OCCUPANT BEHAVIOUR MODELING FOR BUILDING ENERGY CONSERVATION: AN INTEGRATED APPROACH USING AGENT BASED, SYSTEM DYNAMICS AND BUILDING INFORMATION MODELING

MOHAMMAD NYME UDDIN

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Department of Building and Real Estate

Occupant Behaviour Modeling for Building Energy Conservation: An Integrated Approach Using Agent Based, System Dynamics and Building Information Modeling

Mohammad Nyme Uddin

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CERTIFICATE OF ORIGINALITY

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DEDICATION

To Allah, the Almighty, my family, and friends

ABSTRACT

Energy consumption in buildings is affected by various aspects, including its physical characteristics (i.e., Interior layout, orientations, etc.), the appliances inside (i.e., HVAC, light, other devices.), and the ambient environment. However, the occupant's behaviour that determines and regulates the building energy consumption must not be forgotten. In most previous researches and simulation tools (i.e., EnergyPlus, e-Quest, etc.), occupant behaviour is modelled as static or fixed occupancy profiles. These profiles are acknowledged as the main source of discrepancy between the predicted and actual building energy performance. Therefore, researchers attempt to model occupants' presence, movement, and adaptive actions more realistically.

Based on the identified knowledge gap, this research focuses on comprehensive energy behaviour representation in reviewing the occupant perception, attitude, and behaviour mechanisms considering the Theory of Reasoned Action (ToRA) model. It introduces a new hybrid modelling approach using an Agent-Based Modelling (ABM), System Dynamics (SD), and Building Information Modeling (BIM) that helps to predict the occupant stochastic energy consumption behaviours and indoor ambient parameters in the existing buildings. Moreover, it also calculates the existing building indoor layout impact on energy conservation behaviour through the implementation of Enablement intervention (i.e., Interior Layout deployment). Thus, the primary aim of this research is to develop an integrated framework between the ABM-SD and BIM, which is capable of analyzing and prompting the building's energy conservation with improved accuracy by considering the dynamic influencing factors through an interdependent analysis. In line with this aim, five objectives were set.

i) To identify the theoretical framework of energy consumption behavior and mutual factors (i.e., social and factors related to building and layout) involved in building energy conservation due to dynamic human behavior (Literature Review).

ii) To develop an integrated (ABM-SD-BIM) model that appraises and investigates the various energy consumption events with the variation of indoor parameters contributing to occupants' satisfaction (Java-based modelling tools: AnyLogic, Revit Dynamo).

iii) To appraise the comprehensive energy-related behavior determinants (i.e., psychological and physiological) and monitor the stochastic behavior pattern for the building occupants (From model).

iv) To investigate the influence of interior layout deployment (i.e., placement of stuff) on the building energy conservation under a contextual intervention (i.e., Enablement) for an individual and group of occupants from low-income economies (i.e., Bangladesh)..

v) To validate the hybrid model using real data (e.g., customized sensors) and paper-based surveys to check the model performance and improve the energy conservation events.

The validation study has been conducted to test the behavior hybrid model with the visualization techniques and calculation of confusion metrics for model performance evaluation (i.e., Black-box approach).

As key outcomes, the hybrid model actively predicts the stochastic occupant presence and movement, comfort level, energy consumption patterns, temperatures, and CO_2 concentration in the indoor space. Moreover, it has been shown that the interior layout adjustment (i.e., intervention) can improve the building energy performance by 14.9%. In terms of energy data validation, the proposed hybrid model has been shown an acceptable range of accuracy with an average CV(RMSE) =10.5%, MBE=1.5%, and R^2= 0.77. In addition, referring to the confusion matrix, the proposed model has demonstrated exemplary performance as the average predictions reached a relatively good performance, approximately 70%-90%.

This study adds another contribution to the existing occupant behaviour research and building energy optimization for enhanced simulation performance. The proposed hybrid model differs from other available studies in two prospects. Firstly, the model adopts an interior layout-based human behaviour study that considers the stochastic occupant attitudes and subjective norms. Secondly, the model is created together with the intervention and consequent validation study to promote energy savings. Thus, the study will help develop a flexible and comprehensive dynamic simulation platform to study both energy-efficient building design and occupant well-being.

Keywords: Building; Occupant behaviour; Energy conservation; Agent-Based Modelling (ABM); System Dynamic (SD); Building Information Modeling (BIM); Intervention; and Validation

LIST OF RESEARCH PUBLICATIONS

The following provides a list of research publications that the author of this thesis made during his Ph.D. study, and as shown within the text, chapters of this thesis have been fully or partially published in those that are directly relevant to this thesis.

A. Refereed Journal Papers (published/ accepted)

Those Directly Relevant to This Thesis

1. **Uddin, M. N.**, Chi, H.-L., Wei, H.-H., Lee, M., & Ni, M. (2022). Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling. Renewable and Sustainable Energy Reviews, 161, 112382. https://doi.org/10.1016/j.rser.2022.112382

2. **Uddin, M. N.**, Wang, Q., Wei, H. H., Chi, H. L., & Ni, M. (2021). Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. Ain Shams Engineering Journal. http://dx.doi.org/10.1016/j.asej.2021.04.015

3. **Uddin, M. N.**, Wei, H. H., Chi, H. L., & Ni, M. (2021). Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach. Buildings, 11(2), 41. http://dx.doi.org/10.3390/buildings11020041

4. **Uddin, M. N.**, Wei, H. H., Chi, H. L., Ni, M., & Elumalai, P. (2021). Building information modeling (BIM) incorporated green building analysis: an

application of local construction materials and sustainable practice in the built environment. Journal of Building Pathology and Rehabilitation, 6(1), 1-25. https://link.springer.com/article/10.1007/s41024-021-00106-5

Others

1. **Uddin, M.N.**, Selvam, A., Shahoonda, J., & Prasanth, R. (2018). Optimization of Green Building for Low-income People at Pondicherry. Civil Engineering and Architecture, 6(6), 283-292. http://dx.doi.org/10.13189/cea.2018.060602

B. Journal Papers from This Thesis (Under Review/ Pending Submission)

1. **Uddin, M. N.,** Ruva, I. J., Syed, A. Md., Hossain, D., Tamanna, N., & Rahman A. Occupant Centric Energy Retrofit Strategy for Hospital and Restaurant Building Envelop Using BIM-BPS (Building Information Modelling-Building Performance Simulation) Tools: A Case Study from Low-Income Cultural Context (**Journal Name: Energy & Buildings, Manuscript ID: ENB-D-22-01246, Status: Under Review**).

2. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. An Occupancy Based Building Performance Analysis in South Asian Climatic Regions: A Co-Simulation Approach (**Pending Submission**).

3. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. An Assessment of Occupant Comfort and Behavioural Influence on Building Indoor Layout: A Collaborative Analysis Using Statistical and Agent-Based Simulation (**Pending Submission**).

C. Refereed Conference Papers (Published/ Accepted /Under Review)

1. **Uddin, M. N**., Wei, H. H., Chi, H. L., & Ni, M. (2019, October). An Inquisition of Envelope Fabric for Building Energy Performance Using Prominent BIM-BPS Tools—A Case Study in Sub-Tropical Climate. In *IOP Conference Series: Earth and Environmental Science* (Vol. 354, No. 1, p. 012129). IOP Publishing. http://dx.doi.org/10.1088/1755-1315/354/1/012129
2. **Uddin, M. N**., Wei, H. H., Chi, H. L., & Ni, M. A Study of Building Layout Deployment on Occupant's Energy Consumption Behaviour Using Agent-Based Modeling: An Assessment of Sustainable Behaviour Practice for Low-Income Cultural Background (Poster). 8th Annual International Conference on Sustainable Development (ICSD) on 21-22 September 2020, New York City, USA.https://airtable.com/shrGE5Fxy86XpIANG/tblJMTZhl9vMfsR5E/viwkkDNFoUPvoyW5X/recn31UWcxuuy2ycT?backgroundColor=purple&viewControls=on
3. **Uddin, M. N.**, Anwer, S, Wei, H-H, Chi, H-L, Ni, M and Tamanna, N (2021) Energy Efficient Behavioural Trends in Residential Sectors for Low-Income Cultural Background: A Case-Study of Slums in Chittagong, Bangladesh In: Scott, L and Neilson, C J (Eds) Proceedings of the 37th Annual ARCOM Conference, 6-7 September 2021, UK, Association of Researchers in Construction Management, 774-783. http://www.arcom.ac.uk/docs/proceedings/5c115b4a4db6cf74131ac355c479c01f.pdf
4. **Uddin, M.N.;** Wei, H.-H.; Chi, H.L.; Ni, M.; Tamanna, N. Building Layout Influence on Occupant's Energy Consumption Behaviour: An Agent-Based Modeling Approach. Environmental Sciences Proceedings. https://doi.org/10.3390/environsciproc2022015022

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LIST OF ABBREVIATION

ABM: Agent Based Modeling

ASHRAE: American Society of Heating, Refrigerating and Air-Conditioning Engineers

BPS: Building Performance Simulation

BCVTB: Building Controls Virtual Test Bed

BIM: Building Information Modeling

CV(RMSE): Coefficient of Variation of Root-Mean Squared Error

Co-Sim: Co-simulation

DMP: Decision Making Process

ECBC: Energy Conservation Building Code

FEMP: Federal Energy Management Program

HVAC: Heating, Ventilation, and Air Conditioning

IES-VE: Integrated Environmental Solutions Virtual Environment

IPMVP: International Performance Measurement and Verification Protocol

IEA-EBC: International Energy Agency Energy in Buildings and Communities

MBE: Mean Bias Error

MATLAB: Matrix Laboratory

MLE+: MATLAB Environment

OCD: Occupant Centred Design

OODA: Observe, Orient, Decide, and Action

PTA: Perceive, Think, and Act

PMV: Predicted Mean Vote

RMV: Real Mean Vote

SD: System Dynamics

ToRA: Theory of Reasoned Action

WHO: World Health Organization

CHAPTER 1
INTRODUCTION[1]

1.1 General

This chapter sets the research introduction and background, research problems and questions, aim and objectives, overall research design and process, research significance, contribution, and presents the thesis structure.

1.2 Introduction

Primary energy consumption has increased annually over the past decade. In particular, the construction industry accounts for a substantial part of state and global energy consumption. From the perspective of developed nations or countries where buildings consume around 20-40% of primary energy [1]. For instance, buildings in the United Kingdom (UK) are accountable for 39% of energy usage than other European nations, which is slightly more significant than the average energy consumption (37%). Similarly, in the United States (US), the residential and commercial building sectors accounted for more than 41% of total energy consumption, while 74% of energy was used only for electricity in 2014 [2, 3]. Hong Kong building sectors contribute around 61% of total greenhouse gas emissions, constituting about

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[1] This Chapter is partly published in:

1) **Uddin MN**, Wang Q, Wei HH, Chi HL, Ni M. Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. Ain Shams Engineering Journal [Internet]. Elsevier BV; 2021 May; Available from: http://dx.doi.org/10.1016/J.ASEJ.2021.04.015

2) **Uddin, M.N.**; Wei, H.-H.; Chi, H.L.; Ni, M. Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach. *Buildings* **2021**, *11*, 41. https://doi.org/10.3390/buildings11020041

3) **Uddin, M. N.**, Wei, H. H., Chi, H. L., Ni, M., & Elumalai, P. (2021). Building information modeling (BIM) incorporated green building analysis: an application of local construction materials and sustainable practice in the built environment. *Journal of Building Pathology and Rehabilitation*, *6*(1), [13]. https://doi.org/10.1007/s41024-021-00106-5

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90% of total energy consumption [3, 4]. In Japan, energy expenses in the construction industry accounted for more than 28% of total energy consumption, with 13.2 % and 14.8 % in commercial and residential industries. As stated by the International Energy Agency (IEA), the construction industry in Japan became the biggest energy end-user in 1999 [5, 6]. Thus, energy consumption from construction and building operations is expected to boost by 1.5 percent per year over the 2012–2040 period under the regular communal scenario. It may double or even triple by 2050 compared to 2010 [7-9].

There has been an upward trend toward the building energy demand in both developed and developing countries concerning worldwide construction energy usage [10]. However, the construction industry's enormous, cost-efficient energy-saving possibilities could significantly restrain or even reverse as worldwide energy demand increases within and beyond the buildings [11, 12]. Presently, the building energy industry is essential to accelerate the energy-saving transformation and ensure a worldwide low-carbon future [13-15]. In order to significantly decrease building energy consumption, the Department of Energy (DOE) of the U.S. published a roadmap for HVAC technologies, highlighting top-priority projects for high-efficiency HVAC systems. It also added sophisticated direct-current HVAC systems, low-temperature heat pump performance, and electrochemical compressor installations [16, 17]. Other energy-efficient building systems, such as energy-efficient appliances [16, 18, 19], automation in building, and control systems, were also discussed [11]. However, neither essential improvements in the final energy consumption per capita from buildings nor the predicted reductions in energy use have been achieved [7]. This is due to the low implementation rate of energy-saving technologies that have been somewhat constrained by the higher price [20, 21]. Furthermore, some latest studies in the United Kingdom and Finland reported that more than 40% of the people are not attracted to the latest tools or technologies and therefore unwilling to buy and implement energy-saving technologies [19, 22, 23]. Besides, many researchers have also observed that there can be a tremendous discrepancies between the occupants predicted annual energy consumption and real consumption even for nearly identical buildings [24, 25].

Thus, the latest studies in the literature highlight the importance of occupant behaviours in reducing building energy consumption. Occupant behaviour is characterized primarily by occupant energy-related actions/synergies, i.e., control of systems and appliances such as HVAC control, window control, blind control, lighting control, etc. [26]. The relationship between occupant behaviour and energy consumption is recognized in the pursuit of overall satisfaction by the occupants in the latest IEA-EBC Annex 66 [27-29]. In addition, new study viewpoints are emerging, which aim to investigate and highlight occupant behaviour as a crucial impact on energy consumption in a building. It also maximizes energy-efficient building to the same extent that technical solutions can be performed using the existing Building Performance Simulation (BPS) program [30, 31]. Typically, BPS can play a prime role in current and new buildings in analyzing and maximizing building energy conservation [32, 33]. It significantly impacts on the estimated energy precision [25, 34]. BPS is a tool for evaluating precise building data that can forecast the retrofit energy efficiency by generating existing models, proposing solutions, analyzing and evaluating the building performance [35, 36]. It is also recognized as a method and skill to enhance a project's efficiency and usefulness from initialization to operation and maintenance stages [26, 37]. Although BPS's evolving building technology has the potential to offer win-win scenarios and houses are currently being built in various conditions, some barriers exist to the implementation of existing BPS-based sustainable buildings [38-40].

1.3 Research Background

1.3.1 Existing BPS and Occupants Behaviour

According to IEA-EBC, Annex 53: The overall building performance is affected by six parameters (Figure 1.1) such as (i) building envelope, (ii) climate, (iii) energy and service systems, (iv) interior design conditions, (v) occupant behaviour and (vi) building operation and maintenance [12, 41, 42]. Most of these parameters have been studied by several scholars, and related latest studies are linked to BPS and occupant behaviour (OB). In addition, occupant behaviour is subjected to the variations between expected performance and actual performance of the building [43].

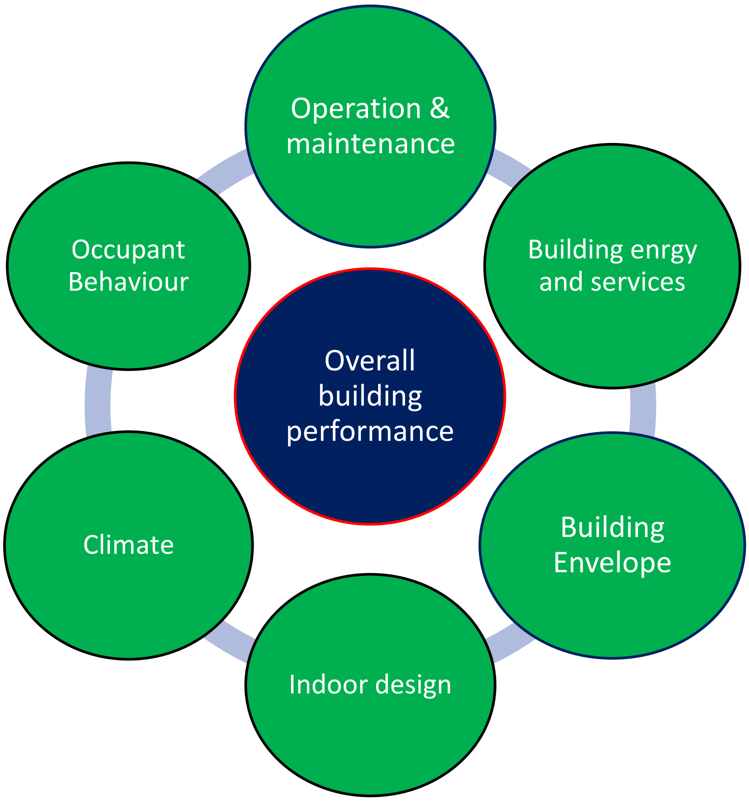


Figure 1.1 Key factors influencing accurate building Energy Prediction

In fact, BPS is a significantly efficient and cost-efficient option for analyzing and improving the building design and systems, where a precise input on occupant behaviour is fundamentally essential [24, 30]. The key advantages acquired from the BPS-based energy simulations in buildings are shown in Figure 1.2.

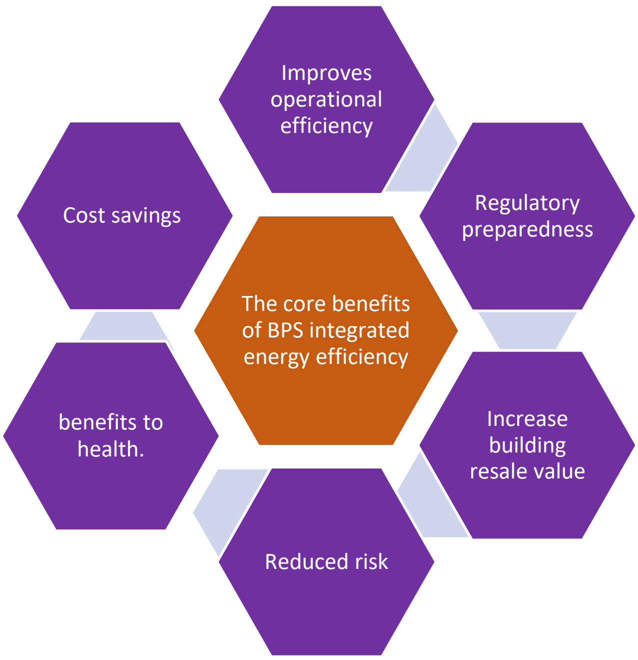


Figure 1.2 Core benefits obtained from BPS

Additionally, BPS can be used in the operating stage to check the real building performance and diagnose building techniques that may not work correctly [44, 45]. If refurbishment or re-modelling is required during the maintenance stage, the most energy-efficient retrofit model can be identified within the BPS tools [26]. In other words, BPS can be used to assist the faults finding in HVAC operation and predict possible energy savings. It is associated with system-level modifications, building redesign and retrofit options in order to expand the overall building performance [46].

However, there are a few constraints on the use of BPS in the building lifecycle operations stage [30]. For instance, an energy-advanced building assessment (e.g., net-zero-energy building) indicates that some real building performance is not similar to planned or designed performance [24]. Another constraint is the inability of BPS to simulate realistic building performance. In order to achieve more precise outcomes [25], it is necessary to simulate building energy efficiency under practical circumstances, including stochastic occupant behaviour [47, 48]. Occupant behaviour (OB) is typically described by occupant-building energy-related associations, i.e., lighting/Fan control, window/blind control, etc. [26]. The relationship between occupant behaviour and energy consumption is ascribed to the pursuit of overall satisfaction by the occupants from the latest IEA-EBC Annex 66 [27].

1.3.2 Problems with Existing BPS Program

In particular, a prevalent and significant source of error in existing BPS tools under realistic circumstances is inaccurate or misleading input associated with occupant behaviour and building operation [49]. Therefore, it is essential to understand the discrepancy between actual and simulated behaviour [50]. Usually, occupant behaviour in the BPS program is represented by setting indoor temperature, scheduling equipment, lighting, and HVAC systems [31, 45]. These are highly variable and totally unpredictable for individual occupants or groups of occupants [38, 51]. These parameters, meanwhile, also have a significant impact on real energy consumption and total building energy performance [41, 52]. Now-a-days, BPS incorporates occupant behaviour has the ability to achieve yield performance near to the real building [53]. Improving the knowledge of occupant behaviour is therefore essential for assessing its influence on the overall output of the building [26, 42].

In order to understand the energy-behaviour interaction, the latest studies in residential and commercial buildings have found that occupants behaviour within an indoor atmosphere has a twofold impact. For instance, the impact relates to overall building energy performance and the occupants comfort with the quality of the indoor environment [54]. Subject to this energy-comfort connection, researchers no longer have the luxury of treating occupant-related factors as a boundary condition; in other words, following default assumptions about occupants' behaviour in energy modelling (in the BPS tool) is disappeared. Intrinsically, in the latest simulation studies, the method of simulating occupant behaviour has gained growing attention, with several advanced modelling approaches that have been applied to mimic the conduct of occupants in buildings research [28, 44, 55-57].

1.3.3 Advanced Behaviour Modelling Approach

Several short-term or advanced variables have been studied while considering the step-by-step behaviour modelling approach. Generally, the occupancy interactions with the building systems have influenced variables that are divided into three primary categories, i.e., time-related, environmentally related, and random. The time-related factors understand the routine of the occupants [44]. Occupancy and interactions with building systems are thus affected by daytime and day of the week. The factors relevant to the environment include a physical element attributed to the features and place of the building. Some examples of environmental variables are solar orientation, envelope, building layout, and the surrounding environment. Due to problems connected with quantifying and observing, psychological variables have been rarely assessed in the occupant behaviour model [46, 54]. Besides, there are two types of OB models that are used, i.e., implicit and explicit [38]. Implicit models deal directly with rules and regulations related to physical building systems (e.g., lights and windows) and include (i) probability calculations, (ii) statistical assessment, (iii) linear and logistical regression (iv) occupancy-based control models (i.e., sub-hourly), and (v) Bayesian estimates. Explicit models address the rules and logic directly associated with the occupants, and it includes: (i) Bernoulli process, (ii) Agent-based modelling, (iii) Markov chain, and (iv) Survival assessment.

Hong et al. [40] and Yan et al. [24] afford a detailed overview of the present state of modeling and simulation of single or multiple occupant behaviour. Solutions that go beyond the conventional behavioural data inputs in various BPS programs, such as deterministic or fixed occupancy schedules, thermostat configurations, HVAC schedules, lighting, and plug-loads schedules, are required to count for the stochastic or random nature of the occupant decision-making process[58]. Some of the more advanced energy modelling techniques include modified or customized code, tools and the co-simulation(Co-Sim) approach. Co-simulation allows a more realistic and accurate depiction of occupant behaviour [38]. Co-Sim's purpose is to combine two or more simulation tools, offering an atmosphere for information exchange between the subsystems [59].

Overall, each advanced behaviour modelling approach involves benefits and limitations. A developed model may be unrealistic while implementing into a behaviour simulation tool as the model data sources are not promptly accessible, i.e., consideration/development of improper behaviour in architecture. Nevertheless, occupant behaviour might be addressed quantitatively at a specific range, regardless of its complex and stochastic nature, through a method for scientific models' development.

1.3.4 Development of Occupant Behaviour in Architecture

The building occupant is a vital part of our built environment, and its importance in building construction research has recently begun to advance concern. The research findings on occupant behaviour in architecture due to comfort and adaptive control [60], lighting control [61], operable window control [62], and shading control[63] are quite a few research subjects that started to investigate behavioural influences and occupant behaviour in building operation. Nevertheless, there are not many cases where this understanding of occupant behaviour plays a complete role in the decision-making process. At the beginning of the building construction process, occupant behaviours like occupancy-based operation schedules play an essential role in the planning stages. It is also related to overall building performance throughout the building life cycle. For instance, occupant behaviours can cause the wear and tear of building architecture and might affect the individual spaces and microclimate, which are intimately linked to the overall building energy performance. Furthermore, there are extensive behaviour assumptions that can be useful to know proper behaviour pattern related to different social contextual factors (e.g., age, gender, and ownership types etc.) that influence the occupant comfort and energy consumption attitude on existing indoor layout systems. The objective of the research is to expose the salient human behaviours in buildings indoor environment, as well as their implications for overall energy performance or conservation. Hence, the study highlights the emergence of human behaviour and its rising part in shaping building energy conservation tasks and research.

1.3.5 Occupant Behaviour Role's (OB) in Energy Conservation

Energy conservation is generally recognized among energy lawmakers. It is described as reduced energy usage through lower energy responses, such as enforcing vehicle speed limits. In the construction sector, the existing methods of energy conservation mainly concentrate on accomplishing its targets by systems-adapted optimization. Nevertheless, this study focuses on energy conservation from a separate perspective by highlighting human-oriented perspectives, based on the assessment of significant conservation issues that ignore the actual energy usage of occupants [64]. This is due to keeping the quality of energy response to the consumers appears that play a vital role in the building's energy efficiency. For example, a lower-quality energy response, such as inadequate heating or cooling in interior space, will enhance the dissatisfaction of occupants with their thermal comfort and increase control over their thermal environment. A typical example of such a control is using a personal fan or space heater, which will assist regain the occupants comfort level and make higher energy consumption. Through occupant control of the built environment, this behaviour is a standard form of a rebound impact that is opposed to building energy conservation whatever of the good efficiency gained by the mechanical systems [65]. It also lessens the ability to make good projections of building energy requirements in the early design stage, which is crucial in making design judgments related to energy saving or conservation.

Therefore, this research aims to explore energy conservation at the occupant user level by developing an integrated framework between the ABM-SD and BIM, which will be quantified the building energy efficiency and effectiveness at the systems level. The activity is built on Ackoff's systems idea, where a system is an operational whole that cannot be separated into independent components [66]. Hence, a building might be regarded as a dynamic, whole operational, and composed of subsystems that construct a hierarchy in the subsequent logic: active systems (occupants or human beings) that intently interact with deterministic systems (mechanisms) and are then affected by social systems, which are all controlled in ecological systems [66]. The system's success is to ensure that the subsystems are incorporated to build a synergy to achieve a common target. This study seeks to predict stochastic energy consumption in buildings space by considering occupant behaviours.

Regarding thermal predictability in most mechanically conditioned buildings, several systematic studies argue that occupants are more satisfied with the various thermal conditions or they feel the necessity to respond due to the changing of environmental stimuli [67, 68]. The concept of adjustment is not a new trend; ancient inhabitants in Mesa Verde caves and Persian Plateau courtyard dwellings shifted within the indoor space to adjust to changing seasonal and diurnal climatic environments [69]. This is also the theory behind the adaptive comfort model that highlights the occupants enhanced tolerance to the abrupt environment through their thermal adjustment [70]. Along with the building occupants, adaptation can also be demonstrated as the active control of their adjacent thermal conditions to enhance the comfort level in a workspace (similar to the prior example of occupants operating personal fans or space heaters). The behaviours that are correlated with these events of active control are a primary concern because they identify the microclimate of an individual's indoor space along with control energy used in the building. A limited number of earlier studies specify this correlation between building energy performance and human behaviour [71-73], which will be expounded later in the study. Accordingly, a better knowledge of occupant behaviour will assist in stimulating an advanced energy prediction model. This explicit intention would contribute to improved systems design and control algorithms with a proper intervention approach. From a different point of view, one could also forecast energy inadequacies caused by occupant behaviour, allowing engineers and architects to better formulate the occupant control (i.e., through several interventions) at an early design stage [71].

1.3.6 Intervention Design

It is evidenced that occupant behaviour assumes a significant position in energy consumption levels. Earlier research on different intervention strategies to change individuals' practices shows productive approaches to sustainable development. There are extensive energy behaviour hypotheses that can be useful to know proper energy usages, remarkably the Theory of Reasoned Action, namely ToRA [72, 73] and later the Theory of Planned Behaviour (TPB), these are generally utilized and analyzed [74, 75]. To expand the benefits of progress, an intervention should be made with a comprehensive knowledge of human behaviour to be changed or transformed, and also the factors of this behaviour might be explored [76-78]. In line with this, Occupant Centred Design (OCD) techniques (i.e., interior layout adjustment) can add to additionally seeing how and why individuals' occupants use energy [79, 80], and this information can advise the plan regarding interventions to advance energy conservation. Fogg [81, 82] presents the target direction on the plan of interventions associated with the Persuasive Systems Design Process [83] that can add to the advancement of effective applications to change individuals' behaviour and improve sustainability. This information, together with general behaviour transformation techniques (i.e., layout modification), design with target tools, and design for efficient behaviour procedures, have been utilized as motivation for the improvement of the interventions exhibited.

Moreover, occupants Interior Layout deployment is one of the design efforts between 'design development' and 'scheme design' in the initial design phase. It is a significant part of the building that affects the overall building energy consumption in the future. Thus, In this study, building Interior Layout is characterized as the interior collocation of various spaces, incorporating inside arrangements, the position of interior furniture, and equipment just as room geometry [84]. Earlier reports have demonstrated that there is an incredible gap between energy-saving prospects and data availability to help design in the early stage [85, 86]. As one significant task in the early design stage, Interior Layout is required to have a great possibility of energy saving. In addition, a few analyses have attempted to assess the impacts of building interior Interior Layout on building energy performance [79, 87, 88]. All investigations have shown that layout can significantly affect building energy performance. In any case, the greater part of these analyses is mixed space design with different factors, for example, occupants movement and operation strategy [26], window to wall ratio [89], and shading framework[90]. It makes it problematic to evaluate the effect of Interior Layout dependent on the existing research. It is fundamental to confine the space plan from different parameters to completely recognize its impact on the energy performance of a building. This comprehensive study targets breaking down the unfinished effect of occupant Interior Layout on building energy performance through the indoor layout-based intervention strategy. As an appropriate intervention strategy, this study takes into attention the Enablement intervention that is mainly considered the advance opportunity or minimizing the barriers/obstacles to perform the human energy related tasks. Here layout deployment or re-organized the layout has been anticipated so occupant may prompt towards the energy savings intention.

1.3.7 Uncertainties of Occupant Behaviour

Although various intervention strategies have been implemented for human behaviour studies, several uncertainties still exist for building occupant behaviour research. Occupant behaviours are usually abundances made that are naturally transient and random. Simon has classified the uncertainties of occupant behaviour as the events and phenomena in an atmosphere where they are regarded as random because we merely have no better way of distinguishing them [91].

The attempt to understand the behaviours and behavioural uncertainties – especially in the context of the built environment – has gained admirable opinion in the building science society. Human behavioural prediction models can be made through literal study in other fields, believing that the behaviour of interest is explicitly described [72]. Fortunately, a small number of latest studies have exhibited promising improvements in uncertainty assessment using computer simulation [28, 29, 91-94]. This study aims to reveal these theoretical and methodological constructions on a building's occupant behaviour prediction.

Due to the complication (behavioural uncertainty) of occupant behaviour prediction, Simon claimed methods of simplification and abstraction without a complete analysis of the interior environment, as the behavioural character seems like only a few properties of the whole [91]. This is similar to how a mathematical model is reduced to simple equations, which is less interpretation of the interior environment and its internal connectivity, but more of the occurrence of interest. These simplification and abstraction are also explained in Poincare's discussion, where he described the rationale by repeating a single formula that comprises an infinite number of logical cases [95]. German theorist Schlick also ensured that using simplicity, researchers succeed in demonstrating a series of understandings through a simple formula or several reliabilities [96]. For a particular methodology or abstraction, the application of probability distribution (mainly used for the stochastic method) is extensively used for uncertainty assessment, such as in occupant behaviour predictions [97].

Although simplification and abstraction can become ambiguous and virtual, the usage of statistics looks to be reasonable for the decision-making process in various areas. The actual challenge is recognizing the activity phenomena and the characteristics or attributes (variables) that trigger occupants, i.e., understanding 'what' to forecast and 'what' suggests them. This method can sometimes be unforeseen, raising the tension by presenting high uncertainty. As a possible direction, this study assumes the mood of the social-constructivist method, which maintains the scientific understanding that incorporates both social and natural events [98]. This is because the behavioural perception in buildings is not expressed in a single causal connection but is complexly interconnected with numerous links – elements that form the psychological, physical, social, cultural, etc. Along the lines of ideas for social constructivism, H.M. Collins recommended a research approach, such as survey questionnaires and other methods for gathering knowledge about the groups. It was built on the hypothesis that beneficial knowledge could be achieved by exploring the behaviour itself and the environment or surroundings in which it occurs and the rules of thumb for resolving complex challenges. For example, it is described as an intelligent knowledge-based system or an expert system that encourages artificial intelligence research [98]. As a combined social and scientific model construction approach, this study considered both phycological and non-phycological parameters through an appropriate hybrid modelling method.

1.4 Research Problem/Problem Statements

Even though the background mentioned above, approaches and uncertainties to the building energy monitoring field encompass numerous difficulties or challenges that should be resolved effectively. The energy usage of a building is highly dynamic and relies on different parameters, for example, environment, climate, and people that persistently influence the building energy performance during the entire life cycle. To break down these components, the integrated methodology needs to simulate to understand the impacts of variables arising during the whole life cycle of a building. For accomplishing this, the modeling structures should cover a system approach and need to support message or data exchange over the agent-based, system dynamics and building information modelling that captures the various elements in the building energy analysis. To summarize, the considerable difficulties or issues that exist in the existing occupant behaviour study in building energy are:

i) Lack of flexibility in the existing simulation method:

Precise methods for estimating and observing energy usage in the building operation and maintenance stage are critical because this stage consumes the amplest energy. Therefore, it gives the most extreme ways of receiving energy-efficient systems [30, 99]. Notwithstanding, the current energy simulation tools allow static parameter which doesn't represent the dynamic behaviour of building frameworks and the occupants. Even though few co-simulation approaches are created to address this, however, the available designs also have several constraints. It doesn't enable an architect to incorporate a simulation model of their choice, which indicates the opportunity of reusing existing modeling systems. Moreover, the existing frameworks comprise an initiating approach that doesn't enable the modelers to address the overall frameworks' adjustment effectively [28, 100]. At last, the current methodology or model in the building energy study area doesn't give a feasible or flexible choice to projects and models to run on controlled workstations while accessible data are exchanged one to another.

ii) Lack of a system approach in the ABM-SD based energy management:

The energy consumption in a current building should be examined by considering the integrated way to deal with capturing the significant connections of the existing parameter between the various energy-saving requirements. Current methods consider the single ABM model with some static natural/environmental parameter and end accumulating evaluations of energy requirements and determine the conclusion dependent on that. However, this methodology misses the loss of the impacts of dynamic events, for example, indoor building performance and occupant perception and cognitive activity during the operation stage [101]. The perfect way should be to visualize the impacts of inter-connections between various energy-related activities inside or indoor building environments, consequently giving alternatives to implement improved energy-saving approaches.

iii) Lack of understanding about the relationship between the interior layout and occupant energy behaviour actions:

Some earlier investigations have considered the effect of building conditions and explicit design features [79, 102, 103]. The Interior plan and design of the space have numerous effects on occupants and their interaction within the building frameworks, so it could influence building energy utilization. A few studies have underlined the thorough impact of interior layout deployment on human behaviour [104, 105]; however, its link or relation to the occupant energy usage behaviour has not been completely realized. Moreover, in earlier studies, new and existing buildings layout considerably accounts for a high amount of energy demand, and building energy refurbishment is essentially required to be energy utilized effectively [56, 57]. Therefore, this research suggests studying the existing interior layout plan and how it could influence or reduce the building energy consumption through a contextual intervention for a specified case study location.

iv) Lack of qualitative occupant behaviour research than quantitative:

As a rule, utilizing both quantitative and qualitative information is inevitable. However, most of the current research used quantitative research techniques. In earlier studies, the researcher concentrated more on "what" occupant behaviour is instead of "how" and "why" occupant behaviour is created [106]. It needs to be noticed that, to reduce the effect of human behaviour on building energy consumption, it is important to have a comprehensive investigation of the structure pattern of occupant energy behaviour, which implies the need of mix methods techniques. Recently, a few researchers started to understand the significant role of mixed methods techniques in investigating the nature of occupant energy behaviour [57, 106]. It tends to be argued that mixed-method techniques in the field of energy-related occupant behaviour are still in its early stages.

v) Lack of accurate data involve in ABM-SD validation:

One of the significant difficulties for the earlier part of the research studies using an ABM approach in the absence of real data. There are a few scholars who validated their ABM or behaviour models using realistic data [12]. In addition, much of the time, the model depends on an example or improved model that may prompt questions about whether the simulated agent will play out the behaviour in which genuine occupants do, consequently prompting inadequacy in model reliable quality. A few numbers of models' validation or verification studies have been seen in the earlier literature. In [107], a validation study was led to assess the ABM, which depends on Perceptual Control Theory (PCT). The model outcomes were seen as practically identical to the field estimations for individual and accumulated projections. However, the model just assumed thermally adaptive behaviour, and just selected behaviours were validated. Putra et al. [108] studied the effect of load shedding on human comfort and behaviour using the ABM approach. The ABM model involved mixed agents/operators and perception capabilities along with a few simulation states. However, just four of the simulation states were analyzed with calculated data, and the test outcomes failed to illustrate an adequate degree of precision.

1.5 Research Questions

The following questions will be answered during the study:

i) What is the current background of study associated with building energy usage by occupants, and how does it influence the potential approaches that guide the energy-saving behaviour through an intervention technique?

Technology alone won't accomplish building energy conservation purposes. People and their energy-related behaviour in buildings should be appreciated for better energy performance. In spite of numerous studies turning about human behaviour relation and building energy performance, the knowledge of occupant behaviour and its position in building energy performance stays complex, unclear, and conflicting. Along these lines, more research spotlight should be put into combining essential human elements into energy strategy formation. For instance, selected intervention systems, i.e., building layout, and information programs for tenants or residents, need to be considered to improve existing building energy consumption. Moreover, interventions reviewed include the provision of information, enablement, feedback, and rewards, all of which aim to change individuals' knowledge and perceptions of energy conservation activities.

ii) What are the critical energy-related determinants (i.e., Bengali cultural background), and how are these determinants associated with the building operation phase?

Occupant behaviour on building energy consumption is very complex as it is reliant on several factors or determinants. Rapidly growing, particularly in developing nations, the building occupants provide the major, most cost-effective possibilities for energy efficiency and the most significant co-benefits. A wide-ranging state of the art review of more than 128 articles documented or marked by the author to identify the impact of occupant behaviour on energy consumption. It suggests that personal (i.e., psychological, physiological), climatic (i.e., physical, environmental), economic, social, and legal parameters in cooperation with building plan and design criteria are the main features considered by numerous researchers across the globe. Inadequacy of information about significant determinants of energy used in the building's operation phase is treated as a substantial hindrance to promoting overall energy performance.

iii) What extent an integrated framework (ABM-SD-BIM) would be robust enough to support the upgrading of planned behaviour modeling?

The modelling and simulation of complex (social and group) behaviours in residential buildings with occupant comfort and appliance operation are not insignificant. Hence, the research aim is to propose an integrated or hybrid framework to facilitate more realistic occupant behaviour. Even though occupant behaviour is challenging to model due to occupants' randomness or stochastic and unpredictable nature, it is essential to explore the common pattern of their behaviour and represent the robust data with System Dynamics (SD), ABM, and BIM tools. In the context of building energy efficiency and built environment, particularly in residential houses, the key driving factor that variations of occupants behaviour are their physical comfort in contrast to other norms such as social aspects or economic concerns.

iv) What is the acceptance of suggested energy-saving practices (interventions), and how an interior layout deployment can be influenced by the individual or a group of people?

Several efforts have been built to change occupant behaviour over design-led interventions to bound its climatic or environmental problems. Moreover, there is a deficiency of knowledge of occupants insights and perceptions of building interior layout regarding the particular intervention context. This context includes culture, habits, economy, and level of influence (LI) of the energy uses as well as behaviour-changing appliances. Moreover, specific contextual intervention (e.g., economy or ownerships) also influences the energy-saving practices for the group of occupants, i.e., tenants and landlords.

Only an empirical (changes in windows, door, orientation, layout, etc.) intervention-based approach might not be significantly influenced the occupant energy savings prospects. Both physical and phycological parameters have combinedly involved the usefulness and suitability of the proposed intervention. So, the study highlights a primary step for promoting energy conservation using the most acceptable interior layout deployment and human perception as the wide-ranging design concepts to tap the stockholder by providing improved and sustainable usage experiences.

v) How can the developed hybrid models (ABM-SD framework) be validated using real data to ensure it's representativeness or performance?

The validation and verification (V&V) of simulation models are extremely important. Validation usually ensures that the right model has been built, whereas verification involves the model being debugged to ensure it works correctly. Hence, a validation methodology is required for the model to implement in a behaviour study. The validation and fit of the proposed behaviour model are highly critical to make it a representative model to be used during simulations. Importantly, as most of the previous ABM studies stayed on synthetic data and facts, this study aims to fill this gap by offering an integrating method or technique for a hybrid validation approach. It is built on the improved model in terms of model evaluation and realistic data collection.

1.6 Research Aim & Objectives

1.6.1 Research Aim

The primary aim of this research is to develop an integrated framework between the ABM-SD and BIM, which is capable of analyzing and prompting the building's energy conservation with improved accuracy by considering the dynamic influencing factors through an interdependent analysis.

1.6.2 Research Objectives

To achieve the overall aim, the following objectives are outlined.

i) To identify the theoretical framework of energy consumption behaviour as well as common factors (i.e., factors related to building and layout) involved in building energy conservation due to dynamic human behaviour (Literature Review).

ii) To develop an integrated (ABM-SD-BIM) model that appraises and investigates various energy consumption events with the variation of indoor parameters contributing to occupants' satisfaction (Java-based modelling tools: AnyLogic, Revit Dynamo).

iii) To appraise the comprehensive energy-related behavioural determinants (i.e., psychological and physiological) and monitor the behaviour pattern of the building occupants (From model).

iv) To investigate the influence of interior layout (i.e., placement of stuff) on the building energy conservation under a contextual intervention (i.e., Enablement) for an individual and group of occupants from low-income economies (i.e., Bangladesh).

v) To validate the hybrid model using real data (e.g., customized sensors) and paper-based surveys to check the model performance and improve the energy conservation events.

1.7 Research Process

The research process adopted for this study is divided into various stages.

The first stage of the research study contains the theoretical background (systematic review of the literature) on occupant behaviour studies, identifies overall behaviour factors, active and passive energy behaviour, BIM-BPS tools for behaviour research, existing behaviour models and analysis, intervention techniques for building energy conservation, and the influence of interior layout for household energy performance.

The second stage includes the establishment of the research background, describing the research gap, research problem, stating the research aim and objectives, and design of the research methodology. This preliminary stage of the study was developed through a detailed literature review and discussions with academic supervisors and research colleagues.

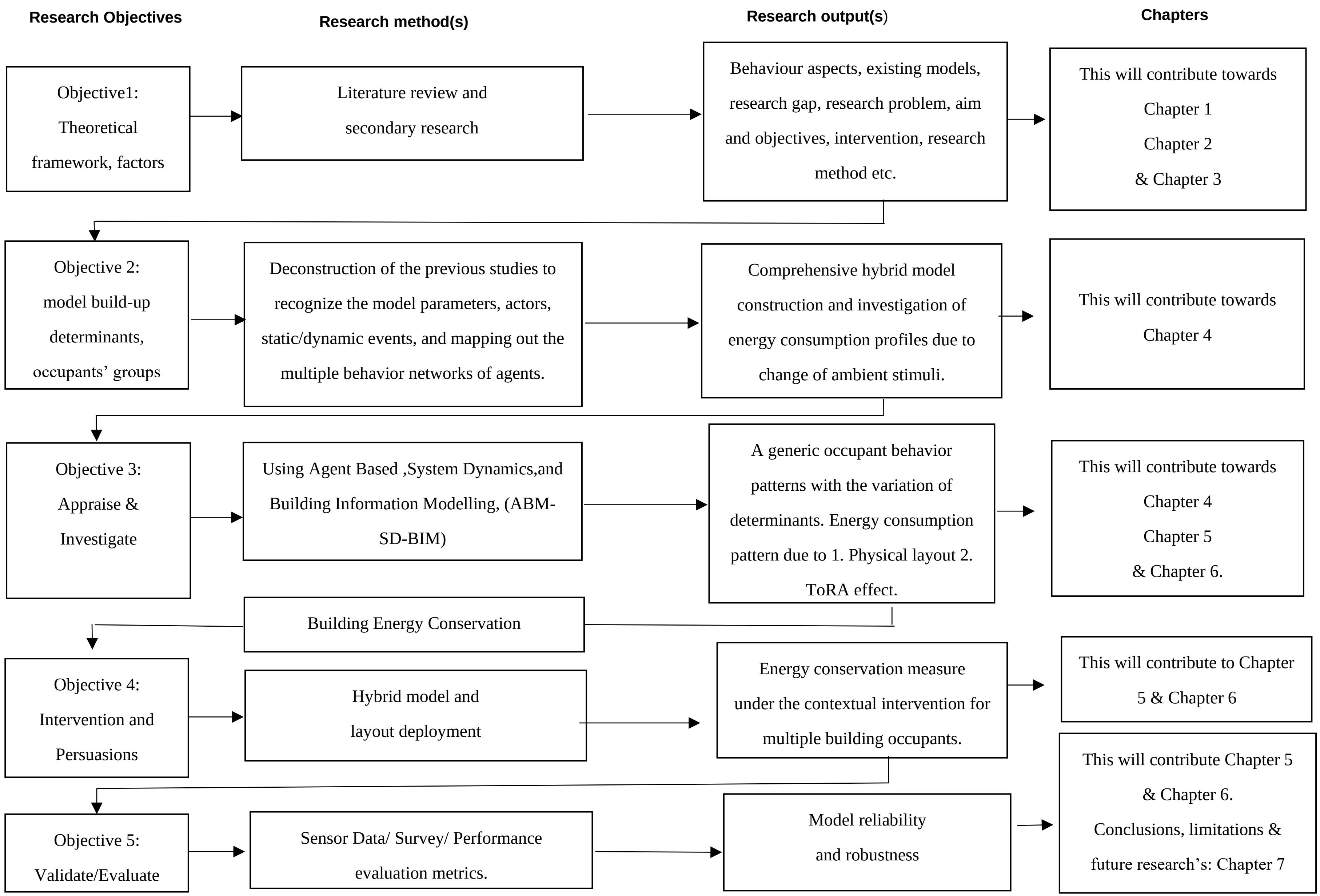
The third stage of the research study involves a detailed description of the research methodology. This includes the research strategy and approach, research technique, and methods.

The fourth stage is to develop an integrated behaviour model (ABM-SD-BIM) to facilitate the comprehensive occupant behaviour simulation. Though occupant behaviour is problematic to model due to the stochastic or random nature and variability of occupants, so it is essential to explore the common behaviour pattern and represent the useful information using System Dynamics (SD) and ABM.

The fifth stage contains the experimental section, which will represent an intervention and sequence of simulation experiments that test the model for validation using real data. Since the proposed integrated model is a simulation-based approach, so a validation/verification framework is required to improve the reliability, trustworthiness as well as robustness of the model. It involves a time interval data record and observation of ambient environmental factors (i.e., temperature, CO_2, etc.), occupant energy consumption, and behaviours pattern due to layout deployment.

The study of model outcomes using the true ambient, behaviour, and energy consumption data can be utilized to evaluate the performance as well as adjust the rules and settings of the ABM. The whole validation works explore how a specific occupant reacts or responds to the dynamic environment and assesses the model data through a complete yield assessment. In that way, the overall research design has been further demonstrated in the following section.

1.8 Overall Research Design



1.9 Expected Research Contribution to Body of Knowledge

i) Understanding the behaviour waves; a salient factor challenges with building energy modeling impacts.

ii) Contributing to the literature on the relationship between occupancy and building energy efficiency.

iii) An integrated platform between ABM-SD-BIM for the promotion of behaviour modeling of building energy conservation.

iv) Understanding human psychology, preferences, and decision-making will enable policy makers and other stakeholders to plan and manage overall building layout and energy management through the framework.

v) The model will help to identify the components with the highest contributions to the energy consumption of a building (e.g., physical, energy behaviour, interventions for energy conservation).

The combined model will be established the probability of using tools or appliances in the occupant-built environmental area. The proposed integrated model also captures the broader aspects of occupant behaviour paradigms while applying the multiple interventions (layout, persuasions, etc.), which may also motivate further development of thoughts and ideas. In the context of building energy efficiency and built environment, specifically in residential households, the main driving issue that changes occupants behaviours is their physical or thermal comfort in disparity to other conditions such as social or economic concerns.

The findings will be drawn from low-income cultural backgrounds and could also be applied to other developing countries or other regions. The fact is that most of the countries share similar energy behaviour in terms of social and economic characteristics.

In contrast, because of the complex system of occupant behaviour, it is hard to show each and every probability with one technique. Subsequently, the modeling approach to occupant behaviour relies upon the degree and motivation behind the study. Actually, this point has been drawn by various specialists' in the past few years. Among various occupant behaviour modleing techniques, ABM was advised by numerous researchers as one of the best approaches. As indicated by [12], ABM can focus on different behaviour together and represent both individual and group level relations of independent agents. Especially, agents in ABM can recreate or reform people by combining qualities of the surrounding condition and adjusting to accomplish a specific objective. On the other hand, with other simulation methods, ABM starts and finishes with the agent's point of view. Agents have their very own attributes, including behaviour and practices, and sensations. Also, they have the capacity of associating with their surroundings condition and different agents that are managed by a characterized set of rules. These rules are established to simulate agents' relations, interactions, and behaviour.

1.10 Structure of Report

This thesis is organized into seven chapters.

Chapter One offers the introduction, background of the study, problem statements, research questions, research aim and objectives, overall research design, and contribution.

Chapter Two presents a comprehensive review study on occupant behaviour literature through a systematic analysis.

Chapter Three offers the adopted overall research process/methodology. Chapters 4-5 build on this overview and explain the methods thoroughly in each chapter.

Chapter Four offers the step-by-step process for ABM-SD-BIM-based hybrid model construction along with model demonstration.

Chapter Five explains the interventions and validations studies for occupant behaviours study that incorporates the experimental structure, data collection, model performance test using evaluation/confusion matrix, and survey questionnaire.

Chapter Six explains the detailed results and discussions about the simulated and experimental outputs along with collaborative discussions.

Chapter Seven gives a summary of the research conclusions based on the specific objective, as well as it also presents research limitations, recommendations, and future research for the occupant behaviour study.

1.11 Chapter Summary

This chapter presented a general overview of the research along with the context/background, research problem, questions, aim and objectives, scope, overall research design, study contribution, and structure of the thesis.

CHAPTER 2

LITERATURE REVIEW[2]

2.1 General:

Based on purpose, the study on occupant behaviour (OB) and energy performance can be split into numerous groups or clusters. One group is to understand the occupants psychology toward environmental conditions by distinguishing and evaluating the key stimuli that impact the building energy-related behaviour. It is very prosperous that research subjects moved from social science and psychological investigation to modeling building occupant behaviour and energy simulation, which proposes a change of research motivations from qualitative to quantitative study or modelings. In recent years, several approaches or models have been developed for occupant behaviour study. The following sections will be described in detail literature about the existing BPS and occupant behaviour model or approach.

2.2 BPS and Co-Simulation Based Model

2.2.1 Stand-alone BPS tools

[2]This Chapter is partly published and under review in:

1. **Uddin, M.N.**; Wei, H.-H.; Chi, H.L.; Ni, M. Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach. *Buildings* **2021**, *11*, 41. https://doi.org/10.3390/buildings11020041

2. **Uddin, M. N.**, Wang, Q., Wei, H. H., Chi, H. L., & Ni, M. (2021). Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. *Ain Shams Engineering Journal*. http://dx.doi.org/10.1016/j.asej.2021.04.015

3. **Uddin, M N**, Anwer, S, Wei, H-H, Chi, H-L, Ni, M and Tamanna, N (2021) Energy Efficient Behavioural Trends in Residential Sectors for Low-Income Cultural Background: A Case Study of Slums in Chittagong, Bangladesh In: Scott, L and Neilson, C J (Eds) Proceedings of the 37th Annual ARCOM Conference, 6-7 September 2021, UK, Association of Researchers in Construction Management, 774-783. http://www.arcom.ac.uk/-docs/proceedings/5c115b4a4db6cf74131ac355c479c01f.pdf.

4. **Uddin, M.N.;** Wei, H.-H.; Chi, H.L.; Ni, M.; Tamanna, N. Building Layout Influence on Occupant's Energy Consumption Behaviour: An Agent-Based Modeling Approach. Environmental Sciences Proceedings (Under Review).

5. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. An Occupancy Based Building Performance Analysis in South Asian Climatic Regions: A Co-Simulation Approach.

Assessment of existing building performance indicates that the real performance of some of them is no longer as designed or predicted. Building performance simulation (BPS) under the practical conditions that includes occupant behaviour is needed to accomplish more accurate results [109]. Incorrect data correlated to occupant behaviour and building operation system is a significant source of error in building simulations function under the realistic conditions [30]. Occupancy-related basic data in the current BPS tools are limited to fixed or constant profiles, and these no longer characterize the reality or truth [30, 110]. The majority of the existing simulation-based investigations involve the energy efficiency assessment for different single or multi-story buildings by ignoring the interaction between the occupants and building systems [2, 111]. Gunay et al. [112] described an application and comparison of existing building occupant behaviour models for an ideal location using a BPS tool (i.e., EnergyPlus). The study also tested how the variations in these models influence the BPS results. Besides, Ouf et al. [113] compared the comprehensive building occupant-related elements between the available BPS tools. Lindner et al. [114] studied 24 behaviour models from the various literature that also approached being linked with a BPS tool (i.e., EnergyPlus) for a case investigation. Jang and Kang [115] studied occupant behaviour for a residential building located in Seoul throughout the stochastic modeling approach. Sang [116] studied the building envelop aspects of a high-rise building in Hong Kong using a BPS tool (i.e., eQuest). This study mainly focused on cooling energy consumption that might be lowered significantly, at nearly 46.81%. Another study [2] also applied a BPS tool (i.e., IDA ICE) for inspecting an office building performance in three distinct climates by ignoring the stochastic occupancy profiles.

2.2.2 BIM Incorporated BPS tools

Turn to BIM combined tools, several studies [117-119] have performed a design selection-making assessment where a green BIM-based selection process incorporates the realistic stages of Building Information Modeling (BIM) and Building Performance Simulation (BPS). Al-Din et al. [120] explored an intense deal of more broad research that may carry out regarding the implementation of thermal comfort performance throughout the building envelope. Moreover, a study [121] launched a shortened tool-based thermal comfort analysis by considering the Predicted Mean Vote (PMV) indicator. Here, the thermal comfort simulations have been accomplished by employing a BPS tool (i.e., Ecotect), whereas 14 different orientations and a type of existing room layout built on window configurations at several locations in India. Dhaka et al. [122] and Tulsyan et al. [123] also applied Building Performance Simulation

(BPS) to assess the energy-saving prospects of the enforcing energy management procedures in the Energy Conservation Building Code (ECBC) and showed that using ECBC may need to result approximatley40% of financial savings [123]. Abanda et al. [124] investigated the influence of building orientation on energy consumption in a residential building using a BIM and BPS tool (i.e., Revit & Green Building Studio). Shahryar Habibi [125] study focused on the integration of BIM and BPS tools (i.e., Revit & IES-VE) for monitoring and optimizing the building environmental factors (e.g., temperature, daylight, etc.). Patiño-Cambeiro's [126] approach designated a multidisciplinary approach for estimating the energy performance of an educational building using BIM and BPS tools (i.e., Design Builder). The scrutiny and analytical phases have been conducted with an accurate study using a BIM-based tool (i.e., Revit).

