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REVIEW ARTICLE

Documenting occupant models for building performance simulation: a state-of-the-art

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ABSTRACT

The number of occupancy and occupant behaviour models developed for building performance simulation (BPS) has steadily increased for the past four decades. However, their use is still limited in practice. This is partly due to the difficulty in understanding their utility and to the challenges related to their implementation into BPS. Both problems can be attributed to the lack of a framework for their description and communication. In this paper, we fill this gap by introducing a framework to document occupant models, that represents the state-of-the-art of available information on the topic. The framework consists of four blocks (description, development, evaluation, and implementation) and can also be regarded as a guideline to help researchers communicate their models transparently. Based on a systematic review, we verify to which degree existing academic papers on occupant models meet the framework, thus providing a self-critical assessment of the state-of-the-art of occupant models' documentation.

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KEYWORDS
Building simulation; occupancy and occupant behaviour models; occupant presence and actions models; evaluation; documentation

1. Introduction

1.1. Context

Occupancy and occupant behaviour have been suggested to significantly contribute to the uncertainty of Building Performance Simulation (BPS) results (O'Brien et al. 2020; Yoshino, Hong, and Nord 2017). In the last four decades, a steadily increasing number of efforts has been undertaken to improve occupant models with respect to their fidelity and resolution. However, the implementation of occupant models is still limited in practice. Evidence from an international survey on current occupant modelling practices and attitudes in BPS suggests that occupant modelling remains mostly an academic exercise, and practitioners' current occupant assumptions are simplistic and either overly optimistic or conservative depending on the application (O'Brien et al. 2017). Similarly, Azar et al. (2020) and Lindner, Park, and Mitterhofer (2017) independently observed that the application of occupant models is still very limited in the building design process. One reason for the limited uptake of occupant models in real-world applications could be the difficulty in adequately understanding their utility and robustness and the challenges related to their implementation into BPS (Lindner, Park, and Mitterhofer 2017). Both problems could be associated with the lack of a standard framework and/or guideline for occupant models' description, documentation, and communication (Mahdavi and Tahmasebi 2019).

1.2. Previous related works

Most of the past reviews on occupant modelling in buildings focused on the employed modelling formalisms and techniques (Jia, Srinivasan, and Raheem 2017; Zhang et al. 2018; Dong et al. 2018; Gaetani, Hoes, and Hensen 2020; Carlucci et al. 2020). Jia, Srinivasan, and Raheem (2017) compared and analysed the advantages and limitations of current occupant modelling approaches (agent-based, statistical, stochastic, and data mining), making

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recommendations for future research, such as the need to collect more empirical data and to further develop agent-based models for integration into BPS tools. Zhang et al. (2018) also reviewed agent-based, statistical, stochastic, and data mining methods for occupant behaviour modelling and identified major research gaps, including the necessity of collecting data at city scale and accounting for the socio-economic status. Dong et al. (2018) presented the most commonly used statistical and data mining models and provided a modelling reference for future researchers to select a proper method or model for a specific research purpose. Similarly, Gaetani, Hoes, and Hensen (2020) focused on introducing and testing a methodology, which comprises uncertainty and sensitivity analysis, to help identify the fit-for-purpose modelling formalism for each occupant aspect. Carlucci *et al.*'s more recent review gave an exhaustive overview of methods and techniques used for occupant behaviour modelling (Carlucci et al. 2020).

Other more conceptual works dealt with framing occupant behaviour to better understand and standardize its semantic representation (Hong et al. 2015; Deme Belafi, Hong, and Reith 2019; Arslan, Cruz, and Ginhac 2019). In this respect, Hong et al. (2015) proposed the '*Drivers – Needs – Actions – Systems*' (DNAs) framework, which is constituted of four key components: i) the Drivers of behaviour, ii) the Needs of the occupants, iii) the Actions carried out by the occupants, and iv) the building systems acted upon by the occupants. Deme Belafi, Hong, and Reith (2019) implemented the theoretical DNAs framework into an XML (eXtensible Markup Language) schema format and represented each occupant model in a separate XML file to form a library of occupant models, which can be used for co-simulation. Arslan, Cruz, and Ginhac (2019) created a framework named '*Occupant behaviours in Dynamic Environments*' (OBiDE) to integrate the DNAs ontology with a trajectory enrichment model for the movements of the occupants.

In closer relation to the present paper, some past works tackled specific aspects related to the process of describing, developing, evaluating, and implementing an occupant model (Lindner, Park, and Mitterhofer 2017; Gunay, O'Brien, and Beausoleil-Morrison 2013; Yan et al. 2015; Mahdavi and Tahmasebi 2017; Mahdavi and Tahmasebi 2016; Li et al. 2019; Wolf et al. 2015; Abuimara et al. 2019; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018). Gunay, O'Brien, and Beausoleil-Morrison (2013) reviewed the research on adaptive occupant behaviour in offices, highlighting existing limitations in observational, modelling, and simulation studies of occupant behaviour. Yan et al. (2015) reviewed the current state of the art and highlighted future challenges in data collection, modelling, evaluation, and integration within BPS programmes. Especially concerning occupant model evaluation, Mahdavi and Tahmasebi (2017) discussed evaluation requirements and promoted a rigorous process towards quality assurance. In another work, Mahdavi and Tahmasebi (2016) dealt with the context-dependence of occupancy-related model use in BPS. Wolf et al. (2015) reviewed evaluation methods of occupant models and criticized internal validation procedures. Lindner, Park, and Mitterhofer (2017) discussed issues and requirements for the proper implementation of occupant models in BPS tools, focusing in particular on an office case study employing different occupant models. Li et al. (2019) created a framework to help understand the process of occupant model development, highlighting associated challenges and establishing a set of criteria for the rational selection from existing occupant models. Abuimara et al. (2019; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018) highlighted the infancy of occupant models in terms of implementation and the need to accommodate occupant models in an easy to apply way to make it more convenient for practitioners to use.

1.3. Research aims

Earlier studies have addressed specific aspects related to the process of describing, developing, evaluating, and implementing an occupant model (Lindner, Park, and Mitterhofer 2017; Dong et al. 2018; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018; Deme Belafi, Hong, and Reith 2019; Gunay, O'Brien, and Beausoleil-Morrison 2013; Yan et al. 2015; Mahdavi and Tahmasebi 2017; Mahdavi and Tahmasebi 2016; Li et al. 2019; Wolf et al. 2015; Abuimara et al. 2019). However, they have rather considered them individually, thus missing considering and including all the aforementioned elements in a more holistic perspective. A view on the whole process of describing, developing, evaluating, and implementing an occupant model, which is independent of the particular modelling formalism adopted, is currently missing. Furthermore, none of the past works has reviewed existing occupant behaviour papers intending to present the current status of occupant models' documentation.

Thus, the first objective of this paper is to derive a framework for the documentation of occupant models based on past works on the topic (Lindner, Park, and Mitterhofer 2017; Dong et al. 2018; Abuimara et al. 2019; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018; Gunay et al. 2014; Fabi et al. 2012; Schweiker et al. 2020; Heinze, Wallisch, and Dunkler 2018; Coleman 1974; Hong et al. 2018; Carlucci et al. 2020; Deme Belafi, Hong, and Reith 2019; Gunay, O'Brien, and Beausoleil-Morrison 2013; Yan et al. 2015; Mahdavi and Tahmasebi 2017; Mahdavi and Tahmasebi 2016; Li et al. 2019; Wolf et al. 2015). The framework includes all the above-cited aspects: description, development, evaluation, and implementation (section 3) and can be regarded as the state-of-the-art of the available information on how an occupant model should be documented. The second objective is to verify to which degree existing academic papers on occupant models meet this framework, thus providing a self-critical assessment of the state-of-the-art of how occupant models are currently documented in reality (section 4 and 5).

The purpose of the presented framework is three-fold. Firstly, to serve as a guideline for documentation that can help researchers transparently communicate their models. Secondly, to facilitate the objective of the evaluation reliability of occupant models. Thirdly, to help modellers, practitioners and stakeholders better comprehend occupant models' utility and direct them in selecting and adopting the most suitable model for their application.

The framework does not aim to guide the development of occupant models. Other works have been dedicated to this scope, in particular focusing on the optimal choice of the model formalism depending on the type of behaviour, building type, and spatial and temporal scale (Jia, Srinivasan, and Raheem 2017; Zhang et al. 2018; Dong et al. 2018; Gaetani, Hoes, and Hensen 2020; Carlucci et al. 2020). Furthermore, the focus of this paper is on occupant models developed for building/district performance simulation, that is on models that are used to predict the performance of a building/district in terms of, for example, energy consumption, carbon emissions, and/or thermal comfort experienced by the occupants. Occupant models integrated into real-time building energy system controls are out of the scope of this work.

