

## Overview of occupant behaviour in modelling high-performance residential buildings

Xu, L.; Guerra-Santin, O.; Boess, S. U.

10.1088/1755-1315/1085/1/012018

**Publication date** 

**Document Version** Final published version

Published in

IOP Conference Series: Earth and Environmental Science

Citation (APA)

Xu, L., Guerra-Santin, O., & Boess, S. U. (2022). Overview of occupant behaviour in modelling high-performance residential buildings. *IOP Conference Series: Earth and Environmental Science*, 1085(1), Article 012018. https://doi.org/10.1088/1755-1315/1085/1/012018

#### Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

#### **PAPER • OPEN ACCESS**

# Overview of occupant behaviour in modelling highperformance residential buildings

To cite this article: L Xu et al 2022 IOP Conf. Ser.: Earth Environ. Sci. 1085 012018

View the article online for updates and enhancements.

## You may also like

- Field test and modeling analysis on unbalance of heat extraction and rejection of GSHP systems with different AC terminal units
- Mingyang Qian, Da Yan and Jingjing An
- A Comparison of Cooling Energy Use of Residential Buildings According to Air Conditioner On/Off Behavior Using Co-Simulation
- Simulation S H Mun, Y H Kwak, I K Kwak et al.
- An Investigation of Occupants' Energy Perceptions in Energy Efficient Retrofitted Residential Buildings: A Review Paper Elham Maghsoudi Nia, Queena Qian and Henk Visscher



IOP Conf. Series: Earth and Environmental Science

doi:10.1088/1755-1315/1085/1/012018

# Overview of occupant behaviour in modelling highperformance residential buildings

#### L Xu<sup>1,2,\*</sup>, O Guerra-Santin<sup>1</sup>, S U Boess<sup>2</sup>

- <sup>1</sup> Department of Built Environment, Eindhoven University of Technology, Eindhoven, The Netherlands
- <sup>2</sup> Faculty of Industrial Design Engineering, Delft University of Technology, Delft, The Netherlands

#### \*1.xu2@tue.nl

Abstract. As the goal-setting in the European Green Deal is to reach carbon neutrality by 2050, great efforts have been put to improve the energy efficiency in residential buildings. As residential buildings are towards high energy efficiency, building envelopes are becoming better thermally insulated and systems are becoming more energy-efficient. Therefore, the role of occupants in the actual building performance is becoming more important. However, contradictions exist between the uncertainties caused by occupant behaviour (OB) and the oversimplified consideration of OB in building design. Therefore, this paper aims to present a state-of-the-art of how OB is represented in residential buildings. Through a literature study, this paper first reviews different occupant behaviours and how they are considered in the design and operation of high-performance residential buildings. Modelling methods are categorized by occupant activities. In addition, behavioural theories in the application of analysing building performance are reviewed. How the behavioural theories are integrated with state-of-the-art building technologies is outlined. Finally, challenges and suggestions for representing the interaction between occupants and buildings in the design and operation of residential buildings are discussed.

#### 1. Introduction

Energy use in buildings contributes almost 30% to the world's total final consumption (TFC). The number is even higher in the European Union which is about 36%. The buildings sector was also in the leading position of the overall TFC increase in 2018 [1]. Within the building sector, residential buildings account for around 70% of TFC for both worldwide and EU countries. In addition, as the goal-setting in the European Green Deal is to reach carbon neutrality by 2050, great efforts have been put to improve the energy efficiency in residential buildings. An Energy Performance of Buildings Directive (EPBD) was established as a part of a legislative framework in 2010 and amended in 2018 to reinforce the energy transition in the buildings sector. Some of the most important elements of the EPBD are the enforcement of the nearly zero-energy concept for all new buildings from 2021 and the urge for a long-term renovation strategy to facilitate existing buildings to transform into nearly zero-energy buildings through a cost-effective method [2].

As residential buildings are towards high energy efficiency, building envelopes are becoming better thermally insulated and systems are becoming more energy-efficient. Therefore, the role of occupants in the actual building performance is becoming more important. Research has revealed a wild range of energy performance gaps (from -30% to 96%) in residential buildings and around 70 % of the studies

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

1085 (2022) 012018

doi:10.1088/1755-1315/1085/1/012018

reported the causes of the energy performance gap as occupant-related [3]. However, the practice still considers occupant behaviour in a very simplified way OB in building design (based on regulations) which neglects the uncertainties caused by occupants.

