

Modelling heterogeneous comfort adaptive occupant behaviours in building performance simulation of office buildings: A choice-based co-simulation approach

HAN LI

Bouwstenen 449

Modelling heterogeneous comfort-adaptive occupant behaviours in building performance simulation of office buildings: A choice-based co-simulation approach

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Technische Universiteit Eindhoven, op gezag van de rector magnificus prof.dr. S.K. Lenaerts, voor een commissie aangewezen door het College voor Promoties, in het openbaar te verdedigen op woensdag 4 november 2026 om 13:30 uur

door

Han Li

geboren te Xi'an, China

Dit proefschrift is goedgekeurd door de promotoren en de samenstelling van de promotiecommissie is als volgt:

voorzitter:	prof.dr.ir. M.C.J. Hornikx
1e promotor:	prof.dr.ir. H.A.J.A. Appel-Meulenbroek
2e promotor:	prof.dr.ir. T.A. Arentze
copromotor:	dr.ir. P. Hoes
leden:	dr.ir. M.G.L.C. Loomans
	prof.dr.ir. A.D.A.M. Kemperman
	prof.dr.ir. P.M. Bluyssen (Technische Universiteit Delft)
	prof. G. Ciaramella (Politecnico di Milano)

Het onderzoek of ontwerp dat in dit proefschrift wordt beschreven is uitgevoerd in overeenstemming met de TU/e Gedragscode Wetenschapsbeoefening.

Acknowledgements

“The Tao that can be told is not the eternal Tao.”

Over the course of this PhD, I have gradually come to appreciate the humility contained in these words. The world is far more complex than any theory, model, or set of words can fully capture. Our understanding of it will always remain partial and imperfect.

Perhaps the same is true of people. We give names and definitions to things because they help us make sense of the world, as no reality can be fully contained within a definition.

People change, environments change, and our understanding of one another changes with them. We are all incomplete, imperfect, and yet still becoming, including the person writing these lines.

A PhD has taught me that there is value not only in seeking answers, but also in recognising the limits of our answers. Imperfection is not necessarily something to eliminate, but something to understand, accept, and continue growing through.

What has made this journey meaningful, then, is not perfection, but the people I have met along the way, those who walked beside me, questioned me, taught me, supported me, challenged my assumptions, tolerated my shortcomings, and helped me see a little more than I could have seen alone.

As someone once put it, *“The test of our progress is not whether we add more to the abundance of those who have much, it is whether we provide enough for those who have too little.--R”* From the sum of our infinite choices, one such future is built on kindness, trust, and mutual understanding. Driving without question towards a light we cannot see, not just for those we hold close, but for those we will never meet.

To all those who have been part of my journey, I am deeply grateful.

And so, the story carries on, still unfinished and still being written.

I will see you again, somewhere in the future.

Summary

Buildings account for a substantial share of global energy consumption, yet a persistent gap remains between actual and predicted building performance across comfort and energy outcomes. Among the various influential factors, occupant behaviour remains less comprehensively understood than technological innovation, owing to its inherently dynamic, stochastic, and complex nature. Despite growing recognition of its importance, occupant behaviour is still represented in building performance simulation primarily through static schedules or simplified assumptions, thereby limiting the behavioural realism of simulation outcomes.

The key challenge in occupant behaviour modelling is to adequately represent the complexity and interdependencies of comfort-related behaviour, including how to cluster multiple contextual factors or inputs into a single equation, how to treat those factors that influence model behaviour independently, and how to account for multiple simultaneous and/or sequential actions that further increase model complexity. Therefore, the aim of this dissertation is to address how occupant behaviour can be modelled comprehensively and dynamically coupled with building performance simulation tools to examine and enhance predictive realism and design relevance.

This research builds on interdisciplinary theoretical frameworks by combining the Adaptive Comfort Theory and the Two-Process Theory of Perceived Control. Through a discrete-choice experiment, occupant behaviour is interpreted as a set of trade-offs between environmental control action(s) and personal adaptive behaviour strategies under varying physical, social, and contextual constraints.

The first study was conducted to establish a common ‘language’ that can be understood by the major disciplines involved, thereby facilitating knowledge exchange and the synergy process between social/behavioural sciences and engineering science. Through a PRISMA-based systematic interdisciplinary

literature review, this study synthesises how occupant behaviour is conceptualised across both fields, resulting in a structured definition of occupant behaviour in offices and a classification of behaviour types, influential factors, and applied theoretical frameworks/constructs.

Using a multi-response discrete choice experiment design, the second study elicits preferences for multiple comfort-adaptive actions under multimodal (dis)comfort scenarios. The average preference for individual and paired actions, as well as preference heterogeneity among individuals, is examined, and occupant adaptive actions are modelled as a (utility) function of building characteristics, contextual conditions, environmental factors, and personal attributes.

Using the same experiment design, the third study provides further insights into the occupants' choice preferences. Through a model-based clustering approach (i.e., latent class analysis) distinct patterns of comfort adaptive actions among three similar clusters of office employees are identified and labelled: Strong reactors, Context sensitives, and Minimalists.

The fourth study extends the choice-based behavioural model into an agent-based framework, enabling the simulation of individual-level decisions in shared office environments. That model is then dynamically coupled with a building performance simulation tool (EnergyPlus) through a Functional Mock-up Unit (FMU) based co-simulation architecture. This approach enables a better representation of occupant behaviour in building performance analysis. Its application is demonstrated through various use cases.

Overall, this research contributes to interdisciplinary occupant behaviour research in office settings by providing an integrated conceptualization of office occupant behaviour, introducing a probabilistic, utility-based representation of comfort-adaptive actions that captures behavioural heterogeneity and social context, and demonstrating a scalable co-simulation framework that integrates occupant

decision-making directly into building performance simulation. For building practitioners, the findings support occupant-centric building design and operation by enabling more realistic evaluation of control alternatives and explicit trade-offs between energy and comfort. While this research is limited by its focus on Dutch office workers, a restricted set of comfort domains, and validation within a single case-study building, it provides a foundation for future work on broader empirical validation, additional comfort domains and adaptive actions, and the modelling of more complex shared-control dynamics across building types and climates. The results advance the development of behaviourally informed, simulation-aided design approaches for sustainable office buildings.

Contents

Acknowledgements 3

Summary 4

Contents 7

List of Figures 11

List of Tables 13

List of Abbreviations 14

1. Introduction 17

1.1. Background and Motivation 17
1.2. Research Questions 20
1.3. Research Philosophy 21
1.4. Research Design 22
1.5. Outline 24

2. Conceptualizing Sustainable Occupant Behaviour in Offices from an interdisciplinary point of view: A Systematic review 29

2.1. Introduction 29
2.2. Background information 30
2.3. Approach of the review 35
2.4. General findings of the review 36
2.5. Occupant behaviour from a multi-disciplinary point of view 40
2.6. Discussion 62
2.7. Conclusion 65

3. Experiment design and data collection 67

3.1. Overview of the research design 67
3.2. Discrete choice experiment 68

3.3. Conceptual and theoretical foundation 71
3.4. Behaviours of interest 71
3.5. Selection of environmental attributes and attribute levels 73
3.6. Generation of choice tasks and randomness control 78
3.7. Choice task 80
3.8. Cross-sectional survey-section 82
3.9. Survey data collection 85
3.10. Conclusion 86
4. Revealing occupants' preferences for comfort adaptive actions in open-plan offices 89
4.1. Introduction 89
4.2. Model development 89
4.3. Results 93
4.4. Discussion 104
4.5. Conclusion 107
5. Profiling office workers' comfort-related adaptive actions: a latent class analysis 109
5.1. Introduction 109
5.2. Model estimation (LCA) 109
5.3. Model generation and evaluation 112
5.4. Results & Discussion 113
5.5. Conclusion 121
6. Development and alignment of a co-simulation framework for advanced occupant behaviour in building performance simulation 123
6.1. Introduction 123
6.2. Baseline EnergyPlus model with conventional occupant behaviour modelling 124
6.3. EnergyPlus model with advanced occupant behaviour modelling 126
6.4. Conclusion 143

7. Demonstration of the advanced model 145
7.1. Introduction 145
7.2. Use Case 1: Annual energy and IEQ comparison between baseline-advanced models 146
7.3. Use Case 2: Zone-level comparison between comparable rooms 153
7.4. Use Case 3: Daily human-building interaction and stochastic variation 160
7.5. Use Case 4: Sensitivity analysis of control and decision rules 169
7.6. Discussion 174
7.7. Conclusion 177
8. Discussion and conclusion 179
8.1. Summary of key findings 179
8.2. Contributions and Implications 181
8.3. Limitations and Future Research 186
References 195
Curriculum vitae 220
Publications 221
Appendix A – Latent class model results 223
Table 21 Summary of the latent class model 223
Appendix B – Survey 238
Appendix C – Comfort and energy trade-off data 253
Table 22 Distribution of cooling-prone commands during cooling period 253
Table 23 Ranking of zones by highest increase in cooling demand 254
Appendix D – Use case 1 extra material 262
Use Case 1 Heatmap 262
Use Case 1 KPIs 267
Appendix E – Use case 2 extra materials 272

Figure 34 Weekly lighting and shading setpoint for west-facing meeting zone 272
Figure 35 Weekly lighting and shading setpoint for east-facing meeting zone 273

List of Figures

Figure 1 Road Map 23
Figure 2 The PRISMA approach 36
Figure 3 Number of published papers in each year 37
Figure 4 Geographic Dispersion of the reviewed papers 38
Figure 5 Network Visualization of keywords 39
Figure 6 Example of a choice task without proposed condition 81
Figure 7 Example of a choice task in the 'proposed' condition 82
Figure 8 Dependent variable consolidation 90
Figure 9 Carpet plot 116
Figure 10 Baseline model approach 125
Figure 11 Advanced model approach 128
Figure 12 Baseline-aligned default rules in advanced model 131
Figure 13 Floor plan of case study building 146
Figure 14 Thermal comfort KPI for core working hours - 9 AM to 5PM (summed hours of all ABM linked zones on the floor) 152
Figure 15 IEQ discomfort summary 153
Figure 16 Weekly temperature setpoint predictions for west-facing meeting zone 155
Figure 17 Weekly temperature setpoint predictions for east-facing meeting zone 156
Figure 18 Weekly natural-ventilation setpoint predictions for west-facing meeting zone 157
Figure 19 Weekly natural-ventilation setpoint predictions for east-facing meeting zone 158
Figure 20 Daily lighting and shading control prediction for single meeting zone in summer 162

Figure 21 Daily cooling setpoint prediction for single meeting zone in summer 164
Figure 22 Daily window control prediction for single meeting zone in summer (From top to bottom including CO_2 concentration level, occupancy level, natural ventilation setpoint, window choice) 166
Figure 23 Daily control prediction summary of all control options for single meeting zone in summer (From top to bottom including lighting, shading, natural-ventilation, and cooling setpoints) 167
Figure 24 Boxplots energy consumption 169
Figure 25 Effective behavioural action status by voting rule 172
Figure 26 Threshold-met rate by room type and voting rule 173
Figure 27 Three months heatmap for meeting room 301, including CO2, indoor air temperature, delta t, and natural-ventilation command state 265
Figure 28 Three months heatmap diagnostic for meeting room 335, including CO2, indoor air temperature, delta t, and natural-ventilation command state 266
Figure 29 CO_2 exceedance thresholds 267
Figure 30 whole building daylighting conditions 268
Figure 31 Excessive daylight/glare conditions by orientation 269
Figure 32 Artificial lighting KPI 270
Figure 33 Artificial lighting discomfort by orientation 271
Figure 34 Weekly lighting and shading setpoint for west-facing meeting zone .. 272
Figure 35 Weekly lighting and shading setpoint for east-facing meeting zone ... 273

List of Tables

Table 1 Current OB classification in different papers 32
Table 2 Type of energy-related occupant behaviour in office buildings 41
Table 3 Influential factors for occupant behaviour in office environments 50
Table 4 Summary of nine theoretical frameworks 58
Table 5 Behaviours of interest 73
Table 6 Attributes and attribute levels that are systematically varied in the experiment 76
Table 7 Pre-defined groups with different levels of communication and social expectation 77
Table 8 Distribution of the "Proposed" condition 80
Table 9 Cross-sectional survey question 83
Table 10 Social-demographic and current workplace characteristics 94
Table 11 Model comparison 95
Table 12 Base utility, pair-wise interaction, and social effect 96
Table 13 Contextual and climatic attributes 100
Table 14 Indoor environment quality indicators 101
Table 15 Model fit 113
Table 16 Classification diagnostic indexes 115
Table 17 Prediction of membership with merged control availability 120
Table 18 Yearly whole-building energy use comparison between the baseline and the advanced model 147
Table 19 Number of active agents to trigger the ABM signal 170
Table 20 Annual energy consumption with different ABM control thresholds 171
Table 21 Summary of the LC model 223
Table 22 Distribution of cooling-prone commands during cooling period 253
Table 23 Ranking of zones by highest increase in cooling demand 254

List of Abbreviations

FMU	Functional Mock-up Unit
LCA	Latent Class Analysis
BPS	Building performance simulation
HVAC	Heating ventilation and air conditioning
FMI	Functional mock-up interface
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
DCE	Discrete choice experiment
IEQ	Indoor environmental quality
OB	Occupant behaviour
SOBO	Sustainable occupant behaviour in offices
TPB	Theory of planned behaviour
AC	Air conditioning
NAM	The norm activation model
MOA	The motivation, opportunity, and ability model/framework
PBC	Perceived behaviour control
DNAs	The driver-needs-action-system framework
TTPC	Two-step Theory of Perceived Control
RPML	Random Parameter Mixed logit
MNL	Multinomial logit
SD	Standard deviation

AIC	Akaike information Criterion
BIC	Bayesian Information Criterion
AvePP	Average posterior probability
OCC	Odds of correct classification ratio

1. Introduction

1.1. Background and Motivation

Both the Paris Climate Agreement and the United Nations' 2030 Sustainable Development Agenda underscore that achieving a sustainable future through climate change mitigation is an imminent topic that needs to be addressed. Globally, buildings contribute approximately 20% to 40% of total energy consumption and carbon emissions, driven by population growth and the increasing demand for service and comfort [1]. Building-related carbon emissions can be attributed to three main sources: fossil fuel-based heating systems, grid-electricity usage, and the life cycle impact assessment across materials and systems [2]. In the building sector, life cycle assessment is applied to evaluate the impact on the natural environment, natural resources, and human health across the production, construction, operation, and end-of-life stages [3]. Though acknowledged, human-related aspects in existing studies are largely focused on how technical design mitigates occupants' exposure to environmental stressors such as odour and noise, leaving human involvement, particularly from a behavioural perspective, largely underexplored.

The perception of reality is often more influential than reality itself. Human behaviour is not a direct or deterministic response to physical conditions but emerges from the interaction between environmental stimuli, comfort/safety needs, social context, and perceived control/knowledge [4]. Comfort-adaptive occupant behaviours are those actions through which occupants actively respond to perceived (dis)comfort by adjusting the indoor environment (e.g., windows, blinds, thermostats, lighting) and/or by adopting personal adaptive strategies (e.g., adjusting clothing level or changing activities) [5]. These behaviours are inherently

dynamic and context dependent. Hence, people behave differently under similar conditions, both inter- and intra-personally.

Within the built environment, such behavioural dynamics have been recognized as one of the major influential factors causing fluctuations in building performance simulation (BPS) outcomes [6]. As a design decision support tool, BPS faces a challenge in that predicted and measured building performance rarely align with each other, in terms of both comfort and energy [7]. Literature attributes this discrepancy in part to occupant behaviour, due to oversimplified assumptions such as static schedules and predefined events [8].

Unlike climate and/or heating ventilation and air-conditioning (HVAC) systems and their efficiency, which are well-studied, occupant behaviour lacks rigorous methods for proper definition and modelling in BPS that capture its stochastic, heterogeneous, and context-dependent traits [9], [10]. More recently, occupant behaviour research has progressively introduced the concept of occupant-centric building design and operation, which takes occupant needs into consideration, both for comfort and health, and uses explicit occupant models to represent the human-building interactions [11]. While this shift moves beyond purely technology-oriented approaches, many existing models remain limited in their ability to represent the full complexity of occupant behaviour. Simplified representations often assume stable behavioural patterns, focus on isolated comfort domains, and neglect social and contextual influences, thereby constraining their capacity to capture realistic behavioural patterns in dynamic and multidimensional indoor environments.

Such simplified behavioural representations lead to a static, homogeneous, and isolated treatment of occupant-related information [12]. Occupant behaviour does not necessarily repeat the same patterns, but instead different people respond differently to the same environment. Empirical evidence suggests that under

identical indoor thermal conditions, people show diverse window opening/closing behaviours [13]. Such heterogeneity reflects differences in comfort preferences, tolerance ranges, habits, and social considerations, suggesting that a one-size-fits-all representation of occupants is insufficient for an accurate simulation. Moreover, multiple comfort-related drivers and adaptive actions often co-exist and happen simultaneously, however, conventional models handle them separately [5], [10], [14]. An occupant's decision is rarely a single-factor or resolved through a single behaviour, but instead, often, it involves multiple options under various environmental, contextual, and social stimuli. Among these, contextual conditions refer to factors such as location within the building, task type, time of day, and organisational policies, while social conditions include the presence of others, shared control conditions, and perceived social norms. These contextual and social dimensions play a crucial part in office environments, where occupants frequently share spaces and building controls. Yet how such environmental, contextual, and social conditions jointly shape comfort-adaptive behaviour remains unclear.

With that in mind, researchers have applied new methodologies and developed tools for practitioners to incorporate diverse occupant profiles and behaviours into design-decisions and performance assessments. Such approaches require input from both social-behavioural science and engineering science. Despite the technological advances, from a social science perspective, occupant behaviour research is still not well supported with a coherent and transferable theoretical construct/approach. Existing models are often difficult to compare or generalise, as they are developed by different research groups using heterogeneous variables, data collection methods, and analytical approaches. For simplicity, behaviour models often depict occupants as rational, independent individuals who formulate their dispositions and respond to external environment variables based primarily on internal attitudes. This assumption overlooks the dynamic, situational, and socially embedded nature of behaviour as it occurs in real office environments.

Furthermore, many models implicitly assume that occupant types are stable characteristics across time, building types, and system configuration [8], [10]. Behavioural models are often treated either as behaviouristic mechanisms designed primarily to generate energy-use outputs, in which case the underlying psychological drivers are considered irrelevant or not explicitly represented, or as abstract constructs that only loosely correspond to psychological realities perceived by occupants. As a result, the identification of behavioural profiles with psychological states is often incidental rather than theoretically grounded. This conceptual ambiguity can limit the interpretability, transferability, and design relevance of occupant behaviour models in building performance simulation.

1.2. Research Questions

With the above background, this dissertation aims to address the methodological and conceptual gaps in modelling heterogeneous, context-dependent comfort-adaptive occupant behaviours. By focusing on modelling comfort-adaptive occupant behaviour in office buildings, and explicitly accounting for behavioural heterogeneity, multi-domain comfort trade-offs, and dynamic interactions between occupants and building systems. By combining behavioural theory, discrete-choice modelling, and co-simulation with building performance tools, the behavioural realism, predictive accuracy, and design relevance of building performance simulation can be enhanced.

This research is framed with several sub-questions to address the main question of this study: **How can heterogeneous, context-dependent comfort-adaptive occupant behaviours in office environments be modelled and dynamically integrated into building performance simulations to improve their behavioural realism?**

The following sub-research questions are seen as the milestones in addressing the main research question:

RQ1: How are occupant comfort-adaptive behaviours conceptualised across social-behavioural and building performance simulation sciences, and which behaviour types and influencing factors are most relevant for office environments?

RQ2: Which preferences do office occupants show in responding to different multi-modal (dis)comfort scenarios with varying environmental, contextual, and social conditions, and how can these be modelled best?

RQ3: To what extent does heterogeneity in occupant preferences give rise to distinct behavioural profiles?

RQ4: How can the heterogeneity be modelled and integrated into a BPS software?

RQ5: How does the inclusion of occupant behaviour in a BPS model affect key performance indicators compared to a baseline model with simplified occupant behaviour inclusion?

1.3. Research Philosophy

This research adopts a post-positivist and pragmatist philosophical stance, informed by elements of critical realism. It assumes that observable behavioural choices in human-building interactions reflect underlying preference structures and decision mechanisms that exist independently of the researcher, yet can only be imperfectly inferred through empirical modelling. Human decision-making in socio-technical systems is therefore understood as structured but heterogeneous, where observable choices provide indirect evidence of latent preference mechanisms.

From an ontological perspective, this study assumes that behavioural patterns in office environments are not random but shaped by underlying psychological, contextual, and social mechanisms. These mechanisms are considered real, although not directly observable, and they manifest through probabilistic choice behaviour. Behavioural heterogeneity is therefore treated as an inherent feature of

reality rather than statistical noise, reflecting differences in preferences, constraints, and contextual influences among individuals.

From an epistemological perspective, this study follows a post-positivist approach, recognising that knowledge about behavioural processes is necessarily provisional and model-dependent. Quantitative models such as mixed logit and latent class models are used to infer unobserved preference structures from stated choice data. These models do not claim to reveal absolute truths about human behaviour, instead, they provide probabilistic approximations that help uncover patterns in decision-making and behavioural diversity.

Methodologically, the research adopts a pragmatic orientation, prioritising explanatory power and practical relevance. Analytical approaches are combined with behavioural theories to bridge behavioural insights with system-level modelling, drawing on methods such as discrete choice modelling, latent class analysis, and agent-based simulation. This methodological integration enables the analysis of heterogeneous behavioural responses and their implications for building performance and sustainability outcomes.

By integrating behavioural theory with empirical modelling and simulation, this research positions itself at the intersection of engineering, behavioural science, and socio-technical systems research. The approach emphasizes interpretability, empirical grounding, and policy relevance, aiming to improve the representation of occupant behaviour in building performance simulation and to support more realistic assessments of sustainability transitions in the built environment.

1.4. Research Design

To address the main research question and to show how each sub-question is inherently connected and contributes to the main research question, a roadmap with four key sections is presented in Figure 1. Each section corresponds to one of the chapters of this thesis, providing a replicable pathway to address office occupant

behaviour in BPS research, combining established theoretical constructs (e.g., adaptive comfort theory and the two-process theory of perceived control) with advanced analytical approaches (e.g., mixed logit model, latent class model).

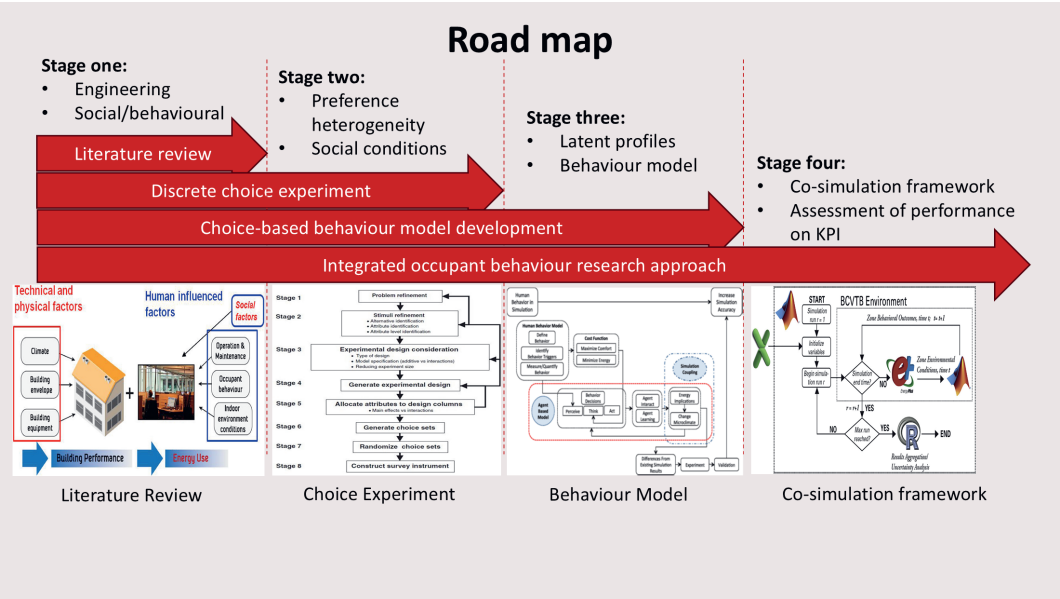


Figure 1 Road Map

To address RQ1, an interdisciplinary systematic literature review is conducted to bridge the knowledge and information gap between workplace social science and the engineering science of BPS, and to identify and categorise the different types of occupant behaviour, the influential factors that drive occupant behaviour, and the theoretical constructs applied for explaining occupant behaviour in buildings and their application.

Based on the results of RQ1, an online survey was designed and distributed through a Dutch panel company among Dutch office workers who follow a hybrid working schedule. Apart from the general questions, a multi-response stated choice experiment was also included in the survey to facilitate exploration of cooperative intentions of individuals in shared environments, and then to identify and model the

preference heterogeneity among individuals through a multinomial logit and a mixed logit model (RQ2).

In addition, the same data were used to create distinct occupant profiles based on identified heterogeneity through latent class analysis (RQ3). In RQ4, the developed latent class model was further transformed into an agent-based choice model and linked with BPS software (e.g., EnergyPlus). Using a functional mock-up interface (FMI) standard based FMU, a coupling framework was established between the choice model and EnergyPlus. With the established coupling framework, a case study with multiple use cases was presented to address RQ5.

The coupling framework was applied to one floor of a university building in the Netherlands, and comparisons were made between simplified occupant behaviour model and choice-based model, in terms of overall heating and cooling demand per annual, the indoor environmental quality on air quality, daylight, and thermal comfort.

1.5. Outline

In Chapter 2, a systematic interdisciplinary literature review was conducted which synthesises insights from social-behavioural sciences and BPS research. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) -based review standard complemented by snowball effect, in total, 134 peer-reviewed journal articles on energy-related occupant behaviour in office environments were analysed. The review reveals that the two research domains conceptualised comfort-adaptive behaviour differently. Social-behavioural sciences predominantly frame occupant behaviour as attitudinal or norm-driven, often pro-environmental, whereas BPS research emphasises observable, comfort-restorative adaptive actions. By reconciling these perspectives, the study identifies four core behaviour types relevant to offices: occupancy-related behaviour, adaptive behaviour, non-adaptive behaviour, and personal adaptive behaviour. Meanwhile, it

classifies relevant key influencing factors into building characteristics, environmental, contextual, and personal categories. The findings further show that comfort-adaptive behaviours in offices are primarily driven by dynamic contextual constraints and access to control, rather than by stable pro-environmental intentions alone. This highlights the need for interdisciplinary conceptualisations that explicitly integrate comfort, control, and situational factors in behavioural modelling.

In Chapter 3, detailed research approaches were presented, including the theoretical framework used, discrete choice experiment design, and survey development along with data collection.

In Chapter 4, building on the findings of Chapter 2, an occupant-centric stated choice experiment approach to address RQ2 was implemented. By combining a cross-sectional survey with a discrete choice experiment (DCE) in which 643 office employees evaluated hypothetical open-plan office scenarios characterized by multiple indoor environmental quality (IEQ) indicators (e.g., thermal, air quality, lighting, and daylight), contextual factors (e.g., outdoor environment, occupancy level, task and location), and explicit social cues in the form of colleagues' proposed actions. Choice data were collected through a panel company and analysed using multinomial and mixed logit models, allowing simultaneous modelling of multiple adaptive actions and preference heterogeneity. The results show that occupants' comfort-adaptive responses are highly situational and individuals often prefer combinations of environmental and personal adaptive measures when facing severe discomfort, particularly under high temperatures and poor air quality. Importantly, social context plays a decisive role in shared office environments, as occupants exhibit strong cooperative tendencies by aligning with colleagues' proposed control actions, which reduces the likelihood of additional personal adaptation. The modelling framework demonstrates how multi-modal discomfort responses and social interactions can be explicitly represented within a stochastic utility-based

model, offering a flexible foundation for integrating realistic occupant behaviour into building performance simulation.

Chapter 5 further explores the heterogeneity of preferences and addresses RQ3, which explicitly models heterogeneity in occupants' comfort-adaptive behaviour through a model-based clustering approach. Using data collected in the previous stage, this study applies latent class analysis within a multinomial logit framework to identify distinct behavioural profiles based on occupants' joint preferences for multiple adaptive actions under multi-modal (dis)comfort situations. Rather than clustering occupants on reported satisfaction or deterministic similarity metrics, the approach probabilistically segments individuals according to observed trade-offs between environmental and personal adaptive controls. The results revealed three behavioural profiles: Strong Reactors, Context Sensitives, and Minimalists, with different sensitivity to indoor environmental quality, contextual constraints, and willingness to intervene in the environment. Class-specific behavioural patterns (utility difference) show that heterogeneity is not only a matter of response intensity but reflects qualitatively different adaptive strategies, ranging from active environmental control to context-dependent cooperation and passive tolerance. Further analysis indicates that class membership is only weakly explained by socio-demographics, with occupation, office size, and conscientiousness emerging as the most relevant membership predictors. These findings demonstrate that preference heterogeneity in offices gives rise to distinct, interpretable behavioural profiles and that a choice-based clustering approach provides a statistically grounded and behaviourally realistic way to represent such heterogeneity for occupant-centric and simulation applications.

Chapter 6 addresses the technical implementation and alignment of the choice-based co-simulation framework. Building on the latent class model developed in Chapter 5, this chapter translates occupants' class-specific preferences into an agent-based behavioural model and integrates it with EnergyPlus. The chapter first

introduces the baseline EnergyPlus model, in which occupant behaviour is represented through conventional schedules and simplified control assumptions. It then presents the advanced model, where individual agents are assigned behavioural profiles and make probabilistic choices among comfort-adaptive actions based on environmental, contextual, and occupancy-related inputs. These choices are translated into zone-level control commands for windows, blinds, thermostats, and lighting. To ensure comparability between the baseline and advanced models, both models use the same underlying physical building model and comparable default operational assumptions, with the main difference limited to occupant-related control logic. The chapter also describes the co-simulation structure, command-transfer process, fallback rules, and logged variables used to verify the alignment and trace the source of control actions. In this way, Chapter 6 provides the technical foundation for applying the advanced model in the following chapter.

Chapter 7 applies the advanced model to a case-study office floor and evaluates how the choice-based representation of occupant behaviour affects building performance and reveals human-building interaction patterns. The chapter presents four use cases. Use Case 1 compares annual energy demand and indoor environmental quality indicators between the baseline and advanced models. Use Case 2 examines zone-level differences between comparable rooms to identify how spatial characteristics, such as orientation, impact behavioural-control patterns. Use Case 3 investigates daily human-building interaction patterns and stochastic variation through multiple simulation seeds. Use Case 4 tests the sensitivity of simulation outcomes to different zone-level decision rules for shared control. Together, these use cases demonstrate how the choice model can be applied within building performance simulation to represent occupant behaviour in a more stochastic and realistic way. Instead of relying on deterministic and fixed schedules or predefined control assumptions, the advanced model allows occupant actions to emerge probabilistically from environmental, contextual, and social conditions. The

chapter therefore examines how this alternative representation of occupant behaviour influences energy demand, indoor environmental quality, zone-level control patterns, daily human-building interactions, and shared-control decision outcomes.

Chapter 8 synthesises the findings and contributions of the dissertation and reflects on the overall research question. In particular, the chapter explains how the research contributes to a more behaviourally explicit representation of comfort-adaptive occupant behaviour in building performance simulation. Finally, the chapter discusses the limitations of the research and proposes directions for future work, including broader empirical validation, the inclusion of additional comfort domains, more detailed personal adaptive actions, further testing of decision rules in shared spaces, and application of the framework to other buildings and climate contexts. The chapter concludes by positioning the proposed choice-based co-simulation approach as a methodological pathway for developing more occupant-centric, behaviourally informed, and design-relevant building performance simulations.

2. Conceptualizing Sustainable Occupant Behaviour in Offices from an interdisciplinary point of view: A Systematic review[1]

2.1. Introduction

This chapter presents the first component of the dissertation and addresses research question one, which focuses on how occupant comfort-adaptive behaviour is conceptualised across different research disciplines. The objective of this chapter is to establish a common conceptual foundation for understanding occupant behaviour in office environments by synthesizing insights from both social-behavioural sciences and building performance simulation research.

While engineering research often focuses on observable interactions between occupants and building systems, social-behavioural research emphasises psychological drivers and decision-making processes. These disciplinary perspectives have developed largely in parallel, leading to differences in terminology, theoretical frameworks, and methodological approaches. As a result, a coherent and transferable understanding of occupant behaviour in office environments remains less explored.

To address this gap, Chapter 2 presents a systematic interdisciplinary literature review that identifies key behaviour types, influential factors, and theoretical frameworks used in occupant behaviour research. The findings provide the conceptual foundation for the empirical studies presented in the following chapters of this dissertation.

[1] This Chapter is adapted from:
H. Li, R. Appel-Meulenbroek, T.A. Arentze et al., Conceptualizing sustainable occupant behaviour in offices from an interdisciplinary point of view: A systematic review, Energy and Built Environment, https://doi.org/10.1016/j.enbenv.2024.08.004

2.2. Background information

On a global scale, the building sector accounts for about 28% of total energy-related CO_2 emissions, due to its dependence on electricity [15]. In the EU, buildings are responsible for 40% of energy consumption and 36% of greenhouse gas emissions [16], where non-residential buildings account for 25% of total energy consumption, among which 23% is consumed by office buildings [17]. In general, Yoshino et al. [6], indicate six factors influencing building energy consumption, namely: climate, building envelope, building services and energy systems, building operation and maintenance, occupants' activities and behaviour, and indoor environmental quality. Among those factors, energy-related occupant behaviour (OB) in office buildings is not yet properly defined or modelled through scientific and robust methods [10].

When assessing the impact of environmental optimizations, the factor of OB is often overlooked [18]. However, OB is identified as one of the main influencing factors that cause a gap between the predicted and the actual building energy performance, mainly due to its stochastic, diverse, and complex nature [5]. Several studies indicate it was the building owners and occupants, who caused that utilities bills were higher and comfort levels lower than expected, because they are often not aware of the building management system [19]. One of the reasons is that the actions of building occupants, which influence the energy performance of the building, are often simplified in the design process of sustainable buildings, e.g., by assuming static occupancy schedules. This was also emphasized by Gaetani et al. [20], and Hoes et al. [21], who suggested that more detailed analysis and comprehensive understanding of different types of OB are needed in research. In addition, in order to capture the full scope of OB under spatial, temporal and social scale, literature [10], [22] suggest that the influence of the OB can only be understood by studying physical, physiological, psychological, and other contextual factors that influence it.

2.2.1. The need for an interdisciplinary approach

Numerous studies indicate the importance and necessity of conducting inter-disciplinary or multi-disciplinary research to better understand how occupant behaviour may influence building design, operation, and management processes (e.g., [6], [23], [24]).

In office building research, such a recognition of the need to conduct inter-disciplinary research between social/behavioural research of the workplace (particularly from the individual decision-making [25] and the environmental psychology perspective) and BPS research, has emerged only recently (e.g., [14]). Conventional workplace design studies have focused on topics such as noise, openness, space size, crowdedness, concentration spaces, communication spaces and energy conservation programs. In most cases, these topics are elaborated partially or as a whole in different office design or management contexts, e.g., activity-based workspaces [26], hybrid office design [27], behaviour-centric conservation programs [28], [29], behaviour change [30], or interactive design [31]. As for BPS research, the focus has shifted to occupancy and occupant adaptive behaviour, and more recently to occupant-centric human-building interaction [32], [33], [34], [35], focusing on aspects such as type of user [36], energy-use patterns [37], window opening/closing [38], [39], [40], blinds/shades usage [41], [42], [43], lighting usage [44], [45], heating ventilation and air-conditioning (HVAC) usage [46], [47], office appliances [48], [49], and occupancy status/control [50], [51], [52], [53]. At a glance, there is a difference in research topic, however, both disciplines focus on buildings' pre-occupancy (design) and post-occupancy (occupation/operation) stages, and on the development of a sustainable building, in terms of both energy efficiency and occupant comfort.

However, the knowledge exchange and synergy process between these disciplines are hampered by several impediments, e.g., theoretical and methodological inconsistency, lack of attention to the psychological/cognitive process of occupants,

and different connotations and terminology being used. Only a handful of papers from the social / psychological field studied energy-related OB in workplace, and the majority of them considered the energy-related OB as a subcategory of environmental behaviour, which is referred to as pro-environmental behaviour, curtailment behaviour or similar. Focusing on making alternative choices between environmentally friendly behaviour and others, e.g. taking the stairs instead of using the lift, or turn-off a monitor instead of leaving it on sleep mode. While for BPS research, the terms used included but are not limited to user behaviour, energy-related behaviour, energy-use behaviour, occupant behaviour, and adaptive behaviour. The current categorization of OB is inconsistent among reviewed papers and it is highly topic oriented (see table 1). As Zambrano et al. [54] pointed out, identifying the influential and non-influential behaviour is crucial for BPS research, which is also true for workplace behavioural research. A collaboration between these two fields could provide valuable insights in OB related research in office environment. The occupant perspective can then be obtained through workplace behavioural research and later integrated in BPS research where comfort is less addressed and often only deterministic occupant settings are applied.

Table 1 Current OB classification in different papers

Terms used for OB	Source	Categorization of behaviour
Energy-related behaviour	[55]	Interaction with windows, blinds and shades, heating and cooling thermostats, lighting and electric appliances, movement and presence of occupants within building
Occupant behaviour	[25]	Adjusting windows, doors, shades and blinds, lighting, thermostats/heaters, personal fans, computers, drinking beverages.
Adaptive behaviour	[56]	Adjusting appliances, clothing, drinking beverages, and moving through spaces.
Occupant behaviour	[57]	Investment behaviour, energy-consuming behaviour, non-energy-use behaviour.

Occupant behaviour	[5]	Energy-related adaptive actions: interact with window, blinds, thermostats, lighting, adjust clothing and moving through the building. Non-adaptive actions: occupancy-presence, and use of plug-ins (personal heaters, fans, electrical system for space heating/cooling) and electrical equipment (e.g., printer).
Occupant behaviour	[14]	Behavioural adaptions and building controls: adjusting thermostat, windows, blinds and shades, and switching on/off artificial lights.
Energy-saving behaviour	[58]	Interaction with ceiling and desk light, portable space heater or personal fan, computer (off/sleep mode), air-conditioner, heating, setpoint adjustment.
Environmentally significant behaviour	[59]	Impact-oriented behaviour: behaviours make a large difference to the environment. Intent-oriented behaviour: environmental intent (people's beliefs, motives, etc.) oriented behaviour that may fail to result in environmental impact.

Previous review studies already explored OBs from these different perspectives. Some provide an overview of OB related research in buildings, for instance, Gunay et al. [60] and Rafsanjani et al. [61], but only summarise the methodologies and approaches used to explore occupant behaviour in office and commercial buildings. Others focus only on one or a few specific domains of OB in buildings, for instance, modelling [62], modelling and simulation [63], contextual factors' impacts on OB in offices [8], manually-operated windows [64], user-centred lighting control [65], occupant control on natural ventilation [66], OB in smart building systems [67], or qualitative approach to assess OB in buildings[68]. Overall, the vast majority of these reviews studied OB from the engineering perspective on how to effectively and efficiently monitor, simulate and model it, which left occupants' perspective less explored, especially for occupants' perspective on indoor environment comfort and control. Recently, Hong et al. [5] and Zhang et al. [57] point out that compared to conventional methods, a full scope understanding of OB needs an interdisciplinary approach, especially including the knowledge from social and

psychology science. An overview is not only missing of relevant behaviours, but also of factors influencing such behaviours, and the theories/models used when conducting inter-disciplinary research, particular for energy-related OB research in office/workplace environments.

2.2.2. The aims and deliverables of the review

For future interdisciplinary research, a better understanding of and among current OB in workplace behavioural research(ers) and building performance simulation research(ers) is essential. The three deliverables of this paper for this are: 1. To identify and categorise the different types of OB; 2. To identify and categorise the influential factors that drive OB; and 3. To identify theories that are being applied to explain occupants' energy-related behaviours and its application. The first deliverable provides an overview of the whole spectrum of relevant OB, regardless of buildings' or occupants' physical, environmental, and/or contextual factors. The second presents the influential factors of OB that have been studied and proven to be significant in energy-related OB research in office buildings. The third deliverable is a list of integrated theoretical frameworks tailored specifically to office environment energy-related OB research. The aim to identify such frameworks is to provide a solid foundation where cognitive processes underlying sustainable occupant behaviour in office buildings (SOBO) can be represented explicitly. Linking above deliverables, SOBO is endorsed by two salient attributes, i.e., occupants' health and well-being (e.g., occupant behaviour) and the energy efficiency of the building (e.g., advanced indoor environment control system which is energy consumption related), which are essential for future sustainable building development. Therefore, with these objectives this review aims to provide a more holistic understanding of energy-related OB for audiences from both/either social science and/or engineering science, and to benefit future inter-disciplinary behavioural research.

2.3.Approach of the review

This systematic review is aimed at scientific journal publications (hereafter referred to as: paper/s) that address OB during the design and use phase of an office workplace environment (hereafter referred to as: office building/s). The PRISMA [69] approach was taken with the Scopus platform as the search engine, since it is able to capture inter-disciplinary research. The keywords "energy/-use/-related", and "occupant behavio(u)r", and "office/workplace", not "residential", limited to "journal", and limited to "English language" formed the search strategy. Along the reviewing progress, a snowball process was applied as well that aimed to trace back the most important social/behavioural theories/frameworks mentioned in the papers (e.g., Theory of planned behaviour (TPB)) and relevant connected (series of) papers.

The main criteria for the selection of eligible papers, besides being related to energy use in office environments, was compliance with at least one of the following rules:

1. The paper measures, analyses, and/or predicts one or multiple aspects of the OB.
2. The paper uses a social / behavioural theory to understand the cognitive process of OB.
3. The paper explicitly or implicitly identifies one or more factor/s that have a direct or indirect impact on OB.
4. The paper introduces, develops or validates an OB model or conceptual framework.

