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A Systematic Literature Review of Occupant- centric modelling in building performance

Master Thesis

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Preface

I am pleased to present my master thesis named "A Systematic Literature Review of Occupant-centric modelling in building performance" which was conducted as part of the SustainSchool research project, funded by the Research Council of Finland (Grant No. 359189). The journey of writing this thesis has been an invaluable learning experience for me. Throughout the process, I have explored a wide range of literature in the field of occupant-centric building performance modeling which covers topics such as occupant comfort, indoor air quality, energy efficiency, and intelligent control systems. However, synthesizing all the selected articles and organizing these diverse state-of-the-art studies into a coherent report was both the most challenging and rewarding part of this work. I hope it will serve as a useful knowledge base for future researchers working in this domain.

I am deeply grateful to Professor Xiaoshu Lü for her insightful guidance, critical feedback, and support throughout the research process. I sincerely thank the Research Council of Finland for their financial support. I am also truly grateful to all the teachers of all the courses at the University of Vaasa for their helpful guidance during my master's journey. More than anything else, I feel that I need to say thank you to my family for their love and support which always been my greatest source of strength in every step of the way.

Vaasa, 15 May 2025

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ABSTRACT: Buildings are complex socio-technical systems, and their performance is greatly influenced by the occupants who use them. In recent years, occupant-centric building performance modelling has gained popularity to capture the impact of human behavior on energy use, thermal comfort and indoor environmental quality. In such contexts, occupants are heterogenous, and their behaviors are driven by comfort needs, routines, and peer influence which results in a significant variability in building performance. While several studies exist that reviews specific behavioral factors or technologies, there is a lack of a comprehensive, cross-disciplinary review that synthesizes the state-of-the-art in occupant-centric modelling approaches for building. This thesis fills the gap by providing a comprehensive review of the state of the art in occupant-centric modelling, with special focus on multi-agent system (MAS) and Agent-Based Modeling (ABM) representing occupant behavior. A systematic literature review was conducted, supported by bibliometric analysis of 101 peer-reviewed articles following PRISMA guidelines.

This bibliometric analysis with VOSviewer software mapped out the structure of the field dividing into five thematic clusters: (1) occupant behavior and building performance, focusing on how dynamic occupant actions influence energy use and indoor climate; (2) integration of digital technologies, integrating occupant information into smart HVAC and lighting control systems; (3) personalized building control using behavioral science, bridging engineering with psychology to tailor building operations to individual preferences; (4) multi-agent intelligent control and optimization techniques, applying multi-agent systems and reinforcement learning to jointly improve energy efficiency and occupant comfort; and (5) social influence on multi-agent decision-modeling in built environment, employing interdisciplinary approaches (e.g., cognitive, social simulations) to capture complex occupant decision processes in buildings. Each cluster is analyzed in terms of central themes, models and theories, methodologies and research gaps.

A unified cross-cluster synthesis shows that despite using the term 'agent' in Reinforcement learning framework of cluster 4, they lack some ABM features like scenario-based exploration, social dynamics and heterogeneity of agent. Conversely Cluster 5 integrated them but lacks quantitative optimization. Using ABM for scenario design and RL for control can bridge the gap. Building on the insights the thesis suggests some future research directions themed: (1) Real-time adaptive systems (2) multi-scale and cross-domain integration (3) Human-centred interdisciplinary frameworks that reflect social, cultural, and psychological diversity (4) AI-driven and hybrid modelling techniques like reinforcement learning, model predictive control (MPC) (5) Practical implementation through standardization, open-source tools.

KEYWORDS: Agent-based modelling and simulation, multi-agent systems, ABM, MAS, Building performance, Smart building

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1 Introduction

As society develops, the demand for comfortable living environment rises which causes excessive energy consumption and greenhouse gas (GHG) emissions (Ding et al., 2019). Approximately 30% of final total energy is being used from the building sector globally while it stands as a major contributor to greenhouse gas (GHG) emissions as well (Constantin et al., 2017). So, building sector is critical to achieve climate and energy policy goals, while demand for comfortable environment also needs to be met. Building modelling and simulation is a popular cost-effective means to address that problem (Yan et al., 2015). However, a major challenge in building energy modelling is the gap between predicted and actual energy use because of oversimplification or neglect of occupant behaviour and their impact in simulation models (Yan et al., 2015).

Human factor is evidently important in building simulation (Attia et al., 2013; Mahdavi & Tahmasebi, 2019). Among the six main factors influencing building energy consumption one of the major factors is occupant behavior adding uncertainty in prediction and simulation of building energy use (International Energy Agency, 2016). Traditional building performance simulations often use static schedules or averages about human behavior, which do not account for human behavior dynamics and heterogeneity (Hong et al., 2016).

In order to overcome limitations of these approaches, researchers have increasingly adopted the occupant centric modeling approach among which Agent Based Modeling (ABM) is being popular. Simulating occupants as autonomous agents that take decisions under individual rules, social influence and feedback from environment, this method allows researcher to develop a realistic model including stochastic occupant behavior and interactions or individualized comfort threshold (Berger & Mahdavi, 2020; Wilke et al., 2013).

In recent years, ABM has been successfully coupled with physics based (e.g : EnergyPlus) simulation engines such that performance in predicting energy use and occupant comfort outcomes are realized more accurately (Langevin et al., 2015). However, Some other modeling approaches are also being used in state of the art research in addition to or instead of ABM to incorporate occupants' impact in the model. Reinforcement learning for adaptive control, probabilistic models (e.g : Markov chains), social network model (includes peer influence and collective behavior) are some of them (Anderson et al., 2014; J. Chen et al., 2012).

This thesis aims to systematically review the state-of-the-art in occupant centric modeling across building types, specially educational buildings. The focus of the study is to explore the application of Agent-Based Modeling (ABM), its integration with complementary modeling approaches, and the challenges associated with its practical implementation. The aim is to analyze how different models incorporate occupant behavior, what theories and models support them and how they can contribute to optimize energy efficiency, occupant comfort, and indoor air quality. Through a bibliometric and thematic synthesis, this study identifies gaps in current research and proposes a research agenda to guide future work in occupant-centric building performance modeling.

2 Theoretical frameworks

This chapter presents the framework and covers the key theoretical components of occupant centric modeling specially agent-based modeling (ABM). An introduction to the concept of ABM, how it performs better than other modeling techniques in building environments, ABM's application in multidisciplinary field and necessary tools for implementing ABM is discussed.

2.1 Definition and Overview of ABM

Agent-Based Modeling (ABM) is a computational approach that simulates complex systems by modeling them as collections of autonomous, decision-making entities called agents. Each agent examines its environment independently and uses pre-defined rules to generate decisions through its network of interactions with both agents and the environment (Bonabeau, 2002). A visual representation of an agent-based system with agent-environment and agent-agent interaction is shown in Figure 1.

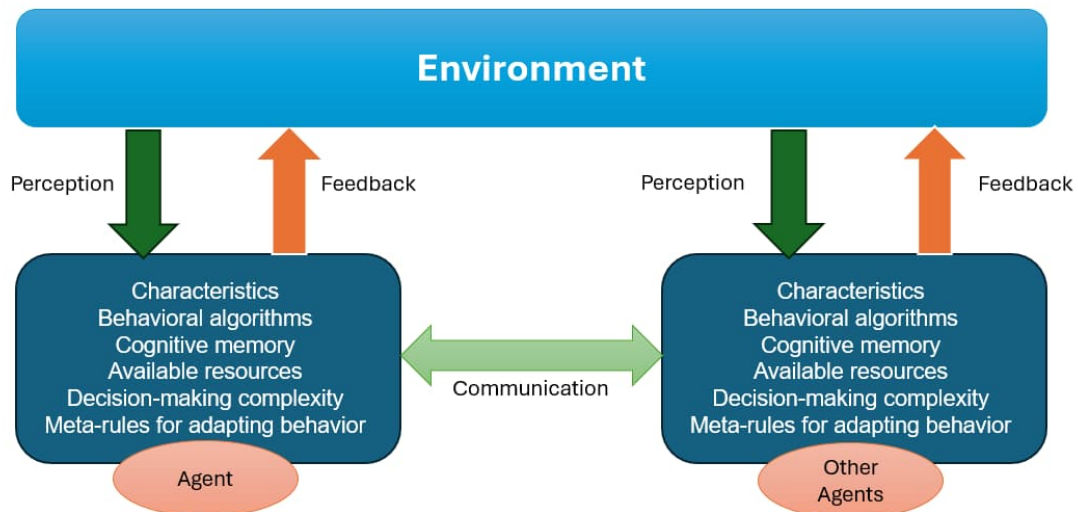


Figure 1: Agent and their interaction among themselves and with environment (Macal & North, 2008; Yao et al., 2023)

In this report agent is used in two scenarios. One for Agent-based modelling and another for reinforcement learning agent. While both ABM and RL use agents, their modeling principles differ: ABM emphasizes explicit rule-based behaviors and emergent system dynamics, whereas RL focuses on optimizing outcomes through learning. To get a clear concept of agent in agent-based modelling, characteristics of agents are described here according to Macal & North (2008).

- An agent is a clearly defined, stand-alone module whose internal attributes and rule set govern what it can perceive and how it can act; because the boundary is explicit, it is easy to tell what lies inside the agent, what lies outside, and what is shared.
- It is autonomous, without needing direct human or external supervision it can interact with another agent and environment.
- The agent can communicate and coordinate with other agents through agreed protocols, and it can recognise and differentiate the characteristics of those counterparts.
- It always operates inside a wider environment: physical or virtual and interacts with that setting as well as with other agents that inhabit it.
- Many agents pursue explicit goals (though not necessarily by maximising a utility function), enabling them to judge whether their recent actions are moving them closer to the desired outcomes.
- Agents can learn from experience, store that knowledge in memory, and, when needed, adjust or even rewrite their own behaviour rules so they perform better in the future.

However, in agent-based modelling, it is possible that one or several of these characteristics are absent in an agent.

2.2 Traditional Modeling Methods vs. ABM

Agent-Based Models (ABMs) demonstrate some fundamental differences regarding the traditional Equation-Based Models (EBMs). Heterogeneity and Individual-Level Modeling is one of the main aspects. Agent-Based Models separate the agents into unique units, the models process through unique behaviors. So, they work better than traditional Equation-Based Models which operate under population-wide homogeneity assumption (Van Dyke Parunak et al., 1998). Additionally, Agents in ABMs represent all activities through distinct events which copy the genuine behaviors found in real systems. The continuous treatment of populations by EBMs can produce unrealistic outcomes. Another advantage of ABM over EBMs is its ability to introduce randomness into the model. ABM allows decisions to be made based on probabilities whereas EBM model rely solely on deterministic decisions (Mazzetto, 2024). As a result, ABM is more suitable for modeling complex systems where behaviors are uncertain. This flexibility is essential for studying systems where complete deterministic models are not feasible due to limited knowledge of the processes (Wilensky & Rand, 2015).

Moreover, the modeling approach of agent-based models diverges from conventional top-down methods such as system dynamics (SD) or discrete-event simulation (DES), since it enables the evaluation of individual agents with diverse attributes which results in objective representation of real-life processes (Ding et al., 2019). It serves as a bottom-up modeling approach which characterizes the behaviours along with attributes and rules of single agents operating in complex adaptive systems to properly represent system dynamics (Ding et al., 2019). The concrete model design increases both model verification accessibility as well as stakeholder interaction potential (Tisue, 2004).

In conclusion, ABM has key benefits like capturing complex behaviors, providing a clear system description, and being adaptable to different scenarios. It can model how agents learn and change over time (Bonabeau, 2002).

2.3 Applications of ABM

The most useful form of Agent Based Modeling (ABM) is when modeling a system with large to medium numbers of interacting agents with heterogeneous behavior and complex interactions (Kaniyamattam, 2022). ABM does so well with individual level variations and their effect on the overall system performance when compared to aggregate models such as system dynamics. It is useful when diversity of agents has a strong impact on the outcomes, for example in financial markets or ecological systems.

Additionally, ABM is good for modeling adaptive behaviors since agents can change their action according to experience, and moreover, ABMs can be used to perform simulations of learning and cooperation (Martin & Thomas, 2016). Spatial and environmental modeling in ABM is rich, because location dependent behaviors are captured and detailed spatial outcomes are produced (Giraudoux et al., 2016). Observing temporal dynamics allows us to observe the system behaviors exhibited over time, a good property for analysis of processes, not just results (Jackson et al., 2016).

Overall, ABM (or mixtures thereof) is most useful where the agents of a system are complex and adaptive, heterogeneous, and interacting over time and space. From literature review it is observed that ABM is being used in a wide range of fields like social sciences (Epstein, 1996; Macy & Willer, 2002), economics (Tsfatsion, 2002), supply chain management (Helo & Rouzafzoon, 2023), architecture (Martinez et al., 2022), computer science, and the health sector (Folcik & Orosz, 2006). Moreover, ABM is used to simulate population dynamics (Karandeep Singh et al., 2016) and processes in archeology (Wurzer et al., 2015). Table 1 illustrates how ABM is being used in interdisciplinary sectors.

Table 1: Multidisciplinary application of agent-based modeling

Discipline	How ABM is being applied	References
Environmental Science	Modeling ecological and agricultural systems by incorporating behavioral dynamics and human-environment interactions	(Smajgl & Barreteau, 2014)
Social Sciences	Exploration of complex social systems. For example: collective behavior, norm diffusion, and social dynamics in policy settings	(Axelrod, 2006)
Engineering & Systems	Modeling distributed control systems, multi-agent systems in smart environments, and complex building systems.	(Blashaw & Fukuda, 2022; Mazzetto, 2024)
Climate & Energy Policy	Policy making assistance by simulating energy usage, emission reduction strategies, and behavioral energy conservation in households and buildings.	(Castro et al., 2020; Paranjape et al., 2018)
Computer Science	Integration with data science and AI for large-scale simulation and visualization	(Hoffmann, 2008)
Economics & Markets	Simulates agent decisions in consumer behavior, market dynamics, and financial systems, particularly in the context of complexity economics.	(UDDIN, 2020)
Health & Epidemiology	Simulates disease spread and intervention strategies, especially under uncertainty and individual-level behavioral variation.	(Folcik & Orosz, 2006)

2.4 Agent development environments

Agent Based Modeling (ABM) is a flexible way to perform simulations on a wide variety of problems; one such problem is how people behave in buildings. ABM has so much

flexibility in terms of the wide range of software tools and frameworks that can be used for its applications. Some of the tools are as simple as user friendly environments that appeal to beginners while others are high level platforms aimed at complex, big scale simulations. In this section, the most important categories of tools for occupant-centric ABM are introduced and some of their strengths will be discussed as well as some typical applications.

2.4.1 Prototyping and Desktop Tools

Most are started with accessible platforms like NetLogo, Repast Symphony and StarLogo for use in the early stages of modeling and learning. They help the user to build relatively simple models as quickly as possible, without requiring extensive knowledge in programming needed. Netlogo was developed by Northwestern University with a simple scripting language and participatory simulations features like HubNet (Wilensky, 1999).

One another common tool is Repast Symphony, which has more advanced features available than NetLogo. It can be used for visual model design, and it can link to external software for interpreting the results. Repast is more flexible and powerful because it is built on Java and it tends to be used for more complex simulations as well (North et al., 2006). These platforms have been commonly used as a place to study how building occupants interact with their environment, e.g. how they adjust lighting, heating, or cooling systems.

2.4.2 Advanced and Scalable Platforms

If researchers want to simulate more complex systems, or larger numbers of agents, they may consort with more powerful tools like Repast, Swarm, MASON, or AnyLogic. Repast is a free open-source platform compatible with both Java and Python. It is appropriate for large scale simulations and has been applied often in social sciences and energy modeling (North et al., 2006).

Another platform is Swarm, one of the earliest ABM platforms used for object oriented programming, developed at the Santa Fe Institute (Minaer et al., 1996). In the other hand, MASON is a fast and efficient Java based simulation library for large population size. In many fields of research where a high level of performance and control over parameters of simulated objects are needed, it is frequently used.

One of the most popular commercial tool is AnyLogic can be used to mix such ABM with other technique, such as simulation or system dynamics. Though flexible, the drag-and-drop interface allows for it to be used in many buildings related simulations, and it is user friendly (Macal & North, 2008).

2.4.3 General Computational Tools

Apart from ABM software designed for their purpose, custom ABM development utilizes various computational tools, such as MATLAB, Python, and C++. Moreover, MATLAB offers the ability to use high level (i.e. scripting) through which functions are utilized for matrix manipulation and visualization via established platforms. These environments are not specifically ABM oriented although they are used often in prototyping algorithms or in simulating occupant-agent systems (often in conjunction with building performance simulation tools such as EnergyPlus).

For example, Perceptual Control Theory (PCT) or Theory of Planned Behavior (TPB) based behavioral decision algorithms have been utilized to do implementation and simulation of its impact on thermal comfort and energy consumption with MATLAB (Langevin et al., 2015). Due to Python's flexibility and the growing library ecosystem (e.g., Mesa, PyABM), Python ABMs also have emerged in custom Python implementations.

2.4.4 Integration with Building Simulation Software

ABM platforms are coupled with many building energy modeling tools like EnergyPlus, eQuest, or Radiance in many studies to model real world and quantify impacts. For

instance, the Occupancy Simulator by Chen et al. (2018) creates ageagent-basedhedules that provide the real life schedules included in EnergyPlus models to investigate this utility in different behavioral assumptions. ABM logic is also linked with spatial data using GIS and BIM platforms by other researchers to better account for the spatial and environmental interactions (Azar & Menassa, 2012; H. C. Putra et al., 2021). For example, the energy performance evaluation method based on the Virtual Retrofit Model (VRM) by Woo and Menassa (2014) includes energy simulation implicitly and agent behavior implicitly integrated with BIM data.

3 Methodology

In this study, a systematic literature review (SLR) approach is chosen to evaluate current research on agent-based modeling in buildings with regards to different building performance metrics, for instance, energy efficiency, indoor environmental quality, and occupant comfort using agent based and multi-agent frameworks. To ensure a transparent review process, PRISMA is one of the preferred guidelines for systematic reviews and meta-analysis (Page et al. 2021). So, using PRISMA protocol supported by a five-step methodological framework based on Figure 2 the research has been conducted.

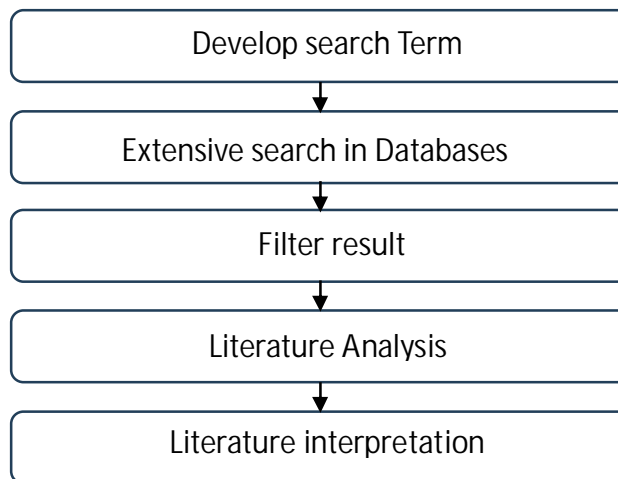


Figure 2: Flow chart of the literature review

After developing a final bibliometric data file following PRISMA flow chart in Figure 3, a bibliometric coupling in VOSviewer was conducted to identify thematic structures in the field, that allowed us to classify the research into five different clusters. Following, each cluster was subjected to analysis to identify central themes, theoretical underpinnings and methodological practices. In addition, the article metadata was used to analyze temporal trends and journal distribution, which resulted in an evidence-based maturity assessment of research as well as an evaluation of the domain focus.

