

Influence of interior layouts on occupant energy-saving behaviour in buildings: An integrated approach using Agent-Based Modelling, System Dynamics and Building Information Modelling

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Abstract

Interior layouts of a building may influence the presence and movement of occupants, which can lead them to participate in a certain activity, energy-saving behaviour for instance, which occurs at a particular location within an indoor space. Moreover, rearranging this interior layout can help understanding how and why occupants use more energy and encourage their energy-saving behaviours through occupancy-based interventions. However, only a handful of studies have attempted to evaluate the effects of interior layout on the energy-saving behaviour of occupants. In light of this, this study offers a comprehensive modelling framework for investigating the influence of interior layouts on occupants' energy-saving behaviours by integrating Agent-Based Modelling (ABM), Systems Dynamics (SD), and Building Information Modelling (BIM). The occupant behaviour within this hybrid model is built based upon the theory of reasoned action. Moreover, while most of the ABM studies related to occupant behaviour are based on synthetic data, this study used real energy data collected from customized sensors to validate the proposed model. As a result, it has been shown that adjustment of interior layout (i.e., occupant intervention) can improve building energy performance by 14.9%. In terms of model validation, the proposed hybrid model has exhibited an acceptable level of accuracy with an average CV(RMSE) of 10.5%, MBE of 1.5%, and R^2 of 0.77. This study differs from other existing studies in that it adopts an interior layout-based human behavioural investigation considering stochastic attitudes and subjective norms of occupants and provides a robust validation through empirical-based intervention.

Keywords: Occupant energy-saving behaviour; Building interior layout; Agent-based Modelling (ABM); System Dynamics (SD); Building Information Modelling (BIM)

1. Introduction

The building and construction industry, which accounts for nearly 40% of global energy consumption, is no longer just an option for accelerating energy-saving transformation and ensuring a worldwide low-carbon future [1-3]. In order to significantly reduce buildings' energy consumption, the Department of Energy (DOE) of the United States (U.S.) published a roadmap for the Heating, Ventilation, and Air Conditioning (HVAC) technologies, highlighting top-priority projects for high-efficiency HVAC systems such as sophisticated direct-current HVAC systems, low-temperature heat pumps, and electrochemical compressor installations [4, 5]. Other energy-efficient building systems, such as energy-efficient appliances [4, 6, 7], automation in buildings, and control systems, have also been discussed [8]. However, neither important improvements in the final energy consumption per capita from buildings nor the predicted cuts in energy use have been achieved [9]. This is due to the low implementation rate of these energy-saving technologies that have been somewhat constrained by their high price [10, 11]. Furthermore, some of the latest studies in the United Kingdom and Finland have reported that more than 40% of people are not attracted by the latest tools or technologies and therefore are unwilling to buy and implement energy-saving technologies and facilities [7, 12, 13]. Besides, many researchers have also observed that there can be tremendous discrepancies between a resident's or occupant's annual energy consumption even for nearly identical buildings depending on the energy-related occupant behaviour [14, 15]. Accordingly, the latest studies in the literature highlight the importance of occupant behaviours in reducing buildings' energy consumption. Occupant behaviour is commonly defined solely by occupant energy-related actions/synergies, i.e., control of systems and appliances such as HVAC control, window control, blind control, lighting control, etc. [16]. The relationship between occupant behaviour and energy consumption is recognized in the pursuit of overall satisfaction by occupants in the latest International Energy Agency Energy in Buildings and Communities (IEA-EBC) Annex 66 [17-19].

As such, building occupants are essential elements in our built environment, and their importance in the research on building energy consumption has been newly highlighted to increase the attention paid to them. Studies on adaptive control and comfort [18, 20, 21], lighting control [21-23], operable window control [24-27], and shading control [26, 28] are some of the limited research areas that have been considered to analyze building occupants' behaviour or behavioural impacts in buildings' operation phase. However, there are not many studies or cases where this knowledge of occupant behaviour plays a complete role in the decision-making in regard to the building design aspect. At the beginning of the design phase, building occupants' behaviours such as occupancy and operation schedules can perform a crucial role in the planning and designing of an indoor space. Furthermore, occupant behaviours can also have a significant impact on the whole-building performance throughout its life cycle for different design elements. For instance, occupant behaviours may affect not only the wear and tear of the entire building but also the environmental conditions of indoor spaces, which are closely related to the total energy performance of a building [19, 29]. In particular, planning a building's interior layout is one of the design efforts between "design development" and "scheme design" in the initial design phase, which is a significant part of a building's design-related activities that affects the overall energy consumption of a building [29]. In this regard, occupant-centred design (OCD) techniques (i.e., interior layout adjustment) should be considered to additionally look at how individual building occupants use energy [29, 30] and how this information can inform the intervention strategy to advance energy conservation. For instance, the difference in the distance between occupant location (for seating and sleeping) and the switch location (for HVAC and lighting), which is a result of interior layout adjustment, may influence the energy-related behaviour of occupants. If the distance is short enough, occupants may interact with the switch location more easily by turning off lights or controlling the HVAC system when it is not necessary, or they leave the space. On the other hand, occupants may cause more energy wastage if they are far from the switch location or the switch location is inaccessible, making it challenging to save energy. Thus, occupant behaviours may vary depending on a building's interior layout, which will ultimately influence a building's energy performance. Moreover, earlier reports have demonstrated that there is an incredible gap between the energy-saving potential and availability of knowledge to assist interior design in the early stage [31, 32]. As one of the significant tasks in the early design stage, interior layout adjustment is expected to have a great potential in energy saving. Despite its significance, there is a lack of studies that evaluate the influences of interior layout on a building's energy performance. These studies [29, 33-37] have indicated that interior layout can substantially influence a building's energy performance; however, most of these studies do not provide specific guidelines to configure the best layout arrangements that significantly impact a building's total energy consumption. In addition, some interior layout-based building energy models have been developed by considering static or fixed occupancy profiles.

Therefore, the main purpose of this research is to uncover the salient aspects of the impact of a building's interior layout on occupants' energy-saving behaviours by proposing a hybrid model using Agent-Based Modelling (ABM), Systems Dynamics (SD), and Building Information Modelling (BIM). The energy consumption of a building is extremely dynamic and depends on multiple factors. Thus, the modelling structure must cover a collective system approach and needs to support 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 [18, 35]. More specifically, the proposed hybrid model is a collective arrangement of ABM for reflecting behavioural theory, SD for dynamic problems and events, and BIM tool for factual layout illustration. Here, the ABM-SD model is built using the AnyLogic modelling tool, a broadly established simulation platform, especially in the engineering, business, and sociology domain, while the BIM model is constructed using Revit 2019. To the best of our knowledge, this is the first study to investigate the impact of buildings' interior layout on occupants' energy-saving behaviours by integrating ABM, SD, and BIM.

In our hybrid model, the target occupant behaviours are the occupants' interactions with the building energy components (e.g., HVAC and lighting), which may vary depending on a building's interior layout and ultimately contribute to a building's energy performance. Here, a building's interior layout is characterized as the interior collocation of various spaces, which incorporates internal arrangements, and the position of furniture, equipment, and appliances, as well as room geometry. As the existing literature has failed to evaluate the sole effect of interior layout, it is necessary to consider the interior layout plan to comprehensively analyze its impact on the energy performance of buildings. To this end, the hybrid model analyzes the energy consumption pattern both before and after the interior layout adjustment (i.e., occupant intervention), which refers to re-organizing or modifying existing problematic interior layouts to provide occupants better access to their switch location for HVAC and lighting. In this way, the proposed hybrid model adds another feature to the existing model of occupants' energy behaviour in order to improve the simulation performance. Most importantly, while the majority of occupant behaviour-related studies or ABM models are based on synthetic data and scenarios, this study also attempts to fill this gap by offering a robust validation approach using realistic data collection from eight customized sensors based on a case study in Chittagong, Bangladesh.

This article is structured as follows: section 2 describes the literature review; section 3 explains the methodology of the study; section 4 illustrates the results and discussions, including the validation approach, and section 5 describes the conclusions and limitations of the study.

2. Literature Review

It may be noticed that research topics related to human behaviour have moved from psychological investigation or social science to occupant behaviour modelling and energy simulation for buildings. This recommends a change of study methods from qualitative analysis to quantitative analysis. In recent years, there have been a number of models or approaches developed for the study of building occupants' behaviour and interior layout. The existing occupant behaviour model in relation to a building's interior layout or ABM approach, as well as the validation study will be described in the following section.

2.1. The literature on the interior layout of buildings

An occupant-centred interior layout can significantly influence a building's energy performance [38]. In particular, several studies emphasize the impacts of the design features of a building, especially interior layout and interior design features, on occupancy and occupants' energy consumption behaviours [29, 38]. A study [39] stated the three types of problems of interior layout, namely multi-floor layout, unequal-areas layout, and row layout, which is a typical class of operations problems in a facility department. Thus, the study concerned finding the optimum configuration for several nonoverlapping united areas within a given facility that contribute to minimizing the cost.

Dino et al. [37] considered the interior layout deployment that satisfies the formal placement constraints and other topological aspects with a single algorithm. The study aimed to optimize the daylighting and energy performance for a typical library interior layout. Typically, interior layout deployments have many applications and can integrate multiple or single goals while identifying the optimal indoor layout configuration. In particular, Goldstein et al. [40] indicated that a building's indoor layout might influence the presence and movement of occupants, which can lead to energy-related activities that occur at a specified location within a space. Other research [41] revealed that the probability of occupant actions can vary based on human factors and spatial layout. Based on sunlight and wind-powered natural ventilation, this study [42] proposed an optimization system to recognize energy-efficient interior layout designs for a high-rise residential building. Furthermore, Du et al. [43] reviewed the gaps, requirements, and challenges of incorporating automatic construction of indoor layouts for energy optimization and performance assessment. This study also revealed that the energy performance of a building cab be significantly improved through optimizing and upgrading layout designs. Furthermore, Becker et al. [44] suggested a quadratic energy optimization technique for large offices with different types of rooms. The relevant literature, including a review of Azar et al. [45] emphasized the energy-related objectives and operation schedules during the performance simulation of a building rather than interior layout analysis. A study [46] also proposed a two-component structure for solving an indoor layout problem followed by a modular approach using discrete event and agent-based simulation. However, other aspects regarding occupants' energy consumption patterns due to interior allocation and interior layout planning are less explored during the energy optimization and design of buildings. Integrating these features would allow exploration of the capability of building occupants to manage their desired activities or actions in relation to energy conservation and comfort. Hence, as indicated by Schweiker [47], attention needs to be shifted from recognizing occupant behaviour to making use of such energy conservation behaviour to improve the energy performance of buildings and occupants' comfort. In this fashion, it requires the incorporation of occupant-centric predictors in the design and operation phases [45]. This study [48] proposed a design-oriented multi-dimensional PBD (Performance-Based Design) approach using BIM coupled with synthetic behaviour simulation and virtual data analytics. The findings also show that energy consumption and temperature largely rely on ABM and the layout geometry.

2.2. The literature on the ABM approach and its validation efforts

Several mathematical frameworks and approaches have been employed in the modelling of building occupants' behaviour, including probabilistic models, statistical models, data mining approaches, and ABM, as exemplified in the numerous review studies [19, 49-51]. Unlike other methods, however, ABM provides distinctive benefits for the modelling of interactions in occupancy-based buildings, and thus, many researchers have actively used the ABM approach for the modelling of building occupants' behaviour [27, 51]. Also, the study of behaviour has the capability to cope with the uncertainties of the real world [27]. Similarly, all components of ABM might be characterized by the agents thinking and performing like a human. However, limitations or inadequacies persist as the implementation of ABM approaches to the research of occupant behaviours is still in its development phase [27, 51].

A test has been conducted on the implementation of ABM for buildings' energy-related occupancy interaction by Lee & Malkawi [52]. This study modelled various occupant behaviour profiles in a sample office building. The study explored five specific behaviours: activity level, space heater/fan use, window use, blind use, and clothes worn. The key aim of this research was to identify how an occupant agent balances the active thermal changes in a typical office space to enhance both comfort and energy savings. The approach allows ABM to incorporate both behaviour and energy application, which might be used as a simulation method for buildings' energy conservation. Putra et al. [21] studied the occupant behaviour and thermal comfort impact due to load-shedding problems. Here, the model incorporates independent or autonomous agents with human perception preferences and limited simulation cases. However, only four simulation cases were investigated with real data and the test outcomes failed to represent an acceptable level of accuracy. A hybrid model was also proposed by Langevin et al. [53] for quantifying occupants' adaptive behaviour and the thermal comfort of an office building along with the occupants' energy consumption. However, concern has arisen about the applicability of the agent-based behaviour model for naturally ventilated buildings and the proficiency of the co-simulation argument. The above approaches used prototype occupancy schedules or building spaces to construct a single ABM or hybrid model. In addition, no study has adequately incorporated or investigated occupants' individual perceptions or norms in regard to their stochastic behaviour within interior space.

Another study [27] also used an ABM method including a realistic validation approach without considering the impact of interior layout. This study mainly considered occupant behaviours regarding window, blind, and door operation, whereas different occupant behaviours depending on the indoor layout were not adequately considered. Validation work [54] was also performed to examine the developed ABM that was originally built based on Perceptual Control Theory (PCT). The model output was similar to the experimental estimations for aggregated and individual expectations. But this model only studied thermal adaptive behaviour, and just a few selected behaviours were validated. One of the major difficulties for the very important part of behaviour studies applying an ABM model is the absence of actual data contribution. Due to this fact, scholars often fail to validate their models by employing real-world data [18, 27]. Only a few ABM validations have been observed in previous works in the literature. Additionally, in the earlier research context, the model is built based on a simple prototype model, which may trigger questions about whether or not the simulated virtual agent will understand the behaviour which real occupants display. Table 1 shows the current studies on occupant behaviour modelling by implementing an ABM approach. As shown in Table 1, there is a lack of studies that not only consider the interior layout, but also implement an appropriate ABM validation approach for studying building occupants' behaviours [55]. Besides, it is necessary to further improve the existing approach or develop a new approach that attempts to go beyond the current behaviour research, together with a more specific model and building component such as occupant-centred layout (using ABM-SD-BIM incorporation) deployment regarding the occupant's behavioural intention.

Table 1. The literature on ABM studies related to occupant behaviours

Building type	Target occupant behaviours	Drivers of behavioural change	Behavioural rules	Tools/Platform	Real building application	Validation	References
Commercial (office)	Lighting; Blind; Hot water	Energy conservation events; Influence of word of mouth	Occupants move from high-energy users to low-energy users over time	e-Quest; AnyLogic	No	No	[56]
Residential	General Modelling (not specified)	Time; Indoor environmental parameters	Belief, Desire, and Intention (BDI) framework	Brahms	No	No	[57]
Commercial (office)	Window; Fan; Thermostat; Clothing	Temperature; Humidity; Air velocity	Perceptual Control Theory and customized modelling rules	EnergyPlus; MATLAB	Yes	Yes	[54]
Commercial (office)	Window; Blind; Door; Clothing; Fan/heater	Temperature; Humidity; Air speed; PMV value	Observe, Orient, Decide, and Action (OODA) loop	EnergyPlus; MATLAB	No	No	[52]
Office (educational)	Occupant comfort level; Space occupancy	Environmental parameters (e.g., temperature and CO_2)	Integrated approach between ABM, SD, and BIM	Revit; Anylogic	Yes	Yes	[18]
Multi-purpose administration building	Open or closed space layout problems	Flow pattern; Energy consumption; Occupancy-based interior layout	Space orientation travel distance view of spaces	AnyLogic	No	Not definite	[46]
Commercial (office)	Fan/heater; lighting; Blind; Task light; Clothing	Load shedding	Building manager, occupant, and tenant have a different behaviour pattern	EnergyPlus; NetLogo	Calibration; Verification	Yes	[21]
Residential	Window; Air conditioning (AC)	Temperature	Probability of certain behaviours that are built on indoor temperature difference	Repast; TAS	Yes	No	[58]
Prototype public space	Space occupancy; Energy use	Room temperature; Illuminance	Virtual agents' self-learning adaptation	BCVTB; Energy Plus; Radiance; scikit-learn 0.20.3	No	No	[48]
Commercial (office)	HVAC; Lighting; Window	Daylight level; Temperature; CO_2 concentration	Drivers, needs, actions, and systems (DNAs)	obFMU	Not definite	No	[59]
Office	HVAC; Artificial lighting; daylighting; Office equipment	Direct and indirect interventions over a three-year period	Occupants tend to shift between being high-, medium-, and low-energy consumers	AnyLogic	No	No	[60]
Commercial (office)	Clothing; Thermostat-set point	Outdoor air temperature; Choice of initial clothing worn	ASHRAE-55 clothing ensembles, probabilities, and user-specified rules	BIM; ABM; EnergyPlus	Verification using a survey	No	[61]

Commercial	Lighting	Occupants' satisfaction with different lighting systems	Theory of Planned Behaviour (TPB) and the Belief-Desire-Intention (BDI)	NetLogo; Radiance	No	No	[62]
Office	Lighting energy saving	Impact of different layouts	Stochastic behaviour of occupants (including presence and movement, among others)	NetLogo; e-Quest	Not mentioned	Not mentioned	[63]
Residential	Thermal comfort; Energy consumption	Outside temperature; Humidity	Built on a Belief, Desire, and Intention (BDI) framework	GAMA	No	No	[35]
House /Office	Window; Lighting; Blind	Environmental parameters	Time-dependent probabilities	Nottingham Multi-Agent Stochastic Simulation; Functional Mockup Interface; EnergyPlus	No	No	[26]
Office	Heating/cooling	Energy; Indoor Environmental Quality (IEQ); Cost	Perceptual Control Theory	BCVTB; EnergyPlus; Matlab	No	Not mentioned	[53]
Commercial (office)	Window; Blind; Door	Perceptions and value systems of humans	Agent's goal, standard and preference	PMFserv	Yes	Yes	[27]
This study	HVAC; Lighting	Attitude and subjective norm of occupants; Building interior layout	Theory of Reasoned Action (ToRA) along with the customized modelling rules for behavioural intention for interior layout adjustment	AnyLogic (ABM+SD); Revit (BIM)	Yes	Yes	-

3. Methodology

3.1. An overview of the research framework and tasks

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

(i) Task 1: The BIM model is used to select and construct the preferred interior layout;

(ii) Task 2: The ABM-SD model is developed to forecast the comprehensive building occupants' behaviour patterns and their individual actions within the interior layout defined in Task 1 and to calculate the corresponding energy consumption profile; and

(iii) Task 3: The proposed hybrid model and its simulation outcome are validated by considering occupant intervention.

