

[145] Y. Chen, X. Liang, T. Hong, X. Luo, Simulation and visualization of energy-related occupant behavior in office buildings, Building Simulation. 10 (2017) 785–798. https://doi.org/10.1007/s12273-017-0355-2.

[146] Y. Wang, C., Yan, D. & Jiang, A novel approach for building occupancy simulation, Building Simulation. (2011).

[147] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings, Energy and Buildings. 87 (2015). https://doi.org/10.1016/j.enbuild.2014.11.067.

[148] W. O'Brien, H.B. Gunay, Mitigating office performance uncertainty of occupant use of window blinds and lighting using robust design, Building Simulation. 8 (2015) 621–636.
[149] Y. Chen, T. Hong, X. Luo, An agent-based stochastic Occupancy Simulator, Building Simulation. 11 (2018). https://doi.org/10.1007/s12273-017-0379-7.
[150] M. Ouf, W. O'Brien, B. Gunay, Optimizing Building Performance using Stochastic Occupant Models, in: ASHRAE Transactions -2019 Winter Conference, Atlanta, GA, 2019: pp. 96–105.
[151] S. Gilani, W. O'Brien, Best Practices Guidebook on Advanced Occupant Modelling, Ottawa, 2018. https://carleton.ca/hbilab/wp-content/uploads/Best-Practices-Guidebook-on-Advanced-Occupant-Modelling.pdf.
[152] F. Haldi, D. Robinson, Adaptive actions on shading devices in response to local visual stimuli, Journal of Building Performance Simulation. 3 (2010) 135–153. https://doi.org/10.1080/19401490903580759.
[153] H.B. Rijal, P. Tuohy, M.A. Humphreys, J.F. Nicol, A. Samuel, J. Clarke, Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, Energy and Buildings. 39 (2007) 823–836.
[154] M. Schweiker, F. Haldi, M. Shukuya, D. Robinson, Verification of stochastic models of window opening behaviour for residential buildings, Journal of Building Performance Simulation. 5 (2012) 55–74. https://doi.org/10.1080/19401493.2011.567422.
[155] A. al Amoodi, E. Azar, Impact of human actions on building energy performance: A case study in the United Arab Emirates (UAE), Sustainability (Switzerland). 10 (2018). https://doi.org/10.3390/su10051404.
[156] M. Bonte, F. Thellier, B. Lartigue, Impact of occupant's actions on energy building performance and thermal sensation, Energy and Buildings. 76 (2014) 219–227. https://doi.org/10.1016/j.enbuild.2014.02.068.
[157] C.M. Clevenger, J.R. Haymaker, M. Jalili, Demonstrating the impact of the occupant on building performance, Journal of Computing in Civil Engineering. 28 (2013) 99–102.
[158] E. Azar, C.C. Menassa, A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings, Energy and Buildings. 55 (2012) 841–853. https://doi.org/10.1016/j.enbuild.2012.10.002.
[159] F. Haldi, D. Robinson, The impact of occupants' behaviour on building energy demand, Journal of Building Performance Simulation. 4 (2011) 323–338.
[160] C. Clevenger, J. Haymaker, The Impact of the Building Occupant on Energy Modeling Simulations, in: Joint International Conference on Computing and Decision Making in Civil and Building Engineering, 2006.
[161] J.D. Barbosa, E. Azar, Modeling and implementing human-based energy retrofits in a green building in desert climate, Energy and Buildings. 173 (2018) 71–80.
[162] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy and Buildings. 41 (2009) 295–302. http://www.sciencedirect.com/science/article/B6V2V-4TPF4FY-1/2/06185922bc642c8d0112c83d9021de78.
[163] D. Bourgeois, C. Reinhart, I. Macdonald, Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control, Energy and Buildings. 38 (2006) 814–823.