This is followed by the mapping of the field's theme landscape, the positioning of the gaps in the research field, the formulation of a target research agenda as well as the

presentation of a cross-cluster synthesis to highlight the broader trends and future directions of research that will optimally benefit from occupant-centric ABM research.

3.1 Developing Search String

Initially a preliminary review of the existing literature on agent-based modeling was made to develop a search term which can narrow down the search results to cover all relevant papers from specific research areas.

Boolean expression used: A AND B AND C

Where A, B, C are search term categories shown in Table 2. The Boolean expression was applied to Scopus for its comprehensiveness and multi-disciplinary database. A search string combined with the TITLE-ABS-KEY was conducted, where records that match the search query in title, abstract, and keywords were returned. The preliminary search returned to 742 records. Then the next stage is literature screening.

Table 2: Search term keywords

Modeling approach (A)	Application domain (B)	Performance focus (C)
"agent-based model*" OR "multi-agent system" OR "ABM" OR "MAS"	"school" OR "building" OR "campus" OR "dormitories" OR "indoor environment" OR "university" OR "classroom"	"energy efficiency" OR "occupant comfort" OR "occupant behavior" OR "HVAC" OR "sustainability" OR "indoor air quality" OR "building management" OR "occupancy"

3.2 Literature screening

This step followed PRISMA guidelines which is considered as one of the most preferred review protocols for systematic literature review and meta-analysis (PRISMA-P Group et al., 2015). The flow chart of the process is shown in Figure 3. In Figure 3 the process starts with the literature search; Scopus was the main database which led to 742 record. At this stage, no records were found to be duplicate.

To conduct further assessments, non-journal records such as conference papers, book chapters, proceedings and letters were excluded in the initial screening phase (n = 378, yielding 364 remaining articles). The second screening excluded fifty-eight articles written in languages other than English or articles that are not in the core domains of engineering, energy, computing and environment, such as social sciences and mathematics.

It then went on to assess 303 articles as being eligible for this review. Excluded papers were for several reasons at this stage. Firstly, exclude articles with less than four citations where 72 articles were excluded. Then, a curated list of high impact journals such as Building and Environment, Applied Energy, and Energy and Buildings were used for maintaining quality of the research articles selected. As exclusion criteria is for papers from journals that are not commonly referenced in the field of occupant centric building modeling and energy systems. A total of 93 articles were excluded in this system. Moreover, a set of high impact papers were included due to the potential to create a repository of models for the suite of benchmark buildings. The remaining exclusion criteria are Insufficient methodological detail or empirical grounding (n = 18), and 19 papers were manually excluded since they lack the specifications of our research scope, for example directly not working with agent based or occupant centric modeling for building environments. Finally, 101 studies remained after applying all inclusion and exclusion criteria, which were qualified for qualitative synthesis and thematic analysis.

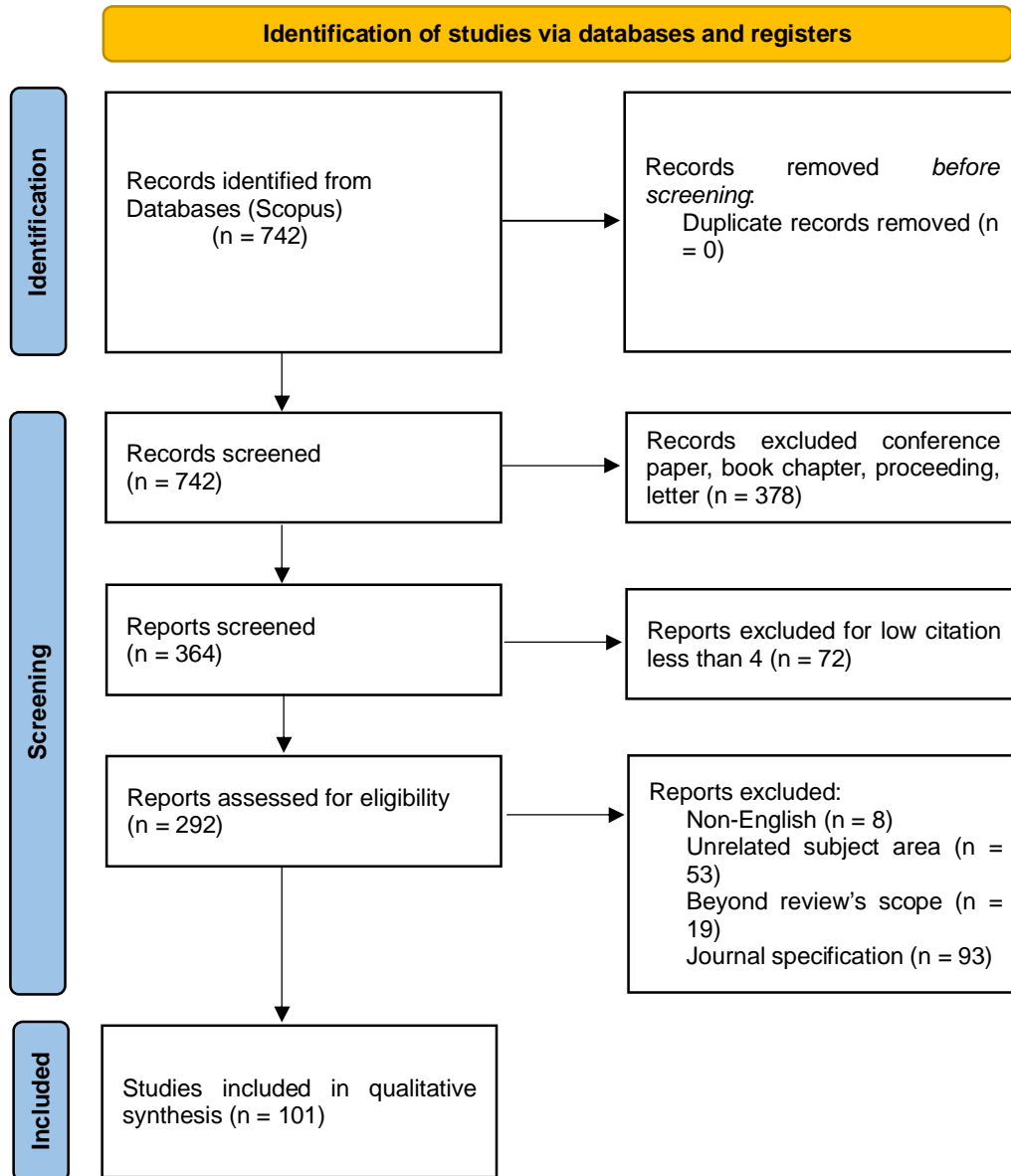


Figure 3: PRISMA flow chart for literature identification, screening and inclusion

4 Article source and Temporal distribution

The source and temporal distributions of the chosen articles are reported in this chapter 4. The primary journals that might be regarded as publication opportunities for further research were identified by the sources. The evolution of this research issue was illustrated by the time distribution.

4.1 Article Temporal Distribution

Figure 4 shows the distribution of publications across the timeline of 2012 to 2023. Over the past decade, the trend of research regarding occupant centered agent-based modeling in buildings has picked up in its interest. The volume of research increased starting from a modest number of publications in 2012 and gradually enlarged, until a sharp uptick after 2020. It has been observed that the maximum in the number of relevant articles occurred in 2022, implying increasing interest in integrating occupant behavior in building performance modeling.

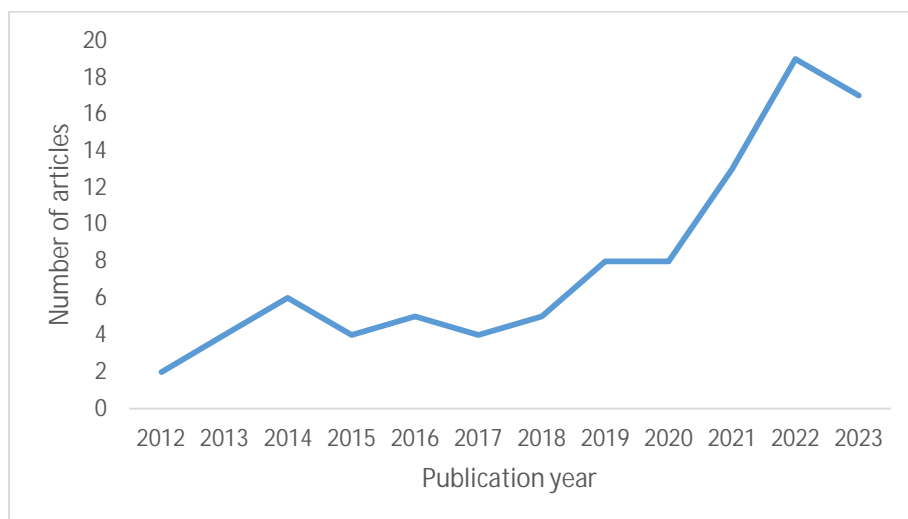


Figure 4: Temporal distribution of selected articles

An exception is having a drop in number of publications in 2023, and 2024. This can be attributed to our exclusion of low-cited papers to maintain the quality of this literature review. Thus, the data of 2024 is not included in the visualization to overcome this

misinterpretation possibility. Overall, the upward trend represents the growing implication of the field in recognizing the necessity of the behaviorally informed modeling framework seeking occupant concerns in building research.

4.2 Article Source Distribution

The selected 101 studies were selected from 16 journals shown in Table 3. Some of the major journals are Applied Energy, Building and Environment, Buildings, Sustainable cities, Automation in construction, Journal of Building Engineering.

Table 3: Source distribution of the selected articles

Journal Name	2012	13	14	15	16	17	18	19	20	21	22	23	24	Total
Applied Energy					1	2			1	1	5	4	2	16
Automation in Construction				2				1		2	2			7
Building and Environment				1				1	2	1	3	1	2	11
Building Simulation						1	1			1		2		5
Buildings										1				1
Energies							1		1	3				5
Energy								1	1		1			3
Energy and Buildings	1	3	3	1	4			2		1	2	3	1	21
IEEE Access								2						2
JASSS									1					1
Journal of Building Engineering										1	1	3	2	7
Journal of Computing in Civil Engineering	1		2											3
Renewable and Sustainable Energy Reviews										1	2			3
Renewable Energy			1											1
Sustainability (Switzerland)						1	3		2	1	2			9
Sustainable Cities and Society		1						1			1	4	1	8

5 Mapping the Structure of the Field & Thematic Distribution

A bibliometric coupling network map was generated using VOSviewer which is shown in Figure 5. The finalized Scopus database of 101 articles was the basis of creating this map using bibliographic coupling strength. Each node refers to an article and the connecting link indicates the degree of reference sharing between two documents. The larger the nodes the higher their citation is and the closer the nodes are the more shared bibliographies exist among them. This algorithm identified five distinct clusters of different themes. We get five different but interrelated research streams with occupant-centric modeling for buildings from this analysis. Red clusters centered around Human-centric behavioral modeling for building simulation whereas the yellow cluster articles, in general, worked on the integration of digital technologies for occupant-aware energy systems which are the most spread clusters here due to the widespread use of digital technologies across all clusters. The blue cluster on the other hand is a bit specific focused on multi-agent intelligent control utilizing AI which has been booming in recent days. The green cluster contains articles focusing on personalized building performance utilizing behavioral science and finally the purple one is the smallest one more correlated to the red cluster describes articles that work on occupant behavior but more into social influence on multi-agent decision modeling.

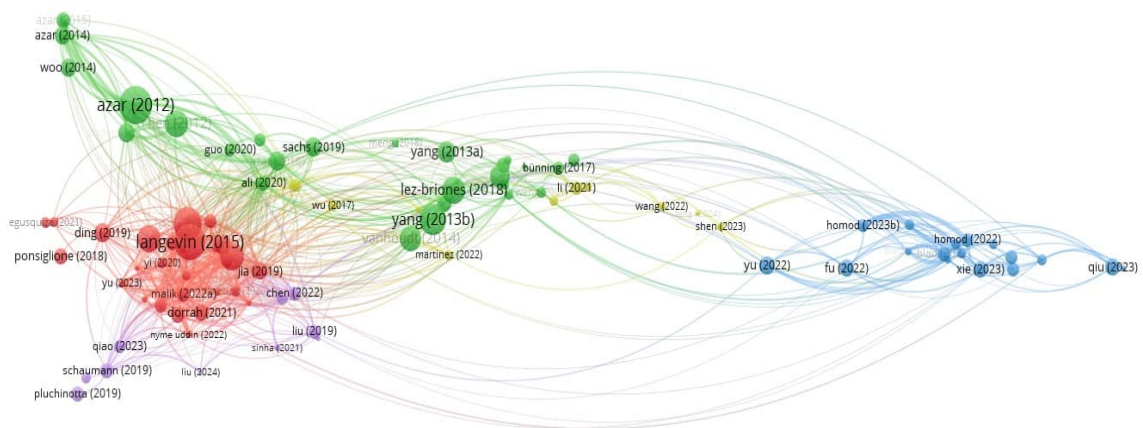


Figure 5: Identification of the clusters

Figure 6 displays the cumulative number of publications each year in each cluster. The trend illustrates that the interest increased in all clusters with a notable acceleration in

publication volume after 2020. However, publication in 2024 is slightly reduced because we excluded articles with low citations for maintaining quality of our review and since articles from 2024 did not get enough time to exceed our citation threshold, the number decreased slightly in our selected database. This does not indicate a true decline. A thematic analysis of all the clusters is presented in the rest of the chapter.

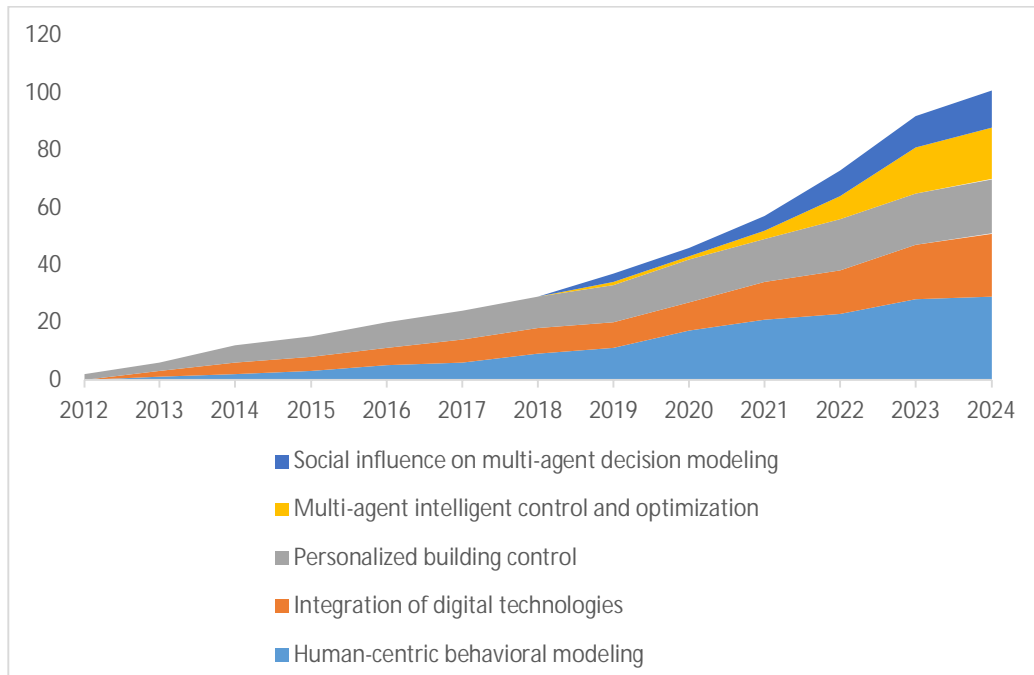


Figure 6: Cluster-wise temporal distribution

5.1 Human-centric behavioral modeling for building performance

5.1.1 Central themes

This cluster focuses on the impact of occupants' behaviours on building performance, especially energy consumption and indoor air quality. The 23 studies included in this cluster highlights that not considering occupant behaviour in building modelling and simulations results in a difference between simulated and actual real life energy consumption (Y. Chen et al., 2018; Norouziasl et al., 2020).

Studies in this cluster have explored methods of quantifying the impact of occupant's interactions. Norouziasl et al. (2020) mentioned occupant behavior as "one of the most influential parameters" affecting the consumption of energy, and overly dependent on static schedules can result in large prediction errors. They found that, in real life scenarios, using occupancy sensors to adjust lighting resulted in 24-33% energy savings in an office whereas static assumptions could not show that savings. Chen et al. (2018) strengthened that concept by recommending seeing buildings as dynamic systems where occupant interactions shape the energy usage and comfort outcomes. Ding et al. (2019) demonstrated that fact in dormitories where they found that occupancy level was the most critical factor for energy use even more than the building systems themselves. Behavior changes of occupant to mindful usage of appliances, such as reducing air-conditioner usage, led to the most significant energy usage reductions (Ding et al., 2019). Wate et al. (2020) showed that variations due to occupant interactions caused an 8-22 kWh/ m² difference in cooling loads which is far greater than the 3 kWh/ m² variation caused by the building envelope parameters. These articles concluded that small behaviour changes like mindful equipment use, modify daily schedules, thermostat settings can lead to substantial shifts in energy consumption at both room and building scales.

Consequently, many studies have explored how energy use remains the same where occupants adjust their environment actively for their comfort. Langevin et al. (2016) developed an occupant behavior toolkit named HABIT that can simulate thermal adaptive behaviors using EnergyPlus model. They demonstrated that engaging occupants in adaptive actions can improve comfort as well as saving energy by testing the scenarios such as personal fans or heaters combined with adjusted thermostat setpoints. According to Mosteiro-Romero et al. (2024), presenting diverse thermal settings and user-operated control elements elevated occupant comfort percentages up to 10% while energy consumption stayed stable. The implementation of thermostat readjustments alongside occupant-driven ventilation systems leads to cooling energy reduction of between 6-15% (Mosteiro-Romero et al., 2024). Thus, it can be concluded

from these studies that when occupants have options like control over fans, and heating/cooling settings, their choices improve both comfort and efficiency.

While Langevin et al. (2015, 2016) focused specially on offices, this cluster spans various building types and scales relevant to occupant behavior. The cluster includes open plan offices, shared spaces (Langevin et al., 2016), student dormitories (Ding et al., 2019), low-income housing (M. N. Uddin et al., 2023), commercial buildings (Jia et al., 2019), and even district level analyses (Mosteiro-Romero et al., 2024; Yao et al., 2023). Among all the sectors, one theme is common, which is occupants' characteristics and daily behavior significantly influences energy use patterns. This effect compounds at community or district level. Yu et al. (2023) mentioned that variability in occupant behavior is the primary source of error for predicted performance not being similar with actual performance, with the gaps widening at larger scales. For example, energy demand can be shifted from office buildings to homes by introducing flexible work arrangements like remote work. So, coordination of energy planning with behavioral patterns is important (Mosteiro-Romero et al., 2024; Z. Yu et al., 2023).

In conclusion, the research in cluster 1 highlights that occupant behavior is critical, dynamic factor in building energy performance and indoor climate. So, it is important to understand, model, and influence occupant behavior to optimize efficiency and comfort. Because buildings and their occupants form an interactive system where occupant behavior patterns such as schedules, adaptive actions, energy-use habits are crucial to address the energy performance gap and achieving both efficiency and comfort.