Fig. 1 represents the main features of the proposed hybrid model.

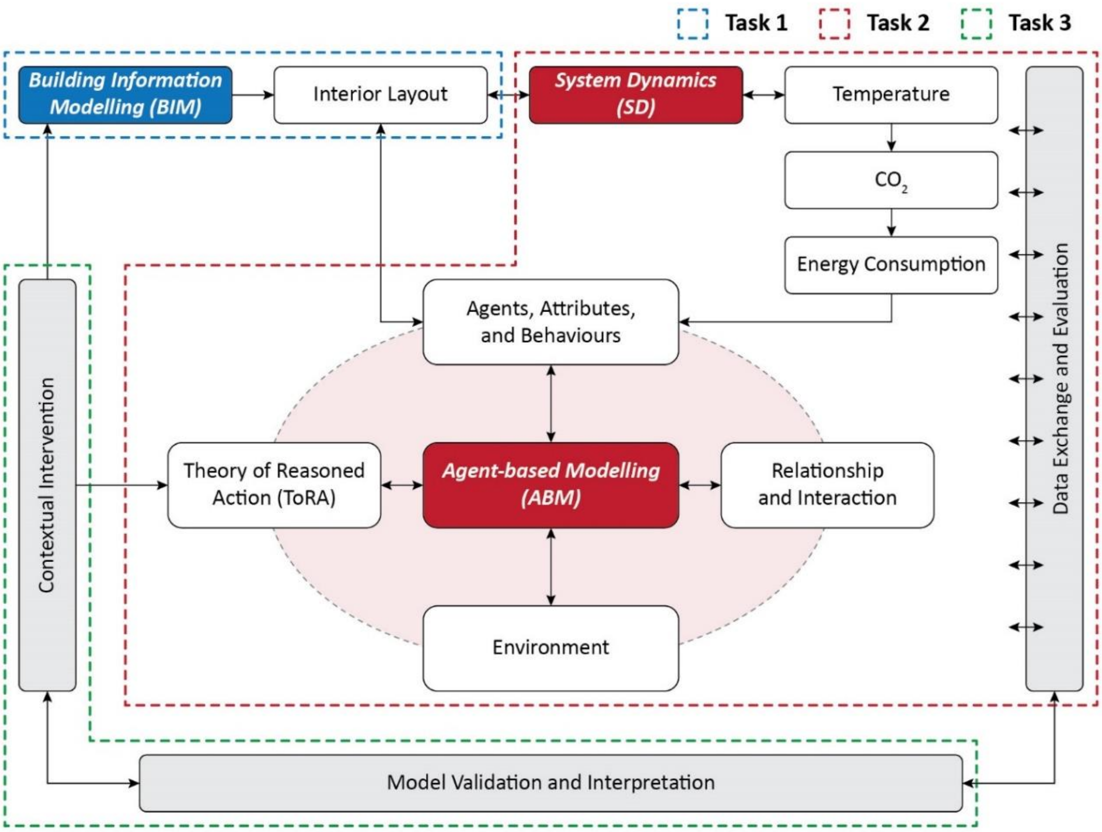

Fig. 1. A conceptual framework of the ABM-SD-BIM-integrated model

In Task 1, the selected interior layout diagram was constructed along with the specific locations (e.g., switch location for HVAC and lighting, occupant location for seating and sleeping, etc.) as well as their coordinates using Revit-2019. Each interior layout pattern was developed based on the real layout pattern available in the case study location. In Task 2, the ABM model that consists of different agents, the surrounding environment, and their interactions was developed based on the behavioural rules (i.e., theory of reasoned action (ToRA)) to forecast building occupants' behaviours within the interior layout. This ABM model simultaneously engages with the SD model to calculate the energy consumption profile according to different occupant behaviours based on the environmental parameters (e.g., temperature, humidity, CO_2, etc.) received from the BIM model. In Task 3, the simulation outcome is validated against the real data through occupant intervention. The details of each task are described in the following sections.

The tasks illustrated in the research framework in Fig. 1, which integrates the BIM platform with ABM and SD approaches, are further expounded in the research flow chart shown in Fig. 2. The following sections explain the research flow chart relating to each task.

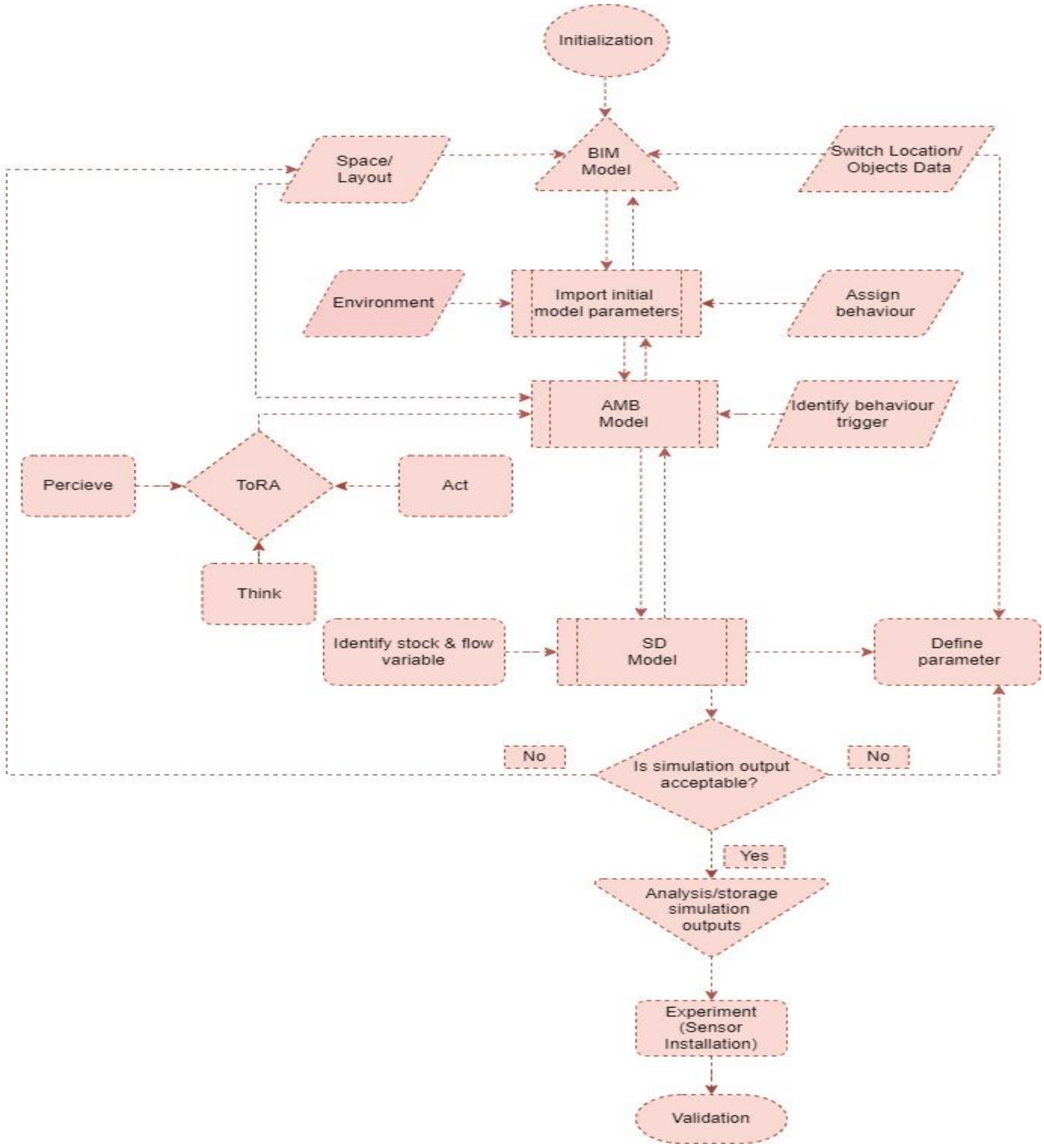

Fig. 2. Flow chart of the research approach

3.1.1. Task 1: Interior layout identification in the BIM model

As shown in Fig. 3, the interior layout settings for the individual indoor space, including occupant location, occupant circulation path, and switch location, are identified in a prototype Revit model for drawing and specifications. Here, the "occupant location" 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. The "switch location" is a particular place in the indoor space where occupants regularly display their dynamic energy-related behaviour (e.g., controlling the HVAC system or turning off the light).

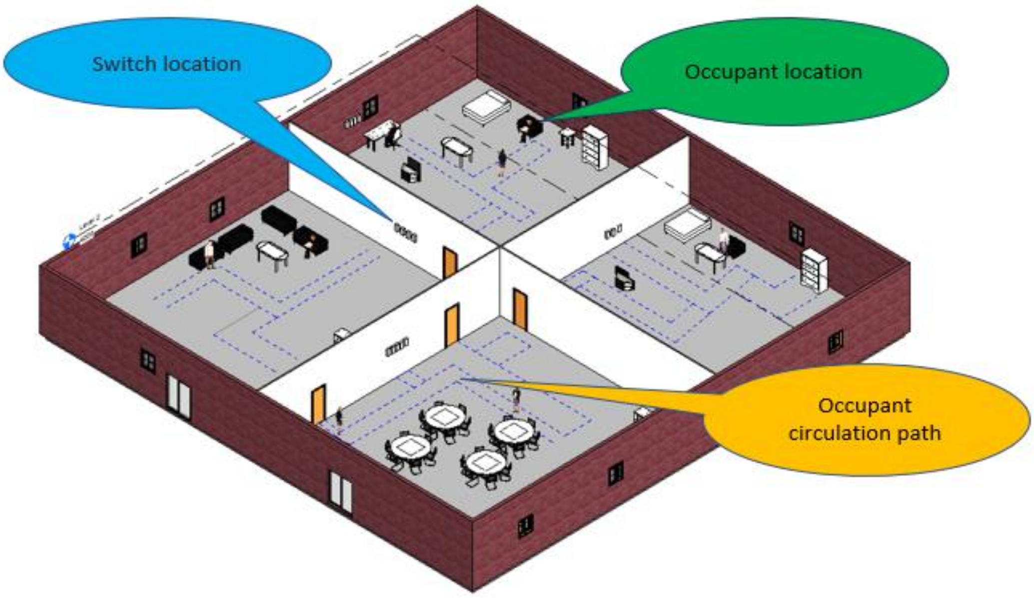

Fig. 3. Occupant location, circulation path, and switch location in the BIM model

The BIM model considers the distance between the occupant location (for seating and sleeping) and switch location (for HVAC and lighting) that supports message/data exchange over the ABM and SD through a DynamoAPI-Excel platform. The platform automatically generates the input data for ABM-SD models based on different physical interior layout conditions illustrated in Fig. 4. Typically, the physical arrangement of interior space can manipulate an occupant's energy consumption behaviour by controlling and using their action scenarios. Several studies have also clearly stated the influence of a building's interior layout on occupants' preferred activities and their desired location [29, 64-66]. Accordingly, this study mainly considers eight different types of interior layout conditions (i.e., sample layouts) according to the accessibility of the switch location in the proposed hybrid model as shown in Fig. 4. Among eight interior layouts, Interior Layouts 1 to 7 include different types of existing problematic layouts that are classified as follows: (i) Type 1: No access to the switch location (i.e., Interior Layout 1); (ii) Type 2: Controlled access to the switch location due to obstructions (i.e., Interior Layouts 2 and 3) or a longer distance (i.e., Interior Layout 4); and (iii) Type 3: Average access to the switch location with a fair (i.e., Interior Layouts 5 and 6) to short distance (i.e., Interior Layout 7) from the different directions. On the other hand, only one interior layout condition (i.e., Interior Layout 8) had easy access to the switch location from the occupant location and is regarded as the best case, which can also be a baseline for further intervention. Here, the distance between the occupant location and the switch location is also considered as a variable that determines the accessibility of the switch location. If this distance is short enough within the human range (i.e., within 2 ft), occupants might easily engage with the building's energy system, and they may frequently follow the energy saving attitude while staying at or away from the occupant location.

This study also considers the rearrangement and modification of objects (e.g., furniture) in problematic interior layouts through an intervention.

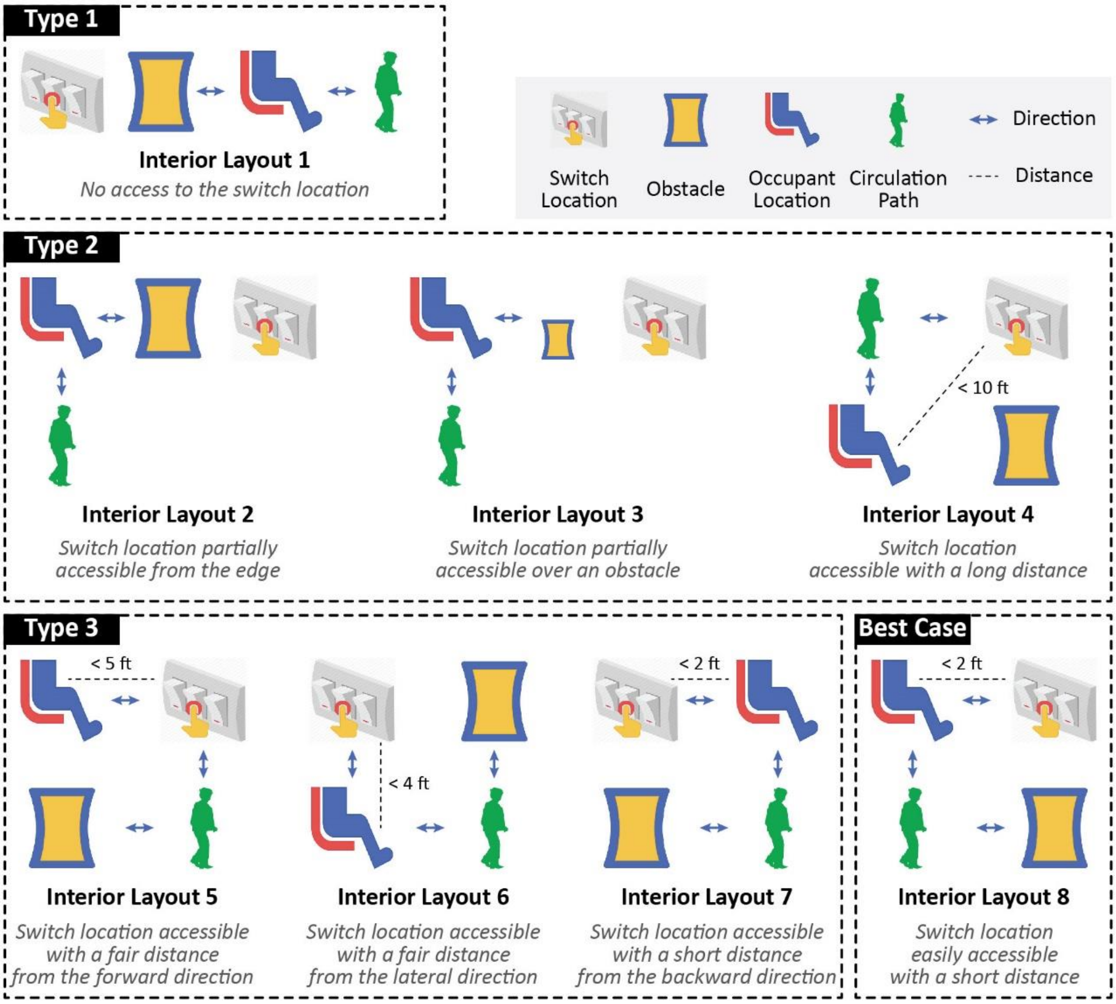

Fig. 4. Eight different types of interior layout conditions (prototype layouts)

3.1.2. Task 2: Development of the ABM-SD model

During the ABM model construction, required parameters (e.g., population, size, etc.) were imported and other specified behaviours assigned within the ABM platform. The respective model parameters, events and variables were also considered for comprehensive construction purposes.