2. Methodology

2.1. Framework development

The framework is based on previous works (Lindner, Park, and Mitterhofer 2017; Dong et al. 2018; Abuimara et al. 2019; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018; Gunay et al. 2014; Fabi et al. 2012; Schweiker et al. 2020; Heinze, Wallisch, and Dunkler 2018; Coleman 1974; Hong et al. 2018; Carlucci et al. 2020; Deme Belafi, Hong, and Reith 2019; Gunay, O'Brien, and Beausoleil-Morrison 2013; Yan et al. 2015; Mahdavi and Tahmasebi 2017; Mahdavi and Tahmasebi 2016; Li et al. 2019; Wolf et al. 2015) and recent reflections and discussions among the authors, who are all participants of Annex 79 of the International Energy Agency's Energy in Buildings and Communities Programme, titled '*Occupant-centric building design and operation*'. In deriving the framework, a '*best practice*' approach could not be followed because there is no real best practice in the literature of occupant behaviour models and no model could be successfully deployed to general practice (e.g. by standards). Therefore, as experts engaged in the work of Annex 79, we discussed and elaborated a framework based on past research efforts on the topic (Lindner, Park, and Mitterhofer 2017; Dong et al. 2018; Abuimara et al. 2019; Abuimara, Gunay, and O'Brien 2021; Abuimara et al. 2018; Gunay et al. 2014; Fabi et al. 2012; Schweiker et al. 2020; Heinze, Wallisch, and Dunkler 2018; Coleman 1974; Hong et al. 2018; Carlucci et al. 2020; Deme Belafi, Hong, and Reith 2019; Gunay, O'Brien, and Beausoleil-Morrison 2013; Yan et al. 2015; Mahdavi and Tahmasebi 2017; Mahdavi and Tahmasebi 2016; Li et al. 2019; Wolf et al. 2015). Toward this aim we would like to emphasize that the framework has been developed to be: *schematic*, to make it easier to find and extract all the information, and *general*, to be adaptable to the different occupant models' formalisms, purposes, and implementation needs.

2.2. Review of papers on occupant models

The bibliographic search to identify academic papers on occupant models was conducted through the Scopus scientific database as part of a recent work reviewing models of occupants' presence and actions in buildings (Carlucci et al. 2020). As part of this search, 278 journal papers were identified. These studies were manually screened to identify those papers dealing with models developed explicitly for building/district performance simulation; this led to 82 papers being selected. We then added four papers (Jin et al. 2020; Panchabikesan, Haghighat, and El Mankibi 2021; Lu et al. 2021; Zhou et al. 2021) published last year (2020) that were not covered in the original review. Papers that were about comparing and/or using previously published occupant models were excluded; thus, only original papers about newly developed models for predicting occupant behaviour in a building/district were retained for review. A total of 86 papers (Jin et al. 2020; Panchabikesan, Haghighat, and El Mankibi 2021; Lu et al. 2021; Zhou et al. 2021; de Santiago, Rodriguez-Villalón, and Sicre 2017; Binini, Munda, and Dintchev 2017; Widén et al. 2009; Yao and Steemers 2005; Bandić and Kevrić 2019; Wang, Yan, and Ren 2016; Stokes, Rylatt, and Lomas 2004; Richardson et al. 2010; Richardson et al. 2009; Zhou et al. 2015; Hunt 1979; Gilani and O'Brien 2018; Richardson, Thomson, and Infield 2008; Page et al. 2008; Andersen et al. 2014; D'Oca and Hong 2015; Aerts et al. 2014; Haldi and Robinson 2010; Belazi et al. 2019; Gunay et al. 2018; Tanimoto and Hagishima 2005; Ren, Yan, and Wang 2014; Fabi, Andersen, and Corgnati 2013; Chen et al. 2017; Schweiker and Shukuya 2009; Bruce-Konuah, Jones, and

Fuertes 2019; Haldi and Robinson 2008; Deme Belafi et al. 2018; Calì, Wesseling, and Müller 2018; Yao and Zhao 2017; Tetlow et al. 2015; Jones et al. 2017; Stazi et al. 2017; Calì et al. 2016; Shi and Zhao 2016; Fabi, Andersen, and Corgnati 2015; Yun and Steemers 2010; Yun, Tuohy, and Steemers 2009; Fritsch et al. 1990; Andersen et al. 2013; Yun and Steemers 2008; Capasso et al. 1994; Haldi and Robinson 2009; Schweiker et al. 2012; Pan et al. 2018; Shi et al. 2018; Li et al. 2015; Wei et al. 2019; Pan et al. 2019; Yun, Kim, and Kim 2012; Barthelmes et al. 2017; Rosemann 2017; Yilmaz, Firth, and Allinson 2017; Causone et al. 2019; Tanimoto, Hagishima, and Sagara 2008; Fischer et al. 2016; Kashif et al. 2013; Widén, Nilsson, and Wäckelgård 2009; Ozawa, Kudoh, and Yoshida 2018; Chang and Hong 2013; Cedeno Laurent, Samuelson, and Chen 2017; Herkel, Knapp, and Pfafferott 2008; Mahdavi et al. 2008; Paatero and Lund 2006; Reinhart 2004; D'Oca et al. 2014; Langevin, Wen, and Gurian 2015; Naspi et al. 2018; Naspi et al. 2018; Schweiker and Wagner 2016; Jia et al. 2019; Widén and Wäckelgård 2010; Gottwalt et al. 2011; Putra, Andrews, and Senick 2017; Wilke et al. 2013; Nord et al. 2018; Lee and Malkawi 2014; Haldi et al. 2017; Baetens and Saelens 2016; Nicol, Humphreys, and Olesen 2004; Andersen et al. 2009; Pflugradt and Muntwyler 2017) were thoroughly read and systematically reviewed by extracting the information of interest according to the documentation framework and collating it in a spreadsheet that is publicly accessible (see Supplementary Materials).

The review presented in this paper addresses only occupant models developed for predicting new or future observations. However, the distinction between occupant models developed for prediction and those built for explanation or description is not always obvious, especially for regression-type models. For example, some papers appear to build a descriptive model, but they concurrently state that their models should be used in BPS (Bruce-Konuah, Jones, and Fuertes 2019; Andersen et al. 2013; Nicol 2001; Schweiker and Shukuya 2009). Some of them are indeed then used in BPS (D'Oca et al. 2014). This is due to the false assumption that models with high explanatory power (i.e. high strength of the underlined casual relationships) also have high predictive power (Shmueli 2010). Given that the distinction between prediction and explanation/description is not always understood, we have decided not to exclude models which seem explanatory or descriptive. Yet, it is of fundamental importance that, in the future, the distinction between prediction and explanation or description is well understood and that the paper clearly states whether the goal of the developed occupant model is predictive, explanatory, or descriptive.

3. The occupant model documentation framework

In this section, we describe the framework developed for the documentation of occupant models used in BPS. Figure 1 provides an overview of the framework whose individual elements are described in detail in sub-sections 3.1, 3.2, 3.3, and 3.4. As it can be noticed in Figure 1, the framework is given in a specific order: '*1. Model Description*', '*2. Model Development*', '*3. Model Evaluation*', and, finally, '*4. Model Implementation*'. This is not necessarily the logical order followed when deriving a model since a model could be implemented before being evaluated and the '*Required Inputs*' in '*1. Model Description*' cannot be identified before doing '*Feature Selection*' in '*2. Model Development*'. Hence, it should be highlighted that the framework is meant to be applied in the specified order only when reporting and documenting an occupant model and not when deriving it. The narrative logic of this documentation framework is to provide first a contextual overview of the model ('*Description*'), then specify how it has been developed ('*Development*') and evaluated ('*Evaluation*'). Finally, technical details for its implementation should be specified.

3.1. Model Description

The description of a model (block 1) represents the first and most crucial step that should be undertaken by the developers of an occupant model when documenting it. This also allows the developers to reflect on the utility of their model and its applicability domain. The elements of the framework related to *Model Description* are summarized in Table 1.