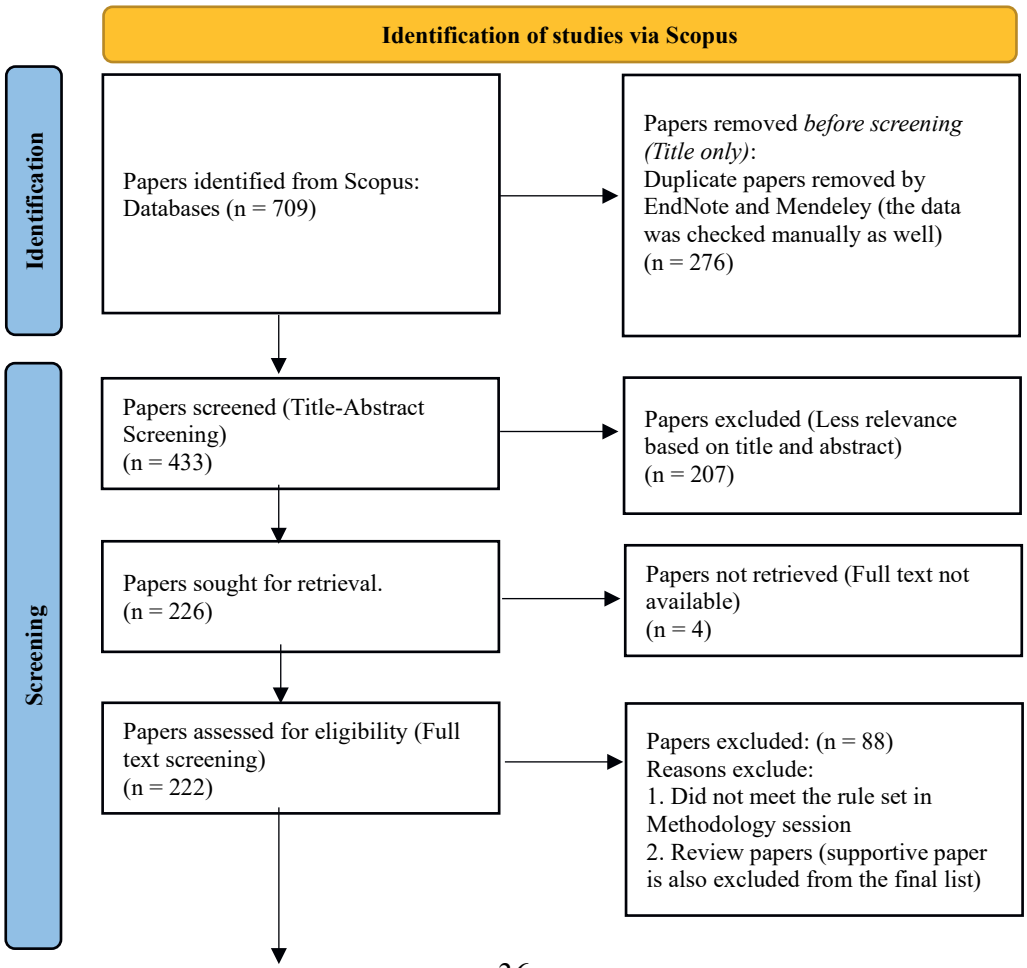
As for selection of type of OB, influential factors, and related theories frameworks, a matrix was created in Excel where each column represents one of the following aspects of each paper: information on type of OB and related terminologies used for it, type of building where the research is performed, research location geographically, method/techniques used to gather/analyse data, theories used as

basis, and influential/significant factors presented. The appearances of above mentioned elements were counted in Excel.

2.4. General findings of the review

Initially, 709 papers were identified. After removing duplicates, 433 papers remained for title-abstract screening. After removing less relevant papers (207) and papers without full text availability (4), 222 papers were eligible for full text screening. By applying the above-mentioned rules, 134 papers made the final selection (excluding review papers). The detailed selection process is presented in Figure 2.

Figure 2 The PRISMA approach



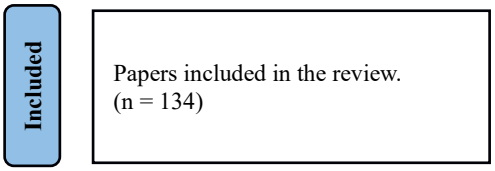


Figure 3 shows that the number of published papers increased gradually in the past two decades. In 2013, in total three papers were found but only one was kept in the analysis, because the other two papers were review papers.

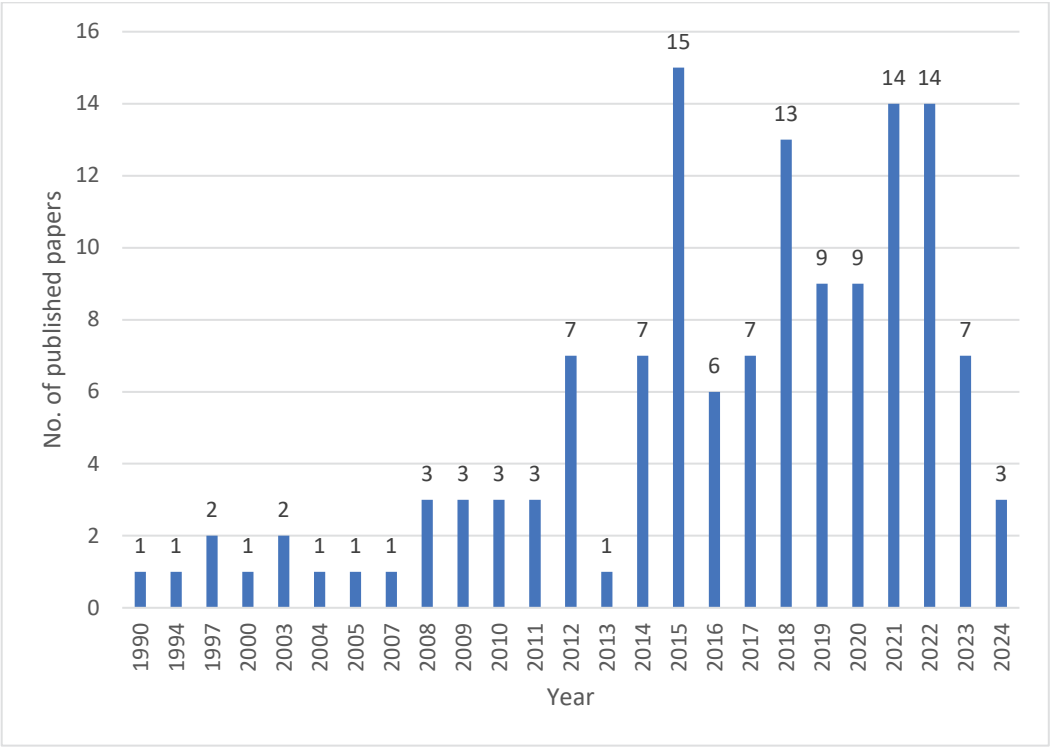


Figure 3 Number of published papers in each year

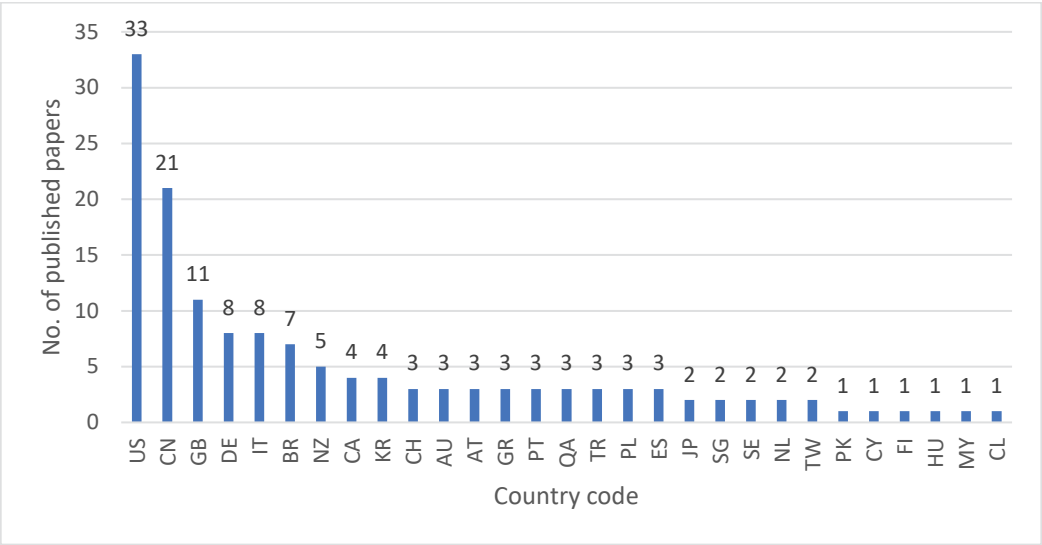


Figure 4 Geographic Dispersion of the reviewed papers

Figure 4 shows that the largest contribution stems from the U.S. with 33 papers, followed by China (21), Great Britain (11), Germany (8) Italy (8), Brazil (7). This suggests that generalization of findings in this review to the Middle East, Southeast Asia, and Africa is not possible.

Regarding the type and design of office buildings, the majority of the papers uses either university office buildings [70], [71] or governmental/public office buildings [72], suggesting there is not substantial data yet to analyse potential differences in OB in commercial office buildings. The spatial scale of this review is not limited to one room or building, but is it case sensitive ranging from multiple/single occupancy office room [73] to multiple open-plan office floors in different buildings [74], in terms of coverage of office types most studies consider single-, double- or triple-occupancy offices, and only a few studies focused on mixed-mode ventilated open-plan office [75]. Most likely this is related to the type of offices that most public institutions occupy.

One keyword visualization map (i.e., VOSviewer [76]) was generated, to have a general idea of the main topics (see Figure 5). The map is created based on

bibliographic data exported from Mendeley reference tools, with co-occurrence of keywords and follows a full counting method. The thesaurus file was used to perform the data cleaning, and the occurrence threshold was set to minimum 5. Each node (circle) represents one keyword and the higher the weight (number of occurrences) of the node the larger the node size. The closer the nodes are the stronger relationship they have. As expected, occupant behaviour and office are the most relevant topics at the core in the centre of the social-psychological field (red nodes), which focuses on explaining individual decision-making or cognitive processes of individual behaviour mostly through study of attitudinal factors. With the same core, the engineering field is more focused on the modelling and simulating building energy use or consumption (blue nodes) from various perspectives, e.g., thermal comfort, window, and lighting usage (green and blue nodes). The yellow nodes in between of the two major fields, energy conservation and building energy efficiency, indicate the connection between these two fields.

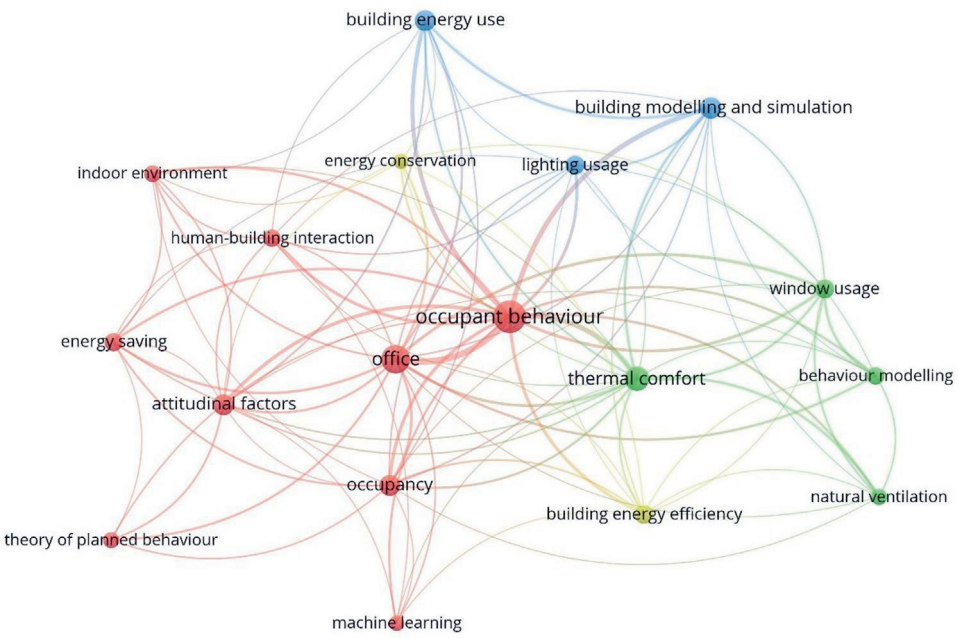


Figure 5 Network Visualization of keywords

2.5. Occupant behaviour from a multi-disciplinary point of view

2.5.1. Type of Occupant behaviours

In workplace research, OB is understood as a type of curtailment behaviour of a repetitive, habitual, reversible nature and resulting in saving energy but with a loss of comfort. For example, Seyler and Mutl [23] defined environmental real estate user behaviours as curtailment behaviours which involve repetitive behavioural efforts to minimise the impact on the natural and built environment, like taking the stairs instead of the elevator. While in BPS research, according to De Dear and Brager's adaptive theory [77], OB is understood as adaptive behaviour which is more infrequent and technical oriented and aimed at restoring comfort, which impose higher impact on building energy consumption. An example of a definition is: "All actions consciously performed by people to alter their surrounding environments to maintain or restore their comfort [77]". Where the former is primarily pro-environmental – intended to change the environment in a beneficial way [59], the latter is pro-comfort whereby the environment is defined as built environment. Despite this difference in view, both fields' overarching goal is to design and develop a sustainable workplace, in terms of energy use and indoor environment that in the long run is comfortable for occupants.

In general, the literature review suggests that four major types of occupant behaviours can be distinguished: occupancy related, adaptive, non-adaptive, and personal adaptive behaviour (see Table 2). The main research focus on behaviour lies on window, lighting, and HVAC system control. It is worth mentioning that some types of OBs are studied in conjunction with other types of OBs. For instance, lighting usage is often studied together with window and blinds usage [78]. The following sections will briefly summarise the state-of-the-art related to the identified OB.

Table 2 Type of energy-related occupant behaviour in office buildings

Related-Behaviours	Sub-Categories	Description/Unit of Measurement	No. of papers
Occupancy	Presence and absence	Status and duration (working hour, intermediate event)	18
	Number of occupants	Individual/Group	
Window usage	Open/close of manual/semi-automated/fully automated	Status and duration	40
Blind/shading usage	Open/close, Manual/Automated usage pattern	Status and duration	27
Lighting usage	On/off, Manual/Automated usage pattern (switch/dimmer)	Status and duration	37
HVAC system control	Usage pattern of temperature controller/thermostat (radiators, heater, heating unit)	Status and duration (heating and cooling)	40
	Usage pattern of mechanical ventilation – type 1 fan[1] and air-handling unit	Status and duration	
	Usage pattern of AC unit (on/off, or certain temperature point)	State and duration	
Office equipment usage (Habitual)	Workstation equipment usage pattern (include but not limited to):		20
	PC	No./Type of equipment[2] Plug load measurement	
	Monitor		
	Printer		
Personal adaptive behaviour	Add/remove clothing	Clothing level	26
	Having cold/hot drinks	Beverage consumption	
	Changing activity level (from sedentary to another)	Type of work (tasks)	
	Type 2 fan: Desk/portable fan[1]	Status and duration	
	Portable heater/blanket	Status and duration	

[1]There are two types of fans in use: type 1 fan is embedded in the building design, e.g., ceiling fans, wall-mounted fan [79]; type 2 fan is personal fan, e.g., desk fan, portable fan [80].

[2]Type of equipment - is the usage of built-in apparatus, e.g., laptop computer is more energy efficient than desktop computer; reduce multiple monitors to one; turn-down computer screen brightness; always print double-sided; use power strips to turn of electronic equipment.

2.5.1.1. Occupancy

Occupancy is studied mostly with its states (i.e., presence/absence, duration, patterns [53], [81]) and number of occupants [82]. Terms used to describe occupancy presence (or absence) include: "arrivals and departures", "periods of intermediate absence", and "effective time spent in the area" [50]. Feng et al. [83] developed an occupancy model capable of predicting different levels of occupancy presence, and number of occupants in buildings. The level of detail increases from the whole building level, up to the most detailed level of individual tracking inside the building. However, their model uses a static occupant schedule and cannot support building managers in managing the building in a timely manner due to the dynamic nature of occupants' activity behaviour. Further development was made by Salimi et al. [84] and Norouziasl et al. [85]. The former developed an adaptive probabilistic occupancy prediction model estimated based on real occupancy data, while the later used agents' presence, location, and interaction with building to simulate a stochastic occupancy profile which makes their model independent from conventional time-use and sensory occupancy data.

Recently, Hammes et al. [86] and Cassola et al. [30] highlighted that the occupancy profile has only a marginal influence on energy conservation in offices. For instance, often the artificial lighting levels are not affected by the occupancy profile [86]. Also, although arrival and departure events impact building energy consumption,

there is limited potential for behaviour changes [30]. Above findings suggest there is a need to distinguish and isolate the influential factors in a more systematic way, to better define and conceptualize the occupancy's role in sustainable building research and development work.

2.5.1.2. Adaptive behaviour

Adaptive behaviour refers to the occupants' interaction with building features or system controls to alter buildings' indoor environments, with the aim to restore a preferred comfort level. The actions studied include window usage, lighting usage, HVAC system control, and blinds (and/or shading) usage.

2.5.1.2.1. Window

Window usage is commonly described by the status of the window (e.g., open or closed) [87], [88], [89], [90], [91], [92] and the length/duration of that status [92], [93], [94] or both [95]. Research focuses on aspects such as predicting window's opening angle, time, frequency [38], [96], [97]; analysing the relationship between window usage and thermal comfort [98], [99], [100]; development of window use algorithms [101]; and predicting window use patterns using novel methodology approaches [102], [103], [104].

Several papers found that window usage behaviour, in most cases, is not an independent event [97], [98], [105]. Rijal et al. [98] suggested that for natural ventilated buildings the window opening status is positively correlated with fan status. Later, Liu et al. [97], [105] provide further evidence that sometimes windows are used in conjunction with air-conditioning, radiator, and fan heater to restore thermal comfort. However, from the simulation point of view it is still difficult to predict the mixed use of adaptive behaviour and the preferences of it, especially under various context scenarios [106].

2.5.1.2.2. Blinds and shading usage

In most situations, the blinds and shading (hereafter referred to as blind/s) are used to moderate the indoor environment comfort levels, and sometimes to meet occupants' psychosocial needs as well. It is often studied in terms of its status (i.e., on/off), slat angle (i.e., fully opened/closed, 0º, 45º, 75º etc.) and frequency of usage (i.e., upon arrival, departure, intermediate absence, [107]).

Newsham [41] found that occupants who work in the office with operable blinds experience a better thermal environment with a 9% decrease of dissatisfied occupants. Both Inkaroirit [108] and Mahdavi et al. [109] studied blind closing behaviour. The former studied the probability of blind closing behaviour, and the latter studied the relative frequency of closing actions. Mahdavi [42] realized that the blinds are not always in fully opened or closed position. Later in Carneiro et al. [110], Correia da Silva et al. [107] and Sadeghi et al. [111] a more detailed and comprehensive research was used to study the intermediate positions of blinds. Additionally, in most of the reviewed papers, blinds were studied in conjunction with window usage and/or lighting usage.

2.5.1.2.3. Lighting

Lighting usage is commonly studied in terms of its status (on/off, frequency of use) [112], [113], [114], patterns of usage [88], [115], [116] and intermediate adjustment [107], [111]. On a typical office workday, the light quality changes dramatically due to the control of artificial light, the position of the sun and weather conditions. Both Moore et al., [117] and Newsham [41] highlighted that lighting schedules should capture the dynamic and diverse features of user preferences, instead of one-size-fit-all. Recently, the immersive virtual environments approach was used quite frequently in exploring the lighting usage preferences in office settings by studying the correlation between efficient lighting choices: with different office contexts [110], with different degree of control over the lighting [118], with default lighting settings [119], and with manual and semi-automatic control [120].

The most referred lighting model is “Lightswitch-2002”, developed by Reinhart [44] which represents a dynamic and stochastic approach to explain the occupants’ control of manual and automated lighting and blinds usage. However, their model does not capture information regarding the ‘intermediate switch-off’ behaviour, which was later explored by Mahdavi [42] and Mahdavi et al. [109].

2.5.1.2.4. HVAC system

In general, HVAC systems’ control [121] includes three sub-systems: 1. Control of thermostat - adjust setpoint temperature [122], use of radiators and heaters [97], [105]; 2. Control of mechanical ventilation, e.g., ceiling fans, air-handling unit and 3. Control of Air-conditioning (AC): adjust or turn on/off AC unit [123]. In different studies, HVAC control behaviour represents different types of control behaviour that varies from case by case, for instance, technical environmental control measures [97], [105], thermoregulatory behaviour - acclimation [124], and primary preference of cooling and heating behaviour [125]. More or less, they all resemble the concept developed by De Dear and Brager, [77], i.e., the concept of thermal adaptation, where thermal adaption is explained and distinguished into three categories – behaviour, physiological, and psychological adaptation.

Above mentioned controls were studied mostly in terms of its on/off state [126], setpoint control [127], [128], frequency of usage [78], [89], and patterns of usage [89], [104], [129], [130]. Only a few studies were found in the reviewed papers adopting complex environment settings. Ozcelik et al. [116] suggested that in response to the above two IEQ discomfort conditions, occupants’ immediate decisions vary significantly in terms of type (i.e. thermal and visual) and kind (e.g., blind, desk fan). This was later confirmed by Zhu et al. [131] and Grassi et al. [132]. Which suggest that apart from the conventional research focusing only on one aspect, there is a need to study the OB from a multi-dimensional perspective.

2.5.1.3. Non-adaptive behaviour

Non-adaptive behaviour refers to individuals' performing an activity that is enabled by the office design or office settings, such as for instance, the usage of office equipment like personal computer [133], [134], printer [48], or computer monitor [135]. Due to the ease of data collection (consumption data) and distinct system state (on/off), non-adaptive behaviours are often included in studies to explain energy-use patterns and validate the effectiveness of intervention strategies. For instance, Rafsanjani, Ahn, and Eskridge [136] studied the energy use pattern at entry and departure events using workstation power consumption data. Kamilaris et al. [133] studied the impact and effectiveness of an intervention approach (i.e., "information feedback") on potential energy reduction of personal desktop computers. In most cases, office equipment was studied to reveal behavioural usage pattern for building operators and decision makers to develop intervention strategies for energy efficient programs. However, with case study involves a single building and study a specific type of occupants and job tasks limits the generalization of the findings [78].

2.5.1.4. Personal adaptive behaviour

Besides the above mentioned three primary building-oriented types of behaviour personal adaptive behaviour has received attention. According to the literature, two types of personal adaptive behaviour can be identified. One is related to the physical/mental state (i.e., feelings, needs, intentions), e.g., adjusting clothing level to warm-up or cool-down [87], [137], [138], [139], [140], [141] or having a cold / hot beverage as a remedy to extreme ambient temperatures [140], [142]. Another one is related to the usage of personal belongings, e.g., portable fan [80], local heater [87]. All those measures are meant to serve as a complementary, secondary, or substitute measure when the primary control is not accessible or not available to occupants [80]. Although both disciplinary fields address it to a certain extent, no holistic understanding has been achieved yet.

2.5.2. Factors influencing occupant behaviour

By assuming OB in office building has the same influential factors as the residential building proved to be inefficient. As it ignores the social dynamics of the workplace when reducing the unregulated energy use in the commercial office. Based on the reviewed papers, four types of influential factors were identified for SOBO related to building characteristics, environmental, contextual factors, and personal factors (see table 3).

2.5.2.1. Building characteristics

Building characteristics can be summarized into two aspects – building system and building design (or features). Building design represents the physical parameters of buildings that are unlikely to change during the whole building-life-cycle. Building system refers to various apparatus that ensure basic building functions controlling comfort, e.g., type of HVAC system, window, and power system [132]. As for design related factors, the most commonly mentioned ones are geographic location and building orientation [74]. It is basic yet important to include those parameters, because external conditions like climate, type of occupant, and functions can be identified and are essential factors for building performance. Also, the scope and scale for generalization of results are deeply bounded by those factors.

2.5.2.2. Environmental factors

Environmental factors refer to the environmental conditions created before any technological interference is involved, for instance, solar radiation [143], season [47]. Depending on the research purpose, several environmental factors were included in the reviewed papers. Regarding occupancy, for instance, Dong et al. [51] studied the correlation between measured environmental factors (i.e., CO_2 and acoustic) and number of occupants in the space in an open-plan office building. Environmental factors for adaptive behaviour are behaviour-specific. For instance, illuminance level falling on the workplane surface is a key predictor in lighting and window usage research, but is not so relevant for thermostat usage (see Table 3).

For non-adaptive behaviour (e.g., office equipment usage), environmental factors are not so relevant, as this type of equipment only enables or facilitates daily office tasks. This implies that the primary influential factor for non-adaptive behaviour is task (or job) driven.

2.5.2.3. Contextual factors

Contextual factors were found in almost all reviewed papers, but none provided an exhaustive account of these factors. According to the theory of environmentalism, contextual factors are conceived as barriers for conducting specific pro-environmental behaviour. In addition to social/culture [144], economic and political factors [72], Stern [59] listed three contextual factors related to the built environment: the physical difficulty of implementing specific actions and the capabilities and constraints provided by technology and the built environment. O'Brien and Gunay [8] further introduced nine OB-related contextual factors in office environments. Regardless the disciplinary differences, the most salient element of contextual factors is that they are dynamic. For instance, the level of control depends on the combination of presence (e.g., mixed-mode ventilation building [98]), availability (e.g., adjustable degree of window [93]), accessibility (e.g., access to daylight control [145], access to general indoor environmental controls [146], access to temperature controls [147]), available information (e.g., prior knowledge [148], and feedback information [149]), and/or spatial layout [150]. For all these factors holds that their state and condition might change due to maintenance, break downs, or renovation works.

2.5.2.4. Personal factors

For personal factors, engineering research focuses on non-attitudinal factors (e.g., age, gender, personality [5], [151].) to explain the pattern of usage (e.g., passive/active user), while social science research focuses predominantly on attitudinal factors (e.g., attitude [152], energy awareness [153], value, belief [154], social/personal norm [73], [155], [156], [157], self-efficacy [70], [158], habits

[159]). Compared to the residential sector, savings in the commercial sector can be realized without significant changes to pro-environmental attitude or perceived social norms of users [160]. Apart from the social-psychological attributes that are well established in social research, another important and less studied influential factor for energy-related OB in office environment is habit (automaticity). Tetlow et al. [161] used the choice behaviour regarding turning off small power workstations as an example, demonstrating that habit was the sole predictor which is significantly correlated with daily small power consumption at workstations. Kamilaris et al. [133] indicated that habit is one of the reasons that occupants do not try to save energy in office environments. Rissetto et al. [162] included habit as a non-attitudinal predictor in their theoretical behaviour framework. However, due to some difficulties in data collection they only analysed the cognitive process.

Table 3 Influential factors for occupant behaviour in office environments

Related Behaviours	Sub-Categories	Influential factors			
		Building Characteristic	**Environmental**	**Contextual**	**Personal**
Occupancy	Presence and absence		• Acoustic • Lighting • CO2 • Temperature	• Time of day (event) • Length of time spends in a state • Type of task	• Patterns of user (passive or active; inactive, slightly active, and active)
	Number of occupants		• CO2 concentration • Acoustic	• Time of day • Space arrangement (layout and location)	
Window usage	Window opening/closing (fully/partial)	• Type of building (NV, AC, MM, Free run) • Geographic location • Orientation • Type of window	• Outdoor/indoor (temperature, relative humidity) • Outdoor noise • CO2 concentration	• Type of office • Seasonal effect • Time of day • Previous window state • Controllability • Spatial layout • Type of AC and AC status	• Patterns of user (passive or active) • Perceived thermal feelings/comfort • Privacy • Habit (routine) • Personal preferences • Attitudes • Age • Gender

		(operable or not)			• Desire to improve indoor thermal and air quality • Social norms • Awareness of consequence • Ascription of responsibility,
Blind/shading usage	Blind/shading opening/closing	• Type of building (NV, AC, MM, Free run) • Orientation • Geographic location • Type of shading	• Outdoor/indoor temperature • Overheating • Irradiance (radiation) • Wind (speed & direction) • Working area/plane illuminance	• Time of day • Layout of office • Availability to control • Performed task • Occupancy pattern • Aesthetic	• Sensitivity to brightness • Habit (routine) • Experience of visual conditions • Perception of discomfort conditions • Age • Perception of opportunity • Awareness of consequence • Ascription of responsibility
Lighting usage	Lighting control	• Orientation • Control options	• Outdoor/indoor temperature • Working area/plane illuminance	• Type of office • Time of day • Occupancy pattern (No. and P/A)	• Experience of visual conditions • Habitual • Peer-to-peer effect • Patterns of user (passive or active)

				• Level of control (distance and access to control and distance to window) • Availability of daylight	• Perception of discomfort conditions • Ascription of responsibility • Injunctive norms • Descriptive norms • Perceived ease of access • Personality (openness people)
HVAC system control*	Heating/Cooling	• Type of building (NV, AC, MM, Free run)	• Outdoor/indoor temperature	• Time of day • Occupancy status • Seasonal effects • Access to control • Time spend in office • Availability • Spatial layout	• Beliefs • Desires • Attitude • Awareness of consequences • Perceived control level • Past thermal experience • Habit (routine) • Patterns of user (passive or active) • Individual preferences • Ascription of responsibility • Injunctive norms, descriptive norms

					• Perceived ease of access • Gender • Age • Knowledge • Intention to conform to the norms of sharing controls
	Ventilation (Mechanical, built-in ceiling fan)		• Outdoor/indoor temperature	• Seasonal effects	• Perceived control level • Past thermal experience • Perception of discomfort conditions
	Air-conditioning (AC)	• Type of building (NV, AC, MM, Free run) • Geographic location	• Outdoor/indoor temperature	• Seasonal effects,	• Perceived control level • Peer-to-peer effect • Past thermal experience • Perceived thermal sensation
Office equipment usage	**Workstation (include but not limited to):**				
	PC			• Time of day • Office type • Type of equipment	• Habits (routine, automaticity) • Peer-to-peer effect

	Monitor			• Management strategy • Flexible in working condition (working schedule) • Type of task/work	• Patterns of user (passive or active) • Thermal sensation • Preference • Acceptability • Attitude • Awareness of consequence • Ascription of responsibility
	Printer				
Personal adaptive behaviour	Clothing level	• Geographic location • Type of building (NV, AC, MM, Free run)	• Indoor air temperature • Outdoor weather	• Type of office • Dress code • Seasonal effects • Controllability	• Gender • Habit (routine) • Perceived thermal sensation • Preference • Acceptability • Experienced indoor thermal conditions
	Beverage		• Cold- indoor and outdoor thermal conditions • Hot – indoor thermal conditions		• Hot – thermal sensation before the action of drinking
	Desktop/ Portable Fan	• Geographic location	• Indoor air speed/temperature	• Controllability	• Thermal sensation • Preference • Acceptability • Perception of discomfort conditions

	Local heater	• Geographic location	• Indoor air speed/temperature	• Type of activity (sedentary work)	

2.5.3. Relevant theories and synergy progress

The research focus has shifted gradually from the conventional behavioural research to a combination of behavioural and psychological (and./or physiological) aspects. In total nine papers attempted to describe the cognitive process underlying energy-related behaviour based on three well-established theories: the TPB [163], [164], [165], [166], the norm activation model (NAM) [167], and the motivation, opportunity, and ability (MOA) model [168]. The identified theories either built upon or extent the factors considered in TPB or NAM construct, or a combination of them (see Table 4).

In general, these papers all used TPB as the main conceptual structure. Different papers incorporated different elements in the TPB structure, for instance, "wanting, motivation, and timely feedback" in Vastamäki et al. [149] and habit (automaticity) in Tetlow et al. [161]. More recently, both Xu et al. [169] and Rissetto et al. [162] added ascription of responsibility (former) and personal norm (latter) from NAM to the TPB construct. Both extent the TPB attribute "perceived behaviour control (PBC)", where the former add "ease of access to controls" and the latter add "expectation" (from self-efficacy theory).

Besides these attitudinal factors, D'Oca et al., [14] incorporated the driver-needs-action-system (DNAs) framework and motivational attributes from social cognitive theory in the TPB construct. Another example of a way to further extend TPB and NAM is using the MOA framework, originating from the consumer and marketing research fields. Li et al. [58], [148] proposed an integrated MOA framework, where motivation refers to inner needs and values; opportunity refers to the external environment regarding availability and accessibility; and ability refers to proficiencies (capabilities) with respect to energy use knowledge. Based on Li's integrated MOA framework, Weerasinghe et al. (2023) proposed a modified MOA framework by removing some of the attitudinal (e.g., awareness of consequence) and contextual factors (e.g., time availability) to explain energy-related OB in office

environments. Although the above three approaches involved two different behavioural constructs, they all tried to model the occupants' behaviour from both the inner person world (needs, value, etc.), and external world (environmental, interpersonal, etc.).

Table 4 Summary of nine theoretical frameworks

Name	Source	Theoretical background	Behaviour of interest	Application example	Significance
Value-belief-norm (VBN)	[59]	• Value theory • Norm activation model (NAM) • New environmental paradigm	Environmental significant behaviour	Not applicable	Specified the importance to synthetic theories, having not only the impact-oriented framework but also to include the intent-oriented framework when study environmentally significant behaviour.
Model of action circle (MAC)	[149]	• Philosophy of practical reasoning • Few social psychological theories	Temperature controller usage for energy saving	Not applicable	The model postulate that a series of correct action on a new device depend on the timely feedback present to the user.

		• Action model			
Dual process model of cognition	[161]	• Theory of planned behaviour (TPB) • Theory of interpersonal behaviour (TIB)	Small power electricity consumption	Open-plan office in UK	Highlight the irrational side of the occupant behaviour - when habit (routine) is in conflict with rational controlled process, most of the time habit will prevails.
Driver-needs-action-system (DNAs) cognitive behavioural framework	[55], [170]	• Nine cognitive-behaviour frameworks	Occupancy and Energy-related behaviour in the building indoor environment	[14], [171]	On top of theories using only attitudinal factors, DNAs framework also incorporate contextual factors.
Interdisciplinary research framework	[14]	• TPB • Social cognitive theory (SCT)	Human-building interaction behaviour	University and research facilities	A rather exhaustive energy-related behaviour research framework. A cross-country survey was developed and

		• DNAs framework			distributed in six countries. Sample application and results can be found in [172]
Adapted motivation-opportunity-ability (MOA) model	[148]	• Motivation, opportunity, and ability (MOA) model	Energy conservation behaviour	Multi-purpose university building in USA	A flexible evaluation framework that can be generalized to different building types, including office building.
Integrated MOA model	[58]	• MOA model • NAM • TPB	Energy saving behaviours in office environment	Multiple office building in USA	The integrated MOA has similar but different predictive power as NAM, this is explained with different dependent variable of interest.
Extended model of theory of planned behaviour	[169]	• TPB • NAM	Energy saving behaviour in single and shared office	Full-time office employees from USA	Both attitudinal and contextual variable were included in the research, also highlighted the

					impact difference of attitudinal factors in different office type.
Unified theory of behaviour	[162]	• TPB • NAM • Self-efficacy theory	Thermal comfort adaptive behaviour (i.e., fan usage)	Online survey with office workers in Germany	Expectations and past experience significantly affect occupant's comfort and behaviour.

2.6. Discussion

Based on 134 journal articles, this study provides a systematic review on the sustainable OB research in office environments by integrating the knowledge of OB related research from two disciplinary fields, i.e., building performance simulation research and social/behavioural workplace research. It shows that current research on OB in office environments is still in its formative stages. The information is dispersed and obscured, especially in the context of cross-disciplinary research. Information gathered from paper-list suggested that for energy-related occupant behaviour research in office environments exhibits a general and unilateral trend. This is evident in three aspects: geographical dispersion of publications, a predominant focus on university or faculty office buildings in case studies, and the majority of the studies focus on single behaviours.

Compared to OB's categorization in table 1, this review provided a rather consistent approach and summarises OB into four major types: occupancy-related, adaptive behaviour, non-adaptive behaviour, and personal adaptive behaviour. The four types of OB would facilitate problem refinement in future studies, for instance, how is individual preference of adaptive behaviour and personal adaptive behaviour under multi-modal discomfort situation. Which types of such behaviours are relevant for specific future office OB studies depends on the research purpose [20]. In addition, two suggestions might benefit future OB research, particularly from this interdisciplinary knowledge exchange: 1. Besides focusing on one or two adaptive behaviours, more research needs to look into simultaneous behaviours (e.g., AC is used for cooling, while windows are opened for fresh air.) and on multi-modal IEQ discomfort including the psychological and physiological aspects. 2. Instead of assuming that occupants behave rationally or irrationally, it is more concise and clearer to assume that occupants may not actively perform energy-saving behaviour,

but may perform adaptive behaviour to restore or maintain their comfort [173]. From the user's perspective, the behaviour of interest is not necessarily pro-environmental but also can be (or only be) pro-comfort.

Significant influential factors on behaviours were found in all reviewed papers. Nevertheless, different research purposes and scopes result in a lack of insight in the whole spectrum of influential factors regarding SOBO. This synthesis study does so and showed four major categories: building characteristics, environmental factors, contextual factors, and personal factors. For the first two, building characteristics refer to building systems and design features, while environmental factors refer to long-term and/or short-term atmospheric conditions created or caused by nature or the human before any technology involvement. Both of these factors can be found in most of the reviewed papers and are well documented. On the other hand, there is no clear classification yet for the contextual and personal factors categories. Therefore, this review suggests that contextual factors should reveal the most important element of a factor, which is dynamics, e.g., availability, accessibility, and prior or feedback information of human-building interactions. During a building's life-cycle the condition/situation may change due to various reasons, for instance change of tenant, change of office typology, or change of interior design/layout. Compared to such dynamic factors, factors like building orientation and geographic location of a building are highly unlikely to change. The basic social-psychological attributes, such as personal factors, are well established in the residential research sector and social science, but not in office environment research.

Also, some papers use personal factor and demographic factor in a mixed way, but technically they are different in nature. Personal factors focus more on individual characteristic and behaviours, it is subjective and used in the literature to understand individual consumer behaviour or individual preference. Demographic factors are more focused on the characteristics of sample populations, it is objective and used

in the literature to understand the overall/general population trends. Since this review intent to focus on individual-decision making of occupants, personal factors (including some demographic factors) are used. This does not mean that workplace behaviour research does not generate insights in group or collaboration behaviour in office environments. On the contrary, social-effects can be integrated in the studies to reveal group decision-making preferences, e.g. [174] and [175]. The identified two main categories of personal factors are attitudinal factors (e.g., value, belief, norms) and non-attitudinal factors (e.g., passive/active user, past experience). The attitudinal factors relate to theoretical frameworks or behaviour constructs that are used in workplace research and social science research to recreate the decision-making process or cognitive structure of occupant behaviour. While the non-attitudinal factors refer to behaviour patterns considered mostly in building performance simulation research so far. Future studies should integrate factors from all four categories to be complete.

In addition, this review provided a first overview of potential theories/frameworks for SOBO, identifying and summarizing nine theoretical frameworks from the literature, where each has its innovative points and critical thinking. The general trend is using the TPB principles as the primary theoretical framework, with some attempts on extending or delving into it with one or more attributes from NAM (e.g., ascription of responsibility) or MOA (e.g., motivation). As Klöckner [176] already points out, the "comprehensive action determination model" built upon the TPB, the NAM and the VBN theory developed by Klöckner et al. [177] and is a comprehensive framework to address environmental behaviour of human. However, it is rare to include all the attributes identified here, due to its complexity and relevance. Which is why the previous two deliverables on type of OB and influential factors of OB are essential and critical. A feasible and rigorous research design not only relies on a well-developed theoretical framework but also on the iterative process of problem and stimuli refinement. Take norm for instance: injunctive

norms have a strong influence on OB in both private (single) and shared office, while personal and descriptive norms have a strong influence on OB in private (single) office [73]. A handful of other frameworks not only included the attitudinal factors in their theoretical framework, but also the physical factors, i.e., the interdisciplinary research framework by D'Oca et al. [14] integrates the social cognitive theory [178], DNAs ontology [55], [170], and the theory of planned behaviour [163].

So far, the theoretical framework (or structure, construct) development to address individual decision-making processes is still in its infancy, there is no consensus on one overall framework yet. The "interdisciplinary research framework" by D'Oca et al. [14] and "the integrated MOA construct" by Li et al. [148] are the only two attempts to model energy-related OB by considering both internal (e.g., needs) and external factors (e.g., environmental, physical). However, with limited empirical evidence to support this in the reviewed papers, they are still rather vulnerable. Moreover, energy behaviour is also said to be connected with determinants of individual decision-making theory [179], apart from social and environmental psychology, and sociology, the knowledge from conventional and behavioural economics might also contribute to this.

2.7.Conclusion

This chapter establishes a structured conceptualisation of occupant behaviour in office environments and highlights the importance of considering behavioural heterogeneity, contextual constraints, and multiple adaptive actions. This review synthesis distinguishes four major types of occupant behaviour, i.e., occupancy-related behaviour, adaptive behaviour, non-adaptive behaviour, and personal adaptive behaviour. It further identifies four categories of influential factors, i.e., building characteristics, environmental factors, contextual factors, and personal factors. The review also identifies nine theoretical frameworks used to explain

energy-related occupant behaviour. These insights underline that occupant behaviour is not only dynamic and context-dependent, but also shaped by interactions between environmental conditions, individual preferences, and social influences. Previous literature provides valuable insights into the behaviour through empirical observations, but only limited information that addresses the underlying decision-making processes that govern how occupants select among multiple adaptive options. There is a need for approaches that can explicitly capture behavioural trade-offs, preference heterogeneity, and the multi-dimensional nature of comfort adaptation. Building on the theoretical framework and identified behaviour, the next chapter develops these conceptual insights into an empirical research design, which focuses on introducing the methodological approach and data collection strategy adopted to investigate how occupants make adaptive decisions under different environmental and contextual conditions.