The study aimed to identify the behaviour triggers (events or actions that perform a role in driving a specific behaviour) that were also incorporated into the physical layout conditions assigned in a prototype BIM model. On the other hand, as a decision-making process, the theory of reasoned action (ToRA) was applied as this is one of the most popular theories in the study of human behaviour. A detailed explanation of this theory is provided in the next section.

3.1.2.1. Theory of Reasoned Action (ToRA)

The primary theory implemented in the study for behaviour representation is the reasoned action model established by Fishbein and Ajzen [67]. Fig. 5 illustrates a simplified schematic concept of behavioural intention, which is a fundamental concept of ToRA.

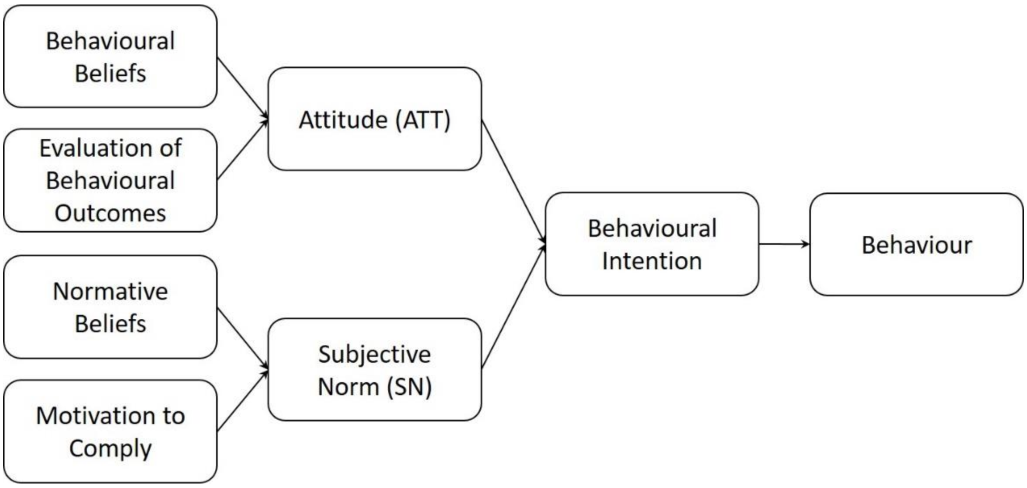

Fig. 5. The behavioural model based on ToRA, adapted from Fishbein and Ajzen [67]

With this theory, Fishbein and Ajzen looked at several factors, primarily "Attitude" (ATT). Attitude is an occupant's belief about the behaviour they know, which they think is actually going to benefit themselves in the end. It is not just an attitude about the outcomes of the behaviour but also includes an evaluation of the outcomes, how occupants think about the outcomes, and whether they are beneficial or not. For example, occupants who believe that exercising every day can help them be healthy will form a positive attitude about exercise. If occupants have a positive attitude about exercise, hopefully, that informs their intention to exercise every day, thus leading to a behaviour. But intention does not just rely on attitude where it gets a little bit more complex because if occupants do everything that they have a positive attitude about, it would probably provide them a lot healthier and happier life. Nevertheless, a second component called "Subjective Norm" (SN) has much more influence on occupants' beliefs about the desirability of certain behaviours. For example, exercise can be regarded as something that people view as a good thing, since being healthy is highly valued in society. Subjective Norm focuses on the social desirability or the acceptability of the behaviours that occupants are ultimately trying to display. Occupants can create this norm, but they have to understand the belief about the desired behaviour from other people's perspectives. If the occupant is doing something, they should think about how others are going to think about it. The complete ToRA is portrayed as Eq. (1).

$$O_{BI} = O_{ATT} \times X_1 + O_{SN} \times X_2 \quad (1)$$

where O_{BI} is the occupant's behavioural intention, O_{ATT} is the occupant's attitude toward a behaviour, O_{SN} is the occupant's subjective norm related to the behaviour, and X_i (i = 1, 2) is the corresponding weight explaining how important the component is to individual occupants (e.g., 0.5 for both cases).

There exists an extension of this theory called the theory of planned behaviour (TPB), which additionally considers the perceived behavioural control, i.e., an individual's perceived ease or difficulty to behave in a certain way, as an additional behavioural element. This study, however, assumes that occupant behaviour is unconstrained or associated with spontaneous control, and they behave based on their pre-existing behavioural attitudes and intentions. So, without any further behavioural control, the occupant could behave or change to behaving in a specific way within a convenient environment. In this context, although TPB is one of the widely used models to explore energy-related behaviour, this study considered the ToRA as our primary behavioural model.

Based on this behavioural model, ToRA, the decision-making process of occupant behaviour has been further interpreted using a perceive, think, and act (PTA) loop, which will be explained in detail in the following sub-section.

3.1.2.2. Perceive, Think, and Act (PTA) loop in the ABM model

The PTA loop was adopted to describe the decision-making process of the occupant behaviour applied in the ABM model. Table 2 represents the model agents, essential parameters, events, and variables. The model adopts four types of agents including an active agent (e.g., Occupant) and three passive agents (e.g., EnergyPoint, HVAC, and Light). Herein, Parameters mainly consider the “int” or “double” types with certain initial values wherein Event considers the model actions in a cyclic mode. In addition, all agent variables were considered as a “double” type with certain initial values.

The PTA loop in Fig. 2 has been extended to the observe, orient, decide, and action (OODA) loop shown in the statechart in Fig. 6 (a) for further identification of the process. The detailed explanation of the OODA loop is as follows: (i) Observe: An occupant agent recognizes its environment or surroundings (e.g., interior layout and climatic conditions) of a given space; (ii) Orient: An occupant agent orients and spends some time evaluating its perception of the behaviour options; (iii) Decision: Based on its environment or surroundings as well as occupant attitude and subjective norm, an occupant agent makes behavioural decisions to address the task; and (iv) Action: An occupant agent performs the task or comes back to its idle position.

Usually, an occupant agent observes its environment, which is well-described by the input data, interior layout and environmental information of the specified spaces. The interior layout conditions correspond to the circulation path and switch location mentioned in the prototype Revit model, which also includes physical parameters (e.g., the distance between the occupant location and switch location). Based on this observation, the occupant agent evaluates its motivation to engage in the behaviour.

Table 2. Model parameters, events, and variables

Agent	**Active**	**Passive**		
	Occupant	**Energy Point**	**HVAC**	**Light**
Parameter	Prefer_HVAC Maximum_Time_Decision Interaction Rate Occupant size PMV value Occupant Intervention Circulation, energy spot, destination High & Low Perception Attitude and Subjective norm	Inaccessible Distance Switch_Point HVAC_Control EnergyPointInteraction_Rate	HVAC/Fan MinPreference_HVAC MaxPreference_HVAC Energy_coefficient_HVAC	Light
Event	EnergyPoint_interaction_Event Intervention_Event Occupant_Satisfaction_Event Update_Occupant_Perception Orient No_Task	-	-	-
Variable	HVAC_Dist ConsiderThermal Comfort_HVAC Decision_Time Thinking_Approaching Thermal_Sensation Occupant_Perception_Layout Colour	-	Temp_Dynamic	-

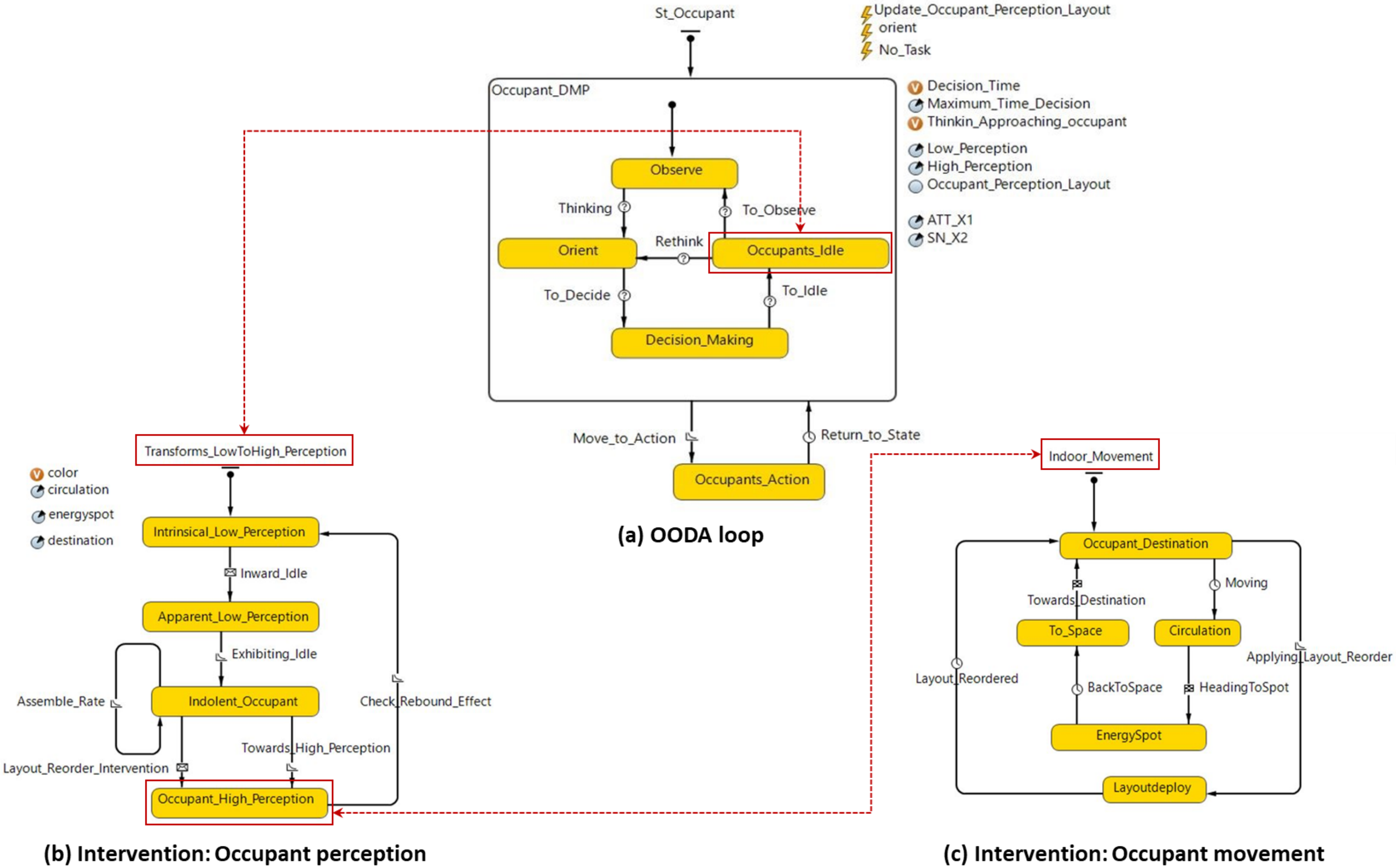

Fig. 6. Statechart for the decision-making process (e.g., OODA loop) and intervention

As shown in Fig. 6 (a), if more occupant agents go into an idle state (i.e., Occupants_Idle in Fig. 6 (a)), it indicates that occupants are not satisfied (less intention or low perception) with the existing interior layout, and they are not engaging in any energy-saving behaviours. Thus, occupants exhibit more energy-consuming behaviours rather than energy-saving behaviours. In this case, the model considers the intervention shown in Fig. 6 (b) and (c) to reduce the number of occupant agents in the idle state. The following steps were considered for the agent shifting from low to high perception during the intervention cycle.

(i) The intervention statechart consists of two components describing the shifting of occupant perception from low to high by completing the multiple stages within the indoor spaces. Firstly, the model considered the statechart entry point (Fig. 6 (b)) "Transforms_LowToHigh_Perception" that is mainly linked to the previous statechart (e.g., Occupants_Idle in OODA loop). Occupants belong to innately low perception at the "Intrinsical_Low_Perception" stage.

(ii) Afterward, the inward idle occupant shifts to "Apparent_Low_Perception," where occupants' limited idle status has been visible for a certain period of time.

(iii) Next, the occupant gradually shifts to a visible indolent stage and represents entirely unshifting categories. Now they are willing to change their perception as the layout reordering has been accomplished within the spaces.

(iv) Thus, the intervention was implemented to try to convert an occupant's existing low perception to high perception.

(v) The above process within the space was also coupled with the statechart "Indoor_Movement," which primarily represents the occupant's physical movement from their destination to switch location or other directions.

After the intervention cycle, the occupant perception value increases, which leads to a positive attitude toward energy-saving behaviours.

Typically, occupants' perception values (from -1 to +1) vary based on eight different interior layouts as mentioned in Fig. 3. Here, occupants' perception value is estimated based on triangular distribution while it is applied as a functional form of areas for fuzzy logic due to the simple application on the modelling platform. It is also assumed that occupants' perception values are higher after intervention and lower before intervention. For instance, if the switch location is accessible and within the human range (less than 2 ft), it means that the perception value is higher and the occupant has a positive behavioural intention towards energy saving. It is noted that the aforementioned model has considered both psychological and non-psychological parameters within the framework.

The next component of the hybrid model is energy calculation (before and after intervention) after the agent's interaction and learning process. The purpose of the energy estimation is to capture how occupants' agent behaviours can influence a building's energy consumption under different interior layouts. Here, the SD model interconnects the ABM-generated final perception factors of occupants, ambient parameters, along with the mathematical expressions, and occupants' energy usage characteristics, as shown in Fig. 7, which can influence the overall energy consumption of a building. In this way, the SD model describes how the behavioural changes made by occupant agents influence energy consumption.

3.1.2.3. Energy calculation loop in the SD model

System dynamics (SD) helps to recognize the nonlinear behaviour of complex structures over time using flows, stocks, interior feedback loops, time delays and table functions. The model structure in system dynamics is implemented using Anylogic, since the mathematical expressions can be easily inputted into the system. In this study, the complete structure of system dynamics is the executed form shown in Fig. 7. Here, occupants' perception factors from the ABM model, along with the intervention, are linked with the first components (Fig. 7 (a)) of the SD model that directly influence the amount of energy available within a space and consumed by HVAC and lighting. In addition, energy consumption by HVAC components is also connected to the cooling load, ambient parameters (e.g., temperature, CO_2 concentration), and additional presumed factors for a higher accuracy. Thus, another three components (i.e., 7 (b), 7 (c) and 7 (d)) have been considered within the SD model. More specifically, the first component (Fig. 7 (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. 7 (b)). The third component (Fig. 7 (c)) calculates the cooling load, which is linked to the second component (Fig. 7 (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. 7 (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. 7 (b)). Here, the CO_2 concentration (ppm) rate can be changed depending on the number of occupants and interior layout characteristics.

The details of outdoor environmental data such as temperature (℃) and relative humidity (%) and indoor environmental data such as ambient or room temperature (℃), relative humidity (%), CO_2 concentration (ppm), heat gain from occupants, etc. can be defined using the SD model. Other indoor space data in the SD model, such as metabolic gain, floor reflectance, air flow rate, area of interior walls, layout characteristics, etc., are extracted from the BIM model. The cooling load and internal heat gains by occupants can be calculated using the following formulas.

(i) Cooling load

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. [68, 69], from the perspective of occupants, it is 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 s_{in}^*, known as setpoints. The ideal cooling load can be mathematically expressed using Eqs. (2), (3) and (4):

$$q_{cool}^* = H_{cool}^* + LE_{cool}^* \tag{2}$$

$$H_{cool}^* = h \cdot A_{walls} \cdot (T_{walls} - T_{in}^*) + H_{ig} + \dot{V}_{inf} \cdot \rho \cdot c_p \cdot (T_{out} - T_{in}^*) \tag{3}$$

$$LE_{cool}^* = LE_{ig} + \dot{V}_{inf} \cdot \rho \cdot l_v \cdot (s_{out} - s_{in}^*) \tag{4}$$

where q_{cool} is the ideal cooling load (W), H_{cool} is the sensible cooling load (W), LE_{cool} is the latent cooling load (W), h is the 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 (℃) of indoor walls, T_{in} is the indoor temperature (℃), H_{ig} is sensible heat gain (W), $\dot{V}_{inf}$ is the volume flow rate (m^3/s), ρ is air density (kg/m^3), c_p is the specific heat of air (kJ/kg), T_{out} is the outdoor temperature (℃), 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. * indicates an ideal and steady-state condition.