The authors of an occupant model should explicitly report a clear and concise formulation of the problem their model deals with (*Model Purpose*). Indeed, a BPS can be used for different goals and in different phases of the life cycle of a building and/or of the building delivery process, such as a parametric study of a building's design or retrofitting options, a floor's HVAC system sizing, a room's overheating risk assessment, a district's energy flexibility capacity assessment, a building's regulatory compliance, etc. The related definition of the model's boundaries (*Domain of Applicability*) should include different aspects:

- the spatial scale, that is the simulation's spatial extension (e.g. room-zone, floor, building, district, urban);
- the spatial resolution, that is the zonal destination of the model (e.g. room, household, floor, building);
- the temporal scale, that is the simulation time length (e.g. weekly, monthly, annual);

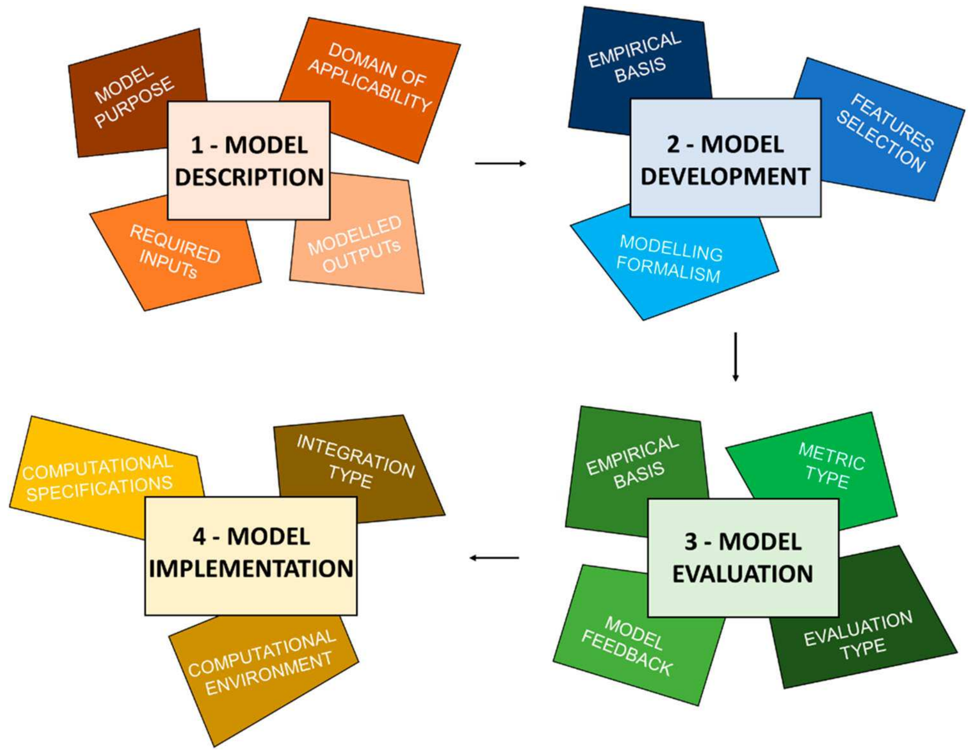

Figure 1. Overview of the 14 elements of the framework, which are distributed into four blocks (Description, Development, Evaluation, and Implementation).

Table 1. The elements of the framework related to block 1.

1 – MODEL DESCRIPTION	
MODEL PURPOSE	
DOMAIN OF APPLICABILITY	spatial scale spatial resolution temporal scale temporal resolution building type demographic, socio-economic, cultural, technological, and climatic context
REQUIRED INPUTs	physical physiological psychological contextual
MODELLED OUTPUTs	

- the temporal resolution, that is the required simulation time-step (e.g. 1, 5, 10 min, half-hour, hourly);
- the building type, that is the dominant function of the building (e.g. residential, office, retail, educational, dormitory);
- the demographic and socio-economic context (e.g. social housing, nursing home);
- the cultural context (e.g. country);
- the technological context (e.g. system type and control);
- the climatic context (e.g. Köppen climate classification, season).

Occupant behaviour is a continuous-time process. However, since in conventional BPS tools time advances in fixed time-steps, it is most common to use a discrete-time rather than an event-driven simulation approach. This discretisation inevitably results in a loss of information. For example, all short dynamics are ignored if they last less than the given time-step. Moreover, the outcome of interest is bound to occur only at the selected time-step (e.g. every 5 min, every 10 min, etc.). The importance of defining the temporal resolution has been stressed by Gunay et al. (2014) and Lindner, Park, and Mitterhofer (2017). Both of them have shown that the most often used discrete-time simulation approaches require an occupant model to have a time step that is fixed both throughout the simulation run and between different runs or experiments. A change in the size of the time-step can result in considerable differences in the predicted outcomes and performances of an occupant model. Consequently, the time-step of the simulation is paramount and should be chosen and communicated carefully. It is essential to underline that the choice of the time-step also depends on the granularity of the data used for constructing the model. The work of Mahdavi and Tahmasebi (2016) further shows that the choice of a specific level of spatial and temporal scale and spatial and temporal resolution depends on the purpose or deployment scenarios of the model.

As part of an occupant model description, the authors should also clearly define the inputs of the model (*Required Inputs*), which are not necessarily continuous variables (e.g. the typical physical ones) but they can also be categorical variables (e.g. arrival/departure times, kitchen/bedroom room types). For example, the occupant model might have different analytical forms in different categories. For facilitating their communication, the required input variables can be classified in:

- *physical*, covering measurable physical properties of the indoor and outdoor environment (e.g. indoor air temperature, indoor transmitted solar radiation, outdoor relative humidity, rain),
- physiological, covering physiological characteristics of the occupants (e.g. occupant age, gender, weight, height, health status),
- psychological, covering psychological characteristics of the occupants (e.g. occupant habits and attitudes, personality traits, mental stress levels),
- *contextual*, that is the set of inputs related to the context (e.g. arrival/departure times, kitchen/bedroom room types, building and system design, time of day, type of day, geographic location).

This classification is based on a simplification of the occupant behaviour drivers identified in Fabi's review (Fabi et al. 2012). For a more complete overview of the contextual variables, see also the work of Schweiker et al. (2020).

The model's output, namely the predicted occupancy and/or occupant behaviour (*Modelled Outputs*), should also be specified. This could be more than one output; for example, the outcome of a model could be both thermostat and clothing adjustment behaviour. We identify the following main targets:

- occupancy (including occupant counting),
- appliance use,
- thermostat adjustment,
- window operation,
- shading operation,
- lighting operation.

3.2. Model Development

The elements of the framework related to block 2 (*Model Development*) are summarized in Table 2. The developers of an occupant model should clearly describe the dataset used to build/train their model (*Empirical Basis*), which should include details on:

Table 2. The elements of the framework related to block 2.

2 – MODEL DEVELOPMENT	
EMPIRICAL BASIS	study type data type sample size building type demographic, socio-economic, cultural, technological, and climatic context sampling frequency length of the monitoring period
FEATURES SELECTION	
MODELLING FORMALISM	

- the type of study carried out for deriving the dataset, which can be either *observational* (in actual buildings) or *experimental* (i.e. laboratory-based in test rooms or living labs),
- the measured variables, that can be *survey-based* (e.g. Time Use Survey – TUS – activity data), *sensor-based* (e.g. PIR records, lighting-switch records) or both of them,
- the sample size in terms of number of buildings (e.g. two buildings), independent surveyed units (e.g. 15 apartments, three open-plan offices), and occupants (e.g. 20 occupants),
- the building type (e.g. residential, office, retail, educational, dormitory),
- the demographic and socio-economic context of the study (e.g. social housing, nursing home),
- the cultural context (e.g. country),
- the technological context (e.g. system type and control),
- the climatic context (e.g. Köppen climate classification, season).
- the sampling frequency of the measurements (e.g. 1, 5, 10 min, half-hour, hourly),
- the length of the monitoring period (e.g. one month or two summers)

It is to be noted that the '*building type*' and the '*demographic, socio-economic, cultural, technological, and climatic context*' characterize both the empirical basis and the domain of applicability of the model. However, they do not necessarily match since the model can be applied beyond the boundaries of the empirical data. Any application beyond the data collection domain needs to be justified and evaluated.

The authors should also clearly define whether *Independent Variables/Features Selection* was carried out to reduce the data dimension by determining the most relevant feature subsets and should also indicate the method employed. Feature (or variable) selection is an important and delicate aspect (arguably one of the most complex parts) in developing a model and is primarily focused on removing non-informative or redundant predictors. It depends on the modelling strategy (for instance, tree-based models inherently perform variable selection), which depends on the aim of the study.

Several approaches can be applied to perform feature selection. In their review on variable selection, Heinze, Wallisch, and Dunkler (2018) categorized the following criteria for variable selection:

- '*Significance criteria*' are perhaps the most popular criteria for variable selection and include hypothesis tests (e.g. Wald test's *p*-value).
- '*Change-in-estimate criterion*' consists of examining the relative change (%) in the parameters of the remaining variables when one is removed. If the difference is above a threshold, it is considered relevant, and the removed variable is added back to the model. This approach can also be used to account for confounders.
- '*Information criteria*' focus on selecting a model from a set of models rather than variable selection. However, these methods penalize model complexity and, therefore, the inclusion of a new variable. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Mallows' C_p are examples that belong to this category.
- '*Penalised likelihood*' is an alternative way to perform model selection. In this case, a model that contains all the predictors is fitted using a technique that shrinks the coefficient estimates towards zero. When the penalty is the ℓ_1 *norm* (i.e. the sum of the absolute coefficients), some coefficient estimates are forced to be exactly zero. Hence, a variable section is performed. Lasso regression belongs to this category.
- '*Background knowledge*' refers to both subject-specific and general knowledge in the domain of application of the model.