As mentioned above, few works incorporate the occupant behaviour in building performance modeling and show less research significance on this. Even though in these works of literature, the importance and uncertainties of occupant behaviour in buildings performance studies are reasonably acknowledged, most of the study findings give no or less consideration to occupant behaviour in building performance simulation (BPS).

2.2.3 Advanced BPS tools/ study

Moreover, a growing area of research has shown that the uncertainty caused by the behaviour of the occupant influences a considerable variation in the building energy consumption [12, 30, 42, 50, 127]. In order to make an occupancy model, existing BPS programs, such as DeST [128] and, EnergyPlus [129], use static and deterministic weekly schedules. In spaces with analogous tasks, BPS mainly uses the same occupancy schedules. As a result, each space represented an identical load/energy pattern. The simulation results use this homogeneous occupancy schedule in energy modeling, and ultimately no randomness is reflected. To end, this leads to a considerable discrepancy between the forecasted and actual energy consumption [130]. However, few investigators have incorporated a distinct occupant behaviour module with an existing BPS tool, using Co-Simulation or other approaches. The Co-Simulation (Co-Sim) approach offers a fascinating option to combine existing BPS's sophisticated capabilities with the broad expertise and software tools available in the field of control engineering. It allows for a further rational and accurate illustration of building occupant behaviour as well [38]. The purpose of Co-Sim is to combine two or more simulation tools, offering a platform for information or data exchange between the subsystems. Similar to the Co-Sim concept, Gunay et al. [131] studied three domains, such as HVAC, occupant, and building, and they coupled these domains by implementing a discrete event system for the building performance model. A study [107] constructed an agent-based (ABM) approach for office occupant behaviours where authors combined the building energy simulation tools, i.e., EnergyPlus, with the ABM in MATLAB through the BCVTB. Likewise, Lee and Malkawi [58] coupled an ABM approach in the MATLAB platform with EnergyPlus, using BCVTB and MLE+ architecture. Other studies [51, 110] also advised that one of the highly significant standards when investigating building occupants' behaviour is Building Information Modeling (BIM) involvement which offers more flexibility and interoperability between the BIM and BPS tools. Typically, Co-Sim also permits interoperability between the building occupant behaviour models and existing BPS tools that allow flexibility to new research and potential application in BIM-based research. Still, the Co-Sim method is often used to simplify, decrease the run-time of simulation, and minimize the complexity of the model. Investigating a building for a specific location has its particular output and limitations; similar building operations may differ in other climatic zones due to the irregular temperature profiles related to geographical location and buildings with inconsistent weather data [132]. This standard approach (i.e., Co-Sim) ignores the opportunity to see occupancy interaction of typical building performance within different locations while using the building performance simulation program [133].

2.3 Explicit/Implicit Model

Building occupants perception not just hinders the completeness of the building energy model using BPS or Co-Sim, yet in addition to prompts errors in particular energy estimation. In spite of the fact that occupant behaviour is difficult to show because of the stochastic nature and randomness of people, it is important to investigate the common pattern of people's behaviour and incorporate the data with the energy simulation model. With regards to assembled condition and building energy conservation, generally in places of offices or houses, the weighty driving variable that changes occupants behaviour is their physical comfort as opposed to other paradigms, for example, economic concerns [79]. Another way, the climatic or environmental conditions where a resident/occupant lives will cause adaptive behaviour, while proper energy use may be ignored. Thus, a robust occupant behaviour model is required that may produce practical building occupants responses within the built environment context.

In the existing advanced modeling method, researchers typically pursue the specific methodology outlined in Figure 2.1. Information related to occupant behaviour and possible environmental or climatic data is collected [106]. Afterwards, they applied quantitative investigation in the signifying part to collect relationships between outdoor and indoor ambient conditions and additionally actions and behaviour inside with a lot of logical elements. Eventually, a precise model assessment/validation needs to be performed to confirm the created models are reliable and powerful. Hence, the behaviour model can be implemented and incorporated into the simulation modeling tools for architects and specialists to utilize. It is important that the procedure isn't once-through yet repeated. For example, throughout the model improvement or assessment, it might be revealed that inadequate data or information is being gathered. Similarly, a developed model may demonstrate to be unrealistic while executing into a behaviour simulation tool as the model data sources are not promptly accessible. To put it clearly, if issues are disclosed throughout a given phase, the researcher may need to rebuild and re-repeat.

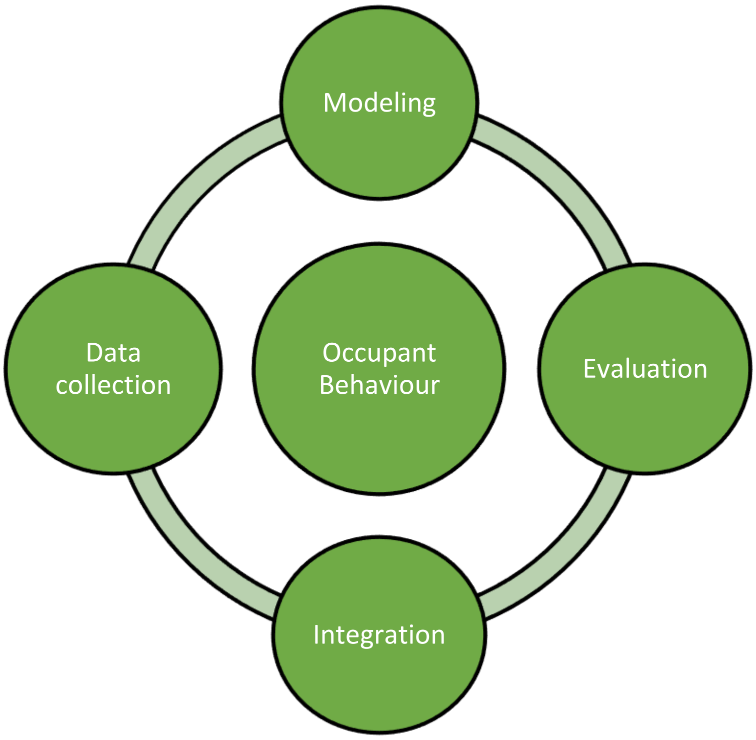


Figure 2.1 Structural framework of behaviour modeling and simulation

Occupant behaviour(OB) can be addressed quantitatively at a specific range, regardless of its complex and stochastic nature, through the methods for scientific model development [24, 106]. Due to the complexity of behaviours, researchers have tried to build various occupant behaviours models in building through several approaches [50, 134]. For example, Papadopoulos and Azar [135] divided human behaviour models into three different parts such as grey-box model built on a statistical and stochastic approach, the white-box model built on physical equations, and the black-box model, which is based on machine learning algorithms.

According to Hong et al. [38], there are two types of OB models, i.e., implicit and explicit. Implicit models deal directly with rules and regulations related to physical building systems (e.g., lights and windows), and it includes (i) Probability calculations, (ii) Statistical assessment, (iii) Linear and logistical regression (iv) Occupancy-based control models (i.e., sub-hourly), and (v) Bayesian estimates. Explicit models address the rules and logic directly associated with the occupants, and it includes (i) Bernoulli process, (ii) Agent-based modelling, (iii) Markov chain, and (iii) Survival assessment. From a detailed survey, this review [50] study offers a model categorization in terms of whether the developed model is based on data and thus they categorized wide-ranging behaviour models into the simulation-based and data-driven approaches. In brief, modeling using data-driven methods involve an extensive amount of data to build a statistical model for selected occupant behaviours, although simulation-based energy models depend on empirical or pre-defined rules that control the occupant behaviour configuration. Behaviour thus would be able to be correlated into modeling and energy simulation to consider its effects on building energy and indoor environmental performance [136].

By considering the importance of occupant behaviour on building energy performance and the lack of systematic review analysis, this study also provides a timely review of the state of the art literature on occupant behaviour research. It is obviously difficult to capture a holistic knowledge of occupant behaviour and its influence on building energy conservation. Particularly, the following questions remain unanswered: a) what is the current understanding of occupant behaviour and influential determinants related to buildings' energy consumption? b) what kind of drawbacks and limitations are involved in the existing occupant behaviour modeling approach? c) how has behaviour research progressed and what are the further research gaps? This study attempts to address the above questions through a systematic review study as well. The following sections will be described the systematic literature review implemented for this study.

2.4 Systematic Literature Review

As shown in Figure 2.2, the methodology adopted in this study is built on a systematic review of the most relevant research that current study arguments about the issue related to occupant behaviour on building energy conservation. This review includes relevant articles that have already been published in peer-reviewed academic journals, while unpublished research works, conference papers, policy or industry reports, short communications, etc., are excluded. The proper justification behind this, peer-reviewed articles are considered the most valuable sources of data or information, as more academic precisions are engaged in their research publications [137]. A systematic search of the literature was conducted, using the most popular search engine, namely Scopus and Web of Science database, to retrieve the related articles for this review study.

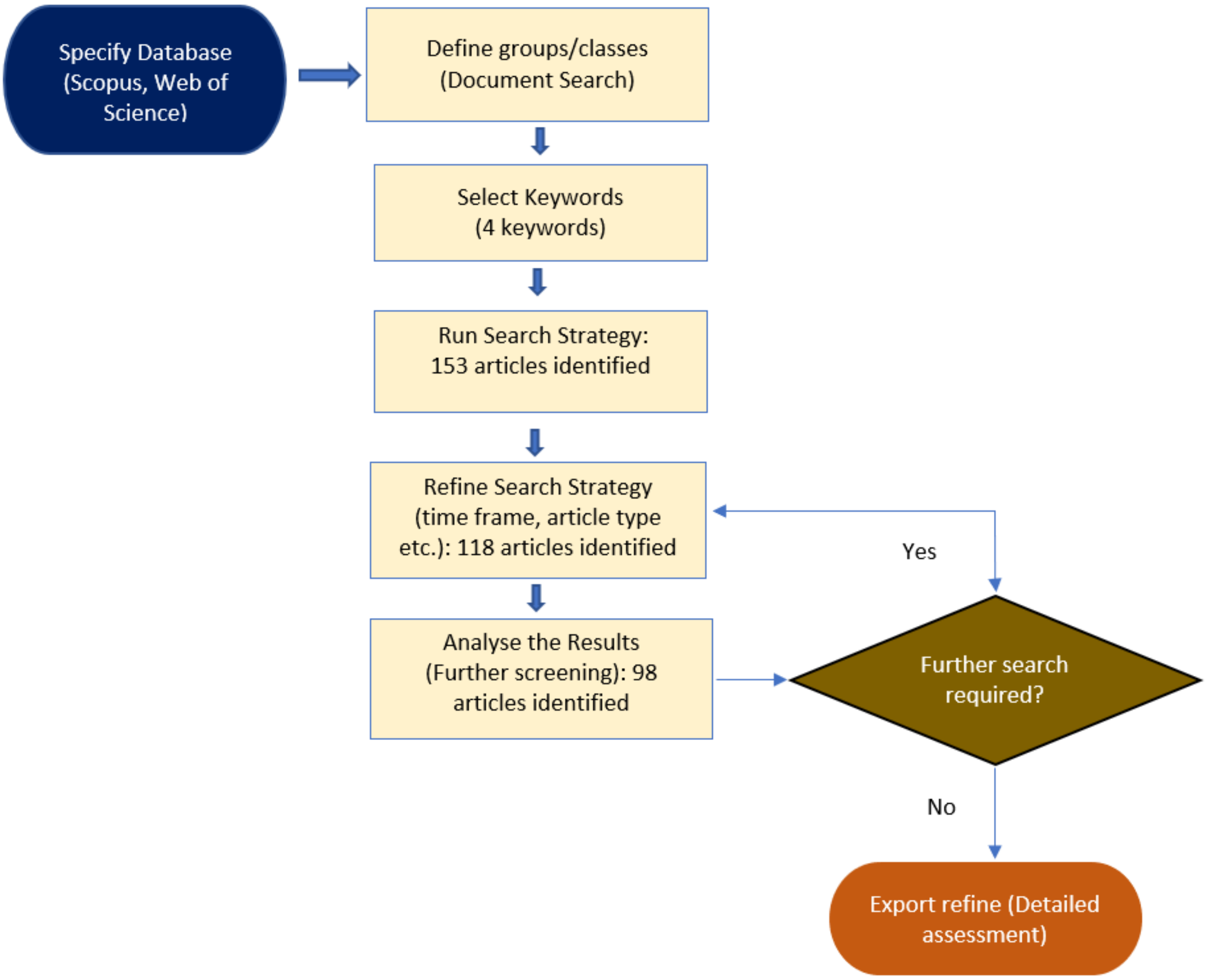


Figure 2.2 Flow chart of the review study

Using document type “Article or Review,” date range “Published 2010 to 2020”, and under the “Article Title, Abstract, Keywords” section of the database, the search for articles relevant to occupant behaviour modeling for building energy conservation was accomplished using the following keywords: “occupant behaviour”, “modeling,” “building,” “energy conservation”. It is also noted that these keywords may not be very comprehensive, but they are helpful to find a possible number of relevant articles for this analysis. The reason for selecting the period 2010-2020 is because the relevant research in the last decade was very active, especially in the last few years [93]. The initial search identified approximately 153 papers. With a focus on articles published in building, energy, and construction-related peer-reviewed journals, 118 articles published in more than 28 different peer-reviewed journals were selected. Furthermore, several articles just mentioned the selected keywords in their title or abstract or keywords sections, and thus, they are excluded. After the detailed screening, a total number of 98 articles (Scopus and Web of Science) were selected for further comprehensive analysis.

2.4.1 Network of countries/regions and co-occurrence of keywords

A network was created showing the contribution and collaboration among various countries. The network diagram of countries was first generated using the VOSviewer software. The bigger the size of a node of a country, the higher the number of connections of the country to other countries in the network. The level of link among countries (shown as connecting lines), determined by the total link strength, depicts the collaboration strength among countries in publications. A thicker link between the two countries indicates a stronger collaboration in terms of article publications (as shown in Figure 2.3).

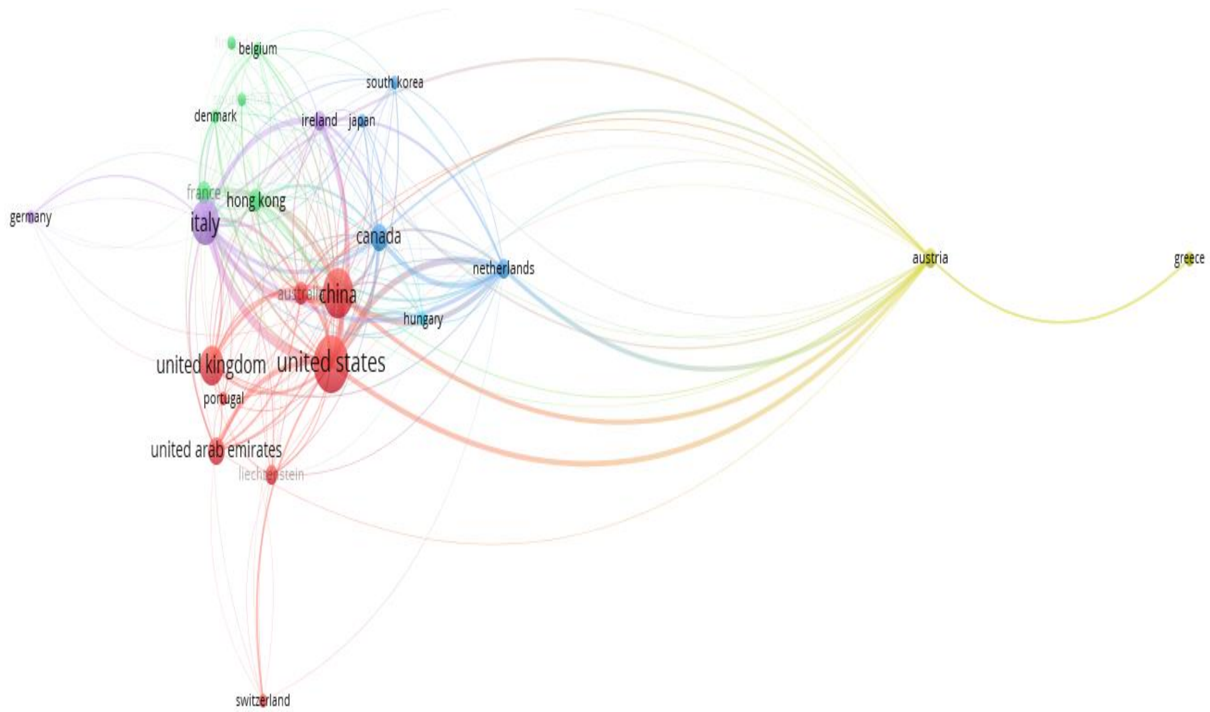


Figure 2.3 Network of Countries/Regions of research publication

The network reveals interesting findings on research collaboration and the contribution of some countries. The United States of America (USA), United Kingdom (UK), People's R. China, Italy, Canada, Austria, Australia, Hong Kong, UAE, Netherlands, Germany, and France, in descending order of degree values, are the top listed countries/regions with high degrees and high total link strength. These countries are the most contributors with a strong collaboration network with regard to the occupant behaviour literature. The highest total link strengths between countries were observed among the following pairs: USA-People's R. China, USA-Italy, USA-UK, USA-UAE, USA-Canada, USA-Netherlands, USA-Hong Kong, People's R. China-Australia, People's R. China-Italy, People's R. China-Austria, People's R. China-France, Canada-Italy, Italy-Ireland, and UK-Italy. Except for People's R. China in these pairs, the other countries are developed countries. One possible reason for the strong link strength among these countries could be cross-country case studies and comparative studies.

Besides the countries/regions, this review study also performed a comprehensive keyword analysis using the VOSviewer tool. According to Zhao [138], keywords represent the main contents of an article and indicate the trend of the development of research topics. Similarly, Su and Lee [139] stated that a network and knowledge map of keywords depict the knowledge structure of a particular field of research. It also reveals emerging elements and shows the vitality of the knowledge structure. Prabhakaran et al. [140] mentioned keywords show the "paradigm" and "paradigm shifts" in a field. Therefore, a keywords co-occurrence network was generated to determine the evolution of knowledge in occupant behaviour studies during the last decades. Figure 2.4 shows the network for only keywords that exceeded the occurrence frequency of 5 in the selected reviewed articles.

The size of the node is a depiction of the frequency of occurrence for keywords while the link and the total link strength attributes and indicate, respectively. The number of links of an item with other items and the total strength of the co-occurrence links of a given keyword with other keywords. A total of 48 nodes, 697 links, 1619 link strength, and five clusters were generated.

During the last decades, several keywords have garnered the attention of researchers and the industry that is worth noting (as shown in **Appendix-I** and Network Figure 2.4). The ten most frequent keywords include "Energy Utilization", "Buildings", "Energy Efficiency", "Occupant Behaviour", "Office Building", "Behavioural Research", "Energy Conservation", and "Architectural Design", "Performance Assessment", and "Simulation". The findings indicate that these keywords have received comparatively much attention in the occupant behaviour literature. However, the other keywords had relatively low frequencies and total link strength.

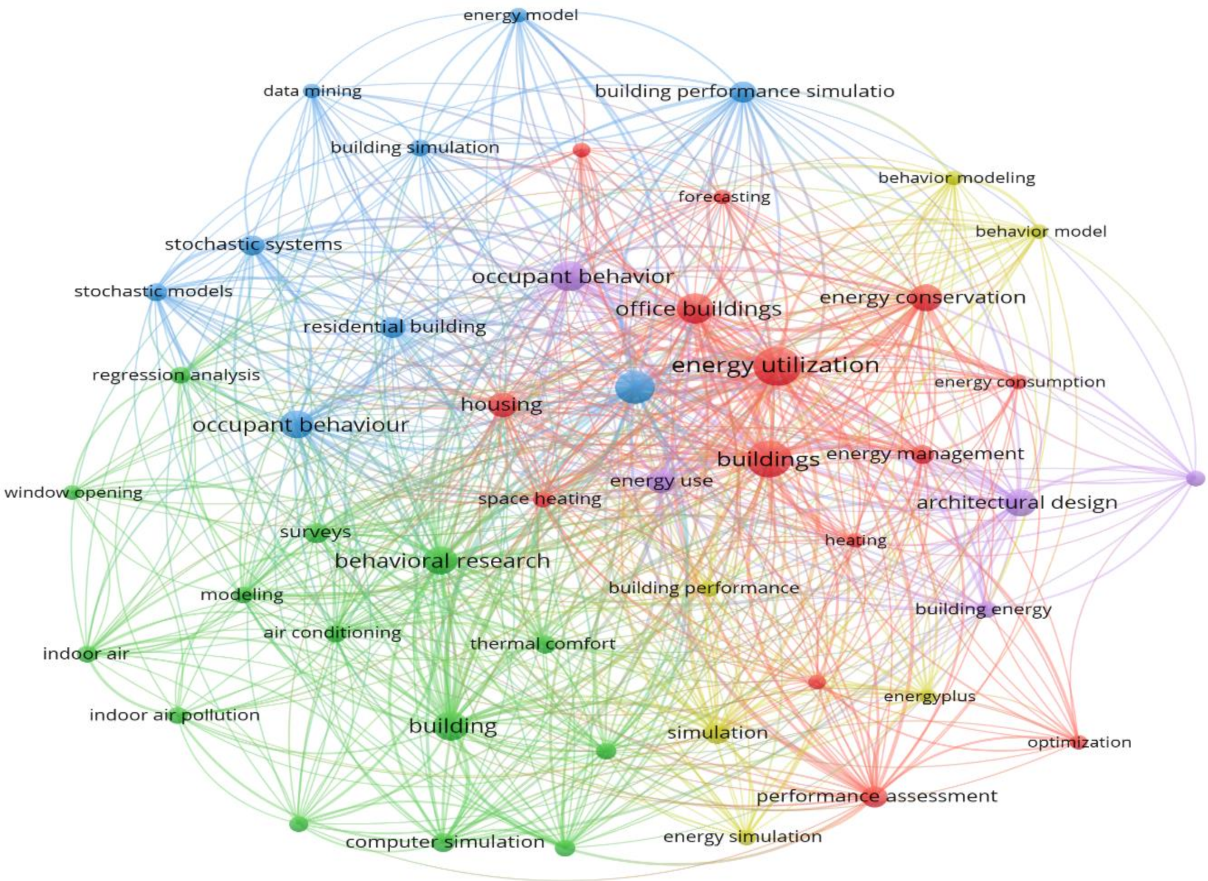


Figure 2.4 A network of Co-occurrence Keywords from the selected articles

Table 2.1 represents the classes of quantitative behaviour models obtained by the systematic review analysis. It needs to be noted that such quantitative behaviour modeling strategies often cover slightly and can be united from numerous points of view for various research purposes. Along these lines, the four classes of the model have been introduced – probabilistic or stochastic, statistical techniques, data mining approach, and agent-based modeling (ABM). These are totally related and well known; still, they are frequently applied in the latest study [30].

2.4.2 Modeling approach

2.4.2.1 Probabilistic or Stochastic Modeling Approach

Probabilistic/ **Stochastic** models capture and represent the probability that particular behaviour happens dependent on recorded or statistical information [141]. In general, there are three kinds of probabilistic or **stochastic** occupants behaviour models that are used: Bernoulli Process [142], Markov Chain [143], and Survival Analysis [63]. All three models have been broadly used to address both occupant movement and occupant action makes to control their interior condition. Usually, Markov Chain (MC) is mostly used as a probabilistic model. It is a time series procedure wherein all conditions of the framework can be straightforwardly noticed. Here the future condition or state depends on the current state and is autonomous of every single past state. Another model called the Hidden Markov Model (HMM) which accepts the potential conditions of a framework connected in a general Markov Chain (MC) however the conditions of the framework are hidden from direct perception; rather, every framework state is related to a probability distribution with a lot of noticeable factors. Several researchers have employed MC models to represent the occupants status and personal behaviour standards. For instance, Liisberg et al. [144] used Hidden Markov Model (HMM) to represent the occupant behaviour relied on indirect perceptions. Their study of typical probability reports as a function of time duration per day that recognized four different occupant behaviour profiles. Also, Survival Analysis (SA) is commonly used to evaluate the time period of a state or events prior to a change taking place, and it can be utilized to assess what extent a building is probably going to be unaffected by building inhabitants or occupants [142]. Because of the randomness and occupant behaviour disparity, stochastic or probabilistic models are more appropriate as far as applicability and validity for explaining the open coordination among the residents and building contexts than deterministic or fixed modeling approaches [145]. According to Gunay et al. [146], existing Building Performance Simulation (BPS) offers an integration opportunity with probabilistic or stochastic governing models. So, this technique could be used to test the effect of occupant energy behaviour. However, the problems of this technique can't be neglected. This modelling approach is best suited for occupant long-term schedule generation or prediction. Comprehensive behaviours or occupant statistics are not being explored with this technique [50].

2.4.2.2 Statistical Modeling Approach

Statistical modeling is commonly built by constructing the numerical connection between occupants behaviour and indoor/outdoor conditions, energy utilization, or time duration. Its outcomes are interconnected by the occupancy state or the probability of observed behaviour [147]. This modeling study can be led to recognize the patterns of behaviour in buildings [148, 149]. A specific study by Fabi and other researchers [150, 151] incorporated the approaches to understanding the two types behaviours in a commercial building (e.g., office), such as light turning on/off and window opening behaviours. Moreover, one common model in a previous research article [152] where logistic regression has been used to examine the impact of human thermal motives on various types of behaviour, for example, doors, windows, and blinds ON/OFF status. The researchers found that indoor conditions such as temperature(^{0}C), and CO_2 is superior indicator than outdoor condition as a driving factor of occupant behaviour. Statistical modeling is a very common and conventional technique in occupant behaviour modeling. In general, this practice is frequently used to analyze the relationship or connectivity between the building occupant behaviour and numerous dynamic factors, i.e., indoor temperature (^{0}C), CO_2 (ppm), and relative humidity (%). However, statistical analysis needs to be upgraded from the two perspectives. Firstly, this system is only confined to one or two fixed categories of behaviours analysis, for example, the status of a light switch on/off and window opening [145]. Even though this technique is slightly straightforward and worthwhile, but it is problematic to develop a comprehensive/wide-ranging model as well as further incorporation with building energy simulation tools (i.e., EnergyPlus). Secondly, it is not a matter in what way the higher probability is forecasted for the occupant behaviour pattern, but in the real-life system, the occupant may behave or follow another pattern, maintaining to individual mindset and general circumstances [142, 153]. Hence, incorporating true-behaviour data (i.e., real data) in the statistical methods will be a better strategy for identifying the human behaviours in buildings.

2.4.2.3 Data-Mining Technique

The Data Mining approach has been utilized in several latest investigations on human behaviour research [154-156]. It is the process of discovering patterns in a large data set. Usually, it requires an enormous database and immense information storage for behaviour investigation. The usage of data mining to describe human behaviour tracks and its application in the study of building energy performance is increasing. D'Oca and Hong [154] employed a three-phase data mining process that involves occupant status data sets from 16 offices in Frankfurt, Germany. It offered some insights and knowledge of an occupancy profile for the office occupants. The main advantage of this technique is data collection and management, which is easy to execute. From the earlier investigation, only occupancy or energy consumption(kWh) data was recorded. The enormous sizes of data on building energy consumption and the energy used by individual appliances have become accessible. Zhao et al. [157] built up an "indirect" real-world data mining technique employing office appliances energy consumption as a representative (i.e., proxy data) for occupants' "passive" behaviour.

Their study found that the average level of specifically categorized individual behaviour occurrences was 90.29%. Also, their experimental outcome indicated a genuinely stable occupancy pattern while taking a wide variety of individual behaviour of using a piece of office equipment or appliances. Whereas a great level of precision of a standard behaviour profile or prediction can be accomplished, the implementation of this technique is limited to occupancy and appliances usage in individual buildings, potentially because of inadequate information and limited access to other behaviour and energy consumption data. Furthermost investigations to date, just domestic energy consumption data has been utilized for data mining study of household’s standards behaviour pattern [30]. This method is planned to defeat the weaknesses of the previously mentioned usual techniques, especially when managing enormous data streams, by suggesting reliable occupant behaviour models with the great potential for a quick examination and better replication [154, 157, 158]. In the opposite sense to the data-mining approaches, agent-based modeling (ABM) is a simulation-based approach that is usually built on real buildings and has been initiated within the occupant-centred virtual environment. As a powerful simulation-based system, recently, ABM has become most popular for occupant behaviour modeling approach in the built environment.

2.4.2.4 Agent-Based Modeling (ABM)

Previously, researchers have given their high efforts to modeling buildings occupant behaviour by using various methodologies. One of the methodologies is the application of the agent-based modelling concept, which could be appropriated for behaviour prediction from the individual occupant level to the group level [30]. ABM is a simulation-based framework that consists of single or multiple autonomous actors, called “agents,” which interact with each other and their exterior/interior environmental state according to definite behaviour rules. Labeodan et al. [159] also referred to ABM usage for multi-agent structures that include self-ruling agents, simulating agents’ and their interaction or relationships with one another within the environments under definite rules and direction. This rule is essential to the energy simulation process as it specifically characterizes how and when agents interact or collaborate with each other by followings conditions within the environments. A test has been conducted on the implementation of ABM for building occupant interaction by Lee & Malkawi's [58]. The study simulated different occupant behaviour in an office building. They analyzed five explicit behaviours: adjust clothes level, activity level, space heater/individual fan use, window use, and blind use. The primary purpose of this study was how an agent balances the dynamic thermal variations in a prototype office space to improve both energy savings and comfort.

This methodology permits the incorporation of ABM models for both behaviour and building energy execution, and that might be utilized as an integrated simulation approach for energy behaviour in commercial buildings. Also, in behaviour study, ABM has the ability to manage the uncertainties of this present world [12]. Likewise, all parts of an agent in ABM could be represented with the goal that the agents could act and think like a human. Nevertheless, inadequacies or limitations remain as the application of the ABM model to building occupant behaviours studies is still a promotion stage. In the future, the completeness and comprehensiveness of ABM-based models are required to be technologically up-to-date [50]. Furthermore, most of the previous research that implemented the ABM approach remained on simulation data only, with no or proper validation [12, 106]. As one of the crucial purposes of promoting occupant behaviour is to reduce the difference between simulated and real energy consumption, so, this discrepancy can't be neglected.

The building occupant is an essential component of our built environment, and its prominence in building research has recently started to advance attention. Since occupant behaviour has been revealed one of the most critical parts of building energy conservation at the design and operation stage., Several methodologies or approaches have been presented to identify and analyze comprehensive behaviour for allowing utmost building energy conservation. Noticeably, it might not be resolved that one specific technique/approach is more suitable than the other approach. However, it is essential to understand the benefits and drawbacks of all approaches also the flexibility of the system. A brief comparative data of the above-mentioned four approaches for behaviour study has been listed in Table 2.2.

Table 2.1: List of quantitative modeling for building occupant behaviour (2010-2020)

Modeling Approach	Study Goal/Technology/Theme	Building Category	Case / Study Location	Modeled/ Targeted behaviours	Tools /Platform	Occupants/ Data sources	Model Validation?	References
Probabilistic or Stochastic Modeling	To identify seven typical occupancy patterns Using hierarchical clustering.	Residential	Belgium	occupancy sequences at (1) home and awake, (2) sleeping or (3) absent.	Not Mentioned	Belgian Time-Use Survey (TUS) Household Budget Survey (HBS)	Not Mentioned	[141]
	Integrating occupants' presence and behaviour data with the urban energy modelling tool.	Laboratory	Switzerland	occupants' presence, opening and closing windows, raising and lowering of blinds	CitySim	Survey data	Not Mentioned	[160]
	Develop an approach for suitable recordings of occupants presence and simulation of single-to multiple-person office environments.	Office	San Francisco	Presence of occupants	Not Mentioned	Passive infrared sensors	Not Mentioned	[143]
	Modelled diary-based individuals' daily activities for 24 hours, starting and ending at 04:00 including weekdays and weekends.	Residential	Denmark	Occupancy pattern, energy-related activities	A questionnaire, a diary, and an expenditure booklet	Danish Time Use Survey (TUS)	Not Mentioned	[161]
	The application of Hidden Markov Models (HMMs) to create methods for indirect observations of energy consumption for 14 residences.	Residential	Spain	Electricity consumption/ Occupancy pattern	Smart meter	Occupant survey	Yes	[144]
	To estimate the predictive accuracy of four sets of models for window opening behaviour.	Residential	Denmark	Window opening	Not Mentioned	Secondary data	Yes	[145]
	Application of probability distribution for occupancy dependent input parameters such as air change rates, and internal heat gains.	Laboratory	Italy	HVAC Energy	Not Mentioned	Sensor	Calibration	[136]
	To determine behavioural patterns associated with the heating energy consumption and identify the household and building energy characteristics.	Office	Netherlands	Behavioural Patterns, HVAC systems	Not Mentioned	A household survey	Not Mentioned	[148]

Statistical Modeling	To construct a multiple linear regression model for four specific parameters.	Residential	Ireland	occupant characteristics of domestic electricity consumption patterns	Smart meter	Survey	Not Mentioned	[162]
	Models of occupants interactions with windows and window opening behaviour were judged using a simulation program.	Residential	Denmark	window opening and closing	IDA ICE	Secondary Data	Not Mentioned	[163]
	A new approach to combine probabilistic user profiles for both thermostat set-point and window opening as well as adjustments into a building energy model	Residential	Denmark	Thermostat and window opening occupant behaviour	IDA ICE	Field monitoring campaign, sensor	Not Mentioned	[164]
	To predict the occurrence and frequency of intermediate activities during office hours.	Office	Netherlands	Intermediate activity behaviour in an office	Not Mentioned	Other resources	Not Mentioned	[153]
	A model that gives the probability of air conditioning turn on, turn off.	Residential	China	AC Operation	EnergyPlus	Field measurement, temperature sensor, Reco APP	Yes	[165]
	To identify the effectiveness and potential of smart meters and real-time IHDs for reducing household energy consumption.	Residential	China	Electricity consumption pattern in two groups of occupants	Not Mentioned	IHD, smart meter, and on-site installation	Not Mentioned	[166]
Data Mining	A three-step data mining framework to discover occupancy patterns in office spaces.	Office	Germany	Occupancy Pattern /Schedule	RapidMiner	Sensor	Not Mentioned	[154]
	To investigate the occupants behaviour for adjusting thermostat settings and heating systems for a housing complex.	Residential	USA	Occupant behaviour patterns (ON/OFF space heating)	RapidMiner Studio 6.0,	Sensor/Manual	Not Mentioned	[155]
	A new methodology for monitoring energy consumption and end-use loads to build a review system.	Residential	Japan	Total energy consumption	Field measurement, a questionnaire	Secondary data (Japan)	Yes	[167]
	To develop an indirect data mining approach using occupant passive behaviour	Office building	USA	occupancy schedules HVAC Operation	Fitbit FlexTM pedometer, Bluetooth Dongle	Plugwise wireless smart meters	Yes	[157]
	To propose an inexpensive and minimally invasive approach to recognize the behavioural data from environmental factors.	Residential	China	AC operations	Algorithms developed to recognize the AC operations	wireless data collection system (WiFi gateway)	Yes	[168]

	To model the occupancy pattern by cluster analysis, decision tree, and inducted rules.	Office building	USA	Occupancy Pattern /Schedule	Matlab 2015 and RapidMiner 6.5	Sensors	Yes	[169]
	To investigate the correlation between energy-related behaviours and cooling energy consumption including empirical data.	Residential	China	energy-related behaviours of male and female	Matlab7.0	Energy Management System and questionnaire	Not Mentioned	[170]
	To examine the influences of occupant behaviour on building energy consumption using a basic data mining technique (cluster analysis).	Residential	Japan	HVAC, Hot Water, Lighting, Refrigerator, other house works	WEKA	Field measurement, Questionnaire, Inquiring survey	Not Mentioned	[171]
Agent-Based Modeling	To propose a new agent-based approach for building energy modeling by considering diverse and dynamic energy consumption profiles among the occupants.	Commercial (Office)	USA	Light, Blinds, Hot water	AnyLogic/ e-Quest	Secondary Data	Not Mentioned	[172]
	To propose a new co-simulation approach for smart homes that take into account occupants dynamic and social behaviour.	Residential	France	Inhabitants behaviour profile, A general Modeling (not specific)	Brahms, MATLAB/Simulink	Assumption	Not Mentioned	[173]
	To develop and validate an agent-based model using data from a one-year field study.	Commercial	USA	Windows; Fans on/off; Thermostat; Clothing adjustment	MATLAB/ EnergyPlus	Survey, Data Logger, WhatsApp	Yes	[107]
	A new simulation approach using agent-based modeling and coupling, the behaviour impact on the thermal conditions and, energy consumption can be scrutinized.	Commercial (office)	USA	Window, Blind; Door; Clothing adjustment; Fan/heater	MATLAB/ EnergyPlus	Secondary data/assumption	Not Mentioned	[58]
	To experience in two office buildings that vary in terms of controllability and the set of adaptive actions available to occupants.	Commercial (office)	USA	Light, task light, and blinds Heater/fan; Adjust clothes;	NetLogo/ EnergyPlus	Baseline survey, BMS	Yes	[108]
	To represent a new OB modeling tool, that enables co-simulation with BPS a program (e.g., EnergyPlus).	Commercial (office)	USA	HVAC, Lighting and Window operation;	obFMU, EnergyPlus	Prototype buildings	Not definite	[38]
	To construct and validate of occupant behavioural model with the visualization approach and calculation of quantification metrics.	Commercial (office),	USA	Window, blinds, and door	PMFserv	Sensor	Yes	[12]
	The developed ABM framework is to illustrate the multidisciplinary approach required to capture the various aspects of building performance.	University Campus	UAE	Occupancy Pattern /Schedule, Comfort level (PPD)	MATLAB-EnergyPlus	Assumption/	Yes	[174]

	To develop an agent-based model as regards to students as heterogeneous occupants.	University	China	Occupancy pattern and appliances using behaviours	AnyLogic	SIMS intelligent electricity query system, survey questionnaire	Yes	[175]
	To propose a new modeling framework that incorporates BPS in the ABM model by using trained regression surrogate models.	Office	USA	Energy use attributes of building occupants and facility managers, uncertainty in occupant actions	MATLAB/ EnergyPlus	prototype buildings developed by US DOE	Not Mentioned	[135]
	A toolkit uses the Building Controls Virtual Test Bed (BCVTB), an agent-based model with EnergyPlus.	Office	USA	HVAC, Plug loads	MATLAB, BCVTB, EnergyPlus	prototype buildings developed by US DOE	Not Mentioned	[176]
	To evaluate the impact of extreme energy users on their peers and the energy effectiveness of commonly employed interventions.	Office	USA	Occupancy interventions	Anylogic	Survey, CBECS	Not Mentioned	[177]
	To develop an agent-based computational model for individual energy consumption patterns.	Residential	USA	Peer networks in buildings and energy conservation behaviours of occupants.	Not Mentioned	Secondary Data	Yes	[178]
	To recognize the gap by suggesting a multilayer ABM approach that serves as a test bed to simulate and optimize.	Commercial	USA	Energy-feedback within social circles	Anylogic	Secondary data	Yes	[179]
Others (BPS, Data-Driven, ANN etc.)	To perform a numerical–experimental operation through sophisticated modeling.	Residential	Italy	Human-based energy retrofit scenarios	EnergyPlus	Field monitoring and occupants survey	calibrated validated	[180]
	To propose an online-learning-based control strategy along with its design method including four domains (e.g., time, indoor and outdoor climates, and occupant behaviour).	Office	Singapore	HVAC systems	Advanced algorithms	Sensors	Yes	[181]
	It recognizes the energy consequences of conventional approaches to occupants behaviour modeling.	Office	Canada	People, lighting and equipment profiles	SketchUp, OpenStudio, MATLAB R2017a	Questionnaire	Not Mentioned	[182]
	To recommend an integrative modelling approach to energy consumption behaviours in the residential background.	Residential	Portuguese	Total energy consumption behaviour	Energy plus/Design-Builder	Time-of-use survey of Portuguese households	Yes	[183]

	To develop a framework for extracting relevant data about the uncertainties relating to occupant profiles of heating energy consumption.	Residential	Canada	Space heating	MATLAB Simulink	Sensor	Not Mentioned	[184]
	To construct a building occupant behaviour model using simulation approaches as well as estimates the potential energy savings.	Office	USA	Lighting Energy Consumption	DeST software	Data Portal	Calibration	[185]
	To assess the energy performance and comfort indices of the building and recognize the reasons for malfunction.	Residential	Hungary	Energy performance and comfort indices	IDA ICE	Self-reported surveys, occupancy sensors and fan-coil	Calibration	[186]
	A centralized system to consider energy-efficient profiles by considering solar energy and high-level services for hot water systems.	Residential	China	Domestic hot water (DHW) system	Not Mentioned	Survey	Yes	[187]
	To develop an activity-based (e.g., socio-demographic and economic attributes) framework for quantifying occupant-energy consumption behaviour.	Residential	France	Domestic energy consumption	Not Mentioned	National statistical data	Yes	[188]
	To establish an engineering-based bottom-up model for cooling energy consumption.	Residential	China	Cooling energy consumption	DeST	Survey, case monitoring	Not Mentioned	[189]
	To improve the accuracy of the energy simulation process by considering the occupancy data to calibrate the energy model.	Residential	Hong Kong	Occupant schedule, devices, air-conditioners, windows, lights, domestic hot water, and cooking	DesignBuilder and EnergyPlus	Questionnaire survey	Yes	[190]
	To evaluate the building energy performance and construct a reliable simulation model for energy and cost-efficient retrofit design.	Residential	UK	Occupancy profile, energy consumption patterns, thermal comfort	Design Builder	A questionnaire, structured interviews, data loggers	Not Mentioned	[191]
	To investigate the role of occupant behaviour in supporting decision-makers dealing with the renovation strategies.	Residential	Italy	Thermostat, heating system, building characteristics	DeST	Surveys and interviews, observations, reading from meters and statistics,	Yes	[192]
	Introduce a simulation approach to estimate five typical occupant behavioural actions for the potential energy savings.	Office	USA	Occupancy schedule, lighting, plug load, HVAC control. Window control	EnergyPlus, Occupancy Simulator	Site survey	Not Mentioned	[193]

	To examine the impact of physical and behavioural variables for energy saving from the retrofitting protected housings.	Residential	London	Energy-saving from selected housing retrofit	IESVE	Existing models and the literature	Calibration	[194]
	To explore the occupant factors, that influence the energy consumption of a case building in Seoul, Tokyo, and Hong Kong under the climatic changes.	Office	Hong Kong, Japan, and South Korea	HVAC Energy	EnergyPlus Runtime Language (Erl)	Prototype building model developed by US DOE	Not Mentioned	[195]

Table 2.2: A Comparison of a different modeling approach

Methodology	Building type (s)	Real-time modelling capability	Incorporation with simulation	Additional remarks
Agent-based modelling (ABM)	Commercial/ Residential	Yes	High	i) Upgrading simulation accuracy. ii) Mostly used in the simulation-based model (lack of real data to support ABM). iii) It can produce more precise schedules as input for EnergyPlus.
Statistical analysis	Commercial	No	Low	To identify the influential factors of occupant behaviour.
Data mining	Commercial/ Residential	No	Medium	To comprehend the behaviour pattern.
Stochastic model	Commercial buildings	Yes	Medium	i) Modeling long-term behaviour profile. ii) Mostly used for occupancy modelling.

From the existing modelling viewpoint, the ABM technique was recommended by many researchers as the most effective modeling technique. According to [12, 58, 107], ABM has the ability to control several behaviours together as well as it can represent both group-level and individual relations of independent agents. Mostly, the ABM agent is capable of simulating each occupant by unifying characteristics, rules, or data items of the indoor/outdoor environment as well as a modification to behaviour changes in order to accomplish a specified task. In contrary to other modelling techniques, ABM starts and ends along with the agent's perception and purpose. Each agent has individual characteristics that include behaviours and responses. They have the ability to interact with other agents and build the surrounding system, which is mainly controlled by user-oriented well-defined rules. These well-defined rules are the groundwork for modeling agents' behaviours, interactions, and relationships. However, there is a lack of proper agreement or rules for building a theoretical foundation for ABM model development [12, 30]. Still, there are several problems that exist in the latest ABM support behaviour studies. The potential research gaps identified from the systematic literature review along with the limitation of existing ABM-based approaches have been described in the subsequent section.

2.4.3 Research gaps from the systematic review study

2.4.3.1 Occupant-centred Interior Layout deployment

The literature review revealed that most of the behaviour research focuses on single prototype buildings, and several city-scale influences have not been studied properly, forming a highly recommended area for future research. Moreover, a few analyses have attempted to assess the impacts of Interior Layout on building energy performance [79]. Numerous investigations have shown that layout can significantly affect building energy performance. Besides, the greater part of these analyses is mixed space design with different factors, for example, occupants movement and operation strategy [26], window to wall ratio [89], and shading framework [90]. In addition, at the micro-level, it includes the influence of building interior arrangement in terms of occupant layout preferences, fittings and fixtures, thermal sensitivities, and accordingly their energy behaviour. It also specified that building space layout might impact occupants presence and movement, as it might link to the individual action or activities which occur at the specified position within a space [57, 79]. The occupants presence and movement probability in a specific position based on several functions (i.e., energy spot distance, occupant circulation/movement path etc.) of the space that could be simulated. So, Occupant Centred Design (OCD) techniques, for example, layout preferences can add to additionally seeing how and why individuals' occupants consume more energy [57, 79, 196], and this information can guide the plan regarding the interventions to advance energy conservation.

2.4.3.2 Occupant behaviour study is required in the context of developing/low-income economies

Beyond the fact that several approaches described for the above-mentioned model developments in the building energy monitoring field, they are still related to numerous difficulties and challenges that should be addressed effectively. This review work exposed that most of the existing research focuses on occupancy or occupants backgrounds from high income or developed economies while occupants from low income or developing economies still remain unclear, complex, and conflicting. So, it is recommended that people from low-income or developing countries and their energy-associated behaviour in buildings should be well-understood in terms of economic, social, and other behavioural contexts. Usually, the energy usage of a building is extremely dynamic and also relies on multiple parameters in terms of socio-economic conditions and energy conservation policy.

2.4.3.3 Higher number of quantitative occupant behaviour research than qualitative

As for a wide-ranging analysis, it is unavoidable to utilize both quantitative and qualitative information. However, most of the current research used quantitative research techniques. In the earlier study, the researcher concentrated more on "what" occupant behaviour is instead of "how" and "why" occupant behaviour is created [106]. It needs to be noticed that, to reduce the effect of human behaviour on building energy consumption, it is important to have a comprehensive investigation of the construction pattern of occupant energy behaviour, which indicates the need for mixed-method techniques. Recently, a few researchers started to understand the significant role of mixed-method techniques in looking into the investigation of the nature of occupant energy behaviour [93, 106, 196]. It is noted that mixed-method techniques in the field of energy-related occupant behaviour are still in its early stages.

2.4.3.4 Extensive use of survey or secondary data and lack of real data involvement for ABM validation

One of the significant complications from the preceding research studies used national surveys or secondary data and building ABM approaches without real data involvement [12, 58]. A few scholars validated their ABM or behaviour models using realistic data [12, 108]. The model often depends on an example or improved model that may prompt questions about whether the simulated agent will play out the behaviour in which actual occupants do, consequently prompting insufficiency in model consistent quality. Just a few model validation or verification studies were seen in the earlier works of literature. In [107], a validation study was led to the assessment of the ABM, which depends on Perceptual Control Theory (PCT). The model outcomes were seen as practically identical to the field estimations for individual and accumulated projections. However, the model just assumed thermally adaptive behaviour, and few selected behaviours were validated. Putra et al. [108] studied the effect of load shedding on human comfort and behaviour whereABM involved mixed agents/operators, perception capabilities and a few simulation states. However, just four of the simulation states have been analyzed with calculated data, and the test outcomes failed to illustrate an adequate degree of precision.

2.4.3.5 Occupant behaviour study is required in the context of diverse category's buildings

Approximately 85% of the peer-reviewed studies in this review work focused on the influence of occupant behaviour on building energy consumption, particularly concentrated on offices and residential buildings (33% and 52%, respectively). However, only very few articles have examined educational or laboratory buildings. In addition, some other building categories such as recreational, exhibitions, hotels, clinics, or hospital buildings have been given spare attention and require further study [100, 197].

2.4.3.6 BIM integration with the existing occupant behaviour modeling/simulation approach

Nowadays BIM implementation for all the advanced stakeholders has been developed because of its plentiful opportunities offered for their construction schemes, inclusive of value and time saving, first-rate performance improvement, decreased human resources, clash detection, greater collaboration, and communication. BIM models can be used for behaviour engineering analyses, while occupant behaviour simulation using BIM models is still lacking [28, 57, 198-200]. BIM incorporated occupant behaviour simulation in buildings helps researchers and engineers to identify the design weaknesses and improve the overall building performance as well as automation capability. Thus, it is necessary to add another feature to the existing occupant behaviour study for upgrading the simulation performance. However, occupant behaviour study using BIM technology is relatively lacking, leading to challenges in understanding the consistency between occupants and buildings.

2.5 Chapter Summary

Chapter two shows the comprehensive literature review, the BPS's base model and explicit/implicit modelling approach, along with the research gaps for the occupant behaviours study. The building occupants and their behaviour are crucial components in our built environment, and their tremendous impact on building energy consumption has recently begun to advance appreciation. The latest studies on occupant comfort and adaptive control, lighting control, HVAC control, operable window control, and shading control are some of the research topics that started to investigate the occupant behaviour or behavioural influences on building energy performance.

CHAPTER 3
RESEARCH METHODOLOGY[3]

3.1 General

In the previous chapter, Chapters 1 & 2, a background study together with the problem statement, research aim, objectives, significance and scope of the study, and detailed literature review have been explained. Although the relevance of the research knowledge gap gives credence to the study, the "how" for the study was not much expatiated. Therefore, this chapter seeks to elucidate the methodology adopted to achieve the stated aim and objectives of the study. First, a description of the research scope and approach for this study is presented. Then, the various stages of the adopted research methodology are stated with explanations on each of them. Finally, the research techniques of the methodology are discussed.

3.2 Scope of Study

This research is focused on human behaviour study for building energy conservation. Initially, it involves the development of the ABM-SD-BIM model to investigate the stochastic nature of building occupants by considering the active influencing aspects through an interdependent investigation. In the beginning stage, the hybrid model has been constructed for a small office space in Hong Kong (i.e., for a pilot study) followed by a large-scale implementation of a residential building located in Chittagong, Bangladesh. Here, the hybrid model has been considered both psychological (i.e., perception, subjective norms and attitudes) and non-phycological parameters (ambient conditions, floor dimensions, windows and doors, switch

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[3]This Chapter is partly published and under review in:

1. **Uddin MN**, Wang Q, Wei HH, Chi HL, Ni M. Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. Ain Shams Engineering Journal [Internet]. Elsevier BV; 2021 May; Available from: http://dx.doi.org/10.1016/J.ASEJ.2021.04.015

2. **Uddin, M. N**., Chi, H. L., Wei, H. H., Lee, M. & Ni, M. Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling (Under Review).

3. **Uddin, M.N**.; Wei, H.-H.; Chi, H.L.; Ni, M. An Assessment of Occupant Comfort and Behavioural Influence on Building Indoor Layout: A Collaborative Analysis Using Statistical and Agent-Based Simulation.

and furniture locations, number of occupants etc.). Afterwards, hybrid model validation approaches are implemented through the usage of customized sensors that capture and record the building indoor environmental data as well as energy consumption patterns due to layout deployments (i.e., intervention). This intervention has been implemented (summer season) in a case study (i.e., residential) location in Chittagong, Bangladesh. Also, a paper-based survey has been used to verify the occupant behaviours data. By observing the monitor occupant behaviour records and simulated data, this study evaluates the built-in model prediction capability, extensibility as well as limitations.

3.3 Research Approach

The research approach deals with the use of theory. According to Saunders et al. [201], there are two main research approaches: the deductive approach and the inductive approach. The deductive approach concerns developing a theory (i.e., model) and hypothesis, which is then followed by the design of a research strategy to test the theory or hypothesis. However, the inductive approach concerns collecting data and developing a theory based on the results of data analysis [202]. This study is an explanatory science since its core purpose is to develop valid knowledge (via a model) to explain and predict a factual reality (human behaviour in building energy conservation). This commences with an acquaintance of the existing problem, a highlight of the problem-solving strategies for energy conservation and performance measure. As such, this study is to investigate the current occupant behaviour profiles and identify the behaviour determinants, active and passive energy behaviour, and factors that influence the layout for building energy conservation. The identification of the energy-saving problems (i.e., distance and barriers) and the energy-saving behaviour are first drawn from the existing theory or knowledge (i.e., literature, theory of reasoned action). At the investigation stage, the real energy data (for model validation) and relevance of the factors (i.e., layout, distance) identified from existing knowledge are tested by soliciting the views of several occupants for their energy-saving intention with the existing house layout. It produces a better understanding of occupant energy usage norms and practices to solve the energy crisis in developing countries. Subsequently, strategies for an improved energy-efficient housing layout will be developed after the data analysis. Accordingly, the research approach for this study is the deductive approach since its end task is the test of theory/assumptions (i.e., validation of hybrid model or theory that influences interior layout deployment on occupant energy uses).

3.4 Time Horizon

The selected type of time horizon determines the model development as well as the type of data to be collected. It is also important for planning the research study [202]. The two main types of time horizons considered for research studies include cross-sectional studies and longitudinal studies. In the cross-sectional horizon, the study is a ‘snapshot’ of events taken at a particular time. It can compare different population groups at a single point in time. However, the longitudinal study involves collecting data to study changes and development over time, sometimes lasting many years. Since this research does not seek to study changes and behaviour over time, it falls under a cross-sectional study.

3.5 Research Methodology

The research method is a broad term encompassing data collection and data analysis. Due to variability among researchers on research objectives, different methods have been adopted in various studies. Thus, there are no strict research methods, and there are only justifiable research methods. Besides the principles of research objectives on the kind of research methods, the significance and replicability of the research findings also play a major role. Rigorous and appropriate research methods lead to a significant contribution to knowledge in academics while advancing industrial practices [203]. The research methods include model development, experiment, survey, case study, action research, ethnography, grounded theory, and archival research [202].

For this study, the whole research workflow, along with its specific objective, is represented in Table 3.1.

Table 3.1: Overall research methodology linked with the specific research objective

Research objectives	Research Methodology									
	Study Options / Approach				Data analysis & collection tools					
	Extensive literature review	Modeling Tools & Analysis			Building Data (Physical Characteristics)	Customize Energy Sensors (Real-time data monitoring)	Environmental Sensor (Real-time data monitoring)	Behaviour patterns	Indoor parameter/ Energy consumption	Model Performance Test
		ABM-SD-BIM	Energy Conservation & Behaviour	Indoor Environmental parameter						
Review										
Develop										
Appraise & Investigate										
Layout Deployment										
Validation										

The first objective covers the study context and background information about the occupant behaviour along with the theoretical framework strategy using the agent-based (ABM), system dynamics (SD), and building information modeling (BIM) (From Literature Review).

The second objective deals with the comprehensive hybrid model construction process to facilitate the realistic occupant behaviour simulation. Even though occupant behaviour is difficult to model due to its stochastic nature, so it is necessary to explore and represent the generic behaviour profiles using the robust modeling approach.

The third objective deals with the hybrid model outputs relating to the human comfort and energy conservation behaviour along with the variation of indoor environmental parameters.

The fourth objective deals with the experimental section that represents the several layout-based interventions and a series of simulation trials that are also used for model validation.

The fifth objective deals with the comprehensive model validation study. As the proposed hybrid model is a simulation-based approach, a validation study is necessary to check and improve the reliability, trustworthiness as well as robustness of the model.