(ii) Internal heat gains by occupants

Sensible and latent heat gains H_{ig} and LE_{ig} can be assessed from measurements of occupancy, lighting, and power supplied to electrical equipment using Eqs. (5) and (6). They can be mathematically expressed as:

$$H_{ig} = \underline{H}_{metabolic} \cdot N_{occ} + \frac{A_{in} \cdot f_{sa} \cdot I_{light}}{\eta_{light}} + \eta_{eqpt}.W_{eqpt} \tag{5}$$

$$LE_{ig} = \underline{LE}_{metabolic} \cdot N_{occ} \tag{6}$$

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

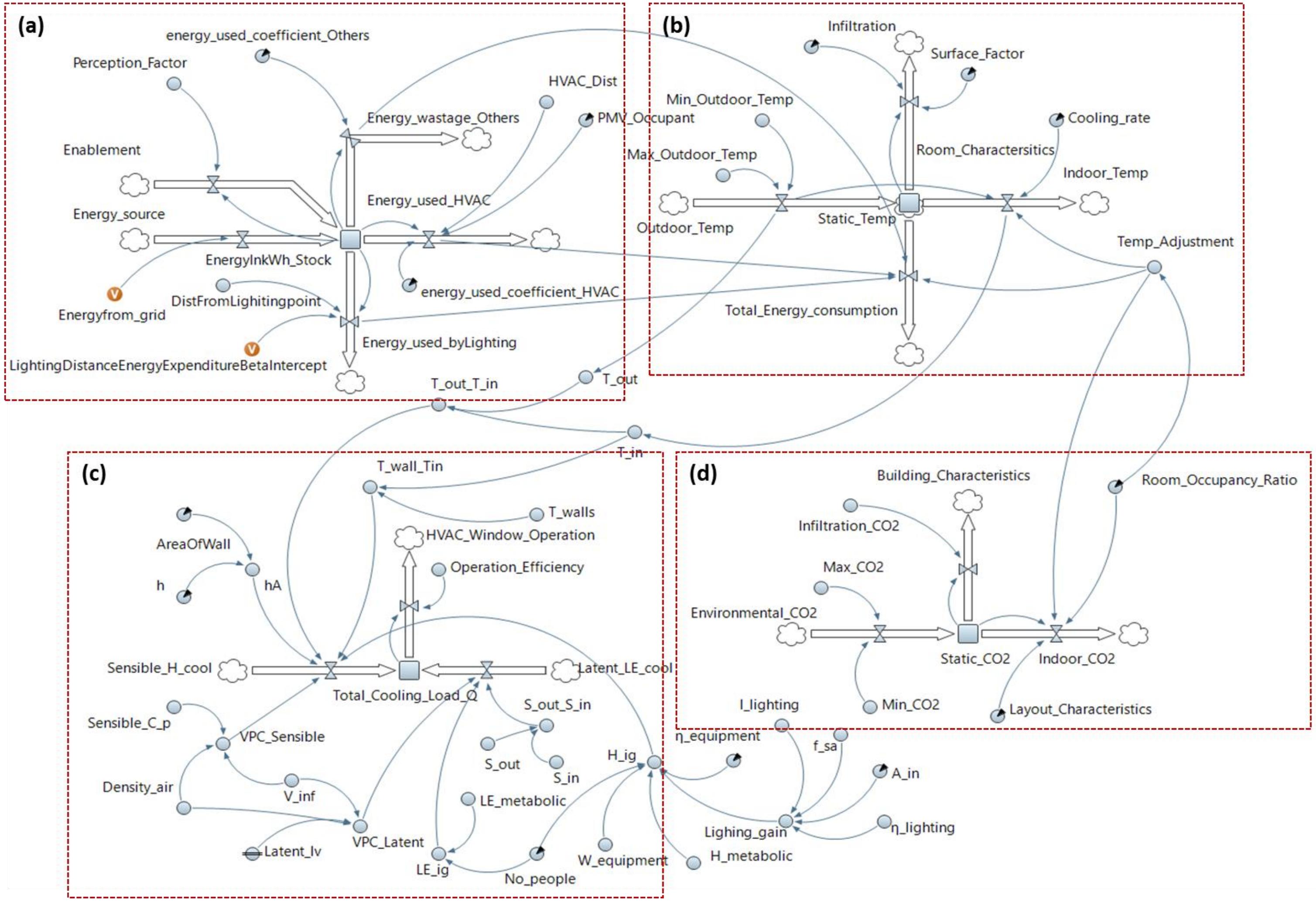

Fig. 7. System Dynamic Model

3.1.3. Task 3: Validation of the hybrid model

The last part of the research is occupant intervention and model validation to determine the flexibility and robustness of the proposed model. Here, the intervention is mainly considered as an enablement intervention where occupants may easily access and interact with the switch location for HVAC and lighting from their location by improving the opportunity/capability or minimizing the barriers/obstacles for them to perform energy-related activities [70, 71]. In this context, this study analyzed the energy consumption pattern both before and after an intervention to investigate the impact of a building's interior layout on occupants' energy-saving behaviour, and eventually, the energy performance of the building. This is one of the physical parameters considered during the model construction process. As a flexible modelling framework, all data can be customized within the model, and other parameters/components can also be adjusted whenever required. After executing the multiple simulations, required outputs are gathered and analyzed for further validation by considering an intervention approach implemented in a case study. It is also noted that the validation study mainly compares/represents the daily energy consumption data obtained from the simulation-based intervention and empirical-based intervention. Here, the simulation-based intervention refers to the occupant intervention simulated within the model while the empirical-based intervention indicates the occupant intervention actually done in the case study.

3.1.3.1. Experimental Settings and Intervention

Eight residential problematic interior layouts (shown in Fig. 8), including their inhabitants, were recruited for this validation study. The occupants comprised 16 males and 16 females from the selected apartments. All occupants were in the age range between 20 and 60. The occupants were provided with an information sheet explaining the study's aims and objectives. In the meantime, the occupants' approval was obtained using the standard approval form. Afterward, the occupants were invited to change their problematic layout position for a particular period of time (i.e., June/July 2020).

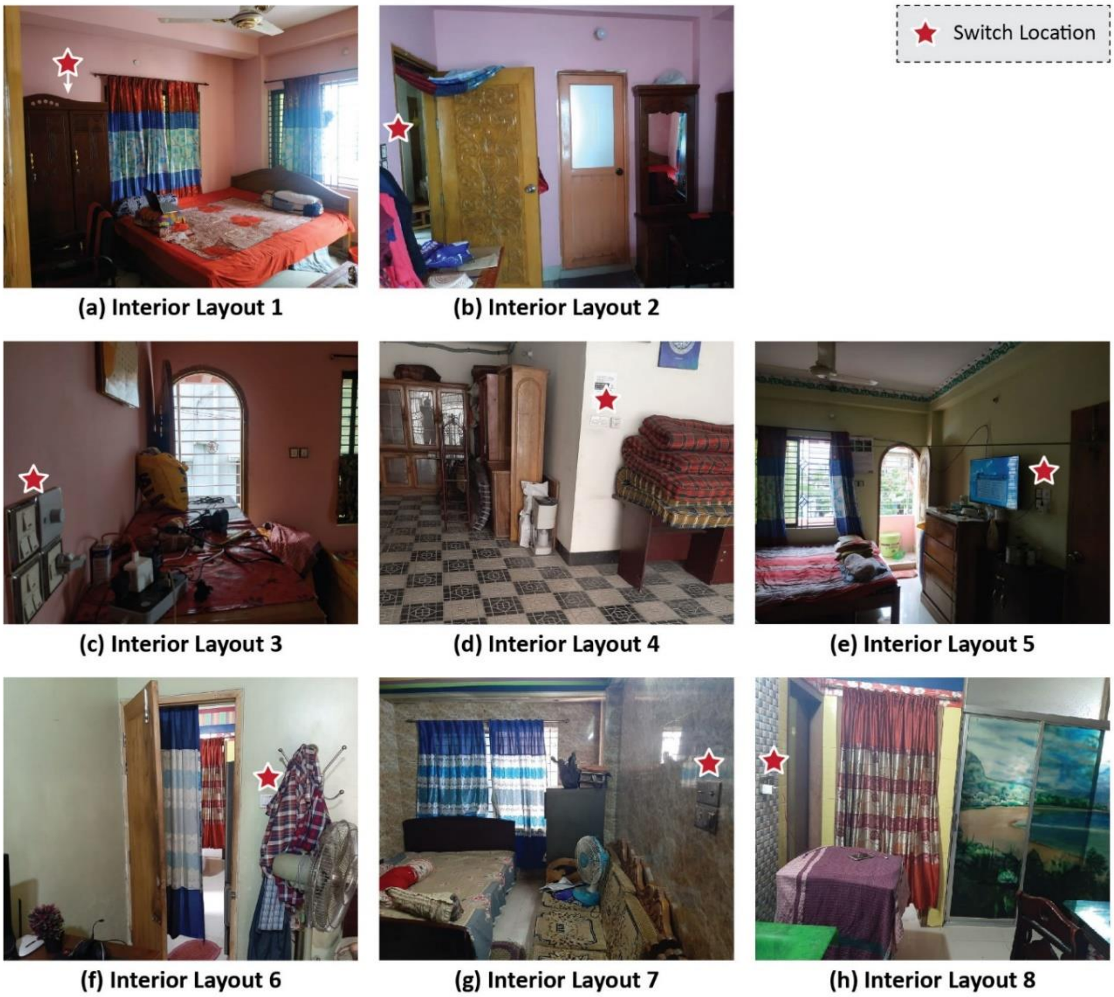

Fig. 8. Eight different types of interior layouts for the case study

In this regard, the occupants were requested to change their problematic layouts to the best possible one (described earlier). For example, if the switch location was inaccessible/not visible, the occupants could change some interior items or re-organize the interior layout, so the switch location becomes visible and is within the human ranges. In addition, it is assumed that climatic conditions at particular times (e.g., during the empirical-based intervention) are similar.

3.1.3.2. Data extraction and processing

During the experiment, energy consumption data from the individual indoor layout were collected using the customized sensor network shown in Fig. 9. 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 were stored on a desktop computer connected to a wireless network with fixed IP as shown in Fig. 10. Finally, with the intention of investigating the hybrid model's validity, the model-generated energy data from the eight indoor spaces were compared with the real data obtained from the sensor network.

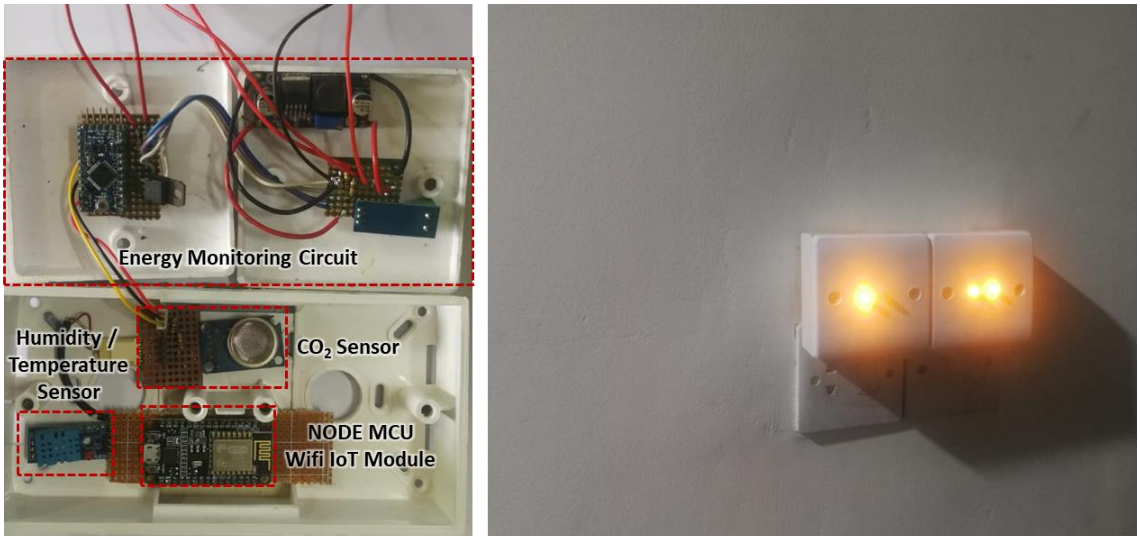

Fig. 9. Customized sensor panel installed in the selected interior layout

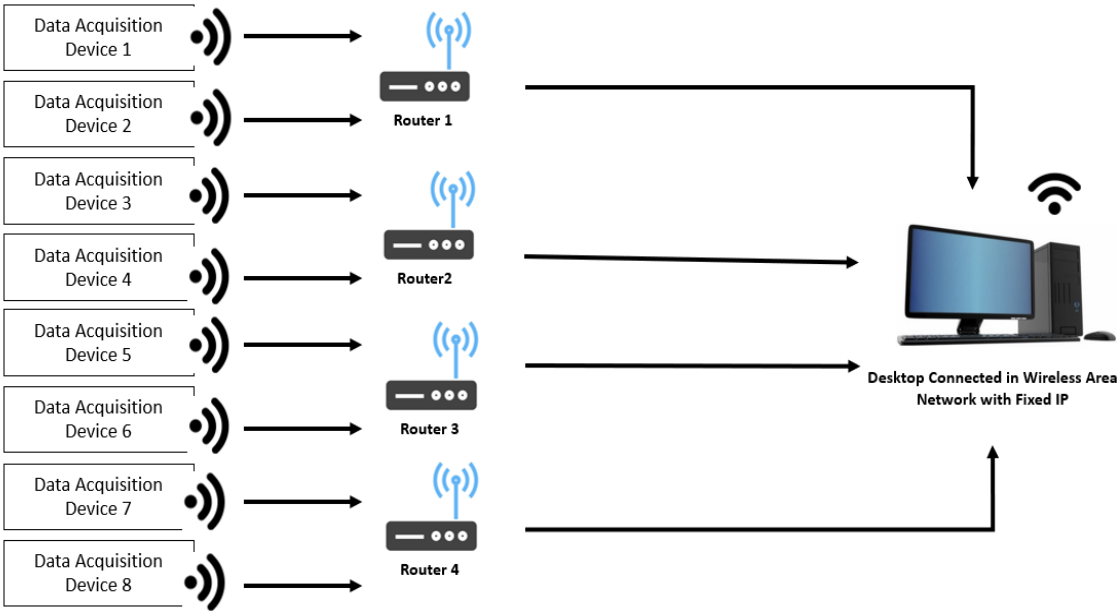

Fig. 10. Data acquisition technique

3.1.3.3. Validation study

The abovementioned simulation-based energy consumption data has been evaluated. The goal of the evaluation was to test the reliability and validity of the simulation-based energy consumption data and the performance of the proposed hybrid model. Herein this study utilized the real data gathered from the customized sensor network for validation. These customized sensor data are empirical, often known as "true" data, and therefore, comparing them with simulation-based data is recommended as a powerful validation approach [3, 72]. Typically, if the results found from the simulation model are reliable, the data derived from these models or tools need to be within an acceptable range [72]. Moreover, for reliability tests (by checking the calibration tolerance), it is essential that depth and scope are 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, the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard 14-2002 [73], the Federal Energy Management Program (FEMP) guidelines [74], and the International Performance Measurement and Verification Protocol (IPMVP) standard [75, 76] 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)), Mean Bias Error (MBE), and Coefficient of Determination (R^2) [76]. According to the ASHRAE standard 14-2002 and FEMP regulations, the typical calibration acceptance of CV(RMSE) and MBE are 30% and ±10%, respectively, while using system-level adjustment with hourly observed data [18, 76]. On the other hand, as stated by IPMVP, the acceptable values of CV(RMSE) and MBE are 20% and ±5% respectively [75]. The CV(RMSE) and MBE are computed and verified to be consistent with the ASHRAE, FEMP, and IPMVP guidelines. Eqs. (7) and (8) were used for CV(RMSE) and MBE calculation.

$$CV(RMSE)\ (\%) = \left(\frac{100}{T_{avg}}\right) \cdot \sqrt{\frac{\sum (T_s - T_m)^2}{n}} \tag{7}$$

$$MBE\ (\%) = \left(\frac{100}{T_m}\right) \cdot \frac{1}{n} \sum (T_s - T_m) \tag{8}$$

where T_{avg} is the average monitored data for n observations, T_s is the simulated data for n observations, T_m is the monitored data for n observations, and n is the number of observations.

On the other hand, R^2 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 a model's uncertainty. Typically, the R^2 value is limited to between 0 and 1, wherein a higher value suggests that the simulated values completely fit the computed value and a lower value does not. According to ASHRAE and IPMVP guidelines, an acceptable R^2 should be greater than 75% [76].

4. Results & Discussions

4.1. Model simulation results

The pattern of occupants' energy consumption before and after the simulation-based intervention is illustrated using several boxplots in Fig. 11. The box plots demonstrate the occupants' daily energy consumption pattern for 60 days for eight different building interior layouts considered in the case study location. It signifies that there are differences in the medians and the interquartile ranges before and after the intervention for each interior layout. The simulation outputs also reveal that before intervention (i.e., original interior layout pattern before the layout adjustment), 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 than Interior Layout 7 (16.58 kWh) and Interior Layout 8 (16.25 kWh). It is noted that, although the model found similar layout patterns, the daily energy consumption profile for each interior layout is somewhat different. For instance, the energy consumption profiles of Interior Layouts 4, 6, and 7 are comparatively higher than others. The number of active occupants is the crucial reason behind this issue. For example, the number of users or occupants for Interior Layout 3 was two, while the number of frequent users for Interior Layouts 6 and 7 was four or five. In addition to this, a building's layout orientation itself and other physical parameters, which are not considered in simulation models, might influence the daily energy consumption outputs [29, 77].