These criteria can be implemented in variable selection algorithms. Some popular approaches are backward elimination, forward selection, and stepwise (forward or backwards) selection.

Regarding the *Modelling Formalism*, occupant behav iour is often modelled by assuming it is a stochastic process. Following the definition of Coleman (1974), a stochastic process can be defined as '*a system which evolves in time while undergoing chance fluctuations*', which means that there is a certain probability of getting a certain outcome for each observation at a specific time. Therefore, to implement occupant behaviour in BPS, two fundamental aspects need to be considered: (i) the probability of a certain outcome; and (ii) the evolution of this probability over time. For modelling the probability of a certain outcome, we can use *analytical* or *statistical* modelling approaches, which include generalized linear models, i.e. a broad class of models where the response *Y* relates to the linear predictor $\mathbf{X}\beta$ through a link function (denoted by $g(\cdot)$). This is not to be confused with general linear models, which refers to conventional linear regression models. However, if the '*identify link*' ($g(\mu) = \mu = \mathbf{X}\beta$) is selected, general linear models can be viewed as a particular case of generalized linear models. For modelling the evolution of the probability over time, we identify the following three main approaches:

- *Bernoulli process* is used to model the probability of having a certain state (or event) independently from the previous state (or event).
- *A discrete-time Markov-chain technique* is used to model the probability of changing state or event (i.e. transitions probabilities) depending on the previous state (i.e. the conditions just before the occupants undertake the action).
- *Survival model* is used to model the time until a certain state or event occurs.

The Markov chain can be homogeneous or inhomogeneous depending on the '*nature*' of the transition probability matrix. If it is time-dependent, the Markov chain is called inhomogeneous. Otherwise, it is called homogeneous.

Apart from the *analytical* approaches, we can identify two other main modelling formalisms:

- *agent-based*, where occupants are modelled as auto nomous agents, which interact with each other and the external environment (e.g. belief-desire-intention model of agency);
- *data-driven*, which can be defined as 'an approach to modelling that focuses on using the computational intelligence and particularly machine learning methods in building models that would complement or replace the 'knowledge-driven' models describing physical behaviour' (Carlucci et al. 2020). Unlike analytical or statistical approaches, data-driven models (e.g. k-means clustering) do not encapsulate scientific understanding and knowledge in explicit mathematical equations and do not assume any prior distribution or relation nor are hypothesis-driven (Ourmazd 2020; Montáns et al. 2019).

3.3. Model evaluation

Ideally, any occupant model should have undergone an evaluation process with a set of data different from the

Table 3. The elements of the framework related to block 3.

3 – MODEL EVALUATION	
EMPIRICAL BASIS	data quality
	study type
	data type
	measured variables
	sample size
	building type
	demographic, socio-economic, cultural, technological, and climatic context
	sampling frequency
	length of the monitoring period
MODEL FEEDBACK	
METRIC TYPE	
EVALUATION TYPE	

dataset used for its development/training (Mahdavi and Tahmasebi 2019; Wolf et al. 2015). The elements of the framework related to *Model Evaluation* (block 3) are summarized in Table 3.

The authors of an occupant model should openly indicate whether the evaluation is done with a dataset different from the development/training dataset (in this case we speak of '*external evaluation*') and specify the quality of the external data used for assessment (*'data quality'*). In the context of model evaluation, data quality depends on where the external data comes from, i.e. whether the external data comes from a different building and/or a different socio-economic, cultural, technological, and climatic context. In the case of external evaluation, the definition of the empirical basis is characterized by the same elements found in section 3.1.

The authors should also indicate whether, in the evaluation process, a dynamic simulation is done and, therefore, the impact of occupant models' output (e.g. window states) is considered on the models' input (e.g. indoor air temperature). This issue is commonly referred to as the model feedback problem (see section 4.3.2 for more details). The idea is that occupants' control actions can influence indoor conditions. Changes in indoor conditions can, in turn, influence future occupant actions.

The type of metric and evaluation used should be clearly stated. The metric can be:

- *direct*, when the evaluation is directly done in terms of the occupant model outputs, that is, the predicted presence and control actions (window opening/closing, thermostat switch on/off, etc.);
- *indirect*, when the evaluation is done with indirect metrics, for example:
  - o energy use (e.g. heating, cooling, primary, total, lighting),
  - o indoor environmental variables (e.g. air temperature, relative humidity, CO_2),
  - o air change rate.

Furthermore, the evaluation metrics can fall into two additional broad categories depending on the level of aggregation of the models' predictions:

- *interval-by-interval*, when the interval-by-interval congruence between predictions and measurements is verified by comparing time series data pairs. This includes all the metrics of type '*machine learning*' (e.g. precision, recall, accuracy, *F*-measure, RMSE, mean bias error),
- *aggregated*, when the evaluation is done by comparing aggregated values (e.g. comparing the simulated and predicted annual energy consumption). The type of aggregation differs depending on the level (e.g. mean, median, minimum, maximum, standard deviation, peak, Jensen–Shannon divergence for comparing predicted and measured probability distributions) and temporal scale (e.g. every minute, hourly, monthly, annual).

Examples of *direct* and *aggregated* metrics for window operation models, which represent the most developed models so far, are:

o window opening/closing ratio
o number of opening/closing actions
o opening/closing duration

This classification of the type of metric and evaluation is based on the work of Mahdavi and Tahmasebi (Mahdavi and Tahmasebi 2017).

3.4. Model Implementation

The elements of the framework related to block 4 (*Model Implementation*) are summarized in Table 4. The authors of an occupant model should clearly describe the computational environment used in terms of building simulation tools (e.g. EnergyPlus, IDA ICE, ESP-r, TRNSYS) and/or programming languages (e.g. Python, MATLAB). Also, the type of integration should be specified; this can be of three types based on the classification provided by Hong et al. (2018):

- direct input or control, where the user defines deterministic or static schedules and/or rules using the semantics of the building simulation tool, similarly to inserting the building geometry's inputs,
- user function or custom code, where the user modifies the source code (e.g. by writing new functions) directly inside the building simulation tool (e.g. through the Energy Management System feature of EnergyPlus),

Table 4. The elements of the framework related to block 4.

4 – MODEL IMPLEMENTATION	
COMPUTATIONAL ENVIRONMENT	building simulation tool programming language
INTEGRATION TYPE	
COMPUTATIONAL SPECIFICATIONS	

- co-simulation, where the user uses different simulation tools running simultaneously and switching information in a combined routine (e.g. FMU, Building Controls Virtual Test Bed).

Finally, the authors should provide some computation specifications (e.g. the computational time).

4. A review of existing papers on occupant models

This section presents the results of the review of 86 academic papers on occupant models to verify to which degree they meet the framework proposed in the previous section. The distribution of the reviewed papers in terms of year of publication and number of modelled occupant behaviours is shown in Figure 2. The figure highlights the increasing volume of scholarly outputs on the topic over the years, especially articles evaluating one or two occupant behaviour targets.

4.1. Model Description

4.1.1. Model purpose

Only a minimal number of articles (about 13% of the total) specifically reports the problem their model is dealing with or is trying to address (*Model Purpose*). In the majority of the remaining papers, the reported purpose is very generic, such as '*energy use prediction*', '*integration in BPS software*', or '*employment in BPS applications*'. Thus, the existing trend is to develop purpose-free models that are, only ideally, suitable to any deployment scenarios. As will be discussed later, the question needs to be answered whether such an approach is meaningful in light of differences between models for explanation and prediction.

4.1.2. Domain of applicability

The domain of applicability refers to the definition of the model's boundary: the context and the extent to which it is '*safe*' to use the model. In this view, it is clear that the intended use of the model must be objectively specified. However, some pieces of information are usually not presented straightforwardly. As a result, it is not easy to assess whether the authors provide this information as a limit of the model's applicability or just for descriptive purposes.

Regarding the definition of the temporal scale and resolution of the model among the reviewed papers, a surprisingly high 45% do not state or clearly specify the time-step, while the temporal scale is not mentioned in 57% of the cases. The majority of remaining papers (25 out of 86) are based on annual simulations but with different granularity: not stated/clear (16%), 1 min (20%), 5 min (12%), 10 min (28%), 15 min (4%), 1 h (20%). Thus, a time-step of 10 min is the one most often adopted.

Other essential aspects concern the spatial scale and resolution of the model. The former refers to the simulation's spatial extension (e.g. building), while the latter refers to the zonal destination of the model (e.g. room). In 21% of the models, the two aspects coincide and concern room-zone level. For 28% of the models, the spatial scale concerns the building level, while only three out of 86 models deal with district/urban area.

Regarding the building type, about 38% are for residential purposes, 36% for offices, 6% for others (such as dormitory, educational), and in 20% of the papers, this information is not stated.