3.5.1 General Overview of the Framework/Task

The research process of this study is divided into three main tasks:

(i) Task 1: It's related to selecting and constructing a preferred building interior layout using the BIM tool.
(ii) Task 2: It deals with the construction of the ABM -SD model to forecast the comprehensive building occupant behaviours patterns and their individual actions within the interior layout defined by Task 1.
(iii) Task 3: It deals with the intervention and validation approach along with the study outcomes.

Figure 3.1 represents the main features of the proposed hybrid model.

In Task 1, the selected interior layout diagram has been constructed along with the specified objects (e.g., energyspot, occupant destination, etc.) and their co-ordinates using Revit-2019. Each interior layout pattern has been developed based on the actual layout pattern available in the case study location.

Task 2 involves the construction of the ABM model that consists of different agents, surrounding environment, behavioural rule, and their interactions (built on the theory of reasoned action) for forecasting building occupant behaviours within the interior layout. This task simultaneously engages with the SD model that describes the various ambient data (e.g., temperature, humidity, CO), and space information from the BIM model and calculates the outputs of the hybrid model for each interior layout pattern.

In Task 3, the simulation outcome is validated against the real data through an intervention. The details of each task are elaborately described in the following sections.

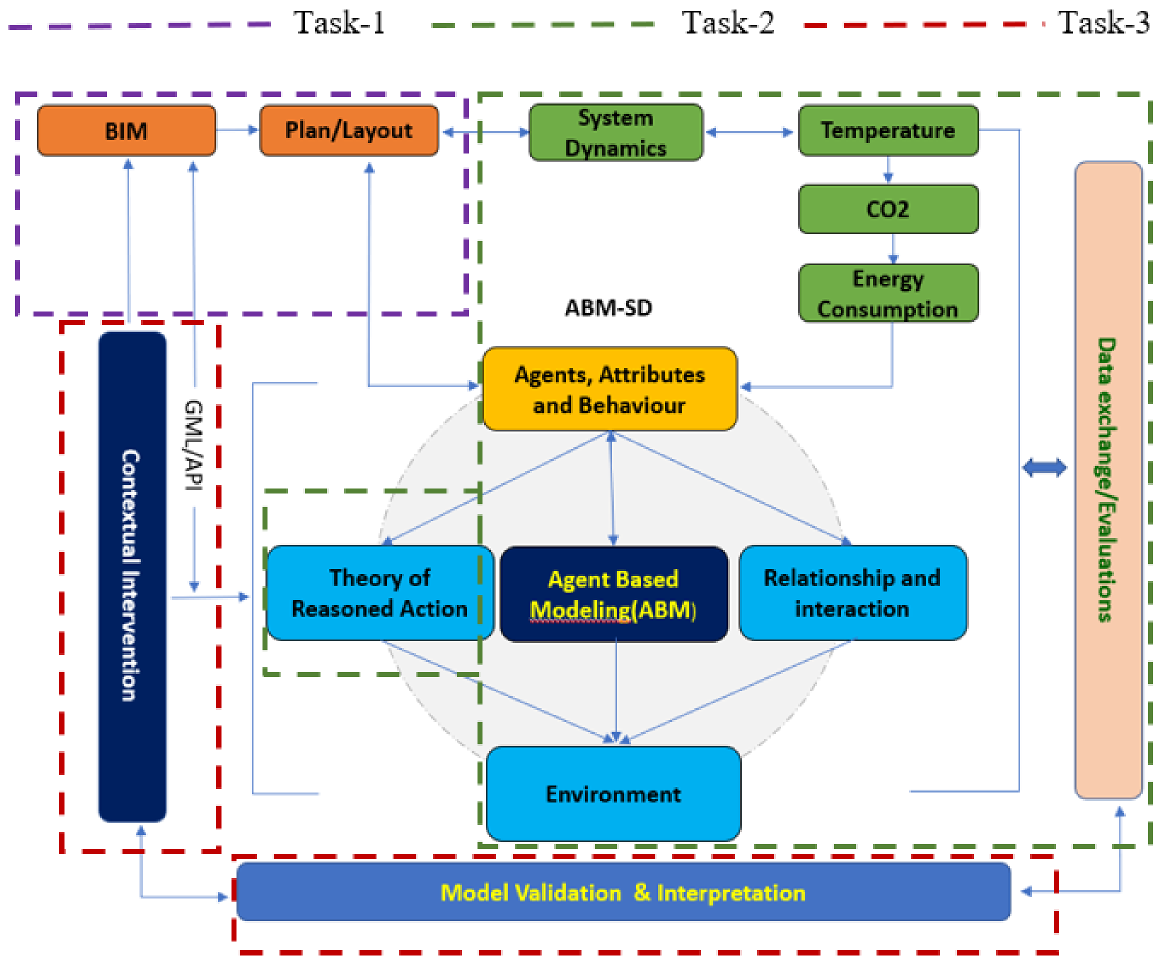

Figure 3.1 A conceptual framework of ABM-SD-BIM

Here, the layout settings for the individual space, including Occupant Station/Destination, Occupant Circulation Path, and Energy Spot, are mentioned in a prototype Revit model (for drawing & specifications) in Figure 3.2. At this point, "Occupant Station/Destination" is the indoor space where the occupant might be seated or stay to accomplish a specific task. On the other hand, occupants usually use the "Circulation Path" to move from one destination to another. Energy Spot (e.g., Light/HVAC point) is the particular position of building indoor space from which occupants often fulfil their dynamic energy behaviour.

The prototype model considers the distance between the energy spot (e.g., switch points) and occupant station/destination (e.g., seating/sleeping place) that support message/data exchange over the agent-based (ABM) and system dynamics (SD) through a DynamoAPI-Excel platform [28]. The platform automatically generates the input data for the ABM-SD model that is built on different physical layout conditions considered in Figure 3.3. Typically, the physical arrangement of interior space has manipulated the occupants energy consumption behaviour by controlling and using their actions scenarios. Several pieces of research also clearly mentioned the influence of Interior Layout on occupant preferences of activities and their desired location [79, 204-206]. This study mainly considers the eight different types of layout (prototypes) conditions that are incorporated in the proposed hybrid model shown in Figure 3.3. Here Interior Layout-1 to Interior Layout -7 have considered the existing different types of problematic layouts in prototype models. On the other hand, only Interior Layout -8 is regarded as the best case, and it might be a baseline/best case layout for further intervention.

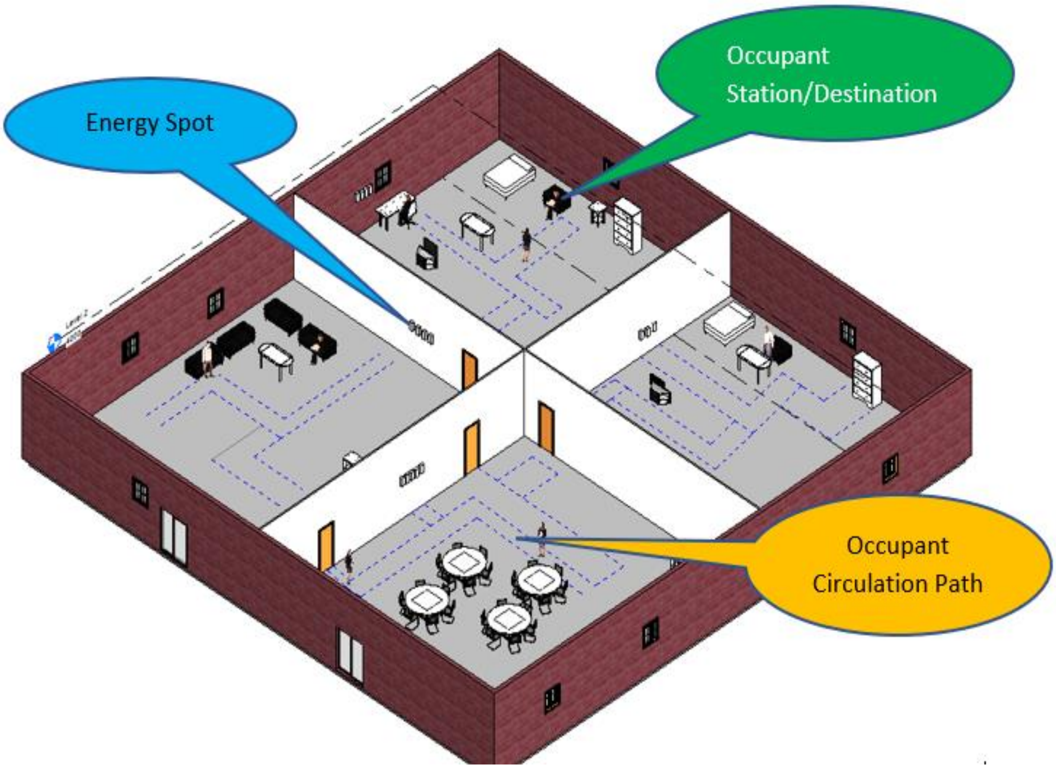

Figure 3.2. Occupant Station/Destination, Circulation Path, and Energy Spot in a prototype Revit model

The selection of these prototype layouts is mainly based on indoor layouts available in a case study location in Chittagong, Bangladesh. Here, the distance between occupant destination and energy spot has been considered as a variable. If this distance is short or the energy spot lies within the human range (e.g., within 2ft), the occupant will engage more with the building energy systems, and they may frequently follow the energy savings attitude while staying or leaving the occupant station. After the remodifications or re-arrangement of objects (e.g., stuff/furniture) of indoor layouts, typically accessible distance has been considered during the intervention (layout deployment). Here the intervention is mainly viewed as an Enablement where the occupant may easily access energy spot at their station or seating place. Enablement intervention is mainly considered the improve opportunity or capability or minimize the barriers/obstacles to performing occupant energy-related activities [207, 208]. Herein, after the intervention, the existing indoor layout is remodified or re-organized so the occupant may easily interact with the energy spot to perform their energy savings behaviour. This is one of the physical parameters that have been considered during the model construction process.

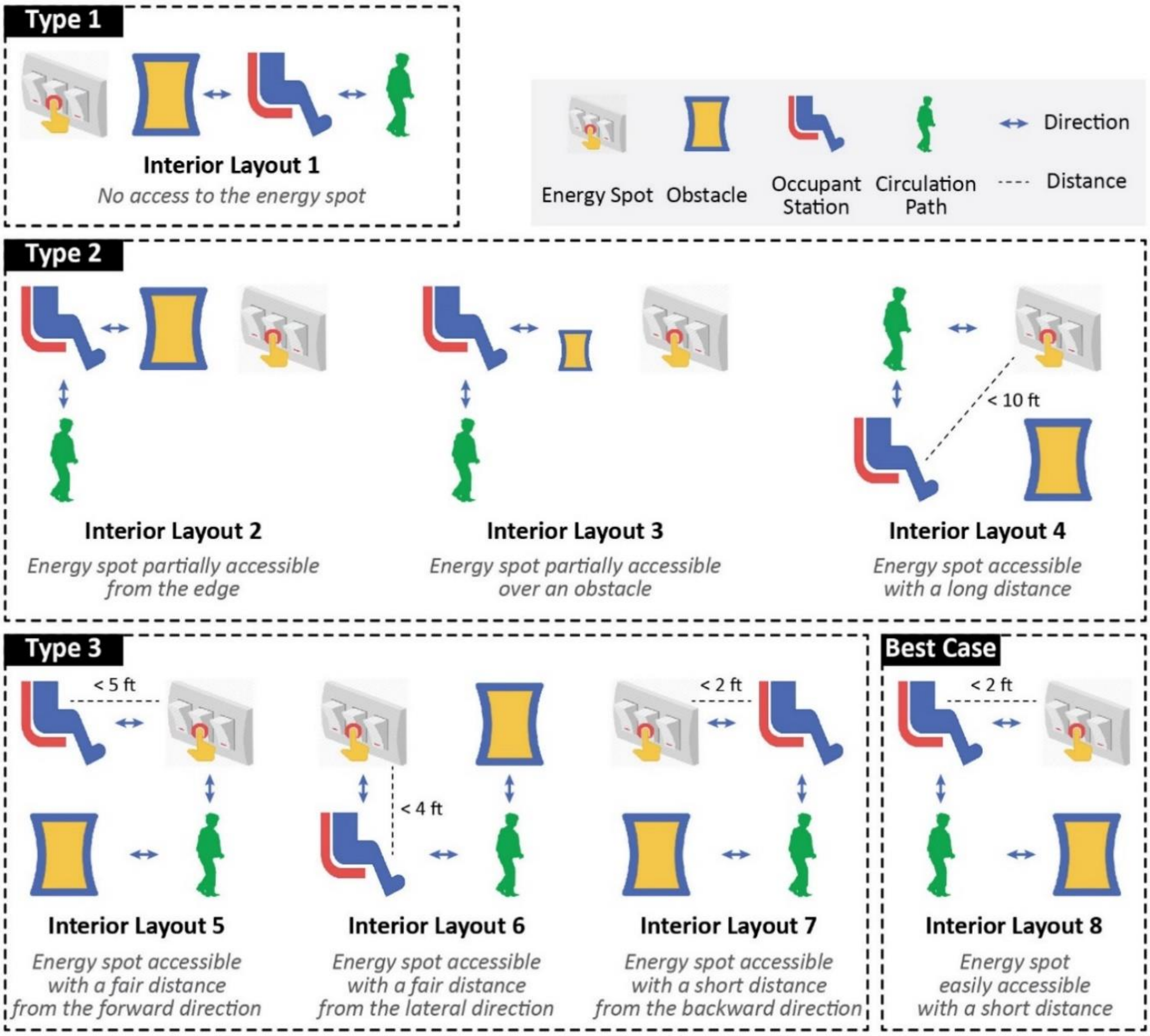

Figure 3.3. Simplified interior allocation within the space

3.5.2 Hybrid model construction approach

The methodology used for the hybrid model construction within the BIM platform, ABM, and the SD approach is further expounded in the research flow chart mentioned in Figure 3.4. A detailed explanation of Task-1 (building interior layout using the BIM tool) is already explained in an earlier section. Task-2 deals with the ABM-SD model construction that primarily consists of the initialization, import model parameters (e.g., population, size, etc.), and other specified behaviours assigned within the ABM platform.

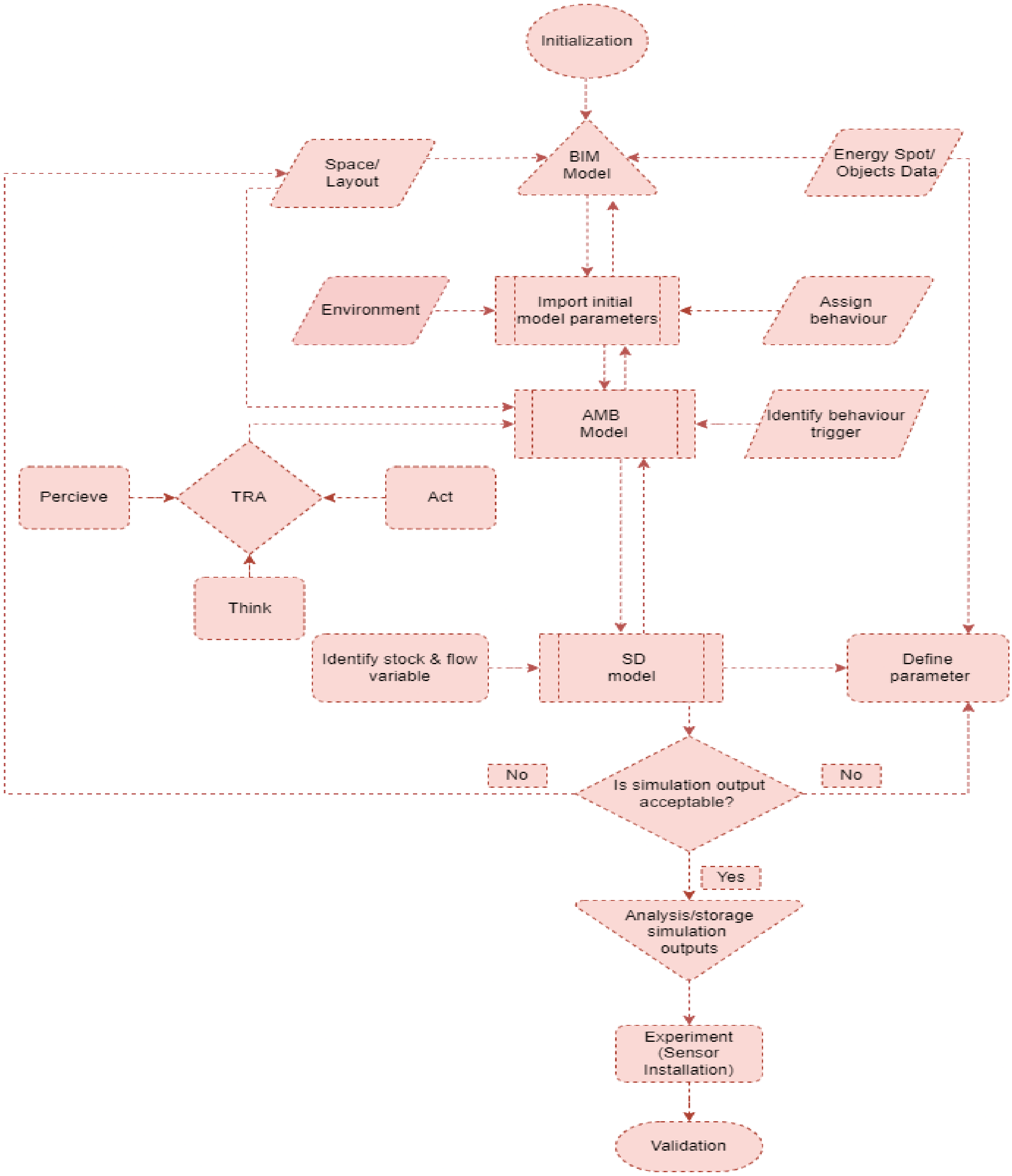

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Figure 3.4. Flow chart of the hybrid model construction and validation

Afterwards, the study needs to identify the behaviour triggers (events or actions that perform a role in inducing specific behaviours) that are also incorporated with the physical layout conditions assigned in a prototype BIM-based model. On the other hand, as a decision-making process, the Theory of Reasoned Action (ToRA) has been addressed as this is one of the most popular theories for human behaviour study. The detailed explanation of this theory is also explained in the subsequent section.

3.5.2.1 Theory of Reasoned Action (ToRA)

The primary theory implemented in the study of occupants behaviour representation is the reasoned action model established by Fishbein and Ajzen [72]. Figure 3.5 illustrates a basic schematic concept of behavioural intention. This is an inherent concept that occupant social behaviour supports rationally and frequently from people's opinions or dominance about the occupant behaviour under a specific knowledge [72].

With this, Fishbein and Ajzen have looked at several factors, primarily "Attitude." Attitude is an occupant belief about the behaviour they know; they think that is a behaviour actually going to benefit themselves in the end. It is not just enough an attitude about the outcomes of the behaviour but also has to feel like those outcomes are going to be beneficial for the occupant. For example, occupants think that exercising every day is going to help them out and form a positive attitude about exercise. If occupants have a positive attitude toward exercise, hopefully, that informs their intention to exercise every day, thus leading to behaviour. But intention does not just rely on attitude where it gets a little bit more complex because if occupants do everything that has a positive attitude would probably be a lot healthier and happier. Nevertheless, a second component called "Subjective Norm (SN)" is really much more influence on occupant belief about the desirability of the behaviour. For example, exercise is something that people view as a good thing and is being healthy valued in society. Subjective Norm focuses on the social desirability or the acceptability of the behaviours that are ultimately trying to get by the occupants. So occupant creates this, but they have to understand the belief about the desired behaviour to specific others view. If the occupant is doing something, they should think about what others are going to think about it. The people close to us so their beliefs about the behaviour as being desirable.

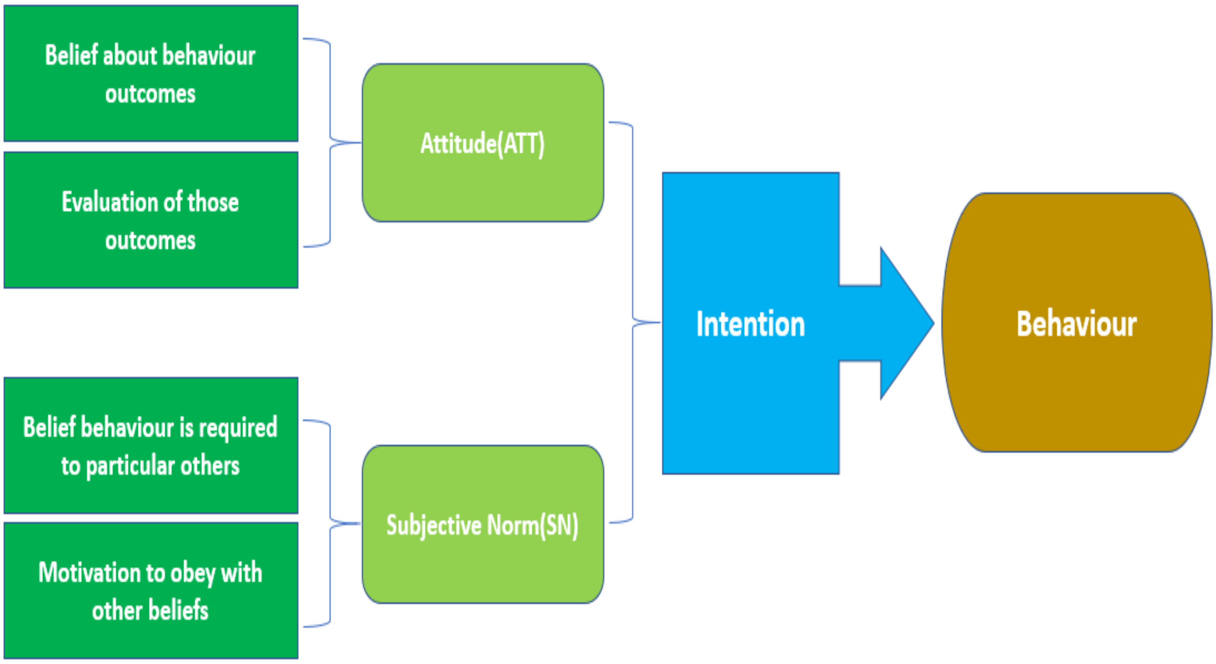

Figure 3.5. The behavioural model based on ToRA, adapted from Fishbein and Ajzen [72]

The complete ToRA is portrayed as an equation 1.1

$$\boldsymbol{O_{BI} = O_{AB} * X1 + O_{SN} * X2} \quad \ldots\ldots\ldots\ldots \quad 1.1$$

Where,

O_{BI} = Occupant behavioural intention,

O_{AB}= Occupant attitude about performing the behaviour,

O_{SN}= Occupant subjective norm about performing the behaviour, and

X1, X2 = How important the component is to the individual occupant (e.g.,0.5 for both cases).

As an earlier interpretation, the decision-making process implemented using ToRA is split into three individual components: perceive, think, and act loop (PTA). A detailed explanation of the PTA loop is also available in the subsequent Chapter (Chapter 4: Hybrid Model Construction:)

3.5.2.2 Model Output

Usually, an occupant agent observes its environment, which is well-described by the input data, layout information, and environmental data of the specified spaces. The layout conditions correspond to the occupant station/destination, circulation path, and energy spot mentioned in the prototype Revit model, including physical parameters (e.g., the distance between energy spot and occupant station/destination) that allow an occupant agent to realize its motivation that keeps track of the energy calculation. Here, the SD model links the environmental parameters, and occupant energy usage characteristics to an agent. This can expressively influence the overall building energy consumption (e.g., output) by having an SD model to describe the behaviour changes made by agents.

3.5.2.3 Experiment/Intervention

The next component of the PTA Loop is energy calculation (before/after intervention) once the agent's interaction and learning process has been accomplished. The purpose of the energy estimation is to capture how agent behaviour influences the different indoor layout arrangements and internal ambient parameters within a space. The last section is intervention and model validation that will determine the flexibility and robustness of the proposed model. The details of the model intervention and validation approach are described in Chapter 5.

As a flexible modeling framework, all data might be customized within the model, as well as other parameters/components are being adjusted whenever required. After executing the multiple simulations, acceptable outputs have been gathered and analyzed for further validation study by considering an intervention approach implemented in a case study location

3.5.2.4 Data collection, validation, and questionnaire survey

During the experimental and intervention study, a survey questionnaire was designed to investigate the influence of social contextual factors. The questionnaire development process is explained in Chapter 5. The questionnaire was used to solicit the occupants perception values as well. Additionally, most ABM studies are established on synthetic/modelled data and scenarios with or without a proper validation/calibration approach. So, this study also efforts to fill this gap by proposing a data validity/reliability test by checking the calibration tolerance (Root Mean Square Error and Mean Bias Error) as per ASHRAE and FEMP guidelines [209, 210]. Moreover, the Blackbox approach (confusion matrix) has been used to check the infiltration and HVAC/light using behaviour as well. In this regard, the customize sensor data (energy and ambient data monitoring) has been collected from several residential apartments located in Chittagong, Bangladesh.

3.6 Chapter Summary

This Chapter illustrates the research framework, model construction methods, theory of reasoned action model, intervention, and validation approach. The consecutive Chapters will be described the compressive hybrid model construction process, validation, and experimental works.

CHAPTER 4
HYBRID MODEL CONSTRUCTION PROCESS[4]

4.1 General

Occupant behaviour modeling is primarily concerned with describing the relationships between human behaviours and surrounding conditions. This can be accomplished in three stages: occupant behaviour selection, measuring the quantified data (i.e., assumptions, information, or database) for behaviours, and building a model for behaviour prediction. The subsequent sections present the details of the hybrid model construction process and intervention methods to achieve the required phases, which served as the foundation for occupant behaviour simulation throughout the study.

4.2 Simulation Model

Typically, a simulation process involves a robust mathematical model, for instance, a utility function in agent-based modelling (ABM) – determined from a commonly acknowledged theoretical background in order to capture the psychological, physical, and social behaviours of the item that it intends to simulate [211]. A similar rule uses the requirement for an autonomous function to accelerate an optimization system in most building-related models [212]. The construction of the model starts with measuring human behaviours into some quantifiable metric (perception factors, information, or database). Since behaviour is a

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[4] This Chapter is partly published and under review in:

1. **Uddin MN**, Wang Q, Wei HH, Chi HL, Ni M. Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. Ain Shams Engineering Journal [Internet]. Elsevier BV; 2021 May; Available from: http://dx.doi.org/10.1016/J.ASEJ.2021.04.015

2. **Uddin, M. N**., Chi, H. L., Wei, H. H., Lee, M. & Ni, M. Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling (Under Review).

3. **Uddin, M.N**.; Wei, H.-H.; Chi, H.L.; Ni, M. An Assessment of Occupant Comfort and Behavioural Influence on Building Indoor Layout: A Collaborative Analysis Using Statistical and Agent-Based Simulation

4. **Uddin, M.N.;** Wei, H.-H.; Chi, H.L.; Ni, M.; Tamanna, N. Building Layout Influence on Occupant's Energy Consumption Behaviour: An Agent-Based Modeling Approach. Environmental Sciences Proceedings (Under Review).

combination of context, target, action, and time [72], one can easily integrate behaviours with several forms of perceptible activities that are obtained from a function of several decision-making variables. In relation to the diagram (Figure 4.1), the time and context elements are ruling variables that are pre-established, together with the target, an objective variable. Thus, the only uncertainties that persist are the unforeseen variables, the action element of behaviour, and a common variable, or the energy requirement.

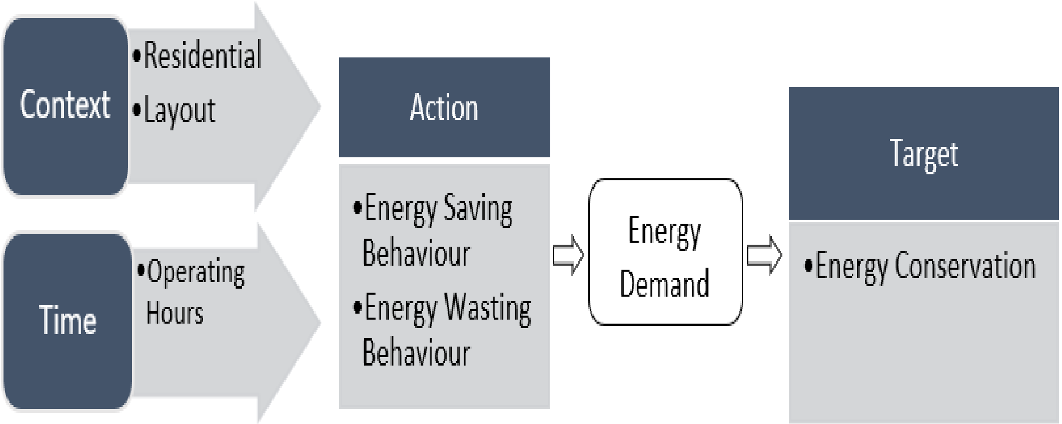

Figure 4.1 Relationship between study purpose and behavioural components

4.3 Modeling Rules of the Proposed Model

In accordance with the literature review, the main elements of an ABM-based simulation involve a set of agents, a specific topology, and rules that address how the approach works within the environment. In connection to the modeling context and background in this study, the particular components of ABM configuration are shown in Figure 4.2.

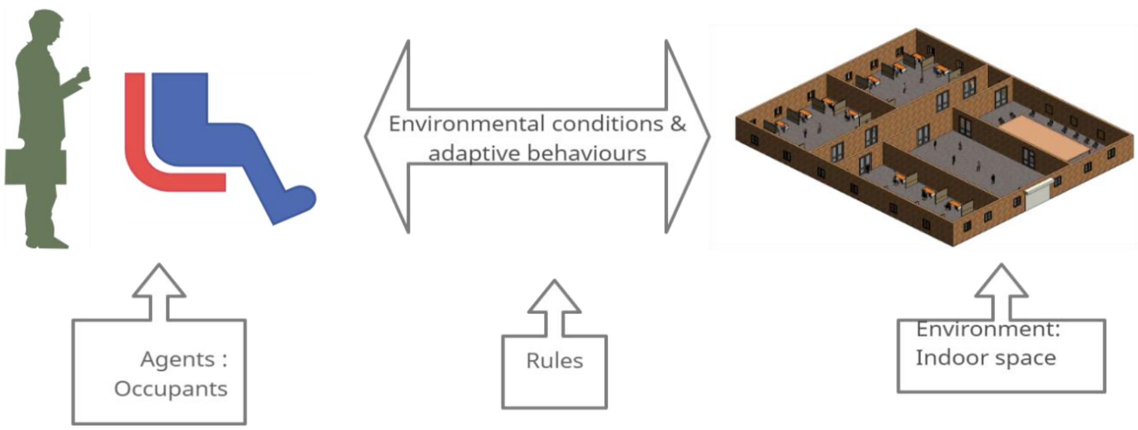

Figure 4.2. Proposed ABM structure within the built environment context

From the outline of a typical ABM structure as considered above, the projected ABM approach is described with three main components. Firstly, the agents in the model are occupants, more particularly symbolizing the building inhabitants. Occupants are rather complex agents in terms of their characteristics and attributes. It is difficult and, sometimes, unnecessary or very challenging to capture all of the occupants attributes or characteristics [213]. In this study, the model considers the occupants attitude and subjective norms as per the theory of the reasoned action model [73]. Meanwhile, some other psychological and non-psychological parameters are also incorporated as a supporting and useful factor for modeling process.

Secondly, the environment where agents interact within the model is properly recognized. The spot where the occupant agent stays is within the inside of an indoor space. The ambient environment is the direct stimulus or driver that influences the agent's behavioural decisions that are also linked with the system dynamics model. In addition, behaviour preferences of the agent in the modelled building are comprised of adapting to surrounding environmental conditions. In the current model development, other building indoor parameters such as room size, number of furniture, window location, orientation, etc., are ignored as these do not impact the occupant behaviour for this study's purposes. Previous scholars also have revealed the model feasibility and validity of the assumption for a single model construction purpose [12, 38, 107].

Lastly, as the building component states and the built environment states are well-informed if the current environment states are out of the acceptable range for the occupant agent, it is projected that the occupant agent will have the possibility to adjust the state of building components to reach their individual comfort level. However, it should be noted that the ambient indoor environment is not the only external factor that influences occupants behaviour in real life [12]. For instance, typical time, occupant age, gender, economic concerns, and other agents influence might also affect the occupants behaviour profile [172, 214], especially in residential buildings. However, under the scope of this study, the ABM is considered to be a more specific parameter of indoor layout influence. Here the dominant trigger of occupant behaviour is one's physical comfort level within the layout and energy expenses rather than other social issues [79].

4.4 Modeling Steps

The modeling steps of the study have been divided into three phases: Phase I: predicting typical stochastic occupant behaviours and their individual action within the layout; Phase II:

calculating the energy consumption using the model (before and after intervention) and Phase III: validate the output with real data. Here, the ABM-SD model is constructed using the Java-based AnyLogic modeling tool, which is a broadly established simulation platform, especially in the engineering, business, and sociology domain. Figure 4.3 represents the basic components of the proposed modelling work. In this modeling, assigning behaviour, behaviour triggers, and function, agent decision-making process (PTA), agent interactions/learning and SD components address phase I; layout deployment, energy interface, Revit, Dynamo_Excel platform (coupling), and simulation outputs address phase II, and the "model validation & experiment" address phase III.

Usually, after initializing the specific behaviour (Light/Fan ON or OFF), the occupants agent identifies the behaviour triggers (both phycological and non-phycological) followed by some pre-defined behaviour rules and conditions. During the agent decision-making process (Perceive, Think, Action known as PTA Loop), an occupant agent observes its surrounding, which is well-described by the input data and the Interior Layout information as well as thermal and visual conditions of the specified spaces. The layout conditions correspond to the individual agent's destination (e.g., seating point) and other parameters (e.g., switch distance) that allow an occupant agent to realize its motivation that keeps track of the energy calculation. The goal of the energy estimation is to describe how agent (occupant) behaviours affect the interior of allocation within the space. This can expressively influence the occupant destination, switch distances also environmental conditions that consider the behavioural variations made by occupant agents. It also noted that as occupant phycological parameters, the proposed hybrid model follows the Theory of Reasoned Action (ToRA) model as a decision-making process.

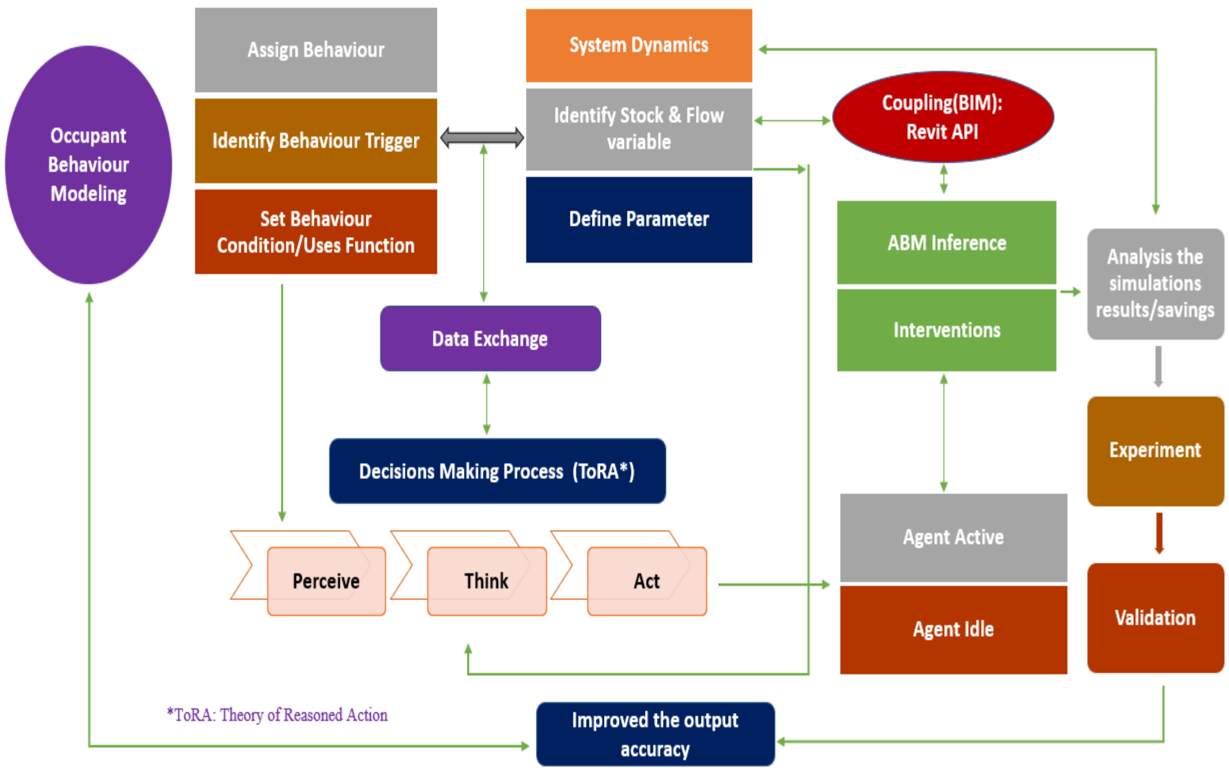

Figure 4.3 Modelling Framework

Herein, the PTA loop has been re-explained to describe the idea of the decision-making comportment (or ABM process) applied in the study. The PTA loop in Figure 4.3 has been extended to the Observe, Orient, Decide, and Action (OODA) loop shown in the statechart in Figure 4.4 for further identification of the process. The detailed explanation of the OODA loop is as follows:

Usually, an occupant agent *observes* its environment, which is well-described by the input data, layout information, and environmental data of the specified spaces. The layout conditions correspond to the occupant station/destination, circulation path, and energy spot mentioned in the prototype Revit model, including physical parameters (e.g., the distance between energy spot and occupant destination) that allow an occupant agent to realize its motivation that keeps track of the energy calculation.

i. Observe: An agent recognizes its environment or surrounding conditions, e.g., layout and climatic circumstances, are given interior space.

ii. Orient: An agent orients and spend a few times evaluating its perception of behaviour options.

iii. Decision: Based on floor layout (i.e., energy spot distance) as well as occupant attitude and subjective norm, an agent makes behaviour decisions to address the task.

iv. Action: An agent performs the task or comes back to its idle position.

It is noted that above mentioned integrated model has been considered both psychological and non-psychological parameters (Figure 4.5 & Table 4.1) within the combined framework system.

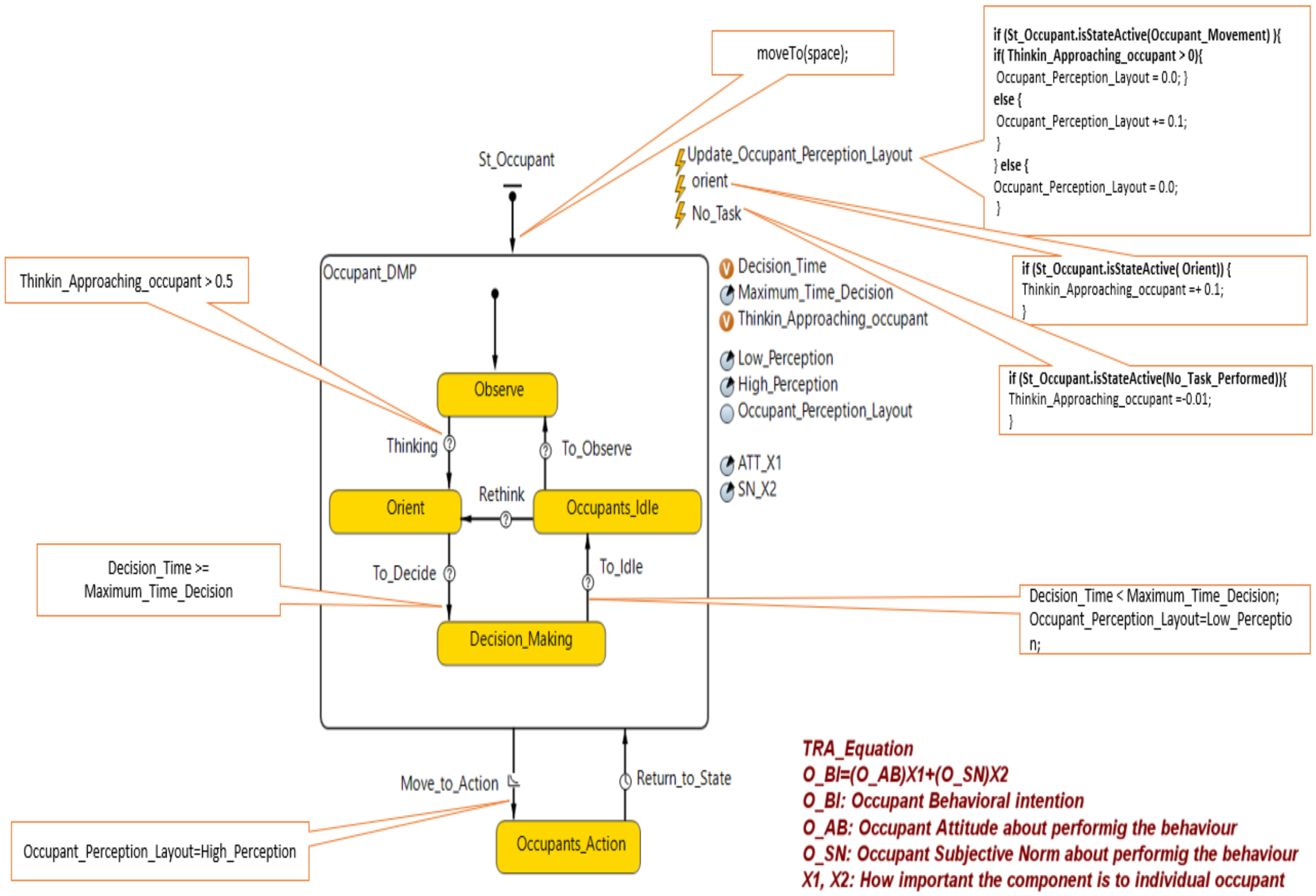

Figure 4.4 State chart for OODA loop

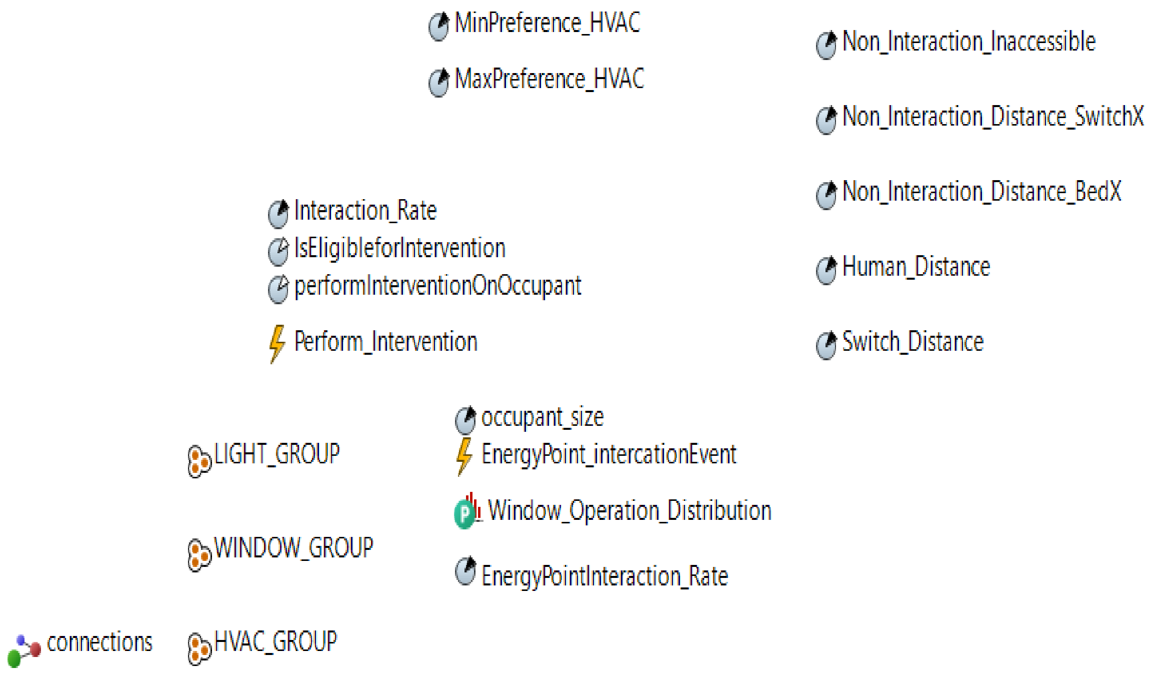

Figure 4.5 Non-psychological parameters

Table 4.1 Model parameters, events and variables

Agent's	**Occupant (Active)**	**Energy Point (Passive)**	**HVAC (Passive)**	**Light (Passive)**	**Space (Passive)**
Parameters	Prefer_HVAC	Inaccessible	HVAC/Fan	Light	Space (Layout)
	Maximum_Time_Decision	Distance	MinPreference_HVAC		
	Interaction Rate	Switch_Point	MaxPreference_HVAC		
	Occupant size	Window_Control	Energy_coefficient_HVAC		
	PMV value	HVAC_Control			
	Occupant Intervention	EnergyPointInteraction_Rate			
	Level of Influence (LI)				
	High & Low Perception				
	Attitude and Subjective norm				

Events	EnergyPoint_interaction_Event				
	Intervention_Event				
	Occupant_Satisfaction_Event				
	Update_Occupant_Perception				
	Orient				
	No_Task				
Variables	ConsiderThermal Comfort_Window				DistFromWindowpoint
	ConsiderThermal Comfort_HVAC		Temp_Dynamic		DistFromHVACpoint
	Decisison_Time				
	Thinkin_Approaching				
	Thermal_Sensation				
	Occupant_Perception_Layout				

If more occupant agents go to an idle state (e.g., No_Task performed), it indicates occupants are not satisfied with the existing layout pattern or are not engaging in any energy-saving tasks. Thus, occupants show more energy consumption behaviour rather than energy savings. In this case, the model considered the intervention strategy to reduce the number of idle agents. After the intervention cycle, agent perceptions value increased, which leads to the energy savings attitude. Refer to **Appendix II** for the sample code used for the occupant decision-making process as well as layout-based intervention.

Typically, occupants perceptions values (+1 to -1) vary based on eight different cases mentioned in the earlier chapter. Here occupant perception value has been estimated based on triangular distribution while it is applied as a functional form of areas for fuzzy logic due to simple application in the modelling platform. It is also assumed that occupant perceptions values are higher after intervention and vice versa before intervention. For instance, if the energy spot is accessible and within the human range (less than 2 ft), it means the perceived value is higher, and the occupant has a positive behavioural intention towards the energy-saving attitude. It is noted that the aforementioned integrated model has considered both phycological and non-psychological parameters within the combined framework. The next component of the PTA Loop is energy calculation (without and with intervention) after the agent's interaction and learning process. The purpose of the energy estimation is to capture how agent behaviours can influence the energy consumption for different indoor layout arrangements. Here, the SD model links the required environmental parameters, several equations, and occupant energy usage characteristics. This can influence the overall building energy consumption by having an SD model to describe the behaviour changes made by agents. The last part of the research is Enablement intervention and model validation which will determine the flexibility and robustness of the proposed model. As a flexible modeling framework, all data can be customized within the model, and other parameters/components can also be adjusted whenever required. After executing the multiple simulations, acceptable outputs have been gathered and analyzed for further validation by considering an intervention approach implemented in a case study. The details of validation and intervention settings have been described in the subsequent Chapter.

4.4.1 Occupant Usages (HVAC/Window) Function

An agent activity function is a numerical formula that an agent estimates to make behaviour choices. The activity function implements the scientific model from the social sciences, where the model includes the collaborative relationship of variables using numerical notions [215]. The model is anticipated to be a projecting model where the interactions between the variables might describe future events. The study considers a simple linear equation, which is one of the most frequently used functions in social science studies

$$f(X) = p + qX + e$$

where p and q are factors, X is a variable, and e is an error entity. Including an “error” term allows for some degree of uncertainty, which is an essential attribute of a stochastic or probabilistic model [215].

The decision-making process in the ABM model is based on the theory of reasoned action (ToRA) model. Considering the relationship between the ToRA model and building occupant behaviours in the existing works of literature, the resulting Figure 4.6 describes the potential causal models that suggest descriptions of the relationship [65]. Since the study performed a survey of actual building occupants, it is expected that the development of the reasoned action model has similar effects on an occupant (agent's) overall belief in their comfort, i.e., Figure 4.6(a).

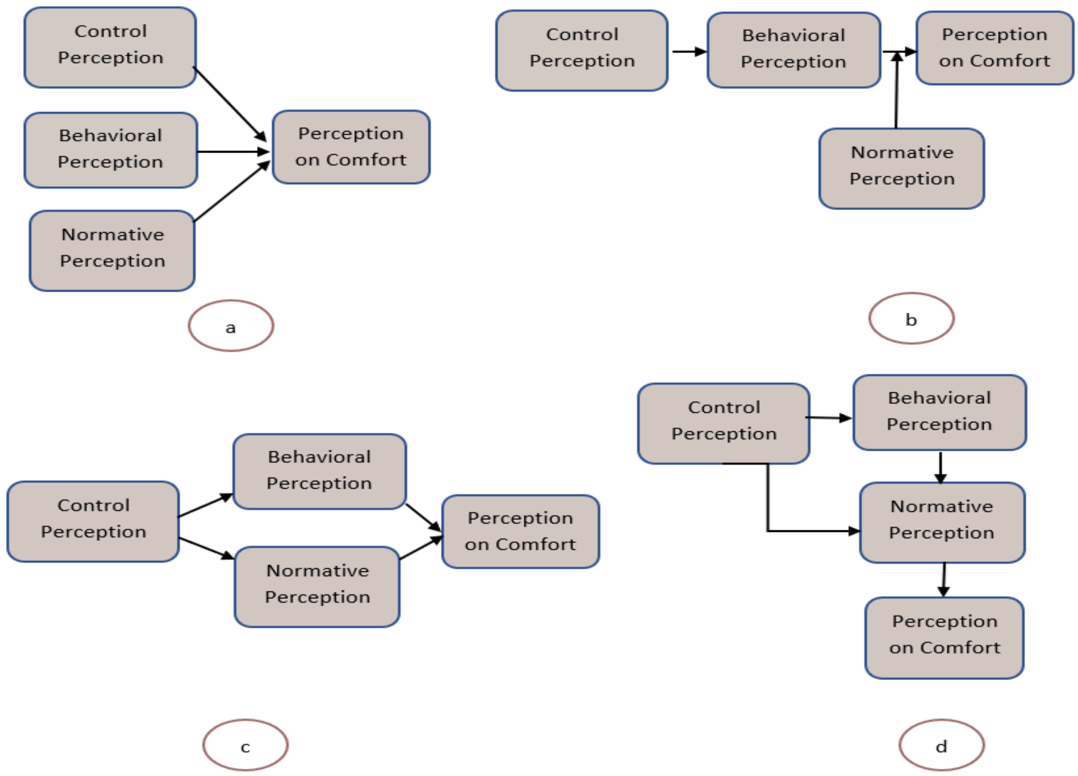

Figure 4.6 Typical causal pattern between the ToRA model and perception of comfort

The activity function supports an occupant agent to construct the optimum behaviour selection to accomplish its objective. An agent goal during the study has regularly stayed the level of agent comfort level, for instance, to achieve and maintain the comfort level in the interior space through adaptive control or behaviour, which is mainly adjusting various building components [216] such as window or HVAC operations. However, an agent's activity function can differ depending on the intentions of ABM, e.g., energy conservation, maximum usage of natural ventilation using the window, etc. State chart 4.7(a) represents the occupant preference of HVAC or window for thermal comfort, which is mainly based on the probability distribution function. On the other hand, state chart 4.7(b) denotes the occupants idle and active state, which is a function of the distance factor (e.g., Energyspot distance for HVAC). A typical action chart (based on ToRA) of HVAC and window operation in space has been shown in Figure 4.8.