3. Experiment design and data collection[2]

3.1. Overview of the research design

This chapter presents the methodological approach used to investigate comfort-adaptive occupant behaviour in office environments. Building on the conceptual foundations established in Chapter 2, this study adopts a stated-preference approach that combines a multi-response discrete choice experiment (DCE) with a cross-sectional survey. This combined survey design was selected to capture not only occupants' stated preferences for adaptive actions under hypothetical multimodal (dis)comfort scenarios, but also the individual, contextual, and psychosocial characteristics that may help explain heterogeneity in those preferences.

The research design follows a structed experimental design process, in which the research problem is translated into experimentally controlled choice alternatives through a sequence of design decisions, including but not limited to: problem refinement (refer to Chapter 1 and 2), alternative identification, attribute identification, attribute level identification, type of design, model specification, reducing experiment size, generate experimental design, allocate attributes to design columns, generate and randomize choice sets, and construct survey instrument [180]. Among which the attributes and attribute levels are designed in advance and presented systematically to respondents, rather than being passively observed. Compared with observational and monitoring-based methods, DCE design offers a way to investigate the trade-offs occupants make when multiple adaptive options are available and when behaviour is shaped by both physical and social context. Hence, it is particularly suitable for studying human-building

[2] This Chapter is adapted from:
H. Li, R. Appel-Meulenbroek, T.A. Arentze et al., Revealing and modelling occupants' preferences for comfort adaptive actions in open-plan offices with the inclusion of contextual and social-psychological aspects, Building and Environment 285 (2025) 113681, https://doi.org/10.1016/j.buildenv.2025.113681
H. Li, R. Appel-Meulenbroek, T. Arentze et al., Profiling office workers' comfort-related adaptive actions: a latent class analysis, Journal of Environmental Psychology 111 (2026) 102979, https://doi.org/10.1016/j.jenvp.2026.102979

interactions in shared office environments, where occupants' adaptive behaviour is affected not only by the indoor environment conditions, but also by social norms (refer to section 3.6).

This chapter is organized as follows. Section 3.2 introduces the discrete choice experiment and the multi-response design. Section 3.3 presents the conceptual and theoretical foundation of the experiment. Section 3.4 defines the behaviours of interest. Section 3.5 explains the selection of environmental attributes and attribute levels. Section 3.6 describes the generation of choice tasks, the randomness of the design, and including the social conditions. Section 3.7 explains the design of the choice task. Section 3.8 present the cross-sectional survey. Section 3.9 describes the survey administration, sample, and statistical adequacy of the dataset. Section 3.10 presents the conclusions.

3.2. Discrete choice experiment

The DCE approach is grounded in random utility theory and provides a systematic framework for measuring preferences and modelling decision-making behaviour based on stated-choice data, where choices are the outcome of a utility maximization process [181], [182]. In stated-choice experiments, individuals are presented with hypothetical scenarios and asked to choose among alternative options. These choices are assumed to reflect the underlying utility that individuals derive from the attributes describing the alternatives and the decision context. In practice, stated choice analysis is regarded as an efficient method to reveal preferences of individuals regarding existing or new choice alternatives. Models generated with the DCE approach are normally used to analyse decision-making by profiling participants based on their behavioural responses and choice preferences.

One important feature of DCE is its experimental control over the variation of attributes. Choice alternatives are structured in such a way that attributes vary independently, allowing researchers to estimate the separate effects of each attribute

while minimizing issues like multicollinearity [181]. Furthermore, the DCE framework allows the investigation of hypothetical situations that may not yet exist, which is particularly useful when evaluating potential building design strategies, control systems, or policy interventions before its implementation. For this research, which focuses on human-building interactions, this capability enables the systematic examination of how occupants might respond to different combinations of environmental and contextual conditions when multiple adaptive opportunities are available in office environments.

In a conventional DCE design, respondents are presented with a series of choice tasks, each representing a decision context defined by a set of attributes [183]. In this study, the decision context corresponds to hypothetical office environments with varying indoor environmental conditions, contextual changes, and social interactions, while occupants are offered comfort-related adaptive behaviour options (e.g., adjusting clothing level, consume hot/cold beverages) and environmental controls (e.g., adjust window, adjust thermostat) that are commonly seen in an office (also see section 3.4). Based on the choice data obtained, DCE models then derive a latent utility value for each alternative using regression-like methods (ranging from closed-form models like multinomial logit to open-form models like random parameter logit) and use these to predict choice probabilities. These models account for random and systematic attribute related components of utility and offer insights into preferences and the scale of heterogeneity associated with choices [183].

Compared to a conventional DCE design, in which participants select one mutually exclusive alternative per choice task, the design in this dissertation allows participants to select multiple adaptive actions for each scenario. Each action represented a binary decision (Yes/No) indicating whether the participant would engage in that behaviour under given contextual conditions. This aligns with a multi-response DCE framework (also called discrete profiling choice) [184]. Under

this specification, participants are allowed to select several actions simultaneously within a single choice task. Then, in the modelling state, the possible combinations of actions are treated as mutually exclusive alternatives (i.e., behavioural bundles), ensuring that each choice task contributes exactly one observation to the multinomial logit likelihood. The utility function of the alternatives (i.e., bundles), therefore, represents the overall attractiveness of the adaptive actions contained within them under a given scenario. This specification enables the analysis of how occupants combine adaptive strategies when facing different types of indoor environmental (dis)comfort in office environments. This formulation is consistent with bundle-based representations of multiple response stated choice data.

To account for heterogeneity in behavioural preferences, different DCE modelling approaches can be applied to capture variations in preferences across individuals. With a random-parameter mixed-logit (RPML) model, which extends the multinomial logit framework by allowing selected parameters to vary randomly across individuals, continuous preference heterogeneity is captured. Additionally, applying Latent Class Analysis within the discrete choice modelling framework adds further insights. Latent Class identifies probabilistic segments of individuals who exhibit similar patterns of preferences and behavioural responses. Each class is characterised by its own set of utility attributes, while individuals are assigned to classes based on estimated class membership probabilities rather than deterministic rules [185]. The RPML model captures continuous heterogeneity in preferences across individuals through random parameters, while the latent class model captures discrete heterogeneity at the sample level by segmenting individuals into a finite number of behaviourally distinct classes. The combined multi-response DCE and modelling framework enables the identification of distinct behavioural profiles based on observed patterns of adaptive actions rather than self-reported comfort evaluations. The detailed attribute specification and generation of choice tasks are introduced in the following sections of this chapter.

3.3. Conceptual and theoretical foundation

The design is grounded in two theoretical perspectives which complement each other: the Adaptive Theory of Thermal Comfort (comfort adaptation model) [186], [187] and the Two-step Theory of Perceived Control (TTPC) [188], [189]. The Comfort adaptation model denotes that comfort regulation involves behavioural adjustment (e.g., thermostat adjustment), physiological acclimatisation, and psychological adaptation (e.g., perceived control). Highlighting that occupants do not respond to indoor environmental conditions solely through passive exposure but actively regulate their comfort by interacting with the surrounding environment and/or by adjusting themselves to the situation. Behavioural adjustments include, but are not limited to, changing the thermostat, opening/closing a window, lowering blinds, or adjusting clothing level, while psychological adaptation includes the role of perceived control in shaping comfort responses.

The TTPC complements this perspective by distinguishing between two types of psychological regulation: assimilation and accommodation. Assimilation refers to changing the environment in order to meet one's preferences, whereas accommodation refers to adjusting one's internal expectations, preferences, or responses to fit existing conditions. In shared office environments, where control is often discussed and social (norm) influences are presented [169], occupants may seek comfort not only by acting upon the environment, but also by adapting themselves or by aligning with others' preferences (if proposed). The integration of the Adaptive Theory of Thermal Comfort and TTPC allows both environmental control actions and internal coping strategies to be interpreted within a unified framework of perceived control.

3.4. Behaviours of interest

Occupant behaviour can be defined as occupant presence, movement, and interaction with building energy devices and systems [190]. Within this broader

domain, two main categories of energy-related occupant behaviour are commonly distinguished: adaptive behaviour and non-adaptive behaviour [6]. Non-adaptive behaviours generally do not directly impact (or cause a fluctuation in) building performance and are not primarily intended to restore or improve personal comfort. These may include routine or passive actions, like using a printer or choosing not to act ("do nothing"). D'Oca et al., [62] further define non-adaptive behaviours as actions not intended to improve (personal) comfort. Accordingly, this study focuses exclusively on adaptive behaviour.

In most literature, adaptive behaviour typically refers to occupant interactions with controls of different building features to maintain or restore indoor environmental comfort, e.g., adjusting a thermostat [128] or adjusting the blinds [111]. Adaptive behaviour can also refer to occupants adapting themselves to the environment, e.g., clothing adjustment, drinking a hot/cold beverage [80], termed as personal adaptive behaviour. Both environmental control actions and personal adaptive actions belong to behavioural adaptation under adaptive-comfort theory, which recognise physiological – acclimatization, behavioural – window opening/adjust clothing, and psychological – perceived control pathways of comfort regulation.

From the perspective of the TTPC, the feeling of control can be obtained by changing the world (assimilation) or changing the self (accommodation) [188], [189]. In shared office environments, accommodation may also be influenced from a social aspect, where an occupant aligns with or accepts other's proposal even if that decision is not optimal for an individual. In this study, occupant behaviour is therefore defined as occupants' interaction with their surrounding environment to maintain or restore comfort through two levels of perceived control: changing the environment, e.g., through environmental control actions and personal adaptive actions, and/or changing the self through cooperative intention, such as aligning with others' proposal.

Based on the above, two categories of adaptive actions: environmental control actions and personal adaptive actions are included in this study (see Table 5). Environmental control actions include window adjustment, blinds adjustment, thermostat adjustment, and artificial lighting adjustment. Personal adaptive actions include clothing adjustment, drinking hot or cold beverages, the use of a personal heater, and the use of a personal fan. These actions are among the most frequently reported and modelled comfort-related adaptive behaviours in human-building interaction research and are directly relevant to both indoor environmental quality and building energy performance.

Table 5 Behaviours of interest

Behaviour	*Description*
Environmental Control Actions	Window adjustment
	Blinds adjustment
	Thermostat adjustment
	Artificial lighting adjustment
Personal Adaptive Actions	Clothing adjustment
	Drinking hot/cold beverages
	Personal heater
	Personal fan

3.5.Selection of environmental attributes and attribute levels

Following experiment design theory, the primary attributes and attribute levels (see Table 6) describing the decision context should be systematically varied across the presented choice tasks [180]. At the same time, the selected attributes must remain theoretically grounded, behaviourally plausible, and cognitively interpretable for participants. The final set of attributes was therefore chosen to capture

environmental, contextual, and social influences on comfort-adaptive behaviour in office environments, while keeping the scenarios manageable in terms of cognitive burden.

Firstly, two outdoor attributes were included: season and weather. Previous literature show that outdoor weather conditions influence perceived comfort temperature and that preferred indoor temperature differs significantly between heating and cooling seasons [162], [191] [47], [97], [128]. Therefore, season was represented by the levels summer, winter, and spring/fall, and weather by sunny, windy, and rainy.

Secondly, to capture occupants' preferences for occupant actions under multi-modal discomfort situations, four IEQ indicators are included: thermal conditions, indoor air quality, artificial lighting, and daylight conditions. The status (e.g., high or low indoor temperature) and combination (e.g., high temperature with stuffy air) of these four indicators are among the fundamental drivers of occupant behaviour, which address the physiological, safety, esteem and self-actualization needs of an individual (Schweiker et al., 2023). Each indicator has three levels, two of which describe less comfortable conditions related to that IEQ indicator, where the third level is a reference level (indicating a neutral comfort condition) (see Table 6).

For IEQ thermal conditions, one previous study suggests that window adjustment is less frequent when the indoor temperature is around 23 °C, while it is more frequent when it is above 26 °C or below 20°C. Similar for thermostat adjustment, it is more frequent when it is above 28 °C and below 16 °C, and less frequent when the indoor temperature is between 22 to 24 °C [104]. Therefore, considering the acceptable upper and lower limits of indoor temperature for moderate environments in the Netherlands [193], the following three levels are selected: 'higher than 24 °C', 'lower than 18 °C', and 'between 18 and 24 °C.

For IEQ indoor air quality, discomfort is commonly associated with unpleasant smell and static air due to insufficient ventilation and/or a source of odour [194]. Indoor air quality is often measured objectively using proxies such as $PM_{2.5}$/PM_{10} concentration, CO, O_3, etc., [92], [195]. While in surveys, perception-based terminology is commonly used. Torriani et al., [194], summarized four descriptive components that are commonly used in surveys to collect occupants' perception on air quality, i.e., satisfaction (38%), acceptability (21%), freshness/stuffiness (18%), and odour (22%) (roughly 2% using quality). As the DCE requires systematically variable scenario descriptions rather than satisfaction evaluation, the three levels of IEQ-air quality were 'stuffy air', 'odour air' and 'air quality is fine'.

For visual comfort, two separate IEQ attributes were included: artificial lighting and (indoor) daylight. These factors influence not only task performance, but also visual comfort, well-being, privacy, and control needs in office environments. Prior research suggests that occupants' visual preferences differ depending on both natural and artificial light conditions [196]. Ozcelik et al. [116] found that when experiencing a multimodal discomfort condition, occupants prefer visual control as an immediate decision over thermal control, i.e., occupants adjust the blinds to avoid the synthetic glare, then adjusting the thermostat or desk fan for thermal comfort. Furthermore, Sadeghi et al. [111] confirmed that reducing/increasing overall indoor brightness and minimising the glare from artificial lighting and daylight are the main reasons for lighting and blinds usage. Based on these, IEQ-lighting conditions were defined as 'Glare from the artificial lighting', 'Dimmed artificial lighting', and 'Adequate lighting', and IEQ-daylight conditions were defined as 'Glare from the Sun', 'Minimum daylight', and 'Soft daylight'.

Lastly, occupancy status is included because of its key role in shaping occupant interactions with the building and its influence on the level of social interactions that an individual experiences. Typically, the occupancy status is studied with the number of people and the presence or absence of an individual or a group of people

in a space. For this study, three levels of occupancy status were selected: 2 to 3 people, 4 to 9 people, and 10 to 15 people. Similarly, three basic open-plan office areas (locations) are selected: concentration area, collaboration area, and meeting room. Definition of these areas does not assume any time-related occupancy, instead it only reflects the social complexity in terms of peer-pressure and communication level (see Table 7). Within the selected area, three types of work activities (tasks) are also defined, i.e., individual concentration work, formal meeting, and informal meeting. As some combinations of the location and task are not realistic (e.g., a formal meeting in a concentration area), a new attribute with four levels defining realistic combinations is introduced (see Table 6 and 7). This avoids bias, which may result from presenting cognitively unacceptable combinations to participants [180].

Table 6 Attributes and attribute levels that are systematically varied in the experiment

Attribute	***Levels***
Season	*Summer*
	Winter
	Spring/Fall
Weather	*Sunny*
	Windy
	Rainy
Number of occupants	*2 to 3 people work in this space*
	4 to 9 people work in this space
	10 to 15 people work in this space
IEQ – thermal	*Temperature is below 18 degrees*
	Temperature is 18 to 24 degrees
	Temperature is higher than 24 degrees

IEQ – indoor air quality	*Odour in the air* *Stuffy air* *Air quality is fine*
IEQ – artificial lighting	*Dimmed artificial lights* *Glare from artificial lighting* *Adequate lighting*
IEQ – daylight	*Glare from the Sun* *Minimum daylight* *Soft daylight*
Location and task	*Group 1-Individual concentration work in concentration area* *Group 2-Formal meeting in meeting room* *Group 3-Informal meeting in collaborative area* *Group 4-Informal meeting in meeting room*

Table 7 Pre-defined groups with different levels of communication and social expectation

Task/Type of workplace	Concentration area	Collaborative area	Meeting area	(Communication level)
Concentration work	Group 1	-	-	Minimum
Informal meeting	-	Group 3	Group 4	Moderate
Formal meeting	-	-	Group 2	Highest
(Peer-pressure level)	Minimum	Moderate	Highest	-

To achieve choice tasks that are feasible for participants, the combined location and task attribute was kept fixed for each respondent (see 3.6). Furthermore, respondents were instructed to imagine that the indoor environmental controls were available and accessible in all hypothetical situations, which may not always be the case in real settings [8] Attributes like 'distance to control', 'sitting orientation', and 'acoustic level', which may also be influential, are difficult to manipulate in the DCE survey and are therefore not included in this study.

3.6. Generation of choice tasks and randomness control

The final DCE design includes eight attributes that are systematically varied in the choice task, of which seven had three levels and one with four levels. The design was structured so that the main effects and selected two-way interactions between the dependent variables could be estimated. For two-way interactions, outdoor temperature and weather conditions were picked to interact with the other four IEQ-indicators, which makes 32 interaction parameters. In total, there are 49 parameters to be estimated. Using the Ngene experiment design tool [197], an orthogonal and balanced design with 72 profiles was generated. The design was optimized without any prior information and yields a D-error of 1.216, and a corresponding D-efficiency of 99.6%, indicating a highly efficient design for the estimated attributes.

The scenario descriptions resulting from the design were intended to reflect the complex nature of real-world office discomfort situations, while remaining concise enough for survey implementation. Since the four-level (location and task) attribute defines a major office setting rather than a within-scenario fluctuation, it was held constant within respondents. This effectively created four groups of participants, each associated with one of the predefined workplace task settings. Participants were first randomly assigned to one of these four groups, identifying themselves with assigned tasks and designated locations (e.g. individual work in a

concentration area). Within their assigned group, each participant received eight choice tasks out of a total of eighteen available from that group. This random assignment strategy reduced individual burden while preserving overall design convergence across the sample. As recognised in the design literature, assigning subsets of tasks to different respondents is a common and effective way to manage participant burden while retaining sufficient variation in choice observations [180].

So far, the DCE design described above captures individual choice preferences with respect to environmental and contextual factors. However, office environments are inherently social and social interaction among co-workers may influence individual decision-making processes [169], i.e., people value others' opinions and make collective decisions under certain situations [174], [175]. Xu et al., [169] showed that social norms affect energy-related intentions differently in single and shared offices. Their results indicate that injunctive norms (i.e., what people believe other people approve of) have a significant impact on occupants in single offices, while descriptive norms (i.e., what people actually do) have a significant impact on occupants' energy-saving intention in shared offices.

Therefore, the DCE design includes a special "Proposed" condition (see Figure 7). Under this condition, respondents receive information about what some other (imaginary) co-worker in the space has proposed to do (e.g., change the window or blinds, etc.). The information is provided by assigning the label 'proposed' to one of the environmental control options (e.g. "Adjust window (Proposed)", which does not imply the state of the proposed option, e.g., the window can be in open, close, or semi-closed position. The state is purposely left unspecified to not further complicate the described scenarios. The number of choice tasks in the "Proposed" condition for each respondent is random ranging from none to a maximum of eight. The final distribution of the two types of choice tasks is 50.4% (2591 with proposed conditions) and 49.6% (2553 without it), respectively. The proposed conditions

were evenly distributed across environmental control types and participant groups, as shown in Table 8.

Table 8 Distribution of the "Proposed" condition[3]

	Group 1	*Group 2*	*Group 3*	*Group 4*	*Sum*
Total number of choice tasks within one group	18	18	18	18	72
No. of choice tasks without proposed condition	9	9	9	9	36
No. of choice tasks with proposed condition	9	9	9	9	36
Window (Proposed)	2	2	3	2	9
Blinds (Proposed)	2	3	2	2	9
Thermostat (Proposed)	3	2	2	2	9
Lighting (Proposed)	2	2	2	3	9

3.7.Choice task

Before starting the DCE questions, an introduction page was presented to the participants with the following instructions:

- You will receive 8 imaginary office scenarios with a pre-defined location and task, along with the description of environmental conditions (see Figure 6).
- You can choose any preferred building system control or controls (i.e., window, blinds, thermostat, lighting) and/or personal measures (i.e., personal fan, adjusting clothing) to improve your comfort or choose ‘do nothing’.
- In some choices, there will be the presence of a co-worker’s proposed control option (see Figure 7) to improve comfort.

[3] Table 8 ensures that the proposed conditions for each environmental control option are evenly distributed. For each group, the number of choice tasks with proposed conditions is 9. Also, for each environmental control option, the proposed conditions are 9.

- You have the possibility to choose multiple-choice options.
- The office scenario setting is NOT based on your current office environment or availability of controls.

For each task, participants first read a contextual description of a hypothetical office setting where the indoor environment conditions may or may not be optimal. The available control options were labelled identically across all scenarios and consisted of four environmental control options, four personal adaptive control options, and the 'do nothing' option. Then participants were asked to select any preferred control option or combination of options (i.e., single, multiple, or none) that they would use to improve their comfort.

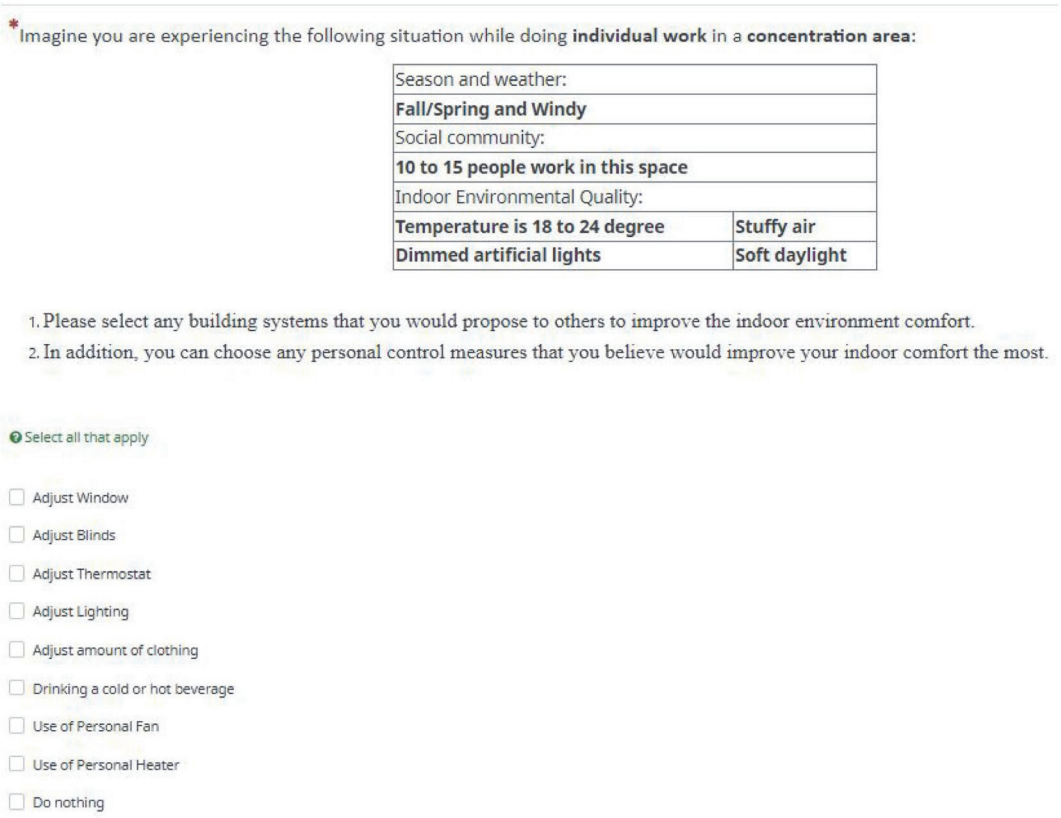
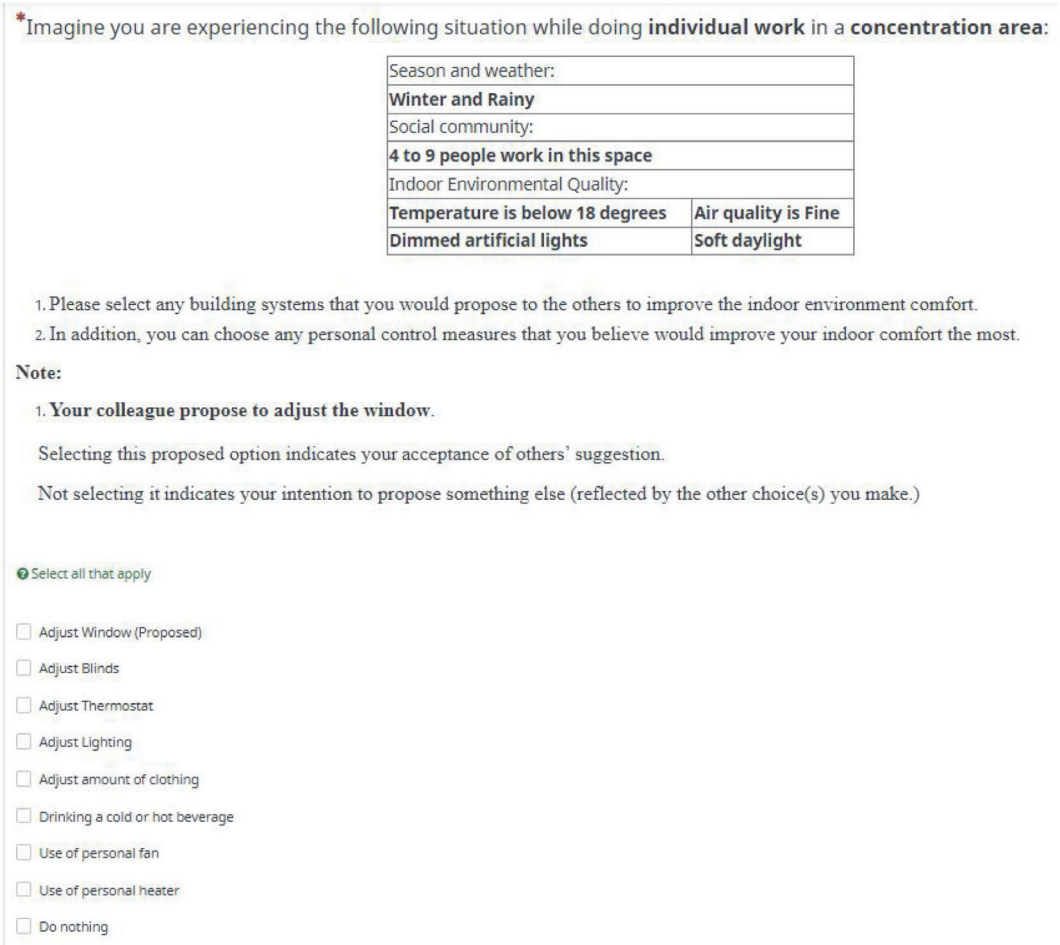


Figure 6 Example of a choice task without proposed condition


*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Winter and Rainy	
Social community:	
4 to 9 people work in this space	
Indoor Environmental Quality:	
Temperature is below 18 degrees	**Air quality is Fine**
Dimmed artificial lights	**Soft daylight**

1. Please select any building systems that you would propose to the others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Note:

1. **Your colleague propose to adjust the window**.

Selecting this proposed option indicates your acceptance of others' suggestion.

Not selecting it indicates your intention to propose something else (reflected by the other choice(s) you make.)

Select all that apply

- ☐ Adjust Window (Proposed)
- ☐ Adjust Blinds
- ☐ Adjust Thermostat
- ☐ Adjust Lighting
- ☐ Adjust amount of clothing
- ☐ Drinking a cold or hot beverage
- ☐ Use of personal fan
- ☐ Use of personal heater
- ☐ Do nothing

Figure 7 Example of a choice task in the 'proposed' condition

3.8. Cross-sectional survey-section

As previously mentioned, the survey consists of two integrated components, i.e., the multiple response DCE and a cross-sectional survey section. While the DCE explore stated preferences for adaptive actions under hypothetical office scenarios, the cross-sectional survey collects qualitative responses of participants by asking about their current office environment and perceptions, and their demographic information. Previous studies suggest that female occupants show consistently lower thermal comfort satisfaction levels compared to men [198], for instance, female occupants often report more building-related symptoms than males [199].

Ortiz et al. [196] further depict that IEQ preferences are situation-dependent, and demographics like gender may also shape the IEQ preferences. Thus, the information collected includes demographics (e.g., age, gender), current workplace and occupancy (e.g. type of workstation, size of offices, accessibility and availability to building controls), energy-saving attitude, perceived control, personal/social norm, personality traits, and organisational policies (see Table 9).

Table 9 Cross-sectional survey question

Attribute	***Description***	***Scale/Source***
	Demographics	
Age	Numerical input	-
Gender	Male, Female	-
Occupation	Education and research, Healthcare, Business/finance/trade, Others	-
	Workplace and occupancy	
Type of workplace	1. Private (single) room (1 person). 2. Shared room (2-3 persons). 3. Small open-plan work area (4-9 persons). 4. Medium-sized open-plan work area (10-24 persons). 5. Large open-plan work area (More than 25 persons)	[200]
Type of workstation	1. Assigned desk/workstation 2. Flexible use of desks/workstations	-

Years worked in current office	Numerical input	-
Building control feature		
Current building control possibility	1. I can open/close the window. 2. I can adjust the blinds/shades 3. I can adjust the lighting 4. I can adjust the thermostat	-
Organization		
Organizational pro-environmental attitude	1. My organization/company is interested in supporting environmental policies. 2. My organization/company believes it is important to protect the environment. 3. My organization/company emphasizes the use of less paper, energy and disposable products.	5-point scale [201]
Attitudinal attributes		
Energy saving attitude in office	1. I am actively focused on energy saving. 2. I am neutral towards energy saving. 3. I am less inclined (mindful) towards energy conservation.	[202]
Perceived control belief	I believe it is easy to use the building control system in my office to regulate the indoor environmental quality	5-point scale [162], [203], [204]

Social norm and personal norm		
Descriptive norm in office	How often do your colleagues/boss perform energy-related adaptive behaviours while in office? (e.g., open window for fresh air, turn on Air-conditioning to cool down the room, etc.)	6-point scale [169], [205]
Personal norm in office	Do you feel morally obliged to conserve energy in your office environment?	5-point scale [162], [167], [169]
Personality		
Personality trait	1. Extraverted, enthusiastic. 2. Critical, quarrelsome. 3. Dependable, self-disciplined. 4. Anxious, easily upset. 5. Open to new experiences, complex. 6. Reserved, quite. 7. Sympathetic, warm. 8. Disorganized, careless. 9. Calm, emotionally stable. 10. Conventional, uncreative.	7-point scale [206], [207]

3.9.Survey data collection

Limesurvey is used to implement the 72 profiles into an online questionnaire. The survey was reviewed and approved by the Ethical Review Board of Eindhoven University of Technology on the 10th of January 2024, with reference number ERB2024BE2. The final survey was sent to a national panel company (i.e., Panelclix), with two selection criteria for participants: the person should be an

office employee and work in the office at least two days a week. Initially, 704 respondents participated, but after removing invalid cases (time used is less than 5 minutes or answers show unlikely repetitive patterns), the final dataset consists of 643 respondents and 5144 observations, with a mean completion time of 15.12 minutes.

With 72 profiles and each profile planned to collect a minimum of 30 observations, that gives 2160 observations. Each respondent was expected to answer 8 profiles, so a minimum of 270 participants were needed. In practice, a target was set with a minimum valid sample of 300 participants, and aimed for 600, taking into account future research needs (e.g., latent class analysis). Eventually, on average, there were 104 observations per parameter for the RPML model.

For the latent class model, though there is no universal rule for latent class model power assessment, methodological guidance indicates that stable class recovery generally requires a sample size above 300 respondents and a sufficiently effective sample within each class [208], [209], [210]. The sample of 643 respondents, therefore, exceeds recommended thresholds, and the class-specific observation-to-parameter ratios surpass the commonly applied heuristic of maintaining at least 10 observations per parameter for a reliable estimation of latent classes. Eventually, the class-specific observation-to-parameter ratios are approximately 29, 12, and 17 observations per parameter, for Class1, Class2 and Class3 membership with their corresponding estimated posterior class membership probabilities. Hence, the sample provides adequate statistical power for identifying latent preference segments and estimating class-specific behavioural patterns.

3.10. Conclusion

This chapter has described the experiment design and data collection procedures that underpin the empirical analyses presented in the following chapters. Building on the conceptual foundation established in Chapter 2, a multi-response discrete

choice experiment was developed. This design allowed participants to express preferences for multiple adaptive actions under multimodal (dis)comfort situations, while the accompanying cross-sectional survey collected information on current workplace conditions, psychosocial factors, and individual characteristics.

The collected dataset provides an empirical basis for analysing occupants' adaptive preferences and behavioural heterogeneity in office environments. It supports both the estimation of utility-based choice models and the identification of latent behavioural profiles. Building on these, Chapter 4 turns to the modelling of these stated preferences using multinomial and mixed logit models to quantify the utility associated with the studied adaptive actions.

4. Revealing occupants' preferences for comfort adaptive actions in open-plan offices[4]

4.1. Introduction

Chapter 4 investigates how office occupants respond to indoor environmental discomfort by analysing their preferences for different comfort-adaptive actions. It applies utility-based discrete choice modelling, specifically multinomial logit (MNL) and random parameter mixed logit (RPML) models to do so. These models estimate the probability that occupants select particular adaptive actions as a function of environmental conditions, contextual characteristics, and social cues embedded in the choice tasks. The MNL model is a baseline representation of average behavioural preferences across occupants, while the RPML model extends this by capturing unobserved preference heterogeneity through random coefficients. Together, these models enable a more nuanced understanding of both aggregate behavioural patterns and individual-level variance in adaptive choices.

This chapter is organized as follows: section 4.2 introduces the model development, including defining the choice alternatives, multinomial logit model, and random parameter logit model, section 4.3 presents the findings of the model, section 4.4 presents the discussion, and section 4.5 presents the conclusions.

4.2. Model development

The model-based analysis is performed with NLOGIT 6 and explained below.

4.2.1. Defining the choice alternatives

The different options for personal adaptive actions were merged into a single choice alternative, in the following referred to as personal adaptive (see Figure 8), due to

[4] This Chapter is adapted from:
H. Li, R. Appel-Meulenbroek, T.A. Arentze et al., Revealing and modelling occupants' preferences for comfort adaptive actions in open-plan offices with the inclusion of contextual and social-psychological aspects, Building and Environment 285 (2025) 113681, https://doi.org/10.1016/j.buildenv.2025.113681

insufficient appearances in the sample. Since respondents can select multiple options in each presented choice task, from a choice modelling point of view, the choice alternatives consist of all unique combinations of the provided options. With 5 options (the 4 controls and the personal adaptive actions) there were a total of 32 (2^5) alternatives. The 'do nothing' alternative was identified as the alternative where none of the options is selected.

In the model, only the combination of maximum two options were considered with interaction effects (10 alternatives out of 32) and specified in the dataset. As for, three-, four-, five-way interactions, they were not specified in the model but considered as a combination of base and two-way interactions (see Eq. 3 and 4).

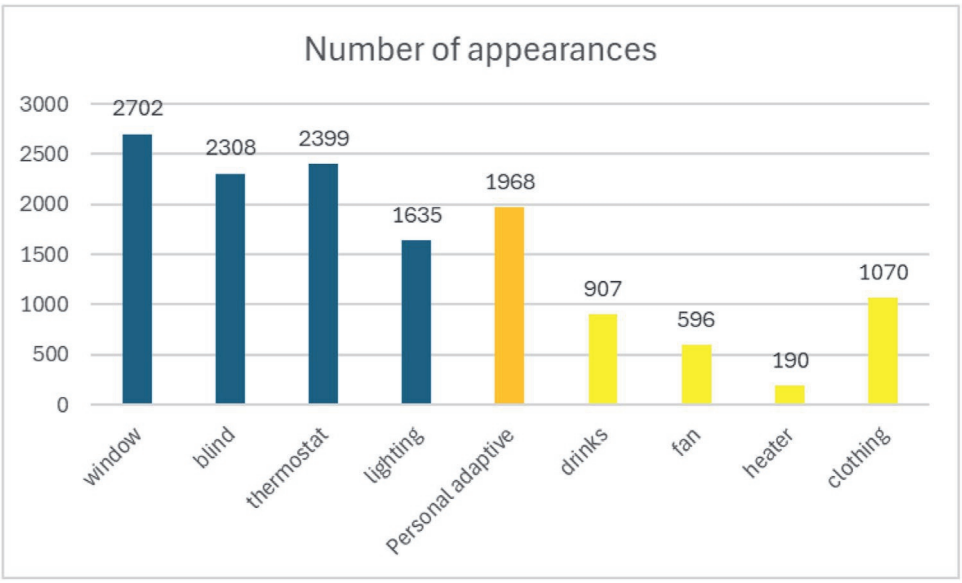


Figure 8 Dependent variable consolidation

4.2.2. *Multinomial logit model*

The multinomial logit (MNL) model is used as a framework to estimate the preference parameters. A MNL model can be described as:

$$U_{nsj} = V_{nsj} + \varepsilon_{nsj} \, (Eq. 1)$$

where U_{nsj} represents the utility of alternative j for respondent n in choice situation s , V_{nsj} is the structural component, and ε_{nsj} is the random component of the utility. The structural component V_{nsj} is defined as a function of K attributes, x_{nsk}, with associated preference weights, β, as:

$$V_{nsj} = \beta_{0j} + \sum_{k=1}^{K} \beta_k x_{nsk} \ (Eq. 2)$$

where β_{0j} is an alternative-specific constant (base utility for alternative j), x_{nsk} is a scalar that indicates the value of attribute k for individual n in choice situation s and β_k is the coefficient associated with attribute k.

Equation 2 shows the main components of the utility function which hold in general. In this study, the utility function is further specified as:

$$U_{nsj} = \sum_{i \epsilon I_j} \beta_{is} + \sum_{i \epsilon I_j} \sum_{i' \epsilon I_j, i' < i} \beta_{ii'} + \sum_{i=1}^{4} \delta_i R_{is} + \sigma_0 Q_j + \varepsilon_{nsj} \ (Eq. 3)$$

$$\beta_{is} = \beta_{0i} + \sum_{k=1}^{K} \beta_{1ik} x_{nsk} \ (Eq. 4)$$

Where:

I_j : is the set of adaptation options included in alternative j.

β_{is} : is the preference for option i in alternative j in choice situation s.

$\beta_{ii'}$: is an interaction effect between options i and i'.

δ_i : is the base preference of accepting a proposal for environmental control option i by someone else.

R_{is} : is a binary variable indicating whether option i in scenario s is proposed by others.

σ_0 : is a base preference for a personal adaptive option.

Q_j : is a binary variable indicating whether alternative j includes a personal adaptive option.

β_{0i} : is a base preference for option i.

K : is the number of attributes.

β_{1ik} : is the preference for option i with attribute k in choice.

x_{nsk} : value of attribute k for individual n in choice situation s.

And other symbols are defined as before.

In above equation, environmental control options are indexed as $i = 1\ to\ i = 4$, and the personal adaptive option is indexed as $i = 5$.

The first term on the RHS ($\sum_{i \epsilon I_j} \beta_{is}$) implements the summation over options i included in I_j in choice situation s. This captures a base utility for alternative j depending on the unique combination of options i and the attributes of the choice situation. The base utility consists of a base preference for the option β_{0i} and β_{1ik} related to the attribute k in choice s (x_{nsk}).

The second term on the RHS ($\sum_{i \epsilon I_j} \sum_{i' \epsilon I_j, i' < i} \beta_{ii'}$) implements a summation over the two-way interactions between options i included in I_j.

The third term on the RHS ($\sum_{i=1}^{4} \delta_i R_{is}$) represents an intention to be cooperative, that is to adopt the option proposed by someone else. The expectation is that people tend to accept a proposal ($\delta_i > 0$).

The fourth term on the RHS ($\sigma_0 Q_j$) represents a base preference to adopt a personal adaptive option or do nothing.

4.2.3. The mixed logit model

An MNL model represents average preferences across, in this case, occupants. However, several studies point out that heterogeneity exists in preferences related to many aspects, e.g. comfort temperature [211], situational-dependent [196]. The ML model is an extension of the MNL model that considers heterogeneity by assuming random parameters:

$$\beta_{kn} = \overline{\beta}_k + \sigma_k v_{kn} \ (Eq.5)$$

Where β_{kn} represents the random parameter k for individual n. $\overline{\beta}_k$ represents the average marginal utility of k and σ_k is the standard deviation for attribute k, $v_{kn} \sim N[0,1]$ is standard normal random variable. The random terms are obtained by drawing from a distribution (in this study a normal distribution is assumed for each parameter) [212]. A stepwise approach was used to identify which parameters should be retained as random in the final model.

4.3. Results

4.3.1. The sample

The sample consists of office employees with flexible schedules. Descriptive statistics of the sample are shown in Table 10. Gender is nearly equally balanced with 51% female and 49% male, the average age of the respondents is 42 years old, and the average years worked in the current office is 8 years. With respect to occupation, 18% of the respondents work in education and research, 17% in healthcare and medicine, 36% in business, finance, and trade, and 29% in other sectors (i.e., administration, government, legal and law enforcement, information technology, engineering and technology, and arts and entertainment). Five typical open-plan office room/areas where respondents work are identified, with 13% of

them in real life working in private offices (single occupancy), 29% share one room with others, 28% work in small open-plan areas with 4 to 9 co-workers, 20% in medium size open-plan area with 10 to 24 co-workers, and 10% in an open-plan area with more than 25 co-workers. Regarding workstations, 58% of respondents have an assigned desk, while 42% are used to flexible workstations.

Table 10 Social-demographic and current workplace characteristics

	Category	***%***
Age	< 30 years	21%
	30 – 49 years	49%
	50 – 64 years	28%
	65+ years	2%
Gender	Female	51%
	Male	49%
Occupation	Education and Research	18%
	Healthcare and Medicine	17%
	Business, finance and trade	36%
	Others	29%
Type of Office	Private office	13%
	Shared room	29%
	Small open-plan area (4-9)	28%
	Medium open-plan area (10-24)	20%
	Large open-plan area (Moren than 25)	10%
Type of Workstation	Assigned workstation	58%
	Flexible workstation	42%
Years worked in current office	Equal and less than 8 Years	67%
	More than 8 Years	33%

4.3.2. Estimation Results

The estimation results are shown for different sets of parameters in Tables 11, 12 and 13, based on the Mixed Logit model with 500 Halton draws and 75 parameters. The McFadden adjusted-Rho square (ρ^2_{adj}) equals 0.127, which, considering the size of the model, indicates a moderate model performance. Table 11 compares the McFadden adjusted-Rho square with the original MNL model. Though the improvement is minor, still the mixed logit model offers a better estimation. In

addition, with a mixed logit model the preference heterogeneity can be revealed, as discussed in following sections.