The '*cultural context*' is the most reported among the contextual information, with 62% of the papers reporting the city and/or country. Following there is the '*technological context*'' (35% of the papers), which includes information about system type and control. The least reported information is the '*climatic context*' and the '*demographic and socio-economic context*', each mentioned in only seven out of 86 papers. Among those mentioning the '*climatic context*', three mention the season, while four explicitly mention the climatic zone as Köppen classification (indirectly, this information can be retrieved from the city).

4.1.3. Modelled outputs

The majority of the reviewed papers cover a single output category (67%), while the rest cover two (22%), three (7%), and four (3%) target behaviours simultaneously. As an example of the latter, Nicol modelled the impact of outdoor temperature on four occupant behaviours, namely thermostat adjustment, window, shading, and lighting operation (Nicol, Humphreys, and Olesen 2004). However, it is worth noting that all the studies covering multiple occupant behaviours, including Nicol's, derive each behavioural model independently of the others, overlooking potential impacts of one occupant behaviour (e.g. thermostat adjustment) on another (e.g. window operation). Figure 3 presents the percentage of articles that modelled each target behaviour, from which we can notice that window operation is the most covered output category.

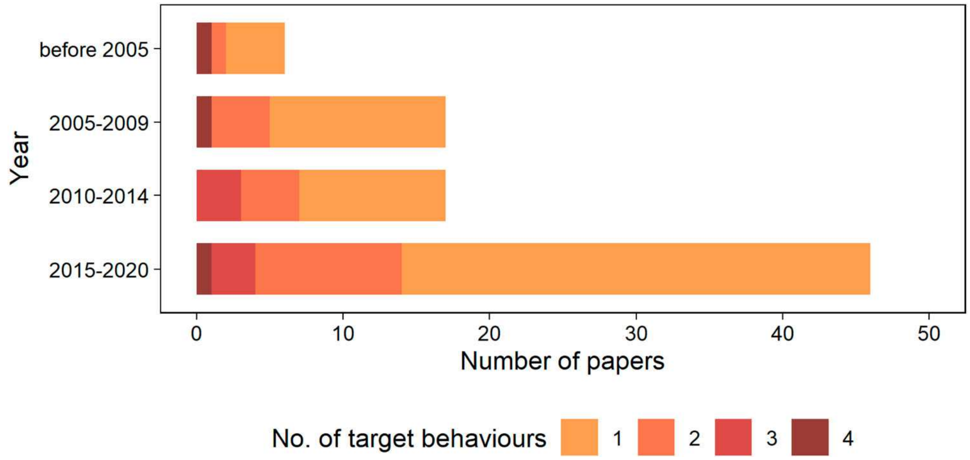

Figure 2. Distribution of the reviewed papers in terms of year of publication and number of modelled behaviours.

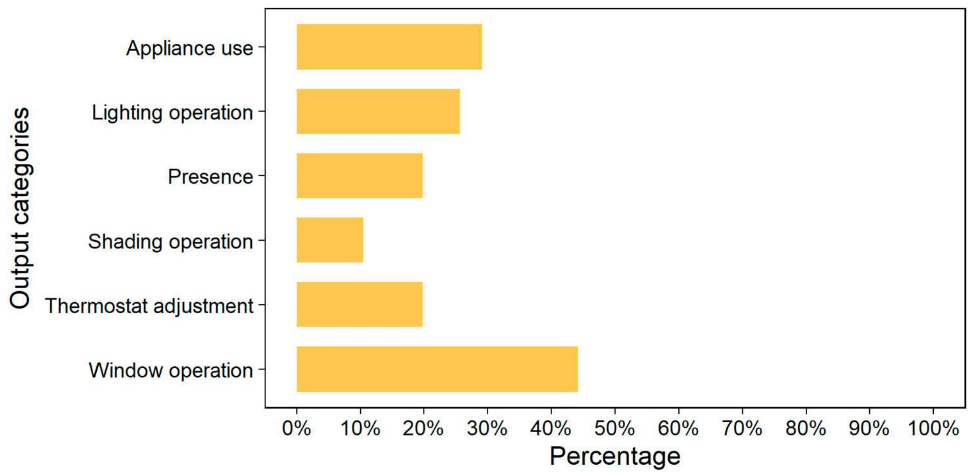

Figure 3. Coverage of output categories in the reviewed articles.

4.1.4. Required Inputs

The inputs used to model the outputs above are categorized as (i) physical, (ii) physiological, (iii) psychological, and (iv) contextual. As shown in Figure 4, physical and contextual inputs are used in the majority of the studies. On the other hand, less than 10% of the studies include physiological or psychological inputs to their models.

To shed more light on the use of input variables in the models, Figure 5 presents a matrix that maps the input categories (shown in rows) to the output categories covered in the previous section (shown in columns). Results re-iterate the frequent use of physical and contextual categories to predict all output categories. It is also observed that appliance use is mostly modelled using contextual input parameters (e.g. Wilke et al. 2013). This finding is not surprising as plug-loads, such as computers and printers, are not driven by environmental factors but rather working schedules and requirements (e.g. tasks). Time of day and arrival/departure times are the two most common contextual input variables used in the reviewed articles (e.g. Jin et al. 2020; Widén et al. 2009). In contrast, behaviours such as window opening are often driven by physical conditions (e.g. temperature, humidity, and indoor air quality) (Deme Belafi et al. 2018; Yao and Zhao 2017), which explain the higher use compared to contextual inputs (see '*window operation*' column in Figure 5).

Figure 6 illustrates the surveyed '*physical*' environmental variables and their frequency of occurrence for each output category in a matrix format. Indoor and outdoor temperature are the two most often used input parameters. Window operation models show the highest diversity in their input parameters, covering multi-domain indoor and outdoor conditions, namely thermal (e.g. temperature and humidity), visual (e.g. illuminance and radiation), and air quality (e.g. CO_2 and PM2.5 concentrations).

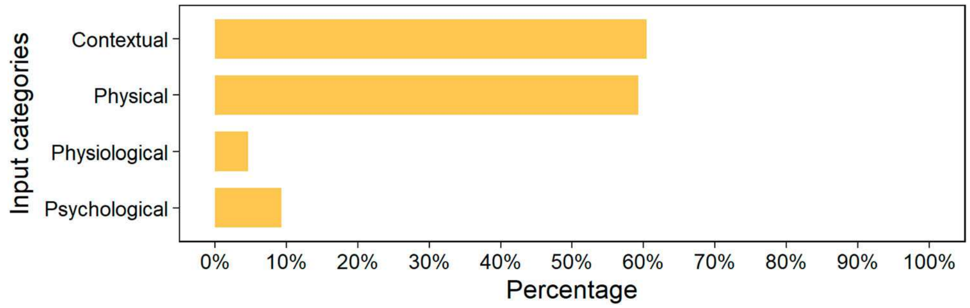

Figure 4. Coverage of input categories in the reviewed articles.

Modelled inputs	Modelled outputs: Appliance use	Lighting operation	Presence	Shading operation	Thermostat adjustment	Window operation
Contextual	18	13	6	4	11	21
Physical	7	13	4	5	10	29
Physiological	1	1	0	1	2	2
Psychological	2	2	0	1	4	3

Figure 5. Mapping of inputs and outputs in the reviewed articles. The values show the number of studies that satisfy each combination, where darker cells reflect higher frequencies.

4.2. Model Development

4.2.1. Empirical basis

Regarding the documentation of the empirical basis used to derive the model, a very limited number of articles (about 7% of the total) do not report the type of study (i.e. either observational or experimental) carried out and the type of variables (either survey-based or sensor-based) measured during the study. Only one of the reviewed studies is based on experimental research (Schweiker and Wagner 2016); all the others are observational studies. In 49% of the studies, the variables are measured based on sensors, while for 13% of the papers, the model is developed from survey-based data. The rest of the models are derived using both types of measurements or get data from the literature (mainly for lighting operation and appliance use). Models of appliance use are the ones most often using survey-based data, mainly coming from time-use surveys.

Modelled inputs	Modelled outputs: Appliance use	Lighting operation	Presence	Shading operation	Thermostat adjustment	Window operation
Indoor						
Air temperature	5	3	1	2	4	22
CO2/PM2.5 concentration	1	3	1	2	0	12
Illuminance	0	7	1	4	0	5
Radiant temperature	2	1	1	1	4	6
Relative humidty	0	2	0	1	3	8
Outdoor						
Air temperature	5	2	2	2	7	24
CO2/PM2.5 concentration	0	0	0	0	1	3
Rainfall	0	1	0	1	1	3
Relative humidity	2	0	0	1	2	12
Solar radiation/Illuminance/Hours	3	6	2	3	4	10
Windspeed/Direction	1	1	0	1	3	11

Figure 6. Coverage of 'physical' input categories and mapping to modelled outputs.