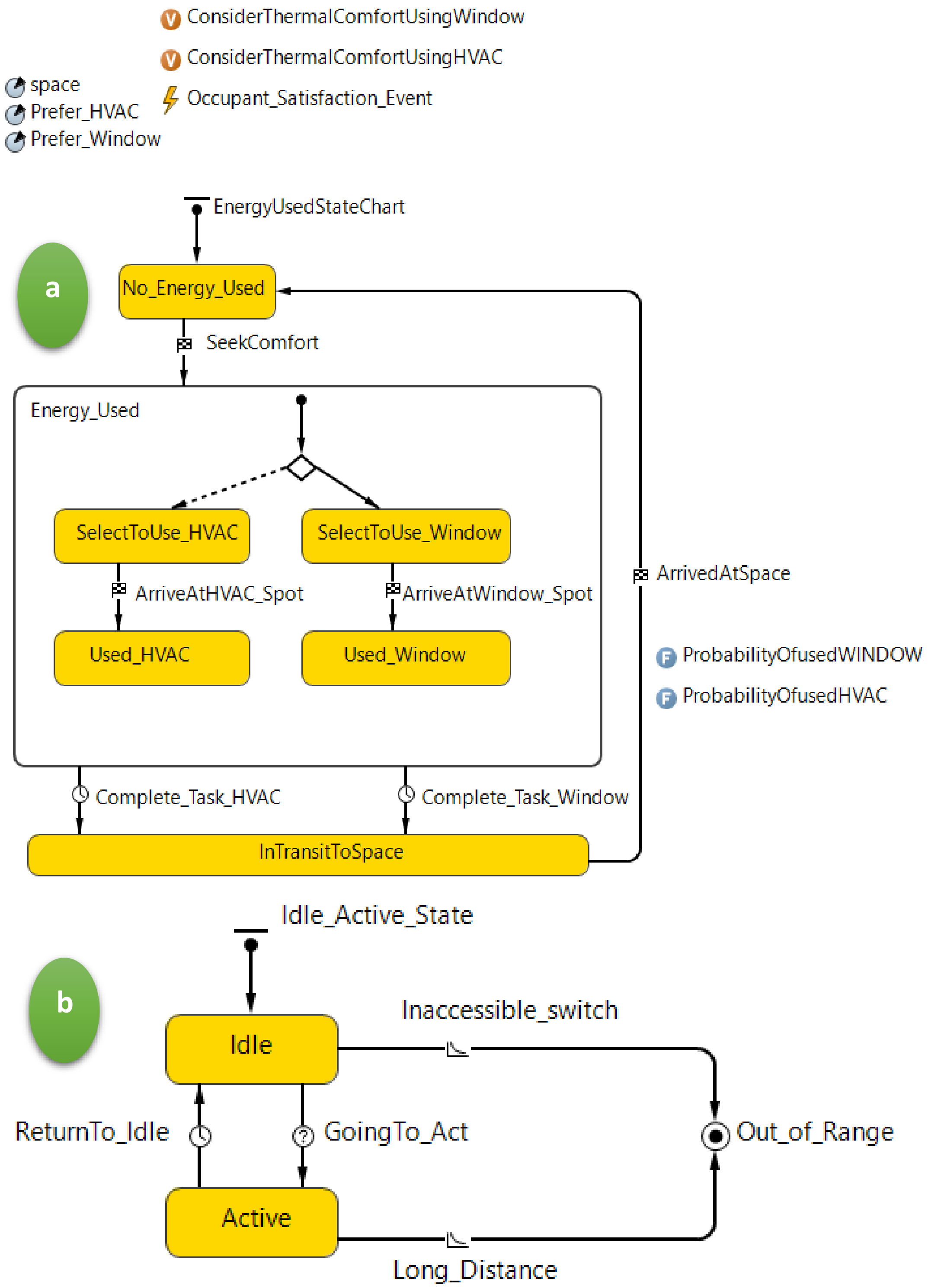

Figure 4.7 State chart for HVAC/ Window selection

BP: Behaviour Perception; NP: Normative Perception, CP: Control Perception; PC: Perception on Comfort

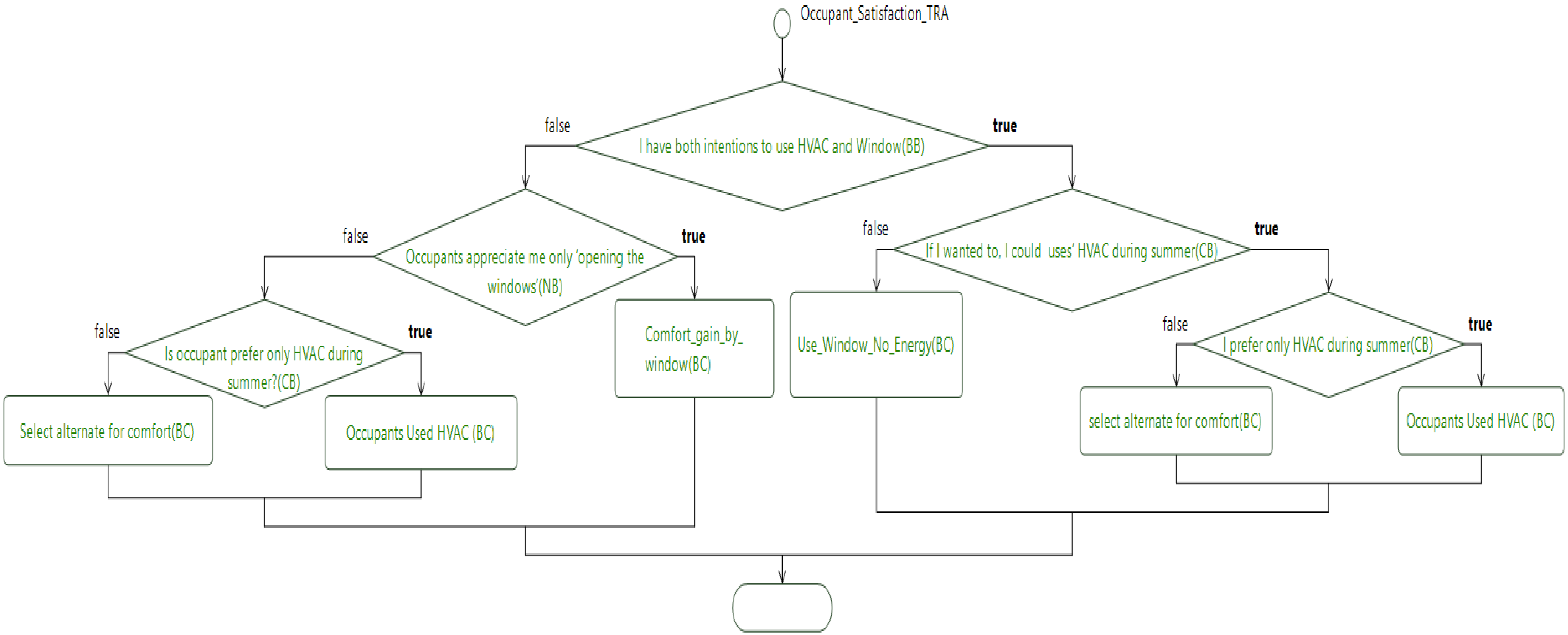

Figure 4.8 Action chart of HVAC and Window operation for occupant stisfaction (Anylogic 8.5)

The primary agent uses function implemented in the study is stated as follows

$f_{ij}\ (t) = p_{ij}x_{ij} + q_{ij}y_{ij} + r_{ij}z_{ij} + s_i x'_i - e_{ij}y'_{ij}$

f_{ij} = Comfort perception for occupant agent i (here i = 1… n) and specific behaviour j (here j = 1…..m)

x,y,z represent Behavioural Perception (BP), Control Perception (CP), and Normative Perception (NP), respectively.

x', y'represent characteristics of an agent and agent distance to the energy system (e.g., switch)

t represents the current time, and p, q, r, s, e represent the corresponding weight-factors at time t,

Here parameters x, y, z, x', and y' estimate the occupant agent i's general perception of a specific behaviour j. The greater the usage f_{ij}, the more possibility for specific behaviour j would be treated by an occupant agent i for addressing its comfort range. Improving the activity function begins with expressing the weight factors in the above formula. Initial weights value can be defined by a simple survey, as specified in the survey section, which will be further validated through experiments and calculated data from the actual buildings.

4.4.2 Agent learning and Interaction

Agent learning and interaction are the crucial aspects of an autonomous, intelligent agent within the modeling process. The study uses the ToRA model as a decision-making framework to fulfil agent learning and interaction in the AnyLogic platform. In addition to making agent behaviour decisions, one more intervention state chart was also added in Figure 4.9.

4.4.3 Agent Intervention

The specific intervention rules implemented for this occupant behaviour study have been described as follows:

4.4.3.1 Combined Intervention Approach:

The combined intervention approach has been studied where the hybrid model considered all occupants to act randomly together within the space. So, in this case, the hybrid model estimated energy consumption and comfort profiles for a group of occupants rather than the individual. The detailed state chart for the combined intervention approach is shown in Figure 4.9.

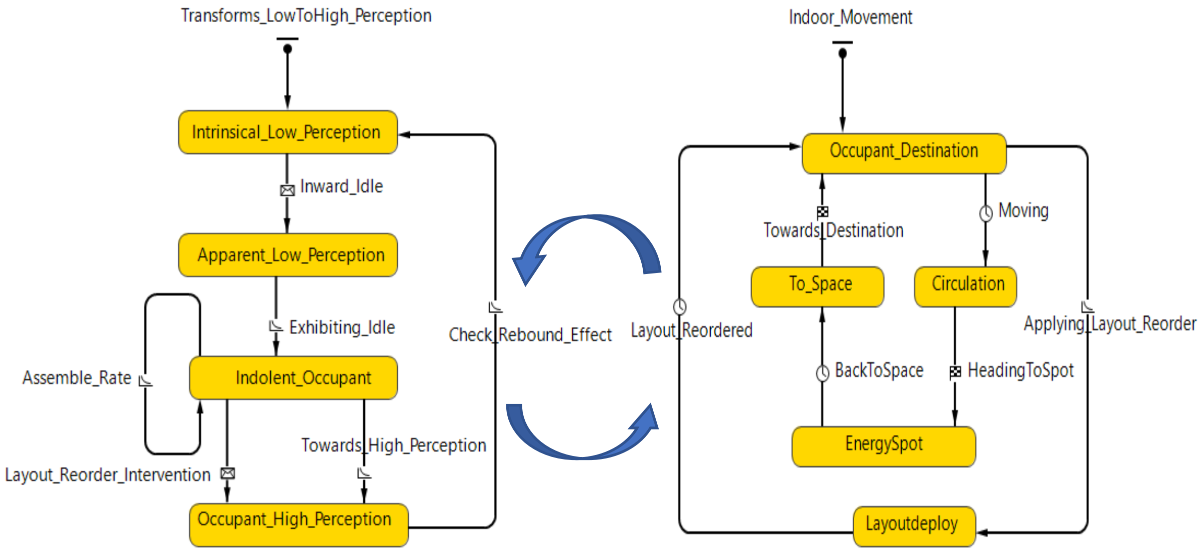

Figure 4.9 Statechart of occupant activity in space (During Combined Intervention)

a) The above state chart consists of two components describing the movements of occupant perception from low to high perception by completing the multiple stages within the indoor spaces. Firstly, the model considered the state chart entry point "Transforms_LowToHigh_Perception" that mainly linked with the previous state chart (e.g., Occupants Idle/No_Task_Performeed in OODA loop) through appropriate rules. Occupants belong to innately low perception at the " Intrinsical_Low_Perception" stage (Here, occupant color: blue).

b) Afterward, the inward idle occupant moves to "Apparent_Low_Perception," where the occupants fractional idle status has been visible for a certain period of time (Here, occupant color: magenta).

c) Next, the occupants turn to the indolent stage and represent entirely stationary categories (e.g., energy wastage behaviour) within the spaces (Here, occupant color: cyan).

d) Now model-based intervention (e.g., layout deployment) has been implemented that tries to convert the occupant existing low perception to high perception (Here, occupant color: green).

e) The above process within the space is also coupled with the statechart " Indoor_Movement" which primarily represents the occupants physical movement from their destination to the energy spot or other directions. The required codes for occupant color in the various stage has been demonstrated in **Appendix II**.

4.4.3.2 Individual Intervention Approach:

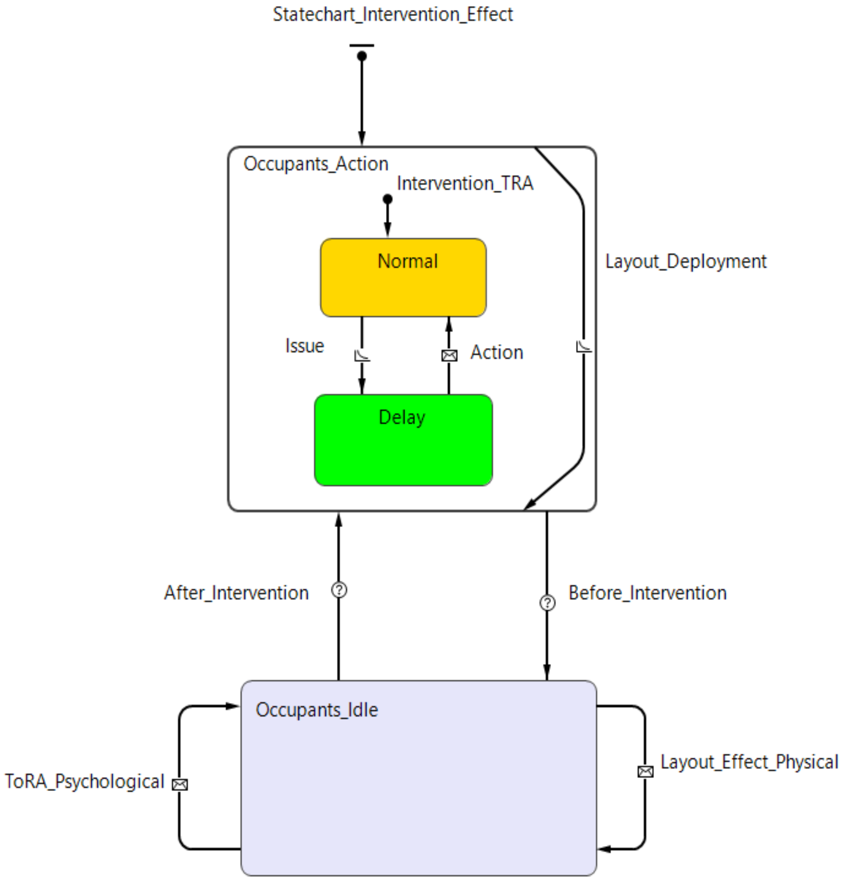

Figure 4.10 Statechart of individual occupant activity in space (During Intervention)

a. Each statechart is initiated with a "Statechart Entry Point." The inside of the state chart is the "Occupant" agent that has two main states: "Occupants_Action" and "Occupants_Idle."

b. The entry action for the "Occupants_Action" state is to choose the color of the "person" sign to blue.

c. The entry action for the "Occupants_Idle" state is to select the color of the "person" sign to red.

d. “Occupants_Action” state is a compound state, which includes two states called “Normal” and “Delay” states.

e. It is required an “Initial State Pointer” inside the compound state to specify the primary state inside the compound state.

f. Two transitions occur between “Normal” and “Delay” states called “Issue” and “Action”.“Issue” transition is triggered by Rate, and the “Action” transition is triggered by Message.

g. Another two transitions between “Occupants_Action” (complex state) and “Occupants_Idle” state. They are called “Before_Intervention” and “After_Intervention.” These transitions are both triggered by conditions. For now, set their condition to “false” in the following step, and it connects these conditions to a System Dynamics component.

h. Now, when we run the model and then double click on the “people” population, we are able to see that agent remains in the “Normal” state for a moment; afterward, it moves to the “Delay” state and stays there continually. For a prosecution purpose, the typical energy consumption pattern and occupant idle/active state before and after intervention as shown in Figure 4.11.

Before Intervention **After Intervention**

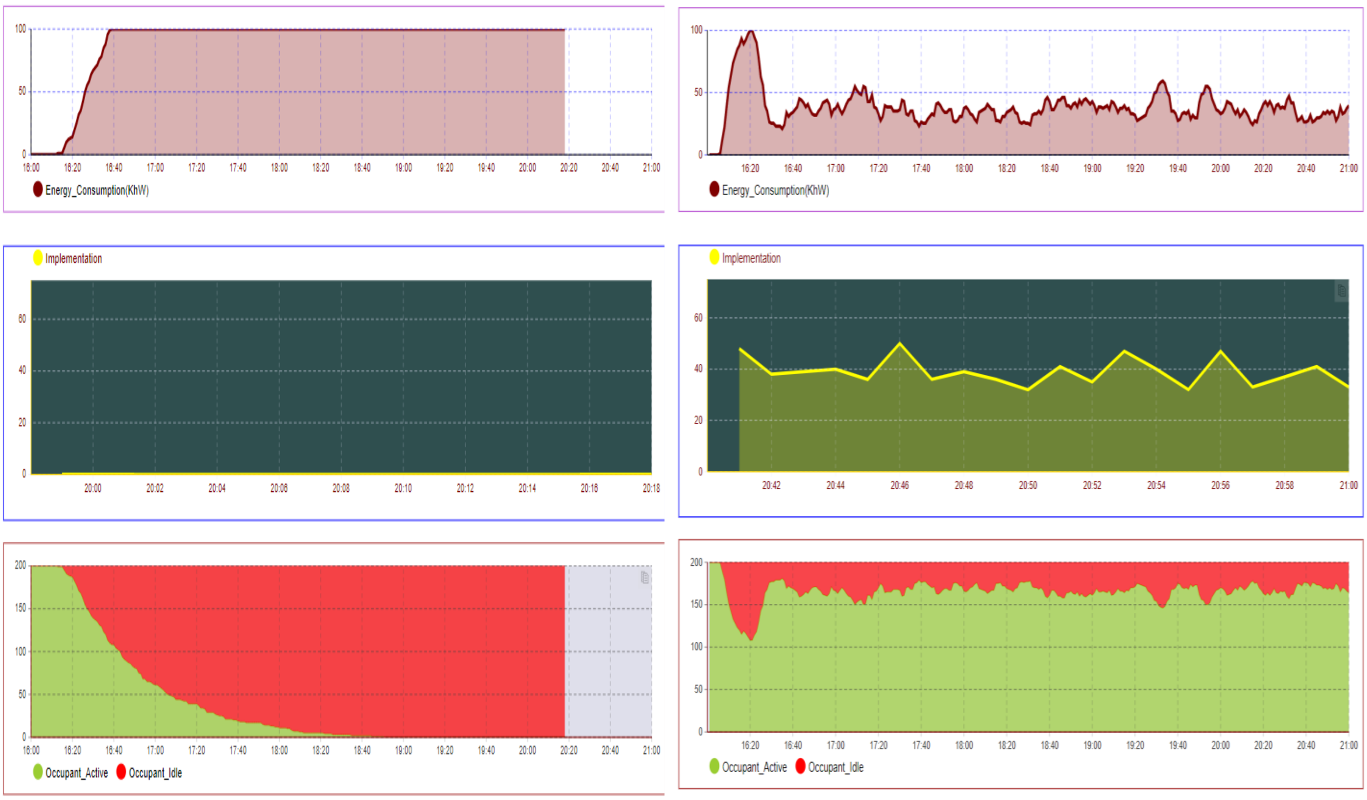

Figure 4.11 Before and after intervention state

During the modeling process, the SD model links the environmental parameters, and occupant energy usage characteristics to an agent. This can expressively influence the overall building energy consumption by having an SD model to describe the behaviour changes made by agents. The last part of the research is intervention and model validation that will determine the flexibility and robustness of the proposed model.

As a flexible modeling framework, all data might be customized within the model, and other parameters/components are being adjusted whenever required. After executing the multiple simulations, acceptable outputs have been gathered and analyzed for further validation study by considering an intervention approach implemented in a case study location. The details of validation and intervention settings have been described in the validation section.

4.5 Development of Hybrid ABM-SD-BIM Model

The idea of agent-based (ABM) -system dynamics (SD) and several capabilities are previously discussed. It highlights the ABM-SD as a favourable 'methodology' for studying occupant behaviour. ABM is usually described as either a programming language or a simulation tool as a prediction model [217-219]. On the other side system dynamics (SD) is a methodology and mathematical modeling technique to, construct, understand and discuss the complex issues and problems. System dynamics is an aspect of systems theory as a method to understand the dynamic behaviour of complex systems [220].

ABM-SD is a computational method that simulates individuals making decisions according to programmable rules. The modeler sets those rules to represent key elements of real-world evaluations, including the individuals' own characteristics and their social and physical environment. Needless to say, the selection of one ABM-SD over another will be decided by the scope of the research and the questions asked [221, 222]. On the other hand, a previous study described the interoperability and data exchange issues between the BIM tool and facilities management for improved occupancy-based building performance [28]. This study also highlighted the potential issues related to BIM implementation for effective construction management.

The aim of this section is to represent the ABM-SD-BIM employed in the study, which also supports addressing the following additional research problems concerning occupant behaviour in buildings:

a. How is the proposed ABM-SD-BIM model unique from the current behaviour simulation approaches?

b. What would make the ABM-SD approach improved than the existing behaviour simulation method?

c. How important are the occupants movement and action in making behaviour decisions in a selected building space?

The proposed hybrid model has three key components. Firstly, the active agent in the model is the household occupants. The proposed model in this study reflects the occupants physical observations and subjective norms as the vital characteristics of an agent. In the meantime, space circulation, decision time, thinking mechanism, and persuasions are also involved as relevant factors for modeling. Secondly is the dynamic environmental data where agents interact inside the model space zones or specified rooms. The ambient environmental condition is the direct stimulant that affects the agent’s behavioural selection. Other criteria such as room dimensions, occupant heat gain, wall properties, air density, etc. are also considered under the existing model (e.g., BIM model). Working schedule, rest time, walking, etc., are not considered in the model as these factors have fewer effects on the occupant behaviours in this study. Finally, when a built environment condition and building energy component are recognized, it is usual that the occupant agent will react with available building segments for their comfort level. Nonetheless, it needs to be noticed that environmental conditions aren't the main exterior factors impacting human behaviour in the real world. For instance, time, age, economic matters, feedback programs, and different directions of the agents can furthermore influence the individual behaviour norms of building occupants, particularly in residential households.

4.6 System Dynamics(SD) Model

System dynamics (SD) is an approach to understanding the nonlinear behaviour of complex systems over time using stocks, flows, internal feedback loops, table functions, and time delays.

The model structure in the system dynamics is implemented using AnyLogic since the mathematical expressions can be easily put into the system. In this study, the complete structure of system dynamics is the following form in Figure 4.12. The details of outdoor environmental data: temperature(^{0}C) and relative humidity (%); Indoor environmental data: ambient or room temperature(^{0}C), relative humidity (%), CO_2 concentration (ppm), heat gain from occupants, etc. can be calculated using SD model.

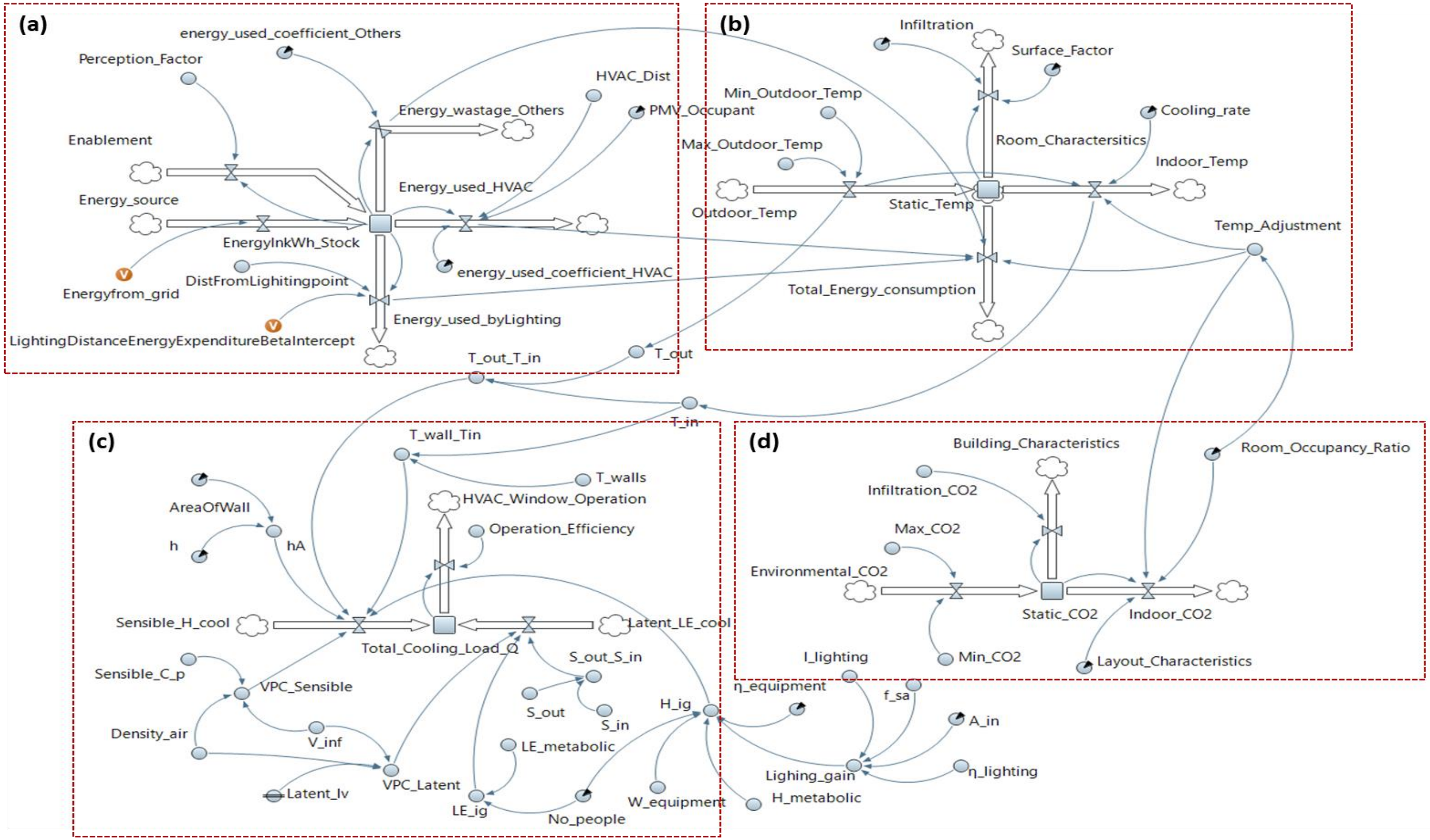

Figure 4.12 System Dynamics Model

More specifically, the first component (Fig. 4.12 (a)) calculates the individual energy consumption for HVAC and lighting while the total daily energy consumption (i.e., final outcome) is calculated in the second component (Fig. 4.12 (b)). The third component (Fig. 4.12 (c)) calculates the cooling load, which is linked to the second component (Fig. 4.12 (b)) to calculate the total daily energy consumption. Typically, the cooling load is greatly influenced by various factors such as the wall temperature, wall area, heat transfer coefficient, flow rate, heat gain from occupants, etc. Furthermore, as a secondary component, the fourth component (Fig. 4.12 (d)) calculates the indoor CO_2 concentration (ppm) to consider it as one of the factors in the energy calculation of the second component (Fig. 4.12 (b)). The calculation of cooling load and internal gain can be found using the following formulas.

4.6.1 Cooling load estimation

The cooling load corresponds to the total rate of energy required to keep both indoor temperature and humidity at a given value. In accordance with Bueno et al. [223, 224], from the perspective of occupants, it is preferably expected that the cooling system provides the exact amount of fresh air to keep the indoor temperature and specific humidity at given values T_{in}^* and $\mathrm{s}_{\mathrm{in}}^* = f(T_{in}^*, \Phi_{in}^*, p_0)$, known as setpoints. The ideal cooling load $q_{cool}^* = H_{cool}^* + LE_{cool}^*$ can be mathematically as:

$$H_{cool}^* = hA_{walls}(\underline{T}_{walls} - T_{in}^*) + H_{ig} + \dot{V}_{inf}\rho c_p(T_{out} - T_{in}^*) \quad (4.1)$$

$$LE_{cool}^* = LE_{ig} + \dot{V}_{inf}\rho l_v(s_{out} - s_{in}^*) \quad (4.2)$$

Equations (4.1) and (4.2) consider the steady state of indoor temperature and specific humidity. Where, h is convective heat transfer coefficient (W/m^2 K), A_{walls} is the total surface area (m^2) of indoor walls, T_{walls} is the average temperature (^0C) of indoor walls, T_{in} is the indoor temperature (^0C), H_{ig} is sensible heat gain(W), $V_{inf}^{\cdot}$ is the Volume flow rate (in m^3/s), C_p is the specific heat of air (kJ/kg), ρ is air density (Kg/m^3), T_{out} is the outdoor temperature (^0C), LE_{ig} is latent heat gain(W), l_v is Latent heat of vaporization (J/kg), S_{out} is outdoor specific humidity, and S_{in} is indoor specific humidity.

4.6.2 Internal heat gains by occupants

Sensible and latent heat gains H_{ig} and LE_{ig} will be assessed from measurements of occupancy, lighting, and power supplied to electrical equipment. They can be mathematically expressed as:

$$H_{ig} = \underline{H}_{metabolic} \cdot N_{people} + A_{in} \cdot f_{sa} \cdot (\eta_{lighting})^{-1} \cdot I_{lighting} + \eta_{equipment} \cdot W_{equipment} \tag{4.3}$$

$$LE_{ig} = \underline{LE}_{metabolic} \cdot N_{people} \tag{4.4}$$

where $\underline{H}_{metabolic}$ is the sensible metabolic heat gain from occupants (W/person), $\underline{LE}_{metabolic}$the latent metabolic heat gain from occupants (W/person), A_{in} the floor surface area of the indoor space (m^2), $f_{sa}$the special allowance factor related to the type of light is available (dimensionless), $\eta_{lighting}$the efficiency of lighting (lumen/W), $I_{lighting}$ the average illuminance of lighting (lux), $\eta_{equipments}$the efficiency of electrical equipment (W/W), and $W_{equipments}$ the total power supplied to electrical equipment(W).

Similarly to occupancy, the average illuminance $I_{lighting}$ and the total power consumption of electrical equipment $W_{equipments}$ will be computed by averaging measurements within a 1-hour time frame. Characteristics of fluorescent light (i.e., f_{sa} and $\eta_{lighting}$) can be found in ASHRAE standards [225]. Electrical equipment is primarily computers and monitors.

4.6.3 Indoor temperatures and CO_2 generation

In this stage, the SD model will run based on two formulas. The first formula (Equation 4.5) established by Givoni [226] for indoor temperatures prediction for the similar types of thermal mass is as follows:

$$\text{Tmax} - \text{in} = \text{Tmax} - \text{out} - 0.31(\text{Tmax} - \text{out} - \text{Tmin} - \text{out}) + 1.6 \ldots\ldots\ldots\ldots\ldots (4.5)$$

Here,

T_{max-in} = Maximum indoor temperature (^{0}C).

$T_{max-out}$ = Maximum outdoor temperature(^{0}C); and

$T_{min\text{-}out}$ = Minimum outdoor temperature(^{0}C).

The above formula expresses building with the continuous cross-ventilation system, where the maximum indoor temperature (i.e., Tmax-in) leads to the variation of maximum outdoor temperature (i.e., $T_{max\text{-}out}$).

The second formula (Equation 4.8) defines the current technique which is used in the ventilation and Indoor Air Quality (IAQ) study to estimate the amount of CO_2 generated from the building inhabitants. Currently, the ASHRAE Fundamentals Handbook [227] and ASTM D6245 [228] define the rates of CO_2 generation as follows.

The oxygen consumption rate (L/s) per occupant is specified by Equation 4.6,

$$\text{Volume of O2} = \frac{(0.00276 * \text{AD} * \text{M})}{(0.23 * \text{RQ} + 0.77)} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.6)$$

Here:

AD = DuBois surface area (m^2);

M = Rate of metabolic (met); and

RQ = Respiratory quotient (dimensionless).

Usually, DuBois surface area (AD) is estimated from occupant height H (m) and the body mass W(kg) as follows:

$$\text{AD} = 0.202\text{H}^{0.725} * \text{W}^{0.425} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4.7)$$

So, the rate of CO_2 generation (L/s) per occupant is given by Equation 4.8,

$$\text{Volume of CO2} = \text{Volume of O2} * \text{RQ} = \frac{0.00276\text{AD}*\text{M}*\text{RQ}}{0.23*\text{RQ}+0.77} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4.8)$$

The above-mentioned resulting indoor data (i.e., room temperature) generated by the SD model was further used to run the ABM model. So, in this stage, to create an ABM model that contains individual occupant comfort levels (i.e., PMV indices) with the dynamic variation of indoor parameters at different time intervals. The details of java codes in any logic platform for the SD model have been demonstrated in **Appendix II.**

4.7 Model demonstration

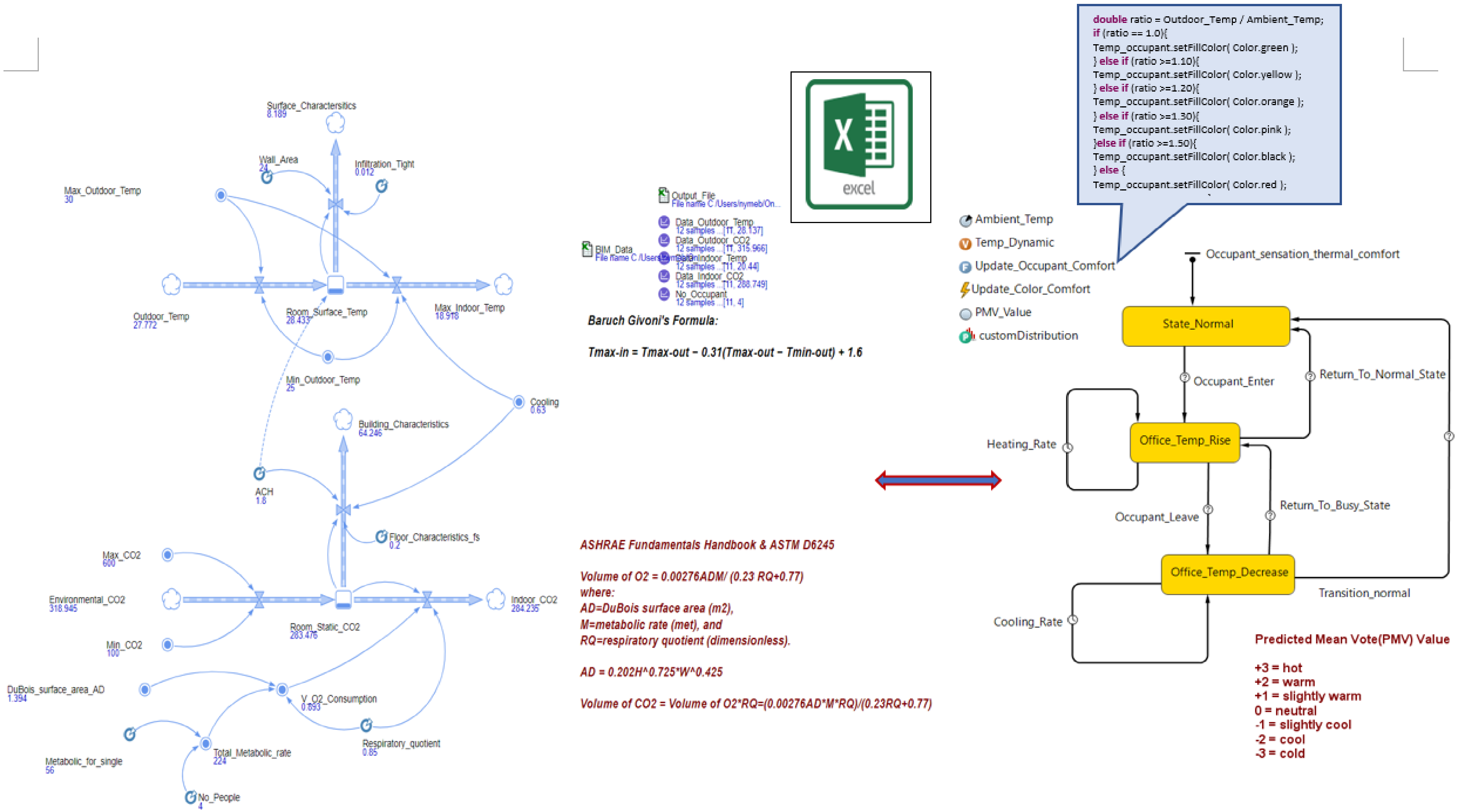

Figure 4.13 Data exchange between SD (Left) and ABM (Right)

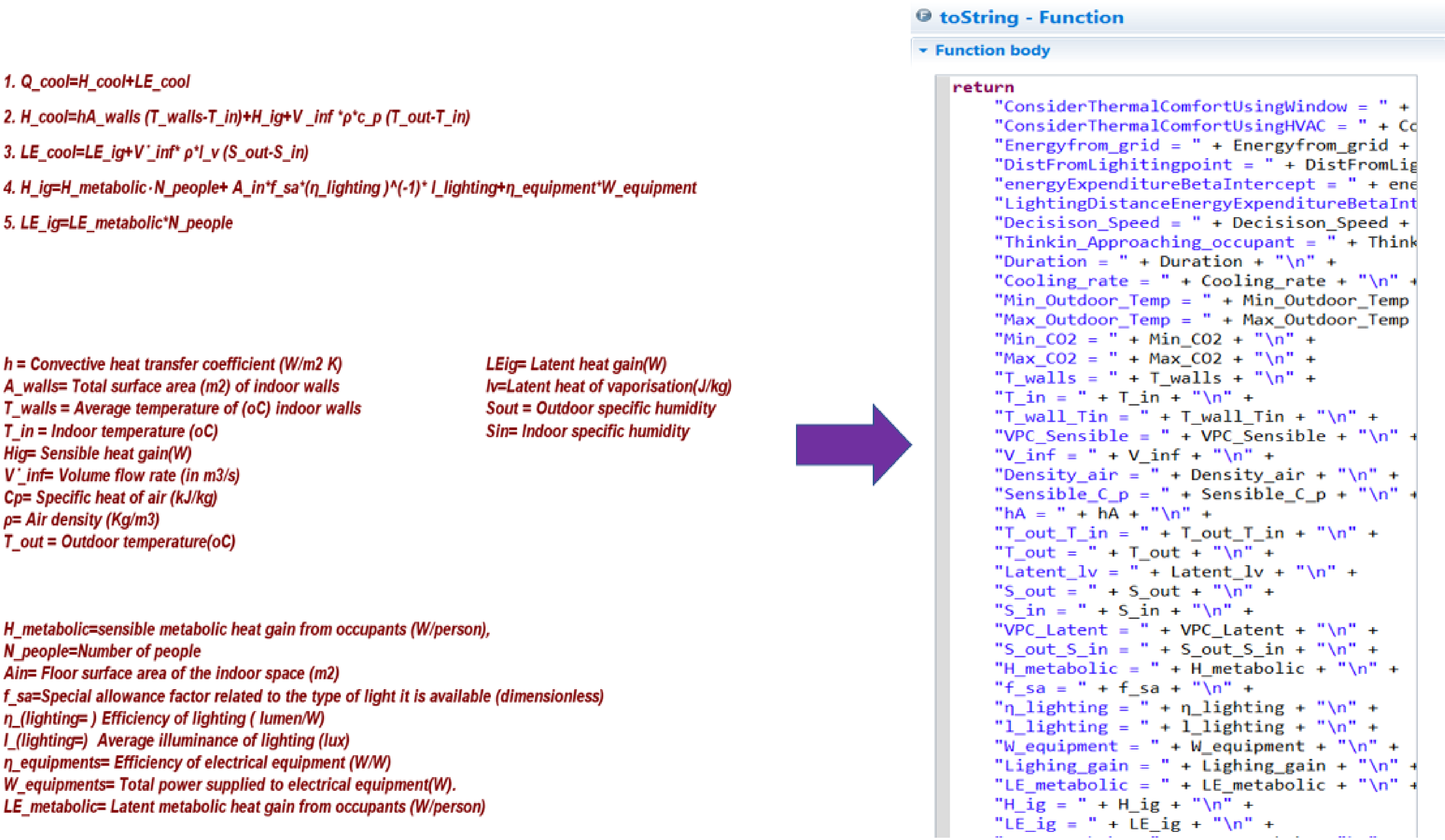

Figure 4.14 Function body for the required equations (SD component)

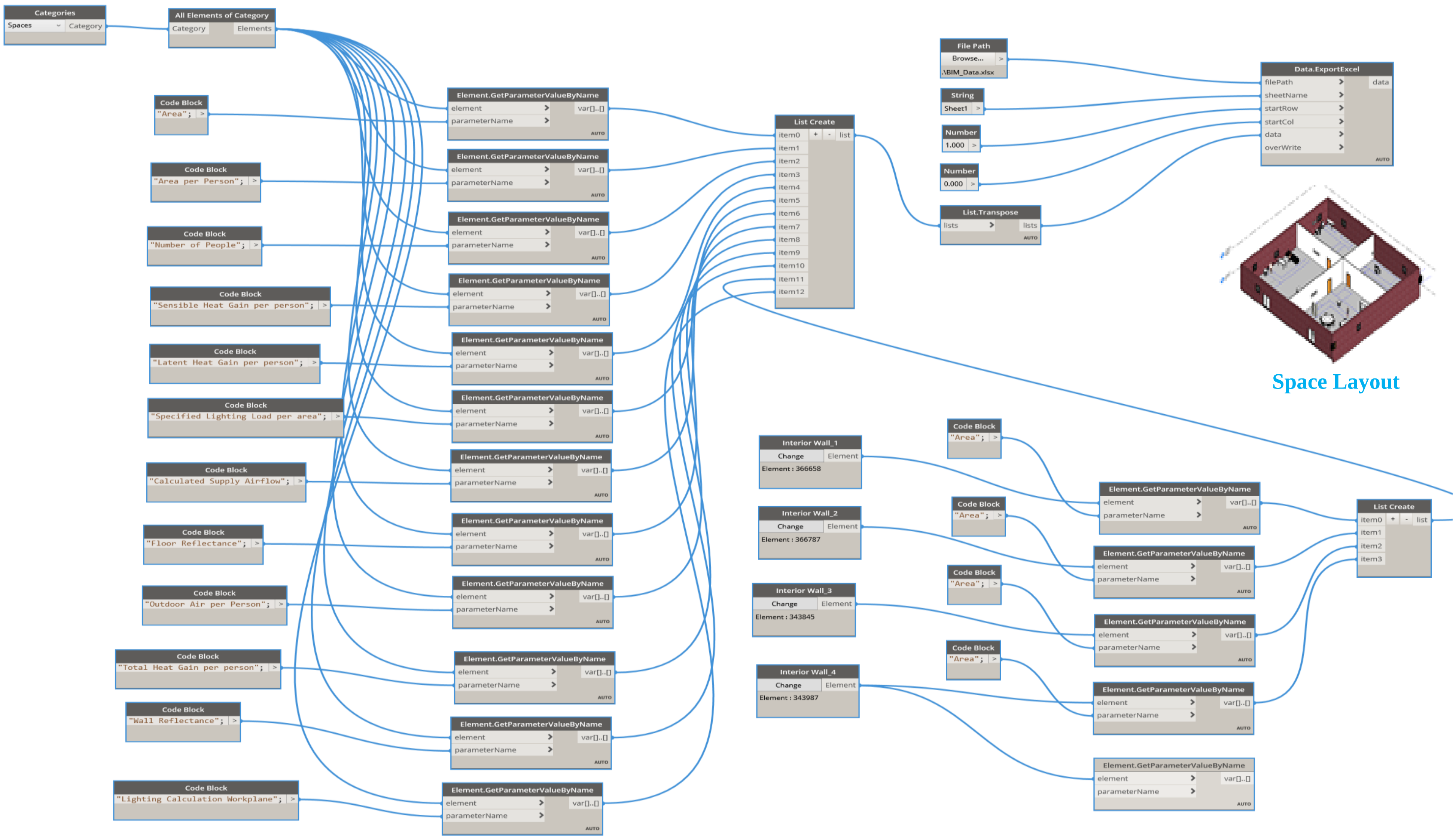

Figure 4.15 Automated Space Data Generation using Dynamo_API (Application Programming Interface)

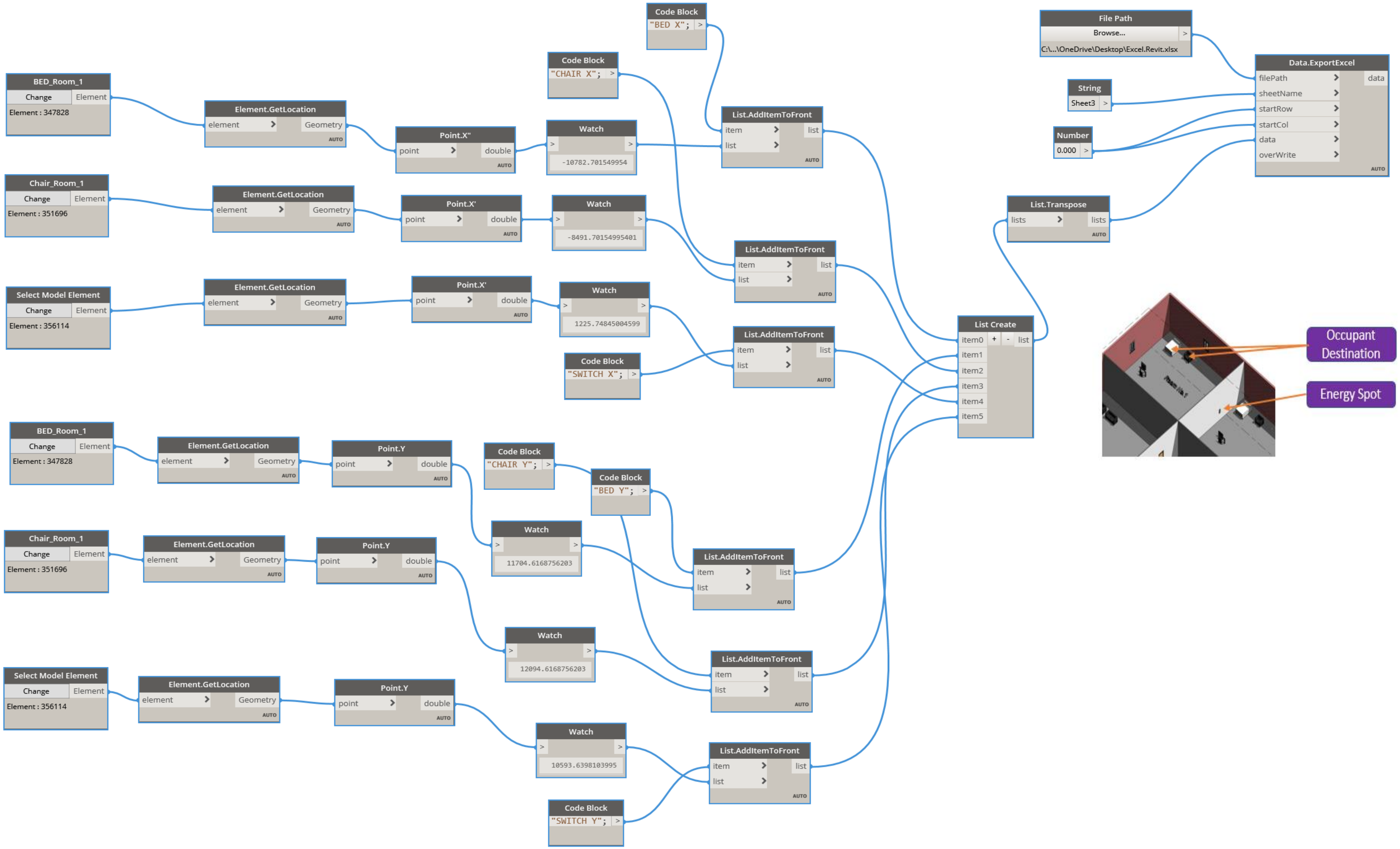

Figure 4.16 Automated Coordinate Data Generation using Dynamo_API (Application Programming Interface)

4.8 Chapter Summary

This chapter step by step explained the model construction process along with some demonstrative examples. The study fulfills its aim by proposing and constructing a comprehensive hybrid model using ABM-SD-BIM for the indoor layout based occupant behaviour study. The subsequent Chapter will be described the thorough intervention and validation approach implemented for this model as well as fill the research objectives 4 and 5.

CHAPTER 5
INTERVENTION & VALIDATION [5]

5.1 General

Technology alone won't accomplish occupants' energy conservation purposes. Occupants and their associated energy behaviour in buildings should be understood for better energy performance. Despite numerous studies pointing out the inhabitants' behaviour relation and building energy performance, the knowledge of occupant behaviour and its position in overall energy performance stays complex, unclear, and conflicting. Along these lines, more research spotlight should be put on combining occupants basic elements into energy consumption profiles. For instance, selecting intervention systems, i.e., building layout deployment, and information programs for occupants, needs to be considered to improve the existing energy consumption. Thus, this chapter mainly described several contextual interventions followed by the intervention and validation approach implemented in this study.

5.2 Several Contextual Intervention

It is shown that the residents behaviour adopts a considerable position in energy consumption in line with the earlier research on different intervention strategies to change behavioural practices. As an efficient behaviour measure, Azhar & Pisello [179, 180] have been presented a target direction on the plan of interventions for residential dwellers. It is also associated with the design process of persuasive systems [83] that may add to the advancement of effective actions to change occupants behaviour and improve sustainability. Hook and Wyon [229, 230]

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[5] This Chapter is partly published and under review in:

1. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. An Assessment of Occupant Comfort and Behavioural Influence on Building Indoor Layout: A Collaborative Analysis Using Statistical and Agent-Based Simulation(Under Review).

2. **Uddin, M. N**., Chi, H. L., Wei, H. H., Lee, M. & Ni, M. Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling (Under Review).

have observed particular social interventions to lessen energy consumption by as much as 20% while several energy behaviours transitions and action plans were executed. In this context, social interventions are consciously applied that can change energy consumption behaviours amongst the occupants. The method utilized for social interventions is mostly dependent on the users in question and what matters/issues need to be focused on [231]. Especially, energy-linked social interventions are useful when this one fits the occupants engaged and are inexpensive in terms of time, effort, money, or social dissatisfaction, and when occupants do not cope with severe behavioural limitations [232]. Moreover, interventions can expose the behaviours/attitudes that are not environmentally friendly and why homeowners/inhabitants are unresponsive in implementing sustainable behaviour profiles [56]. These all findings guide the researchers on the greatest intervention method to implement. For instance, Zvingilaite [233] emphasized the advantages of regular intervention, prolonged, disaggregated, and continuous feedback. Another study [234] found that direct feedback provided by In-Home Display (IHD) encourages the inhabitants to make more energy-efficient behaviour. However, a growing body of research [56, 119, 235-238] has now begun to investigate several contextual factors (e.g., social, economic, housing structure). The research involves the low-income dwellers that contribute to universal studies on the advancement of energy-efficient behaviour, and products, and offers insights for policymakers in Bangladesh and other developing economies. Thus, interventions reviewed include the provision of information, feedback, and rewards, all of which aim to change individuals' knowledge and perceptions of energy conservation activities. This comprehensive study [239] offered nine different types of intervention for specific purposes. Among these, this study mainly considered the Enablement intervention that mainly deals with the reducing barriers or obstacles to prompt occupant behaviours towards the sustainable attitude. During the experimental phase, this study primarily reorganized the indoor layout configurations based on potential flexibility that eventually minimize the challenges or impediments for individual occupants. In this sense, Enablement is the appropriate approach as an intervention strategy.

Therefore, the study implemented a real-time indoor layout-based intervention approach by considering the Interior Layout deployment on occupant energy conservation behaviour. Here, Interior Layout is characterized as the interior allocation of various spaces that incorporate the interior arrangements of buildings, such as interior furniture, equipment, etc.[79, 100]. The detailed intervention approach implemented in a selected case study location in Chittagong, Bangladesh, has been described as follows:

5.3 Experimental Settings for Intervention

Eight residential problematic Interior Layouts (shown in Figure 5.1), including their inhabitants, have been recruited for this experimental study. The occupants comprised 16 males and 16 females from the selected apartments. All occupants were in the age range between 20 and 60. Usually, occupants have been provided with an information sheet explaining the study's aim and objective. In the meantime, occupants' approval **(Appendix-III)** was taken using the standard approval form. Afterward, the occupants were invited to change their problematic layout position for a particular period of time (i.e., May 2020-July 2020).

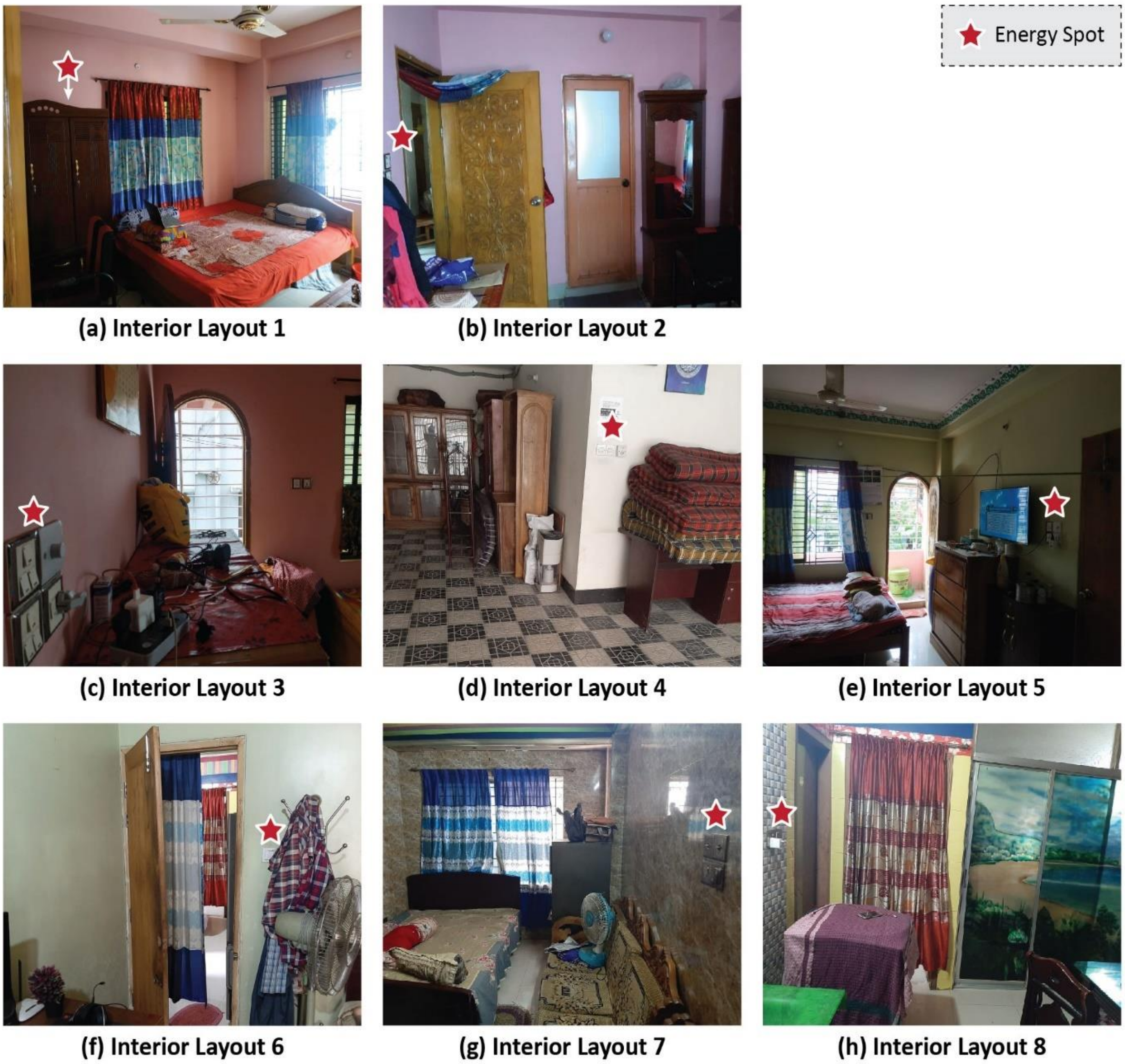

Figure 5.1. Typical problematic layout in a case study location: a) Interior Layout 1: Energy spot inaccessible, b) Interior Layout 2: Energy spot partially accessible from an adjacent edge, c) Interior Layout 3: Energy spot accessible over an object, d) Interior Layout 4: Longer distance (>10ft) between occupant station and energy spot, e) Interior Layout 5: Average distance (>5ft) between occupant station and energy spot (forward direction), f) Interior Layout

6: Average distance (>4ft) between occupant station and energy spot (lateral direction), g) Interior Layout 7: Short-distance (3ft) between occupant station and energy spot (backward direction), h) Interior Layout 8: Energy spot is a forward direction (short distance, 2ft)

In this regard, occupants were requested to change their problematic layouts to the best possible one (described earlier/similar to Interior Layout 8). It is also noted that selected Interior Layouts have similar dimensions/areas that are approximately 180-200 square feet. Typically, these selected layout helps the better rearrangements of interior stuff due to adequate indoor space dimensions/area. For instance, if the energy spot is inaccessible/ not visible, occupants change some interior stuff or re-organize the interior allocation, so the energy spot is easily visible and within the occupant ranges. In addition, it is assumed that ambient conditions during the real-time intervention are analogous.