In addition, high-performance residential buildings are often equipped with advanced building systems e.g. low-temperature heating (floor heating, low-temperature radiator or convector), heat pump, heat recovery ventilation with demand control, etc. This increases the complexity of system control and the ease of use by occupants.

Despite its acknowledged importance, studies that incorporate behavioural theories in occupant behaviour models to analyse building performance have not yet been well identified. A systematic research framework is needed to better understand occupant behaviour [4]. It is presently unclear about the status of how a certain behavioural theory is integrated with advanced building systems in newly built or renovated houses.

Therefore, this study aims to provide an overview of occupant behavioural models based on building science and the state-of-the-art behavioural theories based on social and phycological science and the integration among theories.

#### 2. Occupant behaviour models for residential buildings

#### 2.1. Overview of occupant behaviour in residential buildings

In residential buildings, occupants' interaction with building components (lighting, window, blinds, plug-in equipment, etc.) and systems (e.g., ventilation system, the thermostat of heating/cooling system, etc.) can affect the building's energy use directly through the control of the systems or indirectly through the influence on heat gains from lighting and plug-in equipment and heat losses through windows. Due to the stochastic nature of occupant behaviour, these influences can create great uncertainty in estimating and predicting a building's energy use.

In addition to their interaction with buildings, occupants sometimes adapt themselves to the indoor climate by changing their clothing, having cold or warm drinks, or changing their activity levels. Together with the upper mentioned behaviours that influence the indoor climate directly or indirectly (by interacting with buildings), these occupant behaviours are categorized as adaptive behaviours [5]. There is another group of occupant behaviours, non-adaptive behaviours, which do not associate with restoring (thermal, visual, acoustic) comfort and improving indoor air quality, and yet still have a great impact on a building's energy use. Non-adaptive occupant behaviours are driven by non-physical factors (routine, privacy, cultural background, etc.). Appliances use behaviours are typical non-adaptive behaviours.

It is worth noting that certain occupant behaviour can be adaptive and non-adaptive under different circumstances. For example, lighting use to maintain visual comfort is an adaptive behaviour while switching off lights once leaving a room is a non-adaptive behaviour; similarly, opening a window to get fresh air is an adaptive behaviour while opening a window to hang duvets out is a non-adaptive behaviour.

#### 2.2. Model forms

There are several ways of categorizing occupant behavioural models. **Hong et al** categorized behavioural models as *implicit models* and *explicit models* by the predictors and outputs of the models [6]. *Implicit models* are used to predict the state of the building or the building system, or the probability of action occurring, or to derive the driver(s) of certain behaviour. *Implicit models* are developed based on predictor variables [7], e.g. indoor (and outdoor) air temperature, CO<sub>2</sub>, relative humidity, etc. Typical implicit occupant behavioural models are schedules/profiles and deterministic models, probability equations, Bayesian estimations, and Bernoulli process models. On the other hand, *explicit behavioural models* directly predict occupants' behaviour or their interaction with buildings (system). Depending on modelling methods, *explicit models* are able to predict behaviour or a system's state based on the previous state (discrete-time Markov chain model) or estimate the time duration of an event/action (survival process model) or predict behaviour (state transition) based on external events

1085 (2022) 012018

doi:10.1088/1755-1315/1085/1/012018

(discrete-event Markov chain model). Explicit models are developed based on monitored behaviour (presence, movement, window opening/closing, etc.). In addition, Gaetani et al categorized behavioural models according to their size, resolution, and level of complexity [8]. Three categorizations were identified, namely: non-probabilistic models (level 0), probabilistic/stochastic models (level 1), and agent-based models (level 2). The level 0 models contain both the conventional non-probabilistic models (i.e., schedules/profiles and deterministic models) and the data-driven non-probabilistic models. The main difference between the conventional non-probabilistic models and the data-driven non-probabilistic models is how the "rules" are defined. In the conventional non-probabilistic models, "rules" are mainly provided by building regulations/design standards. In the data-driven non-probabilistic models, "rules" are "learned" from data. Carlucci et al [9] categorized behavioural models into (conventional) rule-based models, (conventional) stochastic models, and data-driven models / methods.