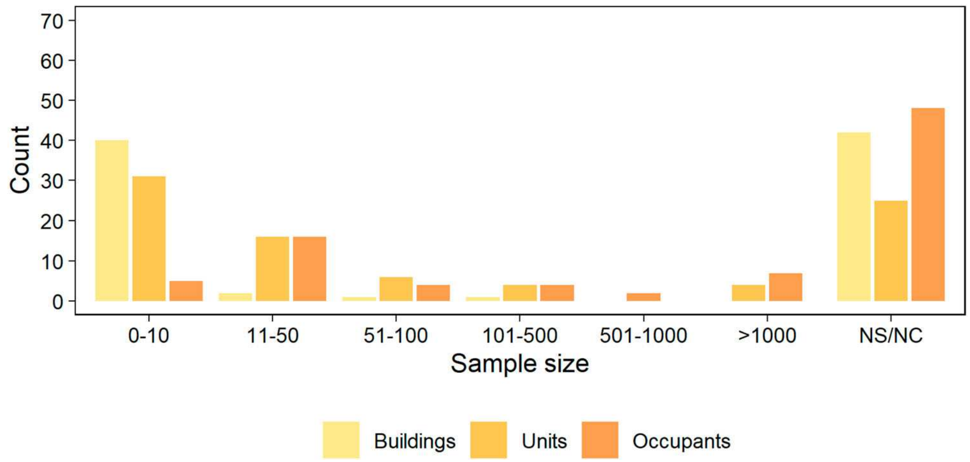

Figure 7. Distribution of the sample size for the monitored buildings, units and occupants. NS/NC stands for Not Stated/Not Clear.

The distribution of the number of monitored buildings, units, and occupants is shown in Figure 7. For '*unit*', we mean the smallest enclosed space controlled by one person or a specified group of people: a room, an apartment, or a house. About 16% of the reviewed works do not clearly describe the sample size, while only 20% of papers declared all three levels of sample size (buildings, units, occupants). The number of monitored occupants is the most difficult sample-related information to be found in the reviewed papers. Most often, the authors indicate the number of occupants indirectly by giving information on the number of monitored workplaces or rooms. Papers having appliances use, thermostat adjustment, shading, and lighting operation as target modelled variables document their sample size less often than papers about windows and occupancy models but tend to declare the number of occupants more frequently than the others. From Figure 7, we can also observe that the number of monitored buildings is very rarely above ten, and the number of monitored occupants is most often between 10 and 50.

Only 5% of the papers do not describe the building type from which the empirical basis is collected. The empirical basis for the rest of the papers is mostly based on measurements from residential buildings (see Figure 8), followed by commercial buildings (which are always offices), representing about 50% of the cases with respect to the monitored residential buildings. Only for the development of shading models, commercial buildings are more often monitored than residential buildings (see Figure 9). While for windows, the types of monitored buildings are equally distributed among residential and commercial buildings.

About 77% of the papers provide contextual information on the empirical data used to derive the model. The cultural and climatic contexts from which the empirical data are derived are described in about 60% of the papers. The technological context is described 40% of the time, while the demographic and socio-economic context is described only 16% of the time. The papers considering shading as target behaviour are the least documented in terms of context and do not include any context description 67% of the time. It is to be noticed that these numbers are different from those related to the domain of applicability stated by the authors (section 4.1.2), and, in particular, the domain of applicability is less well documented than the empirical basis.

The distribution of the empirical dataset's length in days and the frequency in data collection in minutes is given in Figure 10 and Figure 11, respectively. In about 19% of the reviewed papers, the length of the dataset (i.e. the duration of the monitored period) is not reported. For those reporting the dataset's length, the most often employed monitored period is one year, followed by a length from 28 to 90 days, which corresponds to a couple of months. About 27% of the papers do not clearly describe the frequency of data sampling. A sampling frequency equal to or less than 10 min is most often employed.

4.2.2. Features Selection

Among the analysed papers, 28% did perform feature selection, 42% did not, while for 30%, it is not clear. Figure 12 shows the distribution of the selection criteria among the papers that perform feature selection. It can be seen that the two prominent methods for feature selection are '*information criteria*' and '*significance criteria*'. Also, and not surprisingly, 83% of the articles that performed feature selection relied upon logistic regression for this important step.

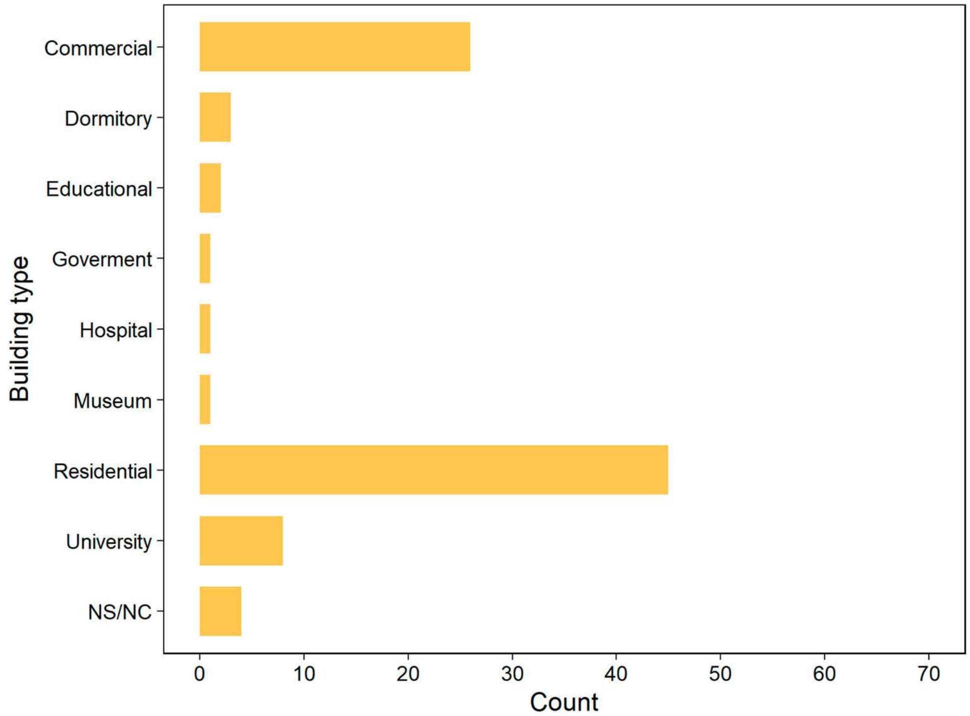

Figure 8. Distribution of the type of monitored buildings. NS/NC stands for Not Stated/Not Clear.

	Modelled outputs					
Building type	**Appliance use**	**Lighting operation**	**Presence**	**Shading operation**	**Thermostat adjustment**	**Window operation**
Commercial	3	7	5	5	3	16
Dormitory	0	0	0	0	2	1
Educational	0	1	0	0	0	1
Goverment	0	1	0	1	0	0
Hospital	0	0	0	0	0	1
Museum	0	0	1	0	0	0
Residential	21	11	9	2	11	15
University	0	4	0	2	1	5
NS/NC	1	2	2	2	0	1

Figure 9. Coverage of monitored building type and mapping to modelled outputs. NS/NC stands for Not Stated/Not Clear.

4.2.3. Modelling formalism

The majority (43%) of the reviewed papers adopt generalized linear models to calculate the probability of an outcome. Logistic regression is the most used (37%), while probit regression is used only in 3% of the cases. To account for the diversity of occupant behaviour, Haldi utilized generalized linear mixed models (Haldi et al. 2017). Few studies (3%) adopt the approach proposed by Wang et al. (2016), which is based on a discrete three-parameter Weibull cumulative function and can consider the time-step as a model parameter explicitly.

In BPS, the time-step is discrete, and the transition probabilities vary with time (i.e. they are not constant at each time step). This results in a discrete time-inhomogeneous Markov chain, which is used in 26% of the models. The term '*Markov chain*' is commonly used instead of '*Markov process*' with a countable state space.

Data-driven models are only found in 13% of the reviewed papers, there is no clear tendency, and different modelling techniques are adopted. The works of Wei et al. (2019; Pan et al. 2019) compare the performance of data-driven models with stochastic analytical models.