After the intervention (i.e., improved interior layout after the layout adjustment), the energy-saving profiles for different interior layouts changed significantly. In particular, after the intervention, the highest daily energy saving (35.13%) was found in Interior Layout 2. Before the intervention, Interior Layout 1 (i.e., with no access to the switch location) can be regarded as more problematic than Interior Layouts 2 and 3 (i.e., with partial access to the switch location due to obstacles); however, the energy-saving contribution in Interior Layout 1 (14.69%) is relatively less than that in Interior Layout 2 (35.13 %) and Interior Layout 3 (15.81%). In this regard, the findings reveal that occupants feel more discomfort when a switch location is only accessible from an angular side (e.g., Interior Layout 2) or partially accessible over an object (e.g., Interior Layout 3). In compliance with this, some experimental studies [78, 79] have shown that humans prefer to walk in straight and circular directions than angular tracks. Moreover, these studies [79, 80] also mentioned that human behaviour significantly changes if their straight path is occupied, leading to discomfort concerning their desired actions. Meanwhile, the energy saving after the intervention for Interior Layout 4 (i.e., having partial access to the switch location due to a long distance) was calculated to be 13.6%, whereas for Interior Layouts 5 (i.e., with average access to the switch location with a fair distance from the forward direction) and Interior Layout 6 (i.e., with average access to the switch location with a fair distance from the lateral direction) the energy savings were 9.7 % and 12.2%, respectively. Although both Interior Layouts 5 and 6 had access to the switch location with moderate distances, occupants' movement paths for these two layouts were different due to the direction towards the switch location . Accordingly, the occupants' movement paths can also be one of the factors that contribute to the difference in energy-saving potential. Besides, Interior Layouts 7 (1.08%) and 8 (0.8%) exhibited relatively lower energy savings after the intervention as these layouts were very close to the best cases. Overall, the average daily energy saving due to the intervention was about 14.9%. From the previous investigations, assessments of the effectiveness of the interior layout-based intervention are not widely available. However, this study has shown that the energy savings due to the interior layout-based intervention are quite significant compared to other intervention-based modelling studies [81-83]. For instance, Abdallah et al. [84] used an agent-based modelling approach for energy messaging intervention while average energy savings for wasteful occupants was 11% and for green occupants was 13%. On the other hand, Xu et al. [83] 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. [85] studied a knowledge-based intervention that exhibited a difference of 12.9% in occupants' energy consumption before and after the intervention.

In summary, it is noticed that, although almost analogous layout patterns were considered, the energy-saving profiles from the particular layouts were entirely different, including the best case (e.g., Interior Layout 8). Moreover, Interior Layout 2 exhibited higher energy savings than others. In addition to the accessible switch location from the edge, Interior Layout 2 is relatively small and more compact than other layouts. Before the intervention, it also comprises a higher number of obstacles (at random position) than Interior Layouts 1 and 3. The energy consumption variation is also noticeable due to the number of active occupants defined within the hybrid model. Although there was no solid object or barrier defined within the Interior Layout 4, herein the occupant idle stage mostly reflected the longer distance. Besides the directional effects of Interior Layouts 5 and 6, a few window or door variations exist in these layouts. For example, Interior Layout 5 consists of windows and an additional balcony door that marginally impacts the occupants' thermal comfort. The model also considered that occupants may frequently use both windows and balcony doors for their thermal comfort. Thus, the occupant may use less HVAC systems for their thermal comfort fulfilment. Before intervention, Interior Layout 6 also consists of a higher number of obstacles than Interior Layout 5. These are the probable reasons why the energy-saving potential for Interior Layout 6 was higher than Interior Layout 5. Obviously, Interior Layouts 7 and 8 did not show much energy-saving potential since they were the least problematic layouts as defined within the hybrid model.

Still, there are also other reasons for showing different energy-saving profiles, such as typical occupant behaviours being highly stochastic [27] including their random perceptions of the space [64, 65, 86]. Interior space allocation/arrangement [27, 64, 65] and indoor ambient data [18, 35, 87] also play an essential role in changing the energy consumption pattern. In addition, in all cases the energy medians were uneven, and the interquartile ranges varied due to the occupants' stochastic energy consumption behaviour. Previous findings [18, 19, 29, 46] also revealed that space orientation and interior allocation (e.g., entrance, windows, doors, and furniture's position, etc.) of the space within the design plan of a building and its other structural elements, 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 that changed or reduced the energy consumption after the intervention.

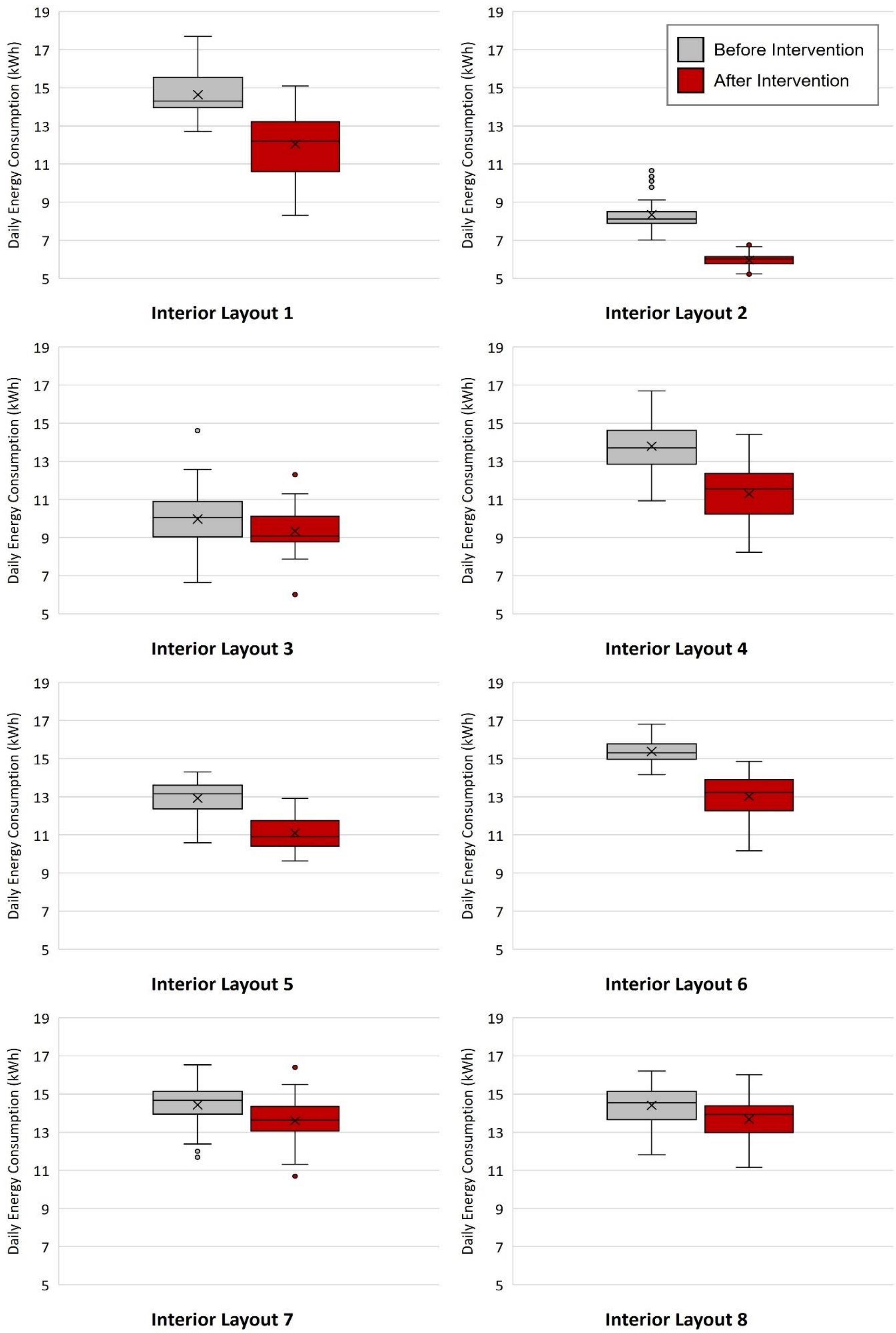

Fig. 11. Simulation-based daily energy consumption before and after intervention

4.2. Validation Results

Table 3 compares the CV(RMSE) and MBE values of the simulation-based and empirical-based energy consumption data. All simulation-based and empirical-based daily energy consumption data for 60 days are also presented in Fig. 12. It has been shown that implemented simulation or a hybrid model provides data within the acceptable range for all interior layouts as defined by ASHRAE, FEMP, and IPMVP guidelines. Interior Layouts 4 (CV(RMSE): 15.71%) and 5 (CV(RMSE): 16.7%) exhibited marginally more errors as compared to other interior layouts. There are several reasons for this. Basically, the original Interior Layout 4 comprised two rectangular shapes (almost L shape), although the model considered a single rectangular/square shape. In addition, Interior Layout 5 consisted of windows and an additional balcony door which partly impacted the occupants' thermal comfort. Here, occupants may frequently interact with both windows and balcony doors to ensure their thermal comfort. Therefore, an occupant may use less HVAC/Fan for their thermal comfort, which eventually influences their energy consumption profile. However, the hybrid model considers a similar number of windows and doors for each interior layout. Furthermore, frequent load shedding is also a common problem in this space area that may significantly affect the model's performance as the model does not consider any load shedding issue. Nevertheless, compared to other previous studies [88, 89], the average error from the proposed hybrid model is quite considerable.

Compared to Interior Layouts 4 and 5, other interior layouts showed a relatively higher prediction accuracy in terms of both CV(RMSE) (all below 10.5%) and MBE (all below 2%). Among them, Interior Layouts 6 (CV(RMSE): 9.11%; MBE: -0.9%) and 8 (CV(RMSE): 9.10%; MBE: -0.8%) demonstrated a slightly better fit of the predicted data while over-estimating the energy consumption (negative MBE value). The variations of prediction mainly occurred due to an occupant's presence and movement within the realistic layouts. The best prediction was observed in Interior Layout 7 (CV(RMSE): 8.30%; MBE: 0.7%). In addition to CV(RMSE) and MBE, the R^2 was estimated to assess the accuracy of the simulated-based energy consumption data for different layouts and a scatter plot has been presented to validate the model performance as shown in Fig. 12. Herein, Interior Layouts 1, 3, and 8 showed a relatively higher performance, with R^2 nearly 0.8. However, Interior Layouts 4 and 6 are demonstrated to have a slightly lower performance, showing R^2 below 0.75, possibly due to the variation of windows/doors and over-prediction, respectively. Meanwhile, Interior Layouts 2, 5, and 7 showed R^2 close to 0.75, but still reaching the marginal level of goodness of fit defined by the guidelines.

Table 3. CV(RMSE) and MBE values for different interior layouts

Interior Layout	CV(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

Overall, the study revealed that the R^2 has a considerable variation of occupant daily energy consumption pattern for both simulation-based and empirical-based data while some values fall below the acceptable limit of 0.75 (e.g., Interior Layouts 4 to 6). On the other hand, data obtained from this investigation are within the acceptable limit of CV(RMSE) and MBE. Similar findings were also found in previous studies [89-91] as well. The possible reason for these discrepancies is occupants' intrinsic nature of turning switches on or off for a prolonged period of time to fulfil their visual and thermal comfort. Also, most of the variation in energy savings can be described by other critical variables that are not incorporated into this model [91]. Although some interior layouts generated slightly lower values for the R^2, the study may help to capture the diversity of realistic occupant behaviour profiles in the residential sector rather than fixed or static behaviour profiles. In this regard, the findings indicate that the hybrid framework offers a holistic assessment of the interior layout-based energy performance of buildings.

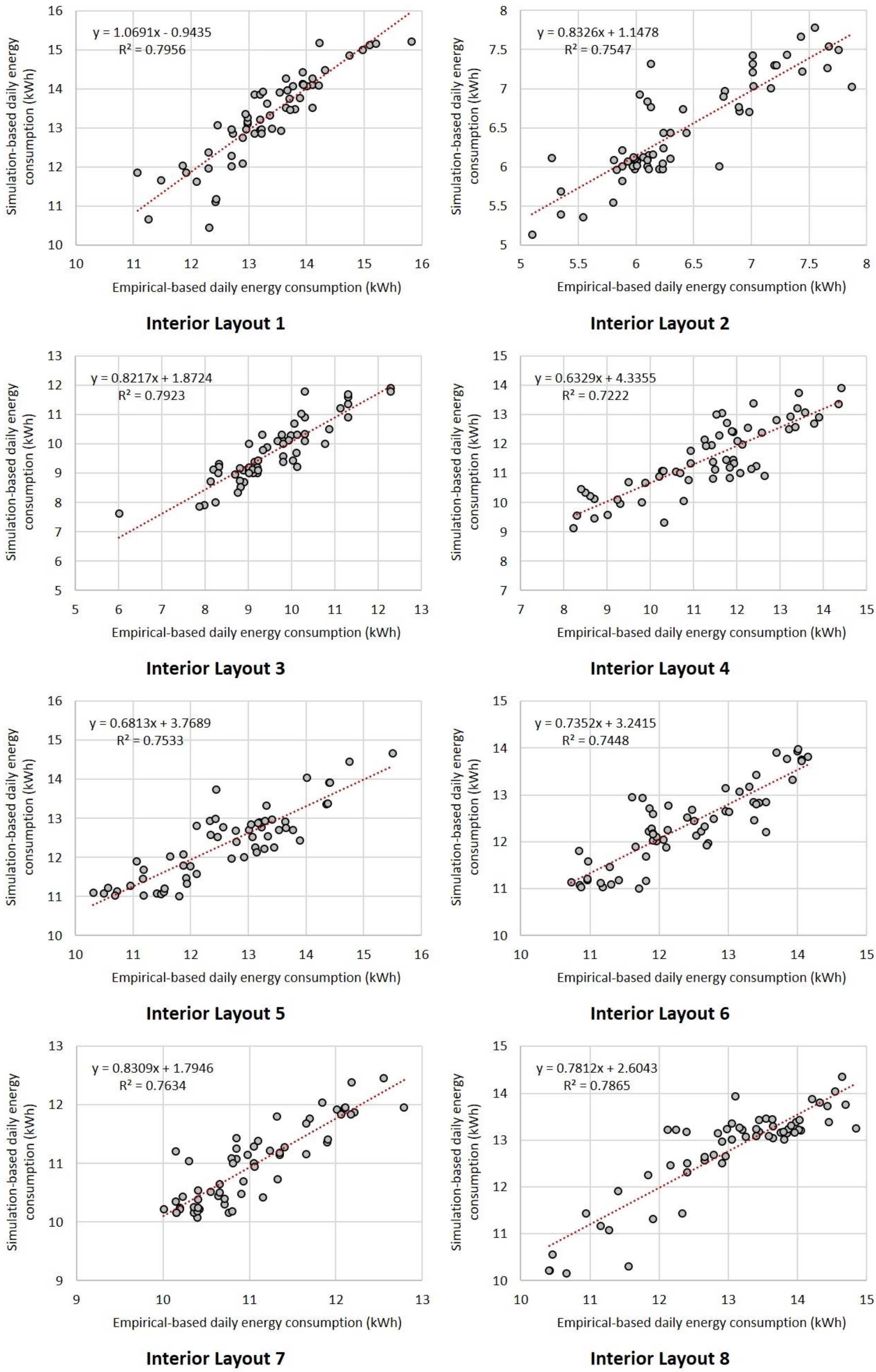

Fig. 12. Coefficient of determination (R^2) for different interior layouts

5. Conclusion

Occupant behaviour is a critical parameter to assess the building energy consumption, which also can be a substantial consideration in regard to the technological tactics used for enhancing energy efficiency in buildings.

The study investigated the influence of occupant behaviour in regard to energy conservation in the context of interior layout configuration adopting a holistic approach using 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 system for buildings and identify the key players involved in energy saving through appropriate occupant intervention. The study also offers a validation approach using a real-data collection system of customized sensors to improve the simulation reliability, trustworthiness as well as robustness of the proposed model. Herein the validation and fit of the proposed model are highly important to make it a representative model to be used during the simulation process. Although only a small energy-saving potential has been noticed through the applied occupant intervention, both the simulation and experimental study revealed that interior layout adjustment (i.e., occupant intervention) has a significant influence on the energy consumption profile of occupants. Thus, the proposed integrated model captures the broader aspects of occupant behaviour paradigms in the context of energy efficiency and the built environment.