5.1.2 Models and Theories

This cluster employs Agen-Based Modeling (ABM) to model occupant behavior in a building. This method is an effective approach for capturing the stochastic and heterogeneous characteristics of human behavior (Mosteiro-Romero et al., 2024). In the research of Norouziasl et al. (2020), they established an ABM occupational simulation system for office spaces that simulated dynamic states for each occupant including their location and interaction parameters and movement. Stochastic scheduling became

possible instead of using historical data through this approach. ABM served as the basis for Chen et al. (2018) to construct an occupancy simulation for their research. They modeled occupants and space as agents and the behaviors of agents follows a probabilistic rules. ABM is applied in Langevin et al. (2015, 2016) to evaluate comfort-driven actions and their impact on HVAC performance. It illustrates the impact of actions such as opening windows, adjusting heaters on the indoor environment and energy consumption.

5.1.2.1 Stochastic and probabilistic models

An advantage of working with ABM is its ability to be integrated with stochastic and probabilistic models. In this cluster, there are many studies that use Markov chains for simulating the unknown occupant behavior. For example, Chen et al. (2018) used a homogeneous Markov chain for this purpose to model the probability of occupants moving between spaces, including the observed occupancy patterns in a probabilistic way. Moreover, the arrival and departure times are represented by stochastic models and the event completion times are taken from empirical probability distributions (Y. Chen et al., 2018). There is also variability in daily behavior which is introduced using Monte Carlo simulations. Jia et al. (2019) combined stochastic models to simulate occupant interactions with window, blinds and door interactions with EnergyPlus to assess energy impacts. (Langevin et al., 2016). While traditional occupant models were using Markov chains or logistic regression, aggregated stochastic methods, ABM offers granular simulation at the individual level (Schweiker & Wagner, 2016).

5.1.2.2 Behavioral Decision Theories

In this cluster of studies, there are several studies which model occupant actions using behavioral decision theories. For example, Langevin et al. (2015) applied Perceptual Control Theory (PCT) to the simulation of occupants' way of maintaining thermal comfort through adaptive actions. These agents monitor their perceived thermal state and act instantly to correct themselves by, for example, using a fan or changing clothing, in order

to remain within a comfort range (Langevin et al., 2015). Much related to PCT, the adaptive comfort model assumes that occupants do adapt their behavior with respect to the comfort temperature range with seasonal variations. For that adaptive comfort Langevin (2015) refers that the behavioral target is "seasonally acceptable sensations". In more recent studies, psychological theories have been introduced in addition to PCT. Theory of planned behavior (TPB) is one of such theories which has been implemented by Uddin et al. (2023) in their occupant comfort ABM study. They selected attitudes, subjective norms and perceived control as key drivers of behavioral intentions. This study extends beyond physical stimuli, including social and psychological factors influencing occupant behavior. Another such psychological model is Theory of Reasoned Action (TRA) which also was employed by M. Uddin et al. (2022) for modeling occupant decision-making in a hybrid agent based system dynamics model. They also captured the impact of social influences on the occupant behavior for energy saving (M. Uddin et al., 2022). These theoretical implementations studies highlight a growing trend to focus not only how occupants react but also the reasoning behind their behavior to occupy in energy-efficient or comfort-driven actions.

5.1.2.3 Feedback and adaptive control models

This is another theoretical model involved in this cluster. When occupants respond to any environmental conditions it is called feedback, and their actions impact the building environment which creates continuous interaction. For enabling co-simulation of occupant behavior and HVAC systems, Langevin et al. (2016) implemented the Building Controls Virtual Test Bed (BCVTB). Both occupant behavior and HVAC systems were enabled to influence each other dynamically in that study. This approach derives from the control theory where occupant actions are real time inputs to the building systems let alone a predetermined schedule. Putra et al. (2017) also applied feedback mechanism in demand-response simulations, where occupants responded to load-shedding events by taking adaptive measures. They incorporated a psychological concept "locus of control" which distinguishes between two types of building systems control; one with building systems regulation and another where occupants take direct control over their

surroundings. Results show that occupant-building interactions are dynamic, it requires feedback-driven approaches to accurately model the impact of occupant behaviors.

5.1.2.4 Complex Adaptive Systems

Some studies explicitly stated that the building-occupant system is a complex adaptive system (CAS), meaning that interactions of many individual agents and environment can lead to emergent patterns and the system can adapt over time. Ding et al. (2019) describes student dormitories as complex systems because student behaviors interact non-linearly with building operations that influence energy use at multiple scales. Egusquiza et al. (2021) applied a CAS perspective to urban districts. They treated the environments as multi-agent discussion arenas where adaptive solutions evolve over time (Egusquiza et al., 2021). These perspectives highlight the necessity of modeling occupant-building systems as evolving networks rather than static environments.

5.1.2.5 Hierarchical and Modular Modeling Approaches

Managing complexity is one of the key challenges to model building occupant interaction. To manage this complexity, some models introduce hierarchical and modular structures. Chen et al. (2018) introduced a hierarchical data model for occupancy. They divided occupant into categories such as staff, visitors, each with characteristic activity patterns, to simplify input data requirements. Dorrah and Marzouk (2021) incorporates a modular ABM approach which integrates queuing theory to simulate movement patterns of occupant in a building spaces. They consider occupants as customers in a service queue that helps to predict congestion and movement efficiency within different building layouts. This interdisciplinary integration of ABM and queuing theory enables detailed assessments of arrangements in terms comfort, energy efficiency, and operational performance.

Overall, cluster 1 combines different approaches to model occupant behavior and their interaction in buildings. ABM provides simulation at individual level, while stochastic

models like markov chains and monte carlo simulation introduce randomness in the system. Behavioral theories like PCT, TPB, TRA add psychological and social factors and feedback control and CAS perspective emphasize adaptability. By integrating these methods, the studies in this cluster create realistic, behaviorally informed models capturing both short-term decisions and long-term adaptations in building performance analysis.

5.1.3 Methodological approaches

5.1.3.1 Computational Simulation and Tool Development

Developing simulation tools and computational frameworks to model is the focused methodology of this cluster. Several studies built customized simulation models, based on agent-based modeling (ABM) and conducted simulation. Chen et al. (2018) is one of them who developed an occupancy simulator, a web application which can generate detailed sub hourly occupant schedules for different spaces in a building. They validated it by simulating a year of occupancy in a small office building. Similarly, Norouziasl et al. (2020) developed a simulation tool that can predict real-time occupancy in offices. They used stochastic occupancy schedules to evaluate lighting strategies.

Monte Carlo simulation method is used for most of the simulations to account for variability. It can generate outputs such as energy consumption patterns or comfort metrics. While NetLogo and AnyLogic are common platforms, custom coding is also being used in many papers. Putra et al. (2017) used a combination of NetLogo and EnergyPlus to simulate demand-response scenarios in office buildings. Yu et al. (2023) used AnyLogic for a multi-agent occupant model in a district heating scenario. To evaluate the impact on energy use, some studies analyzed occupant behavior in different scenarios, like normal vs. energy saving behavior (Ding et al., 2019; Langevin et al., 2015).

Co-simulation is a key methodology within this cluster. It is also important that occupant behavior models interact with building performance simulation (BPS) tools in real-time.

Langevin et al. (2016) used Building Controls Virtual Test Bed (BCVTB) to run their ABM (HABIT) alongside an EnergyPlus model of a medium-sized office building. ABM is linked with an EnergyPlus model to co-simulate with real time interactions between occupants and building systems in the study of Jia et al. (2021). This ensures that occupant actions like opening windows or changing thermostats are dynamically mirrored in the simulation. Although the concept of co-simulation is technically complex, it enables a more contextual apprehension of the effect of occupant behavior on building performance, i.e., variations of the thermostat setpoint impacting energy efficiency (Langevin et al., 2016).

5.1.3.2 Field Experiments and Empirical Data Collection

Many studies integrate empirical data beyond simulations. They used data as input for models or to validate simulation results. Schweiker and Wagner (2016) worked in a field study of 36 agents who worked in a controlled office environment for three days under different conditions (alone vs. Sharedspaces). They collected data on occupants' comfort (neutral temperature, perceived control) and behaviors (adjustments made) in these scenarios. The experiment provided insights into how "negotiated behaviors" occur when multiple people share a space, which can inform ABM rules for multi-occupant settings. Langevin et al. (2015) relied on a long-term field monitoring. They took a year-long dataset of occupant interactions (heater use, fan use, window opening) and comfort surveys in a real office building to develop and validate their ABM by comparing predictions against observed behaviors (Langevin et al., 2015). Result shows that ABM could more accurately predict individual and aggregate behaviors compared to traditional static models (Langevin et al., 2015).

Other studies rely on sensor data to capture real occupant behavior. Jia et al. (2019) installed embedded sensors in an office testbed to record environmental conditions, and conducted occupant surveys/logs to capture real behavior (window/door adjustments). Then they simulated their ABM under the same conditions and compared between simulated and actual behaviors for validation. Uddin et al. (2022) implemented custom

IoT sensors to collect energy use data in an office with different interior layouts for validation of their hybrid ABM-system dynamics-BIM model with the real data. Their result shows a good statistical validation metrics result.

Another data source is Wi-Fi tracking data which is used by Mosteiro-Romero et al. (2024). They collected campus Wi-Fi connection logs to infer where and when people were present in different buildings, providing realistic occupant movement patterns as input to their district-scale ABM. For developing an occupant comfort profile, they used non-intrusive comfort sensing such as wearable to get real time thermal preference votes from occupants.

5.1.3.3 Hybrid Modeling and Integration with Other Techniques

Several methodologies blend occupant behavior modeling with other analytical techniques. Dorrah and Marzouk (2021) integrate Discrete Event Simulation (DES) with ABM. DES handles processes like people moving through corridors or waiting in queues, which is useful for high-traffic spaces, while ABM handles individual variability and decision-making. They then feed the results into a multi-objective optimization solver. Specifically, they formulate the space layout optimization as a linear assignment problem and use the simulated occupant-based performance metrics (energy use, flow efficiency, satisfaction) to find an optimal layout solution (Dorrah & Marzouk, 2021). This combination of simulation and optimization is a methodological advance that allows design exploration with occupant behavior in the loop. It provides a decision-support tool for architects/planners to evaluate layouts not just by geometry but by how well they perform once occupied (Dorrah & Marzouk, 2021). Another hybrid approach is combining System Dynamics (SD) with ABM. Uddin et al. (2022) built an integrated framework using ABM for individual occupant interactions and system dynamics (stock-flow models) for aggregate building dynamics (like thermal or air flow processes), all implemented within a BIM environment. The ABM simulated whether occupants in certain layouts would engage in energy-saving behaviors and the SD model captured how those behaviors impact energy flows over time. By validating in a BIM-based simulation

and real data, this methodology shows the feasibility of linking micro-scale occupant actions to macro-scale building performance in a unified model.

5.1.3.4 Validation and Sensitivity Analysis

Validation remains a major challenge in occupant behavior modeling, but several studies put effort into it. Langevin et al. (2015) compared their ABM outputs to real usage frequencies of fans, heaters, and windows in the field study, and also checked that the ABM reproduces known regression relationships (like higher window opening when warmer). Jia et al. (2019) conducted a comparative validation ; they note that few prior ABM studies have rigorous validation, so they explicitly test their model's predictive ability against real occupant actions recorded by surveys and sensors. Many studies also analyze model sensitivity and uncertainty. Wate et al. (2020) introduced a Gaussian Process emulator methodology to perform efficient uncertainty quantification on a stochastic ABM+BPS co-simulation. They ran many simulations varying parameters (insulation values, occupant behavior parameters, etc.), used a machine learning surrogate to emulate the simulator, and then decomposed the output variance to see which uncertainties dominate (Wate et al., 2020). This methodological framework allowed them to state, for instance, that cooling load uncertainty is dominated by occupant behavior variability, whereas heating load uncertainty is dominated by envelope properties (Wate et al., 2020).

5.1.3.5 Human-Centered Methods (Living Labs & Co-Creation)

A few studies are more participatory and bring the real occupant into the process of creating energy saving strategies. As in the historic buildings, Egusquiza et al. (2021) treated the retrofit process as a social experiment and have implemented the living labs. Local authorities, residents and experts in sustainable developing worked together in a multiagent "discussion arena" to co create and test sustainable solutions (Egusquiza et al., 2021). Instead of just modeling behavior, they actively involved occupants in decision-making. They ensured that interventions were not only technically but also

socially acceptable based on monitoring energy and hygrothermal performance before and after (Egusquiza et al., 2021). While this is qualitatively different from ABM, it underscores a methodological commitment to real-world validation and human-centered experimentation to complement computational modeling.

5.2 Integration of digital technologies for occupant-aware energy systems

This cluster consists of 22 research articles, centers on intelligent building energy management focusing occupant behavior and multi-agent systems (MAS). Central themes, models and theories and methodologies of the cluster is being discussed in this chapter.

5.2.1 Central themes

As noted in studies, how people interact with their environment (adjusting thermostats, opening windows, lights) influences HVAC operation as much as energy use (Heydarian et al., 2020; Yang & Wang, 2013), This cluster includes some papers that model occupancy patterns, comfort preference functions as themselves, to achieve energy efficacy while still maintaining comfort (Woo & Menassa, 2014).

5.2.1.1 Multi-agent systems for energy optimization

Multi agent system (MAS) frameworks are applied towards optimizing building energy use which is a dominate theme in this cluster. Distributed control using MAS allows autonomous agents (e.g. equipment, zones, and even occupants) to interact and coordinate to control the energy supply and demand (González-Briones et al., 2018). The capabilities for communication, coordination and cooperation among agents, in fact, made MAS to be adopted widely in energy optimization problems (González-Briones et al., 2018).

5.2.1.2 HVAC control and demand response

Almost all cluster papers consider solutions to heating, ventilation and air conditioning (HVAC) systems and their control strategies. Energy use is reduced by intelligent control schemes (typically MAS based) or by responding to demand or renewable supply. In fact, one example of MAS was developed for controlling a residential heat pump, slashing peak power demand and maximizing on site renewable energy use (Vanhoudt et al., 2014). Other papers investigate comfort driven HVAC control where the HVAC setpoints are a function of a person's comfort models, attempting to provide comfort without wastefully high energy usage (Jung & Jazizadeh, 2020). In addition, MAS frameworks are examined under which demand response strategies are implemented to adjust the loads of buildings according to the grid conditions (Vanhoudt et al., 2014).

5.2.1.3 Integration of renewable energy and smart grids

Several works integrate renewable energy sources (solar PV, wind) and energy storage into building management. They investigate how intelligent control (often via agents) can better match energy demand with renewable supply. For instance, market-based multi-agent controls were used for coordinating a heat pump with a home's PV generation (Vanhoudt et al., 2014). The cluster also touches on smart grid interactions, where buildings act as intelligent nodes that can import/export or shed loads in coordination with the grid.

5.2.1.4 IoT and building automation

An emerging theme is the use of Internet of Things (IoT) devices and advanced building automation systems to enable these smart controls. Some studies specifically address IoT-enabled sensors and controllers in buildings, proposing distributed control architectures suitable for wireless sensor networks (Li et al., 2021a; Li & Wang, 2022a). In their article Li & Wang (2022) introduced a fully distributed HVAC control where IoT

network has been used to develop communication among agents without any central coordinator (Li & Wang, 2022a).

5.2.1.5 Artificial intelligence and predictive approaches

Rulebased and optimization strategies and AI techniques are included along with artificial intelligence and predictive approaches. More recent works tends to be exploring reinforcement learning (RL), for example in this cluster, a deep reinforcement learning based control for multiagent electric heating with renewables was used (Shen et al., 2023). A separate study used a neural network (Adaptive Resonance Theory Map) to the simulation of a MAS to automatically adjust building thermal comfort (Mokhtar et al., 2014). It shows a certain trend that is moving to data driven or learning based methods to address the complexity and uncertainties in occupant behavior and renewable energy.

Overall, the central themes of cluster 2 are to create smart, energy efficient buildings that account for human factors (occupants) and use the deployment of some form of distributed intelligence (agents). Keywords for this cluster, according to the VOSviewer keywords for this cluster, high light terms like 'occupant behavior,' 'multi-agent system,' 'HVAC control' and 'energy optimization' also confirm these focal topics. Taken together, the papers represent the idea that future buildings, usually referred to as intelligent buildings or smart buildings, can suitably do so by dynamically adjusting to occupant needs, and grid conditions through distributed, cooperative, automated agents (González-Briones et al., 2018; Yang & Wang, 2013).

5.2.2 Theoretical Models and Frameworks Applied

The studies in this cluster developed a theoretical frameworks and models to design and analyze intelligent building systems.

5.2.2.1 Multi-Agent System (MAS) Frameworks

This cluster has nearly all studies founded on the foundation of the Multi-Agent System (MAS). It is used for market-based MAS control, where agents use an economic bidding to distribute energy resources or to establish dynamic loads (Vanhoudt et al., 2014). Coordination algorithms, such as consensus algorithms are used to achieve a global optimum in the solution to energy management (Li & Wang, 2022b).

A theoretical point of view clearly connects MAS to concepts associated with distributed artificial intelligence and game theory in the sense that the agents play in a common environment and try to cooperate to satisfy energy demands in order to minimize costs. The MAS models are compared to the traditional control theory and in some cases, the integration of both of them was proffered to improve flexibility and decision making in the complex building energy systems (González-Briones et al., 2018)

5.2.2.2 Occupant behavior models

Within this cluster several studies employ behavioural science frameworks to combine realistic human patterns of behavior into energy management models. One such approach taking advantage is the stochastic occupancy modeling whereby we simulate probabilistic presence patterns within the buildings using Markov chains for example. Such models output dynamic occupancy schedules which provides variation of space usage as opposed to usage patterns from static assumptions (Heydarian et al., 2020). Furthermore, HVAC control strategies consider probabilistic thermal comfort models that are based on the fact that comfort is very personalized and adaptive. For example, one study showed that individuals modify their clothing, behavior or even adjust the thermostat setting to keep within thermal comfort (Jung & Jazizadeh, 2020)

Surveys data, experimental studies and time use patterns are also integrated into these models to increase their realism. To improve predictive accuracy, many studies parameterize occupant agents based on such empirical data including the occupant

preferences, comfort votes, and adaptive behaviors. Better simulations of actual human occupant and building system behavior are achieved because this interdisciplinary approach reconciles human behavioral models with engineering models. These studies incorporate occupant behavior modeling that is important for the development of smarter, more human centered building management.

5.2.2.3 Control theory and optimization models

Several control theoretical models for HVAC optimization and energy management are used for cluster studies. Baseline control such as Rule based Control (RBC) and Model Predictive Control (MPC) are generally used. Studies used mathematical optimization of thermal dynamics in MPC and heuristic if-then rules in RBC (Shen et al., 2023). Nevertheless, limitations on adaptability and the modeling complexity led to the usage of multi agent systems (MAS) and consequently AI based adaptability (Shen et al., 2023).

Considerably, MAS embeds optimization models such that each agent tries to minimize local energy use and jointly optimizes with others in order to reach a global optimum of the problem (Li & Wang, 2022b). Multi-zone HVAC control without centralized oversight (Wenzhuo Li, 2022) can be done by means of distributed optimization algorithms like Incremental Cost Consensus (ICC) and average consensus.

5.2.2.4 Reinforcement learning (RL) and AI models

Reinforcement learning (RL) and AI models have been integrated into recent works to enhance control flexibility (Shen et al., 2023). Dueling Deep Q-Network (DQN) as well as Deep Deterministic Policy Gradient (DDPG) based Deep Reinforcement Learning (DRL) methods are used to train the HVAC controllers to optimal policies from simulation data (Shen et al., 2023). Furthermore, Gaussian Adaptive Resonance Theory (gART) Maps based on neural network theory improve pattern recognition and adaptive control on building thermal management (Mokhtar et al., 2014).

These AI driven approaches further provide data adaptive control strategies that are more than optimal compared to conventional RBC/MPC approaches for smart building management which are more efficient and responsive.