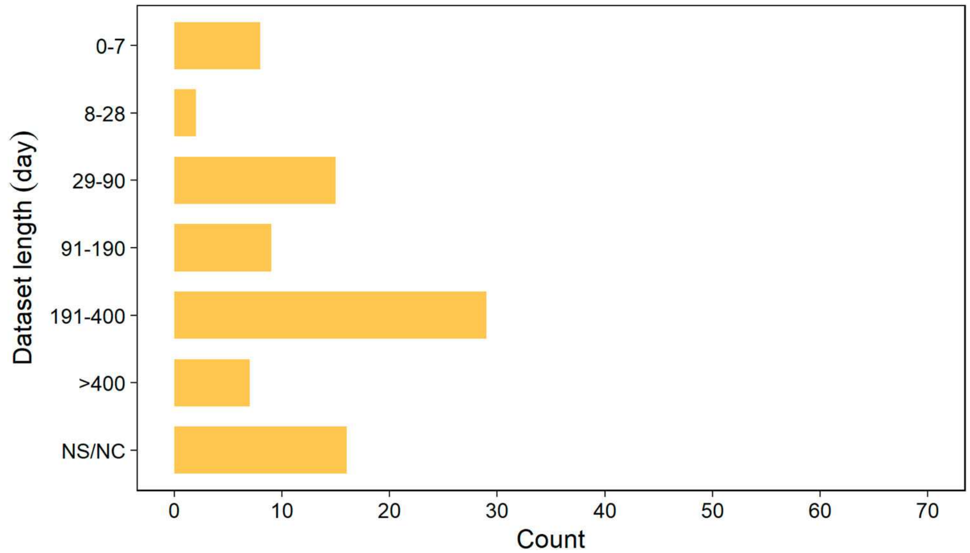

Figure 10. Distribution of dataset length. NS/NC stands for Not Stated/Not Clear.

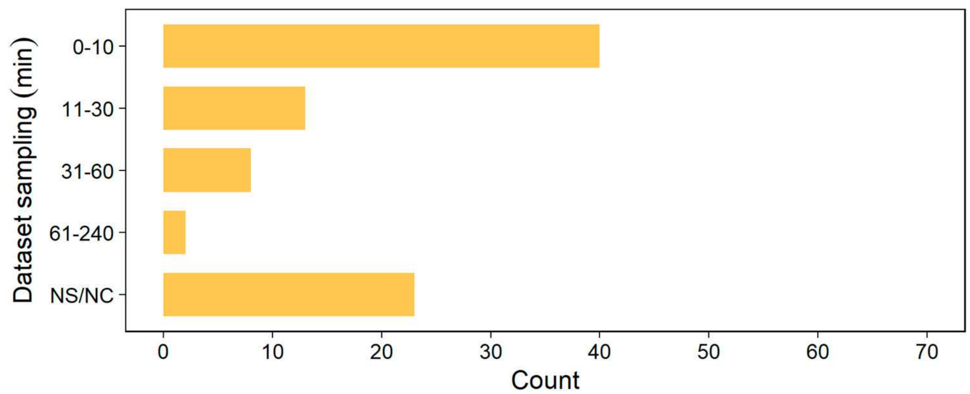

Figure 11. Distribution of frequency of data sampling. NS/NC stands for Not Stated/Not Clear.

They both conclude that the data-driven models have better predictions.

Agent-based models, even if particularly suited to simulating complex systems, are the least used (6%).

4.3. Model evaluation

4.3.1. Empirical basis

A total of 47 out of the 86 reviewed articles included some form of evaluation. Out of these 47 articles, 23 used external data for evaluation. Hence, in these cases, the evaluation was conducted using datasets different from the development dataset. Such external datasets included in the reviewed articles were either from the same building (Zhou et al. 2021; Binini, Munda, and Dintchev 2017; Widén and Wäckelgård 2010) or from another building (Richardson et al. 2010; Schweiker et al. 2012; Ozawa, Kudoh, and Yoshida 2018; Schweiker and Shukuya 2009). In the former case, data involved either different occupants (Widén and Wäckelgård 2010; Widén, Molin, and Ellegård 2012) or was from another period (Zhou et al. 2021; Binini, Munda, and Dintchev 2017).

4.3.2. Model feedback

As mentioned previously in section 3.3, the comparison of predictions of (especially stochastic) occupant models with empirical data represents a significant challenge in model evaluation. This circumstance is commonly referred to as the model feedback problem: occupants' actions (e.g. opening the windows, closing the shades) are likely to influence indoor conditions (e.g. room air temperature, task illuminance level), and this, in turn, can influence subsequent occupant actions (e.g. adjustment of the thermostat, switching on the lights). The majority of the reviewed articles do not address this challenge. However, a small number of the reviewed papers (about 10% of the total) entail content relevant to the problem of model feedback (Zhou et al. 2021; D'Oca and Hong 2015; Yun and Steemers 2010; Yun, Tuohy, and Steemers 2009; Fischer et al. 2016; Langevin, Wen, and Gurian 2015;

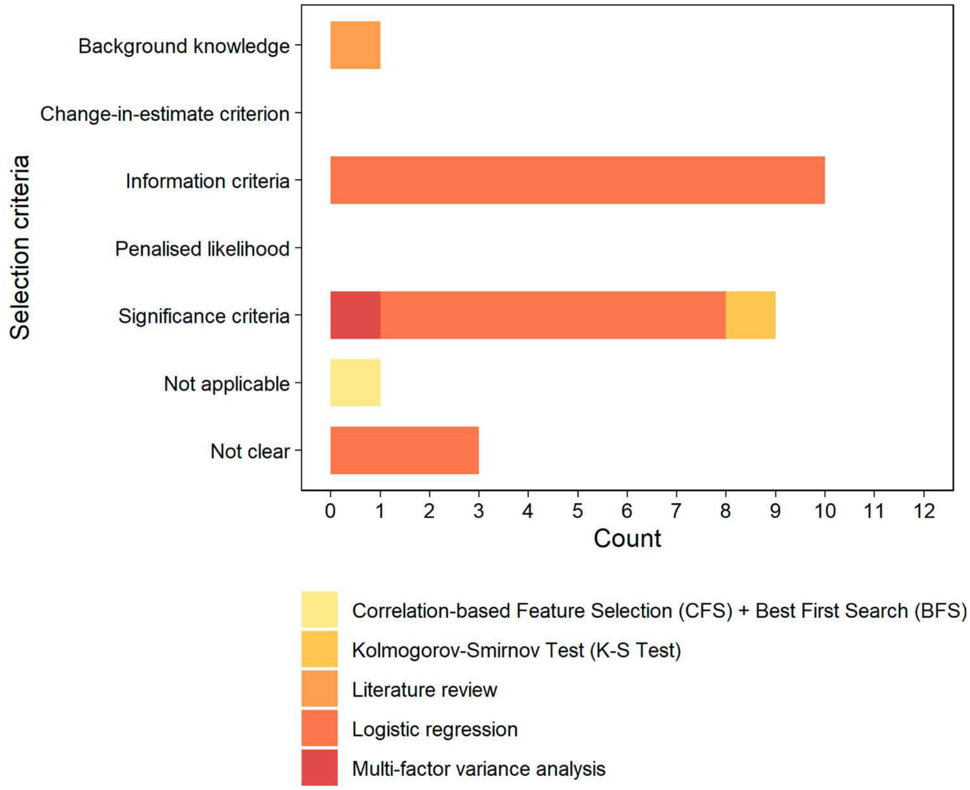

Figure 12. Distribution of the methods used for feature selection

Widén and Wäckelgård 2010). For instance, Yun, Tuohy, and Steemers (2009) and Yun and Steemers (2010) developed a behavioural algorithm of window-control by using Markov chain and Monte Carlo methods that '*generates a time series of window states as a function of the indoor thermal stimulus*' and implemented it into a dynamic energy simulation tool.

4.3.3. Metric type

The present review examined the articles in terms of the types of behaviourally relevant model output or metric (see section 2.3 for more details). Thereby, a differentiation was made between direct metrics regarding, for instance, window operation or thermostat control actions and indirect metrics such as resultant heating or cooling energy use. Among all reviewed articles including an evaluation, the majority (78%) included a direct metric type and relatively few of them (22%) use an indirect metric type.

4.3.4. Evaluation type

The reviewed studies entail a large spectrum of different evaluation approaches. These include evaluations (comparison of simulation results with corresponding observations) performed on an interval-by-interval basis as well as those involving the comparison of aggregated values. The subject of modelling was in roughly 30% of the articles related to window operation. The most common mode of evaluation in these studies involved the comparison of aggregated values. Thereby, different metrics were subjected to evaluation, including the number of opening/closing actions (in seven papers), the duration of window opening/closing (in five papers), and the probability of window opening/closing (in four papers). Eight articles address indirect metrics on energy use.

The temporal scale of aggregation varies considerably among the reviewed articles, ranging from short intervals (e.g. every minute Widén et al. 2009; Stokes, Rylatt, and Lomas 2004; Richardson et al. 2010), every five minutes (Haldi and Robinson 2009; Cedeno Laurent, Samuelson, and Chen 2017), every fifteen minutes (Page et al. 2008; Gottwalt et al. 2011) to extensive periods (e.g. annual in 8 articles). Likewise, the reviewed studies employ different modes of aggregation. A majority of 16 articles use a form of '*sum*', other nine articles compare by using mean. Median (Schweiker et al. 2012), peak (Paatero and Lund 2006), or density functions (Page et al. 2008) are less used.