This study makes an original contribution of the body of knowledge in exploring the influence of building interior layout on the energy-saving behaviour of occupants. By integrating different models (i.e., ABM, SD, and BIM), the hybrid model allows to better represent the occupants' stochastic behaviour, building energy consumption, and interior layout within the built environment. Validation efforts through an occupant intervention also contribute to demonstrating the performance and feasibility of the hybrid model. The study offers a comprehensive validation approach by considering both the simulation-based and empirical-based occupant interventions based on the real data collected from the customized sensors.

This study offers automatic integration of the ABM-SD-BIM framework that facilitates occupancy-based building simulation and supports engineers, researchers, and policymakers to improve overall building designs as well as interior layout improvement. However, 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 collection is not possible due to the COVID-19 pandemic. Wide-ranging interior layout selection and broader data collection, including additional behavioural rules, should be identified and incorporated into the framework for modelling more complex occupant comfort and behaviour in buildings. Moreover, comprehensive knowledge of occupant behaviour will assist in stimulating an advanced energy prediction model 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 of design.

Author Contributions:

Mohammad Nyme Uddin: Conceptualization, Methodology, Investigation, Validation, Resources, Data curation, Visualization, Writing - Original Draft. Hung Lin Chi: Supervision, Writing - Review & Editing. Hsi Hsien Wei: Supervision, Writing - Review & Editing. Minhyun Lee: Supervision, Visualization, Writing - Review & Editing. Meng Ni: Supervision, Writing - Review & Editing.

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Conflict of Interest:

There is no conflict of interest.

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Figure 1

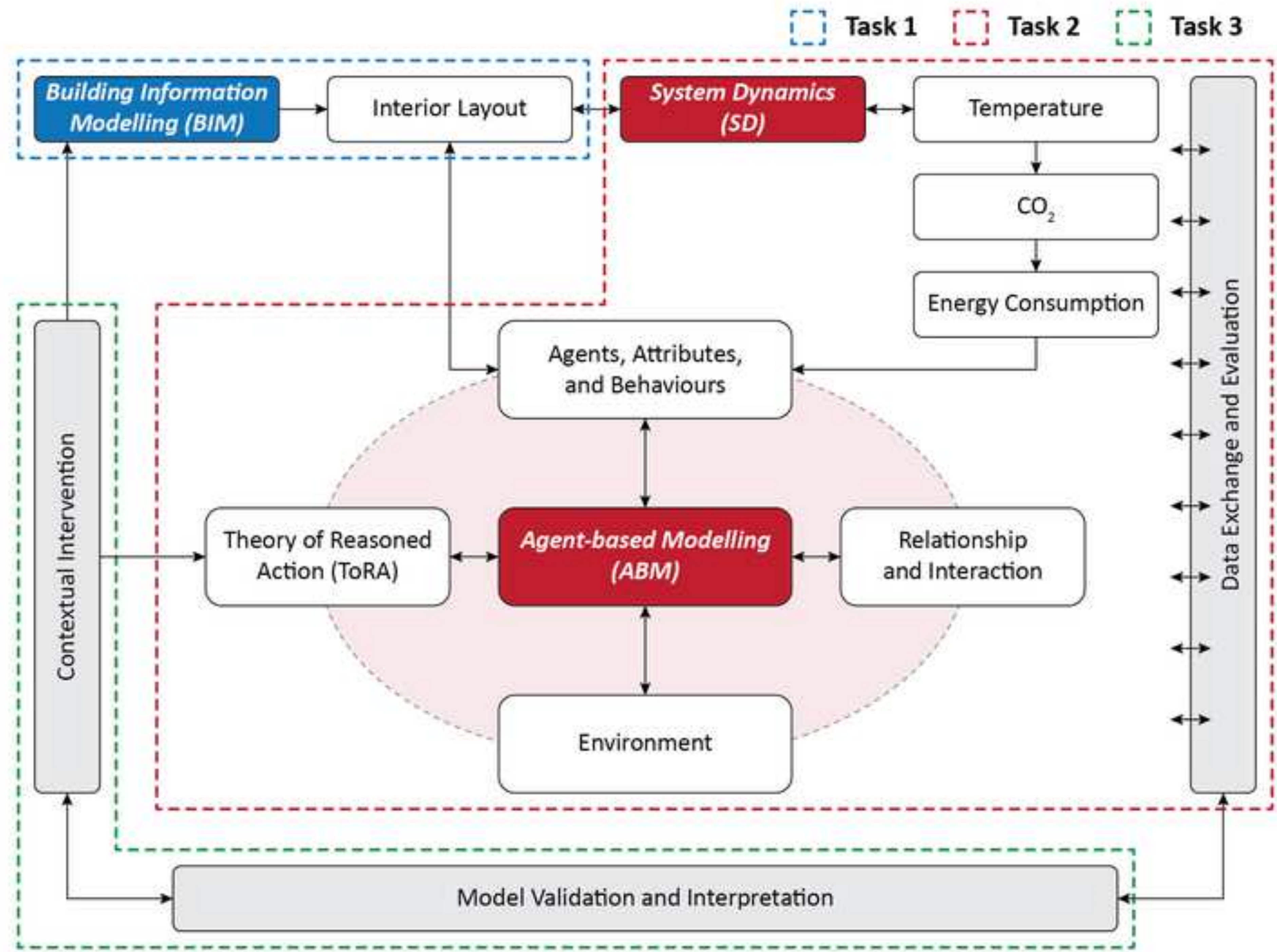
Task 1
Task 2
Task 3
Building Information Modelling (BIM)
Interior Layout
System Dynamics (SD)
Temperature
CO2
Energy Consumption
Data Exchange and Evaluation
Contextual Intervention
Agents, Attributes, and Behaviours
Theory of Reasoned Action (ToRA)
Agent-based Modelling (ABM)
Relationship and Interaction
Environment
Model Validation and Interpretation

Figure 2

Click here to access/download;Figure;Figure 2.jpg

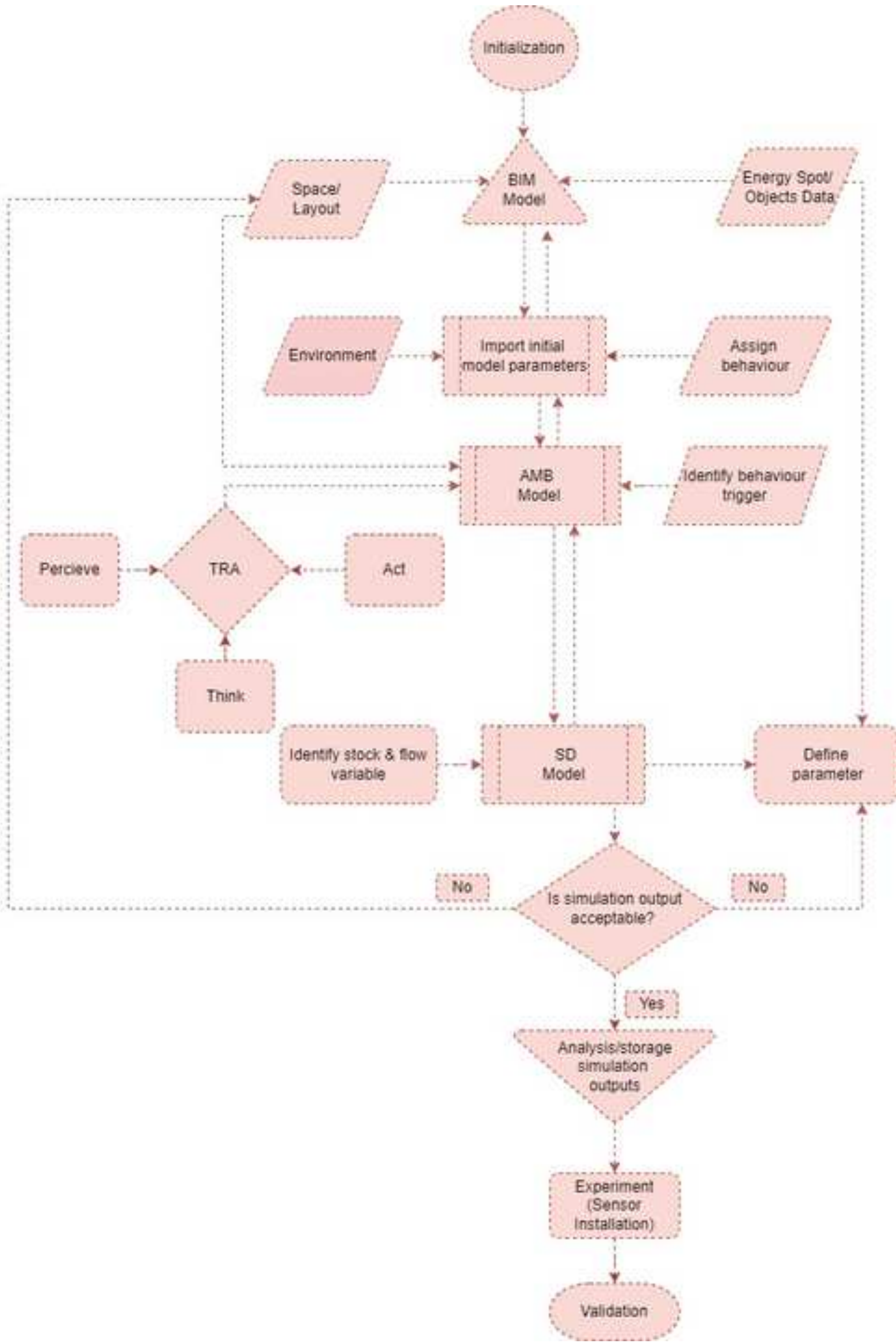

Figure 3

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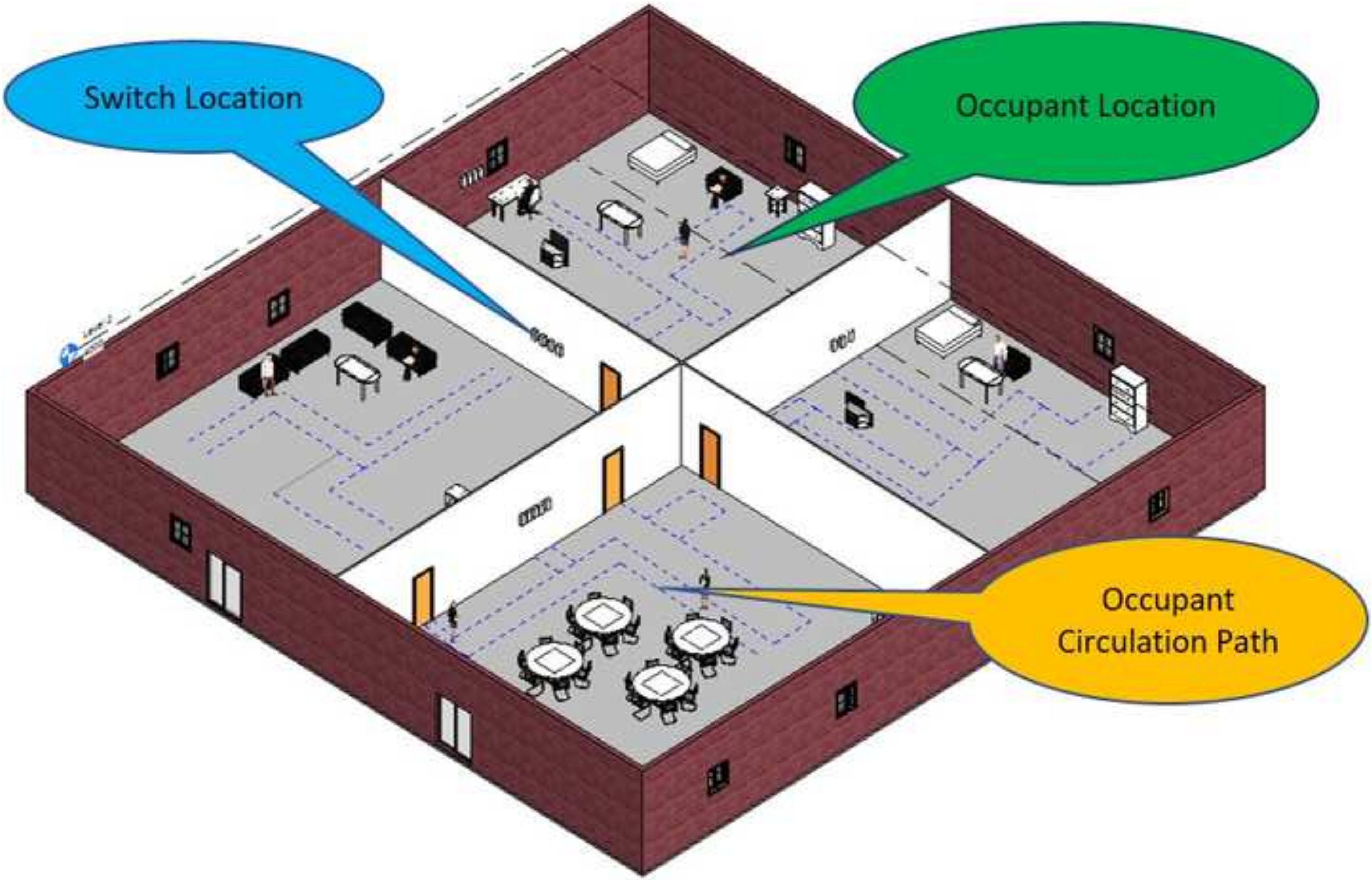

Figure 4

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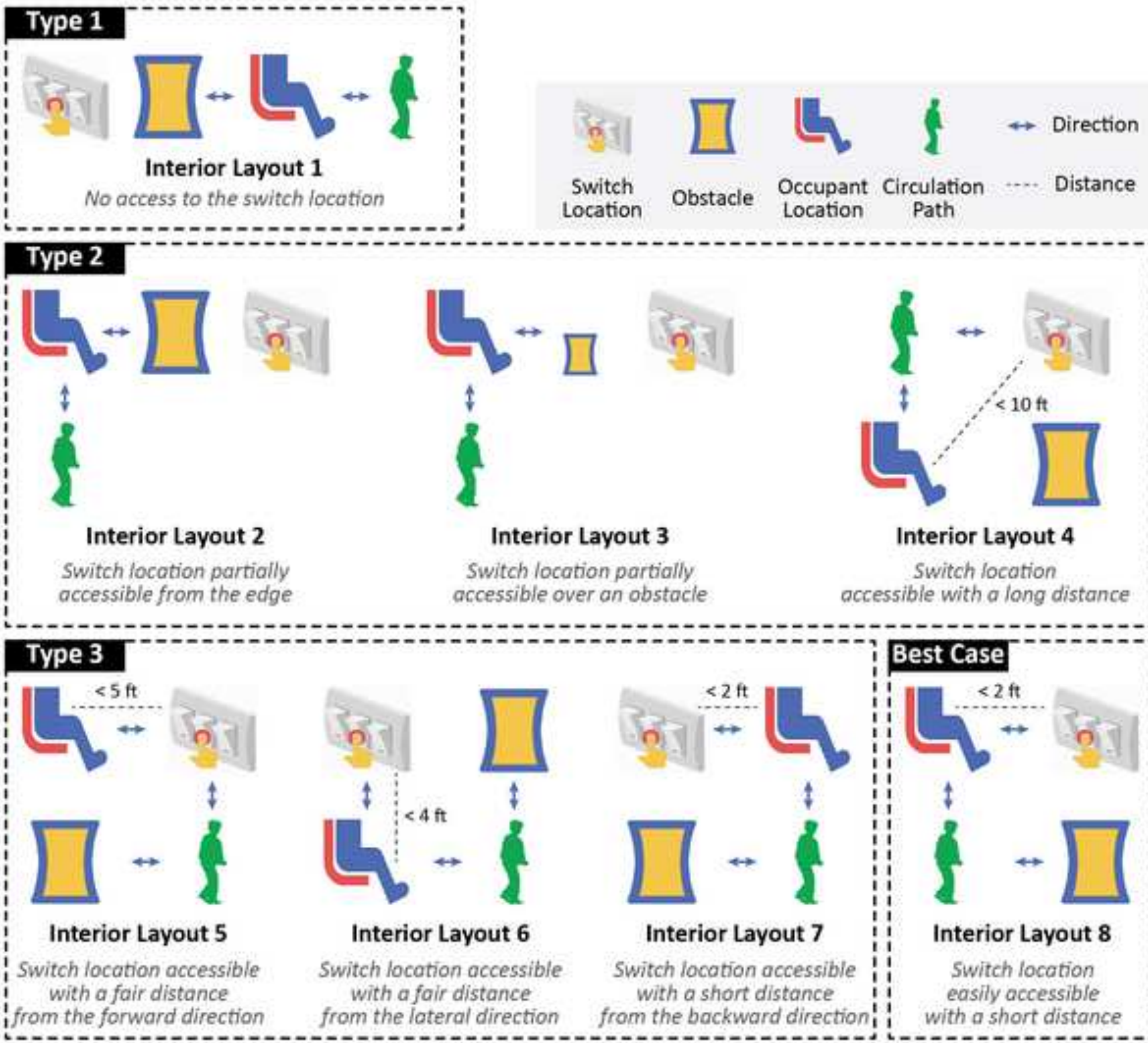