5.3.1 Data Monitoring Devices/Customize Sensors

During the experiment, energy consumption data from each Interior Layout were collected using the fitted customize sensors shown in Figure 5.2. Each sensor network comprises four sensors (e.g., temperature, humidity, CO_2, and energy calculation). The time period for energy data extraction was 1 minute, and these data have been stored on a Desktop connected to a wireless area network with fixed IP shown in Figure 5.3

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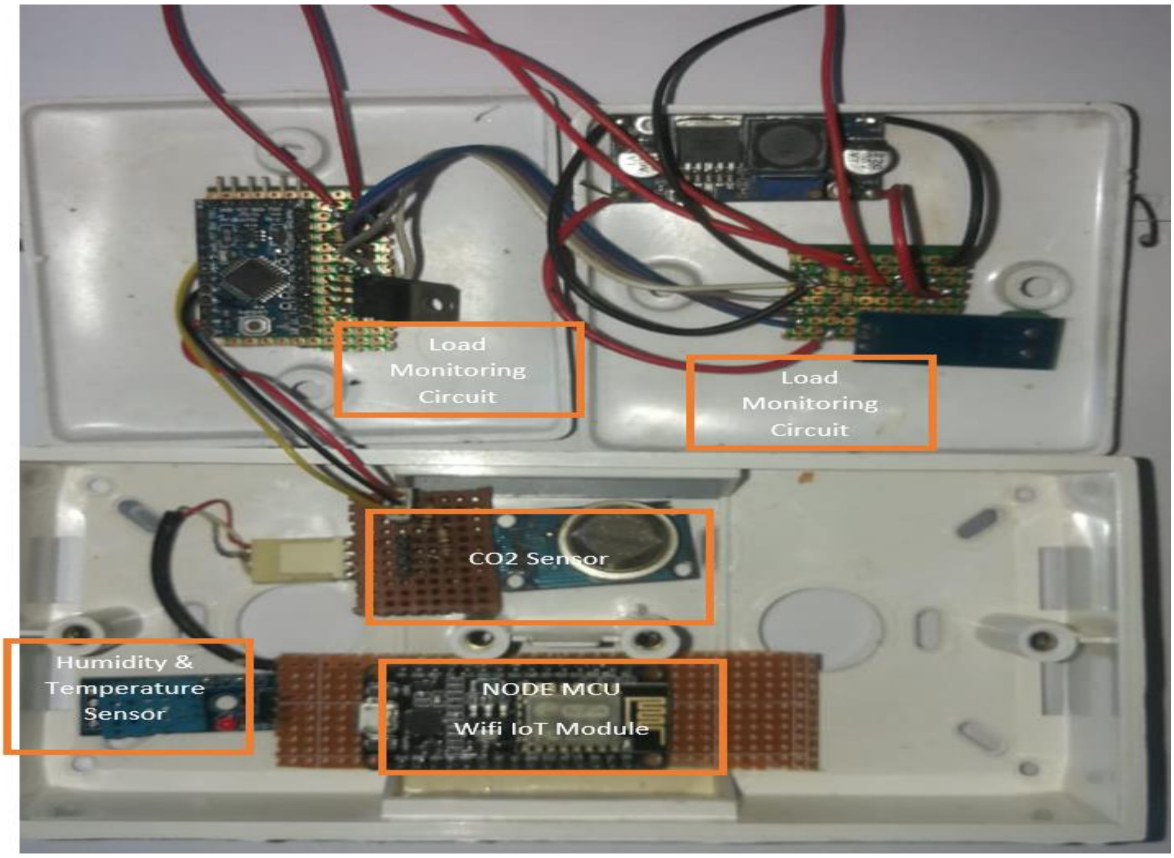

Figure 5.2 Interior components of the customized sensor panel

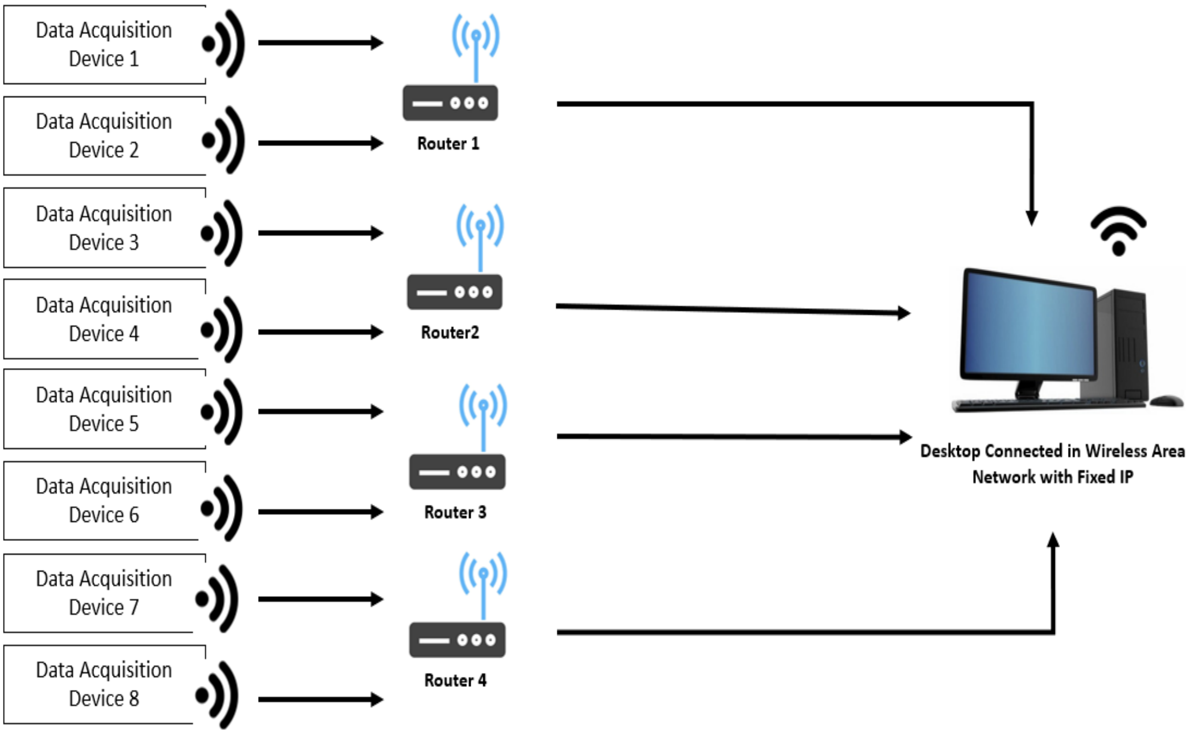

Figure 5.3 Data acquisition technique

5.4 Data Collection Techniques

Data collection techniques enable the systematic gathering of information about the object of study while taking into consideration the setting of the information gathering. In choosing the data collection method, it is important that the depth and scope should be taken into consideration [240]. The data collection process in this study mainly two parts, such as

1. Energy consumption (HVAC/Fan, Light) data and
2. Environmental (Temperature, CO_2, etc.) data

Before starting the experiment, above mentioned customized sensors and environmental sensors have been installed and run for the selected eight rooms. Considering the scale of the Interior Layout, eight customize sensors have been installed, and each customized sensors include four monitoring sensors.

5.4.1 Energy consumption data using customized sensor platform

Other than building energy modelling, which is a largely passive approach, active methods could provide better control through timely data. The latter can be directly measured by the use of customized sensor nodes or by using the smart meter for several components of the cooling system [241-243]. A network of sensors and smart power meters can be a new way to minimize the cooling energy use within a building while maintaining a satisfactory level of indoor comfort [244]. With the smart sensors, building energy usage and indoor condition can be collected in real-time. Occupancy corresponds to the number of people within a building that can be managed easily at a given instant. In contrast with occupancy, light intensity (in lumen/m^2) is directly measured from a sensor [245]. In addition, the power consumption (W or kWh) of electrical equipment like TV or computers can be collected from a smart sensor or power meter as well [246].

Thus, in this study, the customized sensor node has measured related energy consumption data from individual appliances. This sensor node consists of an embedded board microcontroller computer where three isolated sensors record energy consumption by HVAC/Fan(kWh), Light(kWh), and ambient data. The time duration for data collection was 1 minute for three months, and all data were stored on a desktop PC via Wi-Fi networks.

5.4.2 Environmental data monitoring

Similar to energy consumption data, indoor environmental data were also collected using the customized sensor. From each sensor, dry bulb temperature (^{0}C), relative humidity (%), and CO_2 concentration(ppm) have been collected.

For the occupancy rate, it is referred to as binary values, where “0” means that nobody is detected, and “1” indicates someone is present in the room. The active rate of electrical energy consumed by HVAC and Light has been measured by the smart sensor. Table 5.1 shows the dimensions of each indoor space and the number of occupants where customized sensors and environmental sensors have been installed. Also, the individual floor plan has been employed to estimate the floor surface area of a specific room. By considering the average floor height of 3.5 m, the indoor air volume was assessed from the floor surface area.

In the meantime, an occupancy-based survey covered a broader scope of study purposes through the use of some questionnaire surveys, structured observations, and interviews to collect quantitative and qualitative data. Representative sample data could be collected economically with the help of a survey. Since this research seeks to collect data from a narrow scope (energy saving intention on layout preference) of respondents from the households, the questionnaire survey is the most appropriate data collection technique.

Table 5.1: Indoor space information for both landlord (L)and Tenant (T)

Room No	Occupant Type (L/T)	A_{in} (ft^2)	A_{walls} (ft^2)	No. of People
Room No.1	L	180	300	4
Room No.2	L	190	320	5
Room No.3	L	180	300	4

Room No.4	L	190	320	5
Room No.5	T	200	340	6
Room No.6	T	180	310	4
Room No.7	T	180	320	5
Room No.8	T	190	330	5

In addition, a daily survey with multiple behaviour decisions and related time intervals or duration was also recorded. For adjusting the data accuracy and to minimize the occupants disturbance, the time record interval was set to around 60 minutes from 8:00 to 23:00. Further schedule may be added as per occupants (both tenants and landlords) actual timetable. The typical survey/data collection sheet is attached in Figure 5.4. The targeted occupants have been asked to modify the starting condition of the specified building components (Light, Fan usage, etc.) every day; afterward, they manually make a tick sign at a specified box related to a definite time period while a household behaviour appears. This daily survey has been used only for validating the sensor data for several days (cross-validation). The human survey was also approved (**Appendix-III**) by the prescribed authority to protect the people's privacy in the experiment. In the meantime, a set of customized and environmental sensors have been installed in individual rooms to collect their energy consumption and ambient data (i.e., Temperature, CO_2, etc.).

Room No.

Date:

Time	Door		Windows			Heating/Cooling state		Light		TV	
	On	Off	On	Off	Partial	On	Off	On	Off	On	Off
12:00-12:30											
12:30-1:00											
1:00-1:30											
1:30-2:00											
2:00-2:30											
2:30-3:00											
3:00-3:30											
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10:00-10:30											

Figure 5.4 Daily Survey Data sheet (Only for cross validation)

5.5 Model Validation/ Performance Test

The reason for building a hybrid model is to assess how the building occupants interact with different building energy components under a particular environmental condition. The simulation outcomes from the developed ABM-SD-BIM are verified with the recorded behaviour by implementing calculated performance metrics as well as visualization.

5.5.1 Validation using Error Metrics

The above-stated hybrid model-produced energy data evaluation process has been reviewed. The goal is to check the energy data reliability/validity and the performance of the proposed hybrid model. Herein the data validity approach of computational results has been presented utilizing the practical data gathered from the customized sensor network. Primarily, practical or realistic data is empirical, often known as "true" data, and it is recommended as a powerful validation system [119, 124]. Typically, results found from the simulation model to be reliable, the data made from these models or tools need to be within an acceptable limit [124]. Moreover, for reliability tests (by checking the calibration tolerance), it is essential that depth and scope have to be taken into account.

Here, energy data produced from the hybrid model are validated against the real energy data collected from the eight customized sensor panels installed within the eight residential apartments located in Chittagong, Bangladesh. In this practice, ASHRAE standard 14-2002 [209], FEMP guidelines [210], and IPMVP standard [247, 248] have been followed to verify the data acceptance. This checking includes verifying three dimensionless indexes of errors, for instance, Co-efficient of Variation of Root Mean Square Error CV(RMSE), Coefficient of Determination (R^2), and Mean Bias Error (MBE) [248]. According to ASHRAE standard, 14-2002 and FEMP regulations, the standard calibration acceptance of CV(RMSE) and MBE are 30% and ±10%, respectively, while system-level adjusted with hourly observed data [28, 248]. On the other hand, as stated by IPMVP, the acceptable values of CV(RMSE) and MBE are 20% and ±5% correspondingly [247]. The MBE and CV(RMSE) are calculated and verified to be consistent with the ASHRAE, FEMP, and IPMVP guidelines. Equations (5.1) and (5.2) have been used for CV(RMSE) and MBE calculation. Here, Tavg.m. is the average monitored data for n observations, n is the number of the observations, Ts and T_m are the simulated and monitored data, respectively for n observations.

$$\mathrm{RMSE}(\%) = \left(\frac{100}{T_{avg}}\right) \times \sqrt{\frac{\sum\ (T_s - T_m)^2]}{n}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5.1)$$

$$\mathrm{MBE}\ (\%) = \left(\frac{100}{T_m}\right) \times \frac{1}{\mathrm{n}} \sum (T_s - T_m) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (5.2)$$

On the other hand, R^2 (coefficient of determination) signifies how close the model-produced simulated energy data are to the regression line of the computed energy data. This one is another statistical indicator frequently used to assess the model's uncertainty. Typically, the R^2 value is limited to between 0 and 1, wherein the higher value suggests that the simulated values completely fit the computed value and the lower value does not. According to ASHRAE guidelines, the acceptable R^2 should be greater than 75% [248].

5.5.2 Validation using Evaluation Metrics

The black-box validation technique has been proposed for the study validation as the White box validation approach already performed by Bharathy and Silverman [218] for human behaviour platforms. In Black-box validation, the validation primarily focuses on the final energy consumption outcomes, whereas the White-box validation approach emphasizes the internal structure and mechanism. There are two reasons for choosing the Black box approach: Firstly, AnyLogic is a java-based platform that is already well established and tested by previous researchers. Moreover, several documents have discussed the technical particulars of the AnyLogic tool [249-251]. So, it is not essential to assess the inner algorithms in this study. Secondly, as the study aim is to improve household energy conservation by adding/ calculating the occupants behaviour component, a Black-box approach is adequate to establish the model validity for the developed model. Thus, the model justification can focus on whether the outcomes of the developed energy behaviour model reflect reality. Therefore, integrating the data to further energy model would theoretically develop the modeling skill.

For validation purposes, four evaluation metrics have been used in this study to compare model simulation and real behaviour information, i.e., precision, recall, accuracy, and F1 score.
The numerical value covers the above four metrics from 0 to 1. The descriptions of each metric are simply explained using the information in this analysis. The condition of "occupant active" is supposed to be positive sample for all targeted behaviour components, and "occupant idle" is considered a negative sample. Hence, every simulation outcome of an energy behaviour element is categorized as:

i) Positive True (PT),
ii) Positive False (PF),
iii) Negative True (NT), and
iv) Negative False (NF)

For better understanding, for the HVAC/FAN, PT specifies the number of time stages when the model predicts the occupants/residents select the HVAC/FAN for their thermal comfort when he/she usage really. However, NF is the number of time stages when the model predicts the occupants/residents do not select HVAC/FAN while it's selected. Likewise, NT represents the number of time phases when the model predicts the occupants/residents do not use HVAC/FAN when really it is unused, and PF means the model predicts HVAC/FAN is used by the occupant, but really it is unused. Based on the above classes, the estimation for the evaluation metrics is as follows:

Precision = PT / (PF+ PT); Recall = PT / (NF+ PT); Accuracy = (NT +PT) / (PF + PT + NT + NF); and F1 score = 2PT / (PF + NF+ 2PT)

5.6 Statistical Analysis Using SPSS

5.6.1 Questionnaire Survey

A questionnaire survey has many advantages that make it suitable for this study. Notwithstanding the benefits, challenges such as selection bias and low response rate have been acknowledged [252]. Yet, in the light of the merits and demerits, a questionnaire survey stands out as the best option for human social contextual factors (e.g., age, gender, economy, etc.) analysis and comfort data collection.

Unless there are several ways to direct behaviour observations, the best alternative is simply to invite the person using a free-response structure. An inductive study looks like a favourable approach, asking respondents to illustrate a list of behaviours that reflects energy savings and comfort. It is similar to making the modal set of relevant beliefs in the ToRA model and might be a set of possible behaviours that would be focused on the study. The objective of the inductive study is to get a fast sense of fundamental concerns that best address the interior layout question in the study. Ultimately to use the responses from the induction survey as a foundation for building the general survey questionnaire. The first part of the questionnaire labelled "**Section A**" contains questions about the available information of occupants; the second part of the questionnaire labelled "**Section B**" includes questions about the occupant current perception of existing layout systems; the third part of the questionnaire labelled

"**Section C**" contains occupant core preference and opinion (Please **see the Questionnaire survey (c) in Appendix-III**).

From the survey study, two pieces of data might be gathered: a collection of salient behaviours that have effects on individual occupant energy consumption and comfort and the occupant attitude depth in presenting the energy savings behaviour in residential sectors. While the later can be applied as a rationalization for the selection of one layout categorization over the other, the relevant behaviours are crucial to further developing the questionnaire that will assess and gather data for hybrid model construction. The questionnaire mainly inquires about the several perceptions mentioned in the ToRA and questions related to some background information.

5.6.1.1 Location, occupants, and building types

Overspread an area of 2510 km^2 and 29 m above the mean sea level, Chittagong has a population of 2.59 million, and it is a large port city on the south-eastern coast of Bangladesh. The summer and the rainy season are from May to October, which is cloudy, warm, and wet. This study (questionnaire survey) was conducted in the summer month of July 2020. Occupants from 29 residential apartments were surveyed, including tenants and property owners, where all the apartments are in the residential areas of the central parts of Chittagong. The survey buildings are generally up to 3-5 stories and 10–30 years old.

5.6.1.2 Data sample and measurement

In this study, 104 occupants (both males and females from 19 apartments) were enlisted from the selected location for the semi-structured interview-based survey analysis. We do not want to disclose the actual address of the building's site for data security purposes. All occupants were in the age range between 17 and 75. As a convenient day for occupants, the data collection period was set from 1st July to 30th July 2020. Usually, selected occupants were provided with a data sheet explaining the study's aim and objective. In the meantime, occupants' agreement has been taken using the standard consent form. Afterward, the occupants were asked to freely mark their satisfaction level (satisfied/unsatisfied/neutral) anywhere on the questionaries' sheet. The sheet contains 7 Point Likert scale that offers satisfaction and unsatisfaction as to the polar points and a neutral option **(Appendix-III).** The data samples were grouped based on their sex, age, and ownership types. Subsequently, a descriptive statistical analysis was performed that quantitatively analyzed the data collected from the questionnaire survey. Data were analyzed using the Statistical Package for the Social Sciences (SPSS), window version

22. Herein, the Chi-Square test was used to examine the influence of contextual factors on the satisfaction of existing indoor layout systems. A $p<0.05$ was considered for statistically significant results. Furthermore, the 7-point Likert scale was used for calculating subjective PMV as a reliability study. The whole research methodology is also clearly elaborated in Figure 5.5

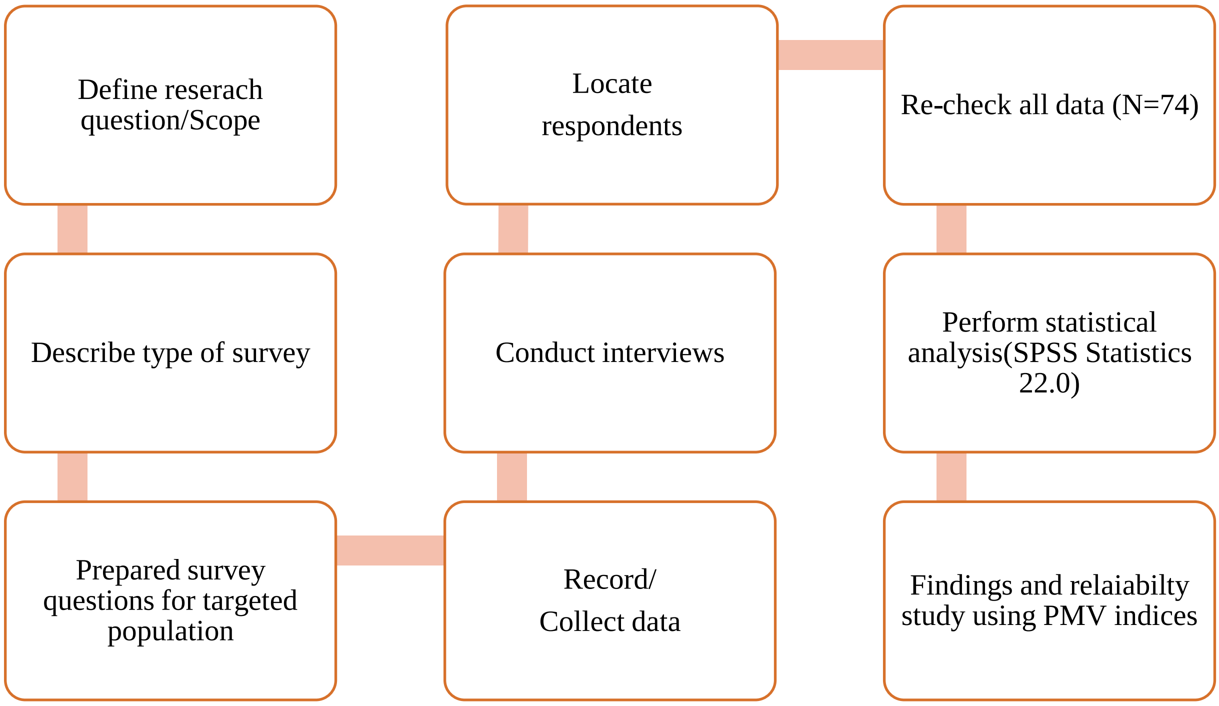

Figure 5.5 Statistical research procedure using the SPSS & PMV indices

5.7 Chapter Summary

This Chapter mainly explained the detailed intervention and validation study implemented in this study. This validation study has been used to check the hybrid model performance. Here, two types of validation studies have been considered, such as estimation of error metrics and confusion/evaluation matrix. Besides this, an occupant questionnaire survey was also used to investigate the influence of social contextual factors on existing building indoor layout systems.

CHAPTER 6
RESULTS & DISCUSSIONS[6]

6.1 General

The proposed hybrid model offers the generic functional modeling components and significant evaluation systems for the occupant decision-making process. Nevertheless, creating an occupant behaviour model for the particular built environment requires identifying the essential modeling rules, design components, etc. Additionally, there are no pre-defined standards or modelings rules for building occupant behaviours. The construction of occupant behaviour model should rely on the physical characteristics of preferred building types (or rooms) and their inhabitants. For instance, the activities and schedules of different rooms might differ due to their functionalities. Moreover, occupants may have full or limited control access to certain building systems. So, in this study, similar eight types of residential building spaces are selected as the case study testbed. Thus, the hybrid model construction, testing, and application are all based on the real conditions of the building. The detailed discussions on the hybrid model produced simulation output, and realistic data have been described in the following sections.

6.2 Simulation-based Outputs

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[6] This Chapter is partly published and under review in:

1. **Uddin MN**, Wang Q, Wei HH, Chi HL, Ni M. Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an integrated approach. Ain Shams Engineering Journal [Internet]. Elsevier BV; 2021 May; Available from: http://dx.doi.org/10.1016/J.ASEJ.2021.04.015

2. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. An Assessment of Occupant Comfort and Behavioural Influence on Building Indoor Layout: A Collaborative Analysis Using Statistical and Agent-Based Simulation (Under Review).

3. **Uddin, M. N.,** Chi, H. L., Wei, H. H., Lee, M. & Ni, M. Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling (**Under Review: Renewable & Sustainable Energy Reviews**).

4. **Uddin, M.N.;** Wei, H.-H.; Chi, H.L.; Ni, M.; Tamanna, N. Building Layout Influence on Occupant's Energy Consumption Behaviour: An Agent-Based Modeling Approach. Environmental Sciences Proceedings (Under Review).

6.2.1 Pilot Study for occupancy-based ambient data generation

The developed programmatic hybrid model was tested using an office building located in Hung Hom, Hong Kong, as a pilot case study. In this case, multiple simulations have been performed by considering a simple office building located at Hong Kong Polytechnic University. The following figures (Figure 6.1, Figure 6.2, and Figure 6.3) show the simulation outcomes of each category. These include individual comfort level, dynamic indoor/outdoor temperature, and CO_2 variation, as well as the stochastic nature of occupants presence in the indoor space. Usually, the simulation outcomes were calculated at a 1-minute interval. In general, indoor data in the office space is related to the individual occupants satisfaction level. The PMV value represents (Figure 6.1) that the occupant comfort level is not neutral (i.e., PMV = 0) throughout the simulation periods, whereas it was slightly hot or cool in summer (Figure 6.1: Left) and mostly cool during the winter season (Figure 6.1: Right). It was also observed that model calculated thermal comfort indices repeatedly fluctuated due to indoor temperature, CO_2 concentration, and occupants metabolic rate. There is a need to understand the relationship between the PMV values, clothing level, indoor temperature, and CO_2 concentrations. Generally, a wide variety of thermal conditions among the office occupants is a significant factor. And offices with warmer temperatures during the winter necessarily required a greater number of occupants. For further validation, the actual PMV indices have been obtained from the occupants (as individual comfort levels from cold (-3) to hot (+3)), and the calculated PMV indices are averaged. This describes how realistically the PMV indices can capture the actual comfort level under the current modelling approach. Moreover, it also appears that the blunder is higher in the hot climatic region compared with the cold climatic region. It is possible because the occupants' tolerances for thermal conditions of the hot and cold regions are completely disparate. Since this model was preliminary designed in Hong Kong, which is located in a hot, humid climatic region, the occupants who live in this zone may be more responsive to hot environments and have less tolerance for these conditions. Nevertheless, the indoor temperature and CO_2 concentrations are key factors dominating the occupant comfort level. Figure 6.2 and Figure 6.3 indicate the 10-day simulation outcomes of temperatures and CO_2 concentration as well. These outcomes reveal that indoor temperature and indoor CO_2 distribution in the office space are quite steady.

Typically, a rise in indoor temperature in an office room depends on both the occupant number (due to metabolic gains from occupants bodies) and the outdoor temperature intensity. In general, while the outside temperature and solar radiation are high during the daytime, heat gains from the building envelope (i.e., windows, walls, etc.) raise the interior temperature. The variability of the indoor and outdoor temperature was observed and shown in

Figure 6.1 Stochastic thermal comfort level for four occupants: summer season (Left) and winter season (Right).

Figure 6.2. The highest temperatures have been found on June 1st, 4th, 5th, and 6th during the daytime while the maximum occupancy. Moreover, the CO_2 concentration level and indoor temperature were also higher during this period. Throughout the 10-day simulation period, the

indoor temperature (^0C) in an office space has been measured in a range of 18.31^0C to 20.97^0C whereas the outdoor temperature was measured in a range of 25.5^0C to 29.87^0C. The peak level of the outdoor temperature is 29.87^0C which was recorded on June $1^{st,}$ while the interior temperature was stated to be 20.27^0C due to the control HVAC and tight infiltration system. The outcomes of the model computed indoor carbon dioxide levels based on several equations are presented in Figure 6.3. For most of the days, the indoor CO_2 levels started at *~575* ppm and rose to a stable value within 10-20 mins. There is a good correlation visible between the indoor CO_2 levels and the number of occupants. But indoor CO_2 levels did not exceed 1000 ppm on any of the days, staying below 900 ppm on most of the days. So, it indicated that the office had appropriate ventilation and air quality and was not a cause for occupant concern. Moreover, this value is accepted by the World Health Organization (WHO) as the maximum allowable value for indoor environments [253]. The highest level of outdoor CO_2 concentration observed for ten days of the simulation period was June 5^{th} (approximately 408.39 ppm). This is also a daytime fact when the office space is mostly occupied.

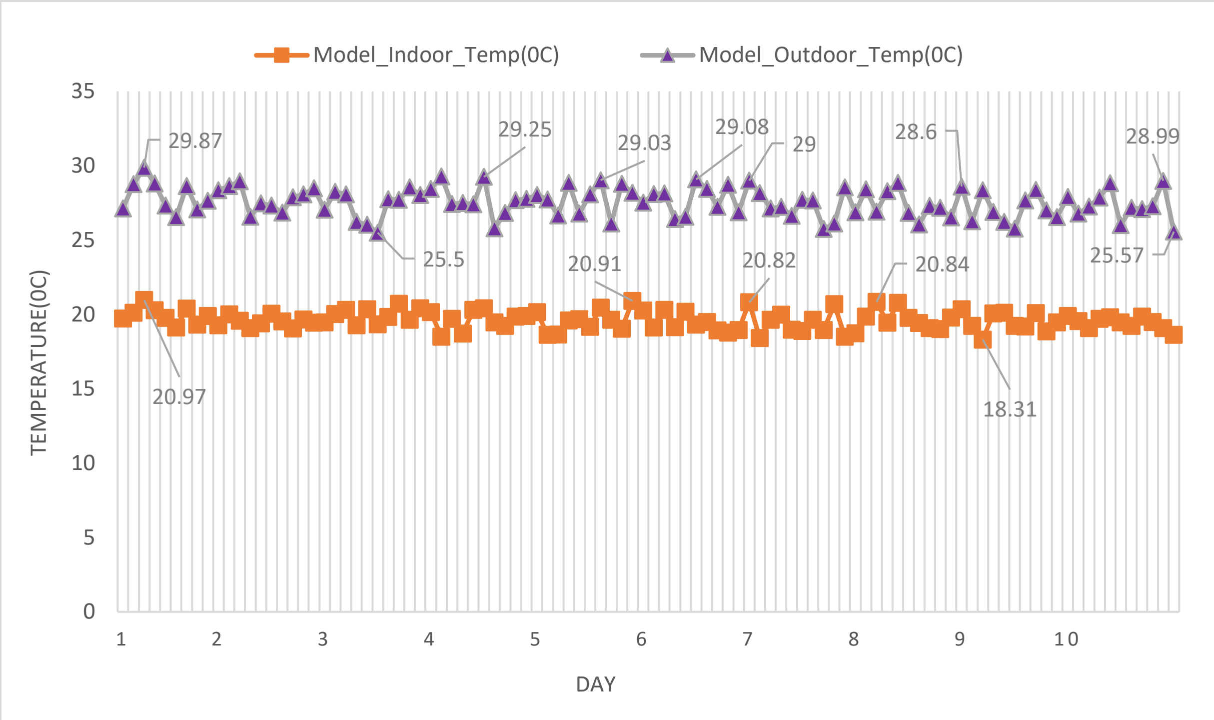


Figure 6.2 Indoor and outdoor temperature (^{0}C) variation in office space

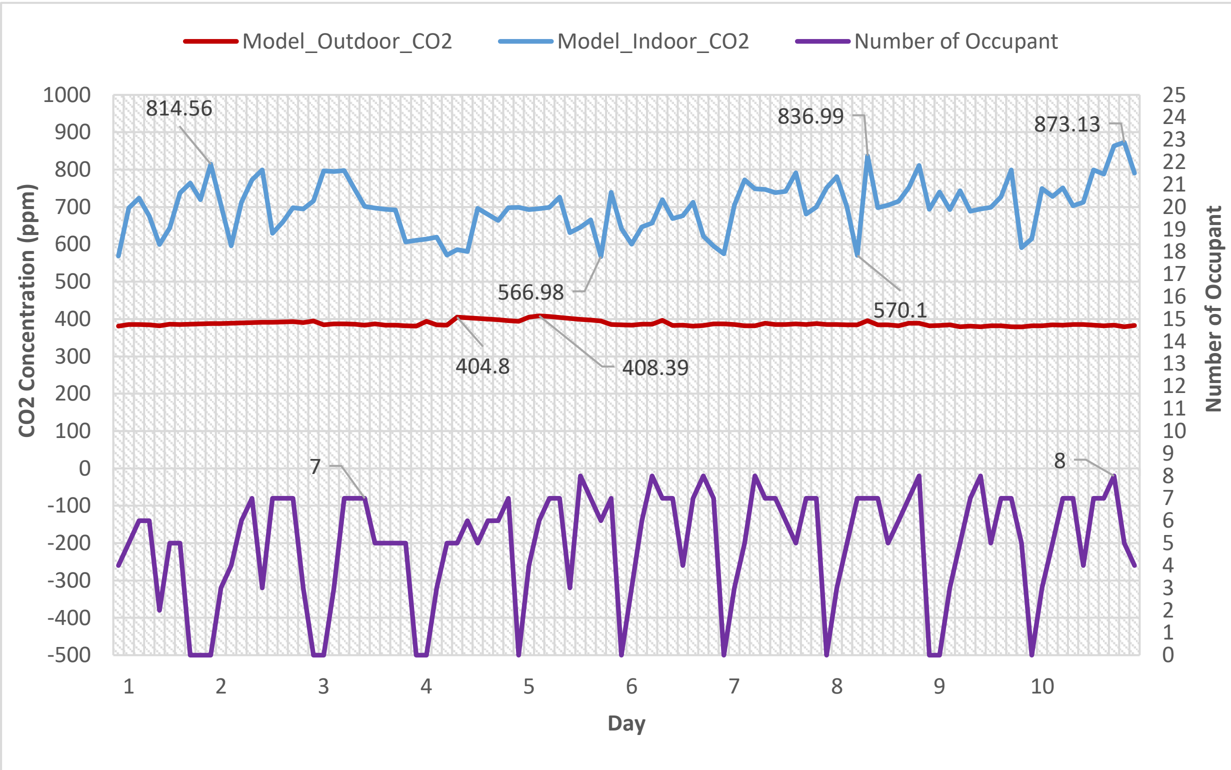


Figure 6.3 Stochastic nature of occupants with indoor and outdoor CO_2 concentration (ppm)

6.2.2 Simulation-based energy consumption profile for individual occupant

It is evidenced that individual behaviour assumes a significant position in energy consumption levels along with the past research. However, occupant behaviour is completely stochastic and random. So, model-generated energy consumption profiles for individual occupants are also random (Figure 6.4). From Figure 6.4, it has been revealed that under a similar environmental condition and the same time period, individual energy consumption profile is different when considering with intervention and without intervention. For instance, at a specific time period and ambient condition, an occupant agent, only consumes lighting energy while another occupant may use both HVAC and lighting energy. So, in this case, energy consumption patterns and potential savings for similar rooms are also different. Usually, occupant behaviour is illustrated by setting indoor temperature, scheduling equipment, lighting, and HVAC controls [31, 45]. These are exceedingly unpredictable and entirely random for an individual or group of occupants [38, 51]. Additionally, these factors also have a considerable effect on real energy consumption. Despite numerous studies pointing out the occupant behaviour relation and building energy performance, the knowledge of occupant behaviour and its position in overall energy performance stays complex, unclear, and conflicting.

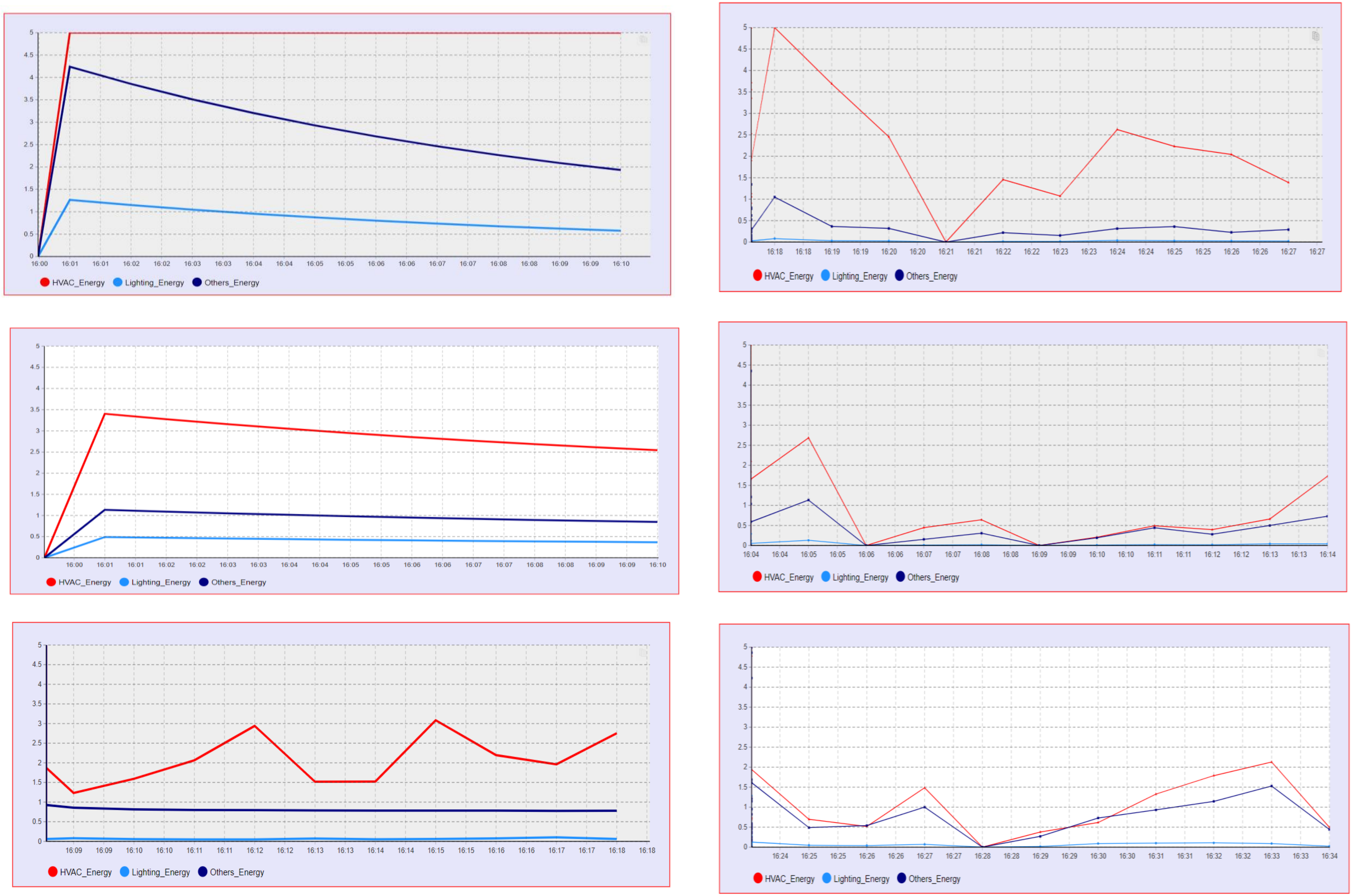


Figure 6.4 Stochastic energy consumption profile for three individual occupants (before & after intervention)

6.2.3 Simulation-based energy consumption profile for a group of the occupant (Residential)

The occupant energy consumption pattern before and after the intervention has been illustrated using several boxplots in Figure 6.5. The boxplot shows the minimum, maximum, mean, and median values, as well as the median 95% confidence in shading areas, first quartile, and third quartile. More specifically, the lines in the boxes stand for the median values, the boxes also encompass the mean 50% of the energy data, and the thin lines indicate the entire range of all data. The tiny circles show the outliners. The box plot demonstrates the occupant energy consumption pattern for different Interior Layout configurations considered in the case study. It signifies that not only the medians are unequal, but the interquartile range in each specified layout is also different. The simulation outputs also reveal that before intervention (i.e., considering the existing problematic layout), Interior Layout 1 (17.7 kWh), Interior Layout 2 (10.76 kWh), Interior Layout 3 (14.61 kWh), Interior Layout 4 (16.69 kWh), Interior Layout 5 (14.31 kWh) and Interior Layout 6 (16.80 kWh) have a higher energy consumption pattern than Interior Layout 7 (16.58 kWh) and Interior Layout 8 (16.25 kWh).

After the intervention (layout modification/restructured of layout) energy savings profile for different Interior Layouts has been changed significantly. More elaborately, due to applied intervention, the highest energy saving was found for Interior Layout 2, which was approximately 35.13%. At this point, the study noticed that before the intervention, it seems Interior Layout 1 was more problematic (as the energy spot is inaccessible/invisible) than Interior Layout 2 and Interior Layout 3; however, the energy-saving contribution from Interior Layout 1(14.69%) is comparatively less than Interior Layout 2 (35.13 %) and Interior Layout 3 (15.81%). In this regard, the findings reveal that occupants feel more discomfort whenever an energy spot is only accessible from an angular edge (e.g., Interior Layout 2) or partially accessible over an object (Interior Layout 3). In compliance with this, Consolo and others [254, 255] experimental studies showed that humans prefer to walk in straight and circular directions than angular tracks. Moreover, another study [255, 256] also mentioned that human walking path is significantly changed while their straight path is occupied, leading to occupant distress. Actually, occupant directional tendency is complex, and it is a multifactor event that varies from person to person and from culture to culture as well.

Furthermore, the energy savings trend as a result of intervention for Interior Layout 4 (longer distance) was 13.6%. In contrast, Interior Layout 5 (moderate distance, forward direction) and Interior Layout 6 (moderate distance, lateral direction) were 9.7 % and 12.2%, respectively. Although Interior Layout 5 and Interior Layout 6 are considered moderate distances, still occupant movement paths are different. Besides the complex human attitudes, occupant movement paths are also one of the reasons to show the distinct energy savings. Besides, Interior Layout 7 (1.08%) and Interior Layout 8 (0.8%) have been shown relatively lower energy savings as these layouts are approximately close to the best cases. Overall, the average daily energy reduction due to the applied intervention was about 14.9 %. From the previous investigations, assessments of effective indoor layout-based intervention are not widely available. However, these energy savings are quite significant compared to other intervention-based modelling studies [257, 258]. For instance, Abdallah et al. [259] used an agent-based modelling approach for energy messaging intervention while the average energy savings for wasteful occupants was 11% and for green occupants was 13%. On the other hand, Xu et al. [260] offered a five-element conceptual framework consisting of a reward-based integrated intervention approach. The framework generated energy savings of 8.18% and 12.56%, while the energy-saving targets were 5% and 10%, respectively. Moreover, Fijnheer et al. [261] studied a knowledge-based intervention that exhibited a difference of 12.9% in occupants energy consumption before and after the intervention.

It is noticed that, although there are almost analogous layout patterns that have been considered, however, energy-saving profiles from the particular layouts are entirely different, including best-case (e.g., Interior Layout 8). Moreover, Interior Layout 2 has shown higher energy savings than others. There are several reasons exists behind these, such as typical occupants behaviours are highly stochastic [12], random occupant perceptions of the space [204, 205, 262], interior space allocation/ arrangement [12, 204, 205], indoor ambient data [28, 199, 263], etc. Previous findings [28, 29, 79, 264] also revealed that space orientation and interior allocation (e.g., entrance, windows, door, and furniture's position, etc.) of the space within the design plan of the building and its other structural element, have a substantial effect on the individual energy consumption profile. This study also revealed that occupants' attitudes and social norms are the key influential drivers to changing or reducing the energy consumption pattern after the intervention.

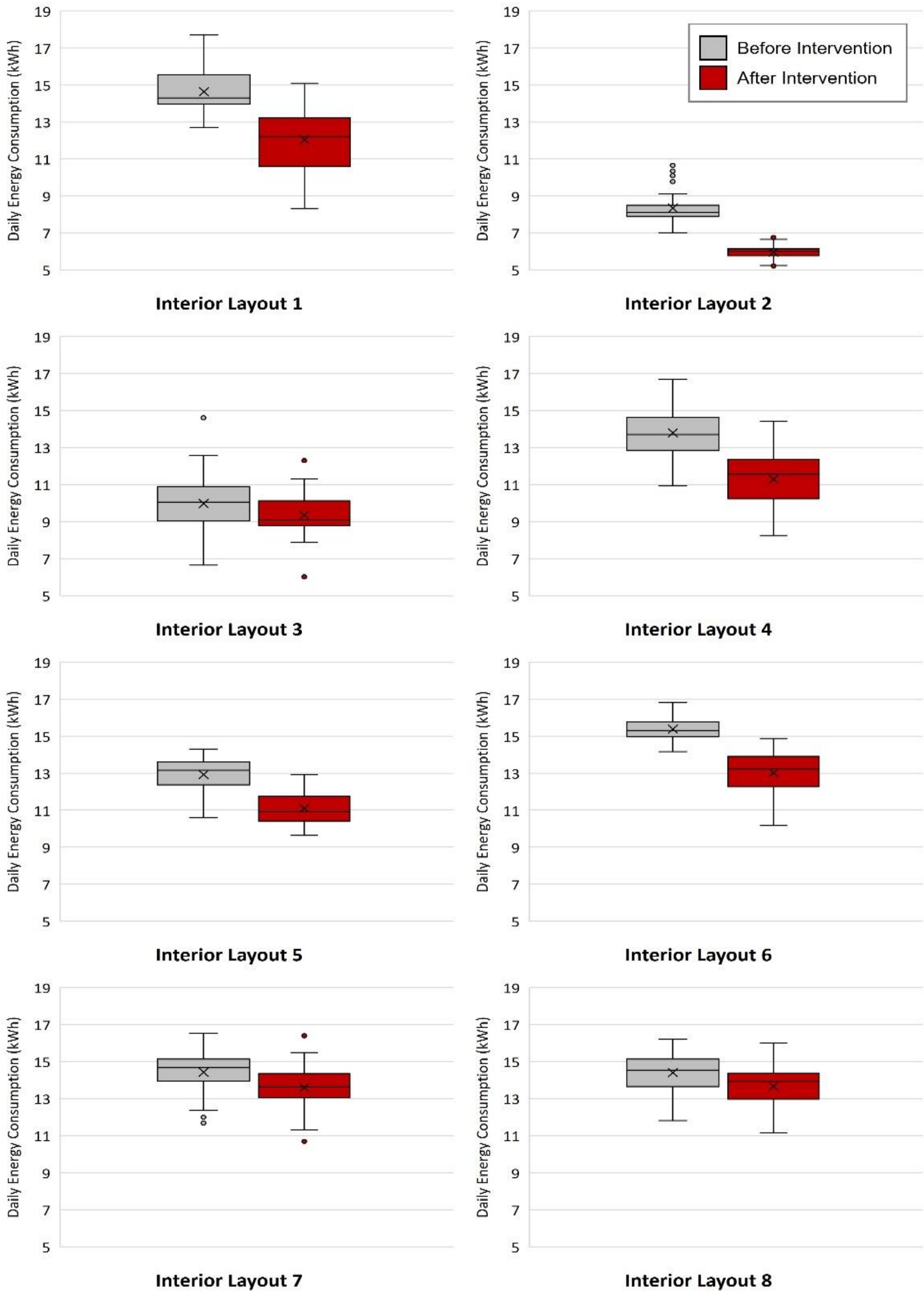


Figure 6.5 Simulation-based occupant daily energy consumption pattern before and after intervention

6.2.4 Thermal comfort for males and females (Residential)

After the multiple simulations, the individual comfort pattern has been categorized for both male and female occupants, shown in Figure 6.6. The simulation outcomes revealed that individual comfort patterns for a specific period are entirely random.

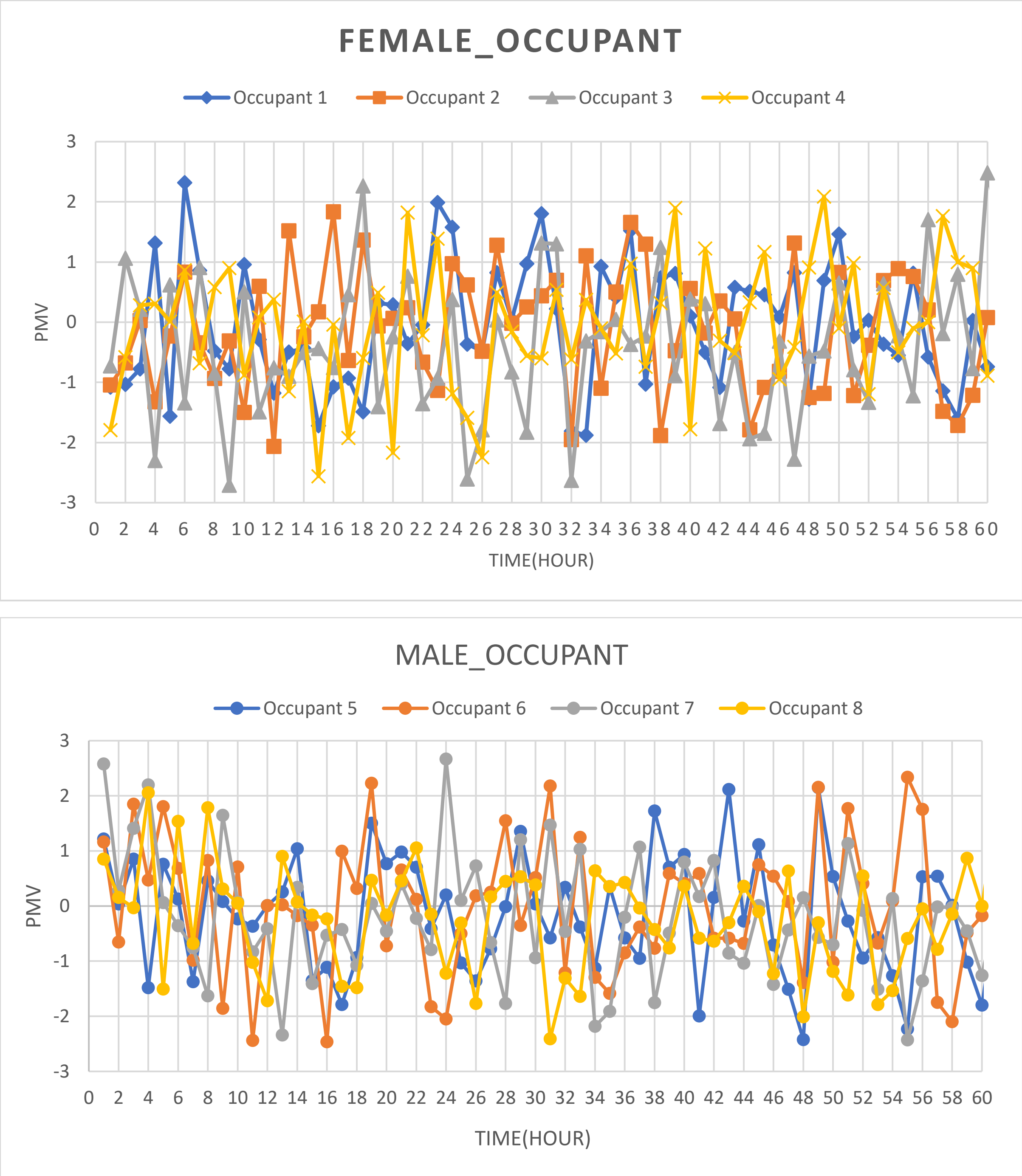


Figure 6.6 Stochastic comfort level for four females (upper) and four males (lower)

For PMV estimation, the hybrid model has been considered some essential quantities such as air temperature, humidity, airflow rate, clothing level and metabolic heat gains from the occupants. Several data are also (i.e., air velocity, mean radian temperature etc.) considered from the specified location context i.e., based on local building codes and the weather station (i.e., Chittagong weather station and Hong Kong Observatory). The model produced individual comfort levels throughout the simulation period suggesting that the comfort level for both male and female occupants was not neutral (e.g., PMV=0). If we evaluate both male and female occupants comfort levels using the PMV indices, it has been noticed that male occupants slightly felt a warmer environment (PMV≈+1). In contrast, female occupants slightly felt a cool environment (PMV≈-1) at the beginning of the simulation period. There is a comparatively higher dissatisfaction rate for female occupants than males. Several previous studies also revealed that female occupants are typically 1.5-2 times more likely dissatisfied with the indoor environment and layout systems than males [265-267]. Usually, occupant comfort and satisfaction level due to indoor layout configuration depend not only on interior layout configuration or design. It also relies on dynamic indoor environmental parameters such as temperature, CO_2, etc. Moreover, occupant metabolic heat gains are also important parameters to control comfort [28, 267].

6.3 Validation

6.3.1 Validation of PMV indices (For Pilot Study)

Ten office occupants were enlisted for the validation study as a preliminary pilot investigation. The office occupants have been working in a large office space situated in the Hong Kong Polytechnic University. The occupants comprised five males and five females from various nationalities. All the office occupants were within the age range of 23 to 35. The occupants were distributed with an information sheet clarifying the study's aims and objectives. Meanwhile, the occupants consent was obtained using the typical consent form. Afterward, the occupants were asked to assess their thermal sensation based on ASHRAE seven-point scale from cold (-3) to hot (+3). This was to collect the computed thermal sensation of the office occupants (-3 to +3) known as Real Mean Vote (RMV) where similar quantities (i.e., temperature, humidity etc.) have been assumed. The occupants were requested to freely mark anywhere on the scale at every 20-minute interval. These are the values that Fangers' PMV equation tries to forecast. Finally, in order to investigate the initial model validity, the model-generated PMV indices were compared to the real PMV data obtained from the office occupants. Figure 6.7 indicates the model-calculated PMV indices and occupant-reported

RMV indices for 20-minute intervals. Generally, the prediction success of the earlier PMV model never exceeded 30% [268]. When the PMV fails to predict the occupants thermal sensation perfectly, it usually undervalues it, especially the occupants stochastic nature and air speed within the space. In this study, the model-predicted PMV findings coexist with the other previous studies from different regions as well [268-271]. Also, this study revealed that there is an acceptable calibration tolerance level of MBE and CV(RMSE) for both simulated and experimental comfort indices. The current values of MBE and CV(RMSE) are 0.35% and 2.70%, respectively, while the acceptable tolerance of MBE and CV(RMSE) are ±10% and 30%, respectively.

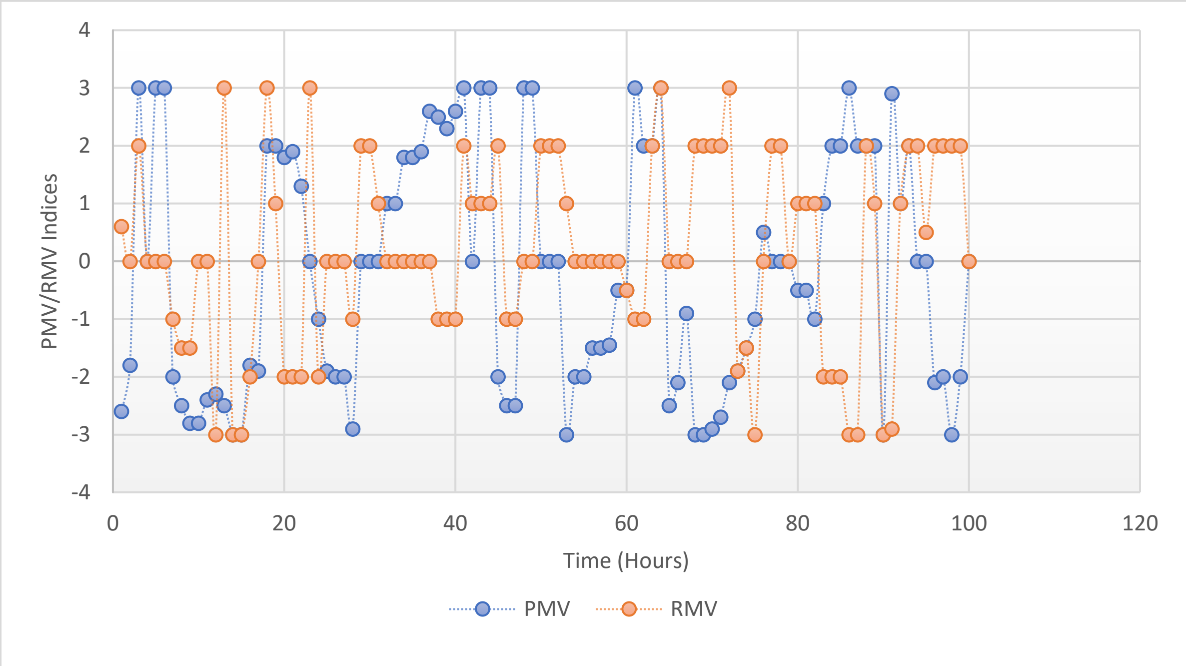


Figure 6.7 Simulation-based PMV indices and occupant-reported RMV indices

6.3.2 Validation of Ambient Temperature

For pilot study validation, indoor and outdoor environmental data have been collected using customized sensors. The time interval for environmental data collection was 1 minute, and these data were stored on a Micro-SD card. One of the key benefits of the customized sensor is its flexibility which allows more sensors to be added whenever required.

The temperature computed from the model versus the actual temperature obtained from the sensors is plotted in Figure 6.8. The model-predicted maximum and minimum indoor temperatures were 20.97ºC and 18.31ºC, respectively, while sensor-recorded maximum and minimum indoor temperatures were 22.2 ºC and 21.5 ºC. The average difference between the maximum and minimum indoor temperatures was roughly 1.13 ºC and 3.18 ºC. This indicates that the model-predicted indoor temperatures were slightly lower than the actual temperature. Some other occupant comfort studies [272-274] also revealed several reasons for this discrepancy between the model- and sensor-predicted temperatures. The difference between the predicted and actual temperatures was also observed in these studies [270, 275, 276]. Naramura's [275] study revealed that the influence on the curve of indoor temperature trend is about 0.24 °C/5 min in the predictive model and about 0.28°C/5 min in the calculated results. Also, in Smith et al. [276], the predictive model error was within ±2 ◦F (±1.11◦C) of ground truth.