Table 11 Model comparison

	MNL	ML (500 Halton)
LL0	-17827.745	-17827.745
LL-fitted	-15475.900	-15456.207
McFadden R^2_{adj}	0.126	0.127

4.3.3. Base preference and pair-wise interaction effect

The base utility for all adaption options, except for the window option, is statistically significant and has a negative coefficient, i.e., window, blinds, thermostat, lighting, and personal adaptive action (see Table 12). This suggests that occupants tend to prefer to do nothing when all attributes are at the base level (the middle level, indicating normal conditions).

The two-way interactions are statistically significant for four combinations. Three of which have a positive coefficient value, i.e., 'window + blinds', 'thermostat + lighting', and 'thermostat + personal adaptive action' and one has a negative coefficient value, i.e., 'blinds + lighting' (see Table 12). This indicates that some combined choices are more preferred by the occupants in multimodal discomfort situations than others, which might reflect either a positive or negative synergy effect between those options. For instance, thermostat and visual comfort are often linked [213]. Adjusting thermostat or blinds for thermal comfort can also influence the visual comfort with how lighting and glare are perceived in the space. Hence, the interaction makes sense in terms of synergy effects.

Table 12 Base utility, pair-wise interaction, and social effect

	Description	Coefficient (β)	z	p-value	St. Dev.	p-value
Constant	Window	-0.017	-0.37	0.710		
	Blinds	-0.294***	-5.45	0.000		
	Thermostat	-0.243***	-6.05	0.000		
	Lighting	-1.369***	-8.46	0.000		
	Personal adaptive action	-0.379***	-8.37	0.000		
Two-way interaction	Window + Blinds	0.221***	2.98	0.003		
	Window + Thermostat	-0.034	-0.44	0.659		
	Window + Lighting	-0.019	-0.2	0.843		
	Window + Personal adaptive action	0.016	0.18	0.854		
	Blinds + Thermostat	-0.026	-0.3	0.763		
	Blinds + Lighting	-0.227**	-1.97	0.048		
	Blinds + Personal adaptive action	-0.005	-0.05	0.964		
	Thermostat + Lighting	0.217**	2.11	0.035		

	Thermostat + Personal adaptive action	0.367***	4.27	0.000		
	Lighting + Personal adaptive action	0.161	1.34	0.182		
Social effect	Window - proposed	0.901***	5.1	0.000	1.576***	0.000
	Blinds - proposed	0.592***	2.67	0.008	1.970***	0.001
	Thermostat - proposed	0.335***	3.21	0.001		
	Lighting - proposed	1.254***	6.14	0.000		
	Personal adaptation under social conditions	-0.332***	-6.04	0.000		

4.3.4. Social effects

The proposed status has a statistically significant and positive effect for all environmental control options (see Table 12), suggesting that occupants are inclined to be cooperative and go along with proposals of others. The cooperation tendency regarding the thermostat and lighting options can be considered to consist in general. However, the standard deviation (SD) for the window and blinds options are statistically significant, indicating that here the cooperation tendency differs among individuals. Hence, for window and blinds options, the results indicate that preferences regarding being cooperative vary among individuals.

The presence of the social condition (that is, others have proposed something) has a negative effect on the base utility of the personal adaptive option (see Table 12). This indicates that when someone has proposed a solution to resolve the indoor

environmental discomfort, whether in line with their own preference or not, occupants are less likely to adopt a personal adaptive option (as an extra measure).

4.3.5. Location and task

Table 13 shows the estimation results regarding preferences for environmental control options for different levels of the environment-condition attributes (x). The results indicate that preferences for certain adaptive behaviours depend on task and location, which might be related to the expected social interactions in offices. People tend to prefer the personal adaptive option when performing individual work in concentration areas, and are less likely to perform personal adaptive action when having a formal meeting in a meeting room. This might be caused by the fact that social interactions differ in location-task contexts. When having an informal meeting in a collaboration area, people exhibit a preference for environmental control options, particularly with regards to lighting and window options. However, the model reveals heterogeneity in preferences for the window option, though its average marginal utility is not statistically significant.

When having a formal meeting in a meeting room, people prefer not to change the thermostat, lighting or perform a personal adaptive action. This aligns with previous findings on social effects, indicating that people are less active when social interaction expectations are high, as a solution to resolve the discomfort situation is (likely) already proposed by their colleagues. Hence, in such cases, the performed behaviours are more of a collective decision.

4.3.6. Outdoor environment

In summer, the base preference for lighting and blinds options increases, and there is preference heterogeneity for the blinds option. The base preference for thermostat options decreases during summer. In winter, inversely, the base preference for the thermostat option increases. For the lighting option, the SD is significant indicating that with respect to this option the winter effect differs across persons, whereas the

average base preference is not statistically significant. The base preference for window options decreases during winter (see Table 13).

On a sunny day, the base preference for the blinds option increases. For the lighting option, the SD is significant indicating that this sunny day effect differs across persons, whereas the average base preference is not statistically significant. On a windy day, the base preference for thermostat and lighting options increases. For the window option, the SD is significant indicating that the windy-day effect differs across persons whereas the average base preference is not statistically significant (see Table 13).

Preference heterogeneity has been identified for the lighting option across both season and weather conditions, highlighting the need for occupant-centric lighting control systems in office environments.

4.3.7. Occupancy

The results suggest that occupancy levels influence individuals' decisions on the use of blinds and lighting options. When there are 10 to 15 people working in the same area, the base preference for blinds option increases compared to 4-9 people (the base level). The pattern is different for lighting. When there are 2 to 3 people working in the same area, the base preference for lighting option increases compared to 2-9 people (see Table 13). The findings indicate that when more colleagues are present, people prefer to interact with controls that have the minimum impact on others, such as blinds. On the contrary, with fewer colleagues around, individuals tend to adjust the lighting level according to their own preference.

Table 13 Contextual and climatic attributes

Attributes	*Attribute levels*		*Wind*	*Blinds*	*The*	*Lighti*	*Pe*
Location and tasks	Individual work in a Con. area	***β***	-.097	-.121*	-.064	.012	.220***
		Z	-1.450	-1.660	-1.190	1.290	4.270
		SD					
	Formal meeting in a MR	***β***	.112	-.062/	-.103*	-.323***	-.484***
		Z	1.630	-0.850	1.930	-3.630	-8.770
		SD					
	Informal meeting in a Col. Area	***β***	.006	-.059	.034	.174**	.041
		Z	.090	-.880	.690	2.340	.840
		SD	.670*				
	Informal meeting in a MR	***β***	-.021	.242	.133	.137	.223
Season	Summer	***β***	.028	.242***	-.233***	.198**	.040
		Z	.540	3.790	5.440	2.070	.950
		SD		.749*			
	Winter	***β***	-.152***	-.040	.192***	-.023	.012
		Z	-2.840	-.680	4.520	-.320	.290
		SD				1.506***	
	Fall/Spring	***β***	.124	-.202	.041	-.175	-.052
Weather	Sunny	***β***	-.051	.270***	-.053	-.076	-.023
		Z	-1.000	4.230	-1.230	-1.030	-.550
		SD				1.224***	
	Windy	***β***	.044	-.073	.075*	.193**	-.027
		Z	.820	-1.270	1.710	2.040	-.650
		SD	.910***				
	Rainy	***β***	.007	-.197	-.022	-.117	.005

Occupancy level	2 to 3 people	***β***	.034	-.021	-.051	.109*	-.022
		Z	.640	-.360	-1.180	1.680	-.530
		SD					
	10 to 15 people	***β***	.001	.125**	.015	-.103	.065
		Z	.030	2.230	.350	-.200	1.570
		SD					
	4 to 9 people	***β***	-.035	-.146	.036	-.006	-.043
	(***), (**), (*) Sig. at 1%, 5%, 10%.						

4.3.8. Indoor environmental quality indicator

Table 14 presents an overview of the effects of the IEQ attributes and attribute levels on adaptive behaviour.

Table 14 Indoor environment quality indicators

Parameters			*Occupant behaviour*				
Attributes	**Attribute levels**		**Window**	**Blinds**	**Thermostat**	**Lighting**	**Personal adaptive**
IEQ – Temperature conditions	Temperature is below 18°C	***β***	-.379***	-.072	.438***	-.077	.202***
		Z	-5.960	-1.210	10.170	-1.190	4.780
		SD					
	Temperature is higher than 24°C	***β***	.260***	.319***	.527***	-.029	.185***
		Z	4.730	5.110	12.590	-.460	4.460
		SD		1.124***			
	Temperature is 18 to 24°C	***β***	.119	-.247	-.965	.286	-.387
IEQ – Air quality	Odour air	***β***	.898***	-.121**	.042	-.012	.057
		Z	10.450	-2.130	.980	-.190	1.350
		SD					
	Stuffy air	***β***	.707***	-.002	.141***	.220***	.153***
		Z	9.680	-.040	3.170	3.130	3.590
		SD					

	Air quality is fine	***β***	-1.605	.123	-.183	-.208	-.210
IEQ – Lighting conditions	Dimmed lighting	***β***	.054	-.351***	-.028	.180***	1.6 x 10^{-4}
		Z	.990	-5.570	-.660	2.630	.004
		SD					
	Glare from the lighting	***β***	-.064	.572***	.019	1.011***	.005
		Z	-1.180	7.760	.440	9.100	.110
		SD					
	Adequate lighting	***β***	.010	-.221	.009	-1.191	-5.16 x 10^{-3}
IEQ – Indoor daylight conditions	Glare from the Sun	***β***	-.186***	1.562***	.057	-.218***	-.012
		Z	-3.260	11.000	1.300	-3.150	-.280
		SD					
	Minimum daylight	***β***	.301***	-.445***	.010	.611***	.034
		Z	5.220	-6.670	.230	7.210	.810
		SD					
	Soft daylight	***β***	-.115	-1.117	-.067	-.393	-.022

(***), (**), (*) Sig. at 1%, 5%, 10%.

4.3.8.1. Temperature

The model shows that with a lower indoor temperature (below 18°C), people's preference for the thermostat and personal adaptive option increases (see Table 14). The base preference for the window option decreases when the indoor temperature is below 18°C. If the temperature is higher than 24°C, preferences for thermostat, window, blinds, and personal adaptive options increase. For the blinds option the SD is also statistically significant, indicating that for this option the temperature effect differs across people. This suggests that occupants 'endure' lower temperatures better than higher temperatures and consider a 'hot' indoor environment as a situation of more severe discomfort that requires more adaptations.

4.3.8.2. Air quality

When experiencing an odour in the air, the base preference for the window option increases and decreases for the blinds option (see Table 14). When experiencing stuffy air, preferences for window, thermostats, lighting, and personal adaptive options increase. The lighting option is a bit unexpected but could be explained perhaps through the previously mentioned synergy effects. The results indicate that occupants consider a stuffy indoor air as a severe discomfort in indoor environment.

4.3.8.3. Lighting and daylight conditions

As expected, when experiencing sub-optimal indoor lighting and daylight conditions, preference for blinds and lighting options increases. The source of the dimmed lighting condition is normally located within the current work area. The source of glare from light can be located within the current work area or stem from an adjacent area, e.g. adjacent room, or corridor. Preferences for the lighting option increase when experiencing dimmed lighting and glare from lighting (see Table 14). While preferences for the blinds option increase when experiencing glare from the lighting (to stop the glare from adjacent areas) and decrease when experiencing dimmed lighting.

As expected, indoor daylight conditions can be regulated by various control measures, including but not limited to lighting control, blinds/shade systems, and the window option (e.g. electrochromic window or manually applied privacy film.). When experiencing glare from the sun, the base preference for the blinds option increases, and the base preference decreases for the window and lighting options. When experiencing minimum daylight, the base preference for the window and lighting options increases, and decreases for the blinds option (see Table 14).

Both indoor lighting and daylight conditions do not seem to affect personal adaptive action as the coefficients are not statistically significant. Not a surprise, as is it uncommon in the studied country to see tools like a personal fan in offices.

4.4. Discussion

In this study, knowledge from behavioural, social, and engineering sciences is employed to investigate occupants' comfort adaptive actions in hypothetical open-plan office settings. By combining a conventional cross-sectional survey and a DCE, this study offers a novel methodological approach for both building practitioners and academics to study occupant adaptive behaviour in complex office environments. The cross-sectional survey was used to capture occupants' experiences on current workplace usage, while the DCE allowed to explore occupants' preferences for various building control measures under multi-modal discomfort situations across hypothetical office settings. Instead of asking participants about their comfort or satisfaction level within each setting, the DCE survey asked participants to state their choice preference for specific adaptive actions.

Compared to other occupant-perspective methods mentioned in [214], the DCE approach enables the quantification of behavioural trade-offs that people are willing to make when facing alternative adaptive options. A benefit from its rigorous design process ([215]) is that DCE surveys generate choice data that can be used to estimate predictive models; in this case of specific occupant behaviour, regardless of whether it is a single or multiple choice (e.g., combined/simultaneous choice like window and blinds adjustment), where conventional methods are often limited to single behaviours or single factor analysis.

The choice response data can be analysed using various modelling approaches in order to explore: 1) the average preference of particular or paired actions in response to IEQ discomfort situations (e.g., using multinomial logit models); 2) preference heterogeneity for comfort adaptive actions (e.g., using random parameter mixed logit models); and 3) latent variables that are not observed in real world cases (e.g., using latent class models). The first and second approaches are

used in this chapter, focusing on modelling (multi-) occupant adaptive actions as a function of building characteristics, contextual conditions, environmental factors, and personal attributes, as well as on identifying any potential preference heterogeneity among individuals. Within the context of occupant behaviour research, this research approach offered an advancement in methods by enabling the modelling of both average and individual-level preferences, as well as the inclusion of social-effect parameters to capture cooperative intentions in shared spaces.

Several findings emerged from these analyses. In open-plan office environments, occupants interact not only with various building (control) features, but also with their co-workers and, in a behavioural sense, with themselves. The presence of other controlling agents, e.g., the presence of colleagues, influences individuals' actions, and sometimes this leads to using personal adaptive actions to maintain or improve comfort [188], [189]. Interestingly, when the workplace design does not meet the needs of the occupants (e.g., due to limited availability and accessibility of building control options), it does not necessarily result in dissatisfaction with the environment[188]. Instead, occupants may adopt a personal adaptive action as a back-up means to restore their comfort (further), either together with environmental control action(s) or as a standalone strategy.

Second, occupants may prefer more than one adaptive solution in the work environment, when available, especially when they expect to experience severe discomfort situations. The base preferences for all the studied behaviours suggest that when the situation is comfortable, occupants would tend to avoid engaging in adaptive behaviour in open-plan office environments, regardless of whether it is an environmental control action or a personal adaptive action. However, when the situation becomes uncomfortable, occupants show increased preferences for both environmental and personal adaptive actions to restore their comfort. Occupants consider a high indoor temperature and stuffy air as the most severe discomforting

situation, and in such situations four of the five modelled adaptive options show increased preference (see Table 12). This aligns with the findings of Weerasinghe et al., [216], who indicate that the main comfort preferences in office settings are related to thermal conditions and air quality.

Third, the behaviour performed by individuals in office environments may not be solely their personal choice but rather the results of a collective group decision implemented after being proposed by a single representative. By incorporating social conditions, this study provides further empirical evidence supporting the earlier findings of Xu et al. [169], which suggest that descriptive norms are important predictors of occupant behaviour in shared office spaces. Notably, this study is the first to show that in hypothetical open-plan areas or shared offices, individuals tend to align with the proposed behaviour preferences of a colleague. This finding highlights cooperative intentions and suggests that decisions regarding thermostat and lighting settings in open-plan offices and shared rooms can involve socially influenced or cooperative decision-making rather than reflecting solely individual preferences.

Fourth, by providing office occupants with full access to various basic IEQ controls, the model suggests that heterogeneity in preferences exists for certain adaptive behaviours. Specifically, within the experimentally defined conditions in which the control options were assumed to be available and accessible, this study highlights how preferences for adjusting windows, blinds, and lighting vary under different social, environmental, and contextual conditions. This variation can be explained from a psychological perspective, as Karjalainen [173] highlighted that increased perceived behaviour control leads to greater tolerance for discomfort, which, in turn, results in a broader range of control behaviours. However, characteristics of the control systems themselves, such as the specific control interface, ease of use, controllability, and perceived effectiveness, were not varied in the experiment. These factors may also influence occupants' willingness or ability to use a control

and should therefore be considered when transferring the estimated preferences to real office environments.

4.5. Conclusion

This chapter introduced a novel occupant-centric approach to examine the preferences of office workers for adaptive behaviours under multimodal indoor environmental (dis)comfort scenarios. The DCE approach effectively captured the occupants' preferences for multiple adaptive behaviours within hypothetical office settings. By accounting for both environmental and contextual factors, occupant preferences were estimated and modelled using a mixed logit discrete choice model. Furthermore, this chapter explored cooperative intentions of individuals in office settings, providing novel insights into shared behavioural dynamics that influence the energy use of office buildings. The comprehensive approach of this study enriches the understanding of occupants' adaptive choices in response to workplace discomfort, allowing building practitioners to identify not only dominant adaptive strategies but also substantial heterogeneity across individuals, thereby advancing the predictive capability of occupant behaviour models.

RPML models revealed average/aggregate preference heterogeneity, indicating that occupants differ in their sensitivity to environmental conditions and willingness to interact with building controls. This suggests that representing occupants homogeneously in building performance simulation can lead to unrealistic behavioural assumptions. To further explore the nature of behavioural heterogeneity identified in this chapter, the following chapter adopts a model-based clustering approach: to identify distinct behavioural profiles among office occupants and to examine how different groups respond to environmental and contextual conditions.

5. Profiling office workers' comfort-related adaptive actions: a latent class analysis[5]

5.1. Introduction

To gain further insight into the structure of behavioural differences among occupants, this chapter adopts a latent class modelling approach to identify distinct behavioural profiles. Using the same discrete choice experiment dataset described in Chapter 3, this chapter will utilise latent class choice models to segment individuals into groups with similar preference structure. Instead of assuming that behaviour follows continuous distributions, the latent class model identifies discrete groups of occupants who exhibit distinct patterns of adaptive behaviour. Latent class models provide a more interpretable representation of occupant heterogeneity. In addition, this chapter also examines socio-demographic characteristics and psychological attributes related to class membership, offering insights into the drivers underlying different behaviour patterns.

This chapter is organized as follows: section 5.2 latent class mode estimation, 5.3 model generation and evaluation, 5.4 presents the results alone with discussions, 5.5 presents the conclusions.

5.2. Model estimation (LCA)

Commonly, a multinomial logit (MNL) model is used as a framework to formulate the utility function of choice alternatives defined as [215]:

$$U_{nsj} = V_{nsj} + \varepsilon_{nsj} \; (Eq.1)$$

[5] This Chapter is adapted from:
H. Li, R. Appel-Meulenbroek, T. Arentze et al., Profiling office workers' comfort-related adaptive actions: a latent class analysis, Journal of Environmental Psychology 111 (2026) 102979, https://doi.org/10.1016/j.jenvp.2026.102979

where U_{nsj} represents the utility of alternative *j* for respondent *n* in choice situation *s*, V_{nsj} is the structural component, and ε_{nsj} is the random component of the utility. The structural component V_{nsj} is defined as a function of *K* attributes, with associated preference weights, β, defined as:

$$V_{nsj} = \beta_{0j} + \sum_{k=1}^{K} \beta_k x_{nsk} \ (Eq.2)$$

where β_{0j} is a constant for alternative *j*, x_{nsk} is a scalar that indicates the value of attribute *k* in choice situation *s*, and β_k is the coefficient associated with attribute *k*.

In this study, the DCE has a multiple-response format where participants are free to choose any of the available options, so the choice may consist of the selection of multiple options. With five options[6] available to the respondent, there are 32 possible unique combinations of yes/no responses. The combinations represent mutually exclusive choice alternatives, whereby the structural utility of each choice alternative is built up from the utilities assigned to the adaptation options it includes (under the scenario conditions). Therefore, the structural utility component for this case can be specified as:

$$V_{nsj} = \sum_{i \epsilon I_j} \beta_{is} \ (Eq.6)$$

with β_{is} defined as:

$$\beta_{is} = \beta_{0i} + \sum_{k=1}^{K} \beta_{1ik} x_{nsk} \ (Eq.7)$$

[6] Four environmental control actions and one personal adaptive action. The original four personal adaptive actions were merged into one, because of the insufficient number of appearances of each of them in the sample (refer to Chapter 3). As a result, five options are distinguished: four environmental control actions and one personal adaptive action, which is referred as secondary approach.

Where:

I_j : is the set of adaptation options included in alternative *j*.

β_{is} : is the preference for option *i* in choice situation *s*.

β_{0i} : is the base preference for option *i*.

K : is the number of attributes.

β_{1ik} : is the preference for attribute *k* of option *i* in choice situation *s*.

x_{nsk} : is the value of attribute *k* for individual *n* in choice situation *s*.

ε_{nsj} is the random component of the utility.

In the latent class model, class-specific utilities are estimated, assuming that individuals are grouped into a finite number of classes *c* where each class has its own set of parameters. Hence, the structural component of the utility function becomes:

$$V_{nsjc} = \sum_{i \epsilon I_j} \beta_{isc} \ (Eq. 8)$$

With:

$$\beta_{isc} = \beta_{0ic} + \sum_{k=1}^{K} \beta_{1ikc} x_{nsk} \ (Eq. 9)$$

The probability of individual *n* in class *c* choosing alternative *j* (a combination of selected options) in multiple response choice situation *s* is defined as:

$$P_{nsjc} = \frac{\exp(V_{nsjc})}{\sum_{j-1}^{J_{ns}} \exp(V_{nsjc})} \ (Eq. 10)$$

c : is the class individual n belongs to.

P_{nsjc} : is the probability that an individual n of class c chooses alternative j in multiple-response choice situation s.

J_{ns} : is the total number of alternatives available to individual n in multiple-response choice situation s.

In the latent class model, class membership is estimated simultaneously with the class-specific utility coefficients. For individual n the probability of belonging to latent class c is defined as:

$$P_{nc} = \frac{\exp(\theta_c Z_n)}{\sum_{c=1}^{C} \exp(\theta_c Z_n)} (Eq. 11)$$

Where:

P_{nc} : is the probability that individual n belongs to class c.

Z_n : is the vector of individual-specific characteristics (e.g. demographics, income).

θ_c : class-specific membership parameters.

In this study, there are no covariates included in the membership function of the latent class model, which means that Z_n is empty and only a constant is estimated for each class.

5.3. Model generation and evaluation

Nlogit6 is used to estimate the latent class model. A two-, three-, and four-class model is tested to find the optimal number of classes. The four-class model could not successfully be estimated as the large number of parameters led to convergence issues. Therefore, model selection remains between the two-class and three-class

models. The Akaike Information Criterion (AIC) [217] and the Bayesian Information Criterion (BIC) [218], are used to identify the best-performing model. Adjusted McFadden's pseudo R-square is used as an indicator of the goodness of fit of the estimated model.

To evaluate the 3-Class segmentation in terms of how well the segments are separated and differentiated, Table 16 shows the results on several diagnostic indices [208], [209], [210]. Shown are the relative entropy, average posterior probability (AvePP), and odds of correct classification ratio (OCC).

With the identified 3-class model and the data collected by the cross-sectional survey, a multinomial logit model is estimated to predict the class of an individual by using socio-demographics, contextual attributes, and other factors (see Table 21 in Appendix A). Individuals are assigned to the class with the highest membership probability. All attributes are categorical and, therefore, dummy coded. The model selection is based on a manual selection of variables by stepwise elimination of those variables that are not statistically significant at a 5% level, and with the highest p-value first.

5.4. Results & Discussion

5.4.1. Model selection

Table 15 shows the results of model selection. Even though the BIC value for the 2-class model is slightly better than for the 3-class model, the AIC and adjusted McFadden's pseudo R-square are both substantially improved when going from a 2-class to a 3-class model. Therefore, the 3-class model is selected as the final model for the analysis.

Table 15 Model fit

	MNL	*2-class*	*3-class*	*Information*

Number of observations (n)	5144	5144	5144	
Number of estimated attributes (β)	90	181	272	
LL fitted	-15586.3	-14948.3	**-14563.6**	Log likelihood of estimate model
LL base (null)	-17827.7	-17827.7	-17827.7	Log likelihood of the base model
AIC	31352.7	30258.5	**29671.3**	[-2(LL fitted - K)] [217]
BIC	31941.8	**31443.2**	31451.5	[In(n) * k – 2 * LL fitted] [218]
Rho-square	0.126	0.162	**0.183**	[1 - (LL fitted/LL base)]
Adjusted Rho-square	0.121	0.151	**0.168**	[1 - (LL fitted - k)/LL based]

5.4.2. Model-diagnose

Relative entropy offers insights into the degree of differentiation in posterior class probabilities across classes and individuals in the sample. A value larger than 0.80 suggests an overall good classification of individuals into the correct class [219]. For the 3-class model, it is 0.88. AvePP assesses how well the latent class model classifies individuals into their most likely class [220]. A value larger than 0.7 [210], [220], indicates that the segments are well-separated with sufficient assignment accuracy. The AvePP for classes one, two, and three are 0.960, 0.937, and 0.950, respectively. Finally, the OCC indicates classification accuracy. OCC is based on AvePP, and the larger the OCC values are, the better the class separation and assignment accuracy are. As a rule of thumb, an OCC value larger than 5.0 for each

segment indicates a satisfactory accuracy [210], [220]. The OCC values for the identified classes are 25.16, 56.13, and 44.21, respectively, indicating that the 3-class model has a good class separation and high assignment accuracy. Based on the above diagnostic indices, the estimated 3-class model shows a good performance in separating classes and assignment accuracy.

Table 16 Classification diagnostic indexes

	Segment 1	***Segment 2***	***Segment 3***	***Source***
Entropy		0.88		>.80 [219]
AvePP	0.960	0.937	0.950	≥0.7 well-separated classes [220]
OCC	25.163	56.132	44.211	≥5.00 indicate a good separation and high assignment accuracy [220]

5.4.3. Identified classes

Appendix A shows the detailed estimation results of the 3-class model. The estimated class probabilities are 48.8%, 21.1%, and 30.1% for classes 1, 2, and 3, respectively. For this latent class model, all attributes are effect-coded, where the most comfortable level (e.g., air quality is fine) is taken as the reference level.

Using a carpet diagram, Figure 9 presents the estimates graphically, where every parameter value is represented with blue/red radiant colour indicating the size and sign of each parameter value. The different adaptive controls and the classes are presented in the vertical axes on the right and left sides of the plot, respectively. The attributes and attribute levels are presented in the horizontal axes on the top and bottom of the plot, respectively. The colour-coded estimates represent the utility value of using the control (located on the right-hand side of the vertical axis) under the condition indicated by the attribute level (located on the bottom axis) for

individuals of a particular class (located on the left-hand side of the vertical axis). The colour red indicates a positive effect, and blue indicates a negative effect. White blocks indicate that the attribute level is not statistically different from zero. In other words, a white block indicates that the utility value of the attribute level does not deviate from the average preference utility across the attribute's levels. The interpretation of this figure is discussed next.

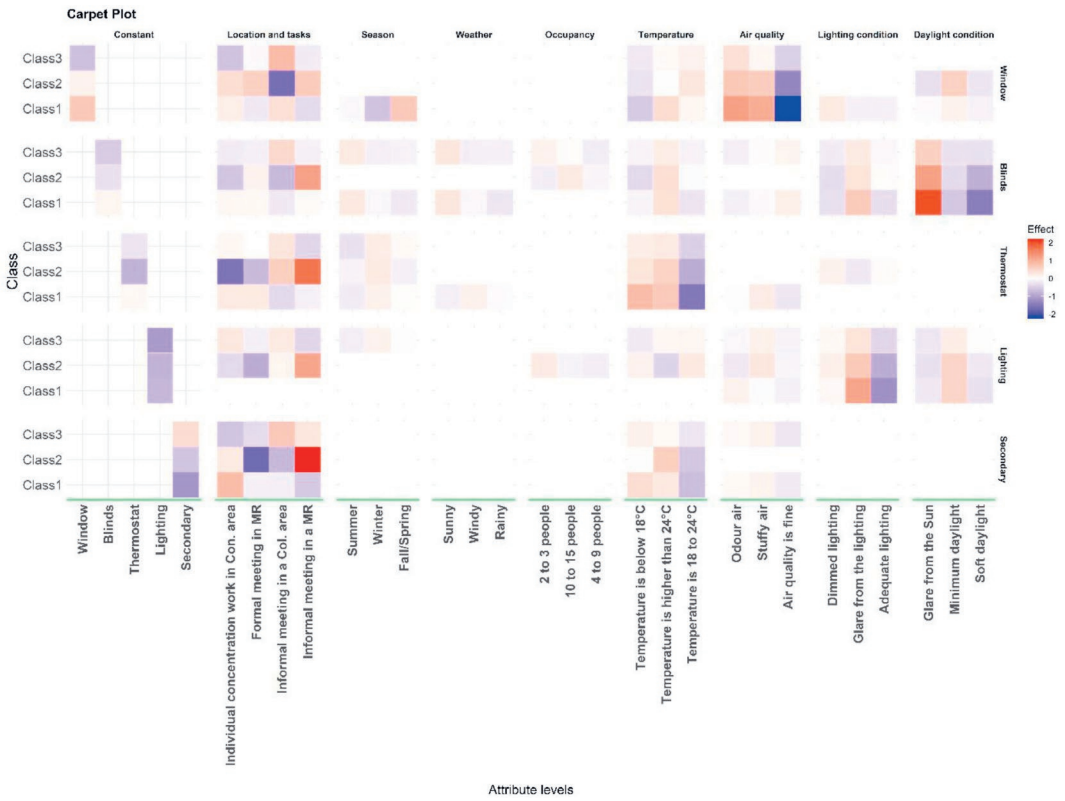


Figure 9 Carpet plot

5.4.3.1. Class differences and similarities

Based on the colour patterns, a number of observations can be made. First, all three classes show unified response patterns for certain adaptive behaviours under particular contexts. For example, using the window control has a positive utility in

case of poor indoor air quality, as indicated by the consistent red colour across all three classes in the Air quality-by-Window block. The contrast in colour intensity across the levels of an attribute (horizontally) in each class indicates how strong the class's response is to the attribute. In the case of the window control, for example, individuals in class 1 are the most sensitive segment to air quality discomfort, followed by classes 2 and 3. This gradient in colour suggests differences in behavioural magnitude across classes, indicating that discomfort triggers substantially stronger behavioural adjustments among some groups than others. A similar finding holds for the use of blinds control in response to indoor daylight conditions, thermostat control in response to indoor temperature, and lighting control in response to indoor daylighting conditions.

Secondly, some contextual attributes do not trigger any behavioural response. This is indicated by white-coloured levels within one attribute block. For instance, Class 2 individuals' blinds control behaviour is not influenced by season, weather, or indoor air quality conditions. Importantly, the white colour does not indicate an absence of preference; it only means that the parameter is not statistically significant. These non-significant responses imply that certain contextual factors may fall below occupants' perceptual thresholds or be deemed less relevant for maintaining perceived control in shared spaces.

The third observation is that individuals' preference for the use of specific controls depends strongly on particular context conditions, with notable class-specific differences, as below:

Class 1 individuals exhibit the strongest response pattern for all controls under different IEQ contexts, as indicated by the strong colour contrast (in terms of a pronounced shift in preference direction) in the blocks on the level of IEQ attributes and corresponding controls for this class. A strong response is observed in this class related to window control in case of poor indoor air quality conditions, blinds

control in case of poor indoor daylight conditions, thermostat control in case of poor indoor temperature conditions, and lighting control in case of poor indoor lighting conditions. The strength of these contrasts suggests that Class 1 individuals actively regulate the surrounding environment when discomfort arises, reflecting a high perceived control and profound assimilation-oriented adaptive strategies. Hence, Class 1 individuals can be labelled as Strong reactors.

Class 2 individuals exhibit the least responsiveness of comfort adaptive behaviour regarding the outdoor environment context. Only a relatively weak response to season for the use of the thermostat can be observed. Apart from that, their comfort adaptive behaviour is not affected by season or weather at all. They do exhibit a similar but also weaker response to IEQ conditions compared to Class 1. On the other hand, Class 2 is the most sensitive segment to location and task context. Class 2 displays the strongest contrast in colour for all controls across different locations and task contexts. For instance, they are more responsive in terms of window control and less in terms of thermostat control when having a formal meeting in a meeting room. In addition, they are more responsive regarding thermostat control and less responsive regarding window control when having an informal meeting in a collaboration area. These context-driven preferences indicate that social norms and situational expectations play a key role in sharing their behavioural preference, suggesting a tendency toward accommodation-based strategies when social expectations and expected communication levels are salient. Hence, Class 2 individuals can be labelled as Context sensitive.

Class 3 individuals exhibit the weakest response patterns to IEQ contexts, which distinguishes them from the other classes. They are, however, scenario sensitive. For instance, compared to other controls, their preference pattern for blinds control is influenced by all attributes, although some attributes' utility values are small but still statistically significant. Also, Class 3 is the only segment whose preference patterns for lighting control are affected by differences in season. Moreover, Class

3 individuals are more scenario sensitive, as indicated by a clear preference for window control in case of poor air quality (i.e., odour air condition), and an average utility preference for window control in case of poor air quality (i.e., stuffy air condition). Similar findings can be observed with window control in response to location and task attributes, blinds control in response to occupancy levels, and secondary approach in response to poor air quality. The generally inactive response suggests minimal intervention tendencies, aligning with a rather passive adaptive preference and reduced perceived behavioural control, where individuals rely more on tolerance (e.g., the weakest contrast in both discomfort situations of IEQ temperature suggests a wider range of temperature tolerance) rather than active adjustment. Hence, Class 3 individuals can be labelled as Minimalists.

In line with profiles reported in other studies [196], [221], these three identified profiles provide further evidence that occupants' preferences are highly diverse and situationally dependent, particularly with the irregular response patterns and diverse colour contrasts for attribute 'location and tasks' in response to the studied adaptive behaviours (see Figure 9). Integrating the above findings with established psychological constructs highlights that differences in perceived control (e.g., changing the environment and/or changing the self), social influence (e.g., peer-pressure and expected communication level), and adaptive strategies (e.g., preference for one or multiple environmental or personal adaptive options) fundamentally shape the behavioural heterogeneity observed across classes.

5.4.3.2. Predication of class membership

Class 3 is set as the reference category when performing the prediction of class membership. The detailed model estimation results are presented in Table 17. It appears that only occupation, type of offices, and conscientiousness are statistically significant in the model. The results indicate that working in the healthcare sector is positively associated with membership in both Class 1 and Class 2, with stronger statistical evidence for Class 2. Eijkelenboom et al. [222] report similar findings:

outpatient staff tend to show moderate dissatisfaction with certain aspects of IEQ, while the only consistently comfortable group are those working in newly built or renovated offices that provide personal control over the environment, particularly temperature. Furthermore, the results indicate that workers in medium-sized offices and with a conscientious personality are more likely to belong to Class 1 (Strong reactors). This is in line with findings in the literature [221], which show that office employees with a conscientious personality are more likely than others to seek and apply an adaptive strategy.

In contrast to findings reported in other studies [196], [221], socio-demographic attributes such as gender and age did not emerge as statistically significant predictors of class membership. The identified classes are primarily shaped by individuals' preferences rather than demographic characteristics.

Table 17 Prediction of membership with merged control availability

			Attributes	**β**	**P**
		Constant	Class1	-1.263**	0.033
			Class2	-1.311*	0.063
Latent Class1		Occupation	Education	-0.111	0.706
			Healthcare	0.536*	0.090
			Business/Finance/Trade	-0.277	0.208
			Others	0	0
		Type of offices	Shared office	0.570*	0.072
			Small office	0.277	0.387
			Medium office	0.741**	0.031
			Large office	0.368	0.347
			Private office	0	0
		Control availability	Lighting control Yes	-0.342*	0.073
			No	0	0
		Personality trait	Conscientiousness	0.274***	0.003
Latent Class2		Occupation	Education	-0.322	0.394
			Healthcare	0.801**	0.023
			Business/Finance/Trade	-0.324	0.239
			Others	0	0

		Type of offices	Shared office	0.262	0.475
			Small office	0.163	0.659
			Medium office	0.110	0.791
			Large office	-0.314	0.530
			Private office	0	0
		Control availability	Lighting control Yes	-0.288	0.215
			No	0	0
		Personality trait	Conscientiousness	0.181	0.105
Reference category LC3			****, **, * ==> Significance at 1%, 5%, 10% level.*		

5.5. Conclusion

This chapter examined preference heterogeneity from an alternative angle compared to existing studies by focusing on the identification of segments in complex and multi-modal situations. It does so to better understand occupant behaviour in complex indoor environments and create a rather sophisticated occupant profile that addresses the dynamic and complex nature of occupant behaviour from a multidisciplinary perspective. Three classes were identified and labelled as: Strong reactors, Context sensitive, and Minimalists. These classes demonstrated differences in preferences for comfort adaptive behaviours under various conditions. Class membership prediction suggests that the 'Contextual sensitives' are more likely to work in the healthcare sector, while the 'Strong reactors' are more likely to work in medium-sized offices and/or exhibit a conscientious personality.

This chapter provides a statistically rigorous (model-based) approach to profiling behavioural patterns and trade-offs occupants make in their choices for the use of comfort-adaptive controls under complex scenarios. The model-based approach focuses on the choices made by the occupants, instead of their reported satisfaction levels, and offers insights into preference heterogeneity by segments, predicting

both class-dependent choice probabilities and class membership. Compared to conventional field experiments (e.g., climate chamber studies, which focus on a single IEQ perspective – thermal, lighting, acoustics, etc.), the unsupervised clustering approach of latent class modelling requires fewer resources and offers more flexibility, especially for multimodal discomfort research and allows one to model choice behaviour considering multiple options within a single framework. Discrete choice experiments, whether single or multiple-response, are particularly effective for studying behavioural trade-offs and assessing the potential of new or hypothetical interventions, such as innovative environmental controls and office space configuration alternatives.

The findings demonstrate that occupant heterogeneity is not only a matter of varying response intensity but also reflects fundamentally different behavioural strategies. Representing occupants through distinct behavioural profiles, therefore, provides a more realistic foundation for modelling human-building interactions. With that in mind, the following chapter extends the developed behavioural models into a simulation framework that integrates occupant decision-making with building performance simulation. It introduces an agent-based modelling approach that embeds the identified behavioural profiles into a co-simulation coupling framework through EnergyPlus via Functional Mock-up Interface (FMI) standard, to examine how heterogeneous behaviour influences overall building performance.

6. Development and alignment of a co-simulation framework for advanced occupant behaviour in building performance simulation

6.1. Introduction

The previous chapters established an empirical and behavioural modelling framework for understanding occupant decision-making in office environments. Building on these results, this chapter extends that work by coupling the behavioural models with a building performance simulation tool (EnergyPlus). By moving beyond conventional deterministic representations of occupants, the proposed framework provided a more realistic representation of human-building interactions and their influence on building performance.

Conventional occupant behaviour models in building performance simulation (BPS) are typically based on deterministic rule-based logic sensitive to predefined threshold values and limiting behavioural realism. In contrast, the choice-based behavioural model developed in the previous chapter represents occupant actions as probabilistic and context-dependent decisions. Embedding this model within an agent-based simulation framework allows occupant behaviour to emerge dynamically in response to changing environmental and contextual conditions, thereby improving the behavioural realism of building performance simulations.

To demonstrate and evaluate the influence of choice-based occupant representation on simulated building performance, two comparative BPS models were developed using an identical building model, zone configuration, weather file, simulation timestep, and HVAC system representation. The main difference between the two models lay in how occupant-related controls are represented. The baseline model followed a conventional BPS approach, in which control actions were regulated by predefined schedules and deterministic EnergyPlus control objects. The advanced

model replaced these controls with dynamic zone-level logic, where control signals were generated by a Python-based agent behavioural model and exchanged with EnergyPlus through Functional Mock-up Unit (FMU) actuators and variables.

The following sections first present the baseline simulation model, followed by the advanced behavioural model using the co-simulation framework, including the modelling approaches, the comparison between the baseline and advanced models, behavioural context generation, decision-making process, aggregation of zone-level commands, and verification.

6.2. Baseline EnergyPlus model with conventional occupant behaviour modelling

The baseline model represented the conventional EnergyPlus simulation approach used as the reference case in this study. In this configuration, the simulation is self-contained, with all control actions implemented through native EnergyPlus objects and predefined schedules (see Figure 10). The control logic followed a deterministic sequence in which EnergyPlus first solves the building energy balance and then updates the zone-level control states based on fixed schedules or built-in rule-based control objects.