5.2.2.5 Building performance simulation models

Typically, a great number of works have used building simulation tools or customized thermal models as part of their framework. To evaluate under various scenarios, agent models are combined with EnergyPlus and other building simulators (Jung & Jazizadeh, 2020).

5.2.2.6 Ontology and semantic frameworks

In the study of Mousavi & Vyatkin (2015), one unique approach added semantic agent capabilities onto a standard IEC 61499 function block architecture (as a model of distributed control systems). Then, each control function block in this framework turns out to be an intelligent agent endowed with an ontology (a representation of knowledge) concerning energy devices and contexts. Qualitatively, semantic agent approach enables the system to reason, e.g. to reason about device context and energy versus saving actions. This cannot be completed by traditional function blocks (Mousavi & Vyatkin, 2015). It is based on semantic web theory and knowledge representation forming a synthesis with the automation system theory. The motivation is to increase interoperability and intelligence in building automation by having a common semantic model of devices, settings and goals (Mousavi & Vyatkin, 2015).

5.2.3 Methodologies Employed

The research methodologies in this cluster are mainly statistical and computational in nature at the scientific research level. They aim simulation-based studies, experimental validation, optimization models and bibliometric analysis.

5.2.3.1 Simulation-Based Studies

Most studies employ simulation environments for testing control strategies. According to an agent-based modeling framework in combination with EnergyPlus, Jung & Jazizadeh (2020) studied the occupant comfort and energy efficiency. A residential heat pump with PV integration was simulated with peak demand control based with MAS at (2014).

5.2.3.2 Laboratory Experiments

Simulations are validated by some experiments using different laboratory setups. In this cluster Vanhoudt et al. (2014) validated by some experiments using hardware in the loop (HIL). Sensitivity to operating conditions for a real heat pump system.

5.2.3.3 Computational Optimization and Case Studies

There are several studies in which optimization models are applied to case study buildings. As implemented by Li & Wang (2022), a former developed a distributed HVAC control algorithm and compared it with centralized and hierarchical control strategies (Li & Wang, 2022b). Evaluation was made on metrics such as energy savings, peak demand reduction and computational efficiency.

5.2.3.4 Agent-Based Modeling and Algorithm Development

There are multiple studies on designing the MAS algorithm, including event driven control mechanism and deep reinforcement learning (DRL). Event triggering for HVAC control in IoT networks has been proposed by Li et al. (2021a), where the MAS can be used to reduce the sensor energy consumption. Shen et al (2023) discussed this as a DRL-based MAS framework with agents autonomously learning optimal control policies.

5.2.3.5 Evaluation Metrics

Energy efficiency (in the form of kWh savings), occupant comfort (e.g. PMV score), renewable energy utilization, as well as computational performance are studied as evaluation metrics. Energy savings under varying comfort profiles were assessed by Jung & Jazizadeh (2020), and stability and optimality of distributed control approach were studied by Li & Wang (2022b).

This prevalent approach in this cluster is experiment driven research with research taking a computational simulation, laboratory experiment to advance intelligent building energy management. With this approach, adaptive, autonomous control strategies for future smart buildings can be achieved through the integration of MAS, reinforcement learning and optimization techniques.

5.3 Occupancy-centric and personalized building control utilizing behavioural science

5.3.1 Central themes

This cluster revolved around occupant behavior and decision making in the building energy use. All studies have a common theme of dynamic, heterogeneous human behavior opposed to traditional models that often treat occupants as static variables. For instance, Azar & Menassa(2012) showed that stochastic process models based on ABM based modelling of different occupant behaviors vary by 25% from static models. This highlights that there is an energy performance gap where the design prediction of energy use does not match real use because of occupant variability (Ali et al., 2020).

Social influence and occupant network are also a high order subtheme. Occupants are socially connected, and their energy decisions are influenced with aggregating peer dynamics. Behavioral studies have shown that energy information propagates through

social networks and spreading energy information has a significant effect on consumption behaviors (J. Chen et al., 2012). For residential energy saving, they found their ABM based on residential experiment data was able to demonstrate the impact of network attributes on success (J. Chen et al., 2012). Anderson et al. (2014) also modeled the impact of the structure of occupant networks (size of the group the occupant belongs) on the diffusion of energy conservation norms. Results shows that the topology of the occupant networks can impact the speed and effectiveness of the energy use interventions (Anderson et al., 2014).

A second recurring focus is the design and testing of behavioral intervention to reduce energy use. Studies simulate this variety of methods such as energy education, peer encouragement, and feedback systems to advance conservation. According to Azar & Menassa (2014), tailoring interventions to internal social subnetworks could maximize energy saving of up to 24 percent. But also, that long-term behavior change is a problem, as occupants tend to revert to old ways. In later work where they introduced the concept of "extreme" energy users, whose disproportionate consumption can undermine group-based interventions (Azar & Menassa, 2015).

Overall, Cluster 3 places the emphasis on an energy modeling paradigm shift from a technological to a human centric enthusiast that incorporates behavioral science into the simulation and controlled operation of building performance. Taken together, these comprise studies that essentially argue that occupants are not passive inputs to the energy equation, but active agents who actively determine the amount of energy used. The cluster adds predictability and equip the user with practical ways to operate more sustainably in the buildings, by embedding the social, psychological and behavioral variables into the energy models.

5.3.2 Models and Theories

This cluster, mainly based on agent-based modeling (ABM), but enhanced it with some theories from the psychology, sociology, behavioral economics, systems engineering,

and control theory. In the cluster all 19 papers select ABM as a basic modeling mechanism, where the building occupants are treated as autonomous agents with diverse goals, behaviors and social interactions. It allows researchers to simulate group dynamics in buildings and communities as well, as well as individual decision making.

5.3.2.1 Social influence and norm diffusion

Many studies use the social influence and norm diffusion theories. For instance, Anderson et al. (2014) use social psychology by combining it with ABM. They meld scholarly principles of social influence and norm diffusion (people's tendency to adopt behaviors because of peer pressure and cultural norms) into their agent rules. According to their model, the agents' network neighbors affect their likelihood to conserve energy through theories of normative behavior spread. It enabled them to explore how different network types (for example, fully connected networks vs. clustered networks) influence the outcomes of the intervention within a building energy model, which is a new theoretical integration in the development of building energy models.

5.3.2.2 Opinion dynamics theory

Another key theoretical framework is opinion dynamics theory especially the Relative Agreement (RA) model wherein people's energy saving attitudes evolve through social interactions. Azar and Menassa (2014) employ RA within an ABM to simulate the way occupants' energy saving attitudes change due to repeated interaction. The RA model assumes agents modify their opinions (willingness to conserve energy) based on communication if opinions are close. Using RA, Azar & Menassa's model incorporates peer pressure. For instance, the extreme 'pro conservation' or 'anti conservation' individual can influence what others' behaviors over time (Azar & Menassa, 2015).

5.3.2.3 Social network theory

Several studies are based on social network theory seeking to understand the impact of network typologies (i.e., homogeneous vs. heterogeneous, centralized vs. decentralized) on the behavioral diffusion. J. Chen et al. (2012) realized that network size, tie, and tie weight are the most influential structural parameters for propagation of energy behavior, their findings relate directly to network theory's concepts of connectivity and influence weight. This implies that energy conservation modeling is relying on theory from network science (such as Granovetter's strength of weak ties but not explicitly referred to) that is conceptually present.

5.3.2.4 Economics and decision theories

The cluster's models also include economic and decision theories in addition to social theories. Being an Integrated Assessment Model framework, Sachs et al. (2019) adopt a multi-agent modelling approach for residential energy technology adoption. In critiquing what classic economists assume about a single rational actor, they don't assume that all agents are the same, every agent can have different decision-making heuristics (Sachs et al., 2019).

Their model is saying that behavioral economics is biased: bounded rationality and heterogeneity, consumers can be aversion to the new tech or interested in comfort rather than cost optimization. They do this through the inclusion of theories of diffusion of innovation and of heterogeneous agent decision processes. What is result is a model that, unlike any purely economic model, technology uptake arises from different behaviors; adoption rate is not imposed (Sachs et al., 2019). This is theoretically important as it bridges micro-level behavior theory with macro-level energy system outcomes.

5.3.2.5 Socio technical systems

This is neither a single named theory, nor really a theory, but a way of investigating a campus as an urban systems theory and sustainability framework of buildings and humans, brought together. They admit there are tradeoffs (energy vs comfort tradeoff theory) and build their framework on validated ideas from literature (for instance, they cite the use of said comfort models as already validated in literature, i.e. support for the ASHRAE standards) (Azar et al., 2016). This theoretical innovation allows linking together these traditional different theories (energy modeling vs comfort vs mobility) in one ABM environment and showing from a socio-technical systems perspective.

5.3.2.6 Virtual Retrofit Model

The Virtual Retrofit Model (VRM) (Woo & Menassa, 2014) shows the reason within the rational decision making. Using BIM data, energy simulations, and cost models and leveraging them in an integrated platform, VRM supports the decision on informed retrofits. The work also follows the principles of system engineering by showing that better data integration leads to better energy decisions (Woo & Menassa, 2014).

5.3.3 Methodologies

In this cluster, researchers use a wide range of methodologies and focus predominately on computational simulations and to a less extent on empirical data collection and analysis. The agent-based modelling (ABM) simulations are the use of the predominant methodological approach. The common tools were used for the ABM simulation were NetLogo, or AnyLogic, or custom code to try out scenarios that would be impossible or unethical to test out in real buildings. These studies use simulation central, whenever possible, in a real data grounded models. Many papers begin with data gatherings to parameterize or validate their models.

5.3.3.1 Empirical Data collection:

Some researchers collected data on occupant behavior and preferences. J. Chen et al. (2012) conducted their research on a mixed method approach. Firstly, they relied on experimental data-based models that were collected from a residential energy use study. They later validated their model parameter through a second experiment (J. Chen et al., 2012). Like Ali et al. (2020), they further collected energy usage and occupant profile data from three office buildings in Pakistan. These clusters were used to categorize occupant users as high, medium, and low energy consumer and assign agent profiles according to more realistically set initial conditions for behavior-based modeling.

5.3.3.2 Case Studies and Monitoring:

Azar and Menassa (2012) compare the ABM framework with what they call their traditional static models using empirical data from a case study of an office building. That shows more than 25% variation in energy use predicted by ABM. This approach was extended by Azar et al. (2016) to a campus scale simulation with real building layouts, HVAC data and occupancy schedules and validated in a larger built environment.

5.3.3.3 Scenario-Based Simulation and Statistical Analysis:

Extensive scenario testing is often done in cluster 3 studies. Researchers have developed the ABM, defined multiple intervention (or behavior) scenarios (e.g., variation in social networks or occupant attitudes), run the simulations many times to isolate stochasticity, and finally analyze the outcomes. For example, according to Anderson et al. (2014), they compared peer feedback interventions to feedback with an intervening agent in different social network structures, and study how network type affects the diffusion of energy saving behavior. Like Azar and Menassa (2015), they also looked at how the proportion of 'extreme' energy users employed in an energy saving strategy affected the success of that strategy using statistical tools of ANOVA and regression analysis to assess the outcome. Many examples are presented of the rigorous use of simulation experiments based on a sound statistical evaluation.

5.3.3.4 Analytical and Validation Techniques

Indeed, many studies do analytical post processing beyond simulations. According to Chen et al. (2012), using logistic regression, they figured out what factors, including network size and the strength of the tie, affected the likelihood of adoption of energy saving behavior. To validate their behavioral ABM, Sachs et al. (2019) embedded it within the Integrated MUSE model to make sure it captures real market dynamics. Likewise, while Ali et al. (2020), have verified the accuracy of their occupant categorization through comparison with baseline simulation outputs that agreed well with empirical energy use data.

5.3.3.5 Tool Integration and Model Coupling

Many computational tools reside in the cluster. As mentioned by Azar and Menassa (2012), it is likely that they coupled their ABM to more conventional tools for energy impact (such as EnergyPlus, DOE-2, etc). Yang and Wang (2013) implemented a multi-agent control strategy using the Particle Swarm Optimization (PSO), with an implementation within a custom simulation environment. Woo and Menassa (2014) integrated Building Information Modeling (BIM) data into the energy and cost simulations and thus have developed a virtual retrofit model (VRM) a format based on systems integration, which supports retrofit decisions.

5.3.3.6 Qualitative Insights in Quantitative Models

Although most of the studies are quantitatively oriented, a few somewhat use qualitative theories to guide the agent behavior. For example, behavioral logic is articulated through the Theory of Planned Behavior (TPB) and other qualitative frameworks which express these qualitative insights (such as social norms or personal attitudes) as probabilistic rules in the ABM.

5.4 Multi-agent intelligent control and optimization techniques for energy management

5.4.1 Central themes

The focus of Cluster 4 is the development and application of multi agent intelligent control and optimization techniques in energy management in buildings as well as smart grids. The paper revolves around the usage of multi agent deep reinforcement learning (MADRL) and related AI methods to enhance energy efficiency and occupant comfort, as well as to facilitate demand side flexibility. All 18 papers in this cluster focused on this topic which explore how multiple cooperative controls can be implemented through multiple autonomous agents (HVAC subsystems, buildings, or devices), and which outperform traditional building management strategies.

MADRL controllers are developed by several studies for HVAC (Heating, Ventilation, and Air Conditioning) systems for personalizing thermal comfort and reducing energy use (Fu et al., 2022; L. Yu et al., 2022). Multi-Agent Learning also has been extended to Demand Response and Smart Grid Integration since the buildings act as agents to try to respond to Grid conditions or price signals (Xie et al., 2023; Zhang et al., 2021). And at the same time there is research into peer-to-peer energy and carbon trading between smart buildings using MARL (Qiu et al., 2023) which shows how multi agent systems can support decentralized energy markets. In one study, an anomaly detection based on multi-agent unsupervised learning approach is provided so that energy management systems can recognize and respond to abnormal consumption patterns in campus energy data (Weng et al., 2019).

The influence on the field is great across these works, as they show that such data driven, self-learning approaches are better able to deal with the complexity of modern energy systems than static or model-based methods. For example, Yu et al. (2022) demonstrate that a cooperative multi-agent RL controller can provide dynamic coordination among an HVAC system and its personal comfort devices to save up to 4% energy while

drastically improving occupant comfort with respect to rule-based control. Apparently, Homod et al. (2022) document that hybrid RL agents can save more than 30% energy and over 20% in terms of the comfort provided by conventional PID controllers in HVAC control. Each paper tackles different parts of the overarching vision of autonomous, smart buildings that choose between efficiency, economics, and comfort using intelligence. Consequently, the overarching theme for Cluster 4 is marriage of multi agent learning algorithms to building energy management towards more adaptive, decentralized and intelligent control strategies for more sustainability and performance in the built environment (Nweye et al., 2023; Xie et al., 2023).

5.4.2 Models and Theories

Reinforcement learning (RL) and multiagent systems are applied in the theoretical frameworks for all entities in Cluster 4 as well as several advanced modeling approaches. One of the common themes is converting a building energy problem (or any engineering black-box problem) to a Markov decision process (MDP) or game, in which each agent (program or building) must learn a policy for maximizing reward (e.g. energy efficiency or cost). Deep reinforcement learning models are used in many studies explicitly. For example, Yu et al. (2022) study coordinated HVAC control as a cooperative Markov game and solve it with an attention based MADRL algorithm. This architecture combines an actor–critic neural network, with an attention mechanism to serve as an agent (comfort device as an occupant) for other agents and be considered in making cooperative decisions. Like Xie et al. (2023), an actor critic MADRL was used where other agents (buildings)'s information is filtered via a sharing attention layer over which agents (buildings) can focus on relevant information from others. It roughly was being taken inspiration from the theory of centralized training and decentralized execution (CTDE). A theoretical approach to maintain scalability and cooperation (Xie et al., 2023), it is to learn with a centralized critic but independently act in CTDE.

A second and important theoretical factor is whether model free or model-based control paradigms are employed. Indeed, developing accurate physics models for buildings can

be difficult which is why several papers are developed only on a model free RL approach. In Fu et al. (2022), they point out this with a model free multi agent RL for a building cooling system that avoids such an explicit HVAC model. They show the theory that RL can circumvent the model inaccuracies by continual learning using a DQN based algorithm (with discrete action) on their agents. In contrast to the latter, some works combine domain models as part of the learning process, where for example Blad et al. (2023) use trained black box neural network models (MLP and LSTM) that represent the HVAC dynamics. This data-driven modeling is blended with RL theory, in which they pre-train RL agents on these surrogate models (offline RL) and then fine tune online. The internalization of RL's sample inefficiency, this approach is structured upon the theory of offline RL (Blad et al., 2022).

Cluster 4 introduces also some hybrid modeling innovations. Homod et al. (2022, 2023) merge fuzzy logic and deep learning into the RL framework by combining them into two papers. In Homod et al. (2022), they convert a Takagi–Sugeno fuzzy inference system (TSFIS) to having a structure of a Hybrid Deep Clustering MARL (HDCMARL), where they create a set of neural network layers. As an example, fuzzy logic acts as a means for state spaces to be handled in a more uncertain manner and at the same time, deep neural networks and RL offer the ability for learning. Their approach allows for quickly tuning parameters in this hybrid model and theoretically produces more stable and scalable learning for continuous control actions in HVAC systems making use of a Quasi-Newton method. In other words, it demonstrates an advanced theory of physical control where it is classical control (fuzzy control) embedded into a learning framework that solves RL challenges in high dimensional problems. Exemplifying this is how the theories (clustering, fuzzy systems, and MARL) can be combined to succeed at controlling nonlinear HVAC systems with many variables (Homod et al., 2022).

Qiu et al. (2023) and Nweye et al. (2023) extend multi agent theories to distributed energy resource and markets. Qiu et al. (2023) propose a building energy trading problem as a Partially Observed Markov Game (PoMG) and propose a novel MARL

algorithm termed Fed-JPC. The theoretical framework here is a centralized critic that approximates functional representation of the global state (i.e. trading interactions and carbon emissions) and trains through multiple agents (buildings) using Federated Learning (FL) without communicating raw data (Qiu et al., 2023). FL, in this sense, is grounded in distributed AI theory. We average the learning updates in FL because each building provides its own updates, but privacy and scalability result from FL. As a result, we have a MARL approach which approximates a centralized solution and has all agents maintaining local data, which is consistent with theories regarding the privacy preserving multi agent learning. On the other hand, Nweye et al. (2023) introduce transfer learning theory to the problem of occupant centric grid interactive buildings. Alternately, they propose the MERLIN framework – the learned RL policy for a particular building with a battery storage system should be able to be transferable to another building similar with respect to thermal characteristics. This theory is that if buildings have similar state action structure, a policy can generalize, and that is based on transfer and generalization theory from the machine learning. Their results confirm the notion that policy transfer can combat RL's generalizability challenge (Nweye et al., 2023).

5.4.3 Methodologies

A range of methodologies were used in this cluster to develop and test the models; quantitative and computational are predominant. A common methodological pattern is associated with designing a new control algorithm, and then evaluation of the new control algorithm via simulation or experimental case study with respect to a baseline method. Yu et al. (2022) developed an attention-based MADRL algorithm for simulating shared office scenario and validated it as well. However, for the occupancy and comfort as input data, they use real world traces, ensuring that the realism maintained, and they compare the algorithm's performance (energy use and comfort metric data) to traditional HVAC control strategies. By targeting the algorithm behavior in this simulation-driven workflow, we are able to test several different methods (e.g. different numbers of occupants, or a variety of comfort preferences) and see the exact behavior of the algorithm. Similarly, Fu et al. (2022) also simulate in detail a building cooling plant

using the combined EnergyPlus (a building energy simulator), along with real HVAC parameters. On this simulation, they run their multi agent RL controller for a long time (i.e. simulated multiple years), and evaluate learning convergence and energy savings, as well as comparing to a rule based controller, a model based optimal controller, and a single agent RL (DQN) controller.