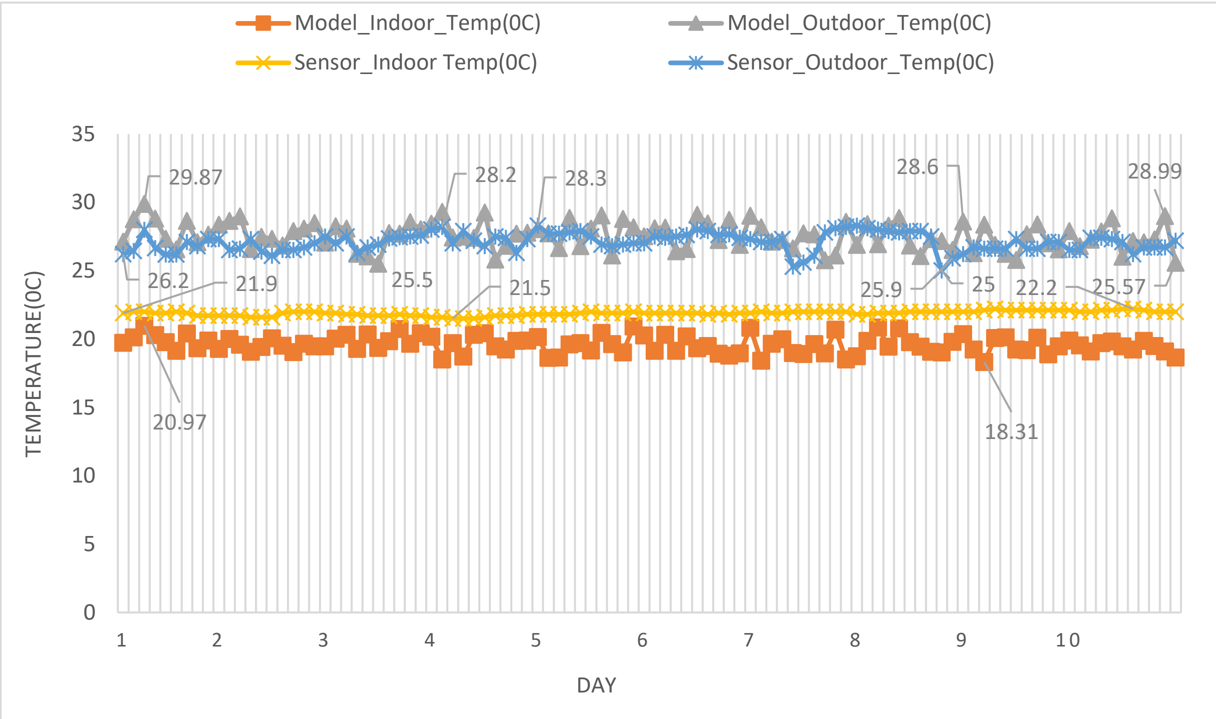


Figure 6.8 Simulation-based and sensor-calculated indoor and outdoor temperatures (^{0}C)

Some other possible reasons for this error or discrepancy include the random door operations, a computer or other electronic device turned on for a longer period of time, and window or blind operation with the constant alternation of opening or closing during the experiment. Also, the model did not consider any heat loss/heat gain or infiltration issues during the simulation process. On the other hand, it has been observed that the proposed model offered an acceptable range of RMSE (2.73%) and MBE (-2.28%) for indoor temperature evaluation as compared with other previous studies [277, 278]. Hence, the computational effects of the integrated framework may be regarded as correct as no additional calibration is required. Pointing to the assessment of outdoor temperature, there was a very slight difference between the model- and sensor-estimated outdoor temperatures as the model employed atmospheric data from the local weather station. The model-estimated maximum and minimum outdoor temperatures were 29.87^{0}C and 25.5^{0}C, respectively, whereas the sensor-estimated maximum and minimum outdoor temperatures were 28.20^{0}C and 25^{0}C correspondingly. It is also noted that the RMSE and MBE values for outdoor temperature were 1.20% and 0.45%, respectively, which stay within an acceptable limit.

6.3.3 Validation of Ambient CO_2

Figure 6.9 shows the indoor and outdoor CO_2 variations for the simulated model and the real data obtained from the CO_2 sensor. During the outdoor CO_2 simulation, the study considered the multiple linear regressions equation within the SD components. This prediction equation mainly considers different ambient environment parameters within the case study location. The required equations that have been considered for indoor CO_2 simulation are already explained in the previous chapter. The results show that the simulated model slightly underestimated both the indoor and outdoor CO_2 levels. The maximum and minimum simulated indoor CO_2 concentrations for this study were 814.56 ppm and 566.98 ppm, respectively, while sensor-estimated maximum and minimum indoor CO_2 were 899 ppm and 574 ppm, correspondingly. However, there is a significant gap between the simulated and sensor-estimated outdoor CO_2 concentration data. Sensor-estimated outdoor CO_2 data provided a higher level of variation (for 3rd June, 4th June, 8th June, and 9th June) than model-estimated outdoor CO_2 levels. A study [279] also showed a similar discrepancy in hourly CO_2 value for three monitored rooms (i.e., office 1, office 2, and library room) in Singapore. Nesibe et al. [280] also found a similar gap between the measured and predicted CO_2 concentration while ignoring the occupants (i.e., students). However, here the stochastic nature of occupant presence, indoor and outdoor CO_2 levels during the HVAC operation were derived from both the model and experimental records. Turning to RMSE and MBE checking, the outdoor CO_2 level (RMSE: 25.94%, MBE:10.01%) was more significantly deviated than indoor CO_2 level (RMSE: 19.22%, MBE: -9.47%). However, in all cases, CV(RMSE) and MBE values lay within the acceptable range. This study [281] also has shown a higher value of CV(RMSE) and MBE for an office building model located in Turkey. Several factors may be involved in this issue; for instance, the selected case study location is a hot-humid climatic zone, and there was a sudden change in the weather conditions during the experiment, i.e., sudden rain, clouds outside of the room, the office occupants may still keep the window open even though the indoor environment is only a little comfortable or highly stochastic movement of occupants in the office space. Similarly, blinds operation and the control of doors are also influenced by environmental factors. So, further model improvement may require resolving of these issues.

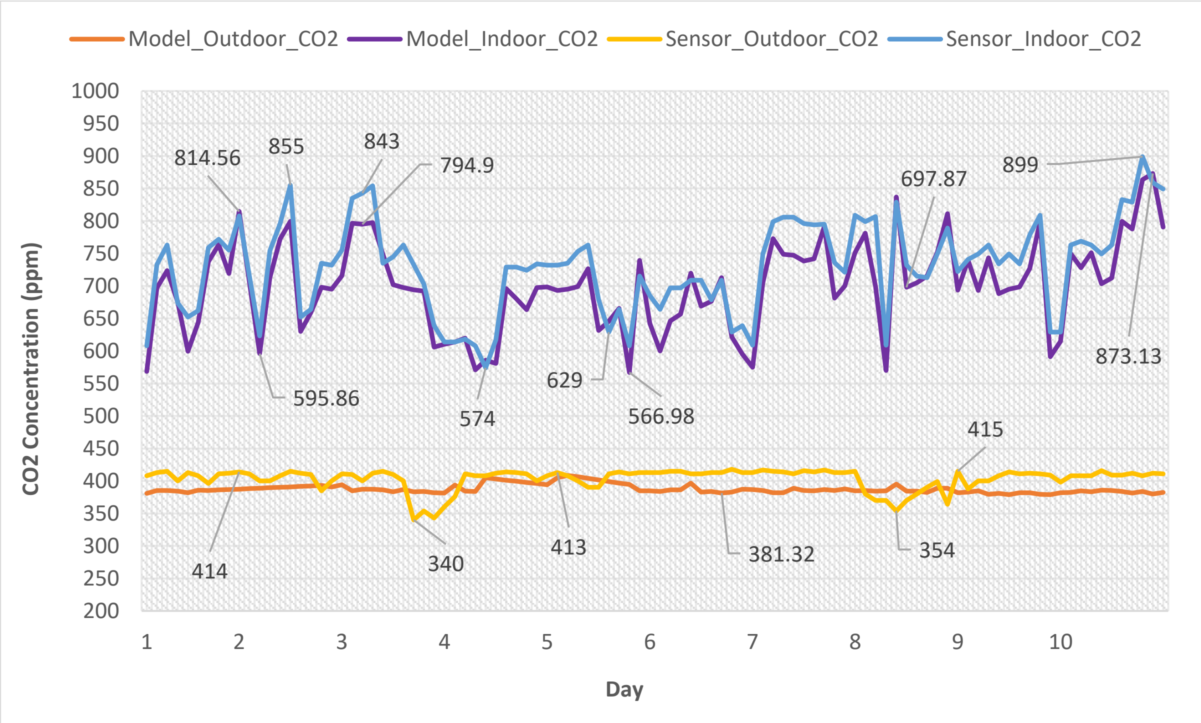


Figure 6.9 Simulation-based and sensor-calculated indoor and outdoor CO_2 (ppm)

6.3.4 Validation of Energy Consumption Data (Intervention Data)

In the end, to investigate the hybrid model validity, the model-generated energy data from the eight indoor spaces have been compared with the real data obtained from the sensors network. It is also noted that this validation study mainly compares/ represents the energy consumption (kWh) data obtained from the model-based intervention and realistic layout-based intervention implemented in the case study location. Table 6.1 indicates the complete value of CV(RMSE) and MBE for experimented and simulated data. It has been shown that implemented simulation or hybrid model provides the data within the acceptable range. All simulated and experimental data are represented using the graphical format (Figure 6.10) in the subsequent section as well. It has been shown that implemented simulation or hybrid model provides the data within the acceptable range defined by ASHRAE, FEMP, and IPMVP guidelines. Interior Layout 4 (RMSE:15.71 %) and Interior Layout 5 (16.7%) have been shown marginally higher errors as compared to other layout systems. Several reasons exist behind the issues. Basically, the original Interior Layout 4 comprises two rectangular shapes (Slightly L shape), although the model considered all are a single rectangular /square shape. In addition, Interior Layout 5 consists of windows and an additional balcony door that slightly impacts the occupants thermal comfort. Here occupants may frequently consider both window and balcony doors for their thermal comfort. Therefore, the occupant may use fewer HVAC systems for their thermal comfort and it eventually influences the energy consumption profile. However, the hybrid model considers a similar number of windows and doors for each space layout. Furthermore, frequent load shedding is also a common problem in this space area that may also significantly affect the model performance as the model did not consider any load shedding issue. Nevertheless, compared to other previous studies [282, 283], the average error from the proposed hybrid model is quite considerable.

This study also revealed that the coefficient of determination (R^2) has a considerable variation in occupant energy consumption patterns for both simulated and experimental data while some values fall below the acceptable limit of 0.75 (e.g., Interior Layout 4, 5, 6). On the other hand, data obtained from this investigation has been presented within the acceptable limit of RMSE and MBE. Similar findings were also found in the previous studies [283-285]. The possible reason for these discrepancies is due to the occupants intrinsic nature of turning ON/OFF switch for a prolonged period of time to fulfil their visual and thermal comfort. Also, most portion of the variation in energy savings can be described by other critical variables that has not been incorporated in this model [285]. Although some Interior Layout shows slightly lower values for the coefficient of determination (R^2), the study may help capture the diversity of realistic occupant behaviour profiles in the residential sectors rather than the fixed or static behaviour profiles. In this regard, the findings indicated that the hybrid framework offers a holistic assessment of occupant Interior Layout-based building energy performance.

Table 6.1: Cv(RMSE) and MBE values for different Interior Layout

Interior layout	**RMSE (%)**	**MBE (%)**
Interior Layout _1	10.5	1.6
Interior Layout_2	9.2	1.1
Interior Layout_3	10.1	1.3
Interior Layout_4	13.71	2.1
Interior Layout_5	14.50	2.3
Interior Layout_6	9.11	-0.9
Interior Layout_7	8.30	0.7
Interior Layout_8	9.10	-0.8

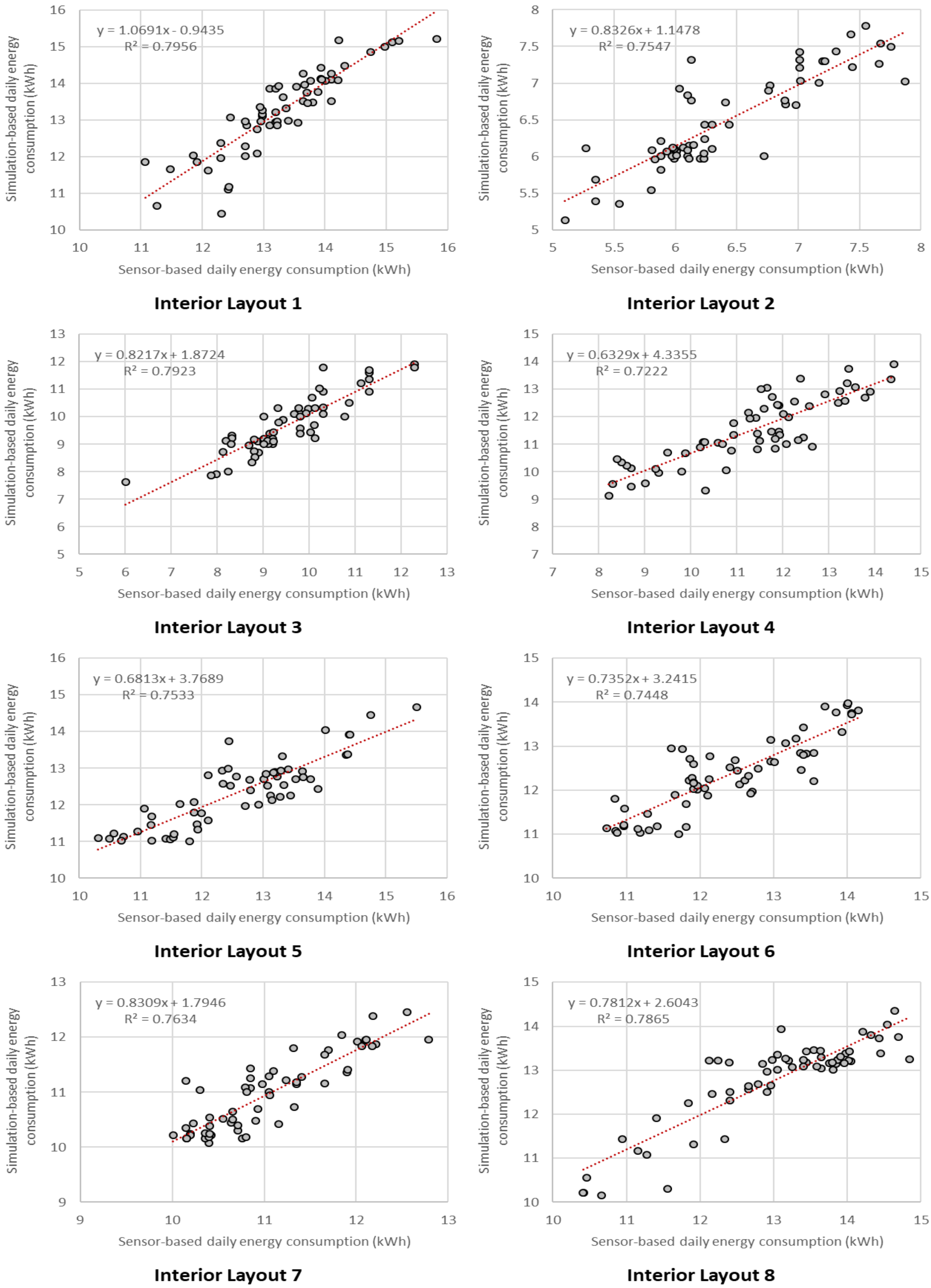


Figure 6.10 Coefficient of determination (R^2) for different space layout

6.4 Evaluation/Confusion Matrix

For validation purposes, four evaluation metrics (precision, recall, accuracy, and F1 score) have been used for this study to compare the simulated and practical information about HVAC/Fan and light ON/OFF behaviour. The numerical value covers the four metrics (precision, recall, accuracy, and F1 score) from 0 to 1.

The detailed evaluation outcomes of lighting and HVAC/Fan use behaviour are summarised in Table 6.2. It is noted that this evaluation performance test used the sensor data collected from the case study building in Chittagong, Bangladesh. Due to the occupants stochastic and complex attitude, the behaviour profile of each component is likely to be different. The overall assessment reveals that the hybrid model provided better performance for both lighting and HVAC/Fan usage pattern while compared with the experimental data. However, few data have been shown slightly lower performance (below 0.5). For instances, detection of lighting schedule for Interior Layout 4 has shown lower metrics (precision: 0.47, recall: 0.38, accuracy: 0.47, and F1 score: 0.42), also detection of Fan/HVAC schedule for Interior Layout5 has shown relatively less performance (precision: 0.47, recall: 0.49, accuracy: 0.47, and F1 score: 0.48).

Table 6.2 Hybrid model performance synopsis

Element	Interior Layout-1		Interior Layout-2		Interior Layout-3		Interior Layout-4		Interior Layout-5		Interior Layout-6		Interior Layout-7		Interior Layout-8	
	Light	Fan	Light	Fan	Light	Fan	Light	Fan	Light	Fan	Light	Fan	Light	Fan	Light	Fan
PT (%)	84.70	68.60	82.10	75.30	67.60	68.90	37.90	67.50	75.20	48.90	77.0	67.0	73.0	69.40	79.10	73.70
PF (%)	21.80	15.60	26.30	18.40	7.70	27.10	43.30	15.0	8.20	54.90	31.3	15.2	14.50	33.30	26.30	34.40
NT (%)	78.20	84.40	73.70	81.60	92.30	72.90	56.70	85.0	91.80	45.10	68.8	84.8	85.50	66.70	73.70	65.60
NF (%)	15.30	31.40	17.90	24.70	32.40	31.10	62.10	32.50	24.80	51.10	23.0	33.0	27.0	30.60	20.90	26.30
Precision = PT / (PF+ PT)	0.80	0.82	0.76	0.80	0.90	0.72	**0.47**	0.82	0.91	**0.47**	0.71	0.82	0.83	0.68	0.75	0.68
Recall = PT / (NF+ PT)	0.88	0.69	0.82	0.75	0.68	0.69	**0.38**	0.68	0.75	**0.49**	0.77	0.67	0.73	0.70	0.79	0.74

Accuracy = (NT +PT) / (PF + PT + NT + NF)	0.82	0.77	0.78	0.79	0.80	0.80	**0.47**	0.76	0.84	**0.47**	0.73	0.76	0.79	0.68	0.77	0.70
F1 score = 2PT / (PF + NF+ 2PT)	0.82	0.75	0.79	0.78	0.77	0.70	**0.42**	0.74	0.82	**0.48**	0.75	0.74	0.78	0.69	0.77	0.71

The prediction accuracy for the Lighting schedule is somewhat low. A low metrics value denotes the hybrid model incorrectly predicted the turn ON Light while, in reality, it was OFF for that time and vice versa. For better understanding, two days of simulation and experimental data have been demonstrated in Figure 6.11. During the time period **(11:30-13:00) mentioned** in Figure 6.11 (Upper), it has been noticed that model has been predicted light is Turn ON while in reality, the Light was OFF. Also, similar situation happened at 14:00-15:30, 16:30-15:30 and 20:00. On the other hand, from Figure 6.11 (Lower), the model predicted the occupant turned OFF the light at 10:00 while in reality occupant turned OFF the light at 10:30. There are several reasons that exist behind the issues. Firstly, the possible reason is that the Light ON/OFF frequency may differ from the sensor records, or sometimes the occupant does not use any light due to daylight availability (>200 lux) as well as the effect of the intervention. Secondly, it is also well noted that actual Interior Layout-4 comprises two rectangular shapes (Slightly L shape) although the model considered all are single rectangular /square shapes. Moreover, due to its highly stochastic or random nature, occasionally, the occupant may be completely absent for a certain period of time for any social gathering or program in the evening or night; however model does not properly identify any such issues. These are might a number of possible reasons to lower the model performance for this particular Interior Layout_4.

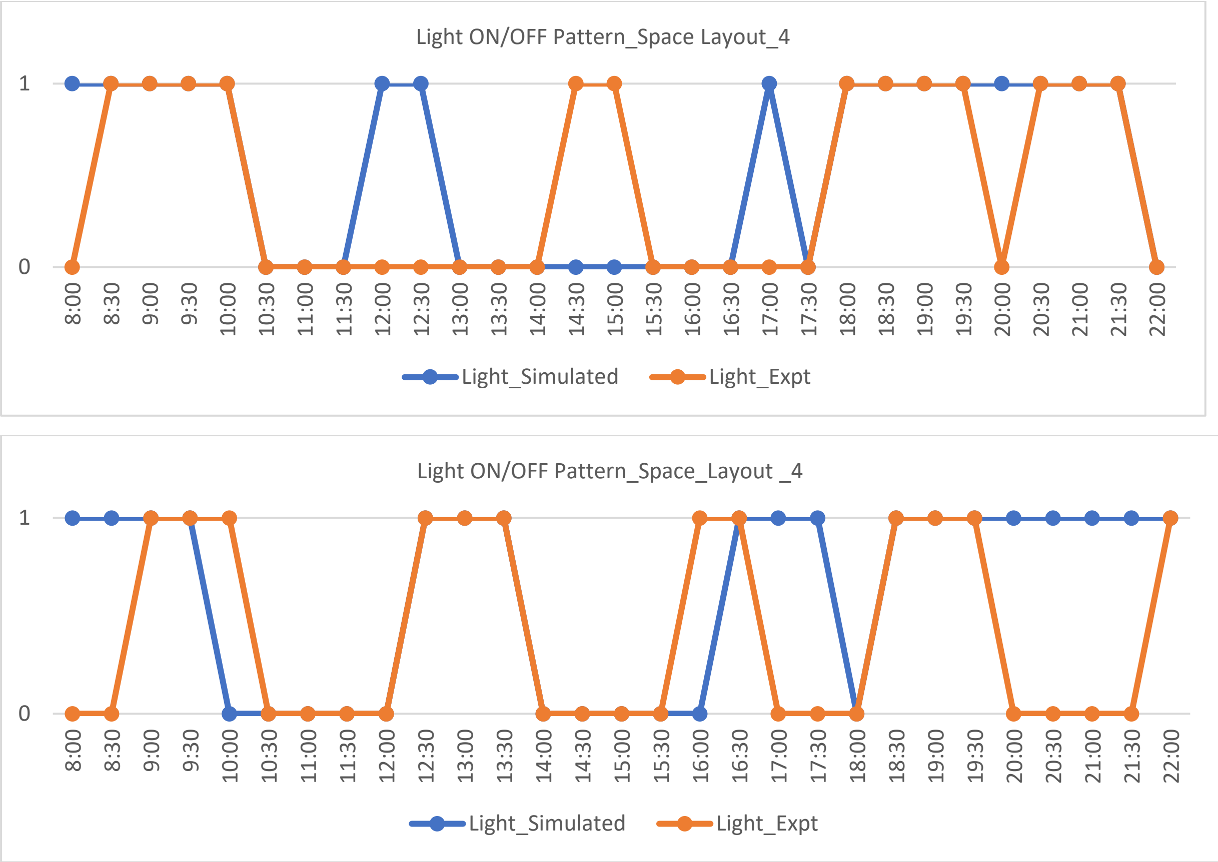


Figure 6.11 Light ON/OFF profile for two days of simulation & experimental data (Interior Layout 4)

Turn to Fan/HVAC schedule for Interior Layout-5, which has also shown a lower performance. For better understanding, a two-day simulation and experimental data have been demonstrated in Figure 6.12. Figure 6.12 (Upper) shows that the occupant does not actually use HVAC/Fan at 8:00-9:00 although the hybrid model predicted it was turned ON. Also, there are variations of the Fan ON/OFF schedule at night (Upper: 20:00-22:00, Lower: 20:30-22:00) and in the evening (Lower: 17:30-19:30).

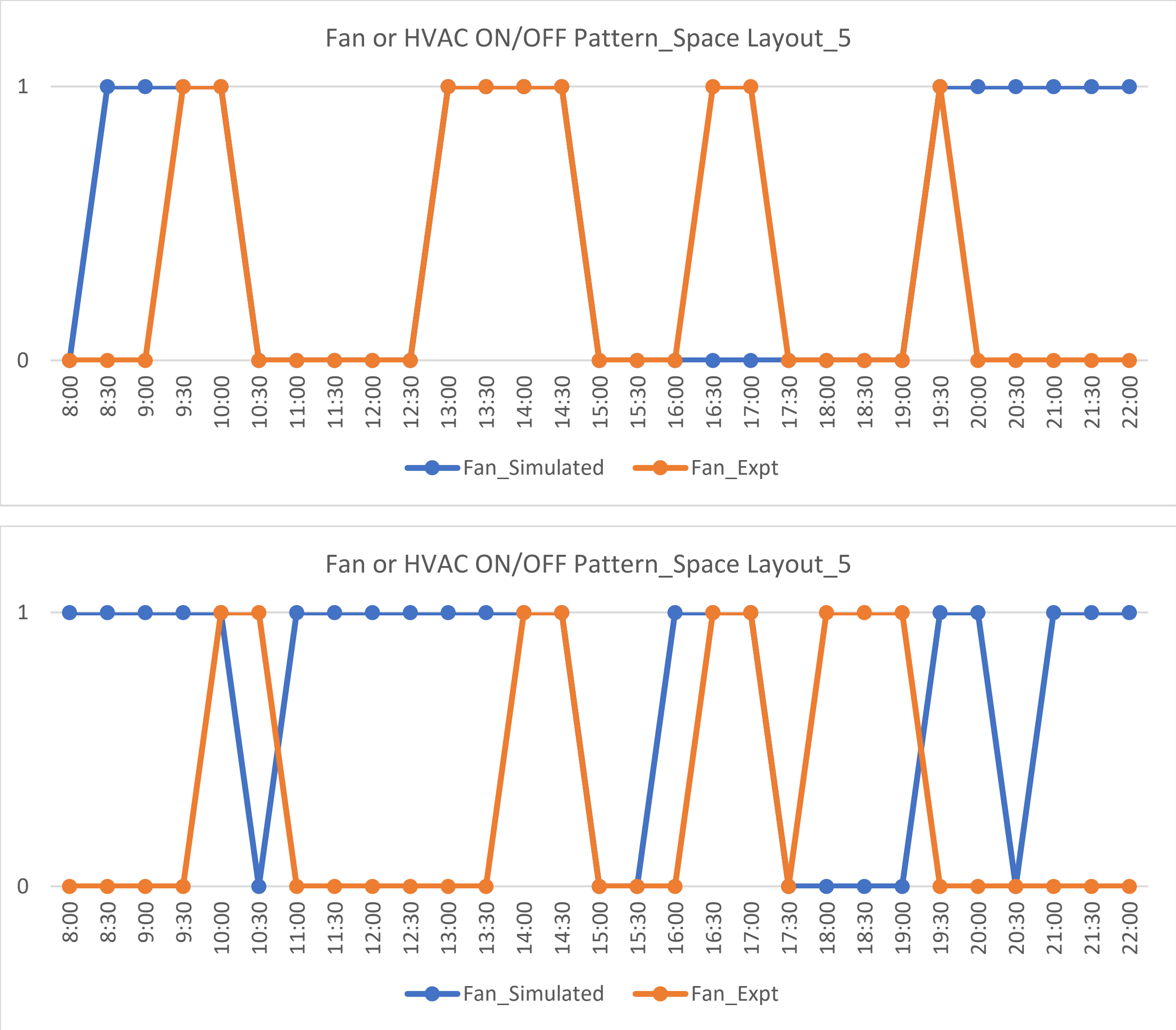


Figure 6.12 Fan ON/OFF profile for two days of simulation & experimental data (Interior Layout 5)

The possible reasons are the following: Even though it was mentioned that there were almost similar space/layout area that has been considered. However, a number of windows/ door variations exist for each Interior Layout. Like this, Interior Layout 5 consists of windows and an additional balcony door that slightly impacts the occupants thermal comfort. Here occupants may frequently consider both window and balcony doors for their thermal comfort. Thus, the occupant may use fewer HVAC systems for their thermal comfort in the morning and night. However, the hybrid model considers a similar number of windows and doors for each Interior Layout. This is one of the possible reasons that the model always predicts a higher HVAC/Fan usage than reality. In addition, frequent load shedding is also a common problem in this space area that may significantly affect the model performance as the model did not consider any load shedding issue. In addition, due to its highly stochastic nature, the simulated model does not seek to track precisely how building inhabitant in the indoor space reacts to specific environmental conditions. However, the proposed model is still to be considered valid as the overall performance achieved within an acceptable limit, according to the evaluation metrics estimated by earlier researchers [286, 287].

From an overall perspective, average predictions reached a relatively good performance which was approximately 70%-90%. Compared to other previous studies [12, 287, 288], the proposed hybrid model has shown better performance in terms of confusions matrix analysis. However, as the behaviour study using ABM-SD-BIM is still in development or initial stage, more data involvement and a more sophisticated simulation approach (i.e., incorporating more factors/parameters) should be considered from the black box validation viewpoint.

6.5 Social contextual factors using SPSS

6.5.1 Statistical analysis

From the overall statistical findings, the male and female occupants have been observed at 49% and 51%, respectively (Figure 6.13a). On the other hand, owners or landlords constituted about 51%, while tenants represented 49% (Figure 6.13b). There are five age groups (Figure 6.13c) in the data samples where approximately 20.27% of occupants are aged below 25, 14.86% of occupants are aged 26-35, 21.62% of occupants are aged 36-45, 16.22% of occupants are aged 46-55, and 27.03% of occupants are aged 56 and above.

It is also noted that comprehensive social contextual factors analysis using the SPSS is not the key aim of this study. As an additional investigation purpose, this study only considered a few social contextual factors that are also required for future investigation. In this context, a Chi-Square test for independence with $\alpha = .05$ was used to assess whether the satisfaction of existing indoor layout systems was related to sex, house ownership, and age. Moreover, Cramer's V and Lambda tests have been considered for symmetric and directional measures, respectively. The interpretation of Cramer's V and Lambda values is shown in Table 6.3 [289-291]. Table 6.4 illustrates the influence of social contextual factors on the satisfaction of existing indoor layout systems in view of the above three statistical parameters, i.e., Chi-Square, Cramer's V, and Lambda.

Table 6.3 Interpretation of Phi and Cramer's V

Cramer's V	Lambda	Interpretation
>0.25	+ 1.00	Very Strong
>0.15	+.30 –.99	Strong
>0.10	+.10 –.29	Moderate
>0.05	+.01-.09	Weak
>0	0	No Association

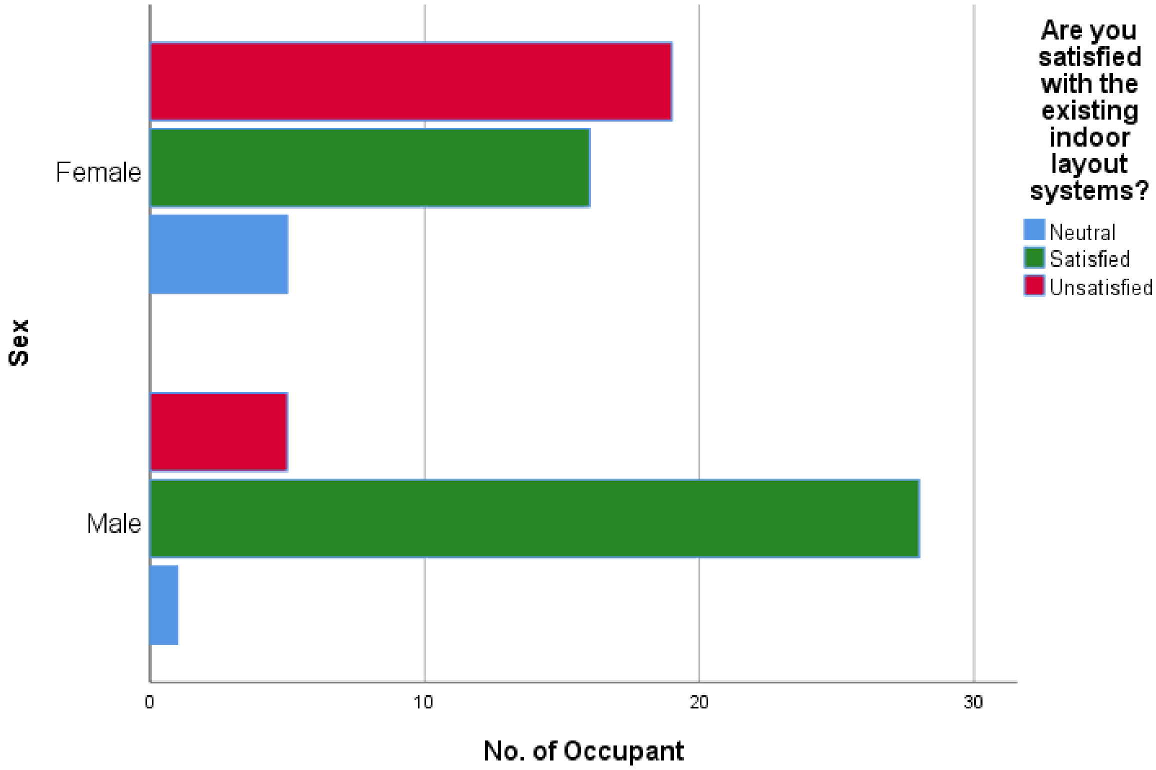
Table 6.4 Impact of contextual factors on the satisfaction of existing indoor layout systems

Social Contextual Factors	Class/ Group	Chi-Square test (Pearson Chi-Square)	Cramer's V test (Symmetric Measures)	Lambda (Directional Measures)
Sex	Male	**0.001**	0.430	0.353
	Female			
House type	Landlord	**0.647**	0.108	0.056
	Tenant			
Age group	<25	**0.101**	0.297	0.130
	26-35			
	36-45			
	46-55			
	>56			

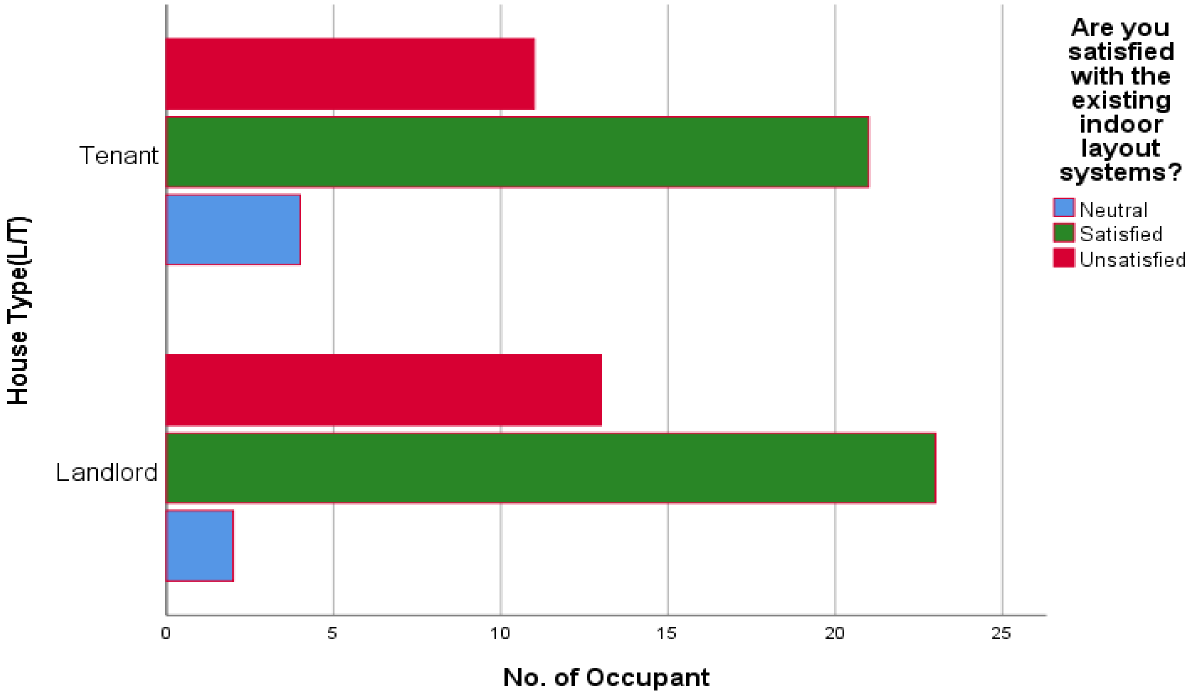
From the statistical findings of male and female occupants, the Chi-Square test has been represented as statistically significant, $\chi^2(1, N=74) = 13.71$, $p = .001$. Moreover, both Cramer's V (0.430) and Lambda (0.353) also represented a strong relationship between the occupant sex and existing indoor layout systems.

However, the Chi-Square test has revealed statistically insignificant findings for ownership types (p=0.647) and age groups (p=0.101). For ownership types, Cramer's V and Lambda values are 0.108 and 0.056, respectively, representing the moderate and weak association between the ownership types and satisfaction of existing indoor layout systems. For age groups, Cramer's V and Lambda values are 0.297 and 0.130, respectively, signifying a strong and moderate association between age and existing indoor layout systems.

From the statistical summary, the current study revealed a significant influence of gender on the satisfaction of existing indoor layout systems (Figure 6.13a). The female occupants were more unsatisfied with the current indoor layout systems as compared to the male occupant. The present study did not find an influence of ownership types or age groups on the satisfaction of existing indoor layout systems (Figure 6.13b and Figure 6.13c). Both landlords and tenants showed almost similar satisfaction with the current indoor layout systems. On the other hand, older occupants (age 56 and above) were found to be mostly satisfied with the existing indoor layout systems than others. This phenomenon was also slightly noticeable from the Cramer's V and Lambda values for occupants age groups (e.g., strong and moderate association). Earlier studies [292, 293] also revealed that female occupants are mostly unsatisfied than male occupants, and there is a substantial gender influence within the eldest group.



(a)



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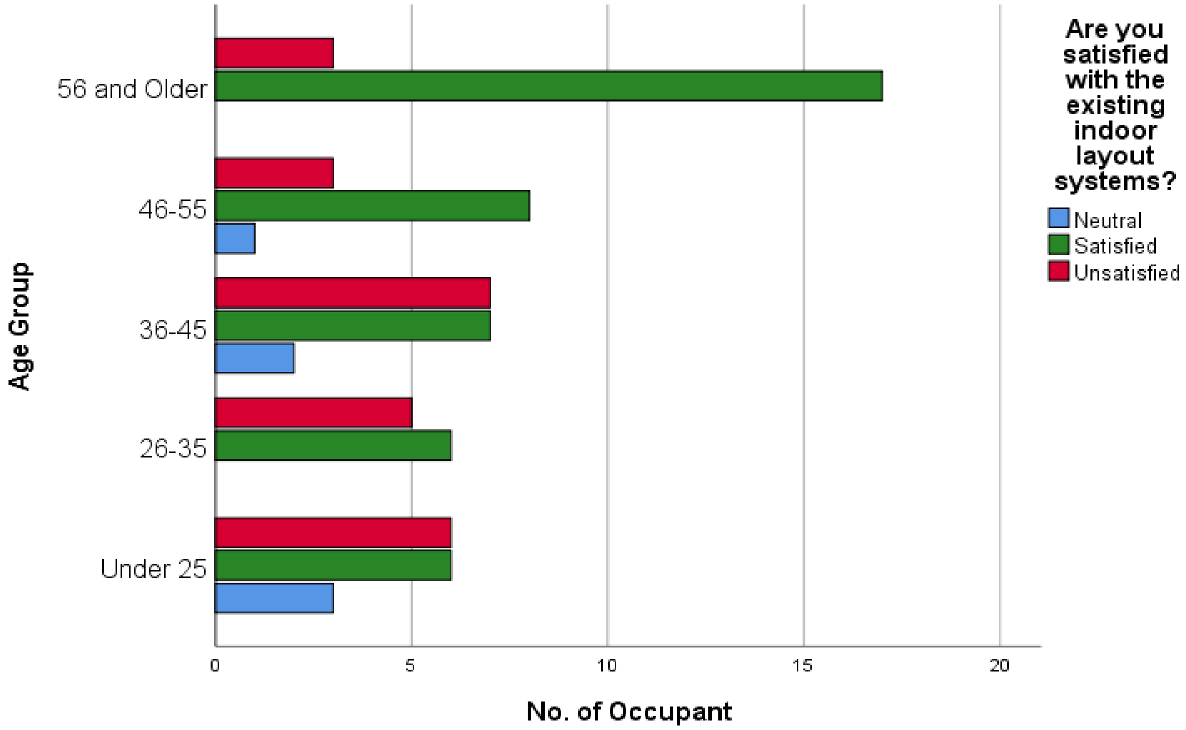

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(c)

Figure 6.13 Occupant groups and response classifications based on a. gender, b. ownership types, c. age

6.5.2 Reliability Study Using PMV Indices (Residential)

Typically, indoor data in the Interior Layout respond to individual occupants satisfaction levels. For the reliability study, data revealed using the statistical and ABM approach have been further investigated using 7-point PMV indices. Herein, the selected occupants (both male and female) from the selected apartments have been requested to evaluate their thermal impression due to the existing layout based on ASHRAE seven-point scale. The residents have been asked to mark anywhere on the scale freely. These are the similar values that Fangers' PMV equation has been attempting to predict. Lastly, in order to assess the PMV indices over the statistical and ABM findings, both male and female PMV indices were compared, as shown in Figure 6.14. From the PMV indices, it has been shown that comfort levels for both males and females were highly fluctuated due to indoor layout variations. Similar to ABM findings, realistic data also indicate that female occupants slightly feel cold (e.g., PMV≈-1) environment than male occupants. However, ABM predicted more highly diverged PMV indices than realistic values. Several reasons exist behind this issue. Firstly, occupant practical PMV (or RMV) indices are greatly influenced by building/housing orientations (e.g., south/north facing); however, the proposed ABM does not consider any room/housing orientations. Secondly, the ABM model does not consider the adjustment of occupant clothing level that significantly influenced the ABM outputs. Thirdly, proper identification of indoor space design or placement of whole furniture's/stuffs within the model is quite challenging that also sometimes leads to incorrect findings.

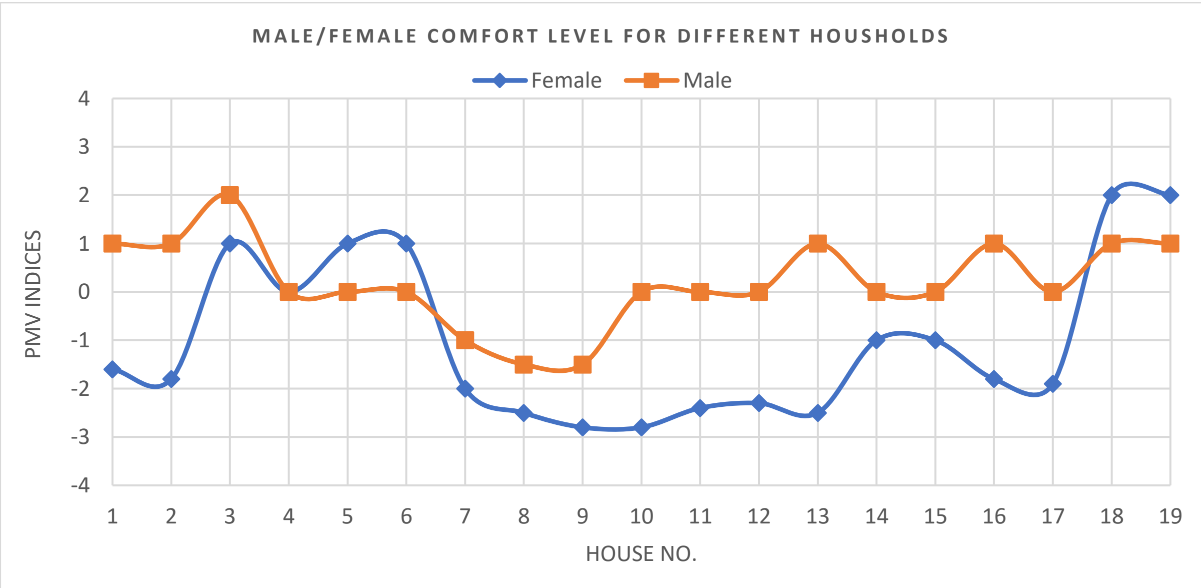


Figure 6.14 Male/Female comfort level for different households

It is also noted that in addition to the above-mentioned reasons, typical human attitudes, social norms, or other cultural backgrounds are also key influential drivers to changing or adjusting the PMV indices [294, 295]. Herein, attitude is an occupants belief about the behavioural influence they know, and they think that is a behaviour that's actually going to benefit them in the end. At the same time, social norm focuses on the social desirability or the acceptability of the behaviours.

6.6 Drive innovation and boost research on social and physical centric layout deployment

Occupant comfort or satisfaction is the feeling of happiness that a resident realizes while staying in an indoor space. Typically, occupiers assess indoor layout environments based on their requirements and desires, which are greatly affected by the occupants' cognitive (objective) and sentimental (subjective) senses. The high degree of similarity between the desired and actual conditions leads to a high level of satisfaction for both male and female occupants [293]. However, the difference between aspiration and housing demands may lead to dissatisfaction or unhappiness. According to Tan et al. [296], residents' satisfaction may depend on the housing contract programs. House or building ownership (e.g., landlord) provides a greater sense of control of the building; indoor layout affords individuals esteem needs of personal security and attainment. Likewise, proprietors or landlords invest in social capital that builds social cohesion, solidity, and interaction among fellow residents. Moreover, according to [297, 298], housing comfort and satisfaction among the tenants involve four key classifications: dwelling unit satisfaction including layout arrangement, satisfaction with the service offered, satisfaction package provided for the rent, and satisfaction with the neighborhoods or localities. This study mainly focuses on the occupant-centric indoor layout arrangements for both landlord and tenant occupants. Herein study tries to identify the significant social and physical design factors that play an essential role in occupant satisfaction. At this point, the critical design factors include occupant destination (e.g., seating place), circulation (e.g., walking path), energy spot (e.g., power switches), room orientation, furniture locations (e.g., object), etc. The survey study also categorized that most of the selected dwelling’s patterns are similar to Interior layout-1 (Energy spot inaccessible). However, occupants are preferably selected for Interior layout -7 or Interior layout -8 for their desired indoor layout systems.

This issue may also add to seeing how and why individual occupants consume more energy for their thermal and visual comfort. This knowledge can advise the plan concerning interventions to increase energy saving as well. Moreover, the occupants Interior Layout deployment is one of the design efforts between 'design development' and 'scheme design' in the initial design phase. It is a significant part of the building that affects the overall building energy consumption in the future [298]. So, the further study aims to break down the unfinished effect of occupant Interior Layout on building energy performance.

6.7 Chapter Summary

This chapter showed and discussed the detailed model and realistic data calculation/estimation of study seeking parameters, namely occupant comfort level in terms of PMV indices, indoor/outdoor temperature, CO_2 concentration, energy consumption patterns and validation study. The study pursues the influence of occupant behaviour in building energy conservation in the context of indoor layout configuration using a holistic approach over an Agent-Based Modelling (ABM), Systems Dynamics (SD), and Building Information Modelling (BIM). The study successfully developed and implemented a hybrid modelling approach to promote an energy-efficient building system and identify the key players through appropriate intervention. Moreover, the study completed a validation approach using real data collected from the customized sensors to improve the simulation reliability, trustworthiness, and robustness of the proposed model. By considering both physical and social contextual factors, this study focussed on the research gap for building and occupant behaviour literature by recognizing the inimitable impact on occupant comfort and behavioural influence of indoor layout systems. In this regard, the study performed a semi-structured interview-based survey from the building's occupants to solicit their opinions of satisfaction with existing indoor layout systems in the context of low-income economies. The data were investigated and classified based on age, gender, and house ownership, followed by a typical descriptive statistical analysis.

CHAPTER 7
CONCLUSIONS & RECOMMENDATIONS

7.1 General

This chapter summarizes the research findings by means of reviewing the research objectives, gives the research significance, states the limitations, and highlights directions for future research.

7.2 Reviewing the Research Objectives

The overall aim of this study was to construct a hybrid model to outline the occupant energy conservation behaviour within the low-income economies, and thus promoting an energy-efficient building system, and identify the key players through the intervention.

To achieve this aim, the following specific objectives have been established:

i. To identify the theoretical framework of energy consumption behaviour as well as numerous factors involved in building energy conservation due to dynamic human behaviour.
ii. To develop an integrated (ABM-SD-BIM) model that appraises and investigates various energy consumption events with the variation of indoor parameters contributing to occupants' satisfaction.
iii. To evaluate the comprehensive energy-related behaviour determinants (i.e., psychological, and physiological.) and monitor the behaviour pattern of the building occupants (From model).
iv. To investigate the influence of interior layout (i.e., placement of stuff) on the building energy conservation under a contextual intervention for an individual and group of occupants.
v. To validate the integrated hybrid model using realistic data (e.g., sensors) and paper-based surveys to check the model performance and improve the energy conservation events.

A range of research techniques has been implemented in realizing these objectives (referred to Chapter 3). At the same time, the model construction, principal findings, discussions, and conclusions relating to each research objective have been described in Chapters 4-7. The individual research objective is highlighted and summarized below.

Objective 1: To identify the theoretical framework of energy consumption behaviour and common factors involved in building energy conservation due to dynamic human behaviour.

To identify the theoretical framework and numerous factors associated with occupant behaviour, a comprehensive review of relevant published literature was first carried out in Chapter 2. This comprehensive review aims to provide a timely review of the state-of-the-art literature on occupant behaviour research. It is obviously challenging to capture a holistic knowledge of occupant behaviour and its influence on building energy conservation. The comprehensive review helps to identify the concept and theory related to human behaviour (e.g., Theory of Reasoned Action) that could be used to develop a new framework for the occupant behaviour study. The literature review exposed that, the most common factors such as personal (i.e., psychological, physiological), climatic (i.e., physical, environmental), economic, social, and legal parameters in cooperation with building plan and design criteria are the main features considered by the numerous researchers across the globe. Inadequacy of information about significant determinants of energy used in the buildings operation phase is treated as a significant hindrance to promoting overall energy performance.

Objective 2: To develop an integrated (ABM-SD-BIM) model that appraises and investigate the various energy consumption event with the variation of indoor parameters contributing to the occupants satisfaction.

The modelling and simulation of complex (social and group) behaviours in residential buildings with occupant comfort and appliance operation are not insignificant. Hence, this research constructed a hybrid model using Agent-Based Modeling (ABM), Systems Dynamics (SD), and Building Information Modeling (BIM). The energy consumption of a building is extremely dynamic and depends on multiple factors. Thus, the proposed modelling structures comprised a collective system approach and supported various data exchanges over the ABM, SD, and BIM that fully capture the various elements in the stochastic nature of occupancy-based building energy investigation. More specifically, the proposed hybrid model is a collective arrangement of ABM for reflecting theory and behaviour, SD for dynamic problems and events, as well as BIM for factual layout illustration. The details of the model construction process are also elaborately described in Chapter 4.

Objective 3: To evaluate the comprehensive energy-related behaviour determinants (i.e., climatic, social, and other contextual) and monitor the behaviour pattern of the building occupants (From hybrid model & SPSS).

Occupant behaviour on building energy consumption is complex as it relies on several critical factors or determinants. The most critical factors recognized from this study include both psychological and non-psychological factors. The elements are directly or indirectly linked to the occupants subjective norms and attitudes on the building's Interior Layout configurations, individual thermal comfort, occupant age, gender, and economy, including qualitative and quantitative behaviours.

Although the study did not find any significant influence of ownership types and age groups; however, both statistical and PMV indices imply that gender plays a considerable impact on the configuration of existing indoor layout systems. Noticeably, male occupants are more satisfied with the existing indoor layout arrangements than female occupants. It is also fundamental to confine space plans from different physical parameters to completely recognize the occupancy incorporated energy performance of a building. The critical factors and model generated various occupant stochastic behaviour profiles are elaborately described in Chapter 5 and Chapter 6.

Objective 4: To investigate the influence of interior layout (i.e., layout remodification) on building energy conservation under a contextual intervention (for individual level and group levels).

A number of attempts have been built to change occupant behaviour over design-controlled interventions to bound its climatic, environmental, or energy conservation challenges. Moreover, there is a lack of knowledge of occupants insights and perceptions of building interior layout concerning the individual perspective. As an indoor layout-based intervention, this study performed both model and experimental-based analyses for the occupants. The framework produced occupant energy consumption patterns before and after the intervention. It is noted that, although there are almost analogous layout patterns that have been considered, however, energy savings profiles from the particular layouts are completely different. For instance, some Interior Layouts have shown higher energy savings than others. There are several reasons that exist behind these, such as typical occupants behaviours are highly stochastic, interior space allocation/ arrangement, indoor ambient data, etc. The detailed intervention approach is also described in Chapter 5.

Objective 5: To validate the integrated hybrid model using the real data (e.g., sensors) and a paper-based survey to check the model performance and improve the energy conservation events.

The validation and Verification (V&V) of simulation models are extremely important. Validation usually ensures that the right model has been built, whereas verification involves the model being debugged to ensure it works correctly. Hence, a validation approach has been implemented for this behaviour study. The goal is to check the data reliability/validity and the performance of the proposed hybrid model. Herein the data validity approach of computational results has been presented utilizing the practical data gathered from the customized sensor network. Here, energy data produced from the hybrid model are validated against the real energy data collected from the eight customized sensor panels installed within the eight residential apartments located in Chittagong, Bangladesh.

The validation study revealed that implemented simulation or hybrid model provides the data within the acceptable range. The details of the experimental settings and validation are also described in Chapter 5 and Chapter 6.

7.3 Research Significance

Beyond the fact that the proposed approaches described for the above-mentioned model developments in the building energy monitoring field are still related to numerous difficulties and challenges that should be performed more effectively. The energy usage of a building is highly dynamic and relies on multiple parameters, for example, indoor environment, climate, people, and even design features such as layout, an orientation that firmly influences the building energy performance during the building operation phase. To break down these components, the integrated methodology needs to simulate the impacts of numerous variables arising during the building operation phase. For accomplishing this, the modeling structures should cover a combined system approach and need to support message/data exchange over the agent-based (ABM), system dynamics (SD), and building information modelling (BIM), which fully capture the various elements in the occupancy-based building energy investigation. Thus, to address the research gaps, this investigation concentrates predominantly on a combined arrangement of an ABM-SD-BIM-based behaviour modeling approach. This arrangement means adding another feature to the existing occupant energy behaviour model to upgrade the simulation performance. The combined framework/model is created on the assumption and theory that occupant behaviour is fundamentally identified within the built environment. The ABM-SD is executed using the AnyLogic modeling tool, an extensively tested simulation environment, especially in sociology, business, and engineering fields.

The combined ABM approach differs from other researchers' ABMs in various aspects. The existing behaviour study just considers the single ABM model with some static natural/environmental parameter using BPS tools (i.e., Energy Plus) and end accumulate estimations of energy requirements and determining the conclusion dependent on that. However, this methodology is missing the loss of the impacts of dynamic events, for example, the indoor building performance and occupant perception also cognitive activity during the operation stage. To address the overall research gaps, this investigation concentrates predominantly on a combined arrangement of Agent-Based Modeling (ABM) for reflecting theory and behaviour, System Dynamics (SD) for dynamic problems and events, as well as Building Information Modeling (BIM) for factual layout illustration. This hybrid modelling process adds another feature to the existing building energy and behaviour model for advanced simulation performance. Thus, the developed model is more comprehensive and closer to the real-world environment. Fundamentally, since most of the previous studies use the ABM approach, which is based upon synthetic data and scenarios, this investigation also efforts to fill this gap by offering a validation approach built on the comprehensive model, with respect to data collection as well as a model evaluation technique. Moreover, collecting actual occupants energy behaviour data (i.e., for validation purposes) supports further deployment of the model, such as integration with building performance simulation (BPS) programs.