[164] C.F. Reinhart, J. Wienold, The daylighting dashboard–a simulation-based design analysis for daylit spaces, Building and Environment. 46 (2011) 386–396.
[165] A. Roetzel, Occupant behaviour simulation for cellular offices in early design stages—Architectural and modelling considerations, Building Simulation. 8 (2015) 211–224. https://doi.org/10.1007/s12273-014-0203-6.
[166] K. Sun, T. Hong, A simulation approach to estimate energy savings potential of occupant behavior measures, Energy and Buildings. 136 (2017) 43–62. https://doi.org/10.1016/j.enbuild.2016.12.010.
[167] S. Gilani, W. O'Brien, H.B. Gunay, J.S. Carrizo, Use of dynamic occupant behavior models in the building design and code compliance processes, Energy and Buildings. 117 (2016) 260–271. https://doi.org/http://dx.doi.org/10.1016/j.enbuild.2015.10.044.
[168] C.F. Reinhart, D. Bourgeois, F. Dubrous, Lightswitch: a model for manual control of lighting and blinds, Solar Energy. 77 (2004) 15–28.
[169] W. Parys, D. Saelens, H. Hens, Coupling of dynamic building simulation with stochastic modelling of occupant behaviour in offices–a review-based integrated methodology, Journal of Building Performance Simulation. 4 (2011) 339–358.
[170] S. Gilani, W. O'Brien, B. Gunay, Simulation of occupants' impact at different spatial scales, Building and Environment. (2018).
[171] J. Sarwono, A.E. Larasati, W.N.I. Novianto, I. Sihar, S.S. Utami, Simulation of Several Open Plan Office Design to Improve Speech Privacy Condition without Additional Acoustic Treatment, Procedia - Social and Behavioral Sciences. 184 (2015) 315–321. https://doi.org/10.1016/j.sbspro.2015.05.096.
[172] K. Sun, T. Hong, A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures, Energy and Buildings. 146 (2017) 383–396. http://dx.doi.org/10.1016/j.enbuild.2017.04.065 (accessed July 3, 2019).
[173] T. Abuimara, W. O'Brien, B. Gunay, J.S. Carrizo, Towards occupant-centric simulation-aided building design: a case study, Building Research and Information. 47 (2019) 866–882. https://doi.org/10.1080/09613218.2019.1652550.
[174] W. O'Brien, H.B. Gunay, Do building energy codes adequately reward buildings that adapt to partial occupancy?, Science and Technology for the Built Environment. 25 (2019) 678–691. https://doi.org/10.1080/23744731.2019.1581015.
[175] S.K. Jeong, Y.U. Ban, Computational algorithms to evaluate design solutions using Space Syntax, CAD Computer Aided Design. (2011). https://doi.org/10.1016/j.cad.2011.02.011.
[176] K. Sailer, I. McCulloh, Social networks and spatial configuration—How office layouts drive social interaction, Social Networks. 34 (2012) 47–58. https://doi.org/10.1016/j.socnet.2011.05.005.
[177] M. Ouf, W. O'Brien, B. Gunay, A method to generate design-sensitive occupant-related schedules for building performance simulations, Science and Technology for the Built Environment. 25 (2019) 221–232.
[178] M. Marschall, J. Burry, Can the use of stochastic models of occupants' environmental control behavior influence architectural design outcomes?, in: Proceedings of the 24th International Conference on Computer-Aided Architectural Design Research in Asia (CAADRIA 2019), The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), 2019: pp. 715–724.

[179] F. Tahmasebi, A. Mahdavi, On the utility of occupants' behavioural diversity information for building performance simulation: An exploratory case study, Energy and Buildings. 176 (2018) 380–389. https://doi.org/10.1016/j.enbuild.2018.07.042.

[180] H.Y. Lee, I.T. Yang, Y.C. Lin, Laying out the occupant flows in public buildings for operating efficiency, Building and Environment. 51 (2012) 231–242. https://doi.org/10.1016/j.buildenv.2011.11.005.

[181] Z. Yang, A. Ghahramani, B. Becerik-Gerber, Building occupancy diversity and HVAC (heating, ventilation, and air conditioning) system energy efficiency, Energy. 109 (2016) 641–649. https://doi.org/10.1016/J.ENERGY.2016.04.099.