Different approaches have been followed within the category of evaluation instances involving interval-by-interval comparisons of modelled and observed results. Eight papers merely provide a graphical comparison without quantified statistics. Five papers rely on '*classical*' statistics such as Pearson correlation coefficient or root mean square error. Confusion matrix and related classification measures (e.g. accuracy, precision, recall) are employed in ten papers.

4.4. Model Implementation

The description of the used computational environment is mostly neglected in the current way occupant models are documented. The building simulation tool is specified in only 17% of the reviewed articles. This can be partly explained by the fact that occupant models are often developed independently of a specific building simulation tool. More worrying is the fact that only 12% of the articles specify the used programming language. The most often used simulation environments are EnergyPlus and ESP-r, followed by IDA ICE and Daysim (RADIANCE-based). These simulation environments allow a physics-based dynamic simulation approach. At the same time, MATLAB is the preferred programming language used 50% of the time. Other used programming languages are VBA (Visual Basic for Applications), Python, Erlang, R, Brahms, and NetLogo. These last two are multi-agent modelling languages used explicitly for developing agent-based models. Similar to what is observed for the computational environment, the adopted or envisaged type of integration is poorly addressed (in only 7% of the reviewed articles). Computation specifications are only provided in one paper (Binini, Munda, and Dintchev 2017).

5. Discussion

This paper presents a framework for reporting occupant models together with a review of the existing literature in view of the degree of its compliance with the framework. Figure 13 summarizes the percentage of articles reporting the corresponding items related to each category of the introduced framework. Overall, the percentage of reported items from the framework varies strongly with the category, while no paper reports all items. The resulting inverted U-shape shows that at least the core elements of an occupant model are reported with high frequencies, whereas model purpose, the domain of applicability, and model implementation are reported least frequently. This observation forms the core of this discussion.

The deeper reasons for the observed lack of declared model purpose are not fully understood, as it was impossible to consult individual authors regarding issues that are not sufficiently explicated in their articles. The reasons may simply be that authors took it for granted that the purpose is obvious or that the corresponding information or explanations are not sufficiently clear in the paper. On the other hand, as noted in section 4.1.1, the low percentage may suggest a trend towards purpose-free models thought by authors suitable for any deployment scenarios. This possible trend – if it exists – would have two problematic aspects. Firstly, leaving out the modelling purpose suggests that modelling is done purely for the sake of modelling without underlying research questions or ideas for future usage of gained knowledge or model parameters. Readers of such work – being scientists, applicants, or the general public – will need to decide whether they see a potential application of the results and, more importantly, whether the presented model is suitable for their purpose. While well-trained scientists may be able to answer both questions, it is doubtful that all those invited to apply occupant models in their work can make such judgements. It appears reasonable to suggest that such an approach needs to be avoided for reasons of clarity and scientific endeavour, which starts with a purpose. Secondly, occupant modelling is often based on a large number of data points derived, for example, from year-long longitudinal monitoring campaigns. With the dependence of significance on sample size, even small effects likely result in significant findings (Sullivan and Feinn 2012). The question remains whether such a significant effect has any scientific or practical relevance. For such a decision, it is crucial to know the purpose of the model and the final variable in question, for instance, differences in energy use or likelihood to observe a specific occupant behaviour.

A second identified issue is related to the diffuse poor description of the model's domain of applicability. Predictive models do not need to rely on a theory but can be purely based on associations found in the available data leading to a good prediction. Such an approach is underlying many data mining methods. A predictive model may predict the energy use of a future building through BPS in a precise and satisfactory way. However, the predictive model needs to be applied with caution to another building because its predictive power depends significantly on the context in which the data was collected. Without an underlying theory or parallel causal study, the observed associations used for the prediction may miss important influencing factors when this model is applied to a different context. For example, a predictive model for window opening derived from data without high outdoor temperatures and a context without cooling capacities by an air-conditioning unit will likely fail to predict the reduced window opening probabilities at very high outdoor temperatures in such context. This case was observed by Schweiker et al. (2012) while evaluating models derived from naturally ventilated rooms in Switzerland with mixed-mode rooms under Japanese summer conditions.

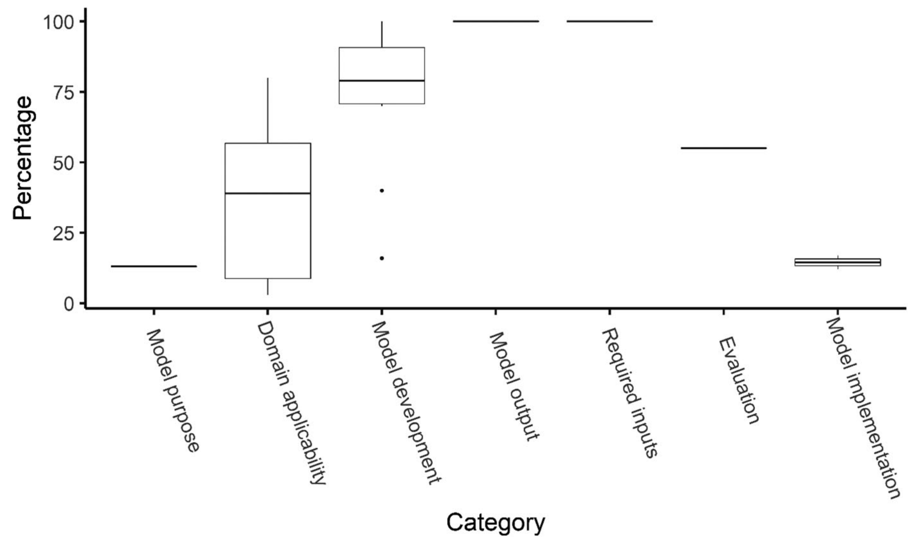

Figure 13. Percentage of articles reporting corresponding items of each category of the introduced framework. Note that categories 'Domain applicability', 'Model development', and 'Model implementation' consist of several sub-categories, which individual percentage values were used to derive the boxplot. For example, 'Domain applicability' (see also section 4.1.2) has 8 sub-categories with season reported the least often (3%) and building type the most often (80%).

This third point of the discussion relates to the next main point of the debate: the low percentage of documentation of items related to implementation. Without knowing the intended purpose for more than 80% of the models presented in the literature, it is without meaning to criticize the lack of such information. Also, authors may consider implementing BPS as an additional, separate step presented in follow-up articles. Therefore, while emphasizing the need to consider the practicability of predictive variables used for modelling when the purpose is to implement the model into BPS (e.g. is the variable available within the BPS environment, or is it possible to emulate it?), we will not go deeper into this point of the discussion.

An open question beyond the scope of this review is to what extent the proposed framework supports a more widespread application of occupant models in practice. First, the question is whether such widespread application is meaningful given the number of open questions and non-evaluated models. For the sake of brevity, we will not deepen this thought but rather point out that a more transparent communication of a model background and evaluation status may at least reduce the chance of models being adopted without reflection. Second, this question requires empirical work, such as intervention studies or interviews with practitioners as suggested by Schweiker, O'Brien, and Gunay (2019) to analyse the strengths and limitations of this framework for practitioners and evaluate those elements most suitable for creating understanding and trust before adopting them. Implementing the proposed framework and raising awareness among editors and reviewers about the importance of each element would be the first step towards this.

6. Conclusion

This paper introduces a framework to document occupant models used in building performance simulation. It consists of four blocks (description, development, evaluation, and implementation) and provides and describes several elements within each block to help researchers transparently document and communicate their occupant models. We cannot prove that the derived framework is a comprehensive one or 'gold standard' for occupant models' documentation and we cannot guarantee that it will be adequate and efficient in all future applications. However, it builds upon current literature as well as a thorough discussion among a group of experts with long-term experience in occupant modelling and establishes a picture that provides means for critically reflecting on how to report and document occupant models in the future. Thus, the introduced documentation schema lays the way to a standardized methodology on how to formulate and document occupant behavioural models for BPS in the future. The efficiency and acceptance of the framework alongside potentially missing elements will need to be revisited several years from now.

Based on a systematic review, we have also verified to which degree existing academic papers on occupant models meet the framework. We have found that most of the papers provide occupant models without specifying their purpose and without providing any information about their implementation. The two aspects appear to be related and indicate that occupant models have been so far developed without any specific BPS application in mind. This is partly understandable given the relatively low maturity of the field. More worrying is the little efforts so far dedicated to defining the domain of applicability of the model and evaluating the model. These results show the need for such a framework as suggested in this work for researchers, reviewers and editors. Without investigating future efforts in such directions, it may remain difficult for practitioners to place confidence and trust in the performances of occupant models and to be able to use them. Consequently, a more widespread application of occupant models in practice may be further delayed. More transparent communication of a model background and evaluation status may contribute to greater awareness of the adoption of occupant models.

Note

1. The shrinkage penalty is composed of a penalty term multiplied by a tuning parameter λ.

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