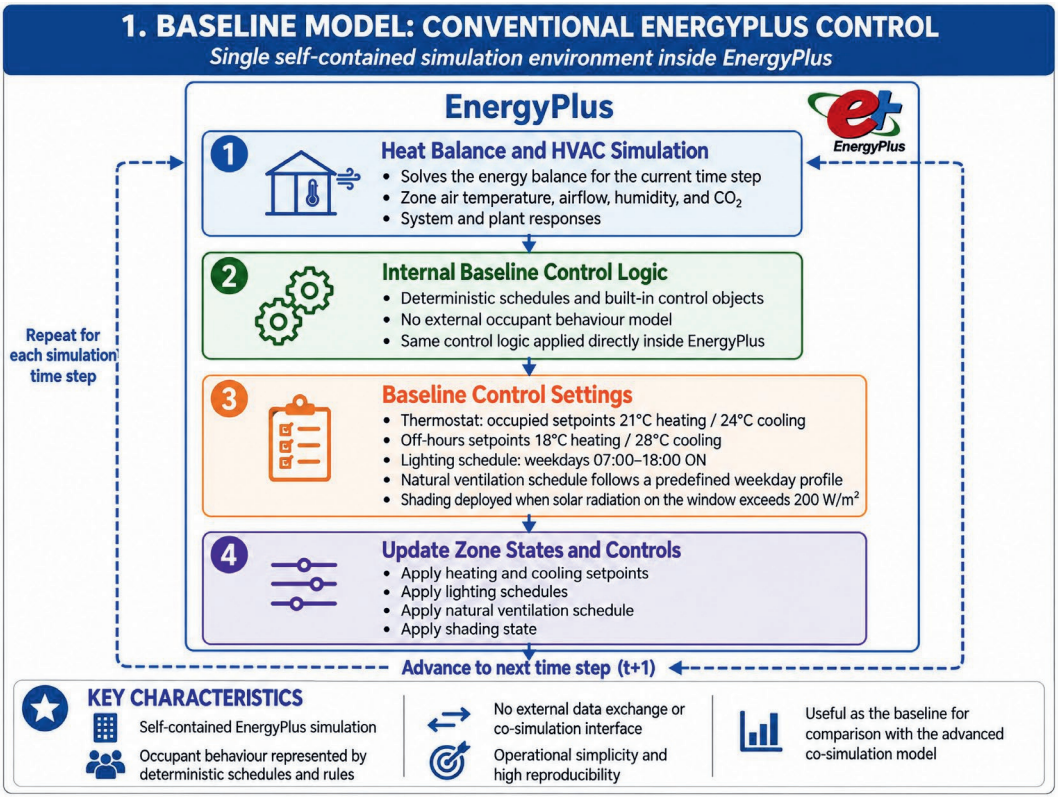


Figure 10 Baseline model approach

Space heating and cooling were controlled through predefined thermostat schedules that were applied uniformly across all zones. During occupied office hours, the heating setpoints were set to 21 °C and the cooling setpoints were set to 24 °C. During off-office hours, the heating setpoints were set to 18 °C, while the cooling setpoints were set to 28 °C. These settings represented the nominal thermostat operation of the baseline model and were later retained as default fallback values in the advanced model to ensure consistency between the two modelling approaches.

The indoor air conditions were controlled by both the mechanical ventilation system and scheduled window operation. The mechanical ventilation system increased the building ventilation rate when the building was occupied, i.e., between 7 AM and 7 PM, and reduced the ventilation rate when the building was unoccupied, i.e., between 7 PM and 7 AM, based on a predefined occupancy schedule used in

'Design Specification: Outdoor Air' object. In addition to the mechanical ventilation, window opening could further increase the ventilation rate, which influenced the indoor heating and cooling load depending on the temperature difference. In the baseline model, window operation was represented using the same predefined schedule, together with temperature-based shut-off thresholds, i.e., window operation was not allowed to operate when the indoor temperature was below 22 °C or when the outdoor temperature was below 10 °C, and was also allowed if the indoor temperature exceeded the outdoor temperature by at least 2 °C.

Lighting was represented using EnergyPlus lighting objects controlled by a standard office schedule, with lights enabled during working hours and switched off during office hours. In zones equipped with daylighting controls, EnergyPlus continuous dimming logic further modulates the lighting power in response to available daylight. Therefore, lighting availability was schedule-based, while the actual lighting power can vary according to daylight conditions.

Shading control was implemented using the EnergyPlus shading objects, where shading control follows the "On-If-High-Solar-On-Window" control type, with blinds deployed when incident solar radiation on the window exceeded 200 W/m^2. Shading operation was therefore governed by a fixed solar radiation threshold rather than by occupant perception such as glare.

Overall, the baseline model provided a benchmark for assessing the impact of the choice-based occupant modelling approach introduced in the next sections.

6.3. EnergyPlus model with advanced occupant behaviour modelling

The advanced model extended the baseline configuration by coupling EnergyPlus with a Python-based agent-based model (ABM). EnergyPlus remained the core simulation engine for representing the building, while occupant behaviour model was represented externally in Python. The two components were linked through an

FMU-based co-simulation interface, which allowed the model to move towards a dynamic, context-dependent, and stochastic representation of occupant actions.

The advanced modelling framework consists of three main components: (i) the EnergyPlus simulation module, (ii) the behavioural decision module based on an empirically estimated latent class model, and (iii) the Python-based co-simulation interface (see Figure 11). At each simulation timestep, EnergyPlus calculated the thermal state of the building and exported relevant state variables (e.g., temperatures) to the ABM. The ABM then generates behavioural decisions and returns corresponding control commands to EnergyPlus via the co-simulation interface.

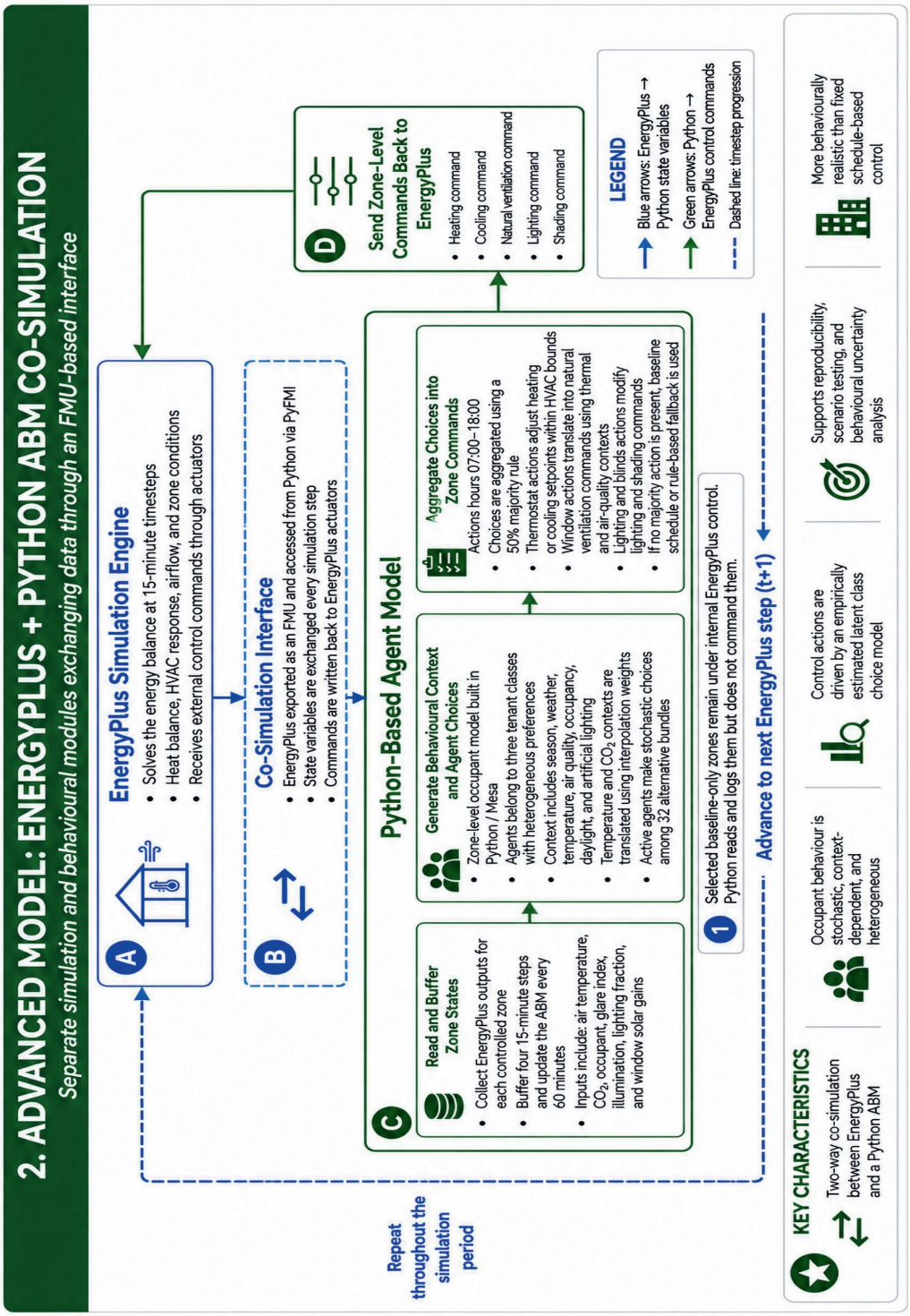


Figure 11 Advanced model approach

The coupling between EnergyPlus and the ABM was implemented through FMU-linked input and output variables. EnergyPlus exported zone-level environmental and system-state variables, including air temperature, CO_2 concentration, occupancy, glare index, illuminance, lighting power multiplier, and window solar gains. These variables formed the basis for constructing the behavioural context experienced by occupants. In return, the ABM sent control commands for heating and cooling schedules, natural ventilation, lighting operation, and shading through FMU actuators, which were applied within EnergyPlus at the next simulation step.

The simulation adopted a dual-timescale structure. EnergyPlus was executed at a 15-min timestep, while the ABM was updated once every hour. At each ABM update step, the preceding four EnergyPlus timesteps were aggregated to represent the indoor conditions perceived by occupants. This aggregation reduced unrealistic behavioural switching while maintaining responsiveness to changing environmental conditions.

Action agents made stochastic choices among 32 mutually exclusive alternative action bundles (refer to Section 3.2). The individual choices were then aggregated at the zone-level using a majority-based rule, under which an action was activated when at least 50% of the active agents selected it. This rule was consistent with the cooperative tendencies identified in the discrete choice analysis, which indicated that occupants in shared office environments often accepted control proposals made by others. The resulting control signals were then sent back to EnergyPlus through the FMU actuators, allowing occupant decisions to directly influence the building performance.

6.3.1. Occupant control override and fallback logic

The advanced model introduced an occupant-driven override mechanism that allowed the ABM to modify default EnergyPlus control settings (e.g., default the

heating temperature) during occupied hours. Because of this override mechanism, additional fallback rules were introduced.

During off-hours (unoccupied hours), the advanced model followed the baseline configuration (see Figure 12, section 1). During occupied hours, if an ABM update occurred but no active agents were present in the controlled zone, then the model reverted to the baseline occupied settings (see Figure 12, section 2). If active agents were present and their choices led to a specific control action, then the corresponding ABM command was applied (see Figure 12, section 3). If active agents were present but no majority decision was reached for a given control option, then the baseline setting for that control option was used (see Figure 12, section 4).

This hierarchical structure ensured that all control states remained well-defined throughout the simulation. It also meant that behavioural overrides only occurred when they were supported by sufficient agent agreement. In all other cases, the model defaulted to the EnergyPlus-native control logic.

In the advanced model, a few zones remained under native EnergyPlus control, allowing them to function as non-ABM-controlled reference zones within the advanced simulation framework.

Figure 12 Baseline-aligned default rules in advanced model

6.3.2. Definition of various control options

6.3.2.1. Thermostat control

In the advanced model, each controlled zone had its own heating and cooling schedule objects. These schedules were exported as FMU actuators to the Python script. The seasonal HVAC mode was determined using the baseline EnergyPlus heating and cooling availability periods. This HVAC mode was treated separately from the behavioural season context used in the choice model.

The advanced model preserved the same nominal thermostat settings as the baseline model. During occupied hours, if agents selected the thermostat option, the magnitude of the setpoint adjustment was determined from the interpolated indoor-temperature context. Indoor temperature was represented by three thermal states corresponding to the DCE levels: cold, neutral, and warm, with interpolation anchors at 18°C, 21°C, and 24°C, respectively. Temperatures between these anchors were converted into fractional cold and warm weights ranging from 0 to 1. These weights translated the selected thermostat action into a setpoint adjustment of up to 1°C per ABM update. For example, at 19.5°C the cold weight was 0.5, resulting in a 0.5°C upward adjustment of the heating setpoint, whereas at or below 18°C the full 1°C adjustment was applied. In cooling mode, the corresponding warm weight reduced the cooling setpoint by up to 1°C. The nominal occupied heating and cooling setpoints remained 21°C and 24°C, respectively, while successive occupant-driven adjustments were constrained to the predefined HVAC operating bounds. As the advanced model actuated zone-level heating and cooling schedules through the FMU, an additional fail-safe was used to suppress unintended opposite-mode operation. For instance, an extreme cooling setpoint could be applied during the heating season to prevent unintended operation, and vice versa. This fail-safe was introduced to stabilise the actuator-based override behaviour rather than to redefine the intended seasonal HVAC strategy.

6.3.2.2. Natural ventilation/Window control

In the advanced model, instead of a unified pre-defined schedule, each zone had a dedicated natural ventilation schedule linked to Python through an FMU actuator. The Python script initialised ventilation with the same baseline weekday profile, which varied from 0 to 1 with 0.25 incremental changes.

During occupied hours, if the agent's selected choice included the 'window' option, an override signal was sent to the natural ventilation command through Python model. The final ventilation level was then determined through a command-translation logic that used both air quality and thermal contexts. Importantly, the interpolation weights were not only used to assign the utility in the choice model, but were also used in translating the chosen window action into a continuous natural ventilation command. For the air-quality component, the measured CO_2 concentration was converted into interpolation weights using anchor values of 1000, 1250 and 1500 ppm. These weights did not determine whether the window action was selected; rather, after a window action reached the aggregation threshold, they were used together with the thermal interpolation weights to determine the magnitude of the natural-ventilation command. For the thermal component, the warm weight increased the natural ventilation opening level, while the cold-weight reduced or closed the natural ventilation command. The final command was then calculated by combining the air-quality-driven and thermal-driven signals. Thus, the selected window action was translated into a fractional natural ventilation command ranging from 0 to 1 rather than a simple binary open/closed state. This natural ventilation control operated separately from the scheduled mechanical ventilation system.

Thus, the advanced model allowed the natural ventilation command to deviate from the baseline schedule based on stochastic occupant window decisions and real-time indoor environmental context. These deviations were implemented using interpolated air-quality and thermal weights, so the final natural-ventilation

command could vary continuously between 0 and 1 rather than only switching between fixed categorical states.

6.3.2.3. Lighting control

In the advanced model, each controlled zone was assigned with its own lighting schedule that could be overridden by Python control through an FMU actuator. During occupied hours, if the agent's selected choice includes the 'lighting' option, an override signal, such as adjusting the lighting schedule value by ± 0.2 bounded within 0 to 1, was sent to the actuated lighting schedule according to the identified lighting context.

The control in the advanced model did not deactivate EnergyPlus daylighting control. Instead, the occupant-driven lighting command acted together with the automated daylighting multiplier. Therefore, the final lighting power remained the product of the design lighting power, the commanded schedule fraction, and the daylighting control multiplier. Thus, the advanced model added an occupant-responsive layer on top of the existing schedule and daylighting dimming logic[7].

6.3.2.4. Shading control

In the advanced model, shading was schedule-driven with the same object, but the control type was changed to a schedule-driven approach. During occupied hours, the shading position was adjusted based on occupant choices according to daylight and glare context indicators obtained from EnergyPlus. The glare index and illuminance at the daylighting reference point were transferred to the ABM, where a glare/excessive daylight context was assigned when the glare index was at least 22 or illuminance was at least 2000 lux, and while illuminance below 300 lux represented insufficient daylight.

[7] Daylight and lighting dimming logic:

$$Final\ Lighting\ Power = Design\ Power \times Schedule\ Fraction\ (LI_{command}) \times Daylighting\ Multiplier$$

To maintain comparability with the baseline model, a solar-triggered fallback rule was added to the advanced model. The Python script reads the incident solar radiation on the controlled window surfaces and calculates the maximum value across the window group. If no active agents are present or if no blinds-related majority agreement reached, shading follows the baseline solar rule, which triggered by incident solar radiation with a 200 W/m2 threshold.

Therefore, shading in the baseline model responded only to a deterministic incident solar radiation threshold, while the advanced model could also respond to occupant choices influenced by simulated glare and daylight conditions. In the meantime, maintaining the baseline solar rule as a fallback for off-hours and no-agent periods, to preserve comparability.

6.3.3. Behavioural context generation and choice model implementation

The co-simulation framework was implemented using the zone-based EnergyPlus model of the case-study office floor described in Section 7.1.1. The floor contains multiple office and meeting zones with different occupancy capacities. The following sections explain how zone-level outputs from EnergyPlus were translated into the categorical context variables required by the behavioural choice model.

6.3.3.1. Temporal and activity-based context

In the advanced model, time-based context generation included two components, i.e., the seasonal context and activity/group context. The seasonal context was derived from the simulation 'day-of-year' and assigned to all behavioural action dimensions, allowing the utility of each adaptive action to vary according to the time of year.

The activity/group context was also time-dependent but constrained by zone type. Each zone type was assigned a restricted set of feasible group contexts to avoid unrealistic combinations between space type and activity. For instance, meeting rooms, single offices, and open-plan offices could only sample from activity

contexts relevant to their design intentions. During office hours between ABM updates, the previously assigned group context was retained.

6.3.3.2. Weather-based context

With a typical year weather file, three environmental variables were extracted, i.e., global horizontal radiation, wind speed, and precipitation. The weather data were read as hour-ending values and shifted back by one hour to align with the ABM update timestep, which occurs at the start of each hour. The categorical states of the weather conditions were determined using the following classification rules. It was classified as rainy if precipitation was more than 0.2 mm. It was classified as windy if precipitation was less than or equal to 0.2 mm and the wind speed was more than 6 m/s. It was classified as sunny if precipitation was less than or equal to 0.2 mm, wind speed was less than or equal to 6 m/s, and global horizontal radiation was higher than 500 Wh/m2. If none of these conditions were met, no explicit weather category was activated for that ABM timestep, and the weather context therefore contributed zero utility in the choice model.

6.3.3.3. Indoor environmental context – EnergyPlus output

The environmental context and occupancy information were obtained from EnergyPlus through FMU-exported variables, including air temperature, CO_2 concentration, occupancy level, daylighting conditions, and artificial lighting conditions. At each ABM update step, the continuous EnergyPlus outputs were converted into categorical context variables used by the choice model (see Figure 11, Step C).

Temperature was classified using the zone mean air temperature exported from EnergyPlus. If the air temperature was below 18 °C, the active temperature context was assigned to ‘t1’, representing a cold condition. If the air temperature was above 24 °C, it was assigned to ‘t2’, representing a warm condition. All remaining cases, between 18 and 24 °C, were assigned to ‘t3’, representing a neutral thermal

condition. However, on top of the above, temperature interpolation was enabled. Therefore, instead of using only hard categorical indicators, the model converted temperature into interpolation weights for three categories. These weights were then applied to option-specific temperature context variables used in utility calculation. The same principle applies to air quality.

Occupancy was classified using the occupancy count exported from EnergyPlus. Occupancy values of three or fewer occupants were assigned to 'p1'; values greater than three and up to nine occupants were assigned to 'p3'; and values greater than nine occupants were assigned to 'p2'. This occupancy context was then assigned to all behavioural action dimensions in the choice model.

As for daylight and artificial lighting contexts, multiple variables were used. Daylight conditions were classified using the daylight glare index, indoor illuminance, and shading command. When the glare index was equal to or above 22 or illuminance was equal to or above 2000 lux, a glare condition or excessive daylight, 'd1' was assigned. When indoor illuminance was below 300 lux, an insufficient daylight condition was assigned. All remaining cases were assigned to 'd3', representing acceptable daylight.

Artificial lighting conditions were classified using indoor illuminance, daylighting power fraction, and daylight glare index. When indoor illuminance was below 500 lux, a dimmed/insufficient lighting condition was assigned. When the lighting power fraction was equal to or above 0.9, and indoor illuminance was at least four times the illuminance setpoint (e.g., 2000 lux), a glare or excessive artificial lighting condition was assigned. All other cases were considered as 'l3', representing adequate lighting conditions.

6.3.4. Utility specification and probabilistic choice selection

The generated context variables serve as inputs to the choice model. At each ABM update step, each active agent evaluates 32 possible alternatives (refer to Chapter

3). Each alternative represented a mutually exclusive bundle of adaptive actions. Within each bundle, a value of one indicated that the corresponding action was included in the selected alternative and zero otherwise.

The utility of each alternative was calculated as the sum of two components, i.e., an alternative-specific action utility and a context-dependent interaction utility (refer to Chapter 5). The alternative-specific component captures the general tendency of an occupant class to select a given action, independent of the current context. The context-dependent component captures how the attractiveness of each action changes under activity, indoor environmental, temporal, occupancy, and weather conditions.

In the advanced model, each agent belongs to one of three latent classes based on the estimated class probabilities (refer to Chapter 5). Class membership was assigned probabilistically using the class probabilities, i.e., 0.49, 0.21, and 0.30, for class 1, 2, and 3, respectively (refer to Chapter 5). Once assigned, the agent uses the corresponding class-specific coefficient set throughout the simulation.

For each alternative, the model first identified which actions were included in the action bundle. The utility was then calculated by adding the relevant action-specific coefficients and the corresponding context-interaction coefficients for those selected actions. For example, if an alternative included both window operation and thermostat adjustment, the utility would include the base coefficients for the window and thermostat actions, together with the active context coefficients associated with the window and thermostat dimensions. Actions not included in the selected alternative did not contribute to the utility of that alternative.

After utility computation, the model converted the utilities into choice probabilities using a softmax function. In the Python implementation, the utilities were shifted by subtracting the maximum utility value before exponentiation. This numerical stabilisation step prevented overflow in the softmax calculation but did not change

the relative utility differences or the resulting choice probabilities. This procedure assigned higher choice probabilities to alternatives with higher utility values, while still allowing alternatives with lower utility values to be selected. Therefore, the ABM used a stochastic choice process rather than a deterministic maximum-utility rule.

Finally, one alternative was selected using a Monte Carlo draw from the calculated probability distribution. The selected actions bundle represented the agent's behavioural decision at that ABM update step. When more than one agent was present in a zone, the selected bundles were aggregated into a zone-level control decision, as described in Section 6.3.5. The resulting aggregated command was then used to update the relevant zone-level variables in EnergyPlus.

6.3.5. Aggregation of agent decisions to zone controls

At each ABM update timestep, individual choices were aggregated into zone-level control commands. As mentioned previously, the ABM was updated hourly, corresponding to every four 15-mins EnergyPlus timesteps. Hence, before each ABM update timestep, the advanced model script stored the latest four EnergyPlus outputs and summarised them into one hourly state, which was later used as the environmental input for the choice model. Occupancy and lighting fraction were represented by their latest values, global radiance by the maximum value, and air temperature, CO_2 concentration, and illuminance by their mean values over the four buffered outputs.

This hourly state was realised through a buffer function, where zone air temperature, CO_2 concentration, and illuminance were averaged over the four EnergyPlus timesteps. The daylight glare index used the peak value over the same period, based on the assumption that people react to peak conditions rather than averaged glare conditions. Occupancy and lighting power fraction were taken from the latest timestep to reflect the most recent conditions.

The number of active agents was determined from the EnergyPlus occupancy output. The occupant number was rounded upward and limited by the maximum number of agents assigned to each zone. Only active agents could make choices at that timestep. Therefore, for instance, if a meeting room had a design capacity of eight people but was occupied by only four at that ABM update timestep, then only those four active agents participated in decision-making.

After each agent's selection, their individual choices were aggregated into zone control commands only if the number of votes for that action satisfied the aggregation threshold. In the Python script, this threshold followed a majority-based rule, meaning that the action was triggered when at least half of the active agents selected the corresponding option. This voting step translated individual stochastic choices into collective zone-level action signals before command translation.

After the voting step, the aggregated action signals were translated into continuous control commands before being sent back to EnergyPlus. This command-translation step used the same interpolated context weights that were generated for the behavioural choice model. For thermostat control, when a thermostat action reached the voting threshold, the cold and warm thermal weights were used to scale the heating or cooling setpoint adjustment. Thus, the thermostat command was not translated as a fixed ±1 °C change, instead, the adjustment could be fractional depending on the strength of the cold or warm context.

For window/natural ventilation control, when a window action reached the voting threshold, the command was translated into a continuous natural ventilation fraction between 0 and 1. The air-quality component was calculated from the interpolated odour and stuffy-air weights, while the thermal component used the warm and cold temperature weights. Poor air quality and warm conditions could increase the natural ventilation command, whereas cold conditions could reduce or limit the

final opening fraction. This allowed the window/NV command to respond proportionally to continuous indoor conditions rather than switching only between fully closed and fully open states.

The resulting translated commands were then used to update the corresponding EnergyPlus control variables. The detailed fallback conditions for off-hours, no active agents, and no majority action are summarized in Figure 12.

Different aggregation thresholds were later tested in the sensitivity analysis to examine how the strictness of the collective decision rule affected model outcomes. These included the at-least-one rule, the majority rule, and the unanimity rule. The sensitivity analysis therefore assessed whether the model outcomes were robust to different assumptions about how individual choices should become effective zone-level actions (refer to 7.5).

6.3.6. Verification and testing

To assess whether the advanced model successfully sends and receives information between the Python script and EnergyPlus, several validation measures were used. During the pre-simulation stage, a Python script was written to test whether the generated FMU file included all the External Interface exported variables and actuators. After a test run, the results showed that, in total, 224 components were exported (actuator) and 601 variables were read from EnergyPlus at each timestep, which was aligned with the defined EnergyPlus input data file (IDF).

In addition to the above, a separate log file was requested at the end of the simulation. The log file contains information such as timestep and hour, ABM update timestep, ABM clock timestep, zone name, zone type, indoor environment conditions (including air temperature, CO_2 concentration, occupancy level, glare index, illuminance, and lighting fraction), current system settings (including heating, cooling, natural ventilation, lighting, and shading), and the current HVAC mode (heating or cooling).

For each ABM update timestep, a series of variables was logged for validation purposes, including ABM update air temperature, CO_2 concentration, occupancy level, glare index, illuminance, lighting fraction, and their corresponding categorical contexts, such as active season, active weather, active lighting, active daylight, active temperature, active air quality, active occupancy level, and active activity. Then, agent choices and the aggregation of these choices were also logged, including the votes for all available control options. For instance, the log records ABM window votes (whether window adjustment is included among selected alternatives) and ABM window majority (whether window adjustment receives enough votes).

Since the shading system in the advanced model was controlled by a dual mechanism, i.e., the coexistence of schedule-based and incident-radiation-based control, the mean and maximum values of incident radiation, the total number of available windows, and the total number of windows used to assess the conditions were logged to monitor shading behaviour during incident-radiation-controlled periods.

Moreover, because there are four control types in the advanced model (see Figure 12), the last four logged variables recorded the source of the control signal for shading, thermostat, window, and lighting. Taking shading for instance, the four sources are baseline_solar_offhour, baseline_solar_no_active_agent, baseline_solar_no_thermal_actions, and abm_blinds_action, each corresponding to one of the control rules mentioned above. In addition, some zones were removed from ABM control and assigned the same control settings as the baseline model. Therefore, these non-controlled zones no longer receive behavioural control signals from the ABM. For these zones, the logged control source indicated baseline-based operation or non-ABM control, while ABM-related logged variables remained empty.

6.4.Conclusion

This chapter presented the implementation and alignment of the baseline and advanced simulation models. The purpose was to ensure that both models were comparable before evaluating the effect of choice-based occupant behaviour on building performance. To reduce simulation bias, the two models were developed using the same underlying physical model and default operational assumption. The main difference between the two models was therefore limited to the representation of occupant-related control logic.

Overall, Chapter 6 demonstrates that the choice-based agent model was successfully implemented and aligned with the baseline model. This provides the technical foundation for the following chapter, where the advanced model is applied and evaluated through several use cases.

7. Demonstration of the advanced model

7.1.Introduction

Building on the technical foundation of the previous chapter, this chapter applies the advanced model to examine how choice-based occupant behaviour affects building performance and human-building interaction patterns.

Four use cases are presented to demonstrate different analytical applications of the same advanced model within the same case-study building. Use case 1 compares annual energy consumption and indoor environmental quality indicators between the two models. Use case 2 examines zone-level behavioural patterns to identify spatial differences in occupant control. Use case 3 focuses on daily human-building interaction patterns and stochastic variation across simulations. Use case 4 tests the sensitivity of simulation outcomes with different zone-level decision rules. With above implementation, the advanced model is assumed to provide a more realistic representation of human-building interactions.

7.1.1. Case study building

The case study building used in this study is a modernised academic office and education building that underwent a major renovation in 2019. After refurbishment, the building was transformed into a high-performance smart building. The building accommodates a wide range of functional spaces, including private offices, open-plan workspaces, meeting rooms, lecture rooms, circulation areas, and shared spaces. This study utilises a previously developed building energy model of the 10th floor developed by Bognár et al. [223]. The 10th floor is a representative office floor containing a range of perimeter and interior zones with different occupancy functions (see Figure 13). This makes it suitable for evaluating human-building interactions. The original building energy model was developed in DesignBuilder and exported to EnergyPlus. Measurement data was used to calibrate the model

[223]. Note that in the present study no measured operational datasets or real-time building management data were directly used, and a typical meteorological year (TMY) weather file was used in the simulation.

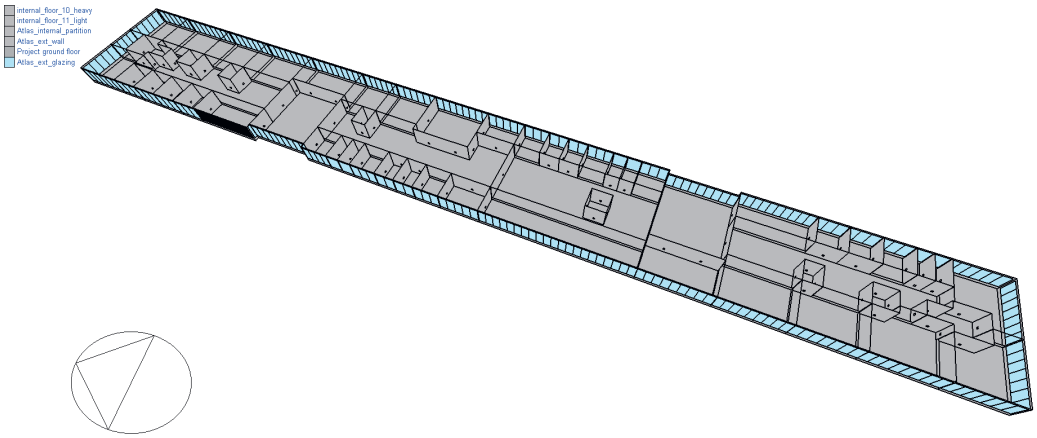


Figure 13 Floor plan of case study building

7.2. Use Case 1: Annual energy and IEQ comparison between baseline-advanced models

Use Case 1 evaluates whether the simplified representation of occupant-driven control in the baseline model produces different performance outcomes compared to the advanced choice-based approach. In addition, annual KPIs may be less sensitive to occupant interactions than hourly or daily KPIs, because short-term behavioural effects can be smoothed out when aggregated over the full year.

Table 18 compares annual whole-building energy use between the baseline model and the advanced model over the one-year simulation period. The advanced model shows a slightly higher electricity use by 21 kWh and a reduced district heating use by 309 kWh compared with the baseline model. However, district cooling demand is substantially higher by 5551 kWh. This indicates that, in this simulation case, occupant-driven heating and cooling-related actions had a stronger influence on

cooling demand than on electricity or heating demand. Overall, the annual comparison suggests that cooling energy demand is sensitive to the occupant behaviour modelling approach used. Because the advanced model represents occupant preferences and actions in greater behavioural detail, it is assumed to produce results that are closer to those expected in the real building.

Table 18 Yearly whole-building energy use comparison between the baseline and the advanced model

Indicators	Baseline	Advanced	Difference (Advanced - Baseline)
Electricity Facility	23077 kWh (7.74 kWh/m^2)	23098 kWh (7.74 kWh/m^2)	21 kWh
District Cooling Facility	64599 kWh (21.7 kWh/m^2)	70150 kWh (23.5 kWh/m^2)	5551 kWh
District Heating Facility	38006 kWh (12.7 kWh/m^2)	37697 kWh (12.6 kWh/m^2)	-309 kWh

The high cooling demand can be explained primarily by the occupant-driven thermostat and window control pathways, including zone size and occupancy capacity, non-controlled zones, and the energy-comfort trade-off. The advanced model added a behavioural control pathway, and the resulting cooling increase is partly associated with ABM-generated occupant control actions. As shown in the heatmaps (see Appendix D, Use Case 1 Heatmap), these behavioural interventions were irregular and context-dependent rather than continuous.

Although each zone received only one aggregated command at each ABM update timestep, the number of active agents affected how individual stochastic choices were translated into a zone-level action under the majority rule. As the number of active agents changed, the absolute number of votes required to satisfy the 50% majority threshold also changed. The realised frequency of thermostat and window commands therefore depended on the interaction between the number of active agents, their stochastic behavioural choices, and the aggregation rule. The larger

cooling increase observed in several open zones may therefore partly reflect this interaction between occupancy and collective decision-making, rather than difference in individual preferences alone. This can be observed from Table 23 (see Appendix C), that those zones with the largest increases in cooling demand are mostly large open-office zones with an occupancy capacity of eight or more people.

During occupied cooling-mode timesteps, the realised cooling commands were concentrated around the nominal occupied cooling setpoint at 24 °C. As show in Table 22 (see Appendix C), the median and 75th percentile cooling commands were 24 °C across the analysed zones. Since 24 °C is also the nominal occupied cooling setpoint in the control configuration, this distribution is interpreted descriptively rather than as direct evidence of occupant-driven cooling. The contribution of occupant behaviour to the increased cooling demand is therefore examined through the realised thermostat and window-control actions and their interaction with the building system, as discussed below.

Window operation provided an additional pathway through which cooling demand could increase. In the advanced model, a selected window action was translated into a fractional natural-ventilation command using both thermal and air-quality conditions. Therefore, window opening was not determined solely by whether the zone was too warm. Occupants could also select the window option in response to relatively high CO_2 concentrations and a perceived need for fresh air. Under such conditions, the model could apply a partial or full natural-ventilation command even when outdoor air was not favourable for cooling. The heatmaps in Figures 27 and 28 were generated to examine this mechanism (see Appendix D Use case 1 Heatmap). The indoor-temperature and outdoor–indoor temperature-difference panels indicate whether natural ventilation was thermally beneficial, while the CO_2 panel helps explain why a window action may nevertheless have occurred. For example, during the third week of July, natural-ventilation commands of approximately 0.5 or 1 were applied at several moments when indoor temperature

was already close to 24 °C and the outdoor–indoor temperature difference indicated that outdoor air was substantially warmer than indoor air. From a purely thermal-control perspective, the window would preferably have remained closed. However, the corresponding CO_2 concentrations were relatively high compared with surrounding periods, suggesting that the window action was driven by the need for fresh air rather than by overheating alone. This example demonstrates an important multi-domain behavioural effect. A window action that improves perceived air quality may be unfavourable from a thermal-energy perspective. When warmer outdoor air enters a mechanically cooled zone, the cooling system must remove the additional heat to maintain the commanded indoor temperature. Therefore, the simultaneous occurrence of relatively low cooling setpoints and natural-ventilation commands under unfavourable outdoor conditions provides a plausible explanation for part of the increased cooling demand. The heatmaps do not explain the entire whole-building energy difference on their own, but they demonstrate the temporal control process through which air-quality-driven window actions could add to the cooling load.

The results of non-controlled zones further support this interpretation. The bottom few rows of Table 23 include zones that were considered corridors (open space). In the advanced model, those zones are intentionally left to remain completely controlled by baseline settings. The results show almost identical cooling demand in the advanced model compared with the baseline model, indicating that the alignment of the advanced and baseline model is generally good, and the cooling increase mainly appeared in ABM-controlled zones. Since warm occupied hours are reduced in most zones, the result should be interpreted as an IEQ-energy trade-off.

The thermal-comfort results show the consequence of this more active control. Warm occupied hours were reduced in most ABM-controlled zones, meaning that the higher cooling demand was accompanied by improved thermal conditions.

Table 23 quantifies this energy–comfort trade-off by showing the additional cooling energy required for each reduced warm occupied hour. For the open-office zones with large cooling increases, an average of 0.93 kWh of additional cooling energy was required per reduced warm occupied hour, with zone-level values ranging from 0.14 to 2.18 kWh. The advanced model therefore produced more responsive thermal and air-quality control, but the improved indoor conditions came at the cost of increased cooling demand.

The whole-building energy results show that the largest performance difference came from the cooling demand. The advanced model increased district cooling demand considerably, while slightly reducing heating demand. Within the selected control configuration, thermostat and window-related actions had a stronger influence on annual HVAC demand than lighting actions. Annual lighting outcomes changed only slightly because occupant's lighting control continued to operate with the existing EnergyPlus daylighting and dimming logic. These results are therefore specific to the control options and system interactions represented in this study, with the strongest annual effect occurring in cooling demand.

The following section focuses on indoor thermal comfort conditions. Figure 14 presents the occupied zone-hour outside the operative temperature comfort range during core working hours, from 9 AM to 5 PM. Two types of thermal discomfort are distinguished: hours below 18 °C and hours above 24 °C. The thermal comfort KPI is the sum of exceeding hours of all rooms on the floor, and the total occupied zone-hours are 106,080 hours.

The results show that the advanced model has a similar number of occupied zone-hours below 18 °C, with 318 hours compared 313 hours in the baseline model. This suggests that the occupant-responsive heating logic and associated fallback rules did not contribute much to the occupied cold discomfort hours. However, the advanced model substantially reduced warm occupied zone-hours. The number of

occupied zone-hours above 24 °C decreased from 8,096 hours, representing 7% of the total assessed occupied hours, in the baseline model to 3,479 hours, representing 3%, in the advanced model, corresponding to a reduction of approximately 57%. The main thermal-comfort improvement therefore occurred through the reduction of warm discomfort rather than cold discomfort.

At the individual zone-level, the open office area (10XZ013) was the worst-performing zone in both models. In the baseline model, it exceeded 24°C for 739 of its 3,120 occupied hours, corresponding to approximately 23.7% of occupied time. In the advanced model, this decreased to 569 hours, approximately 18.2% of occupied time, suggesting a reduction of roughly 23%. Therefore, though the advanced model substantially reduced its duration in the most affected zone, the localized overheating problem remains to some extent.

Figure 14 clarifies the consequence of the higher cooling demand identified in the annual energy analysis. The advanced model generated more frequent and responsive cooling-related interventions through thermostat and window-control actions. These interventions increased annual cooling demand, but they also maintained occupied zones below the warm-discomfort threshold for substantially longer periods. The higher cooling demand should therefore not be interpreted as an isolated deterioration in energy performance. Instead, it represents an energy–

comfort trade-off: additional cooling energy was used to reduce occupants' exposure to warm indoor conditions.

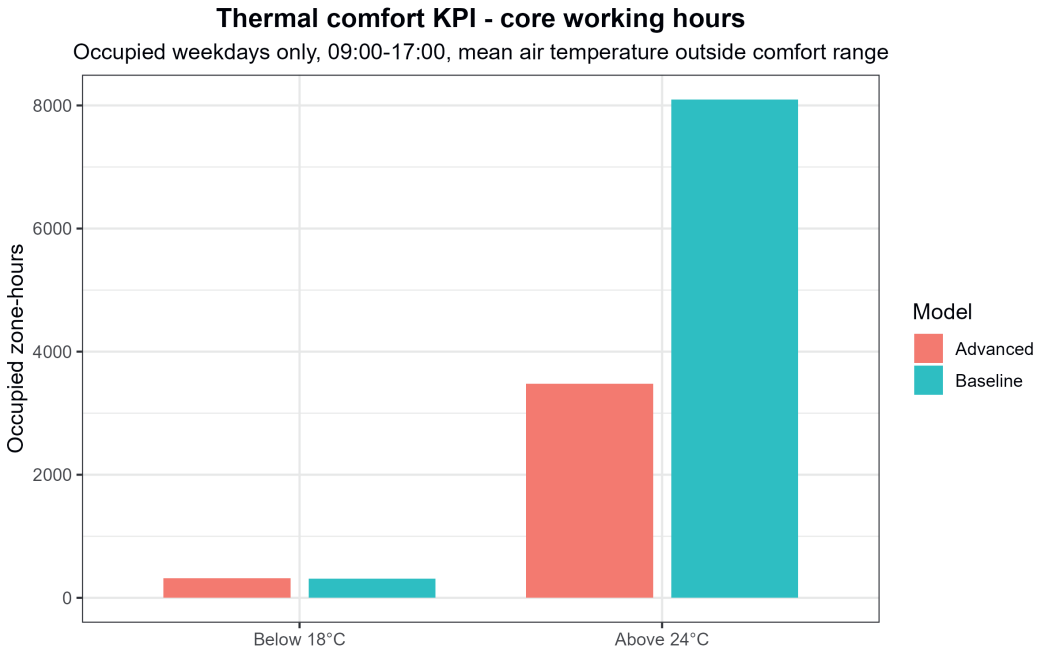


Figure 14 Thermal comfort KPI for core working hours - 9 AM to 5PM (summed hours of all ABM linked zones on the floor)

Overall, the clearest difference between the baseline and advanced models occurs in the thermal domain. The advanced model substantially reduced warm occupied zone-hours in most ABM-controlled zones, while producing little change in cold occupied hours. The additional cooling demand and the reduction in warm discomfort are therefore two connected outcomes of the same occupant-responsive control process. More cooling energy was consumed, but a greater proportion of occupied hours was maintained within the defined thermal-comfort range. Detailed

results for indoor air quality, daylight and artificial lighting are provided in Appendix D – Use Case 1 KPIs and Figure 15.