[182] R.K. Roy, Design of experiments using the Taguchi approach : 16 steps to product and process improvement, Wiley, 2001.

[183] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy and Buildings. 43 (2011) 2798–2805. https://doi.org/10.1016/J.ENBUILD.2011.06.034.

[184] P. Hoes, J.L.M. Hensen, M.G.L.C. Loomans, B. de Vries, D. Bourgeois, User behavior in whole building simulation, Energy and Buildings. 41 (2009) 295–302.

[185] P. Hoes, M. Trcka, J.L.M. Hensen, B.H. Bonnema, Optimizing building designs using a robustness indicator with respect to user behavior, Proceedings of the 12th Conference of the International Building Performance Simulation Association. (2011) 14–16.

[186] S. Karjalainen, Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption, Energy Efficiency. 9 (2016) 1257–1270. https://doi.org/10.1007/s12053-015-9422-7.

[187] T. Buso, V. Fabi, R.K. Andersen, S.P. Corgnati, Occupant behaviour and robustness of building design, Building and Environment. 94 (2015) 694–703. https://doi.org/10.1016/j.buildenv.2015.11.003.

[188] W. O'Brien, H.B. Gunay, F. Tahmasebi, A. Mahdavi, A preliminary study of representing the inter-occupant diversity in occupant modelling, Journal of Building Performance Simulation. 10 (2017) 509–526. https://doi.org/10.1080/19401493.2016.1261943.

[189] W. O'Brien, A. Abdelalim, H.B. Gunay, Development of an office tenant electricity use model and its application for right-sizing HVAC equipment, Journal of Building Performance Simulation. 12 (2018) 37–55. https://doi.org/10.1080/19401493.2018.1463394.

[190] A. Abdelalim, W. O'Brien, S. Gilani, A Probabilistic Approach Towards Achieving Net-Zero Energy Buildings Using a Stochastic Office Tenant Model, Science and Technology for the Built Environment. 0 (2019) 1–15. https://doi.org/10.1080/23744731.2019.1598137.

[191] Austrian Stanards, Thermal insulation in building construction — Part 5: Model of climate and user profiles, (2019).

[192] BRE, National Calculation Methodology (NCM) modelling guide for buildings other than dwellings in England, (2017).

[193] ASHRAE, ASHRAE 90.1-2013, Energy standard for buildings except low rise residential buildings, Atlanta, GA, 2013.

[194] NRC, National Energy Code of Canada for Buildings 2017, (2017).

[195] A. Wagner, W. O'Brien, Occupant behaviour-centric building design and operation EBC Annex 79, 2018.