#### 2.3. Models for each activity

Carlucci et al. [9] provide a thorough review of modelling occupant behaviour in buildings. The review selected 278 publications published from 1979 to 2019. The paper extensively analysed the model type per occupant activity. Most of the OB models were developed for appliance use and thermostat operation in residential buildings. After these two are the models for lighting operation and window operation, followed by the models for occupant presence. There are very limited studies on modelling shading operations in residential buildings.

Regarding the model type, generally speaking, stochastic models are the most common model type for most OB activities and rule-based models occur the least often among the selected publications. It is worth noting that the low appearance of rule-based models doesn't mean that they have little application in practice comparing the other two model types. The fact is actually on the contrary. The higher number of data-driven models and stochastic models reveals the trend that the research community would like to lead. As for each activity, according to the open-access review table [10] provided by Carlucci et al. [9], the most commonly studied models for both appliance use and lighting operation are neural networks and schedules; for modelling presence, schedules, Markov Chain and support vector machine appeared the most; for thermostat adjustment, the most common models were generalized linear models, Markov chain models and logit analysis; the latter two model types were also the most widely applied models for window operation.

#### 2.4. Data source for the development of OB models

Several types of data have been used to develop OB models, e.g., dataset (surveys), measurements, and simulation. Figure 1 presents the number of publications from the upper-mentioned open-access review table using different data collection methods for the development of OB models. The number of publications is depicted in groups by model types and activities.

Dataset (surveys) here refers to measurements and surveys conducted by third parties other than the researchers who used it to develop OB models. It usually contains a relatively large amount of data, from either a longitudinal collection for a few samples or a short-term collection for a large sample size. Frequently used datasets are Time-Use Survey (TUS) and Household Electricity Survey generally collected by national statistical agencies. As shown in Figure 1, datasets are mostly used to develop conventional stochastic models or data-driven models to generate load profiles for appliance use, lighting operation and occupancy (presence) patterns. Two main applications of these models are load disaggregation for household electricity use prediction and energy (optimized) management, and for household energy prediction. Load disaggregation usually requires data every 1 or a few seconds, while for energy prediction, data collected every few minutes to one hour is sufficient.

Measurement refers to indoor/outdoor environmental data (temperature, CO<sub>2</sub>, relative humidity, etc.) or presence data collected by sensors. The figure below shows that most OB models were developed from measurements or together with surveys, especially for the development of conventional stochastic models for window operation and thermostat adjustment. Applications of these models are operational optimisation under the concept of smart homes and smart energy systems,

1085 (2022) 012018

doi:10.1088/1755-1315/1085/1/012018

identifying/predicting the status of building and system (window/lighting/thermostat/etc.), and predicting building energy performance.

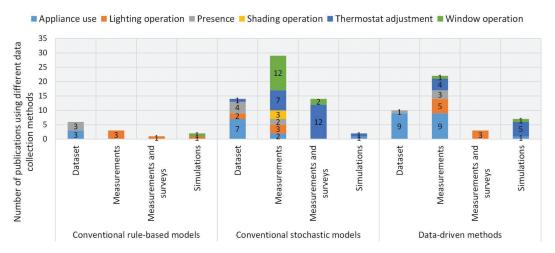


Figure 1 Data collection methods used for the development of each type of OB model for each activity, source: [10]

# 3. Representing the interaction between occupants and buildings in the design and operation of residential buildings

#### 3.1. Behavioural theories

There are various types of behavioural theories that can be applied for different purposes. In terms of behavioural theories that are applied in the field of building performance, Heydarian et al. [11] provided a thorough review of the behavioural theories that were adopted in the prediction and understanding of how occupants interact with building systems. Table 1 summarizes the most commonly adopted behavioural theories for different occupant activities in residential buildings. The research examined the occupant interactions with the building system in two main categories. The first category of studies focuses on how occupants interact with a single building system which includes heating, ventilation and air-conditioning (HVAC), window opening and ventilation, lighting and shading, appliances, and domestic hot water (DHW). The second category of studies considers the building as a whole with the focus on either general building conservation behaviours or an integrated metric analysing the occupant interaction with multiple building systems.