Figure 5

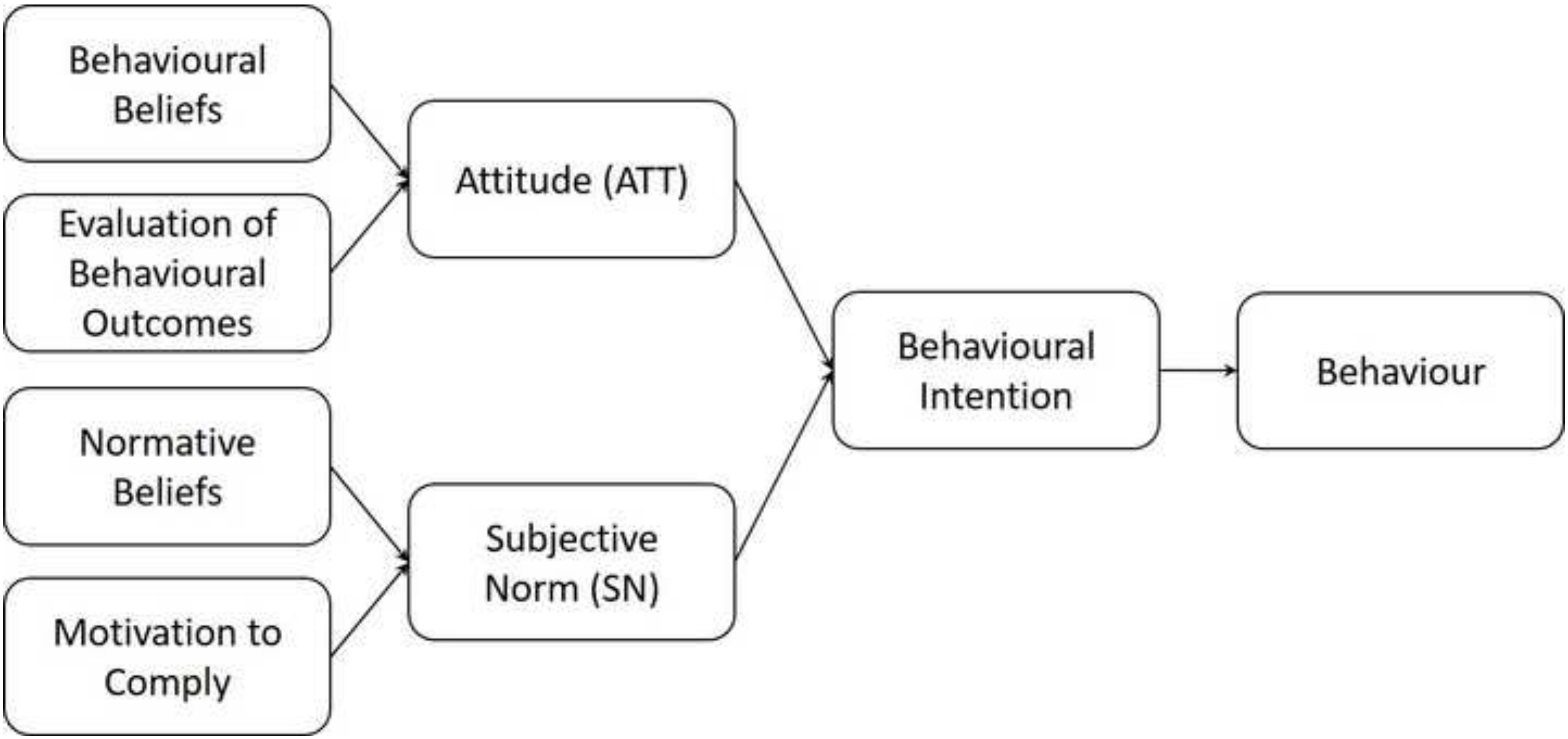
Behavioural Beliefs
Evaluation of Behavioural Outcomes
Normative Beliefs
Motivation to Comply
Attitude (ATT)
Subjective Norm (SN)
Behavioural Intention
Behaviour

Figure 6

Click here to access/download;Figure;FIgure 6.jpg

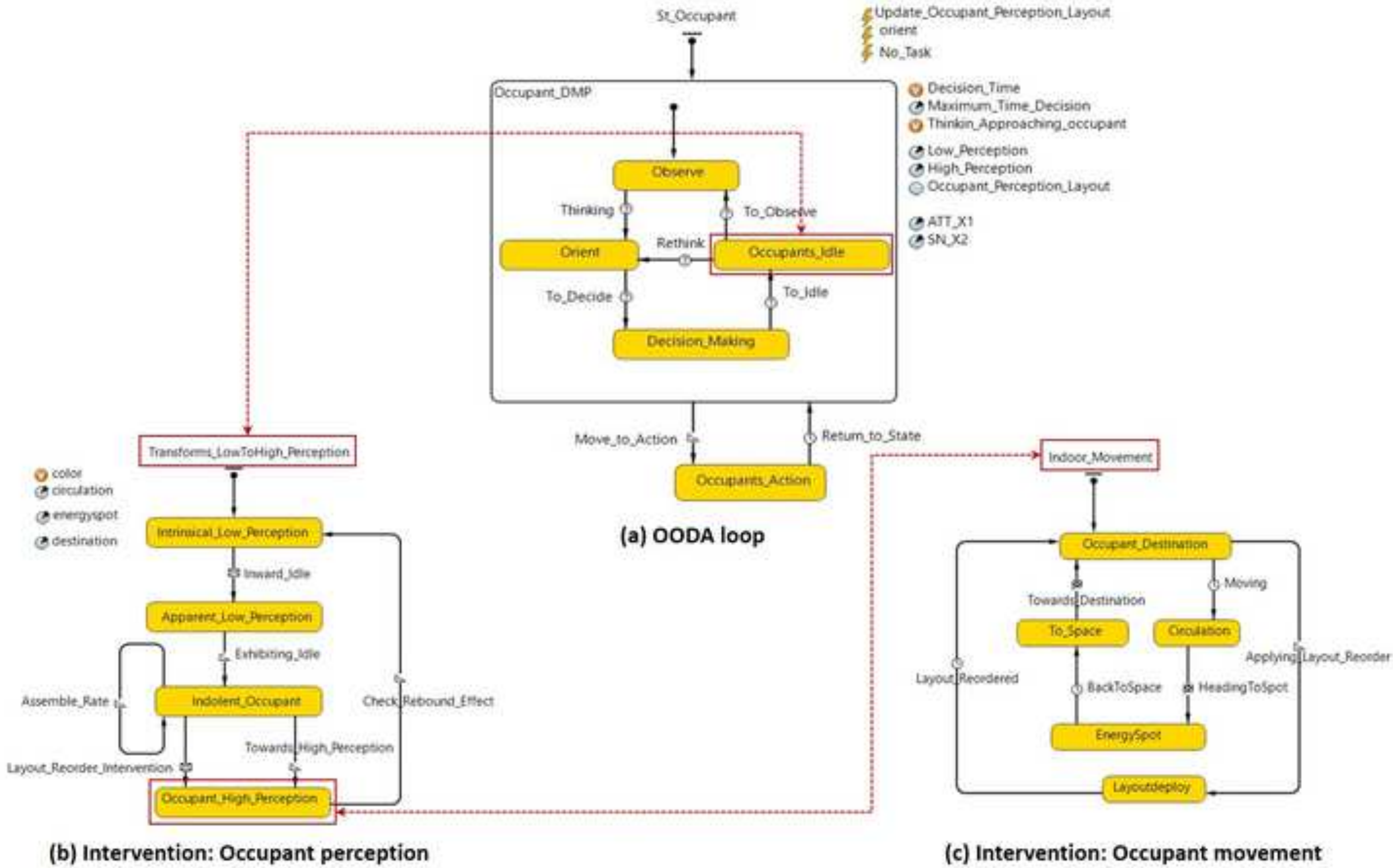

Figure 7

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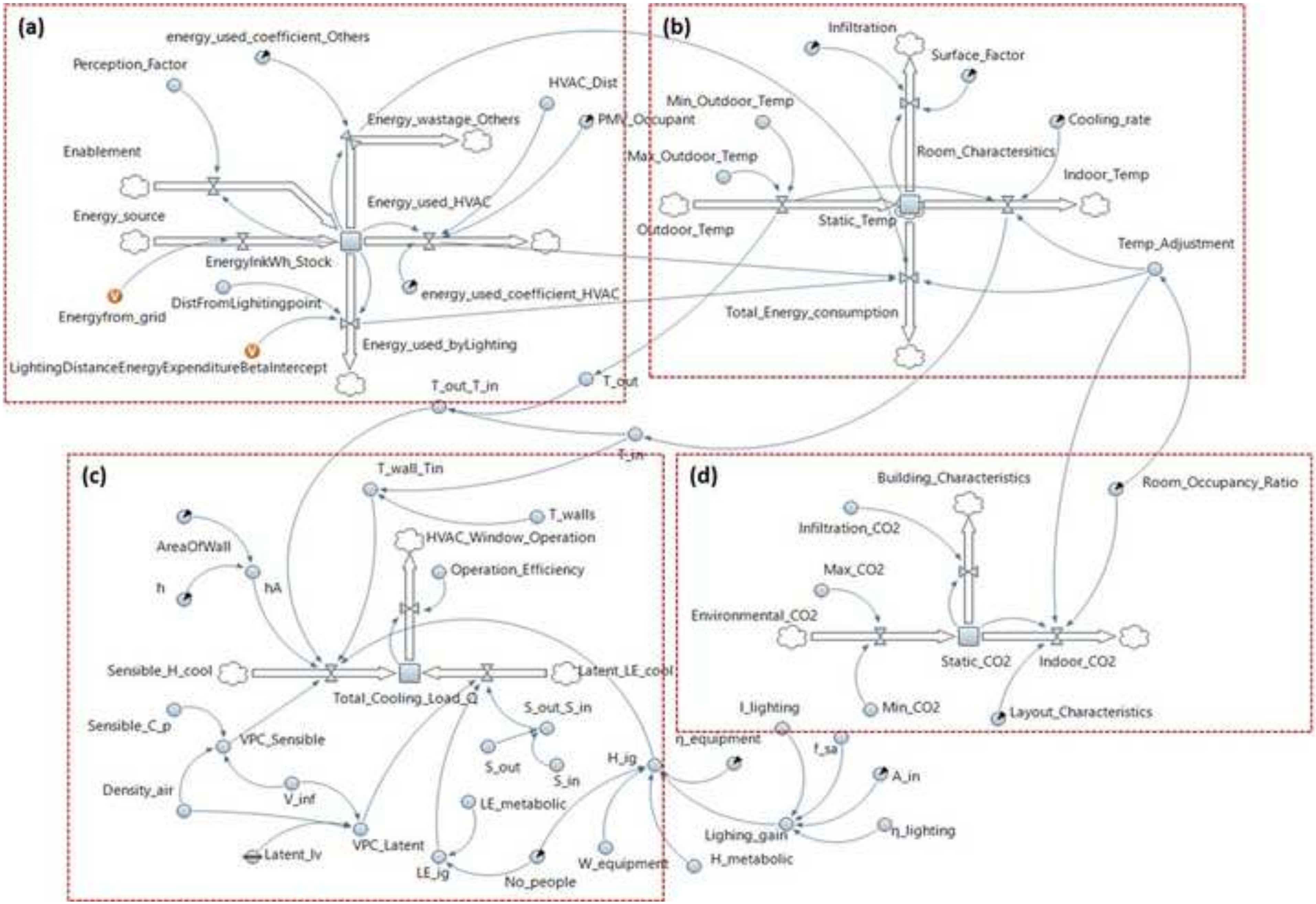

Figure 8

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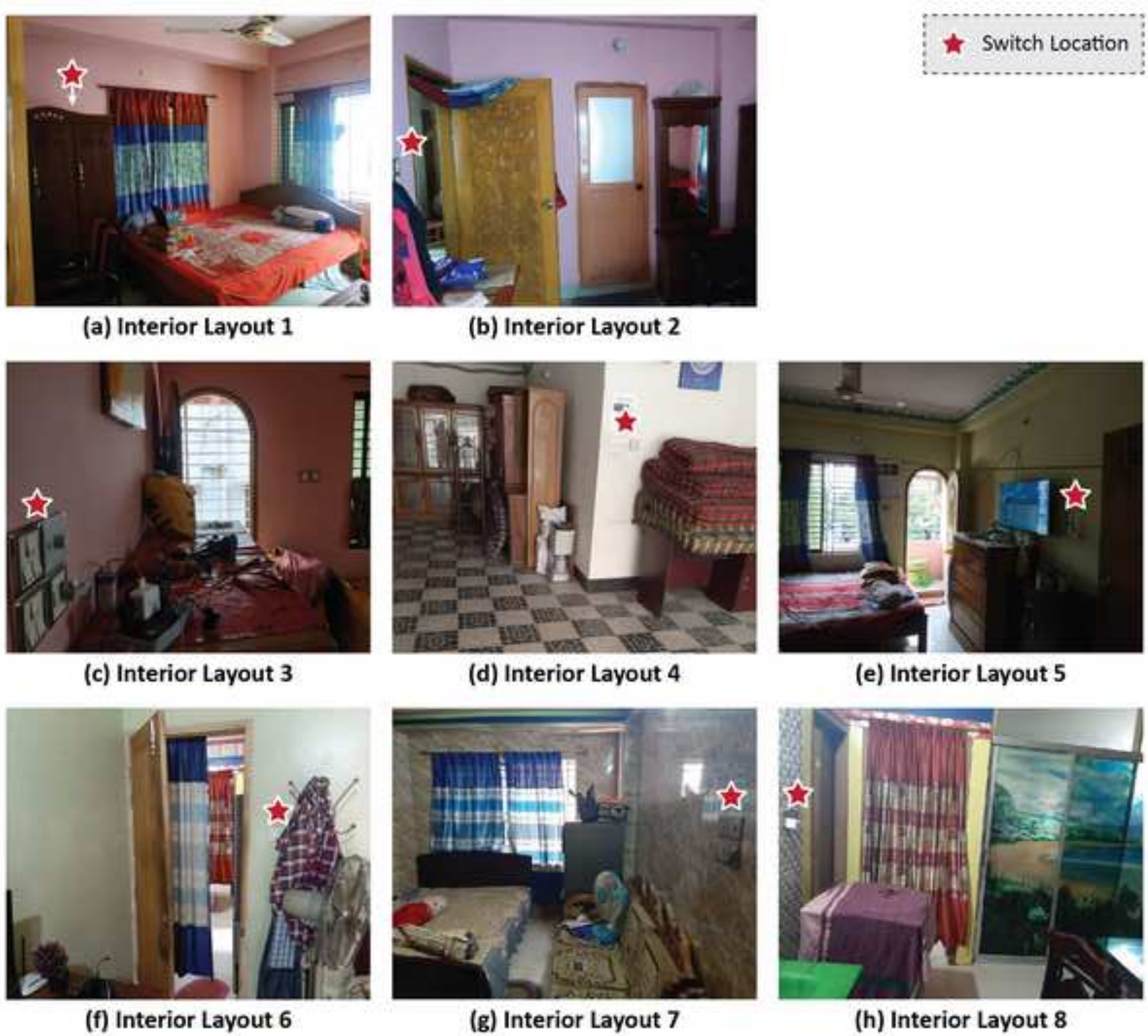