Many studies utilized historical or synthetic datasets to train the algorithms. Blad et al. (2022) train black box models (MLP and LSTM networks) which will represent the environment for offline RL training using logged data from a building's HVAC system. They then place the RL agent on a virtual (simulated) underfloor heating system and fine tune it. In fact, this two-stage methodology (offline pre training + online simulation) is rather similar to running a dry run before full deployment. Just as Nweye et al. (2023) also use a real smart meter dataset from 17 homes to train and test their MERLIN framework. Then, they split the data into the scenarios (for the independent training vs transfer learning structural tests) of cost savings and energy efficiency improvements. They adopt a robust data driven experimental methodology that demonstrates generalizability by training on Building A, transferring to Building B scheme using real consumption data.

The papers have either an experimental or field test component, providing credibility to their methodologies. The laboratory testbed implementation presented by Zhang et al. (2021) is to consider a physical mini grid with controllable appliances (heaters, lights, etc.) and a central energy management system enables such holistic exploration. They implemented their multi agent RL based demand response algorithm on this test bed and perform experiments to see how fast such an algorithm learns and how effective it is at minimizing the peak demand. This is an important methodological step (going through a simulation to a real-world testbed), which allows us to identify concrete practical issues (communication delays, sensor noise), and show that it is feasible in a controlled environment with the real world. Additionally, they conclude that in the case of their experimental methodology their RL agent successfully learned an optimal load

control policy with around 50 training episodes on the testbed, this yielding significant peak load reduction (Zhang et al., 2021), indicating their experimental result.

The assessment relies primarily on quantitative metrics for evaluation purposes. All studies measure energy consumption or savings together with secondary metrics such as thermal comfort (PMV, temperature deviation) and cost/emissions. The research conducted by Homod et al. (2023) determines energy conservation levels and comfort ratings through direct comparisons against a standard PID control system. Xie et al. (2023) determined the net load reduction gain on the power grid reached over 6% better than other control schemes. Qiu et al. (2023) report their model significantly reduces total expenses by 5.87% relative to a peer-to-peer control strategy. The metrics derive data points from simulation snippets or experimental data logs.

Another aspect is the handling methods of multi-agent aspect. Although the distribution of agent-training exists, some research adopts central training facilities such as servers which train agents collectively (Qiu et al., 2023; Xie et al., 2023). According to Qiu et al.'s (2023) federated learning methodology; each building (agent) conducts independent training using its own information before exchanging model parameter changes with a central aggregation point. Through simulation they demonstrate the federated MARL delivers almost maximum performance without requiring data consolidation. By using this method researchers tackle simulated privacy issues. According to Weng et al. (2019), the methodology contains two parts. One is ensemble labeling where multiple anomaly detection algorithms apply consensus on unlabeled data segments to identify normal and anomalous patterns and the other is unsupervised learning where models consisting of LSTM and autoencoder analyze presumed normal patterns to detect deviations. The method gets validated through the injection of known anomalies or the system's capability to detect what has already been identified as anomalous.

Overall, The Cluster 4 methodology consists of three primary approaches including algorithm development through simulation then using realistic data or models for

comparison testing followed by limited cases of physical experiments. The methodologies extend from total computational testing of agents in simulation and result analysis through to physical laboratory testing frameworks. All investigations apply scientific hypothesis testing methodology which begins with an intelligent control outperforming current standards and tests this claim through relevant measurement approaches. The combination of experimental procedures that involve both computational simulations and physical field testing strengthens the process through which theoretical breakthroughs become practical energy management tools which make use of simulation software and neural network training infrastructure.

5.5 Social influence on multi-agent decision modeling in built environments and policy applications

5.5.1 Central themes

The research in this cluster focuses on developing representative models of human occupancy actions and decision processes regarding buildings and building design through agent-based modeling approaches. This cluster stands apart from other clusters because it adds human-centric perspective for agent-based modeling practices (ABM). The papers analyze how simulation models integrate representations of occupant activities together with occupant-building relationships along with multiple stakeholder decision processes to enhance design and forecasting and planning capabilities. Research shows that occupancy behaviors create crucial uncertainties in modeling building performance, yet agent-based modeling provides suitable methods to track human patterns and dynamic activities. Multi-agent narrative simulations help analyze how healthcare clinic architectural choices affect hospital users through simulations that address the need to understand building occupancy patterns before construction begins. The cluster stands alone with its unique approach that demonstrates how accurate building design and operational outcomes, and urban policy results require human behavior modeling from both individuals to collective stakeholder groups.

5.5.2 Models and Theories

A wide range of theoretical frameworks and models were used to model the impact of human decision in buildings. They are listed here:

5.5.2.1 Fuzzy Cognitive Maps (FCM)

Pluchinotta et al. (2019) utilizes Fuzzy Cognitive Maps (FCM) for decision-support modeling through which multiple stakeholders provide their knowledge about urban planning. Experts and citizens have their mental models formalized through this approach which later simulates complex policy scenarios while mainlining multi-agent consideration of urban development decisions (Pluchinotta et al., 2019).

5.5.2.2 Narrative-Based Multi-Agent Modeling

A narrative framework can be built by scripting “stories” for agents. Schaumann et al. (2019) developed such multi-agent narratives for virtual occupants which enables coordination of complex activities such as patients and staff movements through clinics for design evaluation. The integration of storytelling concepts within ABM creates theoretical methods to generate detailed human behavior simulations based on scenarios (Schaumann et al., 2019).

5.5.2.3 Occupant Behavior Theory & Level of Detail (LoD)

Several research studies established behavioral theories as frameworks to develop occupant models. Malik et al. (2022) presented a framework for developing behavioral models in Agent-Based Modeling dedicated to occupant behavior (Malik et al., 2022). This framework outlines conceptual levels of information refinement starting from presence and moving to movement and actions which cover the requirements for modeling occupants. The framework explores theoretical boundaries regarding which behavioral elements (habits alongside preferences as well as schedules) should be introduced into occupant agents.

5.5.3 Methodologies

Articles of Cluster 5 build a connection among computational simulations, empirical data and interdisciplinary process to study human-building interactions. Many studies develop agent-based modelling platforms which incorporate real life case scenarios. Schaumann et al. (2019), for example, simulated agents which are narrative-driven for evaluating the layouts of hospital, while Gath-Morad (2022) tested a cognitive wayfinding model in a BIM environment. Thus, platforms now-a-days extend tools like BIM, game engines, or VR for intelligent behavior modeling. The agent behavior is informed by empirical data. Field surveys, observations such as in airports (Liu et al., 2019; Sinha et al., 2021) provide a definition of movement patterns, and large datasets (e.g. data of smart thermostat (Vellei et al., 2021)) are used to calibrate the probabilities of behaviors.

ABM integrates into several studies that combine ABM with building performance simulations. Their stochastic occupant simulator is integrated to ResStock (a U.S. residential building stock energy model) using OpenStudio to perform aggregation of occupant driven loads at the bottom-up level across thousands of homes (J. Chen et al., 2022). As in, some studies adopt co-simulation approaches whereby agents provide time varying occupancy or control input to energy models (of HVAC or lighting etc.) to bridge the gap between human behavior modelling and physics-based simulation. It is critical to integrate such as when determining outcomes like energy consumption or heat gains (e.g., the agent model by Sinha et al. is included in calculations of HVAC heat loads per zone in an airport) (Sinha et al., 2021).

Validation has always been an important loop of these methodologies. Accuracy is checked by comparing the results of several studies' simulation outcomes with real world, or experimental, data. In the cognitive wayfinding study, researchers conducted a virtual reality (VR) experiment with 149 human participants two different types of buildings, then compared the paths of these 149 human participants to the ABM agents'

paths (Gath-Morad et al., 2022). The results of the model were validated across the cognitive agents' behavior that was very close to the human behavior (Gath-Morad et al., 2022). Vellei et al. (2021) calibrated the probabilistic rules of their thermostat agents using the large thermostat dataset and aligned simulated and actual occupant responses to changes in the thermostat. This empirical calibration process ensures the ABM outputs are credible.

Scenario analysis is also used in the cluster's methodologies. Researchers take different "what if" situations with which by changing input or agent rules. For instance, to determine the benefits of certain design layouts over others, Schaumann et al. (2019) show an example of comparing two proposed design layouts that are simulated; being tested to see how agents (patients, staff) behave in each one. Using FCM based multi agent tool, Pluchinotta (2019) et al built and compared various urban policy scenarios for stakeholders to see how different assumptions result in different outcomes. Qiao and Yunusa-Kaltungo (2023) tested the performance of various machine learning algorithms under vs. without use of ABM-generated occupancy data, finding the synthetic occupant data made a significant contribution. Using such experiments, the methodologies determine lead variables (agent behaviours), performance indicators (energy use, wayfinding success, etc.) and develop a sandbox to test how interventions (e.g., how will a demand response program perform with the realistic occupant thermostat adjustments).

In sum, the most methodological hallmark of Cluster 5 is that of interdisciplinary, data informed simulation. Agent based models designed by the researchers make use of empirical data on human behavior, validate the models with experiments or measurements and integrate them into building performance analyses. Along with a mix of tools such as surveys and VR experiments, they couple with energy simulation engines to have the human interloop simulation be realistic and relevant to real world building design and operation challenges.

6 Research Agenda

After all the systematic review and bibliometric analysis so far, this chapter will identify the current research gaps and outlines the future research directions based on the findings of the research. First, we will assess each theme for gaps in central themes, theories and models, and methodologies in detail, followed by a cross-cluster synthesis for better insights.

6.1 Human Centric Behavioral Modeling for building performance

6.1.1 Thematic gaps

Despite the progress made in occupant behavior analysis for building performance, articles from this cluster addresses several gaps and limitations in current research theme as well. This section will describe those briefly.

6.1.1.1 Limited generalizability

Occupant behavior studies conducted across the clusters are context-specific and their findings may not be generalizable broadly. Langevin et al. (2015) mentioned this limitation of their study by stating that their study only applicable to a mid-sized, air-conditioned U.S. office. In case of naturally ventilated buildings or different climate condition the model might not be applicable directly. Another example is the study of Schweiker & Wagner (2016) conducted in a german office which is different due to diverse social norms or HVAC systems.

6.1.1.2 Lack of broad real-world validation

Even if some papers showed validation, there is a gap in real-world large-scale validation of behavior models. Jia et al. (2019) mentioned this gap. They also mentioned that there is no well-developed standard for testing occupant behavior models. However, small

scale validation has been seen. Jia et al. (2019) validated with five single-occupant offices over four weeks while Schweiker & Wagner (2016) tested 36 subjects for 3 days. As a result, the cluster suggests promise based on simulations and theories, but the confidence in models would increase with more effort in validation.

6.1.1.3 Integration with urban and energy system planning

There is limited research that connects occupant behavior with broader energy system planning or policy making which is addressed recently by Yu et al. (2023), Mosteiro-Romero et al. (2024) and Egusquiza et al. (2021). This confers that if better occupant behavior integration is not addressed to urban energy models, strategies like district heating optimization or demand response programs will fail to achieve optimized outcomes.

6.1.1.4 Simplification of Occupant Diversity and Social Influence

Although the cluster puts a significant effort into the occupant's matter, there is a limitation in defining who the occupants are, how the diversity profiles are and their social interaction patterns. Occupant behavior is influenced by socio-demographic and psychosocial factors which resulted in different characteristics of occupant in different building settings like office, school or industries. Uddin et al. (2023) refers to this gap in their research which shows significant differences of comfort satisfaction level based on gender diversity. Similarly, ages of the occupants or social environments or peer effects can also impact the result which needs to be explored. Schweiker and Wagner (2016) touched on it by incorporating multi-occupant negotiation in a lab setting and Nyme Uddin et al. (2022) also hints at these issues with mentions of subjective norms in TRA/TPB models. However, this is yet to be widely translated into modeling frameworks.

6.1.1.5 Human-in-the-loop implementation challenges

Although research suggest occupant-centric strategies, most fail to go on and adopt in the real world. For example, Putra et al. (2017) have highlighted challenges such as miscommunication through load shedding events amongs occupants that leads to suboptimal responses due to unawareness among them.

Typically, these models assume that occupants behave rationally and knowledgeably e.g., toggling on a fan when the temperature increases, although in reality, they lack engagement, the information or motivation to do such things. If the occupants do not own workspaces within effective interfaces, with good feedback mechanisms or dashboards, they may override systems, or become dissatisfied, violating energy performance goals. In that case, there is a thematic gap in bridging occupant behavior insights with practical interventions and policies that enable the successful alignment of user actions with energy saving objectives.

6.1.2 Models and theories gaps

6.1.2.1 Model Validation, Generalizability, Overfitting and Quantifying Behavioral Uncertainty

Despite the effort to develop complex behavioral models, one of the most pressing theoretical gaps in occupant-centric modeling is that of validation of complex behavioral models. The inferring of data assumptions in many agent-based models (ABMs) is often necessary as endogenous data alone is infrequently available. A key limitation for Jia et al. (2019) is the lack of model accuracy and generalizability due to less actual data involved in the model. Their research, which was based on a small sample of five people, emphasizes how a model's capacity to capture more behavioral diversity might be hampered by insufficient data (Jia et al., 2019). Similarly, Langevin et al. (2015) acknowledged that their ABM did not include some social or psychological constraints because their field data did not accomodate such things into the decision rules (Langevin et al., 2015). It suggests a number of fundamental theoretical gaps; models might be well

scaled computationally but poor on the power of their numerical representations and lack of externally valid behavior.

Yet many occupant models do well under calibration but they do not generalize well across other contexts or populations. Wate et al. (2020) believe that regardless of methods used, there is no dialogue that occupant behavior can be modeled with perfect fidelity and instead propose methods that describe the behavioral variability within such plausible bounds (Wate et al., 2020). Yet most existing ABMs are not quantitative about uncertainty at all. They do not even have their error bounds or confidence intervals. This omission is an issue of overfitting since it allows models to pick up on properties of particular datasets, rather than behavioral tendencies.

6.1.2.2 Scalability vs. Complexity Trade-Off

The theoretical concern is also caused when occupant models become more granular and more different behaviorally. However, these models, while becoming more complex (incorporating all kinds of behaviors, preferences, and interaction rules), become more and more non-scalable. For instance, Mosteiro-Romero et al. (2024) created a district scale ABM, but computational constraints prevented designing comfort modeling at the level of greater than 35 sample agents (Mosteiro-Romero et al., 2024). Although there are many other models in the cluster that limit their operation to the small scale like single occupant offices (Jia et al., 2019) or within individual building zones, we operate in a full building setup. ABMs are however difficult to scale to larger and more complex systems without theoretical frameworks that support the use of abstraction or surrogate modeling (e.g. Gaussian process emulation) (Wate et al., 2020).

6.1.2.3 Incomplete Representation of Social and Psychological Drivers

Even some of the studies include basic comfort seeking behaviors, but most of the models have no representation of more psychological and social variables. As an example of this, Langevin et al. (2015) point out that their model is not sufficient when

dealing with social influence in shared office environments, that is, reluctance to change thermostat setting because others may be uncomfortable (Langevin et al., 2015). However, although frameworks such as the Theory of Planned Behavior (TPB) have been proposed (M. N. Uddin et al., 2023), the alignment with computational models has not been realized due to an absence of empirical data with respect to rates of subjective norms, rates of attitude, and rates of perceived control. Behavioral heterogeneity is also underrepresented. Even though Chen et al. (2018) suggested the usage of the occupant profiles to accommodate various preferences and actions, the gap with real parameterization and validation of such profiles across different populations persists.

6.1.2.4 Narrow Scope of Modeled Behaviors

Generally, current occupant centric models are restricted to thermal comfort related behaviors such as window adjustments or thermostat use. Although Langevin et al. (2015) explicitly excluded behaviors such as lighting use or appliance interaction, sparking their potential impact on energy (Langevin et al., 2015), these were included in the analysis. However, Ding et al. (2019) demonstrated that reducing the computer standby time by so much as a minute can make a huge difference in energy use, yet such actions are rarely part of models of occupant behaviors (Ding et al., 2019). Since such a narrow focus deprives models of their comprehensiveness, it may even exclude nontrivial contributions to the total energy demand.

6.1.2.5 Lack of Models Addressing Long-Term Behavioral Change

The majority of the models are also assumed to have static or short-term adaptive occupant behaviors. Few of these processes occur over lasting periods of time, are indicative of learning, increasing habit formation or behavioral adaptation. The lack of theoretical integration of frameworks like habit theory, for example, to explain how repeated behaviors get ingrained over time is something not discussed. Without this, models may not adequately translate the occupants' responses to new technologies or

interventions either over months or years. ABMs incorporating theories that simulate how users might “learn” optimal behavior or revert to old habits are in early stages.

6.1.3 Methodological gaps

The studies in this cluster demonstrate multiple methodological limitations reducing the effectiveness and generalize problematic in building performance research. Important methodological gaps are discussed in this section.

6.1.3.1 Data Scarcity and Representativeness

One of the most mentioned methodological challenges is acquiring good quality datasets of occupant behavior. Studies mostly depends on small samples, surveys or monitoring for a small period which is not adequately enough to capture the full diversity of occupant behavior. For example, Jia et al. (2019) considered only five occupants over a month for model validation, and Schweiker and Wagner (2016) considered a few days observation period for collecting data. So, longitudinal, high-resolution data (e.g : year round tracking of a large sample size) is a necessity. Seasonal impact is another aspect to consider, because mostly dataset of the studies in this cluster were taken from one specific season which may impact the result.

6.1.3.2 Underrepresentation of Diverse Building Types and Occupant Groups

Although there is an abundance of literature regarding office buildings in high income areas, other important building types and other occupant groups have been overlooked. Ding et al. (2019) mentioned these limitations in his study with student residences and found different behavior patterns influenced by shared rooms and peer interactions. Another research focused on low income household in the warm climate found that there is a great differences in level of satisfactions across gender (M. N. Uddin et al., 2023). These are some evidences which shows that when research goes beyond conventional settings it generates a novel findings. So, future research should take into

account a broader range of situations (building types such as hospitals, schools, shops, and different occupant groups).

6.1.3.3 Limited Real-Time Intervention and Feedback Testing

Despite the many studies which try to simulate hypothetical behavioral interventions, few such studies have implemented and evaluated those interventions in real world settings. For example, Langevin et al. (2016) designed occupant response to thermal discomfort without field trials. Ding et al. (2019) also simulated the effects of energy-awareness campaign but did not practice using them. Additionally, Putra et al. (2017) suggested to develop occupant feedback dashboards to facilitate behavioral change, but such feedback systems were not empirically tested. This is an indication of a need for experimentation in real world settings such as A/B testing of feedback mechanisms or incentive systems as they are proposed to validate and refine behavior change strategies.

6.1.3.4 Co-Simulation and Interoperability Challenges

Co-simulation is a strength, but also a cumbersome methodology. They lack a gap—these methods often need to setup (e.g., BCVTB or coupling code) in custom ways that are not plug and play. Methods to integrate the occupant models with mainstream energy simulation tools should be more seamless for broader adoption. Industries are still working for a standardized occupant behavior schema like obXML which is mentioned through Yan et al. (2015).