In recent years, researchers have made great efforts to push forward the synthesis among multiple disciplines from several perspectives. To promote users' energy conservation intention in offices, researchers proposed methodologies to integrate social-psychological theories with building science [12], [13]. By integrating information and communication technology (ICT) in building science, researchers from energy informatics focus on developing smart energy-saving systems for buildings and smart grid solutions for the energy system as a whole [14]. Based on energy informatics, a new interdisciplinary research area arose in recent years, namely energy social informatics. It is the blending of behavioural and psychological theories from social science and advanced ICT technologies to improve energy efficiency and environmental sustainability in both commercial and residential buildings [15].

### 3.2. The integration with state-of-the-art building systems

Researchers start to recognize the importance of interdisciplinary approaches to consider occupant behaviour in buildings. However, a better understanding is still required to be established of the socio-

IOP Conf. Series: Earth and Environmental Science

1085 (2022) 012018

doi:10.1088/1755-1315/1085/1/012018

technical connection between energy-related occupant behaviour and users' interaction with buildings [16], especially with high-performance buildings.

Table 1. The most commonly adopted behavioural theories for different occupant activities in residential buildings.

Occupant interaction		Total reported	Most commonly adopted behavioural theories
		number	
Single system	HVAC systems	8	Theory of Planned Behaviour, Norm Activation Model
use	Window opening and ventilation	5	Social Practice Theory, Self-Determination Theory
	Lighting and shading	3	Self-Determination Theory, Goal Framing Theory
	Appliances	1	Social Practice Theory
	DHW	4	DNAS, Theory of Planned Behaviour
Mixed system use		34	Theory of Planned Behaviour, Social Practice Theory, Norm Activation Model, Value Belief Norm

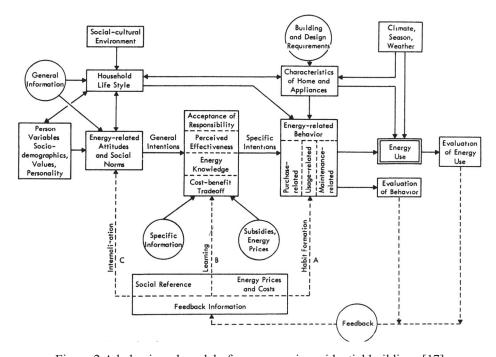


Figure 2 A behavioural model of energy use in residential buildings [17]

Van Raaij and Verlallen [17] proposed a model of energy-related behaviour and energy use in residential buildings. They categorized energy-related behaviours into purchase-related, use-related, and maintenance-related behaviours. Purchase-related behaviour refers to the purchase of household appliances and building components/systems (heating/cooling system, ventilation system). The energy efficiency of the appliances and systems has a direct impact on energy use. Usage-related behaviour, i.e., the frequency, duration, and intensity of daily use of household appliances, systems, lighting and windows, etc. Maintenance-related behaviour includes all the efforts and activities to maintain

appliances and systems. Figure 2 depicts the relationship among the factors that influence energy-related behaviour and energy use. Factors such as lifestyle, energy-conscious attitudes and (energy-efficient) characteristics of home and appliances, etc. play an important role in residents' behaviour when interacting with their homes. It is worth noting that energy-conscious attitudes generally do not influence one's energy-related behaviour directly, but rather through intervening factors, such as acceptance of responsibility (for energy conservation), perceived effectiveness of one's energy conservation contribution, energy knowledge and cost-benefit trade-off.

Similar to Van Raaij and Verlallen's research, a more recent study also contributes to building the social and technical connection for the energy-related behaviours in buildings. D'Oca et al [18] proposed a framework that integrates two social-driven theories, i.e. the theory of planned behaviour (TPB) and the social cognitive theory (SCT), and a physical-led theoretical framework DNAs (Drivers – Needs – Actions – Systems) [6]. The DNAs framework explains the interaction between occupants and building/system as a consequence of occupants' needs to sustain satisfactory performing their daily activities. The needs are driven by several factors, such as building and system characteristics, occupants' energy attitudes, age and gender, time (of the day, week, month), weather, etc. The TPB compliment the DNAs framework by introducing the influence of the social environment aspect (attitudes, social norms, perceived behavioural control) on occupants' needs. In addition, the SCT integrates the TPB and DNAs to emphasise that occupants' behaviour, based on accomplishing their basic biological needs, is also influenced by the social environment and the physical environment. The relationship among the three frameworks is visualized in Figure 3.