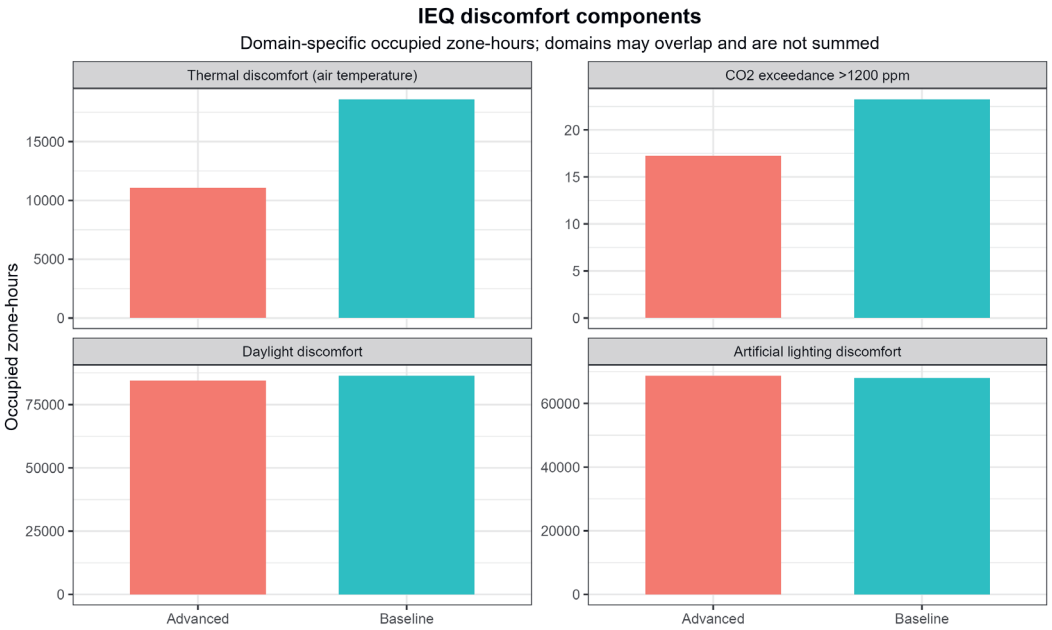


Figure 15 IEQ discomfort summary

7.3. Use Case 2: Zone-level comparison between comparable rooms

Use Case 2 examines whether rooms with similar functions, but different orientations, show different behavioural-control and IEQ patterns under the advanced model. The comparison focuses on two meeting zones with one east-facing and one west-facing.

Lighting control for two meeting zones shows a broadly similar pattern, where frequent ABM decision periods are visible. In both zones, the lighting schedule often returns to the default setting outside office hours, indicating that the baseline schedule remains responsible for switching lights off after working hours. The shading control patterns differ between the two zones for plotted period. Although

both rooms have the same function, their opposite orientations lead to different shading-command patterns. Moreover, the zone-level comparison shows how these different solar conditions were reflected in the simulated shading control process, including both fallback control and occupant driven shading commands. This illustrates how spatial conditions can produce different behavioural control patterns even between otherwise comparable rooms. However, because the comparison is based only on one selected week in July, this result should be interpreted as an illustrative weekly example rather than evidence of seasonal behaviour (see Figures 34 and 35 in Appendix E).

The weekly temperature plots show that both meeting zones have similar thermal behaviour in the baseline and advanced models. Air temperature and operative temperature remain close to the heating and cooling command signals, and the two zones show almost identical weekly thermal profiles. This is expected because they have the same room function, similar occupancy schedules, and the same seasonal HVAC availability and thermostat-control logic. Therefore, unlike shading control, thermal behaviour does not show strong orientation-related variation between these two rooms for plotted week (see Figures 16 and 17).

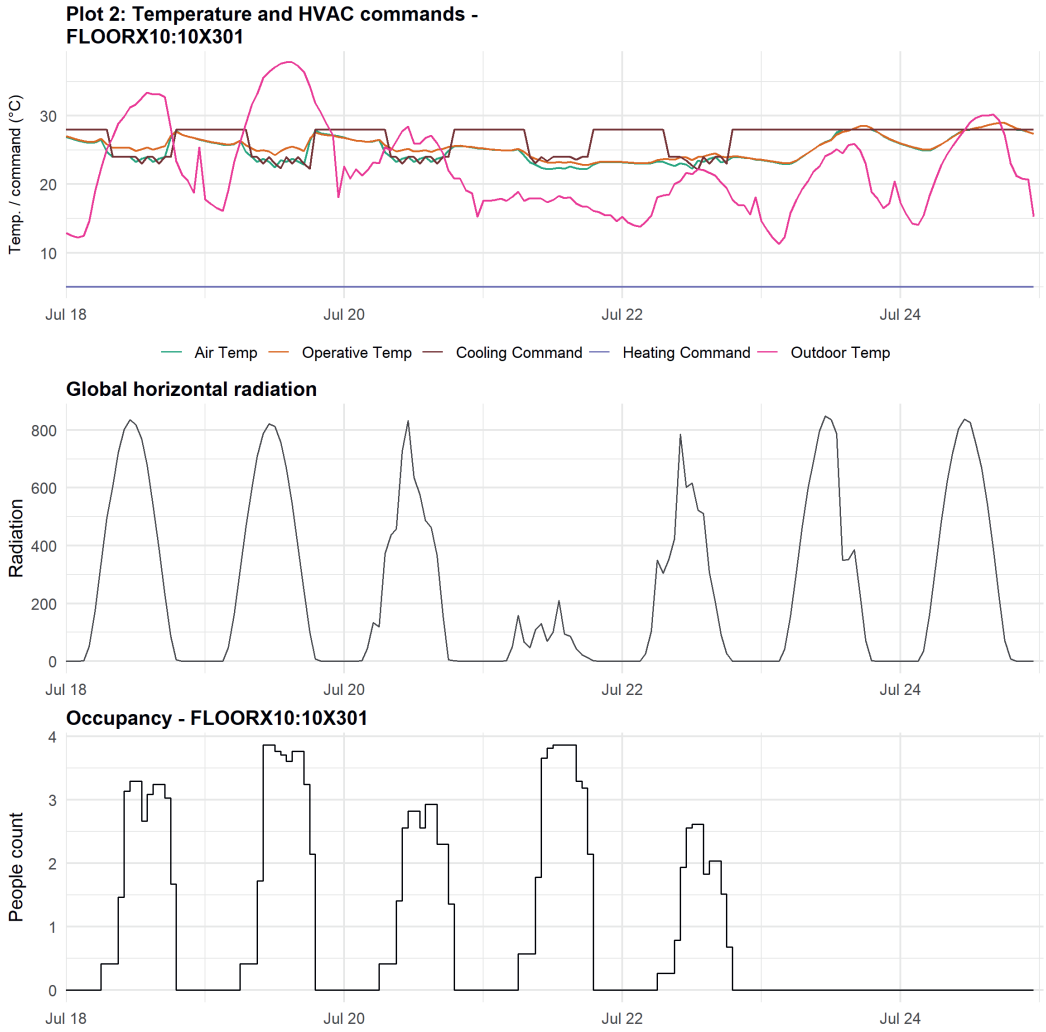


Figure 16 Weekly temperature setpoint predictions for west-facing meeting zone

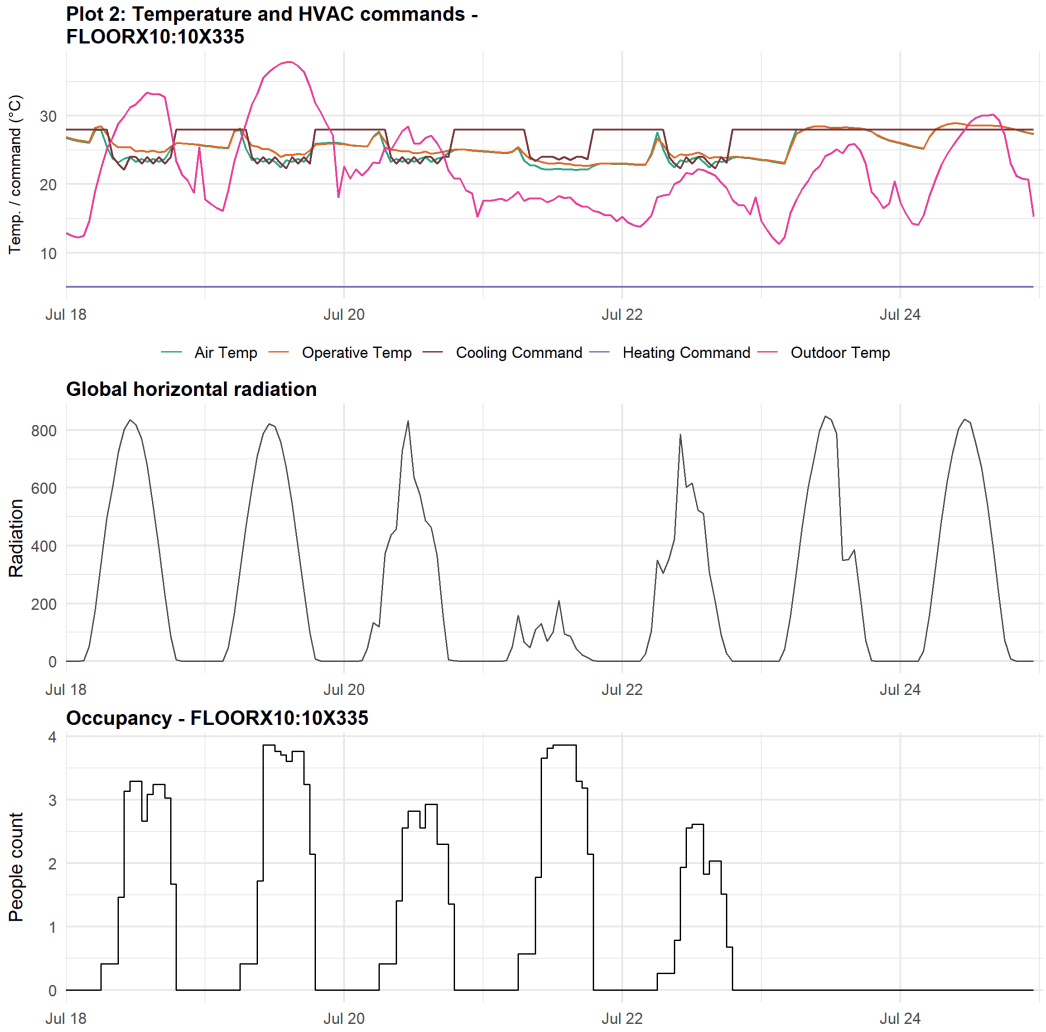


Figure 17 Weekly temperature setpoint predictions for east-facing meeting zone

The CO_2 plots for the west-facing meeting zone and the east-facing meeting zone show very similar monthly air-quality patterns (see Figures 18 and 19). In both zones, CO_2 concentration rises during occupied periods and decreases rapidly during unoccupied periods, returning to an outdoor CO_2 level of around 400 ppm. Peak concentrations in both rooms remain below the 1200 ppm threshold, with the

highest values generally reaching around 1000–1100 ppm during more heavily occupied periods.

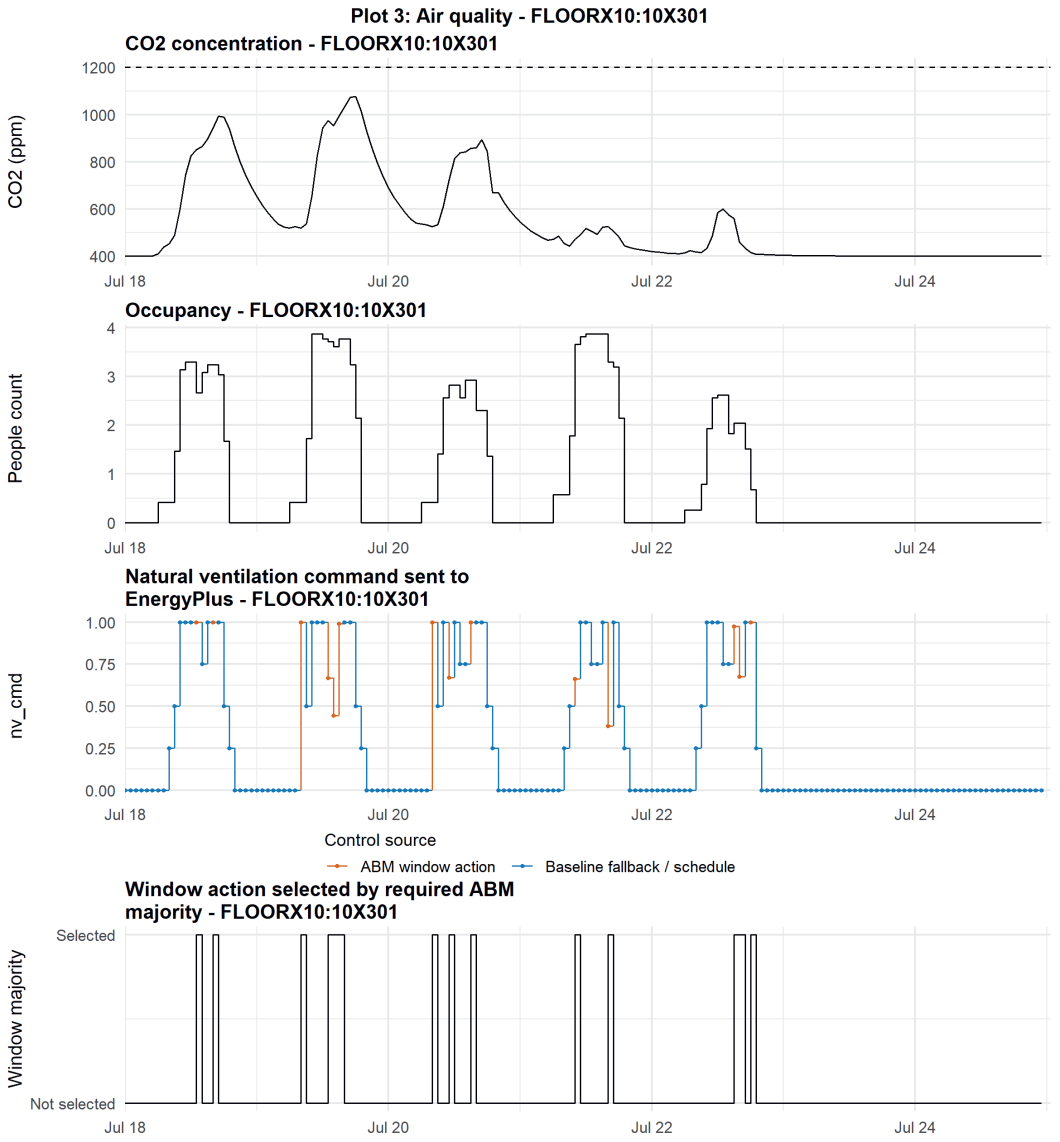


Figure 18 Weekly natural-ventilation setpoint predictions for west-facing meeting zone

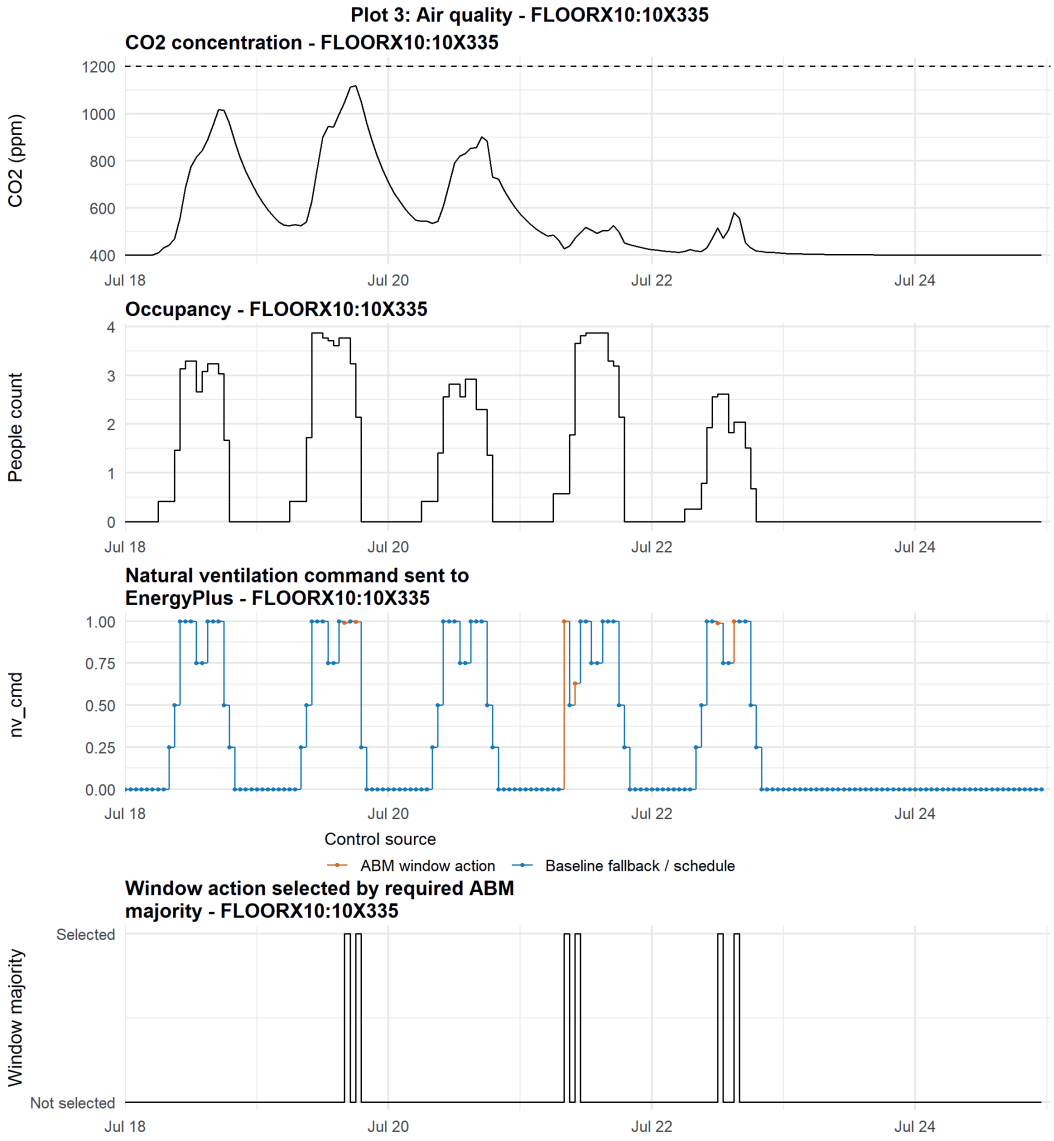


Figure 19 Weekly natural-ventilation setpoint predictions for east-facing meeting zone

The lower panels further show that both meeting rooms have the same occupancy pattern and a similar scheduled natural ventilation baseline. However, their ABM-related control processes are not identical. Window actions were selected more frequently in west-facing zone, and the natural ventilation command is consequently adjusted more often during ABM decision periods. In the east facing

zone, window selections and ABM interventions were less frequent and concentrated within fewer occupied periods. Since the two zones had similar occupancy, CO_2 and thermal patterns, this different cannot be attributed to a single environmental driver from the present comparison. It may reflect differences in the local environmental contexts entering the choice model, together with the stochastic nature of the agent-level choice process. Therefore, the observed difference should be interpreted as a realised zone-level behavioural pattern for the selected simulated week rather than as a deterministic effect of orientation. Besides these differences, the resulting CO_2 concentration profiles remain similar between two zones. Therefore, the baseline ventilation logic and occupancy pattern appears to have a stronger influence on the resulting CO_2 concentration than the observed differences in occupant's window actions during simulated week.

The zone-level comparison demonstrates that the advanced model can capture spatial variation in human-building interaction, i.e., orientation factor. This indicates that occupant-responsive control does not operate uniformly across a building, but interacts with local environmental conditions such as solar exposure and daylight availability.

Overall, the comparison between the west-facing and east-facing meeting zones shows that the biggest zone-level differences are observed in daylighting and shading control, where orientation directly affects solar exposure and control response. Differences are also visible in the frequency of occupants' window actions, though these behavioural differences do not show a substantial difference in the CO_2 concentrations. Thermal and air-quality conditions remain broadly similar between the two rooms, mainly because they share similar occupancy patterns, room function, and underlying HVAC control logic. Therefore, the two-zone comparison is most useful for explaining spatial variation in occupant-

responsive control processes, while it provides more limited evidence of orientation-related differences in the resulting thermal and air-quality conditions.

7.4. Use Case 3: Daily human-building interaction and stochastic variation

Use Case 3 examines the stochastic variation produced by the advanced model under the same daily boundary conditions. The purpose is to investigate whether repeated simulations with different random seeds lead to different occupant control commands, and how this variation is reflected in daily control patterns and energy outcomes. Figures 20, 21, 22, and 23 show the daily variation of the advanced model for a single meeting zone, using 50 randomly generated seeds.

Figure 20 presents a time-series diagnostic of stochastic variation across 50 simulation seeds for a single meeting zone on 1 July. The x-axis represents the hourly simulation timestep over the selected day, while the y-axis differs by panel: illuminance is reported in lux, glare index as a visual-comfort indicator, lighting power multiplier as the simulated artificial-lighting response, occupancy as the number of people, and the lighting and shading commands as ABM-generated control signals ranging from 0 to 1. The black line shows the mean across the 50 seeds at each timestep, the grey band shows the full min–max range across seeds, and the blue band shows the mean ±1 standard deviation.

The lighting and shading setpoints represent the stochastic agent actions, while illuminance, glare index, and the lighting power multiplier represent the resulting visual IEQ condition and system response. Based on the 50-seed data, occupancy and lighting power multipliers are identical across seeds at each hourly timestep, indicating no seed-driven variation for these two variables on the selected day. Stochastic variation is mainly visible in the ABM command variables: the maximum hourly standard deviation is approximately 0.30 for the lighting

command and 0.50 for the shading command. However, the corresponding variation in visual-performance variables is limited and temporally concentrated. Illuminance varies across seeds during only four daytime hours, with a maximum hourly standard deviation of approximately 452 lux, while glare index varies during three daytime hours, with a maximum hourly standard deviation of approximately 0.30. This suggests that, for this zone and day, stochastic variation in agent lighting and shading actions exists, but it only partly propagates into the resulting visual indoor conditions.

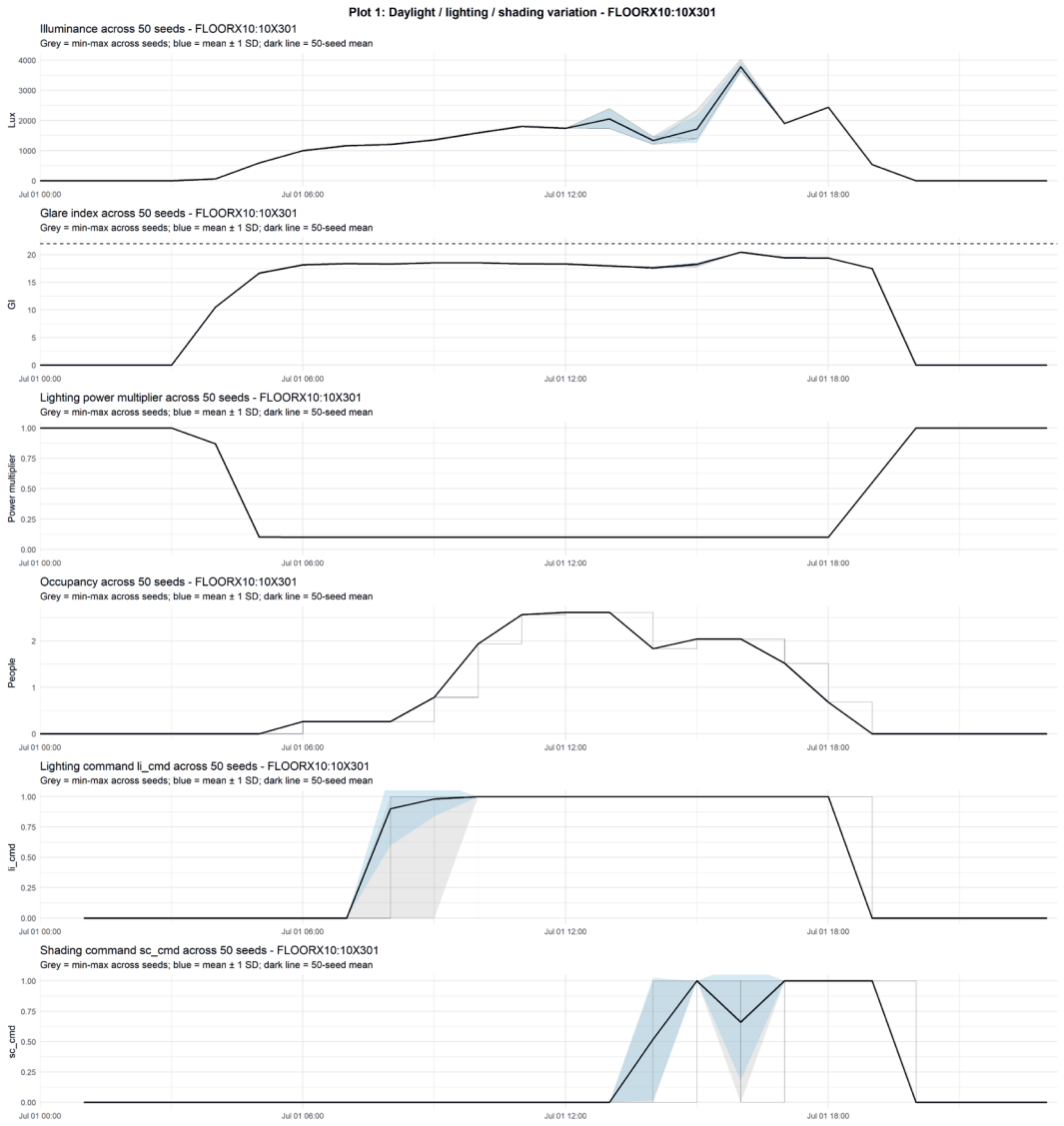


Figure 20 Daily lighting and shading control prediction for single meeting zone in summer

Figure 21 presents the seed-to-seed variation in thermal conditions and HVAC command variables for a single meeting zone on 1 July. The x-axis represents the hourly simulation timestep across the selected day. The y-axis in the first panel shows temperature and HVAC setpoint values, including zone mean air temperature, operative temperature, cooling setpoint and heating setpoint. The second panel

shows global horizontal radiation in W/m², and the third panel shows occupancy as the number of people.

Based on the data, the mean zone air temperature is 24.21 ± 0.97 °C, and the mean operative temperature is 24.76 ± 0.52 °C. However, the hourly seed-to-seed variation is smaller with average hourly SD is 0.22 °C for air temperature and 0.17 °C for operative temperature, with maximum hourly SD of 0.59 °C and 0.42 °C, respectively. This indicates that although the temperatures vary over the day, the random variation between seeds at the same timestep is limited. The cooling setpoint has a daily mean of 25.86 ± 2.28 °C, mainly reflecting the scheduled shift between occupied and unoccupied periods. Its maximum hourly seed-to-seed SD is 0.83 °C, showing some variation in the realised cooling setpoint during occupied periods. The heating setpoint remains constant at 5.00 °C ± 0.00, indicating that heating is effectively inactive during cooling-period. Global horizontal radiation and occupancy are identical across seeds, as these are deterministic input or schedule-driven variables rather than stochastic ABM outputs. Overall, the figure shows that stochastic behavioural variation has only a limited effect on thermal conditions for this specific day and zone, while the larger daily variation is mainly driven by the occupancy pattern. Since control schedule and radiation profile are same across all seeds

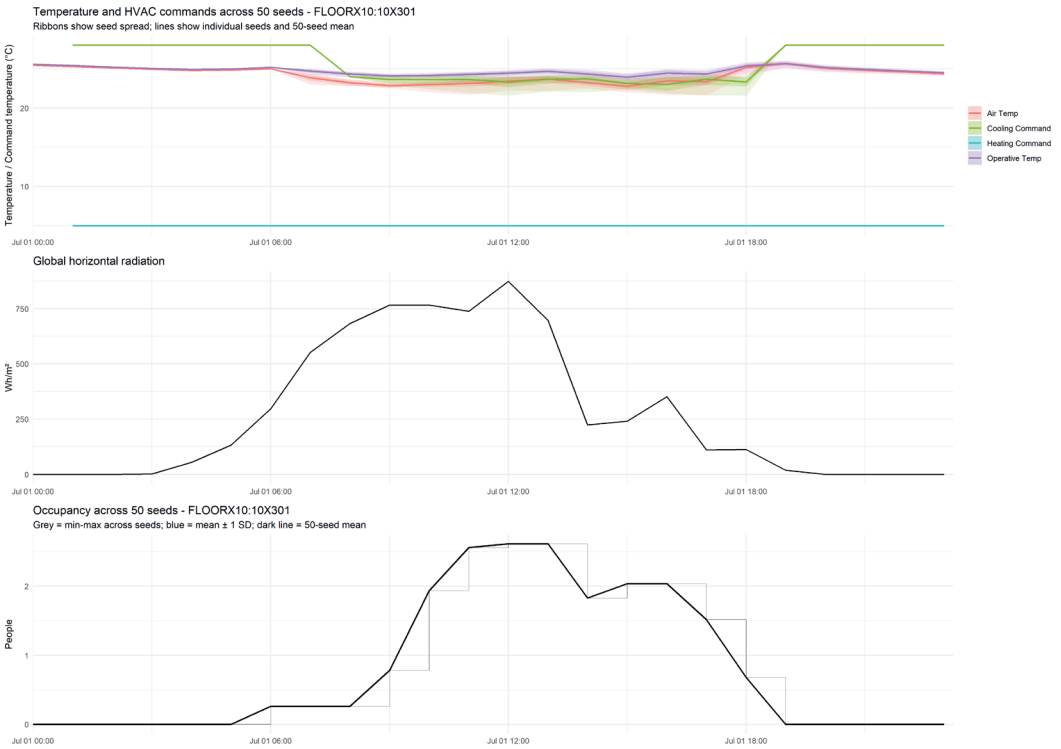


Figure 21 Daily cooling setpoint prediction for single meeting zone in summer

Figure 22 presents the seed-to-seed variation in CO_2 concentration, occupancy and natural ventilation-related variables for the same meeting zone on 1 July. The x-axis represents the hourly simulation timestep across the selected day. The y-axis in the first panel shows CO_2 concentration in ppm, with the dashed line indicating the 1200 ppm reference threshold. The second panel shows occupancy as the number of people. The third panel shows the natural ventilation command, represented as a control signal between 0 and 1. The fourth panel shows whether at least one agent selected the window action.

Based on the data, the mean CO_2 concentration is 429.48 ± 24.35 ppm across the selected day. However, the hourly seed-to-seed variation is smaller, with an average hourly SD of 8.19 ppm and a maximum hourly SD of 30.44 ppm. This indicates that although CO_2 concentration changes during occupied hours, the random

variation between seeds at the same timestep is limited. CO_2 concentration remains well below the 1200 ppm threshold throughout the day, suggesting that the stochastic variation in window-related behaviour does not lead to problematic air-quality conditions for this specific day and zone. Occupancy is identical across seeds because it is schedule-driven rather than a stochastic ABM output in this analysis.

The natural ventilation command shows stronger seed-to-seed variation than CO_2 concentration. Its daily mean is 0.38 ± 0.42, with a maximum hourly seed-to-seed SD of 0.32. The window-action variable also shows clear stochastic variation, with a daily mean of 0.42 ± 0.49 and a maximum hourly SD of 0.50. This suggests that window-related agent decisions vary noticeably across seeds. However, this behavioural variation only partly contributes to the resulting CO_2 concentration. Overall, the figure shows that stochastic variation is more visible in the agent action and natural-ventilation setpoint variables than in the resulting air-quality outcome. Since occupancy is the same across all seeds, the larger daily CO_2 pattern is mainly driven by the occupancy profile, while the seed-to-seed variation is mainly introduced through the ABM window and natural-ventilation control pathway.

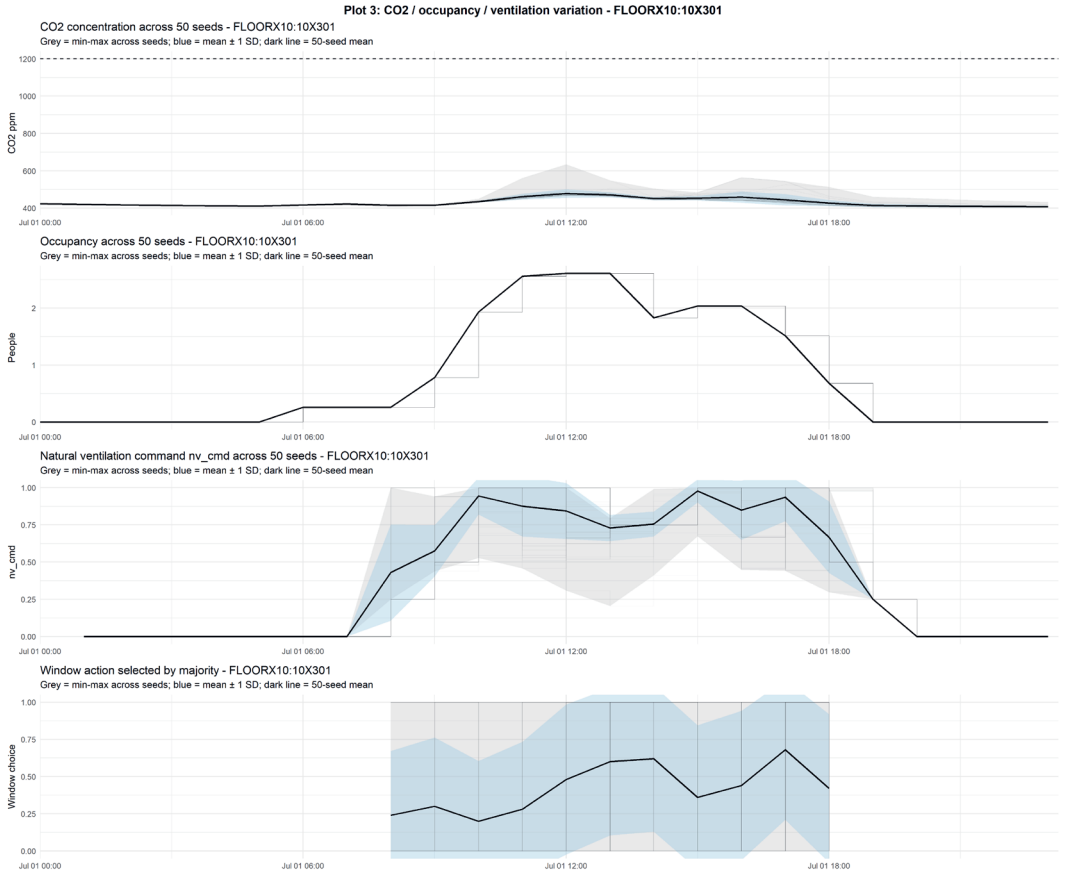


Figure 22 Daily window control prediction for single meeting zone in summer (From top to bottom including CO_2 concentration level, occupancy level, natural ventilation setpoint, window choice)

Figure 23 shows a combined view of the main control commands. Lighting follows a near-binary occupied-period pattern. Some seed variation occurs during the morning transition, but once the command reaches full activation, the seed-to-seed variation becomes limited. Shading commands are more temporally concentrated and mainly occur in the afternoon, indicating that shading behaviour is triggered only during specific daylight or glare-related conditions. Natural ventilation shows the largest and most persistent seed-to-seed variation during occupied hours, suggesting that window-related control is the most sensitive to stochastic agent decisions in this example. In contrast, the heating and cooling setpoints remain

comparatively stable across seeds. The cooling setpoint mainly follows the occupied/unoccupied control pattern. Overall, the figure indicates that stochastic occupant behaviour mainly affects the predicted shading and natural ventilation commands, whereas lighting, heating and cooling commands are more constrained by schedule settings, fallback rules and seasonal HVAC operation strategies.

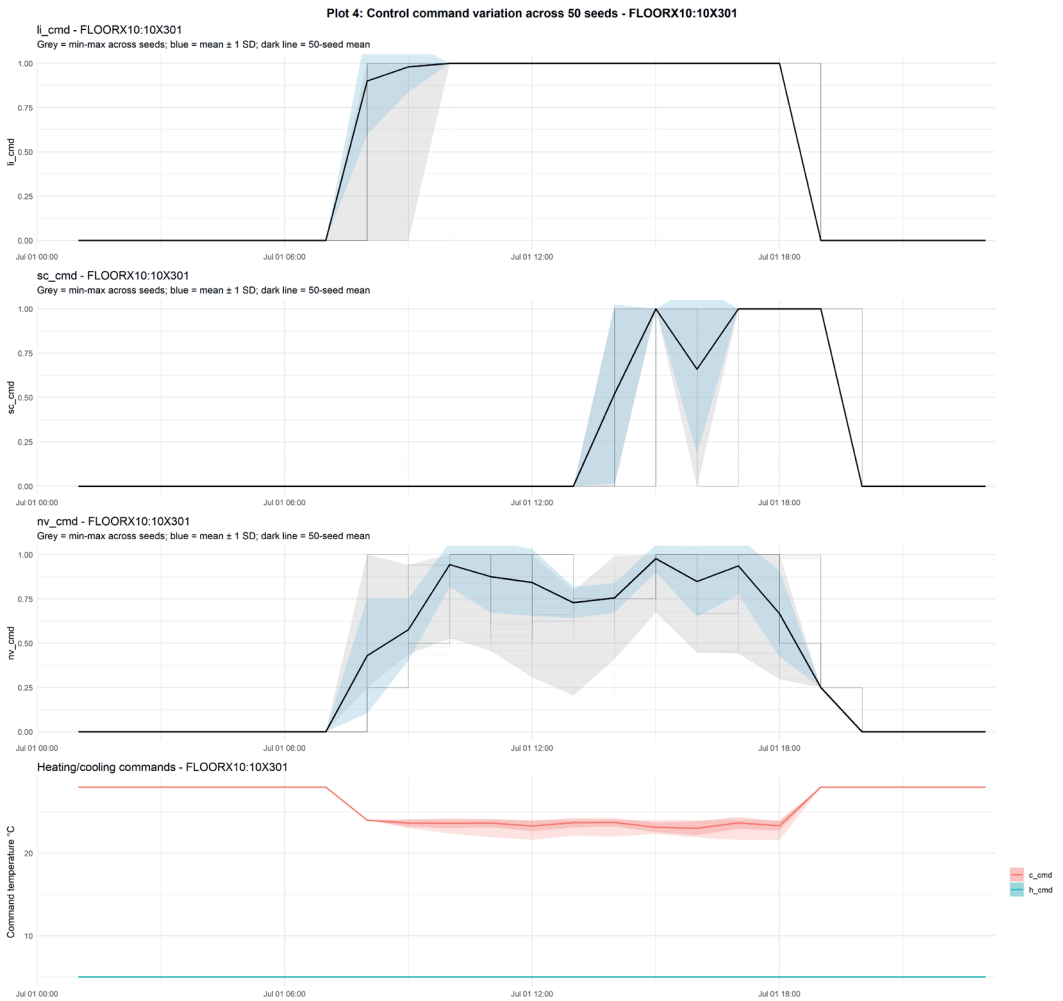


Figure 23 Daily control prediction summary of all control options for single meeting zone in summer (From top to bottom including lighting, shading, natural-ventilation, and cooling setpoints)

Figure 24 presents the 50-seed variation in daily facility energy consumption for the selected simulation day. The x-axis separates the three energy categories: district

cooling, district heating and electricity. The y-axis shows energy consumption in kWh/day. This figure is used as an aggregated energy-performance summary to examine to what extent the stochastic variation observed in the control setpoint affect facility-level energy consumption.

Based on the data, district cooling shows the largest seed-to-seed variation, with a mean daily demand of 405 ± 14 kWh/day. Across the 50 seeds, cooling demand ranges from 378 to 432 kWh/day, with the interquartile range between 395 and 417 kWh/day. This indicates that cooling demand is the energy category most affected by stochastic occupant behaviour on this selected day. The variation is likely caused by the stochastic nature of the model, which can influence ventilation heat exchange, solar gains, internal gains and cooling load.

District heating remains zero for all seeds, which is expected because the selected day is during the cooling season. Electricity consumption is almost unchanged across seeds, with a mean of 63.385 ± 0.002 kWh/day and a very narrow range from 63.381 to 63.388 kWh/day. This suggests that electricity use is mainly constrained by fixed schedules, daylighting control and stable system or plug-load assumptions,

rather than by stochastic behavioural variation. Overall, Figure 24 shows that seed-dependent behavioural variation mainly contributes to cooling demand.

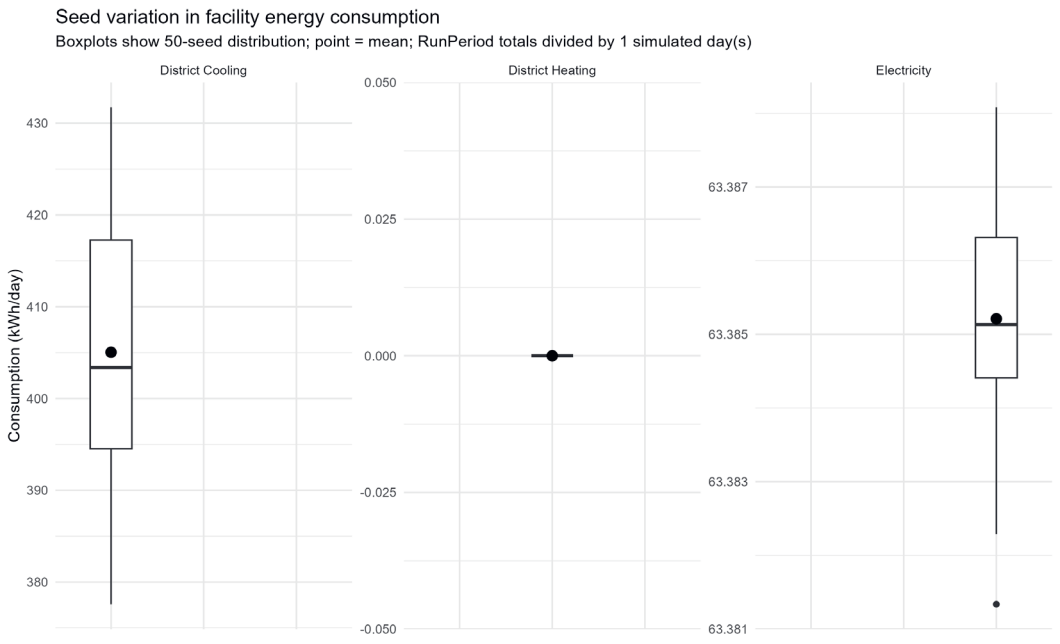


Figure 24 Boxplots energy consumption

7.5. Use Case 4: Sensitivity analysis of control and decision rules

Use Case 4 examines whether different zone-level decision rules affect the translation of individual occupant choices into shared-space control commands. The purpose is to test the sensitivity of simulation outcomes to different aggregation rules. The sensitivity analysis was tested with different ABM activation thresholds. As table 19 demonstrates, ‘at least 1 vote’, ‘at least 50% of the votes’, and ‘unanimity (all votes)’. This was realised in the ‘aggregate_zone_control’ section and logged during simulation for analyses. A demonstration of the potential active agents with different control (aggregation) rules can be found in Table 19.