6.1.3.5 Lack of Real-Time Validation and Adaptive Calibration

Occupancy models are generally calibrated once and later used in the static simulations. An adaptive calibration method is thus needed that adapts predictions by real-time sensor data. However, Wate et al. (2020) proposed an uncertainty framework that generates dynamic predictive ranges which helps to utilize MPC (Model Predictive Control), however, did not actually run such systems in practice. In this fashion, a lack of continuous validation hinders the responsiveness of models to unexpected occupant

behavior or changes in the environment. It is a significant methodological gap to do real time validation protocols that do the comparisons of model forecast to sensor data.

6.1.3.6 Limited Integration of Qualitative and Mixed Methods

Qualitative dimensions like comfort perception, motivation, and social influences encompass the behavior of occupants are difficult to capture by the quantitative data alone. Nevertheless, the subjective side of the cluster has not been much incorporated into most of the studies in the cluster. The only exception is the work by Egusquiza et al. (2021) where stakeholder workshops were used to obtain qualitative insights that were used in the model assumptions. Realism and relevance of occupant behavior models can be increased through incorporation of interviews, surveys and ethnographic methods in modeling the behavior of actual human reasoning and decision-making processes to a high degree of detail.

6.1.3.7 Inadequate Representation of Extreme or Rare Events

The typical operating conditions are most often used to calibrate most occupant models, which do not capture rare but impactful events that include heatwaves, black outs or pandemics. Such as in COVID-19, occupancy patterns changed wildly as offices emptied and residential buildings had more people throughout the day. Mosteiro-Romero et al. (2024) at least briefly touched on post pandemic work arrangements, but there is very little methodological work on how to include external shocks such as those of a pandemic like shock in occupant behavior models. It is important to develop modeling techniques that will allow us to simulate responses to such events in order to improve the predictability of building performance.

6.2 Intelligent Building Energy Management and Occupant-Centric Control

The papers present the progress in this cluster, yet several research gaps were identified in the central themes, models and methodologies of the occupant-centered, intelligent building energy management. Key gaps include:

6.2.1 Thematic gap

6.2.1.1 Inadequate real-world validation

Most of the studies in Cluster 2 are based on simulations, and few field demonstrations. For example, Vanhoudt et al. (2014) evaluated a MAS implementation on a residential heat pump and demonstrated under some circumstances that the MAS consumed more energy than conventional controls for reasons not captured by simulations (Vanhoudt et al., 2014). This demonstrates that the performance of intelligent systems can be overestimated without the real-world test. That is why we see a strong need for more pilot studies in actual buildings.

6.2.1.2 Oversimplified Occupant Behavior Models

The most systems in this cluster focus on occupants, however many models rely on fixed schedules or average comfort preferences. Yet, Jung & Jazizadeh (2020) reported that the most important factor for energy and comfort outcomes was individual thermal comfort preference. Most current systems do not have adaptive behaviors: manual window opening, fan use, for instance, or how occupants will react to automated adjustments to reduce them, and this sets up a dynamic, feedback loop lack of modeling.

6.2.1.3 Lack of Multi-Objective Optimization

It is difficult to obtain both energy efficiency and comfort in many studies. Some MAS controls were able to reduce peak loads effectively, but over certain conditions increased

energy use or discomfort (Vanhoudt et al., 2014). Further, Zhou and Liu (2024) add that energy flexibility and resilience are the two key assets to ensure future ready buildings which are not a consideration for existing systems. Current frameworks that optimize several goals (comfort, energy, cost, resilience) are scarce.

6.2.1.4 Partial Integration of Renewables and Storage

There are some MAS frameworks that integrate solar PV with heating or cooling, but more broadly, the MAS lacks integration of energy prosumers (buildings with solar, batteries, EVs, etc.). Strategies for managing combined thermal and electric storage are currently rather limited, and most studies only consider on one energy source. It prevents agents to optimally use renewables or to flexibly respond to grid demands (Vanhoudt et al., 2014).

6.2.1.5 Challenges in Scalability and Interoperability

Then most of the systems are tested at a single building level. Finally, although MAS could perform at district scale where buildings must communicate and coordinate, it is unclear how. There is also a hurdle in interoperability between agents from different vendors. Moreover, Existing standards like BACnet is not an intelligent agent coordination standard. Recent work on semantic frameworks suggests the need to share ontologies to be able to deploy wider (Gómez-Gil et al., 2022).

6.2.1.6 User Acceptance and Privacy Concerns

Whilst issues such as occupant acceptance and privacy are less discussed, they are serious. For personalized control, comfort preferences or occupancy data must be collected, causing privacy concerns. Otherwise, occupants may resist such systems without user friendly interfaces or override options. For successful adoption, future work must be considered these human factors.

6.2.2 Gaps in models and theory

6.2.2.1 Limited modeling of occupant decision-making

The occupant behavior models use are empirical or probabilistic and does not incorporate deeper behavioral theory into model. The quantity of theoretical models predicting occupant decisions (i.e. when they override a system or comfort vs. energy savings trade-offs) is lacking. Current models are still somewhat passive (as heat sources or preferences for comfort) but the more sophisticated theories of social science (Theory of Planned Behaviour or technology acceptance models) are not employed. The agent-based simulations would potentially miss important emergent phenomena that do not arise from the model of adaptive behaviours determined by the occupant but, rather, involve feedback loops arising from occupant adaptive behaviors when they feel a loss of control rebound effects in the system.

6.2.2.2 MAS theory to practice gap

The use of concepts on multiagent systems (MAS) is conceptually powerful while realizing cooperation in real systems remains very challenging. But in practice, this ideal scenario does not happen. Since, coordination, stability and goal alignment in real systems are still very hard to guarantee (González-Briones et al., 2018).

6.2.2.3 Control theory limitations

These dynamic contexts push the limits of traditional control models (RBC, MPC). It leaves one gap: for MPC, a good model of the building is unavailable or invalid in the light of changing building or occupant behaviour. There are few papers that provide a new theoretical approach to uncertainty or adaptation in predictive control, instead taking a path to RL or MAS. The needs for theoretical frameworks that unify the advantages of MPC (with optimal decisions under constraints) and learning (dealing with uncertainty) such as safe RL or adaptive MPC are pointed out and specifically applied to buildings. Initial RL work provides part of the closure to this gap but not a unified theory.

6.2.2.4 Semantic and knowledge representation gap

The introduction of semantic agent frameworks indicates a gap in how knowledge is represented in building systems. Traditional control logic lacks a world model or ontology, meaning systems cannot reason about concepts like “if a room is unoccupied, then lighting can be off.” One paper’s semantic approach tried to fill this gap, but it remains an isolated example. A broader gap is the lack of a widely adopted ontology for smart building agents. Without a shared theory of how to encode building knowledge (rooms, devices, relationships, goals), each project develops custom agent logic. This limits generalizability. The cluster shows only an initial attempt at applying semantic web theories (Mousavi & Vyatkin, 2015), pointing to an open theoretical frontier.

6.2.2.5 Reinforcement learning challenges

The RL-based approaches are promising but raise theoretical questions. Building systems are safety-critical (e.g: we don’t want an RL policy to accidentally freeze pipes or cause discomfort), yet the cluster’s RL implementations borrow from game or robotics settings without fully developing the theory for constraints and safety in learning. There is a gap in the RL theory application: how to ensure an RL controller respects comfort constraints at all times, or how to handle exploration vs exploitation in a live building. Theoretical work on safe RL or multi-agent RL in the context of buildings is still nascent. For example, Li et al. (2021b) had to introduce feasible action screening and other tricks in their deep RL controller to maintain stability (Shen et al., 2023), but a formal framework for such guarantees is not yet established.

6.2.2.6 Generalizability of models

Many models (both occupant models and control models) are tailored to specific case studies (a particular building or climate). The theories might not generalize well – an agent reward function or comfort model tuned for an office in one climate may perform poorly in another context. This hints at a gap in higher-level theories or frameworks that

ensure adaptability. We lack a unifying theory of intelligent building control that could be applied broadly; instead, we have disparate models for each scenario. Developing model frameworks that can be scaled or transferred between environments is an identified theoretical gap.

6.2.3 Methodological Shortcomings

6.2.3.1 Over-reliance on simulation

As noted, most studies are simulation-based. This raises concerns about simulation validity and robustness of results. Many simulations assume ideal conditions (perfect sensor data, no communication delays, accurate occupant models). The lack of noise and faults means methods might not be battle-tested. An evident shortcoming is the minimal field testing – without real-world experiments or longitudinal studies, it's uncertain how these methods perform over time. Future research needs to incorporate longitudinal deployments or at least high-fidelity building emulators with more real-life uncertainty.

6.2.3.2 Narrow scope of case studies

Methodologically, a number of studies focus on a single building or scenario (e.g. one office building, one week of weather, one occupancy pattern). This limits the generality of conclusions. Some works did vary parameters widely (Jung & Jazizadeh, 2020), but often the scope is still one building archetype. A methodological gap is the diversity of test cases like different building types (residential vs. commercial, new vs. old buildings), different climates, and occupancy cultures are not all represented. For instance, a strategy that works in an office with predictable schedules might fail in a home with irregular occupancy. Thus, methodologies should expand to include multiple case studies and maybe use standardized benchmark scenarios for fair comparison.

6.2.3.3 Comparison with baseline/control

Not all papers rigorously compare their approach against conventional methods. Only some do distribute control vs centralized MPC (Li & Wang, 2022b), or intelligent vs regular heat pump control (Vanhoudt et al., 2014)). On the other hand, others introduce a new framework without quantifying improvement over the status quo. This is a methodological shortcoming. Without benchmarking, it's hard to gauge real benefits. Future studies should include clear baseline comparisons (e.g. how much energy is saved compared to a typical building automation system or a rule-based thermostat). Additionally, few papers compare different advanced methods (like MAS vs. a centralized AI controller). Doing these could clarify the trade-offs of decentralization.

6.2.3.4 Limited consideration of computational and network constraints

Some methodological setups idealize the computation and communication. However, in IoT-based control, agents may run on microcontrollers with limited processing power and battery. Only a couple of studies explicitly considered sensor energy consumption and designed an event-driven method to conserve it (Li et al., 2021c). This indicates a broader gap: methodologies often neglect the overhead of their smart control schemes. Complex algorithms might be impractical if they require too much computation or data exchange. Future methods should account for latency, bandwidth limits, and computational load, possibly by using edge computing or simplified algorithms.

6.2.3.5 User-centric evaluation missing

Methodologically, success is usually measured in energy or comfort terms set by researchers. What's missing is user-centric evaluation e.g. surveys of occupant satisfaction or qualitative feedback from building managers on the system's operation. None of the cluster studies incorporate human subjects in the loop (since most are simulations). This is a shortcoming because a method might meet technical metrics yet fail in user acceptance or operational simplicity. Including user studies or at least facility

manager interviews could strengthen methodologies by aligning them with real-world needs.

6.2.3.6 Transparency and reproducibility

Some papers, especially simulation-heavy ones, may not provide full details to reproduce the results (such as code for the agent algorithms or exact parameter values for occupant models). This makes it difficult for other researchers to validate and build upon the work. A methodological best practice gap is the lack of open-source tools or common platforms. If each group builds their own MAS simulation from scratch, results may not be directly comparable. The field could benefit from shared simulation platforms for intelligent building control (perhaps built on existing simulators) to standardize experiments.

6.2.3.7 Handling of uncertainty

Methodologically, many works do deterministic simulations or assume known parameters (e.g. an occupant's comfort model is known). There's limited use of uncertainty quantification or sensitivity analysis. This is a shortcoming because building environments are rife with uncertainty (weather variations, occupant unpredictability). Few studies conducted sensitivity analyses to see how robust their control is to model errors. Future methodologies should include testing under uncertain conditions, perhaps using Monte Carlo simulation or robust optimization techniques, to ensure the proposed methods are not fragile.

6.3 Occupant-centric and personalized building control utilizing behavioural science

6.3.1 Thematic gap

Although Cluster 3 has substantially advanced the understanding of occupant-driven energy outcomes, there remain notable gaps in the current research themes. One major

gap is the integration of these human-centric models into mainstream practice. Traditional building energy modeling tools still largely treat occupant behavior in a simplistic way (e.g., fixed schedules or averages), whereas the research here shows this is inadequate (Ali et al., 2020; Azar & Menassa, 2012). The challenge is that while we know occupants can cause large deviations in energy use, industry-standard models haven't fully caught up. This creates a gap between research and practice: bridging that performance gap requires incorporating occupant behavior modules into widely used simulation software or design processes.

Another gap lies in the scope of settings studied. As noted by Azar and Menassa (2014), many behavioral intervention studies have been in residential contexts, and results “cannot be directly applied to commercial buildings” due to different social structures. Cluster 3 started addressing this by focusing on offices, campuses, etc., but still, most case studies are office buildings or simulated communities in a relatively homogeneous culture (e.g., university campuses, U.S. or UK contexts). We have limited research on occupant behavior in other contexts like industrial facilities, hospitals, or multi-family apartment buildings. Each of these has unique occupant patterns and organizational structures (consider a hospital with 24/7 shifts and critical equipment—occupant behavior modeling there would differ greatly). Cultural and regional differences also represent a gap: what motivates an office worker in Pakistan (as in (Ali et al., 2020)) may differ from one in the US or Europe, yet models often assume generic behavior rules.

The time dimension of behavior change is another critical gap. Many cluster studies simulate interventions over weeks or months at most (Ali et al. (2020) ran for a three-year period in simulation, which is relatively long for a model, but still a short time in a building's life). The issue is that interventions might work for a while but then fade – a phenomenon known as behavioral relapse. Azar and Menassa (2014) pointed out that even when occupants adopt energy-saving behaviors, those “were rarely maintained over time and relapses...are commonly observed” in residential studies. How to sustain energy-conscious behavior is not well understood. Most models don't incorporate

mechanisms of habit formation or forgetting; an agent either stays saving or not, unless another intervention is applied. In reality, people might need periodic reinforcement, or they might cycle through periods of diligence and neglect. This is a thematic gap: long-term efficacy of interventions and how to model that process.

Additionally, while the cluster's theme is broadening to include comfort and other metrics (Azar et al. (2016) bring in multi-metric considerations), there is a gap in exploring trade-offs explicitly. For example, if an occupant chooses to save energy by tolerating slightly higher room temperature, there's a potential impact on comfort and productivity. The central theme could be expanded to consider holistic outcomes: energy and comfort and productivity. Few studies quantitatively model the productivity impact of interventions (e.g., if it gets a bit warmer because of energy savings, does work output change?). Also, health and indoor environmental quality aspects (air quality, lighting quality) are not deeply integrated yet. These represent gaps in the theme where occupant behavior intersects other domains of building performance.

Another gap is recognizing the diversity of occupant roles and interactions in commercial buildings. Cluster 3 has begun looking at social networks and peer effects, but workplaces have hierarchies and organizational cultures that might influence energy behavior (e.g., if management is strongly pro-energy-saving, employees might follow suit, or vice versa). These organizational behavior aspects are not explicitly modeled – agents in simulations are usually “peers” without hierarchy. The theme so far treats social influence mostly as peer-to-peer network influence, but top-down influence (like company policies or green leadership) is a gap.

Lastly, measurement and feedback loops in real buildings remain a challenge. We know occupant behavior is crucial, but in practice building operators often lack detailed feedback on occupant actions. The cluster's theme could benefit from exploring how to actually measure or infer occupant behavior (through sensors, smart meters, etc.) and then use that to inform building management in real-time. This real-world

implementation aspect (going from simulated occupant models to live adaptive systems) is still in its infancy which means a gap between what the research indicates is possible and what is deployed.

In summary, the current research themes could be broadened and deepened by: (a) applying occupant-behavior-centric models in more diverse and real-world contexts (different building types, cultures), (b) extending the time horizon to study long-term behavioral change and maintenance, (c) integrating additional performance outcomes (comfort, productivity) to fully understand trade-offs, and (d) finding ways to operationalize these models so that building designers and operators can easily use them. Addressing these gaps would ensure that the central theme of “occupants matter” truly permeates all facets of building energy research and practice.

6.3.2 Gaps in Models and Theories

The theoretical and modeling approaches in this cluster (cluster 3), while innovative, also have certain limitations and open questions.

One gap is the breadth of behavioral theories incorporated. Most models in this cluster simplify human behavior to a set of rules that capture a particular aspect (e.g., social conformity, or economic payoff, or comfort-seeking). However, real human decision-making about energy is influenced by a confluence of factors like habits, personal values, financial constraints, awareness, social norms, etc. The models tend to include a few of these but not all. For instance, the social influence models (like the norm diffusion or relative agreement models) focus on how people change due to interactions, but they might not account for an individual’s intrinsic motivation or knowledge. If an occupant is highly intrinsically motivated to save energy (perhaps for environmental reasons), they might conserve regardless of peers; conversely, someone might ignore peer behavior due to skepticism or privacy concerns. Current ABMs rarely include agent personalities or rich internal states beyond a threshold or an opinion value. This points to a gap: incorporating deeper psychological models (such as attitude-intention-behavior models,

or personality traits) into ABMs of energy use. So far, the “personality” of agents is often abstract (extremist vs. moderate, or early-adopter vs. laggard in tech adoption). Cognitive frameworks (how people process information and make decisions) like bounded rationality are partially included (Sachs et al., 2019), but we could integrate models from cognitive science for how people perceive comfort or remember to turn off lights, etc., which is not yet done.

Another theoretical gap is related to the validity and generalizability of the models. Many models are not fully validated against long-term or large-scale empirical data. While some validation is done (e.g., matching a short-term experiment), the theories like RA (relative agreement) or diffusion models are mostly borrowed from other fields and assumed to apply. We don’t yet have studies that conclusively show, say, that a Deffuant-style opinion model accurately predicts how energy behaviors spread in a real office building over several years. The lack of large-scale validation means these theories, as applied to energy use, remain somewhat speculative. It’s a gap that could be closed by longitudinal studies or pilot programs where actual intervention outcomes are tracked and compared to model predictions.

In terms of scalability of theory, ABM is a micro-level approach and the cluster’s theories sometimes struggle to connect micro to macro. For example, we have rich models of individual buildings or small communities, but we lack theoretical frameworks for how those scale to city or national levels in a computationally feasible way. The attempt by Sachs et al. (2019) to integrate ABM into an integrated assessment model is a step in that direction, but it highlighted challenges. They pointed out that many larger models just impose constraints because they can’t derive macro behavior from first principles (Sachs et al., 2019). We need theoretical frameworks for multi-scale modeling – how to nest an occupant behavior model within, say, an urban energy model. The cluster hasn’t fully addressed that, which is an open area.

Simplifying assumptions in many models raise further concerns. For instance, models often categorize occupants into a few archetypes (e.g., low, medium, high users (Ali et al., 2020)), yet real-world occupants exhibit far more heterogeneity. Additionally, while some models permit changes in opinions (e.g., RA-based models), comfort preferences and behavioral norms are often treated as static which contradicting evidence that these preferences evolve with seasons, age, or experience. Similarly, network structures in social influence models are usually fixed, assuming a static set of peer relationships. But real workplace networks shift over time, with employee turnover or departmental changes. The lack of dynamic social network modeling is a theoretical shortcoming that limits realism in simulating behavior diffusion.

In the realm of technical modeling, frameworks like the multi-agent control (Yang & Wang) assume certain model structures (like each zone's comfort can be aggregated into one objective). If building usage changes (a zone that was an office becomes a lab), the model might not adapt, indicating a need for more adaptive or learning algorithms. Current theory uses mostly pre-defined rules and algorithms; incorporating machine learning (where agents learn optimal behaviors or controllers learn occupant patterns on the fly) is a theoretical advancement not much seen in this cluster.