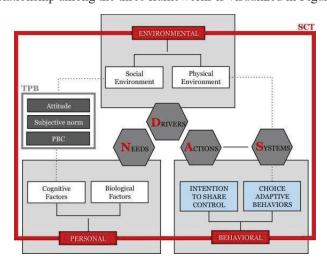


Figure 3. An interdisciplinary research framework of energy-related behaviour and building performance [18]

#### 4. Discussion

As described in Section 2.4, the applications/purposes of current occupant behavioural models are appliance/system setting status, system (operational) optimisation and building energy performance prediction. Although not widely discussed, the first application/purpose can be extended to perform fault detection and diagnosis (FDD). The last application can be further separated into energy performance prediction for social housing energy contracting and for design optimization of owner-occupied houses. Figure 4 shows all the OB models mapping to the activities that they were developed for and the corresponding purposes.

As for the theoretical behavioural framework, maintenance-related behaviour is not extensively discussed in Van Raaij and Verlallen's research [17], mainly because the systems in residential buildings in the 1980s were not as complex as they are now. However, in high-performance houses, maintenance-related behaviour can play an important role in building energy use. Therefore, the question comes to how to quantify the impact of this type of behaviour to achieve a better design for residents in renovation projects. In addition, unlike usage-related behaviour which has been well

covered in BPS tools as well as current occupant behavioural models from the perspective of building science, purchased-related behaviour and maintenance-related behaviour are not yet widely implemented in BPS tools. On the other hand, the interdisciplinary framework proposed by D'Oca et al [18] covers the complex system very well. However, it overlooked the purchased-related behaviour and maintenance-related behaviour. It is simply due to the fact that it was developed for office buildings. Therefore, it would be beneficial to integrate the two frameworks for residential buildings and yet the challenge remains as to how to apply such a framework into practice.

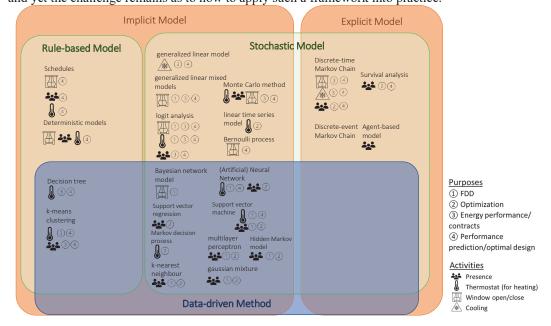


Figure 4 Summary of different OB models per activity for different purposes/applications

#### 5. Conclusion

This paper provides an overview of studies on occupant behaviour in residential buildings. The reviewed studies can be grouped in two areas, namely occupant behavioural models based on building science and behavioural theories based on social and phycological science. The main findings are:

- The most widely adopted/developed occupant behavioural model type for all activities is conventional stochastic models, followed by data-driven stochastic models.
- Models for different purposes may require different collection methods with different collection precision.
- It is essential to consider social-driven factors in the development of occupant behavioural models. However, there are limited studies that adopted/developed a framework that integrates purely social-driven theories with physical/technological-based theories.

The findings lead to the direction of future research on the topic of properly considering occupant behaviour in designing or renovating residential houses. Firstly, a general theoretical framework integrating social and physical-driven theories is required for residential buildings. Secondly, a method to cluster occupants should be developed and then the framework should be refined and tailored to each cluster and/or purposes. Lastly, a methodology to implement occupant behavioural models of adaptive and non-adaptive behaviour is needed according to the tailored frameworks.