Table 19 Number of active agents to trigger the ABM signal

Active agents	At least one rule vote >= 1 (Use case 1)	Majority rule At least 50% vote>= len(thermo_choice) / 2:	Unanimity rule 100% vote == len(thermos_choice):
1	1	1	1
2	1	1	2
3	1	2	3
4	1	2	4
5	1	3	5
6	1	3	6
7	1	4	7
8	1	4	8

Table 20 shows that increasing the voting threshold reduces annual energy use compared with the advanced model using the at_least_one rule. Under the at_least_one rule, a single active agent is sufficient to trigger a behavioural control action, resulting in the highest annual energy use, mainly due to increased district cooling demand. When the threshold is increased to the 50% majority rule (as Use Case 1 used), total annual energy use decreases from 145,508 kWh to 130,945 kWh, corresponding to a reduction of about 10.0%. This reduction is mainly driven by a 17.4% decrease in district cooling demand, while district heating increases only slightly by about 0.5%. The 100% unanimity rule produces the lowest energy use among the ABM cases, reducing total annual energy use by about 12.3% and district cooling demand by about 21.4% compared with the at_least_one rule. Electricity use remains almost unchanged across the three voting rules, indicating that, apart from the EnergyPlus embedded daylight and lighting dimming logic, the voting threshold mainly affects HVAC-related energy demand, especially cooling. However, even with the unanimity rule, annual cooling demand remains slightly

higher than the baseline case, suggesting that occupant-driven control still introduces additional cooling-related impacts compared with the schedule-based baseline model. Such impact can be explained by the previously mentioned IEQ-energy trade-off effect in section 7.2.

Table 20 Annual energy consumption with different ABM control thresholds

Indicators	at_least_one	50% majority	100% unanimity	Baseline
Electricity Facility	23098 kWh	23098 kWh	23099 kWh	23077 kWh
District Cooling Facility	84887 kWh	70150 kWh	66706 kWh	64599 kWh
District Heating Facility	37523 kWh	37697 kWh	37747 kWh	38006 kWh

In the log file, six different control sources were logged, i.e., 'abm_option_action', 'baseline_option_no_active_occupant', 'baseline_no_option_action', 'baseline_offhour', 'ep_internal_non_controlled_zone' ('no_shading' for internal zones). The following plots were generated for zones where control is available (control==TRUE), actual ABM update timestep (abm_update_step==TRUE), and active agents is not zero (abm_n_active > 0).

Figure 25 shows a clear pattern that under the 'at_least_one' rule, almost all possible ABM update moments become an effective vote, so the 'threshold_met_effective _action' share is the highest for all four options. With the voting rule becoming stricter, from 1 to 50% and even 100%, a noticeable increase in the voting situation where no majority or unanimity conditions are met. This suggests that occupants still express their preferences, but the majority or unanimity threshold prevents many actions from happening.

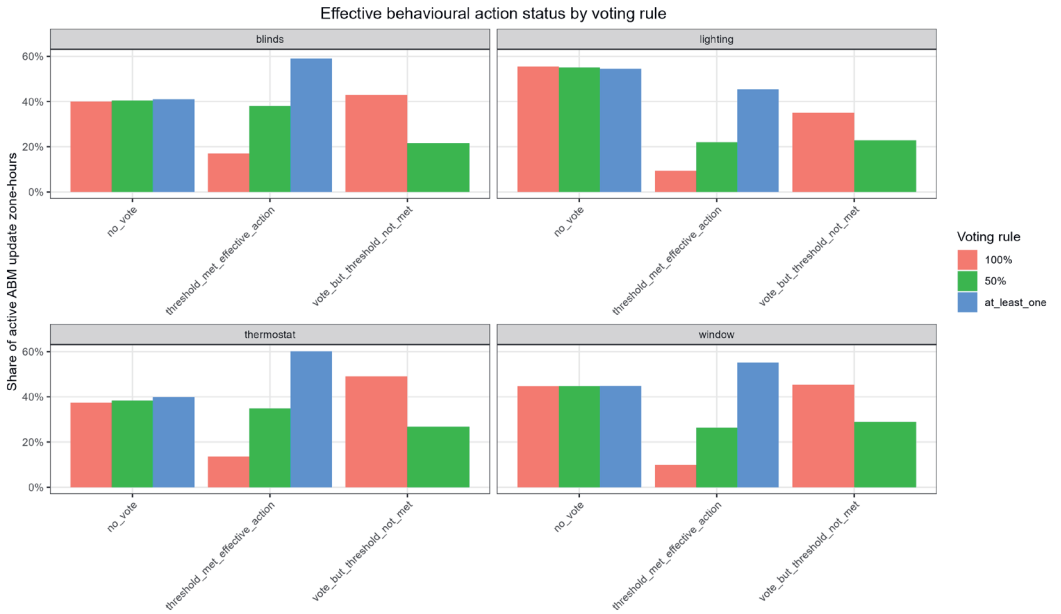


Figure 25 Effective behavioural action status by voting rule

In Figure 26, the effect is strongest in open offices. Under the at_least_one rule, open offices show very high threshold-met rates, especially for blinds, thermostat, and window. But under the 100% rule, the rates drop sharply. This is logical because open offices have more active agents, so full agreement becomes much harder to reach.

For meeting rooms, the same pattern appears but is less extreme. The at_least_one rule still gives the highest effective action frequency, followed by 50%, then 100%.

For single offices, the three rules are much closer. This is also expected because when there is only one active agent, the three rules often behave similarly: one vote is simultaneously “at least one”, “at least 50%”, and “100%”. Therefore, voting-threshold sensitivity is weaker in single-occupant spaces.

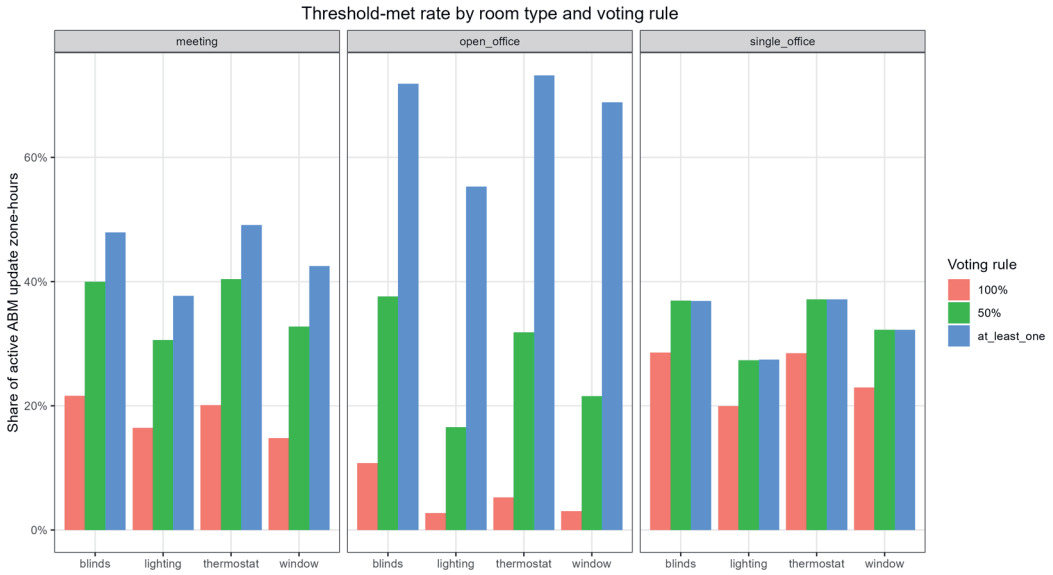


Figure 26 Threshold-met rate by room type and voting rule

The sensitivity analysis shows that the voting threshold has a strong influence on both the frequency of effective occupant–building interactions and the resulting energy performance. Across all adaptive options, the at-least-one rule produces the highest threshold-met rate, followed by the 50% majority rule and the 100% unanimity rule (see Figure 26). This indicates that stricter aggregation rules substantially reduce the number of individual preferences that are translated into zone-level control actions. This reduction in effective actions is also reflected in the energy results, where the majority rule and unanimity rule models reduced energy use by 3.92% and 5.58%, respectively, compared with the model using at-least-one rule. The effect is especially clear in open offices, where a larger number of active agents makes full agreement on something rarely being achieved. In contrast, single offices show smaller differences between these three rules, because the presence of one active occupant often makes the at-least-one, 50%, and 100% thresholds equivalent. Overall, the results suggest that the voting rule is an important modelling assumption, particularly in multi-occupant spaces, as it determines how

strongly individual behavioural responses influence building control signals and, consequently, buildings annual energy demand.

7.6. Discussion

This chapter applied the advanced model to examine how choice-based occupant behaviour modelling affects building performance and revealed human-building interaction patterns. Four use cases were analysed, i.e., annual energy and IEQ comparison between the baseline and advanced model, zone-level behavioural pattern analysis for meeting zones, daily stochastic variation and prediction for a single zone, and sensitivity analysis of collective decision rules for whole-building simulation. Together, the results show that the advanced model provides additional insight not only into annual performance outcomes, but also into when, where, and how occupant-driven control actions occur and how these actions affect, or in some cases have limited effect on the resulting performance indicators.

The annual comparison between the baseline and advanced models shows that some energy-performance KPIs are sensitive to the method used to represent occupant actions. With choice-based behaviour representation, the electricity use changed only slightly because both models included similar dimming logic, while heating demand decreased slightly and cooling demand increased more substantially in the advanced model. The higher cooling demand was partly associated with differences in how occupants' responses to warmer occupied conditions were represented (see Section 6.3.2 and 7.2). These findings suggest that cooling-related operation is more sensitive to the occupant-behaviour modelling method than electricity or heating demand. Therefore, the advanced method may be particularly relevant when investigating cooling performance and energy–comfort trade-offs, whereas a simplified method may be sufficient for KPIs that show limited sensitivity to behavioural representation or for a simplified building with limited control.

The IEQ comparison further supports this interpretation. The advanced model reduced warm occupied hours and slightly improved CO_2 conditions, while the effect on other indicators was more limited. This suggests that the influence of occupant behaviour is not uniform across all performance indicators. Thermal comfort and cooling demand were more sensitive to occupant-driven control actions, whereas CO_2 concentration remained strongly governed by occupancy schedules and the underlying ventilation settings. Similarly, lighting-related outcomes were constrained by the interaction between occupant commands and the existing EnergyPlus daylighting/lighting dimming logic. Therefore, annual KPIs alone are not sufficient to fully evaluate the advanced model, because they may hide short-term or zone-level specific behavioural effects.

Thus, in use case 2 zone-level comparison was introduced. The zone-level comparison showed that the impact of occupant behaviour is spatially heterogeneous. The comparison between west-facing and east-facing meeting zones indicates that orientation-related differences are most visible in daylighting and shading behaviour. These controls are directly affected by solar exposure and glare conditions, so occupant-responsive shading and lighting actions produce clearer spatial variation. By contrast, thermal and CO_2 patterns remained roughly similar between the two meeting zones because they shared similar occupancy patterns, room functions, and control logic. This means that the value of the zone-level analysis lies less in showing large differences in every environmental outcome, and more in revealing where behavioural control processes differ across space.

In use case 3, the stochastic nature of the advanced model was demonstrated. With different random seeds, occupant choices produced visible variation in control commands, especially for lighting, shading, natural ventilation, and thermostat-related actions. However, this behavioural variation did not always translate into equally large differences in environmental outcomes or daily energy use. This is because the final simulated outcomes are also constrained by deterministic building

schedules, HVAC system settings, daylighting logic, occupancy schedules, and physical building response (e.g., the adjustable range for the thermostat was restrained within 18 to 24 °C). Therefore, the advanced model shows that stochastic occupant behaviour can strongly affect the control process, but the magnitude of its effect on energy and IEQ depends on whether those control actions can properly propagate through the building system.

The sensitivity analysis confirms that the aggregation/voting rule used to convert individual choices into zone-level commands is a critical modelling assumption. Under the 'at_least_one' rule, a single occupant can trigger a control action, resulting in the highest frequency of effective occupant-building interactions and the highest annual energy use among the tested rules. Increasing the threshold to a majority rule (at least 50%) or a unanimity rule (100% agreed) reduced the number of effective actions and lowered annual energy use, mainly by reducing cooling demand. The effect is strongest in open offices, where for multiple active agents to reach consensus on a certain option is difficult to achieve. Instead, in single offices the difference between the rules is smaller because one active occupant can satisfy all three thresholds, therefore triggering the action easily. This shows that shared-space decision rules are not only behavioural assumptions but also affect simulated energy performance directly.

Overall, the results show that the advanced model improves behavioural realism by explicitly representing occupant choices, contextual conditions, behavioural heterogeneity, and collective decision-making. However, the results also show that more behavioural realism does not necessarily produce larger changes in every annual KPI. In some cases, the effects of occupant behaviour are constrained by the physical building model, existing control logic, system availability, and aggregation over time. The main contribution of the advanced model is therefore not only the prediction of different annual energy values, but also the ability to make behavioural mechanisms visible and testable. It allows building researchers and practitioners to

examine how individual preferences become zone-level commands, how those commands interact with building systems, and how different assumptions about collective control affect energy and comfort outcomes.

7.7.Conclusion

This chapter demonstrates that the choice-based co-simulation framework can be used as an analytical tool for evaluating occupant-responsive building operation. The four use cases show that occupant behaviour affects building performance through multiple pathways, i.e., through energy–comfort trade-offs, spatially heterogeneous control responses, stochastic daily interaction patterns, and decision-rule sensitivity in shared spaces. These findings support the argument that occupant behaviour should not be represented only through fixed schedules or deterministic assumptions, especially in buildings where occupants have access to environmental controls. Instead, behaviourally informed simulation can provide a more transparent basis for assessing occupant-centric design and operation strategies, particularly when the aim is to understand not only how much energy is used, but also why and under which behavioural conditions that energy use occurs.

8. Discussion and conclusion

8.1. Summary of key findings

This dissertation set out to address how heterogeneous, context-dependent comfort-adaptive occupant behaviours in office environments can be modelled and dynamically integrated into building performance simulation to improve behavioural realism. The research was motivated by the observation that occupant behaviour is still often simplified in simulation practice through fixed schedules, deterministic assumptions, or average-user representations, even though real occupants respond differently to indoor environmental conditions, available controls, social settings, and contextual constraints.

The findings show that a more realistic representation of occupant behaviour requires both conceptual and methodological integration. First, the interdisciplinary review showed that occupant behaviour is understood differently across social-behavioural sciences and building performance simulation research. By bringing these perspectives together, the dissertation clarified which behaviour types, influencing factors, and theoretical constructs are most relevant for studying comfort-adaptive behaviour in office environments. This provided the conceptual basis for modelling occupant behaviour not only as an energy-related action, but also as a comfort-restorative and context-dependent decision process.

Building on this foundation, the empirical choice experiment showed that office occupants do not respond to multi-modal discomfort through one isolated action. Instead, they make trade-offs between different environmental control actions and personal adaptive strategies, depending on thermal, air-quality, lighting, daylight, task-related, occupancy-related, and social conditions. The results also showed that social context matters in shared office environments, as occupants may align with proposed actions from others. These findings support the use of a probabilistic

choice-based approach to represent occupant behaviour, as this approach provides more behaviourally relevant insights, rather than relying on predefined or deterministic control rules.

The latent class analysis further showed that preference heterogeneity can be grouped into distinct behavioural profiles. Differences between occupants are therefore not only random variations around an average response, but reflect different adaptive strategies and sensitivities to the context. This finding is important for simulation because it provides a structured way to represent heterogeneous occupants as behaviourally interpretable agent types, rather than treating all of them as identical.

The co-simulation work demonstrated that empirically derived behavioural profiles can be translated into an agent-based model and dynamically coupled with EnergyPlus. Through this step, individual-level preferences were converted into zone-level control commands for windows, blinds, thermostat, and lighting settings. The case-study application showed that the advanced model can reveal several aspects of occupant-related performance that are not possible to observe in a baseline model, including energy–comfort trade-offs, zone-level differences, variation in predicted outcomes across stochastic simulations, and sensitivity to shared-control decision rules.

Overall, the dissertation shows that integrating a stochastic representation of occupant behaviour into building performance simulation changes how predicted outcomes can be interpreted. The advanced model makes visible how occupant preferences, contextual conditions, social settings, probabilistic decisions, and shared control assumptions can influence predicted energy demand and indoor environmental quality. In this way, the research demonstrates that a choice-based co-simulation approach can provide a more behaviourally explicit and transparent

representation of human-building interaction, while supporting the evaluation of occupant-centric design and operation strategies in office buildings.

8.2. Contributions and Implications

With the above findings, this dissertation contributes to occupant behaviour research in office buildings by developing and demonstrating a choice-based co-simulation approach for representing heterogeneous and context-dependent comfort-adaptive behaviour in building performance simulation. The main contribution lies in providing an alternative and more behaviourally explicit way of representing occupant behaviour in building performance simulation.

8.2.1. Conceptual and theoretical

The first contribution is conceptual. This dissertation provides an interdisciplinary conceptualisation of comfort-adaptive behaviour in office environments by bridging insights from social-behavioural research and building performance simulation research. Previous studies in these two fields (e.g., [29], [35]) often approach occupant behaviour from different perspectives, while this dissertation brings these perspectives together. In doing so, it provides a common language for understanding occupant behaviour in offices. This integrated conceptualisation supports a more comprehensive understanding of office occupant behaviour, while remaining applicable to simulation-oriented research.

The second contribution is theoretical. The dissertation combines Adaptive Comfort Theory [186], [187] and the Two-Process Theory of Perceived Control [189] to explain how occupants perceive and respond to discomfort through different types of adaptive strategies. Adaptive Comfort Theory provides the foundation for understanding occupants as active agents who respond to their environment rather than passive recipients of indoor conditions. The Two-Process Theory of Perceived Control helps distinguish between actions that change the surrounding environment and actions that change the occupants themselves. This theoretical combination is

useful because comfort-adaptive behaviour in offices is rarely limited to one action or one comfort domain. Occupants may respond to thermal, air quality, lighting, and daylight discomfort simultaneously, and their responses are shaped by both physical conditions and perceived control opportunities. By framing occupant behaviour as a set of trade-offs between environmental control actions and personal adaptive strategies, this dissertation provides a theoretically grounded basis for modelling multiple adaptive behaviours within a single framework.

8.2.2. Methodological

The third contribution is methodological. This dissertation shows how comfort-adaptive behaviour can be empirically elicited, statistically estimated, and subsequently prepared for use in dynamic building performance simulation. The multi-response discrete choice experiment not only collected general attitudes or self-reported behaviour, but generated structured evidence on how occupants prioritise different combinations of adaptive actions under specific thermal, air quality, lighting, daylight, contextual, and social conditions. This made it possible to observe behavioural trade-offs that are often missed when occupant behaviour is studied as separate, single-domain actions or as general satisfaction responses. In particular, the experiment showed that occupants do not simply choose whether to act or not, but may combine environmental control actions and personal adaptive strategies depending on the discomfort situation, task context, occupancy level, and perceived social setting.

The use of multinomial logit and mixed logit models provided not only a statistical explanation of survey responses, but also generated a probabilistic behavioural model that could be used as an input for simulation. Through this modelling approach, this dissertation was able to quantify how different environmental and contextual conditions change the likelihood of selecting comfort-adaptive behaviours and personal adaptive actions. The mixed logit model also showed that these responses vary across occupants, suggesting that occupant behaviour cannot

be adequately represented by one fixed response rule or one average profile. These methodological innovations therefore provide the empirical and probabilistic basis for representing occupants as heterogeneous decision makers, which deterministic approaches often fail to capture.

The fourth contribution concerns the modelling of behavioural heterogeneity. The three identified behavioural profiles, labelled Strong Reactors, Context Sensitives, and Minimalists, show that heterogeneity in comfort-adaptive behaviour is not only a difference in response intensity. It also reflects qualitatively different adaptive strategies. Some occupants are more inclined to actively adjust environmental controls, others respond selectively depending on task, context, and social conditions, while also some people are less likely to intervene at all. This class-based representation provides a more interpretable way of modelling heterogeneity than in previous studies treating occupants as either fully homogeneous [20] or only continuously different [212]. It also demonstrates that basic socio-demographic variables alone are insufficient to explain behavioural diversity. Instead, occupant behaviour should be understood through preferences, perceived control, context sensitivity, and interaction with shared environments.

The fifth contribution is the integration of the choice-based behavioural model into a building performance simulation workflow. The dissertation extends the latent-class-based choice model into an agent-based framework and couples it dynamically with EnergyPlus through an FMU-based co-simulation architecture. This enables individual-level behavioural decisions to be translated into zone-level control commands, while EnergyPlus calculates the resulting building performance. This step is important because many occupant behaviour studies stop at statistical modelling and do not demonstrate how their resulting models can be used in building performance simulation [94]. In contrast, this dissertation shows how estimated behavioural preferences can be operationalised within a simulation workflow. The advanced model is therefore not a replacement for conventional

EnergyPlus modelling, but an alternative representation of occupant behaviour that can be used to examine how behavioural assumptions influence simulated energy and indoor environmental quality outcomes.

The demonstration of the advanced model further contributes empirical insights into how occupant behaviour representation affects the interpretation of predicted building performance. The annual comparison between the baseline and advanced model shows that a more behaviourally explicit model can change the balance between energy demand and indoor environmental quality. In the case study, the advanced model made the energy–comfort trade-off more visible by showing how occupant-driven control may reduce warm discomfort during occupied periods while also influencing cooling demand. The zone-level analysis showed that behavioural effects can be spatially differentiated and may interact with room orientation, solar exposure, room function, and fallback control logic. The daily stochastic simulations showed that, with the same building model and control logic, stochastic occupant behaviour representation can lead to variation in predicted short-term outcomes, even when annual results appear relatively stable. Finally, the sensitivity analysis showed that collective decision rules matter in shared spaces, because the way individual preferences are aggregated into zone-level commands can affect simulation outcomes. In shared office spaces, translating individual choices into zone-level commands constitutes an additional methodological step. Different voting thresholds, majority rules, and fallback assumptions can produce different simulated control outcomes. Making these assumptions explicit enables researchers and model developers to assess the sensitivity of model results to uncertain parameter values in collective decision rules. These findings demonstrate the analytical value of the advanced model in helping to explain why simulated performance outcomes occur under specific behavioural assumptions.

For building performance simulation research, this dissertation provides a replicable pathway for integrating empirically estimated stochastic occupant

behaviour models into simulation. The workflow can be adapted to other buildings, office types, control systems, and research questions. It can be used to examine not only annual energy prediction outcomes, but also short-term interaction patterns, comfort-related events, zone-level performance differences, and uncertainty caused by stochastic occupant decisions. The value of this approach is therefore not limited to producing a different annual energy prediction result. Its value also lies in making behavioural mechanisms visible, allowing researchers and practitioners to examine how occupant preferences, contextual conditions, social interactions, and control assumptions shape simulated building performance.

8.2.3. Practical implications

The practical implications of this dissertation are mainly related to occupant-centric building design, operation, and simulation-aided decision-making. For building practitioners (e.g., building managers and sustainability managers), the proposed approach provides a way to evaluate different design and control alternatives before implementation. It can support questions such as how occupants may respond to different levels of control availability, how shared control systems may be used, how different occupant profiles may influence control demand, and how comfort-related actions may affect predicted energy and indoor environmental quality outcomes. This does not mean that the model predicts a universally better or more energy-efficient solution. Rather, it provides a more transparent way to compare alternatives and to understand the behavioural assumptions behind each simulated outcome.

For building designers, the class-based behavioural profiles can support more occupant-inclusive design decisions. For example, workplaces dominated by occupants who prefer active environmental control may require more accessible and decentralised control interfaces. Spaces with occupants who are more context-sensitive may benefit from adaptive or semi-automated systems that respond to task type, occupancy level, and shared-space conditions. Mixed-class environments may

require hybrid control solutions that combine occupant control opportunities with automation. In this way, the behavioural profiles can help designers and facility managers think more carefully about the match between office layout, control availability, and expected occupant interaction patterns.

For building operation, the proposed framework can support the simulation-aided comparison of alternative shared-control strategies before implementation. Building and facility managers can use such analyses to examine how different combinations of occupant control and automation may affect predicted control demand, indoor environmental quality, and energy use in shared office spaces.

Overall, this dissertation contributes to the development of occupant-centric and behaviourally informed building performance simulation. It shows that occupant behaviour can be represented as a heterogeneous, context-dependent, and socially embedded decision process, and that such a representation can be dynamically coupled with building simulation software, like EnergyPlus. The proposed approach supports a more transparent evaluation of energy–comfort trade-offs and provides a methodological basis for designing and operating office buildings with a clearer understanding of the role of occupant behaviour.

8.3. Limitations and Future Research

Although this dissertation contributes to the modelling and simulation of heterogeneous comfort-adaptive occupant behaviour in office buildings, several limitations should be acknowledged. These limitations relate to the scope of the literature review, the stated choice experiment design, the modelling of behavioural heterogeneity, the translation of behavioural preferences into simulation logic, and the empirical scope of the case study. These limitations clarify the boundary conditions under which the results should be interpreted and point to several directions for future research.

8.3.1. Conceptual and literature scope

The first limitation concerns the scope of the systematic literature review. As with any review, the findings are partly shaped by the search strategy, database selection, inclusion criteria, and classification procedure. This dissertation relied mainly on Scopus to identify relevant literature on occupant behaviour in office environments. Although Scopus provides a broad coverage of peer-reviewed academic publications, important studies indexed in other databases may have been missed. These excluded scientific date sources may nevertheless contain relevant insights, particularly in a multidisciplinary field where knowledge is distributed across building science, environmental psychology, workplace studies, facility management, and engineering practice. Furthermore, the literature identified from engineering and building performance simulation research was not necessarily balanced with the literature from social and behavioural sciences. As a result, the synthesis may partly reflect the stronger presence of engineering-oriented studies in the reviewed sample.

Future research could broaden the evidence base by including additional scientific databases. This would be especially useful for capturing practitioner-oriented knowledge and context-specific studies that may not appear in mainstream academic journals. A future meta-analysis could also provide more systematic evidence on the relative importance of different occupant behaviour drivers, behaviour types, and modelling approaches. However, such work would require careful attention to conceptual consistency, as different disciplines use different terminology and assumptions when studying occupant behaviour.

A second limitation concerns the selection of attributes and adaptive actions. To achieve a feasible experimental design, the dissertation focused on a selected set of comfort-related factors, refer to Chapter 3. This selection was grounded in the literature and in the need to keep the scenarios understandable. However, other potentially important factors were not included. Acoustic comfort was not explicitly

modelled, even though noise is an important source of discomfort in open-plan offices [10]. Biophilia, view quality, privacy, office layout, workstation orientation, furniture arrangement, control interface design, and the degree of automation were also not directly represented. These factors may influence both perceived comfort and occupants' willingness or ability to interact with environmental controls [8], [224].

Future research could extend the experimental design to include these additional dimensions. Acoustic conditions could be incorporated using carefully designed sound simulations, virtual reality, or audiovisual experimental environments. Similarly, visual and spatial characteristics such as view, glare source, workstation orientation, and office layout could be represented using virtual environments or high-quality visual scenarios. However, when using visual or immersive tools, researchers should ensure that irrelevant visual details do not introduce unintended bias into the choice experiment.

8.3.2. Experimental design and stated-choice data

A third limitation concerns the use of stated choice data. The discrete choice experiment was designed to explore occupants' preferences for comfort-adaptive actions under controlled hypothetical scenarios. This approach is useful because it allows multiple environmental, contextual, and social factors to be systematically varied and modelled. However, choices made in a hypothetical experiment may differ from actual behaviour in real office environments. Respondents were asked to imagine that different control options were available and then indicate which adaptive action or combination of actions they would prefer. In real buildings, however, control availability, accessibility, controllability, organisational rules, building management systems, spatial layout, and social norms may constrain what occupants can actually do. Therefore, the results should be interpreted as stated preferences or intended behaviour under described conditions, rather than as direct observations of real-time behaviour.

Future studies should validate the stated preference results with revealed preference data. This could be done through field studies, sensor-based monitoring, building management system logs, longitudinal surveys, or mixed-method approaches that combine stated choice experiments with observed control interactions. For example, window sensors, blind position data, thermostat overrides, lighting control logs, occupancy data, and indoor environmental measurements could be used to test whether the preferences estimated in this dissertation correspond to actual adaptive actions in occupied office buildings. Such validation would strengthen the empirical grounding of the behavioural model and help identify where stated preferences and real-world behaviours diverge or converge.

A fourth limitation is related to the complexity of the choice experiment. The experiment included multiple indoor environmental quality indicators, contextual factors, and social cues, and respondents were asked to consider several possible adaptive actions. Although this design reflects the complex nature of comfort-adaptive behaviour in shared office environments, it may also increase cognitive burden. Respondents may not have attended equally to all attributes in every choice task, and some may have focused only on the most salient conditions, such as temperature or air quality. Attribute non-attendance was not explicitly measured through dedicated survey questions or formally incorporated into the model. Therefore, it is possible that some estimated effects reflect low attention to specific attributes rather than true low preference sensitivity.

Future research could address this issue by including attribute non-attendance questions, confidence ratings, eye-tracking, response time analysis, or model-based approaches that allow for partial attribute attendance. At the same time, such additions should be used carefully, because asking more questions can increase respondent's burden and may influence their responses. Future choice experiments could also compare simpler and complex designs options, to determine how many

attributes and action alternatives can be included before response quality begins to decline.

A fifth limitation concerns the treatment of personal adaptive actions. In the empirical modelling, several personal adaptive strategies were combined into one broader category. This made the model more manageable and reduced the number of alternatives, but it also limited the ability to distinguish between specific personal adaptive behaviours, such as changing clothing, drinking warm or cold beverages, using a personal fan or heater, changing tasks, or temporarily moving to another space. These actions differ in terms of energy implications, feasibility, comfort effect, and social acceptability. Treating them as one aggregated category therefore hides potentially meaningful variation.

Future studies could separate personal adaptive actions into more specific alternatives, especially when the research focus is on low-energy comfort strategies or personal comfort systems. A more detailed representation would allow researchers to examine when occupants prefer environmental control actions and when they prefer personal adaptation. This would also support more precise evaluation of energy-comfort trade-offs, since some personal adaptive actions have limited energy consequences, while others may directly affect plug loads or HVAC demand.

8.3.3. Behavioural heterogeneity and occupant profiling

A sixth limitation relates to the modelling of behavioural heterogeneity. The latent class model identified three interpretable behavioural profiles: Strong Reactors, Context Sensitives, and Minimalists. These profiles provide useful insight into preference heterogeneity, but they are also model-dependent. The number and interpretation of classes depend on the included variables, the structure of the choice model, the sample, and the model selection criteria. More complex class structures may reveal additional behavioural profiles, but they may also create convergence

problems, reduce interpretability, or overfit the data. In this dissertation, the chosen class structure represents a balance between statistical fit, behavioural interpretation, and practical usability.

Future research should test whether these behavioural profiles can be reproduced in other samples, countries, office types, and climate contexts. It would be useful to examine whether similar classes emerge in naturally ventilated offices, highly automated smart buildings, activity-based workplaces, hybrid offices, and cellular office environments. Future studies could also explore whether class membership changes over time as occupants become more familiar with a building, experience different seasons, or adapt to organisational norms. This would move occupant profiling from a static segmentation approach towards a more dynamic understanding of behavioural adaptation.

A seventh limitation concerns the explanatory power of socio-demographic and dispositional variables for class membership. The results indicate that only a limited number of personal characteristics were useful for predicting class membership. This suggests that behavioural profiles cannot be fully explained by basic socio-demographic information alone. While this finding is important, it also limits the direct practical application of the profiles. In real design or operation contexts, building practitioners may not have access to detailed behavioural preference data for every occupant group.

Future research could investigate additional predictors of behavioural profiles, such as perceived control, comfort expectations, habits, prior experience with building controls, environmental attitudes, workplace norms, thermal history, personality traits, and organisational culture. Short diagnostic surveys could be developed to estimate the likely distribution of behavioural profiles in a workplace. Such tools would make class-based occupant modelling easier to apply in practical building design and operation.

8.3.4. Translation into co-simulation and building control logic

An eighth limitation concerns the translation of the choice model into the agent-based co-simulation framework. The behavioural model was estimated from stated preferences and then implemented as a probabilistic decision model in Python. This required several modelling assumptions, including how agents are assigned to behavioural classes, how environmental conditions are categorised, how individual choices are aggregated at the zone level, how often the agent-based model is updated, and how fallback rules are applied when no active agents are present or no majority decision is reached. These assumptions were necessary to create a functioning co-simulation model, but they also influence the simulation results.

Future research should further test the sensitivity of the model to these translation assumptions. In particular, on the aggregation of individual preferences into shared-space control commands. The majority-based decision rule used in this dissertation is one possible representation of collective decision-making approach, but other approaches may be equally relevant, such as weighted voting, priority rules, group norms, authority-based control, or conflict-resolution logic. Future studies could also test alternative temporal structures, such as more frequent or event-based behavioural updates, instead of fixed hourly decision moments.

A ninth limitation concerns the representation of building controls in EnergyPlus. The advanced model was designed to replace or override selected baseline control assumptions with occupant-driven commands. However, the final behaviour of the building still depends on the EnergyPlus control structure, actuator availability, fallback logic, mechanical system configuration, and the simplified representation of how commands translate into physical control states. For example, the model can represent whether a window, blind, thermostat, or lighting action is selected, but the exact physical state or magnitude of adjustment is still determined through simplified modelling assumptions, such as predefined behaviour-to-control translation rules.

Future research could develop more detailed behaviour-to-control translation rules. For example, instead of treating window or blind actions as categorical commands, future models could represent opening angle, blind slat angle, thermostat setpoint magnitude, dimming level, or duration of control action. Coupling occupant behaviour models with real building management systems or digital twins could also help make these control representations more realistic. Such integration would allow behavioural models to interact with actual control hierarchies, automation logic, and sensor feedback.

8.3.5. Empirical scope, validation, and transferability

A tenth limitation is related to the empirical scope of the simulation case study. The advanced model was demonstrated using one case-study building and one selected floor. In addition, retaining baseline or non-ABM control in selected zones was an intentional experimental design choice to support model alignment and controlled comparison. Consequently, the case-study results represent a partial rather than whole-floor implementation of the advanced behavioural control framework. This allowed a detailed comparison between the baseline and advanced model, but it limits the generalisability of the energy and indoor environmental quality results. The observed increase in cooling demand, reduction in warm occupied hours, and zone-level behavioural patterns are specific to the case building, with simplified systems, climate file, control assumptions, occupancy schedule, and model settings. Therefore, these results should not be interpreted as universal effects of occupant behaviour modelling. The advanced model is a more behaviourally explicit representation of occupant behaviour in building performance simulation.

Future research should apply the same modelling framework to different buildings on a case-by-case scenario. At an early design stage, where occupant information is limited, the additional computational and data requirements of the advanced approach may not be justified for the intended modelling purpose, and a conventional model may provide sufficient information to support preliminary

design decisions. As more occupant information becomes available, the advanced approach can provide additional behavioural insights.

An eleventh limitation concerns model validation. The co-simulation framework was technically checked and aligned with the baseline model, and several outputs were logged to trace control sources and behavioural commands. However, the advanced model was not validated against long-term measured occupant behaviour data from the same building. Without such validation, the model should be interpreted as a behaviourally informed simulation approach rather than a fully calibrated prediction of actual building operation.

Future research should validate the model using measured data from occupied buildings. This could include indoor environmental sensor data, occupancy records, control interaction logs, BMS data, longitudinal field observations, survey feedback, and qualitative interviews. Validation should not focus only on annual energy demand, but also on whether the model reproduces realistic patterns of control interaction, (dis)comfort events, occupancy-dependent variation, and zone-level behaviour. A combined validation approach would be especially useful because occupant behaviour affects both quantitative performance indicators and qualitative user experience.

Finally, this dissertation focuses mainly on comfort-adaptive occupant behaviour in office buildings in the Dutch context. The survey sample consisted of Dutch office workers, and the simulation case study was located in the Netherlands. Occupant comfort expectations, control preferences, workplace norms, and tolerance ranges may differ across countries, climates, cultures, building types, and organisational settings. Therefore, the behavioural models developed in this dissertation should not be transferred uncritically to other contexts.

Future research should test and adapt the pathway in different geographical and cultural contexts, including warmer climates, colder climates, and regions where

office control norms, energy systems, and adaptive comfort expectations differ from those in the Netherlands. This could include comparative studies in Europe, the Middle East, Southeast Asia, Africa, and other regions with different climatic and workplace conditions. Such work would help determine which parts of the model are context-specific and which behavioural mechanisms are more generalisable.

Overall, future research should move into three main directions. First, the empirical basis of occupant behaviour modelling should be strengthened through longitudinal, sensor-based, and field-validated studies. Second, the behavioural model should be expanded to include additional comfort domains, more detailed personal adaptive actions, and dynamic changes in preferences over time. Third, the simulation framework should be applied and validated across different buildings and control systems, with particular attention to how individual preferences are translated into shared-space control decisions. Addressing these directions would further improve the behavioural realism, transferability, and practical usefulness of occupant-centric building performance simulation.

References

[1] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy Build.*, vol. 40, no. 3, pp. 394–398, Jan. 2008, doi: 10.1016/J.ENBUILD.2007.03.007.

[2] X. Gu, L. Fan, and R. Mahabir, "Building carbon emissions (2016–2025): A PRISMA-based systematic review of definitions, quantification methods and policies," *Environ. Dev.*, vol. 57, p. 101345, Jan. 2026, doi: 10.1016/J.ENVDEV.2025.101345.

[3] H. Birgisdottir and F. N. Rasmussen, "Introduction to LCA of Buildings," 2016.

[4] M. Schweiker, C. Berger, J. Day, and A. Mahdavi, "Fundamentals of IEQ and Occupant Needs," in *Occupant-Centric Simulation-Aided Building Design*, Routledge, 2023, pp. 10–33.

[5] T. Hong, D. Yan, S. D'Oca, and C. Chen, "Ten questions concerning occupant behavior in buildings: The big picture," *Build. Environ.*, vol. 114, pp. 518–530, 2017, doi: https://doi.org/10.1016/j.buildenv.2016.12.006.

[6] H. Yoshino, T. Hong, and N. Nord, "IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods," *Energy Build.*, vol. 152, pp. 124–136, 2017, doi: https://doi.org/10.1016/j.enbuild.2017.07.038.

[7] A. Mahdavi and C. Berger, "Ten questions regarding buildings, occupants and the energy performance gap," *J. Build. Perform. Simul.*, vol. 18, no. 5–6, pp. 676–686, Nov. 2025, doi: 10.1080/19401493.2024.2332245.

[8] W. O'Brien and H. B. Gunay, "The contextual factors contributing to occupants' adaptive comfort behaviors in offices - A review and proposed modeling framework," *Build. Environ.*, vol. 77, pp. 77–87, 2014, doi: 10.1016/j.buildenv.2014.03.024.

[9] D. Yan *et al.*, "IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings," *Energy Build.*, vol. 156, pp. 258–270, Dec. 2017, doi: https://doi.org/10.1016/j.enbuild.2017.09.084.

[10] D. Yan *et al.*, "Occupant behavior modeling for building performance simulation: Current state and future challenges," *Energy Build.*, vol. 107, pp. 264–278, Nov. 2015, doi: 10.1016/j.enbuild.2015.08.032.

[11] W. O'Brien *et al.*, "Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation," *Build. Environ.*, vol. 178, p. 106738, Jul. 2020, doi: 10.1016/J.BUILDENV.2020.106738.

[12] T. Hong, W. O'Brien, H. Li, J. Hahn, C. B. de Souza, and Z. Nagy, "Occupant-centric performance metrics and performance targets," in *Occupant-Centric Simulation-Aided Building Design*, Routledge, 2023, pp. 83–103.

[13] F. Haldi and D. Robinson, "Interactions with window openings by office occupants," *Build. Environ.*, vol. 44, no. 12, pp. 2378–2395, Dec. 2009, doi: 10.1016/J.BUILDENV.2009.03.025.

[14] S. D'Oca, C. F. C.-F. Chen, T. Hong, and Z. Belafi, "Synthesizing building physics with social psychology: An interdisciplinary framework for context and occupant behavior in office buildings," *Energy Res. Soc. Sci.*, vol. 34, pp. 240–251, 2017, doi: 10.1016/j.erss.2017.08.002.

[15] International Energy Agency, *The Critical Role of Buildings Perspectives for the Clean Energy Transition*. 2019. [Online]. Available: https://www.iea.org/reports/the-critical-role-of-buildings

[16] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy Build.*, vol. 40, no. 3, pp. 394–398, Jan. 2008, doi: 10.1016/j.enbuild.2007.03.007.

[17] D. D'Agostino, B. Cuniberti, and P. Bertoldi, "Energy consumption and efficiency technology measures in European non-residential buildings," *Energy Build.*, vol. 153, pp. 72–86, Oct. 2017, doi: 10.1016/j.enbuild.2017.07.062.

[18] S. Kempeneer, M. Peeters, and T. Compernolle, "Bringing the User Back in the Building: An Analysis of ESG in Real Estate and a Behavioral Framework to Guide Future Research," 2021. doi: 10.3390/su13063239.

[19] Z. Belafi, T. Hong, and A. Reith, "Smart building management vs. intuitive human control—Lessons learnt from an office building in Hungary," *Build. Simul.*, vol. 10, no. 6, pp. 811–828, 2017, doi: 10.1007/s12273-017-0361-4.

[20] I. Gaetani, P. J. Hoes, and J. L. M. Hensen, "Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy," *Energy Build.*, vol. 121, pp. 188–204, Jun. 2016, doi: 10.1016/J.ENBUILD.2016.03.038.