Finally, a subtle theoretical gap is the integration of normative vs. incentive-based theories. Some models are purely normative (agents want to conform to social norms), others are economic (agents respond to cost savings). In reality, both operate together, e.g., an occupant might need both a social nudge and a cost incentive to change behavior significantly. A comprehensive theory would unify these: perhaps using multi-criteria decision making per agent (they have a utility function that values comfort, money, and social approval). While the idea is there, most models lean heavily in one direction (either purely social influence as in Anderson 2014, or purely tech-economic as in some adoption models). The gap is a unified agent decision theory for energy behavior that accounts for social, psychological, and economic drivers simultaneously.

6.3.3 Methodological Gaps and Limitations

Although the methodological advances in Cluster 3 still match the comprehensiveness of the analytical benefits and its contribution to the study at hand, several limitations still require further refinement. Scarcity of comprehensive and generalizable datasets for occupant behavior is one of the most important obstacles. The other works of Azar and Menassa (Azar & Menassa, 2011, 2012) or Ali et al. (2020) study only a couple of buildings, and rely on small-scale experiments. These models are usually corroborated in limited situations, representing a potential barrier to generalizability of the models from one climate, building type and culture to another.

Another gap also worth noting is the lack of use of modern data driven techniques. Despite these, agent-based models (ABM) still take a lead for their translucence and rules character. Nevertheless, the model realism could be further improved by doing with machine learning and optimization algorithms. For instance, clustering techniques can be applied to empirically identify the patterns of occupant behavior in a dataset that is too large for humans to comprehend, while reinforcement learning can be used for agents to develop the rule of thumb of their own behavior and adapt to the experience to fit the data. However, many of these methods are lacking from current work, suggesting methodological conservatism that may hamper innovation. The part of the field that could do with improving is a hybrid approach that combines ABM's interpretability with the predictive power of the data-driven methods.

This cluster has some further limitations with respect to its integration of interdisciplinary methods. The methodological approach of the two parties in Cluster 3 stay more or less on separate silos of tradition. For example, human interpretable methods such as interviews, focus groups, or ethnography studies are not used and are often great for enriching quantitative models with contextual perspective. This limited collaboration between disciplines may leave important assumptions on modeling the drivers of behavior unconsidered, specifically for the occupant aspect of modeling. More mixed methods research, both by its use of qualitative data that inform the design and

calibration of quantitative models, but also by its implications that the qualitative data can be used as a surrogate for the realities to be modeled, could offer increasing realism and more relevant policy.

Scalability is another issue. However, most ABM implementations make use of simulations with small populations, or the population is simulated as a single building or a few dozen occupants. Such models are also computationally challenging to scale up to the scale of whole campuses or urban districts. However, there are no efficient methods in the current methodological toolbox to perform large scale simulation, either in terms of agent abstraction or distributed computing. With the shift of research to smart city applications scalability will become increasingly necessary as to address it through computational innovation.

Finally, each study tends to use its own model and assumptions, making direct comparison difficult. There's a methodological gap in the standardization of occupant behavior modeling. The field could benefit from common benchmarks or datasets (similar to how building energy simulation has standard test cases). Without standardized methods or at least common evaluation metrics, it's hard to quantitatively say which intervention is generally more effective. So, results are often context specific. Developing common evaluation frameworks (e.g., percentage energy saved under defined conditions, or a cost-benefit analysis template) would strengthen the methodology. Right now, one paper might report 19% energy savings (Azar et al., 2016), another 25% (Ali et al., 2020), another 40% potential (Azar & Menassa, 2012), but these numbers come from different contexts. Methodologically, a more systematic comparison would be valuable.

6.4 Multi-agent intelligent control and optimization techniques for energy management

6.4.1 Thematic research gap

Many limitations and gaps are present in the current research on multi-agent RL for energy management.

6.4.1.1 Real-World Deployment and Validation

The big gap here is the absence of real-world deployment and validation. There are many such studies that have been successful in simulations or controlled environments, but deployment of these systems in actual buildings or campuses is difficult. Furthermore, Zhang et al. (2021) admit that most RL based DR strategies have never been practically demonstrated, prompting their testbed experiment. The testbed and Blad et al. (2022) simulation are steps in the right direction, but they are still untested to real buildings occupied by people. A simulation alone will not catch everything: unpredictable human behavior, sensor faults, building idiosyncrasies, etc, may build errors not seen in a simulation.

6.4.1.2 Scalability to Larger Systems

Many papers deal with the scenarios with small number of agents (like a few HVAC subsystems, or 2–3 buildings in a community). When trying to scale up to more complex building complexes or city-wide multi agent systems, the central theme faces scalability issues. Qiu et al. (2023) explicitly point out this limitation too: their federated MARL is validated on three buildings; and as agent counts increase, interaction complexity and non-stationarity “quadratically” leading to instability of learning. Similarly, Xie et al. (2023) propose investigating performance at increasing numbers of building-agents. However, the algorithms are not very efficient when having dozens of agents whose state spaces are high dimensional. The existence of this gap indicates a need for new

approaches or hierarchical structures for managing many agents without computational or communication costs exploding.

6.4.1.3 Multiple Energy Domains Integration

Unlike most cluster papers that deal with one domain of control (hardly any cases apart from HVAC is dealt in most cluster papers) at a time. Holistic building control lacks this gap, as single multi agent system is responsible for the control of HVAC, lighting, plug loads and other systems. Future smart buildings will incorporate many subsystems (fire safety, access control, windows, etc.) under a single control system, commented on by Homod et al. (2022, 2023). Today although their HDCMARL approach is shown on the HVAC, it is not yet extended to additional subsystems since such reconfiguration is expensive. Similarly, none of the studies combined, for example, lighting control with HVAC control in a unifying learning framework to take place additional efficiency (for example, balancing daylight use vs HVAC load). Complexity of representing and reward multiple concurrent objectives (comfort, illumination, security) and no work exploring an agent framework handling all together are the gaps here.

6.4.1.4 Economic and Market Considerations

Few works include energy cost and trading (Nweye et al., 2023; Qiu et al., 2023) while others do not consider real economic signals and constraints. However, in many models energy tariffs, demand charges and occupant cost preferences are simplified. For example, demand response studies (Xie et al., 2023; Zhang et al., 2021) assume certain pricing scenarios; however, real programs have uncertainties like event triggers or variable incentives. There is also the question of regulatory and market integration: how would a MARL-based trading system interact with utility regulations or carbon markets in reality? These socioeconomic factors are not deeply addressed, presenting a gap between the technical solutions and the policy environment in which they must operate.

6.4.1.5 Trust, Transparency, and User Acceptance

Implicitly, the central theme postulates that building operator, and occupant will permit the use of AI agents in controlling their environment. There is also a gap in practice of user acceptance. Black-box algorithms making decisions in regard to people's comfort or energy use might be met with discomfort on the part of people. None of the cluster papers focus on this human factor directly, but Nweye et al. (2023) acknowledge the need of "policy explainability" to speed the real-world adoption. More specifically this hints at a gap: the current research is slanted towards performance in optimization while future work might have to consider making these AI controllers understandable and reliable to human stakeholders: we expect no violations of comfort bounds or providing explanations for actions. If we don't address this, there will be resistance or a lot of trust building when deploying at scale.

6.4.2 Gaps in Theoretical Frameworks and Models

Beyond topic-focused gaps, there are limitations inherent to the frameworks and models used in these studies:

6.4.2.1 Limited Handling of Continuous Action Spaces

Implicitly, the central theme postulates that building operator, and occupant will permit the use of AI agents in controlling their environment. There is also a gap in practice of user acceptance. Black-box algorithms making decisions regarding people's comfort or energy use might be met with discomfort on the part of people. None of the cluster papers focus on this human factor directly, but Nweye et al. (2023) acknowledge the need of "policy explainability" to speed the real-world adoption. More specifically this hints at a gap: the current research is slanted towards performance in optimization while future work might have to consider making these AI controllers understandable and reliable to human stakeholders: we expect no violations of comfort bounds or providing explanations for actions. If we don't address this, there will be resistance or a lot of trust building when deploying at scale.

6.4.2.2 Scalability and stability in MARL algorithms

There is a second major theoretical hurdle posed by scalability and learning stability. With generalization of MARL systems, the size of joint action and state spaces grows exponentially. According to Qiu et al. (2023), this “curse of dimensionality,” as well as non-stationarity coming from the agents learning simultaneously, can destabilize training. Although centralized critics are used more commonly as in Xie et al. (2023) and Qiu et al. (2023), the models become computationally expensive when more agents are involved. Drawing from various limitations, such as scalability, there is little theoretical innovation in the form of mean field approximations or value function factorization in the cluster. In addition, most models lack formal convergence guarantees and rely substantially on empirical tuning. This is indicating the necessity of more strong theoretical guarantees in the stability and coordination of MARL.

6.4.2.3 Communication and Coordination Mechanisms

Theoretical interest in how agents coordinate in multi agent systems is very important. Few clusters’ papers model inter agent communication protocols explicitly (basically all employ centralized learning or implicit concurrency using reward design). As pointed out by Fu et al. (2022), their choice of actions by the agents is of independent choice without any direct communication mechanism and could be improved. The absence of explicit communication models is a gap – theories from distributed AI (like agent communication languages or consensus algorithms) haven’t been fully integrated with deep RL in these works. Xie et al. (2023)’s use of an attention mechanism is one way to mediate coordination, but it’s effectively learned implicitly by the critic. A theoretical extension would be to allow agents to exchange messages or learn communication protocols, which could improve coordination in a scalable way. The current models treat the multi-agent system mostly in a centralized training paradigm, which might not be viable when a true distributed deployment is needed.

6.4.2.4 Generalizability and Transferability of Models

In the cluster most of the RL controllers are designed for a certain building or operating conditions. While Nweye et al. (2023) show that battery control policy transfer is possible, it is yet to cover broader generalization. There is no theoretical guidance on when and how RL policies can transfer across environments with different dynamics, layouts, or climates. It is often the case that models can no longer be deployed to elsewhere without retraining or fine tuning, thus, pointing out that meta learning or context aware RL frameworks that do not need as much retraining is a need today.

6.4.2.5 Integration of Domain Knowledge

The Domain knowledge should be integrated equally into the RL framework as well. The majority of cluster studies rely on black box, model free RL methods that are very flexible, but sample inefficient and prone to poor behavior. Except a few exceptions, one: Homod et al. (2022, 2023) utilize fuzzy logic to embed the knowledge of expert into hybrid neuro fuzzy controllers, two: most works do not resort to the knowledge of known physics or comfort models. The broader theory of physics-informed or constraint-aware RL is still emerging. As a result, many current approaches treat hard constraints (e.g., thermal comfort) as soft penalties in the reward function. This may result in occasional violations unless penalties are finely tuned. More robust theoretical approaches, such as constrained Markov Decision Processes or safe RL, offer formal ways to enforce constraints but are rarely applied in the cluster.

6.4.2.6 Privacy and Security in Models

With the introduction of federated learning in one study (Qiu et al., 2023), there's acknowledgment of privacy. However, the theoretical security of these models is not deeply addressed. A federated model still could be susceptible to data poisoning by one agent or inference attacks. In addition, Xie et al. (2023) also discuss that sharing critic information is associated with privacy problems. Here is a gap of lacking thorough theoretical models for privacy preserving multi agent learning, i.e., including

cryptographic techniques and/or formal guarantees of privacy such as differential privacy. It also is important for real deployment (for example, in energy markets or between competitive entities), and theory is lagging behind to know how to robustly achieve this in MARL.

6.4.3 Methodological Gaps and Limitations

6.4.3.1 Over-reliance on Simulation

most results in the cluster are based on simulations and lack real world validity. Most simulations make the assumption (and remove the practical challenges) of perfect information (all sensors work, model of the environment is perfect) and can simplify or ignore existence and effects of practical challenges like communication delays in a multi agent network or unanticipated occupant action. As a result, methods may never have been tested under the conditions of realistic noise and uncertainty. For instance, if the building is different from the simulation model the RL controller tuned using simulation (or a simplified building model) may fail. Blad et al. (2022) go out of their way to emphasize that they simply need a real-world testing to ensure that their offline trained RL agent can actually handle real building dynamics and weather disturbance. The implication of this is a methodological gap: field validation. Due to real or at least high fidelity highly real digital twins you cannot test algorithms and it's also unclear how the gains reported would hold in actual environments.

6.4.3.2 Limited Duration and Scope of Experiments

A large number of experiments in the cluster are carried out over short timescales or in narrow seasonal conditions. A demand response strategy might work well during a few summers' day, but not so well winter or with changing occupancy. Long-term testing remains rare. As mentioned, this is an exception: Nweye et al. (2023) have extended battery control experiments to a year's worth of data. Overall, existing methods do not evaluate if RL policies are robust to months or years. Not only that, but they also tend to narrowly focus on a few metrics, mainly on an energy savings or a cost, and ignore other

such as the wear of equipment, user comfort or maintenance costs. Additional dimensions to consider for the real-world viability of the control strategies than have been included already, need to be considered for a more holistic approach.

6.4.3.3 Data Limitations and Bias

A large number of studies rely on both synthetic and sparsely labelled datasets. For instance, Weng et al. (2019) utilize their own pseudo labelling strategy since no mentioned labelled data was available. It poses questions to the reliability of model evaluation as well as risks of confirmation bias. Finally, cross validation across many different datasets is rare, and therefore makes generalization of the findings difficult. Thus, many models are properly tuned to their context and fail in other contexts. This problem needs to be overcome by working towards making shared datasets, using active learning techniques, and promoting open-source benchmarking for model validation over a wide range of conditions.

6.4.3.4 Computational and Infrastructure Challenges

The methodologies often require significant computation (training deep neural networks, running many simulation episodes). Blad et al. (2022) raise the point that their approach is computationally “orders of magnitude more complex” than current controllers and suggest that cloud computing might be needed. This is a practical gap: deploying these algorithms might require an infrastructure (cloud servers, reliable internet for building controllers) that is not always available or introduces latency. Current methodologies haven’t fully addressed how to implement the algorithms on resource-constrained hardware like typical building management systems or IoT devices. There’s little discussion on the real-time computational feasibility of, say, running an attention-based multi-agent neural net controller every few minutes on an HVAC PLC (Programmable Logic Controller). Methodologically, future work should consider computational optimization, such as model compression or faster inference techniques, to bridge this gap. Similarly, the communication infrastructure for multi-agent systems (especially if

buildings or devices need to talk to each other or a cloud server) is taken for granted in simulations. In reality, network reliability and cybersecurity are concerns. No paper deeply discussed network failures or cyber-attacks (e.g., a malicious agent in MARL), which is a gap in the robustness testing of these methodologies.

6.4.3.5 Validation and Benchmarking

Finally, there is no standardizing of the benchmarking across the field. Each study also imposes its own test cases such that results cannot be compared directly between studies. Specifically, the one algorithm could indicate a 20% energy saving in some building, whereas another algorithm would possibly only indicate a 5% saving in a different context. As there is no commonly agreed upon evaluation environment, it doesn't actually clear which one works better. This step has already been taken by Zhang et al. (2021), who provided a reproducible testbed, but this is not enough. Simulator platforms and performance metrics could be established that would be conducive to comparability and transparency across studies.

6.5 Social influence on multi-agent decision modeling in built environments and policy applications

While there have been significant advances in modeling occupant behavior and decision making in buildings, this cluster (cluster 5) sketches out some challenges yet to be fully resolved on the issue of human dimension in the built environment.

6.5.1 Thematic gaps

6.5.1.1 Holistic Integration of Human Behaviors

Current studies have historically focused on specific aspects of occupant behavior isolated from each other (e.g., only one type of behavior, when triggered by only thermal comfort or movement, or only post patterns of energy use). Currently there is no unified

model that captures the entire range of occupant behavior in buildings (comfort, wayfinding, usage of appliances, social interaction, etc.) within a model. For instance, one refers to a gap mentioning that 'existing application(s) of human building interactions are not adequately grounded in full understanding of occupant behavior' (Malik et al., 2022). Future research may aggregate multiple behavior domains in a simulation such as the building meets the thermal comfort need, but those thermal comfort needs will affect the movement, or the social context affects the energy usage, for a more holistic simulation of occupants in buildings.

6.5.1.2 Generality and Transferability

Very many of these ABM studies are built specifically on the context of some building, culture, or scenario. It is concerning that the findings are generalizable. Occupant behavior is very context based, which prevents development of more general models, as Malik et al. (2022) remark. A model calibrated for a U.S. office building may not directly apply to a residential home in another country.

6.5.1.3 Stakeholder Involvement in Design Simulation

Only one paper in the cluster (Pluchinotta et al., 2019) deals explicitly with stakeholder knowledge and participatory scenario planning. This suggests that, in the context of building design and operation, direct human input or co-creation in modeling is underrepresented. There is a gap in how occupant-centric simulations are fed back to stakeholders (designers, facility managers, or the occupants themselves). For instance, while we can simulate hospital occupant flow, how do these results inform architects or users in practice? The participatory approach used in urban policy FCM could be mirrored in building design (Pluchinotta et al., 2019). It will involve end-users in setting up agent behavior rules or validating scenarios, but such methodologies are not yet common. Bridging this gap could make simulations more relevant and increase stakeholder trust in agent-based results.

6.5.2 Models and Theories Gaps

6.5.2.1 Behavioral Realism vs. Simplification

There is a tension between complex, realistic models and practical simplifications. Some frameworks remain relatively simple, for example, using Markov chains for occupant activities assumes future actions depend only on a limited history, which may ignore deeper cognitive or social drivers. Markovian models capture stochastic patterns but not the reasons behind those patterns (why an occupant chose to cook at a certain time). On the other hand, more realistic cognitive models (like the vision-based wayfinding agent) greatly increase model complexity. A challenge is that many ABMs still lack richer psychological or social underpinnings, focusing on what occupants do without fully modeling why they do it. As a result, models might not predict behavior well if conditions change in ways outside the original assumptions (e.g., an occupant's novel reaction to a new technology or policy). The literature notes that existing ABM applications often are "insufficiently grounded" in empirically validated behavior theory (Malik et al., 2022), meaning there is room to deepen the theoretical basis (e.g., incorporate habit formation theory, social influence, etc., beyond what we see in current models).

6.5.2.2 Interdisciplinary Theory Integration

While cluster studies touch on sociology, cognitive science, and economics (especially in the urban planning example), integration of interdisciplinary theories is still limited. Malik et al. (2022) explicitly point out the opportunity to fuse psychology, sociology, economics, and anthropology insights into future ABM development. In current models, an agent's decision to turn on a heater or move through a space is usually based on straightforward rules (comfort threshold, shortest path, etc.). Missing is higher-level motivations or social context, for instance, economic decisions (like responding to energy prices or budget constraints) are not deeply modeled except as a generic factor, and social interactions between agents (peer influence or cooperation) are seldom included. The theoretical gap here is the absence of a unifying framework that brings these human factors together. Each study introduces a piece (e.g., thermal physiology,

cognitive perception), but a comprehensive theory of occupant behavior in buildings (analogous to, say, well-established physics theories in building simulation) is still emerging.

6.5.2.3 Dynamic Adaptation and Learning

Notably absent in most cluster models is the capacity for agents to learn or adapt their behavior over time. Real occupants learn from experience and adjust (e.g., they might develop new routines or adjust comfort expectations after repeated thermostat changes). Some theoretical discussions (Malik et al., 2022) mention agents' ability to adapt, but the implemented models in these papers largely use fixed behavior rules calibrated from data. For instance, Vellei's (2021) thermostat agents do not change their comfort preferences over the simulation; they react stochastically but do not learn new patterns. This is a theoretical limitation: adaptive learning agents (e.g., using machine learning or feedback mechanisms) could better represent evolving occupant behavior, but incorporating such adaptation is complex and not yet common in building-focused ABM. The result is that current models might not capture long-term shifts (like adaptation to a new building technology or changes in group norms), pointing to a gap in theoretical modeling of behavior over time.