The combined model will be established the probability of using tools or appliances and allocation of inner space in the occupant-built environmental area. The proposed integrated model also captures the broader aspects of occupant behaviour paradigms while applying the multiple interventions (layout, persuasions, etc.), which may also motivate further development of thoughts and ideas. In building energy efficiency and built environment, specifically in residential households, the main driving issue that changes occupants behaviours is their physical or thermal comfort in contrast to other conditions such as social or economic concerns. The findings have been drawn from low-income cultural backgrounds could also be applied to the occupant from other developing countries or other regions. The fact is that most of the countries share similar energy behaviour in terms of social and economic characteristics.

7.4 Limitations & Future Research

i) Diverse Interior Layout Selection:

The proposed framework is still in the prototype stage. It is well noted that this study only considers a few Interior Layouts for data validation purposes as extended data gatherings cannot be possible due to the COVID-19 pandemic. A wide-ranging Interior Layout selection and broader data collection, including additional behavioural laws/rules, should be identified and incorporated into the framework for modelling more complex occupant comfort and behaviour in buildings.

ii) Required Superior Algorithm

Moreover, comprehensive knowledge of occupant behaviour will assist in stimulating an advanced energy prediction model which keeps direct cause and impact that would provide superior control algorithms and systems design. From a diverse point of view, one might also predict energy inadequacies due to occupant behaviour, permitting engineers and architects to improve occupant control at an early phase in the design.

iii) Inclusion of multi-category buildings and big data stream

Approximately 85% of the peer-reviewed studies in this review work focused on the influence of occupant behaviour on building energy consumption, particularly focused on offices and residential buildings (33% and 52%, respectively). However, very few articles have examined educational or laboratory buildings. In addition, some other building categories such as recreational, exhibitions, hotels, clinics, or hospital buildings have been given spare attention and require further study. On this subject, the big data stream also offers a robust system to illustrate the full effects of occupant behaviours from a diverse range of data. In Addition, big data will play a vital role in automatically generalizing valid, novel, and potentially helpful occupancy patterns from a large-scale data set.

iv) Occupant behaviour knowledge in the context of developing and cross-cultural economies

Beyond the fact that several approaches described for the above-mentioned model developments in the building energy monitoring field, they are still related to numerous difficulties and challenges that should be addressed effectively. This study exposed that most of the existing research focuses on occupancy or occupants backgrounds from high income or developed economies while occupants from low income or developing economies remain unclear, complex, and conflicting. So, it is recommended that people from low-income or developing countries and their comprehensive energy-associated behaviour in buildings should be well-understood in terms of economic, social, and other cross-cultural perspectives. Usually, the energy usage of a building is extremely dynamic and also relies on multiple parameters in terms of socio-economic conditions and energy conservation policy.

APPENDIX:

Appendix-I

Keywords Frequency, Link and Total Link Strength (2010-2019):

Keyword	Frequency	Link	Total Link Strength
Energy Utilization	36	47	235
Buildings	32	45	184
Energy Efficiency	25	45	159
Occupant Behaviour	23	39	143
Office building	23	44	138
Behavioural Research	19	38	126
Energy Conservation	17	37	111
Architectural Design	17	35	103
Performance Assessment	11	37	87
Simulation	11	35	79
Building Performance Simulation	11	33	73
Residential Building	11	33	71
Stochastic System	10	29	59
Survey	10	30	56
Computer Simulation	9	28	61
Energy Management	9	26	55
Air Conditioning	8	32	52
Stochastic Model	8	27	51
Thermal Comfort	8	28	45
Intelligent Building	7	33	55
Modeling	7	30	52
Indoor Air	7	25	37
Building Simulation	7	24	41
Regression Analysis	7	24	35
Space Heating	6	26	40
Building Design	6	17	28
Human Behaviour	6	21	31
Heating	5	26	37
Energy Model	5	18	34
Energy Plus	5	25	39
Data Mining	5	21	31
Forecasting	5	24	33
Sensitivity Analysis	5	18	27
Optimization	5	18	25
Window Opening	5	16	22

Appendix-II

Part A: Function Body: Decision Making Process (OODA Loop)

```
public enum St_Occupant_state implements IStatechartState<Occupant,
St_Occupant_state> {
    Occupant_DMP,
    Occupants_Action,
    Observe() {

      public St_Occupant_state getContainerState() {
        return Occupant_DMP;
      }
       },
    Orient() {

      public St_Occupant_state getContainerState() {
        return Occupant_DMP;
      }
       },
    Decision_Making() {

      public St_Occupant_state getContainerState() {
        return Occupant_DMP;
      }
       },
    Occupants_Idle() {

      public St_Occupant_state getContainerState() {
        return Occupant_DMP;
      }
       };


public Statechart<St_Occupant_state> getStatechart( Occupant _a ) {
      return _a.St_Occupant;
    }
  }
 (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
  public static final St_Occupant_state Occupant_DMP =
St_Occupant_state.Occupant_DMP;
 (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
  public static final St_Occupant_state Occupants_Action =
St_Occupant_state.Occupants_Action;
 (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
  public static final St_Occupant_state Observe = St_Occupant_state.Observe;
 (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
  public static final St_Occupant_state Orient = St_Occupant_state.Orient;
  (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
  public static final St_Occupant_state Decision_Making =
St_Occupant_state.Decision_Making;
 (type = AnyLogicCustomProposalPriority.Type.STATIC_ELEMENT)
 public static final St_Occupant_state Occupants_Idle =
St_Occupant_state.Occupants_Idle;
```

```java
private void exitState( St_Occupant_state self, Transition _t, boolean _source ) {
    switch( self ) {
      case Occupant_DMP:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Composite state)
        if ( _source ) exitInnerStates(self);
        if ( !_source || _t != Move_to_Action ) Move_to_Action.cancel();
        return;
      case Occupants_Action:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Return_to_State) Return_to_State.cancel();
        return;
      case Observe:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Thinking) Thinking.cancel();
        return;
      case Orient:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != To_Decide) To_Decide.cancel();
        return;
      case Decision_Making:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != To_Idle) To_Idle.cancel();
        return;
      case Occupants_Idle:
           logToDBExitState(St_Occupant, self);
           logToDB(St_Occupant, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != To_Observe) To_Observe.cancel();
        if ( !_source || _t != Rethink) Rethink.cancel();
        return;
      default:
        return;
    }
  }


public String getNameOf( TransitionCondition _t ) {
    if ( _t == Thinking ) return "Thinking";
    if ( _t == To_Decide ) return "To_Decide";
    if ( _t == To_Idle ) return "To_Idle";
    if ( _t == To_Observe ) return "To_Observe";
    if ( _t == Rethink ) return "Rethink";
    return super.getNameOf( _t );
                                              }

public void executeActionOf( TransitionCondition self ) {
    if ( self == Thinking ) {
      exitState( Observe, self, true );
          enterState( Orient, true );
```

```
      return;
    }
    if ( self == To_Decide ) {
      exitState( Orient, self, true );
          enterState( Decision_Making, true );
      return;
    }
    if ( self == To_Idle ) {
      exitState( Decision_Making, self, true );
          enterState( Occupants_Idle, true );
      return;
    }
    if ( self == To_Observe ) {
      exitState( Occupants_Idle, self, true );
          enterState( Observe, true );
      return;
    }
    if ( self == Rethink ) {
      exitState( Occupants_Idle, self, true );
          enterState( Orient, true );
      return;
    }
    super.executeActionOf( self );
                                          }

public boolean testConditionOf( TransitionCondition _t ) {
    if ( _t == Thinking ) return
Thinkin_Approaching_occupant > 0
;
    if ( _t == To_Decide ) return
Decision_Time >= Maximum_Time_Decision
;
    if ( _t == To_Idle ) return
Decision_Time < Maximum_Time_Decision;
Occupant_Perception_Layout=Low_Perception;

;
    if ( _t == To_Observe ) return
Decision_Time == 0.0
;
    if ( _t == Rethink ) return
Thinkin_Approaching_occupant > 0
;
    return super.testConditionOf( _t );
                                          }
```

Part B: toString (Function Body: System Dynamics)

Section-a

```
return
       "ConsiderThermalComfortUsingWindow = " + ConsiderThermalComfortUsingWindow
+ "\n" +
       "ConsiderThermalComfortUsingHVAC = " + ConsiderThermalComfortUsingHVAC +
"\n" +
       "Energyfrom_grid = " + Energyfrom_grid + "\n" +
       "DistFromLighitingpoint = " + DistFromLighitingpoint + "\n" +
```

```
        "energyExpenditureBetaIntercept = "  + "\n" +
        "LightingDistanceEnergyExpenditureBetaIntercept = " +
LightingDistanceEnergyExpenditureBetaIntercept + "\n" +
        "Decisison_Speed = " + Decision_Time + "\n" +
        "Thinkin_Approaching_occupant = " + Thinkin_Approaching_occupant + "\n" +
        "Duration = " + Occupant_Perception_Layout + "\n" +
        "Cooling_rate = " + Cooling_rate + "\n" +
        "Min_Outdoor_Temp = " + Min_Outdoor_Temp + "\n" +
        "Max_Outdoor_Temp = " + Max_Outdoor_Temp + "\n" +
        "Min_CO2 = " + Min_CO2 + "\n" +
        "Max_CO2 = " + Max_CO2 + "\n" +
        "T_walls = " + T_walls + "\n" +
        "T_in = " + T_in + "\n" +
        "T_wall_Tin = " + T_wall_Tin + "\n" +
        "VPC_Sensible = " + VPC_Sensible + "\n" +
        "V_inf = " + V_inf + "\n" +
        "Density_air = " + Density_air + "\n" +
        "Sensible_C_p = " + Sensible_C_p + "\n" +
        "hA = " + hA + "\n" +
        "T_out_T_in = " + T_out_T_in + "\n" +
        "T_out = " + T_out + "\n" +
        "Latent_lv = " + Latent_lv + "\n" +
        "S_out = " + S_out + "\n" +
        "S_in = " + S_in + "\n" +
        "VPC_Latent = " + VPC_Latent + "\n" +
        "S_out_S_in = " + S_out_S_in + "\n" +
        "H_metabolic = " + H_metabolic + "\n" +
        "f_sa = " + f_sa + "\n" +
        "η_lighting = " + η_lighting + "\n" +
        "l_lighting = " + l_lighting + "\n" +
        "W_equipment = " + W_equipment + "\n" +
        "Lighing_gain = " + Lighing_gain + "\n" +
        "LE_metabolic = " + LE_metabolic + "\n" +
        "H_ig = " + H_ig + "\n" +
        "LE_ig = " + LE_ig + "\n" +
        "EnergyInkWh = " + EnergyInkWh_Stock + "\n" +
        "Static_Temp = " + Static_Temp + "\n" +
        "Static_CO2 = " + Static_CO2 + "\n" +
        "Total_Cooling_Load_Q = " + Total_Cooling_Load_Q + "\n" +
        "Energy_gain = " + Energy_source + "\n" +
        "Energy_used_HVAC = " + Energy_used_HVAC + "\n" +
        "Energy_wastage_Window = " + Energy_wastage_Others + "\n" +
        "Energy_used_byLighting = " + Energy_used_byLighting + "\n" +
        "Outdoor_Temp = " + Outdoor_Temp + "\n" +
        "Indoor_Temp = " + Indoor_Temp + "\n" +
        "Total_Energy_consumption = " + Total_Energy_consumption + "\n" +
        "Environmental_CO2 = " + Environmental_CO2 + "\n" +
        "flow1 = " + Indoor_CO2 + "\n" +
        "Sensible_H_cool = " + Sensible_H_cool + "\n" +
        "Latent_LE_cool = " + Latent_LE_cool + "\n" +
        "space = " + space + "\n" +
        "Prefer_HVAC = " + Prefer_HVAC + "\n" +
        "energy_used_coefficient_HVAC = " + energy_used_coefficient_HVAC + "\n" +
        "energy_used_coefficient_Window = " + energy_used_coefficient_Others + "\n"
+
        "consumptionRate = " + consumptionRate + "\n" +
        "Temp_Adjustment = " + Temp_Adjustment + "\n" +
        "PMV_Occupant = " + PMV_Occupant + "\n" +
        "NumberOfOccupant = " + Room_Occupancy_Ratio + "\n" +
```

```
"Maximum_Time_Decision = " + Maximum_Time_Decision + "\n" +
"Layout_Perception = " + Low_Perception + "\n" +
"Layout_Characteristics = " + Layout_Characteristics + "\n" +
"h = " + h + "\n" +
"AreaOfWall = " + AreaOfWall + "\n" +
"A_in = " + A_in + "\n" +
"η_equipment = " + η_equipment + "\n" +
                        "No_people = " + No_people;
```

Section-b

Static Variable

```
@Override

 public boolean setParameter(String _name_xjal,
Object _value_xjal, boolean _callOnChange_xjal) {

   switch ( _name_xjal ) {

   case "Ambient_Temp":

    if ( _callOnChange_xjal ) {

     set_Ambient_Temp( ((Number)
_value_xjal).doubleValue() );

    } else {

     Ambient_Temp = ((Number)
_value_xjal).doubleValue();

    }

    return true;

   case "Infiltration_Tight":

    if ( _callOnChange_xjal ) {

     set_Infiltration_Tight( ((Number)
_value_xjal).doubleValue() );

    } else {
```

Dynamic Variable

```
// Dynamic (Flow/Auxiliary/Stock) Variables

 public double Outdoor_Temp;

 public double Max_Indoor_Temp;

 public double Indoor_CO2;

 public double Environmental_CO2;

 public double Building_Characteristics;

 public double Surface_Charactersitics;

 public double Min_Outdoor_Temp;

 public double Max_Outdoor_Temp;
```

```
      Infiltration_Tight = ((Number)
_value_xjal).doubleValue();

    }

    return true;

   case "Respiratory_quotient":

    if ( _callOnChange_xjal ) {

      set_Respiratory_quotient( ((Number)
_value_xjal).doubleValue() );

    } else {

      Respiratory_quotient = ((Number)
_value_xjal).doubleValue();

    }

    return true;

   case "Wall_Area":

    if ( _callOnChange_xjal ) {

      set_Wall_Area( ((Number)
_value_xjal).doubleValue() );

    } else {

      Wall_Area = ((Number)
_value_xjal).doubleValue();

    }

    return true;

   case "Metabolic_for_single":

    if ( _callOnChange_xjal ) {

      set_Metabolic_for_single( ((Number)
_value_xjal).doubleValue() );

    } else {

      Metabolic_for_single = ((Number)
_value_xjal).doubleValue();

    }
```

```
public double PMV_Value;

public double Max_CO2;

public double Min_CO2;

public double V_O2_Consumption;

public double DuBois_surface_area_AD;

public double Total_Metabolic_rate;

public double Cooling;

public double Room_Surface_Temp;

public double Room_Static_CO2;
```

```
      return true;
    case "Floor_Characteristics_fs":
      if ( _callOnChange_xjal ) {
        set_Floor_Characteristics_fs( ((Number)
_value_xjal).doubleValue() );
      } else {
        Floor_Characteristics_fs = ((Number)
_value_xjal).doubleValue();
      }
      return true;
    case "ACH":
      if ( _callOnChange_xjal ) {
        set_ACH( ((Number) _value_xjal).doubleValue()
);
      } else {
        ACH = ((Number) _value_xjal).doubleValue();
      }
      return true;
    case "No_People":
      if ( _callOnChange_xjal ) {
        set_No_People( ((Number)
_value_xjal).doubleValue() );
      } else {
        No_People = ((Number)
_value_xjal).doubleValue();
      }
      return true;
    default:
```

```
      return super.setParameter( _name_xjal,
  _value_xjal, _callOnChange_xjal );

    }

  }
```

Part C: Layout-Based Intervention

Intervention-1:

```
// Statecharts
  public Statechart<EnergyUsedStateChart_state> EnergyUsedStateChart = new
Statechart<>( this, (short)3 );
  public Statechart<St_Occupant_state> St_Occupant = new Statechart<>( this,
(short)3 );
  public Statechart<Indoor_Movement_state> Indoor_Movement = new Statechart<>(
this, (short)2 );
  public Statechart<Transforms_LowToHigh_Perception_state>
Transforms_LowToHigh_Perception = new Statechart<>( this, (short)3 );


public String getNameOf( Statechart _s ) {
    if(_s == this.EnergyUsedStateChart) return "EnergyUsedStateChart";
    if(_s == this.St_Occupant) return "St_Occupant";
    if(_s == this.Indoor_Movement) return "Indoor_Movement";
    if(_s == this.Transforms_LowToHigh_Perception) return
"Transforms_LowToHigh_Perception";
    return super.getNameOf( _s );
  }


public enum Indoor_Movement_state implements IStatechartState<Occupant,
Indoor_Movement_state> {
    Occupant_Destination,
    Circulation,
    EnergySpot,
    To_Space,
Layoutdeploy;


public Statechart<Indoor_Movement_state> getStatechart( Occupant _a ) {
      return _a.Indoor_Movement;
    }
  }
public enum Transforms_LowToHigh_Perception_state implements
IStatechartState<Occupant, Transforms_LowToHigh_Perception_state> {
    Intrinsical_Low_Perception,
    Apparent_Low_Perception,
    Indolent_Occupant,
   Occupant_High_Perception;

public Statechart<Transforms_LowToHigh_Perception_state> getStatechart( Occupant
_a ) {
      return _a.Transforms_LowToHigh_Perception;
    }
  }
```

```
private void enterState( Indoor_Movement_state self, boolean _destination ) {
    switch( self ) {
      case Occupant_Destination:
          logToDBEnterState(Indoor_Movement, self);
        // (Simple state (not composite))
        Indoor_Movement.setActiveState_xjal( Occupant_Destination );
        {
this.agentsInRange(1.0).forEach(occupants-> this.connectTo(occupants));
;}
        Moving.start();
        Applying_Layout_Reorder.start();
        return;
      case Circulation:
          logToDBEnterState(Indoor_Movement, self);
        // (Simple state (not composite))
        Indoor_Movement.setActiveState_xjal( Circulation );
        {
this.moveTo(this.circulation);
;}
        HeadingToSpot.start();
        return;
      case EnergySpot:
          logToDBEnterState(Indoor_Movement, self);
        // (Simple state (not composite))
        Indoor_Movement.setActiveState_xjal( EnergySpot );
        {
this.agentsInRange(1.0).forEach(occupants-> this.connectTo(occupants));
;}
        BackToSpace.start();
        return;
      case To_Space:
          logToDBEnterState(Indoor_Movement, self);
        // (Simple state (not composite))
        Indoor_Movement.setActiveState_xjal( To_Space );
        {
this.moveTo(this.destination.object_point)
;}
        Towards_Destination.start();
        return;
      case Layoutdeploy:
          logToDBEnterState(Indoor_Movement, self);
        // (Simple state (not composite))
        Indoor_Movement.setActiveState_xjal( Layoutdeploy );
        Layout_Reordered.start();
        return;
      default:
        return;
    }
  }

private void exitState( Indoor_Movement_state self, Transition _t, boolean _source
) {
    switch( self ) {
      case Occupant_Destination:
          logToDBExitState(Indoor_Movement, self);
          logToDB(Indoor_Movement, _t, self);
      // (Simple state (not composite))
```

```
        if ( !_source || _t != Moving) Moving.cancel();
        if ( !_source || _t != Applying_Layout_Reorder)
Applying_Layout_Reorder.cancel();
        {
this.connections.disconnectFromAll();
;}
        return;
      case Circulation:
          logToDBExitState(Indoor_Movement, self);
          logToDB(Indoor_Movement, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != HeadingToSpot) HeadingToSpot.cancel();
        return;
      case EnergySpot:
          logToDBExitState(Indoor_Movement, self);
          logToDB(Indoor_Movement, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != BackToSpace) BackToSpace.cancel();
        {
this.connections.disconnectFromAll();
;}
        return;
      case To_Space:
          logToDBExitState(Indoor_Movement, self);
          logToDB(Indoor_Movement, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Towards_Destination) Towards_Destination.cancel();
        return;
      case Layoutdeploy:
          logToDBExitState(Indoor_Movement, self);
          logToDB(Indoor_Movement, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Layout_Reordered) Layout_Reordered.cancel();
        return;
      default:
        return;
    }
  }

private void exitState( Transforms_LowToHigh_Perception_state self, Transition _t,
boolean _source ) {
    switch( self ) {
      case Intrinsical_Low_Perception:
          logToDBExitState(Transforms_LowToHigh_Perception, self);
          logToDB(Transforms_LowToHigh_Perception, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Inward_Idle) Inward_Idle.cancel();
        return;
      case Apparent_Low_Perception:
          logToDBExitState(Transforms_LowToHigh_Perception, self);
          logToDB(Transforms_LowToHigh_Perception, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Exhibiting_Idle) Exhibiting_Idle.cancel();
        return;
      case Indolent_Occupant:
          logToDBExitState(Transforms_LowToHigh_Perception, self);
          logToDB(Transforms_LowToHigh_Perception, _t, self);
      // (Simple state (not composite))
```

```
        if ( !_source || _t != Towards_High_Perception)
Towards_High_Perception.cancel();
        if ( !_source || _t != Assemble_Rate) Assemble_Rate.cancel();
        if ( !_source || _t != Layout_Reorder_Intervention)
Layout_Reorder_Intervention.cancel();
        return;
      case Occupant_High_Perception:
           logToDBExitState(Transforms_LowToHigh_Perception, self);
           logToDB(Transforms_LowToHigh_Perception, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Check_Rebound_Effect)
Check_Rebound_Effect.cancel();
        return;
      default:
        return;
    }
  }

public String getNameOf( TransitionRate _t ) {
    if ( _t == Move_to_Action ) return "Move_to_Action";
    if ( _t == Applying_Layout_Reorder ) return "Applying_Layout_Reorder";
    if ( _t == Exhibiting_Idle ) return "Exhibiting_Idle";
    if ( _t == Towards_High_Perception ) return "Towards_High_Perception";
    if ( _t == Check_Rebound_Effect ) return "Check_Rebound_Effect";
    if ( _t == Assemble_Rate ) return "Assemble_Rate";
    return super.getNameOf( _t );
  }


public void executeActionOf( TransitionRate self ) {
    if ( self == Move_to_Action ) {
      exitState( Occupant_DMP, self, true );
      {
Occupant_Perception_Layout=High_Perception
;}
          enterState( Occupants_Action, true );
      return;
    }
    if ( self == Applying_Layout_Reorder ) {
      exitState( Occupant_Destination, self, true );
      {
this.moveTo(this.getNearestAgent(main.energyPoint));
;}
          enterState( Layoutdeploy, true );
      return;
    }
    if ( self == Exhibiting_Idle ) {
      exitState( Apparent_Low_Perception, self, true );
          enterState( Indolent_Occupant, true );
      return;
    }
    if ( self == Towards_High_Perception ) {
      exitState( Indolent_Occupant, self, true );
          enterState( Occupant_High_Perception, true );
      return;
    }
    if ( self == Check_Rebound_Effect ) {
      exitState( Occupant_High_Perception, self, true );
          enterState( Intrinsical_Low_Perception, true );
```

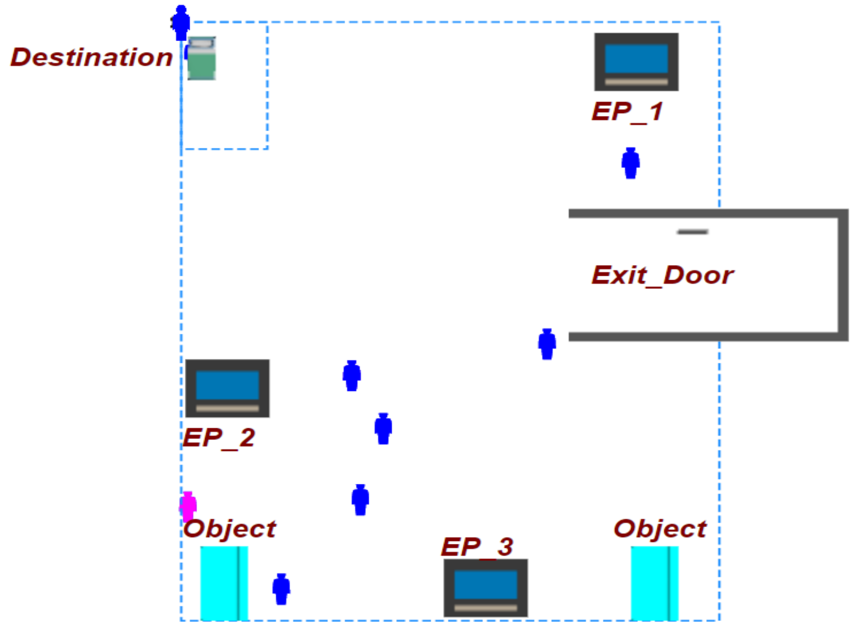
```
      return;
    }
    if ( self == Assemble_Rate ) {
      exitState( Indolent_Occupant, self, true );
      {

this.sendToRandomConnected(Messages.Idle);
;}
          enterState( Indolent_Occupant, true );
      return;
    }
    super.executeActionOf( self );
  }
```

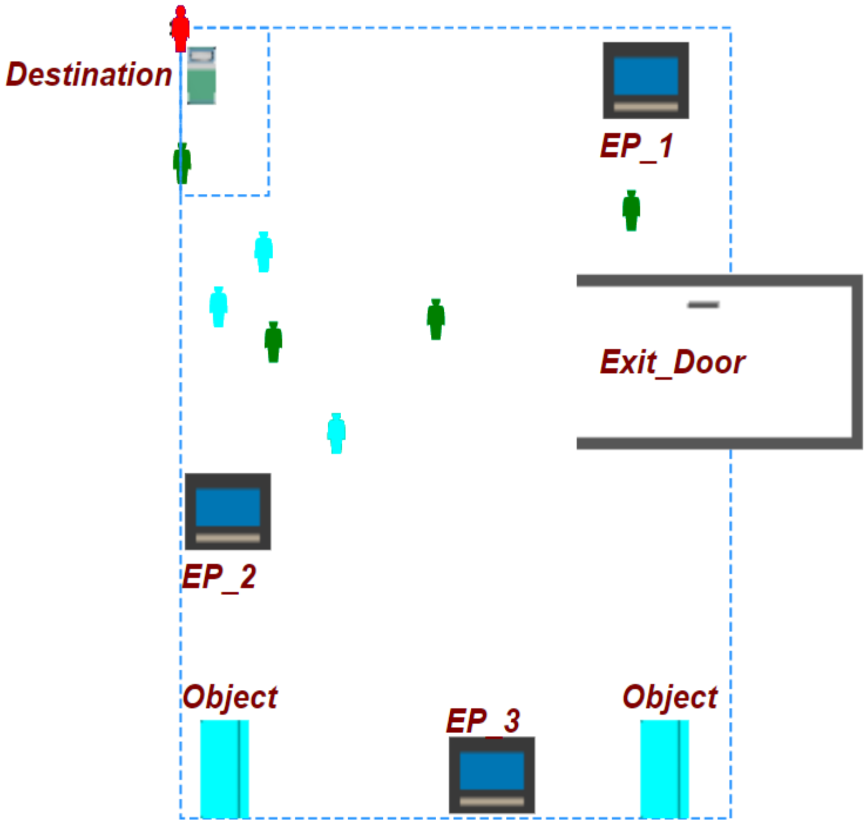
Agent Color Adjustment:

```
private void enterState( Transforms_LowToHigh_Perception_state self, boolean
_destination ) {
    switch( self ) {
      case Intrinsical_Low_Perception:
           logToDBEnterState(Transforms_LowToHigh_Perception, self);
        // (Simple state (not composite))
        Transforms_LowToHigh_Perception.setActiveState_xjal(
Intrinsical_Low_Perception );
        {
this.color=blue;
;}
        Inward_Idle.start();
        return;
      case Apparent_Low_Perception:
           logToDBEnterState(Transforms_LowToHigh_Perception, self);
        // (Simple state (not composite))
        Transforms_LowToHigh_Perception.setActiveState_xjal(
Apparent_Low_Perception );
        {
this.color=magenta;
;}
        Exhibiting_Idle.start();
        return;
      case Indolent_Occupant:
           logToDBEnterState(Transforms_LowToHigh_Perception, self);
        // (Simple state (not composite))
        Transforms_LowToHigh_Perception.setActiveState_xjal( Indolent_Occupant );
        {
this.color=cyan;
;}
        Towards_High_Perception.start();
        Assemble_Rate.start();
        Layout_Reorder_Intervention.start();
        return;
      case Occupant_High_Perception:
           logToDBEnterState(Transforms_LowToHigh_Perception, self);
        // (Simple state (not composite))
        Transforms_LowToHigh_Perception.setActiveState_xjal(
Occupant_High_Perception );
        {
this.color=green
;}
```

```
        Check_Rebound_Effect.start();
        return;
      default:
        return;
    }
}
```

<u>**Agent Color Interface in Any logic Platform:**</u>





Intervention 2:

```
// Statecharts
  public Statechart<Statechart_Intervention_Effect_state>
Statechart_Intervention_Effect = new Statechart<>(this, (short)3 );

public String getNameOf( Statechart _s ) {
    if(_s == this.Statechart_Intervention_Effect) return
"Statechart_Intervention_Effect";
    return super.getNameOf( _s );
  }

public void executeActionOf( Statechart _s ) {
    if( _s == this.Statechart_Intervention_Effect ) {
      enterState( Occupants_Action, true );
      return;
    }
    super.executeActionOf( _s );
  }

private void enterState( Statechart_Intervention_Effect_state self, boolean
_destination ) {
    switch( self ) {
      case Occupants_Action:
          logToDBEnterState(Statechart_Intervention_Effect, self);
        // (Composite state)

        Before_Intervention.start();
        Layout_Deployment.start();
        if (_destination ) {
           enterState(Normal, true );
        }
        return;
      case Occupants_Idle:
          logToDBEnterState(Statechart_Intervention_Effect, self);
        // (Simple state (not composite))
        Statechart_Intervention_Effect.setActiveState_xjal( Occupants_Idle );
        After_Intervention.start();
        ToRA_Psychological.start();
        Layout_Effect_Physical.start();
        return;
      case Normal:
          logToDBEnterState(Statechart_Intervention_Effect, self);
        // (Simple state (not composite))
        Statechart_Intervention_Effect.setActiveState_xjal( Normal );
        Issue.start();
        return;
      case Delay:
          logToDBEnterState(Statechart_Intervention_Effect, self);
        // (Simple state (not composite))
        Statechart_Intervention_Effect.setActiveState_xjal( Delay );
        Action.start();
        return;
      default:
        return;
    }
  }

private void exitState( Statechart_Intervention_Effect_state self, Transition _t,
boolean _source ) {
```

```
    switch(self ) {
      case Occupants_Action:
           logToDBExitState(Statechart_Intervention_Effect, self);
           logToDB(Statechart_Intervention_Effect, _t, self);
      // (Composite state)
        if ( _source ) exitInnerStates(self);
        if ( !_source || _t != Before_Intervention ) Before_Intervention.cancel();
        if ( !_source || _t != Layout_Deployment ) Layout_Deployment.cancel();
        return;
      case Occupants_Idle:
           logToDBExitState(Statechart_Intervention_Effect, self);
           logToDB(Statechart_Intervention_Effect, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != After_Intervention) After_Intervention.cancel();
        if ( !_source || _t != ToRA_Psychological) ToRA_Psychological.cancel();
        if ( !_source || _t != Layout_Effect_Physical)
Layout_Effect_Physical.cancel();
        return;
      case Normal:
           logToDBExitState(Statechart_Intervention_Effect, self);
           logToDB(Statechart_Intervention_Effect, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Issue) Issue.cancel();
        return;
      case Delay:
           logToDBExitState(Statechart_Intervention_Effect, self);
           logToDB(Statechart_Intervention_Effect, _t, self);
      // (Simple state (not composite))
        if ( !_source || _t != Action) Action.cancel();
        return;
      default:
        return;
    }
  }

public Statechart getStatechartOf( TransitionRate _t ) {
    if ( _t == Layout_Deployment ) return Statechart_Intervention_Effect;
    if ( _t == Issue ) return Statechart_Intervention_Effect;
    return super.getStatechartOf( _t );
  }
if ( self == Layout_Deployment ) {
      {
if(Occupant_Comfort>1)
send("Good Layout", RANDOM)
;}
      Layout_Deployment.start();
      return;
    }
    if ( self == Issue ) {
      exitState( Normal, self, true );
      {
main.Idle.take(new Persuasions(this));
;}
          enterState( Delay, true );
      return;
    }

public double evaluateRateOf( TransitionRate _t ) {
    double _value;
    if ( _t == Layout_Deployment ) {
```

```
      _value = 3
;
      _value = toModelRate( _value, PER_MINUTE );
      return _value;
    }
    if ( _t == Issue ) {
      _value = 1
;
      _value = toModelRate( _value, PER_MINUTE );
      return _value;
    }
    return super.evaluateRateOf( _t );


public boolean testMessageOf( TransitionMessage _t, Object _msg ) {
    if ( _t == ToRA_Psychological ) {

Object
msg = (Object) _msg;
      Object _g =
"Layout_Remodification"
;
      return msg.equals( _g );
    }
    if ( _t == Layout_Effect_Physical ) {

Object
msg = (Object) _msg;
      Object _g =
"Good Layout"
;
      return msg.equals( _g );
    }
    if ( _t == Action ) {

Object
msg = (Object) _msg;
      Object _g =
"Order"
;
      return msg.equals( _g );
    }
```

Appendix-III

(a) Approval from Hong Kong Polytechnic University

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

To	Ni Meng (Department of Building and Real Estate)		
From	LI Xiangdong, Chair, Faculty Research Committee		
Email	cexdli@	Date	22-Mar-2021

Application for Ethical Review for Teaching/Research Involving Human Subjects

I write to inform you that approval has been given to your application for human subject's ethics review of the following project for a period from 20-Mar-2020 to 31-Jul-2020:

Project Title:	Occupant behaviour modeling for building energy conservation: An integrated approach using Agent Based, System Dynamics and Building Information Modeling (BIM)
Department:	Department of Building and Real Estate
Principal Investigator:	Ni Meng
Project Start Date:	20-Mar-2020
Project type:	Human subjects (non-clinical)
Review type:	Expedited Review
Reference Number:	HSEARS20200306005

You will be held responsible for the ethical approval granted for the project and the ethical conduct of the personnel involved in the project. In case the Co-PI, if any, has also obtained ethical approval for the project, the Co-PI will also assume the responsibility in respect of the ethical approval (in relation to the areas of expertise of respective Co-PI in accordance with the stipulations given by the approving authority).

You are responsible for informing the PolyU Institutional Review Board in advance of any changes in the proposal or procedures which may affect the validity of this ethical approval.

LI Xiangdong
Chair
Faculty Research Committee (on behalf of PolyU Institutional Review Board)

(b) Intervention Take-up Towards Improving Building Energy Consumption Among Residential Owners and Tenants

Letter to Building Occupant

Dear Participant,

Thank you for your participation. This intervention aims to solicit the energy consumption pattern of building occupants on the existing interior layout systems that influence household energy consumption. It is expected that this intervention will help to improve the overall building energy consumption through an appropriate indoor layout configuration. This aim forms part of an ongoing PhD research at the Hong Kong Polytechnic University. Your support and consent to this research are vital for completing this intervention which will take approximately 3-4 months of your time. Confidentiality of your households and other data will be strictly ensured.

Once again, thank you for your immeasurable contribution to making this study fruitful. If you have queries, please you are most welcome to contact:

Uddin Mohammad Nyme
Department of Building and Real Estate
The Hong Kong Polytechnic University
Tel: +852-6225
Email: nymebd.uddin@

(c) Questionnaire survey

Section A: General Information of Occupant

Q1. Please, indicate your gender

☐ Male
☐ Female

Q2. Please, indicate your age

☐ Below 30 years
☐ 30-39 years
☐ 40-49 years
☐ 50-59 years
☐ 60 and above

Q3. Please, indicate your education level

☐ Primary education
☐ Secondary education
☐ Tertiary and Higher education

Q4. Please, what is your working profile?

☐ Working
☐ Non-Working

Q5. Please indicate the type of housing where you are currently living.

☐ Rented House;
☐ Own House

Q6. Please indicate the number / size of your household.

☐ 1 person;
☐ 2-3 people in the family;
☐ 4-5 people in the family;
☐ Above 6 people in the family

Section B: Occupant Perception on Existing Layout Systems

1. In general, how willing you would be to participate in energy-saving measures in your house by HVAC or Window operation?

   not at all willing (1) (2) (3) (4) (5) (6) (7) extremely willing

2. In general, would you frequently use energy spot for energy-saving measures in your house?

   not at all willing (1) (2) (3) (4) (5) (6) (7) extremely willing

3. My understanding of existing building energy systems (i.e., Energy Spot for HVAC, Light, TV etc.) and/or sustainability compared to an average person is

   extremely bad (1) (2) (3) (4) (5) (6) (7) extremely good

4. I am fully satisfied with my existing house layout system

   not at all agree (1) (2) (3) (4) (5) (6) (7) extremely agree

5. My existing interior layout certainly encourage me more efficient energy behaviour

   not at all agree (1) (2) (3) (4) (5) (6) (7) extremely agree

Section C: Occupant Core Preference Aspects

1. If we wanted to create energy savings in the workspace for the existing layout, what specific actions do you think we could reasonably ask the stockholder to do in order to accomplish this, whether or not you personally would want to do it?

2. If we remained to feel discomfort in the existing layout (due to inaccessible energy spot or longer distance between energy spot and destination), what specific actions do you think we could reasonably do in order to manage this, whether you personally would want to do it?

REFERENCES

[1] M. Santamouris, *Minimizing Energy Consumption, Energy Poverty and Global and Local Climate Change in the Built Environment: Innovating to Zero: Causalities and Impacts in a Zero Concept World*. 2018.

[2] N. Jung, S. Paiho, J. Shemeikka, R. Lahdelma, and M. Airaksinen, "Energy performance analysis of an office building in three climate zones," *Energy & Buildings,* vol. 158, pp. 1023-1035, 2018, doi: 10.1016/j.enbuild.2017.10.030.

[3] C. Spandagos and T. L. Ng, "Equivalent full-load hours for assessing climate change impact on building cooling and heating energy consumption in large Asian cities," *Applied energy,* vol. 189, pp. 352-368, 2017, doi: 10.1016/j.apenergy.2016.12.039.

[4] R. J. Sewell, S. Parry, S. W. Millis, N. Wang, U. Rieser, and R. DeWitt, "Dating of debris flow fan complexes from Lantau Island, Hong Kong, China: The potential relationship between landslide activity and climate change.(Report)," *Geomorphology,* vol. 248, p. 205, 2015, doi: 10.1016/j.geomorph.2015.07.041.

[5] M. Evans, B. A Shui, and T. Takagi, "Country report on building energy codes in Japan (No. PNNL-17849)," Pacific Northwest National Lab.(PNNL), Richland, WA (United States), 2009.

[6] H. Leslie, "THE RECIPE.(International Energy Agency)(energy demand increases)," *Oil and Gas Investor,* 2007.

[7] C. Van Dronkelaar, M. Dowson, E. Burman, C. Spataru, and D. Mumovic, "Corrigendum: A Review of the Energy Performance Gap and Its Underlying Causes in Non-Domestic Buildings," *Frontiers in Mechanical Engineering,* 2016.

[8] V. Chaturvedi, J. Eom, L. Clarke, and P. Shukla, "Long term building energy demand for India: Disaggregating end use energy services in an integrated assessment modeling framework," *Energy Policy,* vol. 64, no. C, p. 226, 2014, doi: 10.1016/j.enpol.2012.11.021.

[9] I. Yarbrough, Q. Sun, D. C. Reeves, K. Hackman, R. Bennett, and D. S. Henshel, "Visualizing building energy demand for building peak energy analysis," *Energy & Buildings,* vol. 91, no. C, pp. 10-15, 2015, doi: 10.1016/j.enbuild.2014.11.052.

[10] P. Nejat, F. Jomehzadeh, M. M. Taheri, M. Gohari, and M. Z. Abd. Majid, "A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries)," *Renewable and Sustainable Energy Reviews,* vol. 43, pp. 843-862, 2015, doi: 10.1016/j.rser.2014.11.066.

[11] L. Gooding and M. S. Gul, "Energy efficiency retrofitting services supply chains: A review of evolving demands from housing policy," *Energy Strategy Reviews,* vol. 11-12, pp. 29-40, 2016, doi: 10.1016/j.esr.2016.06.003.

[12] M. Jia, R. S. Srinivasan, R. Ries, N. Weyer, and G. Bharathy, "A systematic development and validation approach to a novel agent-based modeling of occupant behaviors in commercial buildings," *Energy & Buildings,* vol. 199, pp. 352-367, 2019, doi: 10.1016/j.enbuild.2019.07.009.

[13] E. Institution of Mechanical, "Proceedings of the Institution of Mechanical Engineers. Part A, Journal of power and energy," *Journal of power and energy,* 1990.

[14] H. Wang, W. Chen, and J. Shi, "Low carbon transition of global building sector under 2- and 1.5-degree targets," *Applied Energy,* vol. 222, pp. 148-157, 2018, doi:

10.1016/j.apenergy.2018.03.090.
[15] C. Wang, A. Engels, and Z. Wang, "Overview of research on China's transition to low-carbon development: The role of cities, technologies, industries and the energy system," *Renewable and Sustainable Energy Reviews,* vol. 81, no. P1, pp. 1350-1364, 2018, doi: 10.1016/j.rser.2017.05.099.
[16] Anonymous, "ASHRAE and DOE aim for better buildings workforce.(ENERGYMANAGERQ&A)(American Society of Heating, Refrigerating and Air Conditioning Engineers)(Department of Energy)(Brief article)," *Buildings,* vol. 108, no. 2, p. 12, 2014.
[17] T. A. Reddy, *Heating and cooling of buildings : principles and practice of energy efficient design*, Third edition.. ed. Boca Raton: CRC Press, Taylor & Francis Group, 2017.
[18] G. K. Whitmyre and M. D. Pandian, "Probabilistic assessment of the potential indoor air impacts of vent-free gas heating appliances in energy-efficient homes in the United States," *Journal of the Air & Waste Management Association,* vol. 68, no. 6, p. 616, 2018, doi: 10.1080/10962247.2018.1426652.
[19] H.-L. Kangas, D. Lazarevic, and P. Kivimaa, "Technical skills, disinterest and non-functional regulation: Barriers to building energy efficiency in Finland viewed by energy service companies," *Energy Policy,* vol. 114, pp. 63-76, 2018, doi: 10.1016/j.enpol.2017.11.060.
[20] F. Harkouss, F. Fardoun, and P. H. Biwole, "Multi-objective optimization methodology for net zero energy buildings," *Journal of Building Engineering,* vol. 16, pp. 57-71, 2018, doi: 10.1016/j.jobe.2017.12.003.
[21] K. Zhang, D. Zhao, X. Yin, R. Yang, and G. Tan, "Energy saving and economic analysis of a new hybrid radiative cooling system for single-family houses in the USA," *Applied Energy,* vol. 224, no. C, pp. 371-381, 2018, doi: 10.1016/j.apenergy.2018.04.115.
[22] S. Strunz, E. Gawel, and P. Lehmann, "Towards a general "Europeanization" of EU Member States' energy policies?," *Economics of Energy & Environmental Policy,* vol. 4, no. 2, p. 143, 2015, doi: 10.5547/2160-5890.4.2.sstr.
[23] C. Klessmann, A. Held, M. Rathmann, and M. Ragwitz, "Status and perspectives of renewable energy policy and deployment in the European Union—What is needed to reach the 2020 targets?," *Energy Policy,* vol. 39, no. 12, pp. 7637-7657, 2011, doi: 10.1016/j.enpol.2011.08.038.
[24] D. Yan *et al.*, "Occupant behavior modeling for building performance simulation: Current state and future challenges," *Energy & Buildings,* vol. 107, p. 264, 2015.
[25] A. Thomas, "Modeling Occupant Behavior, Systems Life Cycle Performance, and Energy Consumption Nexus in Buildings Using Multi-Method Distributed Simulation," Doctor of Philosophy
(Civil Engineering), University of Michigan, 2017.
[26] 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 & Buildings,* vol. 116, no. C, pp. 694-702, 2016, doi: 10.1016/j.enbuild.2015.11.052.
[27] Z. Deme Belafi, T. Hong, and A. Reith, "A critical review on questionnaire surveys in the field of energy-related occupant behaviour," *Energy Efficiency,* vol. 11, no. 8, pp. 2157-2177, 2018, doi: 10.1007/s12053-018-9711-z.
[28] M. N. Uddin, Q. Wang, H. H. Wei, H. L. Chi, and M. Ni, "Building information modeling (BIM), System dynamics (SD), and Agent-based modeling (ABM): Towards an

integrated approach," *Ain Shams Engineering Journal,* 2021/05/11/ 2021, doi: https://doi.org/10.1016/j.asej.2021.04.015.
[29] M. N. Uddin, H.-H. Wei, H. L. Chi, and M. Ni, "Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach," *Buildings,* vol. 11, no. 2, 2021, doi: 10.3390/buildings11020041.
[30] 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 & Buildings,* vol. 172, pp. 279-294, 2018, doi: 10.1016/j.enbuild.2018.05.017.
[31] T. Carmenate *et al.*, "Modeling Occupant-Building-Appliance Interaction for Energy Waste Analysis," *Procedia Engineering,* vol. 145, pp. 42-49, 2016, doi: 10.1016/j.proeng.2016.04.012.
[32] R. C. G. M. Loonen, F. Favoino, J. L. M. Hensen, and M. Overend, "Review of current status, requirements and opportunities for building performance simulation of adaptive facades†," vol. 10, ed, 2017, pp. 205-223.
[33] S. Attia and A. De Herde, "Early design simulation tools for net zero energy buildings: a comparison of ten tools," ed, 2011.
[34] S. Attia, A. De Herde, E. Gratia, and J. L. M. Hensen, "Achieving informed decision-making for net zero energy buildings design using building performance simulation tools," 2013.
[35] E. Touloupaki and T. Theodosiou, "Optimization of Building form to Minimize Energy Consumption through Parametric Modelling," vol. 38, ed, 2017, pp. 509-514.
[36] K. Negendahl, "Building performance simulation in the early design stage: An introduction to integrated dynamic models," *Automation in Construction,* vol. 54, pp. 39-53, 2015, doi: 10.1016/j.autcon.2015.03.002.
[37] S. Attia, J. L. M. Hensen, L. Beltrán, and A. De Herde, "Selection criteria for building performance simulation tools: contrasting architects' and engineers' needs," *Journal of Building Performance Simulation,* vol. 5, no. 3, pp. 155-169, 2012, doi: 10.1080/19401493.2010.549573.
[38] T. Hong, H. Sun, Y. Chen, S. C. Taylor-Lange, and D. Yan, "An occupant behavior modeling tool for co-simulation," *Energy & Buildings,* vol. 117, no. C, pp. 272-281, 2016, doi: 10.1016/j.enbuild.2015.10.033.
[39] T. Hong *et al.*, "An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema," *Building and Environment,* vol. 94, no. 1, pp. 196-205, 2015, doi: 10.1016/j.buildenv.2015.08.006.
[40] T. Hong, Amp, Apos, S. 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, no. C, pp. 764-777, 2015, doi: 10.1016/j.buildenv.2015.02.019.
[41] B. F. Balvedi, E. Ghisi, and R. Lamberts, "A review of occupant behaviour in residential buildings," *Energy & Buildings,* vol. 174, pp. 495-505, 2018, doi: 10.1016/j.enbuild.2018.06.049.
[42] T. Hong, Y. Chen, Z. Belafi, and S. D'Oca, "Occupant behavior models: A critical review of implementation and representation approaches in building performance simulation programs," *Build. Simul.,* vol. 11, no. 1, pp. 1-14, 2018, doi: 10.1007/s12273-017-0396-6.

[43] P. de Wilde, "The gap between predicted and measured energy performance of buildings: A framework for investigation," *Automation in Construction,* vol. 41, no. C, pp. 40-49, 2014, doi: 10.1016/j.autcon.2014.02.009.

[44] H. K. Mohamad Hajj-Hassana, "BEHAVIORAL AND PARAMETRIC EFFECTS ON ENERGY CONSUMPTION THROUGH BIM, BEM, AND ABM," in *Proceedings of the Creative Construction Conference (2018)*, Ljubljana, Slovenia, 30 June - 3 July 2018 2018, doi: 10.3311/CCC2018-106.

[45] Y. Chen, X. Luo, and T. Hong, "An Agent-Based Occupancy Simulator for Building Performance Simulation," 2016.

[46] J. Li, Z. Yu, F. Haghighat, and G. Zhang, "Development and improvement of occupant behavior models towards realistic building performance simulation: A review," *Sustainable Cities and Society,* vol. 50, 2019, doi: 10.1016/j.scs.2019.101685.

[47] E. M. Ryan and T. F. Sanquist, "Validation of Building Energy Modeling Tools Under Idealized and Realistic Conditions," *Energy and Buildings,* vol. 47, 2012, doi: 10.1016/j.enbuild.2011.12.020.

[48] J. Deblois, W. Collinge, M. Bilec, A. Jones, and L. Schaefer, "Modeling a Multi-Purpose Public Building with Stochastic Gains and Occupancy Schedules," *ASHRAE Transactions,* vol. 120, pp. O1-O8, 2014.

[49] J. Ligade, D. Sebastian, and A. Razban, "Challenges of Creating a Verifiable Building Energy Model," *ASHRAE Transactions,* vol. 125, no. 1, p. 20, 2019.

[50] M. Jia, R. S. Srinivasan, and A. A. Raheem, "From occupancy to occupant behavior: An analytical survey of data acquisition technologies, modeling methodologies and simulation coupling mechanisms for building energy efficiency," *Renewable and Sustainable Energy Reviews,* vol. 68, pp. 525-540, 2017, doi: 10.1016/j.rser.2016.10.011.

[51] Z. Deme Belafi, T. Hong, and A. Reith, "A library of building occupant behaviour models represented in a standardised schema," *Energy Efficiency,* vol. 12, no. 3, pp. 637-651, 2019, doi: 10.1007/s12053-018-9658-0.

[52] T. Hong, C. Koo, J. Kim, M. Lee, and K. Jeong, "A review on sustainable construction management strategies for monitoring, diagnosing, and retrofitting the building's dynamic energy performance: Focused on the operation and maintenance phase," *Applied Energy,* vol. 155, pp. 671-707, 2015, doi: 10.1016/j.apenergy.2015.06.043.

[53] V. S. K. V. Harish and A. Kumar, "A review on modeling and simulation of building energy systems," *Renewable and Sustainable Energy Reviews,* vol. 56, pp. 1272-1292, 2016, doi: 10.1016/j.rser.2015.12.040.

[54] B. W. Meerbeek, C. de Bakker, Y. A. W. de Kort, E. J. van Loenen, and T. Bergman, "Automated blinds with light feedback to increase occupant satisfaction and energy saving," *Building and Environment,* vol. 103, pp. 70-85, 2016.

[55] X. Chen, Q. Wang, and J. Srebric, "Occupant feedback based model predictive control for thermal comfort and energy optimization: A chamber experimental evaluation," *Applied Energy,* vol. 164, pp. 341-351, 2016, doi: 10.1016/j.apenergy.2015.11.065.

[56] M. N. Uddin, Anwer, S, Wei, H-H, Chi, H-L, Ni, M and Tamanna, N, "Energy Efficient Behavioural Trends in Residential Sectors for Low-Income Cultural Background: A Case- Study of Slums in Chittagong, Bangladesh," presented at the 37thAnnual ARCOM Conference, UK, 6-7 September, 2021.