[196] T. Francom, S.T. Ariaratnam, M. el Asmar, Industry Perceptions of Alternative Project Delivery Methods Applied to Trenchless Pipeline Projects, Journal of Pipeline Systems Engineering and Practice. 7 (2015) 04015020. https://doi.org/10.1061/(asce)ps.1949-1204.0000220.
[197] L. Song, Y. Mohamed, S.M. AbouRizk, Early Contractor Involvement in Design and Its Impact on Construction Schedule Performance, Journal of Management in Engineering. 25 (2008) 12–20. https://doi.org/10.1061/(asce)0742-597x(2009)25:1(12).
[198] B. Franz, R. Leicht, K. Molenaar, J. Messner, Impact of Team Integration and Group Cohesion on Project Delivery Performance, Journal of Construction Engineering and Management. 143 (2016) 04016088. https://doi.org/10.1061/(asce)co.1943-7862.0001219.
[199] D. Alleman, D. Papajohn, D.D. Gransberg, M. el Asmar, K.R. Molenaar, Exploration of Early Work Packaging in Construction Manager–General Contractor Highway Projects, Transportation Research Record: Journal of the Transportation Research Board. 2630 (2017) 68–75. https://doi.org/10.3141/2630-09.
[200] J.S. Shane, D.D. Gransberg, A Critical Analysis of Innovations in Construction Manager-at-Risk Project Delivery, in: American Society of Civil Engineers (ASCE), 2010: pp. 827–836. https://doi.org/10.1061/41109(373)83.
[201] T. Francom, M. el Asmar, S.T. Ariaratnam, Performance Analysis of Construction Manager at Risk on Pipeline Engineering and Construction Projects Introduction to Project Delivery Systems and Pipeline Infrastructure, (2016). https://doi.org/10.1061/(ASCE)ME.
[202] H. Vashani, J. Sullivan, M. el Asmar, DB 2020: Analyzing and Forecasting Design-Build Market Trends, (2016). https://doi.org/10.1061/(ASCE)CO.1943-7862.
[203] D.W. Ramsey, M. el Asmar, Cost and Schedule Performance Benchmarks of U.S. Transportation Public-Private Partnership Projects, Transportation Research Record: Journal of the Transportation Research Board. 2504 (2015) 58–65. https://doi.org/10.3141/2504-07.
[204] K.R. Molenaar, A.D. Songer, M. Barash, Public-Sector Design/Build Evolution and Performance, Journal of Management in Engineering. 15 (2002) 54–62. https://doi.org/10.1061/(asce)0742-597x(1999)15:2(54).
[205] J. Sullivan, M. el Asmar, J. Chalhoub, H. Obeid, Two Decades of Performance Comparisons for Design-Build, Construction Manager at Risk, and Design-Bid-Build: Quantitative Analysis of the State of Knowledge on Project Cost, Schedule, and Quality, Journal of Construction Engineering and Management. 143 (2017) 04017009. https://doi.org/10.1061/(asce)co.1943-7862.0001282.
[206] M. el Asmar, A.S. Hanna, W.-Y. Loh, Evaluating Integrated Project Delivery Using the Project Quarterback Rating, Journal of Construction Engineering and Management. 142 (2015) 04015046. https://doi.org/10.1061/(asce)co.1943-7862.0001015.
[207] H. Sanboskani, N. Cho, M. el Asmar, S. Underwood, Evaluating the Ride Quality of Asphalt Concrete Pavements Delivered Using Design-Build, in: American Society of Civil Engineers (ASCE), 2018: pp. 424–433. https://doi.org/10.1061/9780784481295.043.
[208] H. Abkarian, M. el Asmar, S. Underwood, Impact of Alternative Project Delivery Systems on the International Roughness Index: Case Studies of Transportation Projects in the Western United States, Transportation Research Record: Journal of the Transportation Research Board. 2630 (2017) 76–84. https://doi.org/10.3141/2630-10.
[209] M. Schweiker, E. Ampatzi, M.S. Andargie, R.K. Andersen, E. Azar, V.M. Barthelmes, C. Berger, L. Bourikas, S. Carlucci, G. Chinazzo, L.P. Edappilly, M. Favero, S. Gauthier, A. Jamrozik, M. Kane, A. Mahdavi, C. Piselli, A.L. Pisello, A. Roetzel, A. Rysanek, K. Sharma, S. Zhang, Review

of multi-domain approaches to indoor environmental perception and behaviour, Building and Environment. 176 (2020) 106804. https://doi.org/10.1016/j.buildenv.2020.106804.
[210] ASHRAE, ASHRAE Guideline 10: Interactions Affecting the Achievement of Acceptable Indoor Environments., Atlanta, GA, 2016.
[211] S. Torresin, G. Pernigotto, F. Cappelletti, A. Gasparella, Combined effects of environmental factors on human perception and objective performance: A review of experimental laboratory works, Indoor Air. 28 (2018) 525–538. https://doi.org/10.1111/ina.12457.
[212] S. D'Oca, C.F. Chen, T. Hong, Z. Belafi, Synthesizing building physics with social psychology: An interdisciplinary framework for context and occupant behavior in office buildings, Energy Research and Social Science. 34 (2017) 240–251. https://doi.org/10.1016/j.erss.2017.08.002.
[213] W. O'Brien, F. Tahmasebi, ..., J. Zhou, An international review of occupant-related aspects of building energy codes and standards, Building and Environment. In Press (2020).