6.5.3 Methodologies Gaps

The research methods in this cluster, while innovative, encounter several limitations that suggest areas for improvement:

6.5.3.1 Data Limitations and Calibration Challenges

A persistent methodological gap is the availability and representativeness of data to drive and validate ABM studies. Many simulations had to rely on one-off data collection efforts (e.g., a single airport survey, one dataset of thermostat use) which may not capture the full variability of occupant behavior. For example, the thermostat study used data from households with internet connected thermostats, which are quite possibly

tech savvy, higher income occupants who have a high desire to participate in research. This also suggest that the calibrated model does not generalize for other population. Furthermore, collecting detailed occupant data (activity patterns, comfort responses etc.) is expensive and time consuming and so small samples sizes are obtained or defaults from literature used. Calibration is tricky when data are limited: researchers often had to make do with approximate or aggregate data. This gap could be addressed by establishing shared databases of occupant behavior or adopting “living lab” approaches where buildings continuously feed occupant data for model updates. Until then, calibration and validation will remain a weak link models risk being under or over-fitted to narrow data sets.

6.5.3.2 Computational and Practical Scalability

As models become more detailed (e.g., hundreds of agents with cognitive decision processes or nationwide building stock simulations with stochastic occupants), computational load becomes a concern. Some authors noted the need to improve computational efficiency of ABMs for practical use (Malik et al., 2022). The ResStock integration simulated hundreds of thousands of households (which is computationally intensive, though managed via high-performance computing) (J. Chen et al., 2022). Likewise, running dozens of agents in a vision-based cognitive model or thousands of narrative agents can tax computing resources and simulation time. This limits the ability to scale these methods to larger urban scales or run many design alternatives quickly. It's a methodological gap that many ABM tools are research-grade – not yet optimized for speed or ease of use at industry scale. Additionally, practical scalability in terms of user expertise is an issue: setting up these simulations often requires specialized knowledge (programming agents, linking to BIM or energy software), which can hinder adoption by architects or engineers who are not ABM experts.

6.5.3.3 Integration Hurdles with Traditional Tools

Some progress was made to integrate ABM with building simulation (co-simulation or custom platforms), but it was not a seamless process. Usually, researchers are writing custom code or workflows to connect the occupant models with tools such as EnergyPlus, which is a time-consuming process. Malik et al.'s (2022) review indicates that co-simulation approaches exist but come with technical complexity. This fragmentation means there's no plug-and-play way to add an occupant agent module into, say, a standard energy modeling software. Methodologically, this gap makes it difficult for practitioners to incorporate occupant ABM in projects – one must assemble a bespoke simulation environment. Without easier integration, occupant-centric ABM might remain confined to academia. Furthermore, verification and validation standards for these integrated simulations are lacking; traditional building simulation has well-defined validation tests, but how to verify a human behavior model within those is not fully resolved.

6.6 Cross-Cluster Synthesis and Future directions

This section outlines a future research direction that spans all five of the thematic clusters. Instead of itemizing gaps cluster by cluster, we discussed thematically and methodologically to lead future work. Below, we organize these directions into major themes – from real-time adaptive systems to multi-scale integration, human-centered frameworks, AI-driven methods, and the translation of agent-based models into practice.

6.6.1 Real-Time Adaptive Systems

A unifying future direction is the development of real-time adaptive building systems that learn from continuous data streams and respond to occupant behaviors on the fly. However, as Wi-Fi tracking and occupancy and environmental data from IoT sensors multiplied, buildings now have the means to capture complex, real time data about occupancy and environmental conditions. Future research should leverage these data to generate “live” occupant models that dynamically change, or in other words, that

become occupant digital twins. Digital twins refer to a virtual model that reflect what is actually occurring when an occupant is present in a building. Such models would enable adaptive control strategies: for example, if sensor-fed simulations predict a wing of a building will be unoccupied in the next hour, the HVAC system could preemptively scale back in that zone to save energy. Real-time adaptation also means incorporating occupants into the control loop. Human-in-the-loop frameworks could let occupants provide immediate feedback or override (via smartphone apps or smart thermostats) so that systems learn individual comfort preferences and adjust accordingly. Early studies suggest that giving occupants real-time feedback (e.g. alerts during peak demand events) can actively engage them in energy-saving actions, hinting that interactive, adaptive systems can synergistically combine automation with occupant agency. Furthermore, these real time adaptive control schemes can be prototyped in living labs or pilot buildings to evaluate their performance. It can be used to refine algorithms for reliability under real-world conditions. Thus, the current gap between static building controls and dynamics can be connected with the vision of sentient buildings which can continuously self-optimize by learning from occupants.

6.6.2 Multi-Scale and Cross-Domain Integration

An additional important area is to enlarge the modelling domain in order to go beyond single buildings or single objective system, to multi-scale and cross domain integration. First, it can be viewed as a synthesis of very detailed micro scale occupant behavior models with related macro scale energy and urban systems. For instance, researchers are exploring how simulations of individual occupant decisions can connect to neighborhood or grid-level models to study impacts on peak electricity demand and renewable energy utilization. Future work should enable such interconnected simulations imagine an agent-based model of occupants in many houses responding to a utility's demand-response signal, collectively influencing grid stability and performance. Are emergent effects such as stroke peak or staggered responses possible, or possibly practical, at larger scales of the community or city? What multi-scale modeling offers is the ability to inform urban planning, where do we have to make changes to build to the

requirements and reduce our carbon footprint and also what do we need to do in order to make the whole of the city better? For example, how could we have teleworking or staggered work hours to flatten the power demand curve of a city or how the urban design (transit, public space) affects the occupancy of the buildings. Future research should be taken in the direction of cross domain integration which is a development of combining various performance goals and building subsystems in unified models. In the future, the next generation intelligent buildings will need to achieve energy efficiency concurrently with thermal comfort, indoor air quality as well as public health. The literature points to integrating ventilation and air quality data (heightened by recent public health awareness) into energy control models, so that agent-based systems optimize for occupant health and comfort as well as kilowatt-hour savings. Similarly, a holistic approach would coordinate HVAC, lighting, shading, and even on-site generation/storage through a multi-agent or multi-objective framework. Future work can develop hierarchical control architectures where, for example, one layer of agents manages overall energy and comfort targets, while lower-level agents handle specific subsystems – ensuring, say, that a battery is charged or lights dimmed in concert with HVAC adjustments to maintain comfort. In the city scale, cross domain models may connect building energy simulation with e.g. transportation or microclimate model for looking at e.g. adoption of electric vehicles at city scale affecting the building load, or heat island effects affecting the cooling behavior. The overarching integration goal is a bridge between the human building scale to grid and community scale and between domains that have traditionally been separated (energy, comfort, health, mobility). By doing so, research can better inform policies and design of operations that work under these scales; for example, the coordination of clusters of smart buildings to function as flexible grid resources or the designing of neighborhoods that naturally embrace energy conservant behaviors.

6.6.3 Human-Centered and Interdisciplinary Frameworks

Across all clusters, a prominent message is to strengthen the human-centered foundation of building performance research by drawing on interdisciplinary insights. Future models and interventions must capture the full richness of occupant behavior, which means going beyond simplified or one-size-fits-all assumptions. One must incorporate more of the psychology and social science theory into occupant simulations. Based on these suggestions, virtual occupants should be embedded with models of habit formation, lifestyle, social influence and cultural norms so that they behave and evolve over time like real people. As an example, the agent could integrate the Transtheoretical Model of behavior change or theories of social networks, in that way, the agents gradually adopt energy saving habits, or influence one another, instead of having static rules of behavior. To better broaden the behavioral repertoire of agents, simulations will be made more generalized across a wide group of occupant types by extending an agent's behavioral repertoire to include (e.g.) rebound effects (using an efficient device more because it's efficient) or comfort adaptation. Human centered design principles also recommend for recognizing diversity and equity in occupant needs. Future work should focus on the under studied populations and contexts (i.e. different climates, cultures, genders, age groups) in order to ensure that the smart building solutions are inclusive. For example, the comfort expectations of an elderly home occupant may be different or interaction with controls may be different from that of an office worker who is tech savvy or an individual from different cultural backgrounds. Accounting for these differences in models (and collecting data from a wider variety of occupants) can help avoid bias and design buildings that serve all users effectively. This also ties into an emerging emphasis on occupant well-being: aligning energy-efficiency measures with health, productivity, and comfort so that "sustainable" buildings are also genuinely supportive places for people.

Interdisciplinary method means collaborating from engineering, computer science, and social sciences in a very integrated methodological standpoint. Future research teams might be those where building scientists join hands with psychologists or sociologists or

even with economists to model behavior economics (the way occupants respond to price or incentives) or social behavior (e.g., peer influence, organizational culture). Such collaboration can yield more robust theory-informed agents and ensure that interventions (like feedback mechanisms or incentives) are grounded in evidence of what motivates people. There is also a push for participatory methods – involving actual occupants and stakeholders in the research process. To give a simple example, citizen science, where occupants install apps to log comfort or energy use (with an added element of user engagement!) could be used as a method of collecting data as well as active engagement. Even some scholars view serious games or interactive simulations in which energy scenarios can be experimented with in a virtual environment by occupants or building managers. In addition to validating models (because values shown on a screen will lead to better decisions than the output of a model), using actual human decisions can teach and orient end users with the objectives of the system.

Addressing ethical and acceptance issues is equally important, which is why being human centered is also crucial. As buildings become ever more sensors driven and more AI controlled, questions arise regarding privacy and trust. Future research should incorporate privacy-preserving techniques (for instance, federated learning that allows occupancy data to be used for model training without exposing individual identities). Likewise, transparency and explainability in control actions will be important for user acceptance – occupants and facility managers are more likely to trust an AI-driven system if it can explain its decisions in human terms (e.g., why the heating was lowered at a certain time). They could also study how to present these explanations or give user override such that efficiency and comfort are balanced. Thus, in summary, an agenda for truly human centered smart building is to enrich models with social science, maintain diversity and ethics in the design, while involving occupants as members of the technology design teams rather than sources of smartness to be optimized over.

6.6.4 AI-Driven and Hybrid Modeling Approaches

Since occupant-centric building management systems are becoming more complex, future research might adopt AI-driven and hybrid modeling techniques. One uprising topic is the fusion of data-driven machine learning approaches with prominent simulation methods. Instead of depending on purely rule-based occupant models, researchers can utilize machine learning (clustering, neural networks, etc.) to define patterns in a large dataset of occupant behavior and embed those patterns into simulations. Conversely, agent-based simulations can generate synthetic data to train or test machine learning models, creating a virtuous cycle between data and simulation. Recent work has shown the value of using big data (like Wi-Fi log traces) to constrain or inform agent behaviors, suggesting that hybrid models can outperform either approach alone. Building on this, researchers are eyeing techniques like reinforcement learning (RL) to allow virtual occupant agents to learn optimal behaviors (for comfort or energy saving) through trial-and-error in simulation. On the building control side, RL and multi-agent learning are already being tested for HVAC and lighting optimization; future efforts will likely combine these with model-predictive control (MPC) or other control theory methods to get the best of both worlds. For example, a hybrid controller might use MPC to maintain safety constraints and overall efficiency targets, while lower-level RL agents fine-tune the response in each room or for each occupant to maximize comfort adaptively. Research into safe RL – algorithms that inherently respect comfort limits or equipment constraints – is critical here so that AI can be trusted in mission-critical building operations. This might involve training agents using methods with penalty to enforce violations of the rules, or formally (constrained Markov decision processes) ensuring never to cross given bounds. One area of methodological frontier is scaling and generalizing these intelligent systems. In fact, as the number of agents (be it from devices or occupants) increases, tractability can be maintained using techniques such as hierarchical reinforcement learning or mean field approximations. Consider a two-level hierarchy in which groups of devices are coordinated by a higher level agent that simplifies complexity by way of works with clusters of agents, not hundreds individually. Similarly, the smart building controllers will become more adaptable by meta learning

approaches, an agent could be trained with many simulated buildings and then it only needs to be adaptively to a new building without further training. This kind of meta-RL or transfer learning would drastically shorten deployment time when applying algorithms to different buildings, a practical necessity for real-world adoption. Some envision libraries of pre-trained models or policies that practitioners can tap into for a head start – a concept akin to transfer learning libraries specific to building control tasks. In the simulation domain, surrogate modeling (e.g. using a fast statistical emulator in place of a computationally heavy simulation) is another technique to scale up analyses. By training surrogate models on a sample of detailed simulations, researchers can explore many more scenarios or run city-scale occupant simulations that would otherwise be infeasible. Similarly, adaptive fidelity or Level-of-Detail (LoD) methods could adjust the complexity of occupant models on the fly – using high detail only when and where it matters – to save computation. These innovations in AI and hybrid modeling will allow future researchers to tackle problems of greater complexity (more people, more devices, longer timescales) with manageable computational cost, and with improved predictive accuracy.

6.6.5 Tools, Standards, and Implementation in Practice

Finally, a future direction will be to move research towards practice by developing superior tools, standards and real-world validations for occupant or agent-based approaches. The sophisticated models and algorithms discussed can only have real impact on building designers, engineers, and policymakers if they can be accessed. One area of work is building user-friendly software integration. Rather than requiring every practitioner to be an expert in agent-based modeling, researchers are creating libraries and plugins that embed occupant behavior models into familiar building simulation and design tools. For example, a future energy modeling software might allow users to toggle on an “occupant behavior module” to simulate different occupancy scenarios, or a dashboard might use an underlying agent model to forecast how occupants would react to a new energy policy in an office. Developing open standards for representing occupant behaviors (analogous to Building Information Models for physical data) will facilitate this

integration. If the community can agree on common ontologies or data formats for occupant profiles and actions, different tools and platforms could interoperate – meaning an agent-based model developed by one group could be plugged into another’s building performance simulation seamlessly. Initial progress in this direction involves extending such semantic models, such as Project Haystack or Brick Schema, to include the class of occupant related information. Validation of tools is also necessary for credibility, along with tool integration. It has been suggested that shared datasets and challenge problems are needed to test occupant behavior models in much the same way as benchmark datasets in other fields. By calibrating models to real world data and perform standard scenario testing, both the accuracy and the robustness of these methods to standard scenarios can be built before field deployment. It also includes showing and refining ways to bridge to practice in actual buildings. Both industry and academia see value in living labs – instrumented buildings or apartments where occupant-centric control strategies can be deployed and observed under everyday conditions. Moving from simulation-only studies to long-term field trials will uncover practical challenges (sensor failures, occupant discomfort, maintenance issues) that are often overlooked in silico. For future research, this translates into forming partnerships with building operators and technology firms to pilot new control frameworks (for example, a multi-agent HVAC control system) in actual workplaces or homes. Such trials allow iterative improvement of algorithms with feedback from facility managers and occupants, and they provide essential evidence of energy savings, comfort outcomes, and reliability to convince broader industry adoption. With these efforts, standardization and policy integration hand in hand. Occupant-centric research should be sketched in building codes and utility programs and especially into the design of technical measures: for example, the idea of having stochastic occupant models built in energy compliance calculations or creating demand response programs with some notion of what humans will do. Researchers can play an active role in seeing that regulations and design achieve an awareness of occupant behavior variability, making buildings more resilient to how people do use them.

7 Conclusion

The thesis provides a comprehensive review of the state-of-the-art research on occupant-centric modeling, especially agent-based modeling (ABM) in buildings. It synthesizes findings across a broad range of interdisciplinary fields. Through a systematic literature review and bibliometric clustering, it divided the selected articles into five thematic clusters. Each cluster describes unique themes, models and theories implication, and methodologies.

Cluster 1 is about Human-Centric Behavioral Modeling. It highlighted that occupant behavior is an important factor influencing building energy outcomes. The core theme of this cluster shows if we use stochastic assumptions for occupancy instead of static assumptions, the gap between predicted and actual energy use is significantly reduced. However, these occupant behavior models often remain context-specific and lack generalizability. So, future work must focus on validating and extending these models across different climates, cultures, and building types, as well as developing methods to quantify uncertainty in behavioral simulations.

Cluster 2 is about Intelligent Building Energy Management and Occupant-Centric Control which involves occupancy-based HVAC controls and multi-agent control frameworks. The cluster's findings revealed significant energy savings (often 10–30%) by adjusting operation schedules in response to occupancy patterns or preferences. Yet, an important limitation identified is the lack of real-world implementation. So, robust field experiments and pilot projects are needed to verify performance and uncover practical challenges (such as occupant acceptance or system reliability issues). The cluster also points out that current intelligent controls simplify occupant behavior, which can lead to suboptimal or sometimes flawed control decisions. Thus, it is suggested that embedding more nuanced occupant behavior models into control algorithms (potentially borrowing from Cluster 1 and 3) is a promising direction to improve outcomes.

Cluster 3 (Occupant-Centric and Personalized Control Utilizing Behavioral Science) brought a more human-centered perspective, integrating theories and methods from psychology and social science into building performance modeling. The contributions from this cluster are twofold. First, it provides evidence that personalized control strategies, such as individualized thermal comfort profiles or occupant engagement programs, can lead to improved comfort and energy behavior. It suggests tailoring building operations to actual occupant preferences rather than one-size-fits-all settings. Second, it introduces behavioral theories (for example, the Theory of Planned Behavior or social influence models) into the discourse of energy modeling, arguing that understanding occupant motivation and decision-making processes can substantially enhance predictive models and intervention strategies. A salient finding is that models informed by behavioral science portray occupants as active decision-makers who can learn, adapt, or even rebel against building systems, rather than static inputs. This cluster, however, also revealed methodological gaps, including short study horizons and limited diversity of study contexts. To fully leverage behavioral science, future research should pursue longer-term studies to capture habit formation and decay and expand to varied building types and cultural settings.

In Cluster 4 (Multi-Agent Intelligent Control and Optimization), the focus was on advanced computational techniques, especially multi-agent systems and reinforcement learning for optimizing building energy use while considering occupants and even grid interactions. The cluster's findings demonstrate the technical feasibility and potential of these methods: for instance, multi-agent reinforcement learning has been shown to autonomously discover control policies that achieve meaningful energy savings and load shifting, all while respecting occupant comfort constraints. However, critical gaps temper this optimism. The most important one of these: AI-driven approaches have been proven only in simulation or controlled lab settings. So, actual deployment in real buildings with occupants is the next hurdle which is raising considerations of algorithm reliability, cybersecurity, and occupant trust in automated decision-making. Another identified limitation is scalability; as control problems move from single buildings to campuses or

urban scale (with potentially thousands of agents or millions of data points), computational and coordination challenges grow. The cluster calls for hybrid approaches that combine learning algorithms with domain knowledge (e.g., incorporating known physical constraints or using hierarchical control structures) to ensure solutions remain tractable and safe.

Cluster 5 highlights the importance of interdisciplinary and human-centric approaches in occupant modeling, moving beyond energy efficiency to include factors like social interaction, movement, and user experience. Techniques such as fuzzy cognitive mapping and participatory co-design revealed how buildings affect, and are affected by, human behavior in complex ways. A key insight is the need for holistic integration: current models often isolate specific behaviors, but future approaches should unify thermal comfort, movement, appliance use, and social dynamics within a single framework.

Synthesizing across all clusters, the thesis argues that the future lies in integrative frameworks—where stochastic models, behavioral insights, multi-agent control, and participatory validation come together. Leveraging ABM for rich scenario design and RL for adaptive control could create more robust occupant-centric models. Besides recognizing limitations such as reliance on literature and lack of unified metrics, the work provides a clear roadmap for advancing occupant-centric modeling. It could lead to buildings that are not only more energy-efficient, but also more adaptive, inclusive, and supportive of occupant well-being.

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