[57] M. N. Uddin, H.-H. Wei, H. L. Chi, and M. Ni, "Influence of occupant behavior for building energy conservation: A systematic review study of diverse modeling and

simulation approach," *Buildings (Basel),* vol. 11, no. 2, pp. 1-27, 2021, doi: 10.3390/buildings11020041.
[58] Y. S. Lee and A. M. Malkawi, "Simulating multiple occupant behaviors in buildings: An agent-based modeling approach," *Energy & Buildings,* vol. 69, p. 407, 2014.
[59] T. Blochwitz *et al.*, "Functional Mockup Interface 2.0: The Standard for Tool independent Exchange of Simulation Models," ed, 2012, pp. 173-184.
[60] R. de Dear and G. S. Brager, "Developing an adaptive model of thermal comfort and preference," 1998.
[61] D. Bourgeois, C. Reinhart, and I. Macdonald, "Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control," *Energy & Buildings,* vol. 38, no. 7, pp. 814-823, 2006, doi: 10.1016/j.enbuild.2006.03.002.
[62] H. B. Rijal, P. Tuohy, F. Nicol, M. A. Humphreys, A. Samuel, and J. Clarke, "Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings," *Journal of Building Performance Simulation,* vol. 1, no. 1, pp. 17-30, 2008, doi: 10.1080/19401490701868448.
[63] C. Reinhart, "Lightswitch-2002: A model for manual and automated control of electric lighting and blinds," *Solar Energy,* vol. 77, no. 1, pp. 15-28, 2004.
[64] M. G. Patterson, "What is energy efficiency?(Concepts, Indicators and Methodological Issues)," *Energy Policy,* vol. 24, no. 5, p. 377, 1996, doi: 10.1016/0301-4215(96)00017-1.
[65] Y. Lee, "Modeling multiple occupant behaviors in buildings for increased simulation accuracy: An agent-based modeling approach," A. M. Malkawi, D. E. Leatherbarrow, B. Silverman, and Y. K. Yi, Eds., ed, 2013.
[66] R. L. Ackoff and J. Gharajedaghi, "Reflections on Systems and their Models," *Systems Research,* vol. 13, no. 1, pp. 13-23, 1996, doi: 10.1002/(SICI)1099-1735(199603)13:1<13::AID-SRES66>3.0.CO
2-O.
[67] L. Heschong, *Thermal delight in architecture*. Cambridge, Mass.: MIT Press, 1979.
[68] R. Yao, J. Liu, and B. Li, "Occupants' adaptive responses and perception of thermal environment in naturally conditioned university classrooms.(Report)," *Applied Energy,* vol. 87, no. 3, p. 1015, 2010, doi: 10.1016/j.apenergy.2009.09.028.
[69] M. A. Steane and K. Steemers, *Exploring thermal comfort and spatial diversity*. 2004, pp. 209-228.
[70] M. P. Deuble and R. J. de Dear, "Mixed-mode buildings: A double standard in occupants’ comfort expectations," *Building and Environment,* vol. 54, pp. 53-60, 2012, doi: 10.1016/j.buildenv.2012.01.021.
[71] K. Steemers and G. Y. Yun, "Household energy consumption: a study of the role of occupants," *Building Research & Information,* vol. 37, no. 5-6, pp. 625-637, 2009, doi: 10.1080/09613210903186661.
[72] M. Fishbein, *Predicting and changing behavior : the reasoned action approach*. New York: New York : Psychology Press, 2010.
[73] R. J. Vallerand, P. Deshaies, J.-P. Cuerrier, L. G. Pelletier, and C. Mongeau, "Ajzen and Fishbein's Theory of Reasoned Action as Applied to Moral Behavior: A Confirmatory Analysis," *Journal of Personality and Social Psychology,* vol. 62, no. 1, pp. 98-109, 1992, doi: 10.1037/0022-3514.62.1.98.
[74] E. J. Kothe, "Promoting Fruit and Vegetable Consumption: Modeling Behaviour

Change Using the Theory of Planned Behaviour," ed, 2012.
[75] G. J. Gold, "Review of Predicting and Changing Behavior: The Reasoned Action Approach: by M. Fishbein and I. Ajzen. New York, NY: Psychology Press, Taylor & Francis Group, 2010. 518 pp. ISBN 978-0-8058-5924-9. $69.95, hardcover," vol. 151, ed, 2011, pp. 382-385.
[76] D. Meichenbaum, "Changing Conceptions of Cognitive Behavior Modification: Retrospect and Prospect," *Journal of Consulting and Clinical Psychology,* vol. 61, no. 2, pp. 202-204, 1993, doi: 10.1037/0022-006X.61.2.202.
[77] S. Michie, L. Yardley, R. West, K. Patrick, and F. Greaves, "Developing and Evaluating Digital Interventions to Promote Behavior Change in Health and Health Care: Recommendations Resulting From an International Workshop," *Journal of Medical Internet Research,* 2017.
[78] J. S. Bailey, *Research methods in applied behavior analysis*, Second edition.. ed. New York, NY: Routledge, 2018.
[79] E. Delzendeh, S. Wu, A. Lee, and Y. Zhou, "The impact of occupants' behaviours on building energy analysis: A research review," *Renewable and Sustainable Energy Reviews,* vol. 80, no. C, pp. 1061-1071, 2017, doi: 10.1016/j.rser.2017.05.264.
[80] W. J. O'Brien, S. Ponticelli, Computing, and s. Information Technology Division of the American Society of Civil Engineers, *Computing in civil engineering 2015 : proceedings of the 2015 International Workshop in Civil Engineering, June 21-23, 2015, Austin, Texas*. Reston, Virginia: American Society of Civil Engineers, 2015.
[81] B. Fogg, "Persuasive technology: using computers to change what we think and do," *Ubiquity,* vol. 2002, no. December, p. 2, 2002, doi: 10.1145/764008.763957.
[82] P. Tikka and H. Oinas-Kukkonen.
[83] H. Oinas-Kukkonen and M. Harjumaa, "Persuasive Systems Design: Key Issues, Process Model, and System Features," *Communications of the Association for Information Systems,* vol. 24, no. 1, p. 96, 2009.
[84] C. Pasalar, "The effects of spatial layouts on students' interactions in middle schools Multiple case analysis," 2004.
[85] Y. Chen, T. Hong, and M. A. Piette, "Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis," *Applied Energy,* vol. 205, no. C, pp. 323-335, 2017, doi: 10.1016/j.apenergy.2017.07.128.
[86] N. Soares *et al.*, "A review on current advances in the energy and environmental performance of buildings towards a more sustainable built environment," *Renewable and Sustainable Energy Reviews,* vol. 77, no. C, pp. 845-860, 2017, doi: 10.1016/j.rser.2017.04.027.
[87] C. F. Reinhart and C. Cerezo Davila, "Urban building energy modeling – A review of a nascent field," *Building and Environment,* vol. 97, pp. 196-202, 2016, doi: 10.1016/j.buildenv.2015.12.001.
[88] L. Liu, B. Lin, and B. Peng, "Correlation analysis of building plane and energy consumption of high-rise office building in cold zone of China," *Build. Simul.,* vol. 8, no. 5, pp. 487-498, 2015, doi: 10.1007/s12273-015-0226-7.
[89] L. Troup, R. Phillips, M. Eckelman, and D. Fannon, "Effect of window-to-wall ratio on measured energy consumption in US office buildings," *Energy and Buildings,* vol. 203, p. 1, 2019, doi: 10.1016/j.enbuild.2019.109434.
[90] Y. Han, J. E. Taylor, and A. L. Pisello, "Exploring mutual shading and mutual reflection

inter-building effects on building energy performance," *Applied Energy,* vol. 185, no. P2, pp. 1556-1564, 2017, doi: 10.1016/j.apenergy.2015.10.170.
[91] H. A. Simon, *The sciences of the artificial*, 3rd ed.. ed. Cambridge, Mass, 1996.
[92] A. M. Malkawi, "Developments in environmental performance simulation," vol. 13, ed, 2004, pp. 437-445.
[93] B. Balvedi, E. Ghisi, and R. Lamberts, "A review of occupant behaviour in residential buildings," *Energy and Buildings,* vol. 174, pp. 495-505, 2018, doi: 10.1016/j.enbuild.2018.06.049.
[94] S. D’Oca, T. Hong, and J. Langevin, "The human dimensions of energy use in buildings: A review," *RENEW SUST ENERG REV,* vol. 81, no. P1, pp. 731-742, 2018, doi: 10.1016/j.rser.2017.08.019.
[95] H. Poincaré and G. B. Halsted, *The Foundations of Science: Science and Hypothesis, The Value of Science, Science and Method*. 2012.
[96] K. R. Popper and G. Weiss, "The Logic of Scientific Discovery," *Physics Today,* vol. 12, no. 11, pp. 53-54, 1959, doi: 10.1063/1.3060577.
[97] J. A. Sokolowski and C. M. Banks, *Principles of modeling and simulation: a multidisciplinary approach*. Hoboken: Hoboken: WILEY, 2009, doi:10.1002/9780470403563.
[98] J. K. Smith, "The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology. Edited by Wiebe E. Bijker, Thomas P. Hughes, and Trevor Pinch. Cambridge, Mass.: MIT Press, 1987. 405 pp. Illustrations, charts, notes, bibliography, and index. $35.00," *Bus. Hist. Rev.,* vol. 62, no. 2, pp. 341-342, 1988, doi: 10.2307/3116018.
[99] Z. O'Neill and F. Niu, "Uncertainty and sensitivity analysis of spatio-temporal occupant behaviors on residential building energy usage utilizing Karhunen-Loève expansion," *Building and Environment,* vol. 115, pp. 157-172, 2017, doi: 10.1016/j.buildenv.2017.01.025.
[100] U. Mohammad Nyme, W. Hsi-Hsien, C. Hung Lin, and N. Meng, "Influence of Occupant Behavior for Building Energy Conservation: A Systematic Review Study of Diverse Modeling and Simulation Approach," *Buildings (Basel),* vol. 11, no. 41, p. 41, 2021, doi: 10.3390/buildings11020041.
[101] A. Paone and J.-P. Bacher, "The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art," *Energies,* vol. 11, no. 4, p. 953, 2018, doi: 10.3390/en11040953.
[102] S. Karjalainen, "Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption," *Energy Efficiency,* vol. 9, no. 6, pp. 1257-1270, 2016, doi: 10.1007/s12053-015-9422-7.
[103] M. M. Agha-Hossein, S. El-Jouzi, A. A. Elmualim, J. Ellis, and M. Williams, "Post-occupancy studies of an office environment: Energy performance and occupants' satisfaction," *Building and Environment,* vol. 69, pp. 121-130, 2013, doi: 10.1016/j.buildenv.2013.08.003.
[104] S. Caan, *Rethinking design and interiors : human beings in the built environment*. London: Laurence King Pub., 2011.
[105] S. Augustin, *Place advantage : applied psychology for interior architecture*. Hoboken, N.J.: John Wiley & Sons, 2009.
[106] P. Zou, X. Xu, J. Sanjayan, and J. Wang, "A mixed methods design for building

occupants’ energy behavior research," *Energy and Buildings,* vol. 166, p. 239, 2018.
[107] J. Langevin, J. Wen, and P. L. Gurian, "Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors," *Building and Environment,* vol. 88, pp. 27-45, 2015, doi: 10.1016/j.buildenv.2014.11.037.
[108] H. Putra, C. Andrews, and J. Senick, "An agent-based model of building occupant behavior during load shedding," *Build. Simul.,* vol. 10, no. 6, pp. 845-859, 2017, doi: 10.1007/s12273-017-0384-x.
[109] G. Happle, J. A. Fonseca, and A. Schlueter, "A review on occupant behavior in urban building energy models," *Energy & Buildings,* vol. 174, pp. 276-292, 2018, doi: 10.1016/j.enbuild.2018.06.030.
[110] M. N. Uddin, H. H. Wei, H. L. Chi, and M. Ni, "An Inquisition of Envelope Fabric for Building Energy Performance Using Prominent BIM-BPS Tools - A Case Study in Sub-Tropical Climate," vol. 354, ed, 2019.
[111] O. Oduyemi and M. Okoroh, "Building performance modelling for sustainable building design," *International Journal of Sustainable Built Environment,* vol. 5, no. 2, pp. 461-469, 2016, doi: 10.1016/j.ijsbe.2016.05.004.
[112] H. B. Gunay, W. O'Brien, and I. Beausoleil-Morrison, "Implementation and comparison of existing occupant behaviour models in EnergyPlus," *Journal of Building Performance Simulation,* vol. 9, no. 6, pp. 567-588, 2016, doi: 10.1080/19401493.2015.1102969.
[113] M. Ouf, W. O’Brien, and H. Gunay, "Improving occupant-related features in building performance simulation tools," *Build. Simul.,* vol. 11, no. 4, pp. 803-817, 2018, doi: 10.1007/s12273-018-0443-y.
[114] A. Lindner, S. Park, and M. Mitterhofer, "Determination of requirements on occupant behavior models for the use in building performance simulations," *Build. Simul.,* vol. 10, no. 6, pp. 861-874, 2017, doi: 10.1007/s12273-017-0394-8.
[115] H. Jang and J. Kang, "An energy model of high-rise apartment buildings integrating variation in energy consumption between individual units," *Energy & Buildings,* vol. 158, pp. 656-667, 2018, doi: 10.1016/j.enbuild.2017.10.047.
[116] X. Sang, W. Pan, and M. M. Kumaraswamy, "Informing Energy-efficient Building Envelope Design Decisions for Hong Kong," *Energy Procedia,* vol. 62, no. C, pp. 123-131, 2014, doi: 10.1016/j.egypro.2014.12.373.
[117] C. Shang-Yuan, "A green building information modelling approach: building energy performance analysis and design optimization," *MATEC Web of Conferences,* vol. 169, 2018, doi: 10.1051/matecconf/201816901004.
[118] M. N. Uddin, A. M. Selvam, J. Shahoonda, and R. Prasanth, "Optimization of green building for low-income people at pondicherry," *Civil Engineering and Architecture,* vol. 6, no. 6, pp. 283-292, 2018, doi: 10.13189/cea.2018.060602.
[119] M. N. Uddin, H. H. Wei, H. L. Chi, M. Ni, and P. Elumalai, "Building information modeling (BIM) incorporated green building analysis: an application of local construction materials and sustainable practice in the built environment," *Journal of building pathology and rehabilitation,* vol. 6, no. 1, 2021, doi: 10.1007/s41024-021-00106-5.
[120] S. S. M. Al-Din, M. Iranfare, and Z. N. S. Surchi, "Building Thermal Comfort Based on Envelope Development: Criteria for selecting right case study in Kyrenia- North Cyprus," vol. 115, ed, 2017, pp. 80-91.

[121] P. Anand, C. Deb, and R. Alur, "A simplified tool for building layout design based on thermal comfort simulations," *Frontiers of Architectural Research,* vol. 6, no. 2, pp. 218-230, 2017, doi: 10.1016/j.foar.2017.03.001.

[122] S. Dhaka, J. Mathur, and V. Garg, "Combined effect of energy efficiency measures and thermal adaptation on air conditioned building in warm climatic conditions of India," *Energy & Buildings,* vol. 55, no. C, pp. 351-360, 2012, doi: 10.1016/j.enbuild.2012.09.038.

[123] A. Tulsyan, S. Dhaka, J. Mathur, and J. V. Yadav, "Potential of energy savings through implementation of Energy Conservation Building Code in Jaipur city, India," *Energy & Buildings,* vol. 58, no. C, pp. 123-130, 2013, doi: 10.1016/j.enbuild.2012.11.015.

[124] F. H. Abanda and L. Byers, "An investigation of the impact of building orientation on energy consumption in a domestic building using emerging BIM (Building Information Modelling)," *Energy,* vol. 97, no. C, pp. 517-527, 2016, doi: 10.1016/j.energy.2015.12.135.

[125] S. Habibi, "The promise of BIM for improving building performance," *Energy & Buildings,* vol. 153, pp. 525-548, 2017, doi: 10.1016/j.enbuild.2017.08.009.

[126] F. Patiño-Cambeiro, G. Bastos, J. Armesto, and F. Patiño-Barbeito, "Multidisciplinary Energy Assessment of Tertiary Buildings: Automated Geomatic Inspection, Building Information Modeling Reconstruction and Building Performance Simulation," *Energies,* vol. 10, no. 7, 2017, doi: 10.3390/en10071032.

[127] Y. Chen, T. Hong, and X. Luo, "An agent-based stochastic Occupancy Simulator," *Build. Simul.,* vol. 11, no. 1, pp. 37-49, 2018, doi: 10.1007/s12273-017-0379-7.

[128] D. Yan, J. Xia, W. Tang, F. Song, X. Zhang, and Y. Jiang, "DeST -- An integrated building simulation toolkit Part I: Fundamentals," *Building Simulation,* vol. 1, no. 2, p. 95, 2008.

[129] D. B. Crawley *et al.*, "EnergyPlus: creating a new-generation building energy simulation program," *Energy & Buildings,* vol. 33, no. 4, pp. 319-331, 2001, doi: 10.1016/S0378-7788(00)00114-6.

[130] T. Hong, D. Yan, Apos, S. Oca, and C.-F. Chen, "Ten questions concerning occupant behavior in buildings: The big picture," *Building and Environment,* vol. 114, no. C, pp. 518-530, 2017, doi: 10.1016/j.buildenv.2016.12.006.

[131] H. B. Gunay, W. O'Brien, I. Beausoleil-Morrison, R. Goldstein, S. Breslav, and A. Khan, "Coupling stochastic occupant models to building performance simulation using the discrete event system specification formalism," *Journal of Building Performance Simulation,* vol. 7, no. 6, pp. 457-478, 2014, doi: 10.1080/19401493.2013.866695.

[132] I. Gaetani, P.-J. Hoes, and J. L. M. Hensen, "Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy," *Energy & Buildings,* vol. 121, no. C, pp. 188-204, 2016, doi: 10.1016/j.enbuild.2016.03.038.

[133] J. Huang and K. R. Gurney, "The variation of climate change impact on building energy consumption to building type and spatiotemporal scale," *Energy,* vol. 111, no. C, pp. 137-153, 2016, doi: 10.1016/j.energy.2016.05.118.

[134] S. D’oca, T. Hong, and J. Langevin, "The human dimensions of energy use in buildings: A review," *Renewable and Sustainable Energy Reviews,* vol. 81, no. P1, pp. 731-742, 2018, doi: 10.1016/j.rser.2017.08.019.

[135] S. Papadopoulos and E. Azar, "Integrating building performance simulation in agent-based modeling using regression surrogate models: A novel human-in-the-loop energy modeling approach," *Energy & Buildings,* vol. 128, pp. 214-223, 2016, doi:

10.1016/j.enbuild.2016.06.079.
[136] L. C. Tagliabue, M. Manfren, A. L. C. Ciribini, and E. De Angelis, "Probabilistic behavioural modeling in building performance simulation—The Brescia eLUX lab," *Energy & Buildings,* vol. 128, pp. 119-131, 2016, doi: 10.1016/j.enbuild.2016.06.083.
[137] Amos Darko, Albert Ping Chuen Chan, a. Emmanuel Kingsford Owusu, and M. F. Antwi-Afari, "BENEFITS OF GREEN BUILDING: A LITERATURE REVIEW," presented at the RICS COBRA 2018, RICS HQ, London, UK, 23 – 24 April 2018. [Online]. Available: https://www.rics.org/south-asia/news-insight/research/conference-papers/benefits-of-green-building-a-literature-review/, access date: 19th September, 2019.
[138] X. Zhao, "A scientometric review of global BIM research: Analysis and visualization," *Automation in Construction,* vol. 80, p. 37, 2017.
[139] H.-N. Su and P.-C. Lee, "Mapping knowledge structure by keyword co-occurrence: a first look at journal papers in Technology Foresight," *Scientometrics,* vol. 85, no. 1, pp. 65-79, 2010, doi: 10.1007/s11192-010-0259-8.
[140] T. Prabhakaran, H. H. Lathabai, and M. Changat, "Detection of paradigm shifts and emerging fields using scientific network: A case study of Information Technology for Engineering," *Technological Forecasting & Social Change,* vol. 91, pp. 124-145, 2015, doi: 10.1016/j.techfore.2014.02.003.
[141] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, and F. Descamps, "A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison," *Building and Environment,* vol. 75, pp. 67-78, 2014, doi: 10.1016/j.buildenv.2014.01.021.
[142] D. Yan *et al.*, "Occupant behavior modeling for building performance simulation: Current state and future challenges," *Energy & Buildings,* vol. 107, no. C, pp. 264-278, 2015, doi: 10.1016/j.enbuild.2015.08.032.
[143] P. D. Andersen, A. Iversen, H. Madsen, and C. Rode, "Dynamic modeling of presence of occupants using inhomogeneous Markov chains," *Energy & Buildings,* vol. 69, no. C, pp. 213-223, 2014, doi: 10.1016/j.enbuild.2013.10.001.
[144] J. Liisberg, J. K. Møller, H. Bloem, J. Cipriano, G. Mor, and H. Madsen, "Hidden Markov Models for indirect classification of occupant behaviour," *Sustainable Cities and Society,* vol. 27, pp. 83-98, 2016, doi: 10.1016/j.scs.2016.07.001.
[145] V. Fabi, R. K. Andersen, and S. Corgnati, "Verification of stochastic behavioural models of occupants' interactions with windows in residential buildings," *Building and Environment,* vol. 94, no. 1, pp. 371-383, 2015, doi: 10.1016/j.buildenv.2015.08.016.
[146] H. B. Gunay, W. O'Brien, and I. Beausoleil-Morrison, "A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices," *Building and Environment,* vol. 70, p. 31, 2013.
[147] M. Jia and R. Srinivasan, "Occupant behavior modeling for smart buildings: a critical review of data acquisition technologies and modeling methodologies," ed, 2015, pp. 3345-3355.
[148] O. Guerra Santin, "Behavioural Patterns and User Profiles related to energy consumption for heating," *Energy & Buildings,* vol. 43, no. 10, pp. 2662-2672, 2011, doi: 10.1016/j.enbuild.2011.06.024.
[149] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study," *Energy & Buildings,* vol. 48, p. 240, 2012.
[150] F. V. M. V. C. S. a. A. RK., "Occupants' behaviour in office building: stochastic models

for window opening. ," presented at the Proceedings of 8th Windsor Conference: Counting the Cost of Comfort in a changing world, Windsor, London, 10-13 April 2014, 2014.
[151] V. Fabi, Camisassi, V., Causone, F., Corgnati, S. P., & Andersen, R. K., "Light switch behaviour: occupant behaviour stochastic models in office buildings," 2014.
[152] F. Haldi and D. Robinson, "On the behaviour and adaptation of office occupants," *Building and Environment,* vol. 43, no. 12, pp. 2163-2177, 2008, doi: 10.1016/j.buildenv.2008.01.003.
[153] V. Tabak and B. de Vries, "Methods for the prediction of intermediate activities by office occupants," *Building and Environment,* vol. 45, no. 6, pp. 1366-1372, 2010, doi: 10.1016/j.buildenv.2009.11.018.
[154] S. D'oca and T. Hong, "Occupancy schedules learning process through a data mining framework," *Energy & Buildings,* vol. 88, no. C, pp. 395-408, 2015, doi: 10.1016/j.enbuild.2014.11.065.
[155] X. Ren, D. Yan, and T. Hong, "Data mining of space heating system performance in affordable housing," *Building and Environment,* vol. 89, no. C, pp. 1-13, 2015, doi: 10.1016/j.buildenv.2015.02.009.
[156] H. Zhou, L. Qiao, Y. Jiang, H. Sun, and Q. Chen, "Recognition of air-conditioner operation from indoor air temperature and relative humidity by a data mining approach.(Report)," *Energy & Buildings,* vol. 111, no. C, p. 233, 2016, doi: 10.1016/j.enbuild.2015.11.034.
[157] J. Zhao, B. Lasternas, K. P. Lam, R. Yun, and V. Loftness, "Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining," *Energy & Buildings,* vol. 82, pp. 341-355, 2014, doi: 10.1016/j.enbuild.2014.07.033.
[158] T. Hong, D. Yan, S. D'Oca, and C.-F. Chen, "Ten questions concerning occupant behavior in buildings: The big picture," *Building and Environment,* vol. 114, no. C, pp. 518-530, 2017, doi: 10.1016/j.buildenv.2016.12.006.
[159] T. Labeodan, K. Aduda, G. Boxem, and W. Zeiler, "On the application of multi-agent systems in buildings for improved building operations, performance and smart grid interaction – A survey," *Renewable and Sustainable Energy Reviews,* vol. 50, pp. 1405-1414, 2015, doi: 10.1016/j.rser.2015.05.081.
[160] F. Haldi and D. Robinson, "The impact of occupants' behaviour on building energy demand," *Journal of Building Performance Simulation: Special Issue: Modelling Occupants' Presence and Behaviour - Part I,* vol. 4, no. 4, pp. 323-338, 2011, doi: 10.1080/19401493.2011.558213.
[161] V. Barthelmes, R. Li, R. Andersen, W. Bahnfleth, S. Pcorgnati, and C. Rode, "Profiling occupant behaviour in Danish dwellings using time use survey data," *Energy and Buildings,* vol. 177, p. 329, 2018.
[162] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study," *Energy & Buildings,* vol. 48, no. C, pp. 240-248, 2011, doi: 10.1016/j.enbuild.2012.01.037.
[163] V. Fabi, R. Andersen, S. Corgnati, and B. Olesen, "A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings," *Build. Simul.,* vol. 6, no. 4, pp. 415-427, 2013, doi: 10.1007/s12273-013-0119-6.

[164] S. D'Oca, V. Fabi, S. Corgnati, and R. Andersen, "Effect of thermostat and window opening occupant behavior models on energy use in homes," *Build. Simul.,* vol. 7, no. 6, pp. 683-694, 2014, doi: 10.1007/s12273-014-0191-6.
[165] J. Yao, "Modelling and simulating occupant behaviour on air conditioning in residential buildings," *Energy & Buildings,* vol. 175, pp. 1-10, 2018, doi: 10.1016/j.enbuild.2018.07.013.
[166] X. Zhang *et al.*, "Smart meter and in-home display for energy savings in residential buildings: a pilot investigation in Shanghai, China," *Intelligent Buildings International,* vol. 11, no. 1, pp. 4-26, 2019, doi: 10.1080/17508975.2016.1213694.
[167] M. Ashouri, F. Haghighat, B. C. M. Fung, A. Lazrak, and H. Yoshino, "Development of building energy saving advisory: A data mining approach," *Energy & Buildings,* vol. 172, pp. 139-151, 2018, doi: 10.1016/j.enbuild.2018.04.052.
[168] H. Zhou, L. Qiao, Y. Jiang, H. Sun, and Q. Chen, "Recognition of air-conditioner operation from indoor air temperature and relative humidity by a data mining approach," *Energy & Buildings,* vol. 111, no. C, pp. 233-241, 2016, doi: 10.1016/j.enbuild.2015.11.034.
[169] X. Liang, T. Hong, and G. Q. Shen, "Occupancy data analytics and prediction: A case study," *Building and Environment,* vol. 102, no. C, pp. 179-192, 2016, doi: 10.1016/j.buildenv.2016.03.027.
[170] J. Wang, J. Zhu, Z. Ding, P. X. W. Zou, and J. Li, "Typical energy-related behaviors and gender difference for cooling energy consumption," *Journal of Cleaner Production,* vol. 238, 2019, doi: 10.1016/j.jclepro.2019.117846.
[171] Z. Yu, B. C. M. Fung, F. Haghighat, H. Yoshino, and E. Morofsky, "A systematic procedure to study the influence of occupant behavior on building energy consumption," *Energy & Buildings,* vol. 43, no. 6, pp. 1409-1417, 2011, doi: 10.1016/j.enbuild.2011.02.002.
[172] E. Azar and C. C. Menassa, "Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings," *Journal of Computing in Civil Engineering,* vol. 26, no. 4, pp. 506-518, 2012, doi: 10.1061/(ASCE)CP.1943-5487.0000158.
[173] A. Kashif, S. Ploix, J. Dugdale, and X. H. B. Le, "Simulating the dynamics of occupant behaviour for power management in residential buildings," *Energy & Buildings,* vol. 56, no. C, pp. 85-93, 2013, doi: 10.1016/j.enbuild.2012.09.042.
[174] E. Azar, C. Nikolopoulou, and S. Papadopoulos, "Integrating and optimizing metrics of sustainable building performance using human-focused agent-based modeling," *Applied Energy,* vol. 183, pp. 926-937, 2016, doi: 10.1016/j.apenergy.2016.09.022.
[175] Z. Ding, T. Hu, M. Li, X. Xu, and P. X. W. Zou, "Agent-based model for simulating building energy management in student residences," *Energy & Buildings,* vol. 198, pp. 11-27, 2019, doi: 10.1016/j.enbuild.2019.05.053.
[176] J. Langevin, J. Wen, and P. L. Gurian, "Quantifying the human–building interaction: Considering the active, adaptive occupant in building performance simulation," *Energy & Buildings,* vol. 117, pp. 372-386, 2016, doi: 10.1016/j.enbuild.2015.09.026.
[177] E. Azar and C. C. Menassa, "Evaluating the impact of extreme energy use behavior on occupancy interventions in commercial buildings," *Energy & Buildings,* vol. 97, pp. 205-218, 2015, doi: 10.1016/j.enbuild.2015.03.059.
[178] J. Chen, J. E. Taylor, and H.-H. Wei, "Modeling building occupant network energy consumption decision-making: The interplay between network structure and conservation," *Energy and Buildings,* vol. 47, pp. 515-524, 2012, doi:

10.1016/j.enbuild.2011.12.026.
[179] E. Azar and H. Al Ansari, "Multilayer Agent-Based Modeling and Social Network Framework to Evaluate Energy Feedback Methods for Groups of Buildings," *Journal of Computing in Civil Engineering,* vol. 31, no. 4, 2017, doi: 10.1061/(ASCE)CP.1943-5487.0000651.
[180] A. L. Pisello and F. Asdrubali, "Human-based energy retrofits in residential buildings: A cost-effective alternative to traditional physical strategies," *Applied Energy,* vol. 133, pp. 224-235, 2014, doi: 10.1016/j.apenergy.2014.07.049.
[181] Y. Peng, Z. Nagy, and A. Schlüter, "Temperature-preference learning with neural networks for occupant-centric building indoor climate controls," *Building and Environment,* vol. 154, pp. 296-308, 2019, doi: 10.1016/j.buildenv.2019.01.036.
[182] T. Abuimara, W. O'Brien, B. Gunay, and J. S. Carrizo, "Towards occupant-centric simulation-aided building design: a case study," *Building Research & Information,* vol. 47, no. 8, pp. 866-882, 2019, doi: 10.1080/09613218.2019.1652550.
[183] M. A. R. Lopes, C. H. Antunes, A. Reis, and N. Martins, "Estimating energy savings from behaviours using building performance simulations," *Building Research & Information,* vol. 45, no. 3, pp. 303-319, 2017, doi: 10.1080/09613218.2016.1140000.
[184] T. Sharmin, M. Gül, and M. Al-Hussein, "A user-centric space heating energy management framework for multi-family residential facilities based on occupant pattern prediction modeling," *Build. Simul.,* vol. 10, no. 6, pp. 899-916, 2017, doi: 10.1007/s12273-017-0376-x.
[185] P. Zhu, M. Gilbride, D. Yan, H. Sun, and C. Meek, "Lighting energy consumption in ultra-low energy buildings: Using a simulation and measurement methodology to model occupant behavior and lighting controls," *Build. Simul.,* vol. 10, no. 6, pp. 799-810, 2017, doi: 10.1007/s12273-017-0408-6.
[186] Z. Belafi, T. Hong, and A. Reith, "Smart building management vs. intuitive human control—Lessons learnt from an office building in Hungary," *Build. Simul.,* vol. 10, no. 6, pp. 811-828, 2017, doi: 10.1007/s12273-017-0361-4.
[187] X. Feng, D. Yan, R. Yu, and Y. Gao, "Investigation and modelling of the centralized solar domestic hot water system in residential buildings," *Build. Simul.,* vol. 10, no. 1, pp. 87-96, 2017, doi: 10.1007/s12273-016-0315-2.
[188] Y. Leroy and B. Yannou, "An activity-based modelling framework for quantifying occupants’ energy consumption in residential buildings," *Computers in Industry,* vol. 103, pp. 1-13, 2018, doi: 10.1016/j.compind.2018.08.009.
[189] S. Hu, D. Yan, and M. Qian, "Using bottom-up model to analyze cooling energy consumption in China's urban residential building," *Energy & Buildings,* vol. 202, 2019, doi: 10.1016/j.enbuild.2019.109352.
[190] C. Yu, J. Du, and W. Pan, "Improving accuracy in building energy simulation via evaluating occupant behaviors: A case study in Hong Kong," *Energy & Buildings,* vol. 202, 2019, doi: 10.1016/j.enbuild.2019.109373.
[191] S. Zahiri and H. Elsharkawy, "Towards energy-efficient retrofit of council housing in London: Assessing the impact of occupancy and energy-use patterns on building performance," *Energy & Buildings,* vol. 174, pp. 672-681, 2018, doi: 10.1016/j.enbuild.2018.07.010.
[192] A. Santangelo, D. Yan, X. Feng, and S. Tondelli, "Renovation strategies for the Italian public housing stock: Applying building energy simulation and occupant behaviour

modelling to support decision-making process," *Energy and Buildings,* vol. 167, p. 269, 2018.
[193] K. Sun and T. Hong, "A simulation approach to estimate energy savings potential of occupant behavior measures," *Energy & Buildings,* vol. 136, pp. 43-62, 2017, doi: 10.1016/j.enbuild.2016.12.010.
[194] H. Ben and K. Steemers, "Energy retrofit and occupant behaviour in protected housing: A case study of the Brunswick Centre in London," *Energy & Buildings,* vol. 80, no. C, pp. 120-130, 2014, doi: 10.1016/j.enbuild.2014.05.019.
[195] J. Lim, "Cooling Energy Implications of Occupant Factor in Buildings under Climate Change," *Sustainability,* vol. 9, no. 11, p. 2039, 2017, doi: 10.3390/su9112039.
[196] S. W. Elham Delzendeh, and Rima Alaaeddine, "THE ROLE OF SPACE DESIGN IN PREDICTION OF OCCUPANCY IN MULTI-FUNCTIONAL SPACES OF PUBLIC BUILDINGS " presented at the Building Performance Analysis Conference and SimBuild, Chicago, IL, September 26-28, 2018.
[197] Y. Sofia, S. Nikos, and K. Emmanuel, "An Event-Driven Approach for Changing User Behaviour towards an Enhanced Building's Energy Efficiency," *Buildings (Basel),* vol. 10, no. 183, p. 183, 2020, doi: 10.3390/buildings10100183.
[198] J. C. P. Cheng and J. L. G. Vincent, "Integrating Agent-Based Human Behavior Simulation with Building Information Modeling for Building Design," *IJET,* vol. 5, no. 4, pp. 473-477, 2013, doi: 10.7763/IJET.2013.V5.600.
[199] A. Micolier, F. Taillandier, P. Taillandier, and F. Bos, "Li-BIM, an agent-based approach to simulate occupant-building interaction from the Building-Information Modelling," *Engineering Applications of Artificial Intelligence,* vol. 82, pp. 44-59, 2019, doi: 10.1016/j.engappai.2019.03.008.
[200] A. W. A. Hammad, "Minimising the Deviation between Predicted and Actual Building Performance via Use of Neural Networks and BIM," *Buildings (Basel),* vol. 9, no. 5, p. 131, 2019, doi: 10.3390/buildings9050131.
[201] M. Saunders, P. Lewis, and A. Thornhill, *Research Methods for Business Students*. 2015.
[202] C. Malalgoda, D. Amaratunga, and R. Haigh, "Empowering local governments in making cities resilient to disasters: research methodological perspectives," *Procedia Engineering,* vol. 212, pp. 902-909, 2018, doi: 10.1016/j.proeng.2018.01.116.
[203] D. H. T. Walker, "Choosing an appropriate research methodology," *Construction Management and Economics,* vol. 15, no. 2, pp. 149-159, 1997, doi: 10.1080/014461997000000003.
[204] E. Delzendeh, S. Wu, and R. Alaaeddine, *The Role of Space Design in Prediction of Occupancy in Multi-Functional Spaces of Public Buildings*. 2018.
[205] E. Delzendeh and S. Wu, *The Influence of Space Layout Design on Occupant's Energy Behaviour*. 2017, pp. 601-608.
[206] I. G. Dino, "An evolutionary approach for 3D architectural space layout design exploration," *Automation in construction,* vol. 69, pp. 131-150, 2016, doi: 10.1016/j.autcon.2016.05.020.
[207] A. L. Clarke, M. Jhamb, and P. N. Bennett, "Barriers and facilitators for engagement and implementation of exercise in end-stage kidney disease: Future theory-based interventions using the Behavior Change Wheel," *Semin Dial,* vol. 32, no. 4, pp. 308-319, 2019, doi: 10.1111/sdi.12787.
[208] E. E. Leppien, T. L. Demler, and E. T. Boff, "Exploring the effectiveness of team-based

enablement interventions to improve antibiotic prescribing within a psychiatric hospital," *Innov Clin Neurosci,* vol. 16, no. 5-6, pp. 22-29, 2019.

[209] R. American Society of Heating and E. Air-Conditioning, *Measurement of energy and demand savings*. Atlanta, Ga.: ASHRAE, 2002.

[210] (November, 2015). *M&V Guidelines: Measurement and Verification for Performance-Based Contracts, Version 4.0*. [Online] Available: https://www.energy.gov/sites/prod/files/2016/01/f28/mv_guide_4_0.pdf

[211] B. P. Zeigler, *Theory of modeling and simulation : integrating discrete event and continuous complex dynamic systems*, 2nd ed.. ed. San Diego, [Calif.]
London: Academic, 2000.

[212] W. Wang, R. Zmeureanu, and H. Rivard, "Applying multi-objective genetic algorithms in green building design optimization," *Building and Environment,* vol. 40, no. 11, pp. 1512-1525, 2005, doi: 10.1016/j.buildenv.2004.11.017.

[213] M. JIA, "OCCUPANT BEHAVIOR MODELING FOR IMPROVING COMMERCIAL BUILDING ENERGY USE SIMULATION," PhD, UNIVERSITY OF FLORIDA, 28289322, 2018. [Online]. Available: https://www.proquest.com/openview/7aae9e6434f2d9fd411cb5becca07944/1?pq-origsite=gscholar&cbl=18750&diss=y

[214] M. N. Uddin, Anwer, S, Wei, H-H, Chi, H-L, Ni, M and Tamanna, N, "ENERGY EFFICIENT BEHAVIOURAL TRENDS IN RESIDENTIAL SECTORS FOR LOW-INCOME CULTURAL BACKGROUND: A CASE-STUDY OF SLUMS IN CHITTAGONG, BANGLADESH," presented at the 37th Annual ARCOM Conference, UK, 6-7 September, 2021.

[215] J. Jaccard, *Theory construction and model-building skills : a practical guide for social scientists*. New York: Guilford Press, 2010.

[216] "06/02440 Adaptive temperature limits: a new guideline in The Netherlands. A new approach for the assessment of building performance with respect to thermal indoor climate: van der Linden, A. C. et al. Energy and Buildings, 2006, 38, (1), 8–17," *Fuel and Energy Abstracts,* vol. 47, no. 5, pp. 369-369, 2006, doi: 10.1016/S0140-6701(06)82448-3.

[217] C. M. Macal and M. J. North, "Tutorial on agent-based modelling and simulation," *Journal of Simulation,* vol. 4, no. 3, pp. 151-162, 2010, doi: 10.1057/jos.2010.3.

[218] G. K. Bharathy and B. Silverman, "Validating agent based social systems models," ed, 2010, pp. 441-453.

[219] M. Luck, P. McBurney, and C. Preist, "A Manifesto for Agent Technology: Towards Next Generation Computing," *Autonomous Agents and Multi-Agent Systems,* vol. 9, no. 3, pp. 203-252, 2004, doi: 10.1023/B:AGNT.0000038027.29035.7c.

[220] M. Schwaninger, "System dynamics and the evolution of the systems movement," *Systems Research and Behavioral Science,* vol. 23, no. 5, pp. 583-594, 2006, doi: 10.1002/sres.800.

[221] D.-Y. Lin, N. Eluru, S. Waller, and C. Bhat, "Integration of Activity-Based Modeling and Dynamic Traffic Assignment," *Transportation Research Record,* vol. 2076, no. 2076, pp. 52-61, 2008, doi: 10.3141/2076-06.

[222] S. Yang, Y. Zhao, T. Erdem, and Y. Zhao, "Modeling the Intrahousehold Behavioral Interaction," *Journal of Marketing Research,* vol. 47, no. 3, pp. 470-484, 2010, doi: 10.1509/jmkr.47.3.470.

[223] B. Bueno, G. Pigeon, L. K. Norford, K. Zibouche, and C. Marchadier, "Development and evaluation of a building energy model integrated in the TEB scheme,"

Geoscientific Model Development, vol. 5, no. 2, p. 433, 2012.
[224] B. Bueno, G. Pigeon, L. K. Norford, and K. Zibouche, "Development and evaluation of a building energy model integrated in the TEB scheme," *Geosci. Model Dev. Discuss.,* vol. 4, no. 4, pp. 2973-3011, 2011, doi: 10.5194/gmdd-4-2973-2011.
[225] "ASHRAE Pocket Guide for Air Conditioning, Heating, Ventilation, Refrigeration, 7th ed.(Brief article)(Book review)," ed, 2010.
[226] B. Givoni, "Effectiveness of mass and night ventilation in lowering the indoor daytime temperatures. Part I: 1993 experimental periods," *Energy & Buildings,* vol. 28, no. 1, pp. 25-32, 1998, doi: 10.1016/S0378-7788(97)00056-X.
[227] R. American Society of Heating and E. Air-Conditioning, "ASHRAE handbook. Fundamentals," *ASHRAE handb., Fundam. (SI ed.),* 1985.
[228] D. Sundersingh and D. W. Bearg, "Indoor Air Quality in Schools (IAQ): The Importance of Monitoring Carbon Dioxide Levels," M. M. Design Share, Ed., ed, 2003.
[229] M. Höök and X. Tang, "Depletion of fossil fuels and anthropogenic climate change—A review," *Energy policy,* vol. 52, pp. 797-809, 2013, doi: 10.1016/j.enpol.2012.10.046.
[230] D. P. Wyon, L. Fang, L. Lagercrantz, and P. O. Fanger, "Experimental Determination of the Limiting Criteria for Human Exposure to Low Winter Humidity Indoors (RP-1160)," *HVAC&R research,* vol. 12, no. 2, pp. 201-213, 2006, doi: 10.1080/10789669.2006.10391175.
[231] H. Elsharkawy and P. Rutherford, "Retrofitting social housing in the UK: Home energy use and performance in a pre-Community Energy Saving Programme (CESP)," *Energy and buildings,* vol. 88, pp. 25-33, 2015, doi: 10.1016/j.enbuild.2014.11.045.
[232] L. Steg, "Promoting household energy conservation," *Energy policy,* vol. 36, no. 12, pp. 4449-4453, 2008, doi: 10.1016/j.enpol.2008.09.027.
[233] E. Zvingilaite and H. Klinge Jacobsen, "Heat savings and heat generation technologies: Modelling of residential investment behaviour with local health costs," *Energy policy,* vol. 77, pp. 31-45, 2015, doi: 10.1016/j.enpol.2014.11.032.
[234] A. Faruqui, S. Sergici, and A. Sharif, "The impact of informational feedback on energy consumption—A survey of the experimental evidence," *Energy (Oxford),* vol. 35, no. 4, pp. 1598-1608, 2010, doi: 10.1016/j.energy.2009.07.042.
[235] S. Yang and D. Zhao, "Do subsidies work better in low-income than in high-income families? Survey on domestic energy-efficient and renewable energy equipment purchase in China," *Journal of cleaner production,* vol. 108, pp. 841-851, 2015, doi: 10.1016/j.jclepro.2015.07.022.
[236] N. Uddin, "Assessing urban sustainability of slum settlements in Bangladesh: Evidence from Chittagong city," *Journal of urban management,* vol. 7, no. 1, pp. 32-42, 2018, doi: 10.1016/j.jum.2018.03.002.
[237] K. B. Debnath, D. P. Jenkins, S. Patidar, and A. D. Peacock, "Understanding Residential Occupant Cooling Behaviour through Electricity Consumption in Warm-Humid Climate," *Buildings (Basel),* vol. 10, no. 4, p. 78, 2020, doi: 10.3390/buildings10040078.
[238] R. Debnath, R. Bardhan, and M. Sunikka-Blank, "Discomfort and distress in slum rehabilitation: Investigating a rebound phenomenon using a backcasting approach," *Habitat international,* vol. 87, pp. 75-90, 2019, doi: 10.1016/j.habitatint.2019.03.010.
[239] S. Michie, L. Atkins, and H. L. Gainforth, "Changing Behaviour to Improve Clinical Practice and Policy," ed: Axioma - Publicações da Faculdade de Filosofia, 2016.
[240] R. F. Fellows, *Research methods for construction, fourth edition*, 4th ed ed. S.l.], 2015.

[241] A. A. Chowdhury, M. G. Rasul, and M. M. K. Khan, "Modelling and analysis of air-cooled reciprocating chiller and demand energy savings using passive cooling," *Applied Thermal Engineering,* vol. 29, no. 8, pp. 1825-1830, 2009, doi: 10.1016/j.applthermaleng.2008.09.001.
[242] M. Martin, A. Afshari, P. R. Armstrong, and L. K. Norford, "Estimation of urban temperature and humidity using a lumped parameter model coupled with an EnergyPlus model," *Energy & Buildings,* vol. 96, p. 221, 2015.
[243] E. H. Mathews, C. P. Botha, D. C. Arndt, and A. Malan, "HVAC control strategies to enhance comfort and minimise energy usage," *Energy & Buildings,* vol. 33, no. 8, pp. 853-863, 2001, doi: 10.1016/S0378-7788(01)00075-5.
[244] P. H. Shaikh, N. B. M. Nor, P. Nallagownden, I. Elamvazuthi, and T. Ibrahim, "A review on optimized control systems for building energy and comfort management of smart sustainable buildings," *Renewable and Sustainable Energy Reviews,* vol. 34, pp. 409-429, 2014, doi: 10.1016/j.rser.2014.03.027.
[245] P. J. Littlefair and A. Motin, "Lighting controls in areas with innovative daylighting systems: a study of sensor type," *Lighting Research & Technology,* vol. 33, no. 1, pp. 59-73, 2001, doi: 10.1177/136578280103300112.
[246] A. Barbato, A. Capone, M. Rodolfi, and D. Tagliaferri, "Forecasting the usage of household appliances through power meter sensors for demand management in the smart grid," ed, 2011, pp. 404-409.
[247] "International Performance Measurement & Verification Protocol," United States, 2002, vol. 1. [Online]. Available: https://www.nrel.gov/docs/fy02osti/31505.pdf
[248] G. R. Ruiz and C. F. Bandera, "Validation of calibrated energy models: Common errors," *Energies (Basel),* vol. 10, no. 10, p. 1587, 2017, doi: 10.3390/en10101587.
[249] C. Menassa, V. Kamat, S. Lee, E. Azar, C. Feng, and K. Anderson, "A Conceptual Framework to Optimize Building Energy Consumption by Coupling Distributed Energy Simulation and Occupancy Models," *Journal of Computing in Civil Engineering,* 2013, doi: 10.1061/(ASCE)CP.1943-5487.0000299.
[250] M. Bouden, B. Moulin, and P. Gosselin, "Epidemic propagation of west nile virus using a multi-agent geo-simulation under various short-term climate scenarios," ed, 2008, pp. 98-105.
[251] S. Ruifeng, Z. Shiyao, Z. Chaoqun, and Z. Li, "Study on EV charging station location planning based on the load balance principle with agent-based AnyLogic simulation," ed, 2014, pp. 1515-1519.
[252] P. Akadiri, P. Olomolaiye, and E. Chinyio, "Multi-criteria evaluation model for the selection of sustainable materials for building projects," *Automation in Construction,* vol. 30, pp. 113-125, 2013.
[253] D. A. Krawczyk and M. Żukowski, "Experimental verification of the CO2 and temperature model," *International Journal of Ventilation,* vol. 19, no. 2, pp. 127-140, 2020/04/02 2020, doi: 10.1080/14733315.2019.1592333.
[254] P. Consolo, H. C. Holanda, and S. S. Fukusima, "Humans tend to walk in circles as directed by memorized visual locations at large distances," *Psychol. Neurosci,* vol. 7, no. 3, pp. 269-276, 2014, doi: 10.3922/j.psns.2014.037.
[255] S. Zhang, J. Zhang, M. Chraibi, and W. Song, "A speed-based model for crowd simulation considering walking preferences," *Communications in nonlinear science & numerical simulation,* vol. 95, p. 105624, 2021, doi: 10.1016/j.cnsns.2020.105624.
[256] A. Frohnwieser, R. Hopf, and E. Oberzaucher, "HUMAN WALKING BEHAVIOR – THE

EFFECT OF PEDESTRIAN FLOW AND PERSONAL SPACE INVASIONS ON WALKING SPEED AND DIRECTION," *Human Ethology Bulletin,* vol. 28, pp. 20-28, 01/01 2013.

[257] F. Abdallah, S. Basurra, and M. M. Gaber, "A Non-Intrusive Heuristic for Energy Messaging Intervention Modeled Using a Novel Agent-Based Approach," *IEEE access,* vol. 7, pp. 1627-1646, 2019, doi: 10.1109/ACCESS.2018.2886146.

[258] S.-Y. Song and H. Leng, "Modeling the household electricity usage behavior and energy-saving management in severely cold regions," *Energies (Basel),* vol. 13, no. 21, p. 1, 2020, doi: 10.3390/en13215581.

[259] F. Abdallah, S. Basurra, and M. M. Gaber, "A Non-Intrusive Heuristic for Energy Messaging Intervention Modeled Using a Novel Agent-Based Approach," *IEEE Access,* vol. 7, no. 99, pp. 1627-1646, 2019, doi: 10.1109/ACCESS.2018.2886146.

[260] Q. Xu, Y. Lu, B.-G. Hwang, and H. W. Kua, "Reducing residential energy consumption through a marketized behavioral intervention: The approach of Household Energy Saving Option (HESO)," *Energy and buildings,* vol. 232, 2021, doi: 10.1016/j.enbuild.2020.110621.

[261] J. D. L. Fijnheer, H. van Oostendorp, and R. C. Veltkamp, "Enhancing Energy Conservation by a Household Energy Game," vol. 11385, ed. Cham: Cham: Springer International Publishing, 2019, pp. 257-266.

[262] N. Jung, S. Paiho, J. Shemeikka, R. Lahdelma, and M. Airaksinen, "Energy performance analysis of an office building in three climate zones," *ENERG BUILDINGS,* vol. 158, pp. 1023-1035, 2018, doi: 10.1016/j.enbuild.2017.10.030.

[263] T. Hong, J. Langevin, and K. Sun, "Building simulation: Ten challenges," *Build. Simul.,* vol. 11, no. 5, pp. 871-898, 2018, doi: 10.1007/s12273-018-0444-x.

[264] D. H. Dorrah and M. Marzouk, "Integrated multi-objective optimization and agent-based building occupancy modeling for space layout planning," *Journal of Building Engineering,* vol. 34, p. 101902, 2021, doi: 10.1016/j.jobe.2020.101902.

[265] M. Indraganti and M. A. Humphreys, "A comparative study of gender differences in thermal comfort and environmental satisfaction in air-conditioned offices in Qatar, India, and Japan," *Building and environment,* vol. 206, p. 108297, 2021, doi: 10.1016/j.buildenv.2021.108297.

[266] I. A. Sakellaris *et al.*, "Perceived indoor environment and occupants' comfort in European "modern" office buildings: The OFFICAIR study," *Int J Environ Res Public Health,* vol. 13, no. 5, p. 444, 2016, doi: 10.3390/ijerph13050444.

[267] M. Indraganti, R. Ooka, and H. B. Rijal, "Thermal comfort in offices in India: Behavioral adaptation and the effect of age and gender," *Energy and buildings,* vol. 103, pp. 284-295, 2015, doi: 10.1016/j.enbuild.2015.05.042.

[268] A. Ioannou and L. Itard, "In-situ and real time measurements of thermal comfort and its determinants in thirty residential dwellings in the Netherlands," *Energy & Buildings,* vol. 139, pp. 487-505, 2017, doi: 10.1016/j.enbuild.2017.01.050.

[269] S. I. u. H. Gilani, M. H. Khan, and W. Pao, "Thermal Comfort Analysis of PMV Model Prediction in Air Conditioned and Naturally Ventilated Buildings," *Energy Procedia,* vol. 75, pp. 1373-1379, 2015, doi: 10.1016/j.egypro.2015.07.218.

[270] B. Arash and F. Steven, "A comparison of calculated and subjective thermal comfort sensation in home and office environment," ed, 2011.

[271] R. Becker and M. Paciuk, "Thermal comfort in residential buildings – Failure to predict by Standard model," *Building and Environment,* vol. 44, no. 5, pp. 948-960, 2009, doi: 10.1016/j.buildenv.2008.06.011.

[272] P. Strachan, K. Svehla, I. Heusler, and M. Kersken, "Whole model empirical validation on a full-scale building," *Journal of Building Performance Simulation,* vol. 9, no. 4, pp. 331-350, 2016, doi: 10.1080/19401493.2015.1064480.

[273] N. Pivac, S. Nizetic, and V. Zanki, "Occupant behavior and thermal comfort field analysis in typical educational research institution: A case study," *Thermal science,* vol. 22, no. Suppl. 3, pp. 785-795, 2018, doi: 10.2298/TSCI170915013P.

[274] A. Prashant Anand Chirag Deb Ramachandraiah, "A simplified tool for building layout design based on thermal comfort simulations," *Frontiers of Architecture and Civil Engineering in China,* vol. 6, no. 2, pp. 218-230, 2017, doi: 10.1016/j.foar.2017.03.001.

[275] T. Naramura, J. Morikawa, and C. Ninagawa, "Prediction Model on Room Temperature Side Effect due to FastADR Aggregation for a Cluster of Building Air-Conditioning Facilities," *Electrical Engineering in Japan,* vol. 199, no. 3, pp. 17-25, 2017, doi: 10.1002/eej.22946.

[276] V. Smith, T. Sookoor, and K. Whitehouse, "Modeling building thermal response to HVAC zoning," *ACM SIGBED Review,* vol. 9, no. 3, pp. 39-45, 2012, doi: 10.1145/2367580.2367587.

[277] F. Roberti, U. F. Oberegger, and A. Gasparella, "Calibrating historic building energy models to hourly indoor air and surface temperatures: Methodology and case study," *Energy and buildings,* vol. 108, pp. 236-243, 2015, doi: 10.1016/j.enbuild.2015.09.010.

[278] M. Royapoor and T. Roskilly, "Building model calibration using energy and environmental data," *Energy & Buildings,* vol. 94, pp. 109-120, 2015, doi: 10.1016/j.enbuild.2015.02.050.

[279] A. Pantazaras, S. E. Lee, M. Santamouris, and J. Yang, "Predicting the CO2 levels in buildings using deterministic and identified models," *Energy & Buildings,* vol. 127, pp. 774-785, 2016, doi: 10.1016/j.enbuild.2016.06.029.

[280] A. O. Nesibe YALC¸ Deniz BALTA, "A modeling and simulation study about CO 2 amount with web-based indoor air quality monitoring," *TURKISH JOURNAL OF ELECTRICAL ENGINEERING & COMPUTER SCIENCES,* vol. 26, no. 3, 2018, doi: 10.3906/elk-1612-57.

[281] B. Gucyeter, "CALIBRATION OF A BUILDING ENERGY PERFORMANCE SIMULATION MODEL VIA MONITORING DATA " presented at the Building Performance Analysis Conference and SimBuild Chicago, IL September 26-28, 2018. [Online]. Available: https://www.ashrae.org/File%20Library/Conferences/Specialty%20Conferences/2018%20Building%20Performance%20Analysis%20Conference%20and%20SimBuild/Papers/C074.pdf.

[282] V. Gutiérrez González, G. Ramos Ruiz, and C. Fernández Bandera, "Empirical and Comparative Validation for a Building Energy Model Calibration Methodology," *Sensors,* vol. 20, no. 17, 2020, doi: 10.3390/s20175003.

[283] I. Gaetani, P.-J. Hoes, and J. L. M. Hensen, "Estimating the influence of occupant behavior on building heating and cooling energy in one simulation run," *Applied energy,* vol. 223, pp. 159-171, 2018, doi: 10.1016/j.apenergy.2018.03.108.

[284] I. Gaetani, P.-J. Hoes, and J. L. M. Hensen, "A stepwise approach for assessing the appropriate occupant behaviour modelling in building performance simulation," *Journal of building performance simulation,* vol. 13, no. 3, pp. 362-377, 2020, doi: 10.1080/19401493.2020.1734660.

[285] L. Poznaka, I. Laicane, D. Blumberga, A. Blumberga, and M. Rosa, "Analysis of Electricity User Behavior: Case Study Based on Results from Extended Household Survey," *Energy procedia,* vol. 72, pp. 79-86, 2015, doi: 10.1016/j.egypro.2015.06.012.
[286] A. J. Sonta, P. E. Simmons, and R. K. Jain, "Understanding building occupant activities at scale: An integrated knowledge-based and data-driven approach," *Advanced engineering informatics,* vol. 37, pp. 1-13, 2018, doi: 10.1016/j.aei.2018.04.009.
[287] S. Cao, S. Hou, L. Yu, and J. Lu, "Predictive control based on occupant behavior prediction for domestic hot water system using data mining algorithm," *Energy science & engineering,* vol. 7, no. 4, pp. 1214-1232, 2019, doi: 10.1002/ese3.341.
[288] H. Mo, H. Sun, J. Liu, and S. Wei, "Developing window behavior models for residential buildings using XGBoost algorithm," *Energy and buildings,* vol. 205, p. 109564, 2019, doi: 10.1016/j.enbuild.2019.109564.
[289] H. Akoglu, "User's guide to correlation coefficients," *Turk J Emerg Med,* vol. 18, no. 3, pp. 91-93, 2018, doi: 10.1016/j.tjem.2018.08.001.
[290] J. P. Verma, *Data analysis in management with SPSS software*. New Delhi: New Delhi : Springer, 2013.
[291] D. Britton. SPSS eTutor: Measures of Association and Correlation [Online] Available: https://subjectguides.esc.edu/SPSS
[292] J. Kim, R. de Dear, C. Cândido, H. Zhang, and E. Arens, "Gender differences in office occupant perception of indoor environmental quality (IEQ)," *Building and environment,* vol. 70, pp. 245-256, 2013, doi: 10.1016/j.buildenv.2013.08.022.
[293] K. Yildirim, A. Akalin-Baskaya, and M. Celebi, "The effects of window proximity, partition height, and gender on perceptions of open-plan offices," *Journal of environmental psychology,* vol. 27, no. 2, pp. 154-165, 2007, doi: 10.1016/j.jenvp.2007.01.004.
[294] V. Sevillano and P. Olivos, "Social behavior and environment: The influence of social norms on environmental behavior," *Papeles del psicólogo,* vol. 40, no. 3, pp. 182-189, 2019, doi: 10.23923/pap.psicol2019.2898.
[295] S. Naheed and S. Shooshtarian, "A review of cultural background and thermal perceptions in urban environments," *Sustainability (Basel, Switzerland),* vol. 13, no. 16, p. 9080, 2021, doi: 10.3390/su13169080.
[296] T.-H. Tan, "Meeting first-time buyers' housing needs and preferences in greater Kuala Lumpur," *Cities,* vol. 29, no. 6, pp. 389-396, 2012, doi: 10.1016/j.cities.2011.11.016.
[297] D. P. Varady and M. A. Carrozza, "Toward a Better Way to Measure Customer Satisfaction Levels in Public Housing: A Report from Cincinnati," *Housing studies,* vol. 15, no. 6, pp. 797-825, 2000, doi: 10.1080/02673030020002555.
[298] M. Kwon, H. Remøy, and M. van den Bogaard, "Influential design factors on occupant satisfaction with indoor environment in workplaces," *Building and environment,* vol. 157, pp. 356-365, 2019, doi: 10.1016/j.buildenv.2019.05.002.