#### Acknowledgements

This project is implemented with support from the MMIP 3&4 scheme of the Ministry of Economic Affairs & Climate Change and the Ministry of the Interior & Kingdom Relations.

doi:10.1088/1755-1315/1085/1/012018

#### Reference

- [1] IEA, "World Energy Balances: Overview," Paris, France, 2020.
- [2] European Parliament and Council of the European Union, "Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency," 2018.
- [3] A. Mahdavi et al., The role of occupants in buildings' energy performance gap: Myth or reality?, vol. 13, no. 6. 2021. doi: 10.3390/su13063146.
- [4] Y. Zhang, X. Bai, F. P. Mills, and J. C. V. Pezzey, "Rethinking the role of occupant behavior in building energy performance: A review," *Energy and Buildings*, vol. 172. Elsevier Ltd, pp. 279–294, Aug. 01, 2018. doi: 10.1016/j.enbuild.2018.05.017.
- [5] A. Mahdavi, F. Tahmasebi, B. Gunay, W. O'Brien, and S. D'Oca, "Technical Report: Occupant Behavior Modeling Approaches and Evaluation," 2017.
- [6] T. Hong, S. D'Oca, W. J. N. Turner, and S. C. Taylor-Lange, "An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework," *Building and Environment*, vol. 92, pp. 764–777, 2015, doi: 10.1016/j.buildenv.2015.02.019.
- [7] T. Hong, S. C. Taylor-Lange, S. D'Oca, D. Yan, and S. P. Corgnati, "Advances in research and applications of energy-related occupant behavior in buildings," *Energy and Buildings*, vol. 116, pp. 694–702, 2016, doi: https://doi.org/10.1016/j.enbuild.2015.11.052.
- [8] I. Gaetani, P. J. Hoes, and J. L. M. Hensen, "Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy," *Energy and Buildings*, vol. 121, pp. 188–204, 2016, doi: 10.1016/j.enbuild.2016.03.038.
- [9] S. Carlucci *et al.*, "Modeling occupant behavior in buildings," *Building and Environment*, vol. 174, p. 106768, 2020, doi: 10.1016/j.buildenv.2020.106768.
- [10] M. Schweiker *et al.*, "Dynamic review tables for topical reviews on occupants' perception and behaviour in buildings," 2019. https://osf.io/gnvp2/?view\_only=00b08233881f471795d1d8dee79e9828
- [11] A. Heydarian *et al.*, "What drives our behaviors in buildings? A review on occupant interactions with building systems from the lens of behavioral theories," *Building and Environment*, vol. 179, no. November 2019, p. 106928, 2020, doi: 10.1016/j.buildenv.2020.106928.
- [12] J. K. Day and D. E. Gunderson, "Understanding high performance buildings: The link between occupant knowledge of passive design systems, corresponding behaviors, occupant comfort and environmental satisfaction," *Building and Environment*, vol. 84, pp. 114–124, Jan. 2015, doi: 10.1016/J.BUILDENV.2014.11.003.
- [13] C. F. Chen and K. Knight, "Energy at work: Social psychological factors affecting energy conservation intentions within Chinese electric power companies," *Energy Research & Social Science*, vol. 4, no. C, pp. 23–31, Dec. 2014, doi: 10.1016/J.ERSS.2014.08.004.
- [14] C. Goebel *et al.*, "Energy Informatics," *Business & Information Systems Engineering*, vol. 6, no. 1, pp. 25–31, Feb. 2014, doi: 10.1007/s12599-013-0304-2.
- [15] K. Zhou and S. Yang, "Understanding household energy consumption behavior: The contribution of energy big data analytics," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 810–819, Apr. 2016, doi: 10.1016/J.RSER.2015.12.001.
- [16] T. Hong, Y. Chen, X. Luo, N. Luo, and S. H. Lee, "Ten questions on urban building energy modeling," *Building and Environment*, vol. 168, p. 106508, Jan. 2020, doi: 10.1016/j.buildenv.2019.106508.
- [17] W. F. van Raaij and T. M. M. Verhallen, "A behavioral model of residential energy use," *Journal of Economic Psychology*, vol. 3, no. 1, pp. 39–63, Jan. 1983, doi: 10.1016/0167-4870(83)90057-0.
- [18] S. D'Oca, C. F. Chen, T. Hong, and Z. Belafi, "Synthesizing building physics with social psychology: An interdisciplinary framework for context and occupant behavior in office buildings," *Energy Research and Social Science*, vol. 34, no. August, pp. 240–251, 2017, doi: 10.1016/j.erss.2017.08.002.