Figure 9

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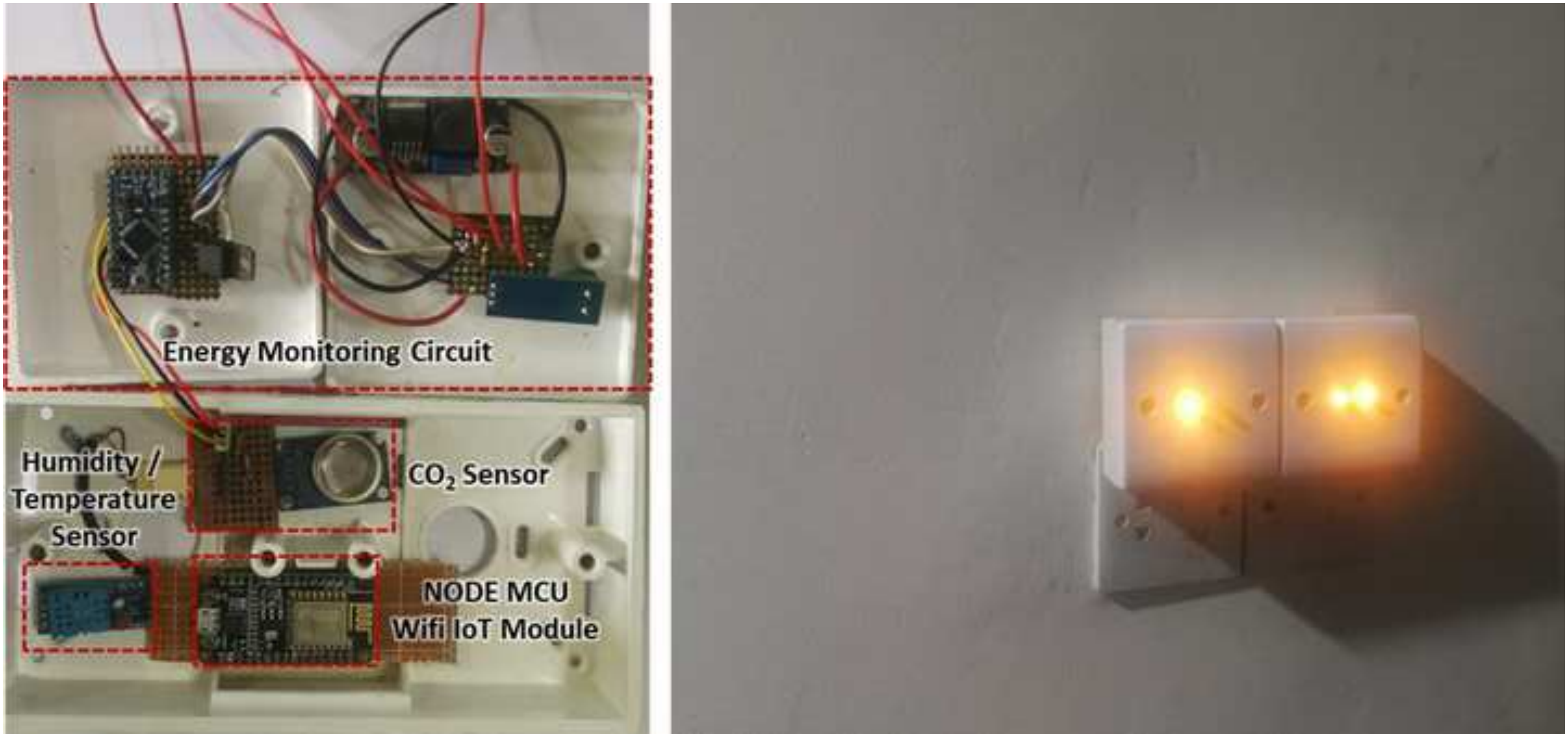


Figure 10

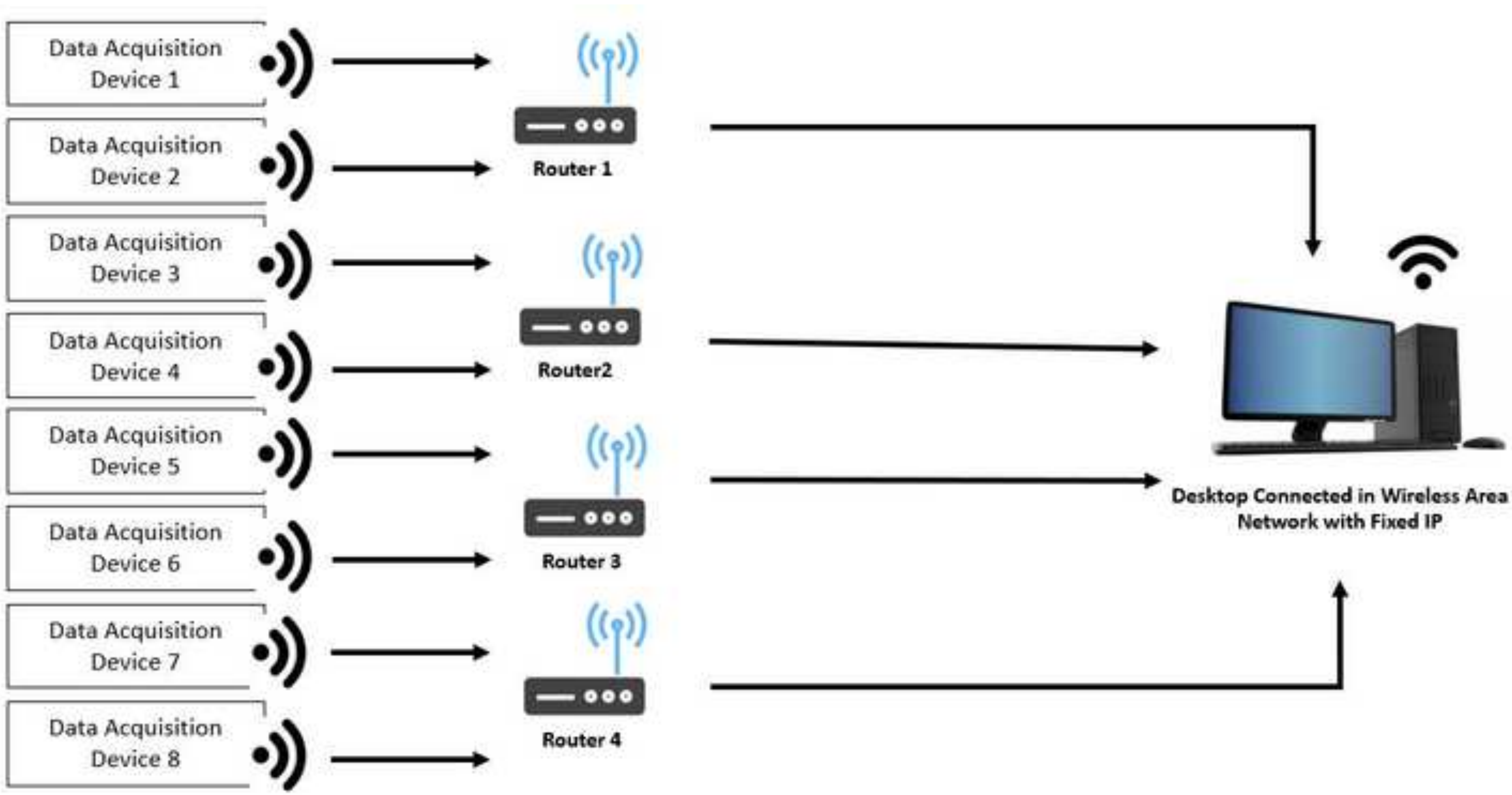
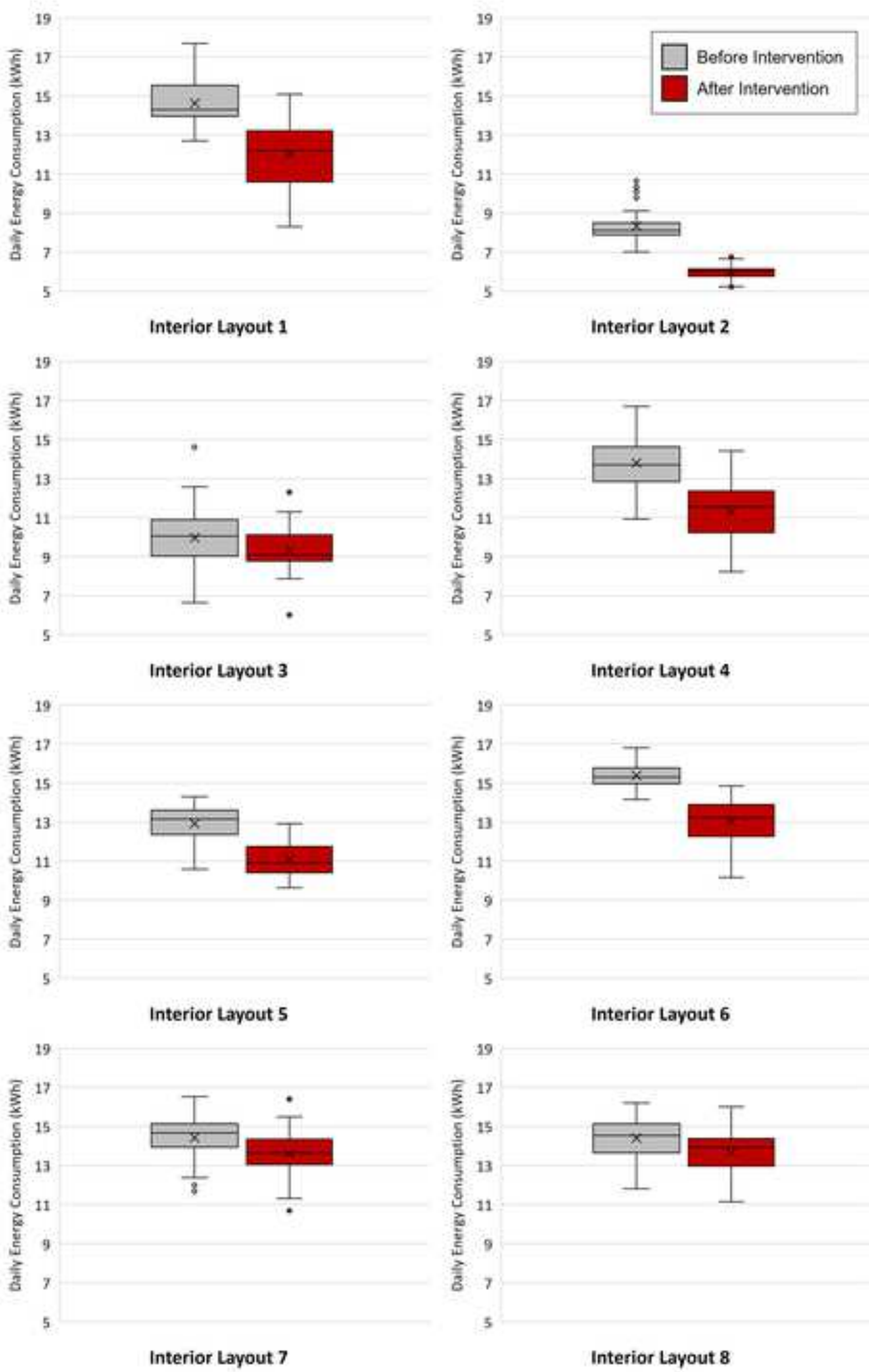

Data Acquisition Device 1
Data Acquisition Device 2
Data Acquisition Device 3
Data Acquisition Device 4
Data Acquisition Device 5
Data Acquisition Device 6
Data Acquisition Device 7
Data Acquisition Device 8
Router 1
Router2
Router 3
Router 4
Desktop Connected in Wireless Area Network with Fixed IP

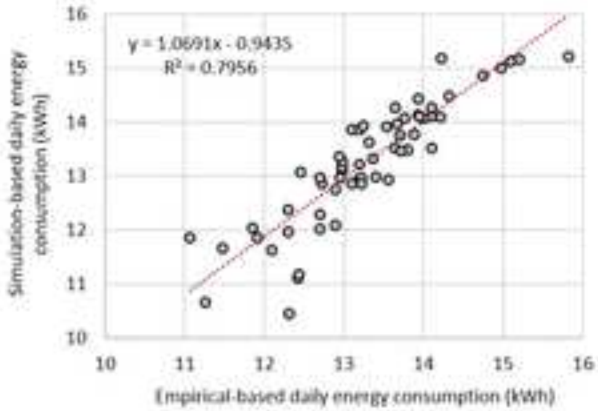
Figure 11



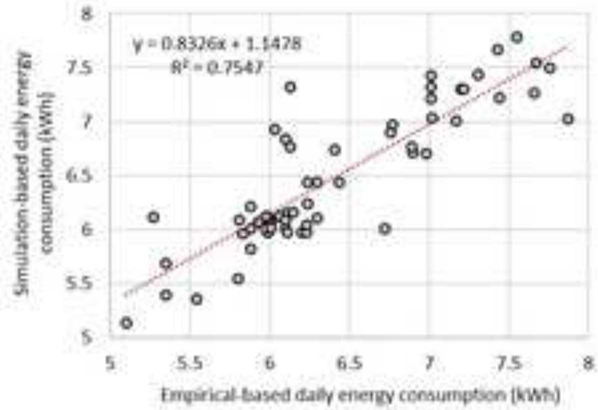
Daily Energy Consumption (kWh)
19
17
15
13
11
9
7
5
Before Intervention
After Intervention
Interior Layout 1
Interior Layout 2
Interior Layout 3
Interior Layout 4
Interior Layout 5
Interior Layout 6
Interior Layout 7
Interior Layout 8

Figure 12

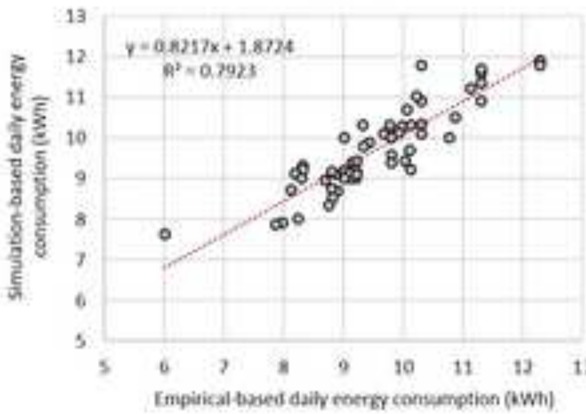
Click here to access/download;Figure;Figure 12.jpg



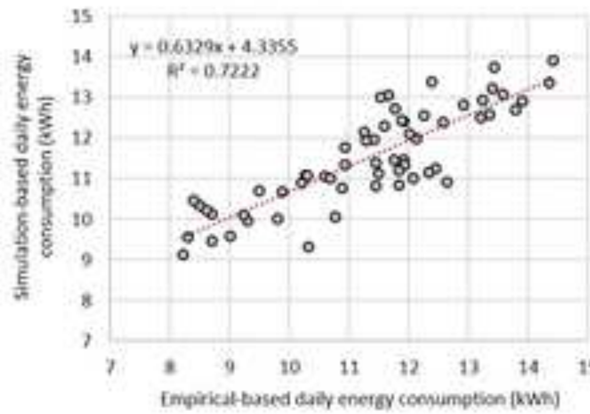
Interior Layout 1



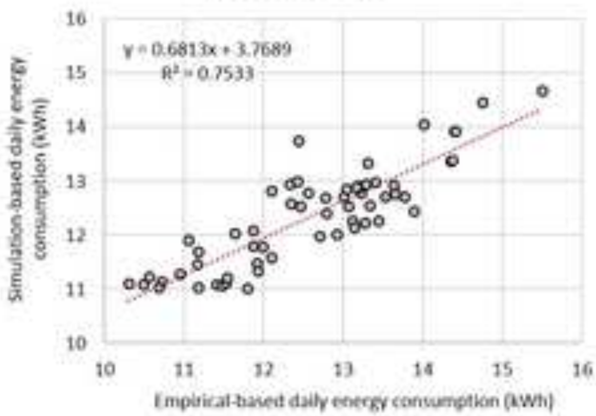
Interior Layout 2



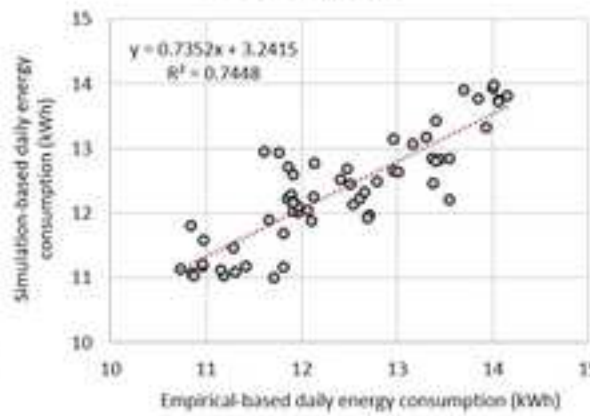
Interior Layout 3



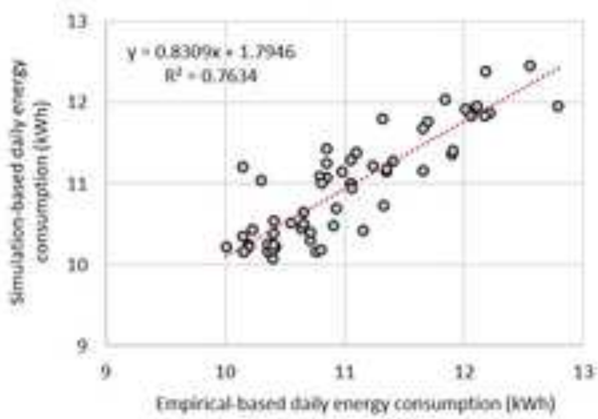
Interior Layout 4



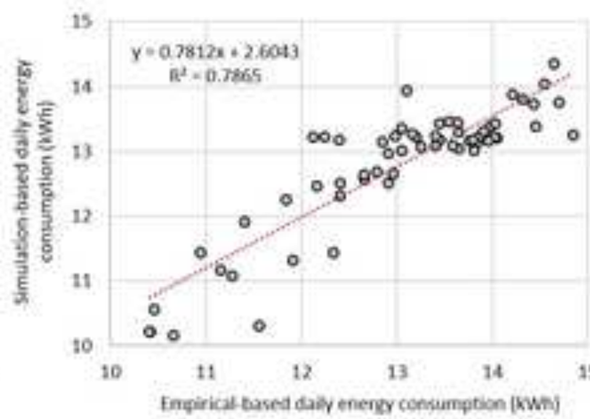
Interior Layout 5



Interior Layout 6



Interior Layout 7



Interior Layout 8