[21] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, "User behavior in whole building simulation," *Energy Build.*, vol. 41, no. 3, pp. 295–302, 2009, doi: https://doi.org/10.1016/j.enbuild.2008.09.008.

[22] A. J. Sonta, R. K. Jain, R. Gulbinas, J. M. F. Moura, and J. E. Taylor, "OESPG: Computational Framework for Multidimensional Analysis of Occupant Energy Use Data in Commercial Buildings," *Journal of Computing in Civil Engineering*, vol. 31, no. 4, p. 04017017, 2017, doi: 10.1061/(asce)cp.1943-5487.0000663.

[23] N. J. Seyler and J. Mutl, "Going beyond buildings: mindfulness and real estate user behavior," *Journal of Corporate Real Estate*, vol. 21, no. 3, pp. 194–211, Jan. 2019, doi: 10.1108/JCRE-10-2018-0039.

[24] E. Azar, C. Nikolopoulou, and S. Papadopoulos, "Integrating and optimizing metrics of sustainable building performance using human-

focused agent-based modeling," *Appl. Energy*, vol. 183, pp. 926–937, 2016, doi: 10.1016/j.apenergy.2016.09.022.

[25] A. S. Weerasinghe, E. O. Rasheed, and J. O. B. Rotimi, "Occupants' Decision-Making of Their Energy Behaviours in Office Environments: A Case of New Zealand," *Sustainability (Switzerland)*, vol. 15, no. 3, 2023, doi: 10.3390/su15032305.

[26] S. Gao, S. Low, and H. Gong, "Effects of activity-based workspaces on employee belongingness," *Facilities*, vol. ahead-of-p, 2021, doi: 10.1108/F-08-2020-0093.

[27] A.-L. Fayard, J. Weeks, and M. Khan, "Designing the hybrid office," *Harv. Bus. Rev.*, vol. 99, no. 2, pp. 114–123, 2021.

[28] R. W. Marans and J. Y. Edelstein, "The human dimension of energy conservation and sustainability: A case study of the University of Michigan's energy conservation program," *International Journal of Sustainability in Higher Education*, vol. 11, no. 1, pp. 6–18, 2010, doi: 10.1108/14676371011010011.

[29] C. Ornaghi, E. Costanza, J. Kittley-Davies, L. Bourikas, V. Aragon, and P. A. B. James, "The effect of behavioural interventions on energy conservation in naturally ventilated offices," *Energy Econ.*, vol. 74, pp. 582–591, 2018, doi: 10.1016/j.eneco.2018.07.008.

[30] F. Cassola *et al.*, "Using Virtual Choreographies to Identify Office Users' Behaviors to Target Behavior Change Based on Their Potential to Impact Energy Consumption," *Energies (Basel).*, vol. 15, no. 12, 2022, doi: 10.3390/en15124354.

[31] C. Baedeker *et al.*, "Interactive design to encourage energy efficiency in offices: Developing and testing a user-centered building management system based on a living lab approach," *Sustainability*, vol. 12, no. 17, p. 6956, 2020.

[32] Y. Ding, X. Pan, W. Chen, Z. Tian, Z. Wang, and Q. He, "Prediction Method for Office Building Energy Consumption Based on an Agent-Based Model Considering Occupant–Equipment Interaction Behavior," *Energies (Basel).*, vol. 15, no. 22, 2022, doi: 10.3390/en15228689.

[33] C. Li, H. Zhu, X. Lian, Y. Liu, X. Li, and Y. Feng, "Study of 'time-lag' of occupant behavior occurrences for establishing an occupant-centric

building control system," *Build. Environ.*, vol. 216, 2022, doi: 10.1016/j.buildenv.2022.109005.

[34] A. Ghahramani *et al.*, "Learning occupants' workplace interactions from wearable and stationary ambient sensing systems," *Appl. Energy*, vol. 230, pp. 42–51, 2018, doi: 10.1016/j.apenergy.2018.08.096.

[35] C. Sun, R. Zhang, S. Sharples, Y. Han, and H. Zhang, "A longitudinal study of summertime occupant behaviour and thermal comfort in office buildings in northern China," *Build. Environ.*, vol. 143, pp. 404–420, 2018, doi: 10.1016/j.buildenv.2018.07.004.

[36] E. Azar and C. C. Menassa, "Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings," *Journal of Computing in Civil Engineering*, vol. 26, no. 4, pp. 506–518, 2012, doi: 10.1061/(asce)cp.1943-5487.0000158.

[37] A. Khosrowpour, R. Gulbinas, and J. E. Taylor, "Occupant workstation level energy-use prediction in commercial buildings: Developing and assessing a new method to enable targeted energy efficiency programs," *Energy Build.*, vol. 127, pp. 1133–1145, 2016, doi: 10.1016/j.enbuild.2016.05.071.

[38] R. Fritsch, A. Kohler, M. Nygård-Ferguson, and J. L. Scartezzini, "A stochastic model of user behaviour regarding ventilation," *Build. Environ.*, vol. 25, no. 2, pp. 173–181, 1990, doi: 10.1016/0360-1323(90)90030-U.

[39] H. B. Rijal, P. Tuohy, M. A. Humphreys, J. F. Nicol, A. Samuel, and J. Clarke, "Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings," *Energy Build.*, vol. 39, no. 7, pp. 823–836, 2007, doi: 10.1016/j.enbuild.2007.02.003.

[40] G. Y. Yun and K. Steemers, "Night-time naturally ventilated offices: Statistical simulations of window-use patterns from field monitoring," *Solar Energy*, vol. 84, no. 7, pp. 1216–1231, 2010, doi: 10.1016/j.solener.2010.03.029.

[41] G. R. Newsham, "Manual Control of Window Blinds and Electric Lighting: Implications for Comfort and Energy Consumption," *Indoor and Built Environment*, vol. 3, no. 3, pp. 135–144, 1994, doi: 10.1177/1420326X9400300307.

[42] A. Mahdavi, “Patterns and implications of user control actions in buildings,” *Indoor and Built Environment*, vol. 18, no. 5, pp. 440–446, 2009, doi: 10.1177/1420326X09344277.

[43] M. V. Bavaresco and E. Ghisi, “Influence of user interaction with internal blinds on the energy efficiency of office buildings,” *Energy Build.*, vol. 166, pp. 538–549, 2018, doi: 10.1016/j.enbuild.2018.02.011.

[44] C. F. Reinhart, “Lightswitch-2002: A model for manual and automated control of electric lighting and blinds,” *Solar Energy*, vol. 77, no. 1, pp. 15–28, 2004, doi: 10.1016/j.solener.2004.04.003.

[45] X. Zhou, D. Yan, T. Hong, and X. Ren, “Data analysis and stochastic modeling of lighting energy use in large office buildings in China,” *Energy Build.*, vol. 86, pp. 275–287, 2015, doi: 10.1016/j.enbuild.2014.09.071.

[46] J. Kim *et al.*, “Occupant comfort and behavior: High-resolution data from a 6-month field study of personal comfort systems with 37 real office workers,” *Build. Environ.*, vol. 148, pp. 348–360, 2019, doi: 10.1016/j.buildenv.2018.11.012.

[47] G. Y. Yun, H. J. Kong, and J. T. Kim, “The effect of seasons and prevailing environments on adaptive comfort temperatures in open plan offices,” *Indoor and Built Environment*, vol. 21, no. 1, pp. 41–47, 2012, doi: 10.1177/1420326X11419929.

[48] A. Roetzel, A. Tsangrassoulis, U. Dietrich, and S. Busching, “Context dependency of comfort and energy performance in mixed-mode offices,” *J. Build. Perform. Simul.*, vol. 4, no. 4, pp. 303–322, 2011, doi: 10.1080/19401493.2011.558212.

[49] B. Orland, N. Ram, D. Lang, K. Houser, N. Kling, and M. Coccia, “Saving energy in an office environment: A serious game intervention,” *Energy Build.*, vol. 74, pp. 43–52, 2014, doi: 10.1016/j.enbuild.2014.01.036.

[50] J. Page, D. Robinson, N. Morel, and J. L. Scartezzini, “A generalised stochastic model for the simulation of occupant presence,” *Energy Build.*, vol. 40, no. 2, pp. 83–98, 2008, doi: 10.1016/j.enbuild.2007.01.018.

[51] B. Dong *et al.*, “An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network,” *Energy Build.*, vol. 42, no. 7, pp. 1038–1046, 2010, doi: 10.1016/j.enbuild.2010.01.016.

[52] M. Kong, B. Dong, R. Zhang, and Z. O'Neill, "HVAC energy savings, thermal comfort and air quality for occupant-centric control through a side-by-side experimental study," *Appl. Energy*, vol. 306, 2022, doi: 10.1016/j.apenergy.2021.117987.

[53] R. Rusek, J. Melendez Frigola, and J. Colomer Llinas, "Influence of occupant presence patterns on energy consumption and its relation to comfort: a case study based on sensor and crowd-sensed data," *Energy Sustain. Soc.*, vol. 12, no. 1, 2022, doi: 10.1186/s13705-022-00336-6.

[54] J. M. Zambrano, I. Gaetani, U. F. Oberegger, and G. Salvalai, "Advancing and demonstrating the Impact Indices method to screen the sensitivity of building energy use to occupant behaviour," *Build. Simul.*, vol. 16, no. 7, pp. 1257–1272, 2023, doi: 10.1007/s12273-023-1004-6.

[55] T. Hong, S. D'Oca, W. J. N. Turner, and S. C. Taylor-Lange, "An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework," *Build. Environ.*, vol. 92, pp. 764–777, Oct. 2015, doi: 10.1016/j.buildenv.2015.02.019.

[56] A. S. Weerasinghe, J. O. B. Rotimi, and E. O. Rasheed, "Modelling of underlying social psychological effects on occupant energy-related behaviours," *Build. Environ.*, vol. 231, 2023, doi: 10.1016/j.buildenv.2023.110055.

[57] Y. Zhang, X. Bai, F. P. Mills, and J. C. V Pezzey, "Rethinking the role of occupant behavior in building energy performance: A review," *Energy Build.*, vol. 172, pp. 279–294, 2018.

[58] D. Li, X. Xu, C. fei Chen, and C. Menassa, "Understanding energy-saving behaviors in the American workplace: A unified theory of motivation, opportunity, and ability," *Energy Res. Soc. Sci.*, vol. 51, pp. 198–209, 2019, doi: 10.1016/j.erss.2019.01.020.

[59] P. C. Stern, "Toward a coherent theory of environmentally significant behavior," *Journal of Social Issues*, vol. 56, no. 3, pp. 407–424, 2000, doi: 10.1111/0022-4537.00175.

[60] H. B. Gunay, W. O'Brien, and I. Beausoleil-Morrison, "A critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices," *Build. Environ.*, vol. 70, pp. 31–47, 2013, doi: 10.1016/j.buildenv.2013.07.020.

[61] H. N. Rafsanjani, C. R. Ahn, and M. Alahmad, “A review of approaches for sensing, understanding, and improving occupancy-related energy-use behaviors in commercial buildings,” *Energies (Basel).*, vol. 8, no. 10, pp. 10996–11029, 2015, doi: 10.3390/en81010996.

[62] S. D’Oca, H. B. Gunay, S. Gilani, and W. O’Brien, “Critical review and illustrative examples of office occupant modelling formalisms,” *Building Services Engineering Research and Technology*, vol. 40, no. 6, pp. 732–757, 2019, doi: 10.1177/0143624419827468.

[63] S. Norouziasl, A. Jafari, and Y. Zhu, “Modeling and simulation of energy-related human-building interaction: A systematic review,” *Journal of Building Engineering*, vol. 44, p. 102928, 2021.

[64] W. O’Brien, K. Kapsis, and A. K. Athienitis, “Manually-operated window shade patterns in office buildings: A critical review,” *Build. Environ.*, vol. 60, pp. 319–338, 2013, doi: 10.1016/j.buildenv.2012.10.003.

[65] S. Hammes *et al.*, “Concepts of user-centred lighting controls for office applications: A systematic literature review,” *Build. Environ.*, vol. 254, 2024, doi: 10.1016/j.buildenv.2024.111321.

[66] A. Roetzel, A. Tsangrassoulis, U. Dietrich, and S. Busching, “A review of occupant control on natural ventilation,” *Renewable and Sustainable Energy Reviews*, vol. 14, no. 3, pp. 1001–1013, 2010, doi: 10.1016/j.rser.2009.11.005.

[67] K. Bäcklund, M. Molinari, P. Lundqvist, and B. Palm, “Building Occupants, Their Behavior and the Resulting Impact on Energy Use in Campus Buildings: A Literature Review with Focus on Smart Building Systems,” *Energies (Basel).*, vol. 16, no. 17, 2023, doi: 10.3390/en16176104.

[68] M. V. Bavaresco, S. D’Oca, E. Ghisi, and R. Lamberts, “Methods used in social sciences that suit energy research: A literature review on qualitative methods to assess the human dimension of energy use in buildings,” *Energy Build.*, vol. 209, p. 109702, 2020, doi: 10.1016/j.enbuild.2019.109702.

[69] M. J. Page *et al.*, “PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews,” *BMJ*, vol. 372, p. n160, Mar. 2021, doi: 10.1136/bmj.n160.

[70] S. Allen and S. T. Marquart-Pyatt, “Workplace energy conservation at Michigan State University,” *International Journal of Sustainability in Higher Education*, vol. 19, no. 1, pp. 114–129, 2018, doi: 10.1108/IJSHE-07-2016-0124.

[71] Z. Deme Bélafi and A. Reith, “Interdisciplinary survey to investigate energy-related occupant behavior in offices - The Hungarian case,” *Pollack Periodica*, vol. 13, no. 3, pp. 41–52, 2018, doi: 10.1556/606.2018.13.3.5.

[72] A. Cibinskiene, D. Dumciuviene, and M. Andrijauskiene, “Energy consumption in public buildings: The determinants of occupants’ behavior,” *Energies (Basel).*, vol. 13, no. 14, 2020, doi: 10.3390/en13143586.

[73] D. Tverskoi, X. Xu, H. Nelson, C. Menassa, S. Gavrilets, and C. fei Chen, “Energy saving at work: Understanding the roles of normative values and perceived benefits and costs in single-person and shared offices in the United States,” *Energy Res. Soc. Sci.*, vol. 79, 2021, doi: 10.1016/j.erss.2021.102173.

[74] L. M. M. C. E. Almeida, V. W. Y. Tam, K. N. Le, Z. Huang, and S. Forbes, “Survey of energy-related occupant perceptions in a green-rated and in a non-rated building,” *Advances in Building Energy Research*, vol. 16, no. 1, pp. 36–63, 2022, doi: 10.1080/17512549.2020.1768897.

[75] Y. Y. Geun, J. K. Hyo, and T. K. Jeong, “A field survey of occupancy and air-conditioner use patterns in open plan offices,” *Indoor and Built Environment*, vol. 20, no. 1, pp. 137–147, 2011, doi: 10.1177/1420326X10388883.

[76] N. J. van Eck and L. Waltman, “Visualizing Bibliometric Networks,” in *Measuring Scholarly Impact: Methods and Practice*, Y. Ding, R. Rousseau, and D. Wolfram, Eds., Cham: Springer International Publishing, 2014, pp. 285–320. doi: 10.1007/978-3-319-10377-8_13.

[77] A. Sharma and R. Tiwari, “Evaluation of data for developing an adaptive model of thermal comfort and preference,” *Environmentalist*, vol. 27, no. 1, pp. 73–81, 2007, doi: 10.1007/s10669-007-9018-7.

[78] U. H. Obaidellah, M. Danaee, M. A. A. Mamun, M. Hasanuzzaman, and N. A. Rahim, “An application of TPB constructs on energy-saving behavioural intention among university office building occupants: a pilot study in Malaysian tropical climate,” *Journal of Housing and the Built*

Environment, vol. 34, no. 2, pp. 533–569, 2019, doi: 10.1007/s10901-018-9637-y.

[79] R. Rissetto and M. Schweiker, “Exploring Information and Comfort Expectations Related to the Use of a Personal Ceiling Fan,” *Buildings*, vol. 14, no. 1, 2024, doi: 10.3390/buildings14010262.

[80] R. F. Rupp, R. K. Andersen, J. Toftum, and E. Ghisi, “Occupant behaviour in mixed-mode office buildings in a subtropical climate: Beyond typical models of adaptive actions,” *Build. Environ.*, vol. 190, p. 107541, 2021, doi: 10.1016/j.buildenv.2020.107541.

[81] F. Banihashemi, M. Weber, F. Deghim, C. Zong, and W. Lang, “Occupancy modeling on non-intrusive indoor environmental data through machine learning,” *Build. Environ.*, vol. 254, 2024, doi: 10.1016/j.buildenv.2024.111382.

[82] B. Dong and K. P. Lam, “Building energy and comfort management through occupant behaviour pattern detection based on a large-scale environmental sensor network,” *J. Build. Perform. Simul.*, vol. 4, no. 4, pp. 359–369, 2011, doi: 10.1080/19401493.2011.577810.

[83] X. Feng, D. Yan, and T. Hong, “Simulation of occupancy in buildings,” *Energy Build.*, vol. 87, pp. 348–359, 2015, doi: 10.1016/j.enbuild.2014.11.067.

[84] S. Salimi, Z. Liu, and A. Hammad, “Occupancy prediction model for open-plan offices using real-time location system and inhomogeneous Markov chain,” *Build. Environ.*, vol. 152, pp. 1–16, 2019, doi: 10.1016/j.buildenv.2019.01.052.

[85] S. Norouziasl, A. Jafari, and C. Wang, “An agent-based simulation of occupancy schedule in office buildings,” *Build. Environ.*, vol. 186, 2020, doi: 10.1016/j.buildenv.2020.107352.

[86] S. Hammes, J. Weninger, R. Pfluger, and W. Pohl, “Take the Right Seat: The Influence of Occupancy Schemes on Performance Indicators of Lighting in Open Plan Offices,” *Energies (Basel).*, vol. 15, no. 9, 2022, doi: 10.3390/en15093378.

[87] Y. Zhai *et al.*, “Use of adaptive control and its effects on human comfort in a naturally ventilated office in Alameda, California,” *Energy Build.*, vol. 203, 2019, doi: 10.1016/j.enbuild.2019.109435.

[88] F. Naspi, M. Arnesano, L. Zampetti, F. Stazi, G. M. Revel, and M. D'Orazio, "Experimental study on occupants' interaction with windows and lights in Mediterranean offices during the non-heating season," *Build. Environ.*, vol. 127, pp. 221–238, 2018, doi: 10.1016/j.buildenv.2017.11.009.

[89] R. Ming *et al.*, "Assessing energy saving potentials of office buildings based on adaptive thermal comfort using a tracking-based method," *Energy Build.*, vol. 208, 2020, doi: 10.1016/j.enbuild.2019.109611.

[90] N. Li, J. Li, R. Fan, and H. Jia, "Probability of occupant operation of windows during transition seasons in office buildings," *Renew. Energy*, vol. 73, pp. 84–91, 2015, doi: 10.1016/j.renene.2014.05.065.

[91] S. Pan *et al.*, "A study on influential factors of occupant window-opening behavior in an office building in China," *Build. Environ.*, vol. 133, pp. 41–50, 2018, doi: 10.1016/j.buildenv.2018.02.008.

[92] Y. Gu *et al.*, "Study on influencing factors for occupant window-opening behavior: Case study of an office building in Xi'an during the transition season," *Build. Environ.*, vol. 200, 2021, doi: 10.1016/j.buildenv.2021.107977.

[93] J. Ren *et al.*, "Comparative analysis of window operating behavior in three different open-plan offices in Nanjing," *Energy and Built Environment*, vol. 2, no. 2, pp. 175–187, 2021, doi: 10.1016/j.enbenv.2020.07.007.

[94] S. D'Oca and T. Hong, "A data-mining approach to discover patterns of window opening and closing behavior in offices," *Build. Environ.*, vol. 82, pp. 726–739, 2014, doi: 10.1016/j.buildenv.2014.10.021.

[95] K. Cheng, J. Yao, and R. Zheng, "Energy Performance of Occupant Behaviors on Windows: A Green Building Based Study," *Energies (Basel).*, vol. 16, no. 5, 2023, doi: 10.3390/en16052209.

[96] K. Schakib-Ekbatan, F. Z. Çakici, M. Schweiker, and A. Wagner, "Does the occupant behavior match the energy concept of the building? - Analysis of a German naturally ventilated office building," *Build. Environ.*, vol. 84, pp. 142–150, 2015, doi: 10.1016/j.buildenv.2014.10.018.

[97] J. Liu, R. Yao, and R. McCloy, "An investigation of thermal comfort adaptation behaviour in office buildings in the UK," *Indoor and Built*

Environment, vol. 23, no. 5, pp. 675–691, 2014, doi: 10.1177/1420326X13481048.

[98] H. B. Rijal, M. A. Humphreys, and J. F. Nicol, "Understanding occupant behaviour: The use of controls in mixed-mode office buildings," *Building Research and Information*, vol. 37, no. 4, pp. 381–396, 2009, doi: 10.1080/09613210902904221.

[99] Y. S. Lee and A. M. Malkawi, "Simulating multiple occupant behaviors in buildings: An agent-based modeling approach," *Energy Build.*, vol. 69, pp. 407–416, 2014, doi: 10.1016/j.enbuild.2013.11.020.

[100] A. Roetzel, "Occupant behaviour simulation for cellular offices in early design stages—Architectural and modelling considerations," *Build. Simul.*, vol. 8, no. 2, pp. 211–224, 2015, doi: 10.1007/s12273-014-0203-6.

[101] G. Y. Yun, P. Tuohy, and K. Steemers, "Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models," *Energy Build.*, vol. 41, no. 5, pp. 489–499, 2009, doi: 10.1016/j.enbuild.2008.11.013.

[102] S. D'Oca and T. Hong, "A data-mining approach to discover patterns of window opening and closing behavior in offices," *Build. Environ.*, vol. 82, pp. 726–739, 2014, doi: 10.1016/j.buildenv.2014.10.021.

[103] X. Zhou, J. Ren, J. An, D. Yan, X. Shi, and X. Jin, "Predicting open-plan office window operating behavior using the random forest algorithm," *Journal of Building Engineering*, vol. 42, 2021, doi: 10.1016/j.jobe.2021.102514.

[104] W. Liu, H. B. Gunay, and M. M. Ouf, "Modeling window and thermostat use behavior to inform sequences of operation in mixed-mode ventilation buildings," *Sci. Technol. Built Environ.*, vol. 27, no. 9, pp. 1204–1220, 2021, doi: 10.1080/23744731.2021.1936629.

[105] J. Liu, R. Yao, J. Wang, and B. Li, "Occupants' behavioural adaptation in workplaces with non-central heating and cooling systems," *Appl. Therm. Eng.*, vol. 35, no. 1, pp. 40–54, 2012, doi: 10.1016/j.applthermaleng.2011.09.037.

[106] H. C. Putra, C. J. Andrews, and J. A. Senick, "An agent-based model of building occupant behavior during load shedding," *Build. Simul.*, vol. 10, no. 6, pp. 845–859, 2017, doi: 10.1007/s12273-017-0384-x.

[107] P. Correia da Silva, V. Leal, and M. Andersen, “Occupants’ behaviour in energy simulation tools: lessons from a field monitoring campaign regarding lighting and shading control,” *J. Build. Perform. Simul.*, vol. 8, no. 5, pp. 338–358, 2015, doi: 10.1080/19401493.2014.953583.

[108] V. Inkarojrit, “Monitoring and modelling of manually-controlled venetian blinds in private offices: A pilot study,” *J. Build. Perform. Simul.*, vol. 1, no. 2, pp. 75–89, 2008, doi: 10.1080/19401490802021012.

[109] A. Mahdavi, A. Mohammadi, E. Kabir, and L. Lambeva, “Occupants’ operation of lighting and shading systems in office buildings,” *J. Build. Perform. Simul.*, vol. 1, no. 1, pp. 57–65, 2008, doi: 10.1080/19401490801906502.

[110] J. P. Carneiro, A. Aryal, and B. Becerik-Gerber, “Understanding the influence of orientation, time-of-day and blind use on user’s lighting choices and energy consumption using immersive virtual environments,” *Advances in Building Energy Research*, vol. 15, no. 5, pp. 603–629, 2021, doi: 10.1080/17512549.2019.1639075.

[111] S. A. Sadeghi, P. Karava, I. Konstantzos, and A. Tzempelikos, “Occupant interactions with shading and lighting systems using different control interfaces: A pilot field study,” *Build. Environ.*, vol. 97, pp. 177–195, 2016, doi: 10.1016/j.buildenv.2015.12.008.

[112] P. Maleetipwan-Mattsson and T. Laike, “Optimal office lighting use: A swedish case study,” *Facilities*, vol. 33, no. 9–10, pp. 573–587, 2015, doi: 10.1108/F-01-2014-0004.

[113] A. Cilasun Kunduraci, T. Kazanasmaz, and T. Hordijk, “Examining occupancy and architectural aspects affecting manual lighting control behaviour in offices based on a user survey,” *Light and Engineering*, vol. 26, no. 2, pp. 139–147, 2018, doi: 10.33383/2017-015.

[114] G. Y. Yun, H. Kim, and J. T. Kim, “Effects of occupancy and lighting use patterns on lighting energy consumption,” *Energy Build.*, vol. 46, pp. 152–158, 2012, doi: 10.1016/j.enbuild.2011.10.034.

[115] B. Gucyeter, “Evaluating diverse patterns of occupant behavior regarding control-based activities in energy performance simulation,” *Frontiers of Architectural Research*, vol. 7, no. 2, pp. 167–179, 2018, doi: 10.1016/j.foar.2018.03.002.

[116] G. Ozcelik, B. Becerik-Gerber, and R. Chugh, “Understanding human-building interactions under multimodal discomfort,” *Build. Environ.*, vol. 151, pp. 280–290, 2019, doi: 10.1016/j.buildenv.2018.12.046.

[117] T. Moore, D. J. Carter, and A. I. Slater, “Long-term patterns of use of occupant controlled office lighting,” *Lighting Research & Technology*, vol. 35, no. 1, pp. 43–57, 2003, doi: 10.1191/1477153503li061oa.

[118] P. Mahmoudzadeh, Y. Afacan, and M. N. Adi, “Analyzing occupants’ control over lighting systems in office settings using immersive virtual environments,” *Build. Environ.*, vol. 196, 2021, doi: 10.1016/j.buildenv.2021.107823.

[119] A. Heydarian, E. Pantazis, J. P. Carneiro, D. Gerber, and B. Becerik-Gerber, “Lights, building, action: Impact of default lighting settings on occupant behaviour,” *J. Environ. Psychol.*, vol. 48, pp. 212–223, 2016, doi: 10.1016/j.jenvp.2016.11.001.

[120] A. Heydarian, J. P. Carneiro, D. Gerber, and B. Becerik-Gerber, “Immersive virtual environments, understanding the impact of design features and occupant choice upon lighting for building performance,” *Build. Environ.*, vol. 89, pp. 217–228, 2015, doi: 10.1016/j.buildenv.2015.02.038.

[121] B. Peng and S. J. Hsieh, “Cyber-Enabled Optimization of HVAC System Control in Open Space of Office Building,” *Sensors*, vol. 23, no. 10, 2023, doi: 10.3390/s23104857.

[122] E. Zaidan, A. Ghofrani, and E. Dokaj, “Analysis of Human-Building Interactions in Office Environments: to What Extent Energy Saving Boundaries can be Displaced?,” *Front. Energy Res.*, vol. 9, 2021, doi: 10.3389/fenrg.2021.715478.

[123] X. Yuan, Y. Pan, Z. She, Y. Pan, Z. Huang, and R. Kosonen, “Modelling method for air-conditioning usage behavior in multi-occupant office space based on group decision-making strategy,” *Energy and Built Environment*, vol. 4, no. 6, pp. 615–628, 2023, doi: 10.1016/j.enbenv.2022.06.001.

[124] H. Pallubinsky, B. R. M. Kingma, L. Schellen, B. Dautzenberg, M. A. van Baak, and W. D. van Marken Lichtenbelt, “The effect of warmth acclimation on behaviour, thermophysiology and perception,” *Building Research and Information*, vol. 45, no. 7, pp. 800–807, 2017, doi: 10.1080/09613218.2017.1278652.

[125] C. fei Chen *et al.*, “Culture, conformity, and carbon? A multi-country analysis of heating and cooling practices in office buildings,” *Energy Res. Soc. Sci.*, vol. 61, 2020, doi: 10.1016/j.erss.2019.101344.

[126] M. S. Mustapa, S. A. Zaki, H. B. Rijal, A. Hagishima, and M. S. M. Ali, “Thermal comfort and occupant adaptive behaviour in Japanese university buildings with free running and cooling mode offices during summer,” *Build. Environ.*, vol. 105, pp. 332–342, 2016, doi: 10.1016/j.buildenv.2016.06.014.

[127] L. R. Glicksman and S. Taub, “Thermal and behavioral modeling of occupant-controlled heating, ventilating and air conditioning systems,” *Energy Build.*, vol. 25, no. 3, pp. 243–249, 1997, doi: 10.1016/S0378-7788(96)01019-5.

[128] Y. Peng, Z. Nagy, and A. Schlüter, “Temperature-preference learning with neural networks for occupant-centric building indoor climate controls,” *Build. Environ.*, vol. 154, pp. 296–308, 2019, doi: 10.1016/j.buildenv.2019.01.036.

[129] B. Pioppi, C. Piselli, C. Crisanti, and A. L. Pisello, “Human-centric green building design: the energy saving potential of occupants’ behaviour enhancement in the office environment,” *J. Build. Perform. Simul.*, vol. 13, no. 6, pp. 621–644, 2020, doi: 10.1080/19401493.2020.1810321.

[130] H. P. Díaz-Hernández *et al.*, “Performance assessment of different measured variables from onboard monitoring system to obtain the occupancy patterns of rooms in an office building,” *Journal of Building Engineering*, vol. 40, 2021, doi: 10.1016/j.jobe.2021.102676.

[131] X. Zhu, B. Gao, X. Yang, Y. Yuan, and J. Ni, “Interactions between the built environment and the energy-related behaviors of occupants in government office buildings,” *Sustainability (Switzerland)*, vol. 13, no. 19, 2021, doi: 10.3390/su131910607.

[132] C. Grassi, K. M. S. Chvatal, and M. Schweiker, “Stochastic models for window opening and air-conditioning usage in mixed-mode offices for a humid subtropical climate in Brazil,” *Build. Environ.*, vol. 225, 2022, doi: 10.1016/j.buildenv.2022.109579.

[133] A. Kamilaris, J. Neovino, S. Kondepudi, and B. Kalluri, “A case study on the individual energy use of personal computers in an office setting and

assessment of various feedback types toward energy savings," *Energy Build.*, vol. 104, pp. 73–86, 2015, doi: 10.1016/j.enbuild.2015.07.010.

[134] Z. Wang and Y. Ding, "An occupant-based energy consumption prediction model for office equipment," *Energy Build.*, vol. 109, pp. 12–22, 2015, doi: 10.1016/j.enbuild.2015.10.002.

[135] N. S. M. Azizi, S. Wilkinson, and E. Fassman, "Do occupants in green buildings practice better energy saving behaviour in computer usage than occupants in conventional buildings?," *Journal of Green Building*, vol. 10, no. 4, pp. 178–193, 2015, doi: 10.3992/jgb.10.4.178.

[136] H. N. Rafsanjani, C. R. Ahn, and K. M. Eskridge, "Understanding the recurring patterns of occupants' energy-use behaviors at entry and departure events in office buildings," *Build. Environ.*, vol. 136, pp. 77–87, 2018, doi: 10.1016/j.buildenv.2018.03.037.

[137] M. Indraganti and D. Boussaa, "Comfort temperature and occupant adaptive behavior in offices in Qatar during summer," *Energy Build.*, vol. 150, pp. 23–36, 2017, doi: 10.1016/j.enbuild.2017.05.063.

[138] C. Morgan and R. de Dear, "Weather, clothing and thermal adaptation to indoor climate," *Clim. Res.*, vol. 24, no. 3, pp. 267–284, 2003, doi: 10.3354/cr024267.

[139] G. R. Newsham, "Clothing as a thermal comfort moderator and the effect on energy consumption," *Energy Build.*, vol. 26, no. 3, pp. 283–291, 1997, doi: 10.1016/s0378-7788(97)00009-1.

[140] A. S. Weerasinghe, E. Onyeizu, and J. O. B. Rotimi, "Environmental and socio-psychological drivers of building users' behaviours: a case study of tertiary institutional offices in Auckland," *Journal of Facilities Management*, 2022, doi: 10.1108/JFM-01-2022-0011.

[141] P. Aparicio-Ruiz, E. Barbadilla-Martín, J. Guadix, and J. Muñuzuri, "Predicting the clothing insulation through machine learning algorithms: A comparative analysis and a practical approach," *Build. Simul.*, vol. 17, no. 5, pp. 839–855, 2024, doi: 10.1007/s12273-024-1114-9.

[142] L. Arpan *et al.*, "The hopeful expect to be comfortable: Exploring emotion and personal norms related to sustainable buildings in the United States," *Energy Res. Soc. Sci.*, vol. 93, p. 102846, Nov. 2022, doi: 10.1016/j.erss.2022.102846.

[143] J. Yao, “Determining the energy performance of manually controlled solar shades: A stochastic model based co-simulation analysis,” *Appl. Energy*, vol. 127, pp. 64–80, 2014, doi: 10.1016/j.apenergy.2014.04.046.

[144] A. S. Weerasinghe, E. O. Rasheed, and J. O. B. Rotimi, “A facilities management approach to rationalising occupants’ energy behaviours,” *Facilities*, vol. 40, no. 11–12, pp. 774–792, 2022, doi: 10.1108/F-02-2022-0025.

[145] J. Day, J. Theodorson, and K. Van Den Wymelenberg, “Understanding controls, behaviors and satisfaction in the daylit perimeter office: A daylight design case study,” *J. Inter. Des.*, vol. 37, no. 1, pp. 17–34, 2012, doi: 10.1111/j.1939-1668.2011.01068.x.

[146] C. fei Chen *et al.*, “Intersecting heuristic adaptive strategies, building design and energy saving intentions when facing discomfort environment: A cross-country analysis,” *Build. Environ.*, vol. 204, 2021, doi: 10.1016/j.buildenv.2021.108129.

[147] M. Indraganti, D. Boussaa, S. Assadi, and E. Mostavi, “User satisfaction and energy use behavior in offices in Qatar,” *Building Services Engineering Research and Technology*, vol. 39, no. 4, pp. 391–405, 2018, doi: 10.1177/0143624417751388.

[148] D. Li, C. C. Menassa, and A. Karatas, “Energy use behaviors in buildings: Towards an integrated conceptual framework,” *Energy Res. Soc. Sci.*, vol. 23, pp. 97–112, 2017, doi: 10.1016/j.erss.2016.11.008.

[149] R. Vastamäki, I. Sinkkonen, and C. Leinonen, “A behavioural model of temperature controller usage and energy saving,” *Pers. Ubiquitous Comput.*, vol. 9, no. 4, pp. 250–259, 2005, doi: 10.1007/s00779-004-0326-3.

[150] L. Marín-Restrepo, M. Trebilcock, and M. Gillott, “Occupant action patterns regarding spatial and human factors in office environments,” *Energy Build.*, vol. 214, 2020, doi: 10.1016/j.enbuild.2020.109889.

[151] S. D’Oca, A. L. Pisello, M. De Simone, V. M. Barthelmes, T. Hong, and S. P. Corgnati, “Human-building interaction at work: Findings from an interdisciplinary cross-country survey in Italy,” *Build. Environ.*, vol. 132, pp. 147–159, 2018, doi: 10.1016/j.buildenv.2018.01.039.

[152] A. L. Pisello, V. L. Castaldo, C. Piselli, C. Fabiani, and F. Cotana, “How peers’ personal attitudes affect indoor microclimate and energy need in an institutional building: Results from a continuous monitoring campaign in summer and winter conditions,” *Energy Build.*, vol. 126, pp. 485–497, 2016, doi: 10.1016/j.enbuild.2016.05.053.

[153] K. Bäcklund, M. Molinari, and P. Lundqvist, “In Search for Untapped Energy-Saving Potential in Green and Smart Higher Educational Buildings—An Empirical Case Study Involving the Building Occupants,” *Buildings*, vol. 13, no. 12, 2023, doi: 10.3390/buildings13123103.

[154] X. Xie, S. Qin, Z. Gou, and M. Yi, “Can green building promote pro-environmental behaviours? The psychological model and design strategy,” *Sustainability (Switzerland)*, vol. 12, no. 18, 2020, doi: 10.3390/su12187714.

[155] R. M. Tetlow, C. P. Beaman, A. A. Elmualim, and K. Couling, “Simple prompts reduce inadvertent energy consumption from lighting in office buildings,” *Build. Environ.*, vol. 81, pp. 234–242, 2014, doi: 10.1016/j.buildenv.2014.07.003.

[156] E. Tezel and H. Giritli, “Understanding pro-environmental workplace behavior: a comparative study,” *Facilities*, vol. 37, no. 9–10, pp. 669–683, 2019, doi: 10.1108/F-12-2017-0134.

[157] G. Yang, R. Hitchings, L. Lotti, and M. Shipworth, “Understanding the social norms of cooling in Chinese offices: Predominance, professionalism, and peer respect,” *Energy Res. Soc. Sci.*, vol. 94, p. 102861, Dec. 2022, doi: 10.1016/j.erss.2022.102861.

[158] C. F. Chen and K. Knight, “Energy at work: Social psychological factors affecting energy conservation intentions within Chinese electric power companies,” *Energy Res. Soc. Sci.*, vol. 4, no. C, pp. 23–31, 2014, doi: 10.1016/j.erss.2014.08.004.

[159] O. A. Nisiforou, S. Poullis, and A. G. Charalambides, “Behaviour, attitudes and opinion of large enterprise employees with regard to their energy usage habits and adoption of energy saving measures,” *Energy Build.*, vol. 55, pp. 299–311, 2012, doi: 10.1016/j.enbuild.2012.08.034.

[160] M. Mulville, K. Jones, G. Huebner, and J. Powell-Greig, “Energy-saving occupant behaviours in offices: change strategies,” *Building Research and*

Information, vol. 45, no. 8, pp. 861–874, 2017, doi: 10.1080/09613218.2016.1212299.

[161] R. M. Tetlow, C. van Dronkelaar, C. P. Beaman, A. A. Elmualim, and K. Couling, "Identifying behavioural predictors of small power electricity consumption in office buildings," *Build. Environ.*, vol. 92, pp. 75–85, 2015, doi: 10.1016/j.buildenv.2015.04.009.

[162] R. Rissetto, R. Rambow, and M. Schweiker, "Assessing comfort in the workplace: A unified theory of behavioral and thermal expectations," *Build. Environ.*, vol. 216, p. 109015, 2022, doi: 10.1016/j.buildenv.2022.109015.

[163] I. Ajzen, "From Intentions to Actions: A Theory of Planned Behavior," in *Action Control: From Cognition to Behavior*, J. Kuhl and J. Beckmann, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 1985, pp. 11–39. doi: 10.1007/978-3-642-69746-3_2.

[164] I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, Dec. 1991, doi: 10.1016/0749-5978(91)90020-T.

[165] V. Blok, R. Wesselink, O. Studynka, and R. Kemp, "Encouraging sustainability in the workplace: a survey on the pro-environmental behaviour of university employees," *J. Clean. Prod.*, vol. 106, pp. 55–67, 2015, doi: https://doi.org/10.1016/j.jclepro.2014.07.063.

[166] M. Greaves, L. D. Zibarras, and C. Stride, "Using the theory of planned behavior to explore environmental behavioral intentions in the workplace," *J. Environ. Psychol.*, vol. 34, pp. 109–120, 2013, doi: 10.1016/j.jenvp.2013.02.003.

[167] S. H. Schwartz, "Normative Influences on Altruism," *Adv. Exp. Soc. Psychol.*, vol. 10, no. C, pp. 221–279, Jan. 1977, doi: 10.1016/S0065-2601(08)60358-5.

[168] F. Ölander and J. Thøgersen, "Understanding of consumer behaviour as a prerequisite for environmental protection," *J. Consum. Policy (Dordr).*, vol. 18, pp. 345–385, 1995.

[169] X. Xu, C. F. C.-F. Chen, D. Li, and C. Menassa, "Energy Saving at Work: Exploring the Role of Social Norms, Perceived Control and Ascribed Responsibility in Different Office Layouts," *Front. Built Environ.*, vol. 6, 2020, doi: 10.3389/fbuil.2020.00016.

[170] T. Hong, S. D'Oca, S. C. Taylor-Lange, W. J. N. Turner, Y. Chen, and S. P. Corgnati, "An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema," *Build. Environ.*, vol. 94, no. P1, pp. 196–205, Dec. 2015, doi: 10.1016/j.buildenv.2015.08.006.

[171] L. Yang, S. Liu, and J. Liu, "The interaction effect of occupant behavior-related factors in office buildings based on the DNAs theory," *Sustainability (Switzerland)*, vol. 13, no. 6, 2021, doi: 10.3390/su13063227.

[172] M. V. Bavaresco, E. Ghisi, S. D'Oca, and A. L. Pisello, "Triggering occupant behaviour for energy sustainability: Exploring subjective and comfort-related drivers in Brazilian offices," *Energy Res. Soc. Sci.*, vol. 74, 2021, doi: 10.1016/j.erss.2021.101959.

[173] S. Karjalainen, "Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption," *Energy Effic.*, vol. 9, no. 6, pp. 1257–1270, 2016, doi: 10.1007/s12053-015-9422-7.

[174] T. A. Arentze, "Individuals' social preferences in joint activity location choice: A negotiation model and empirical evidence," *J. Transp. Geogr.*, vol. 48, pp. 76–84, Oct. 2015, Accessed: Jul. 09, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966692315001593

[175] N. Tiellemans, A. Kemperman, S. Maussen, and T. Arentze, "The influence of group decision-making on residents' preferences for sustainable energy measures of dwellings," *Building Research & Information*, vol. 50, no. 4, pp. 410–423, 2022.

[176] C. A. Klöckner, "A comprehensive model of the psychology of environmental behaviour—A meta-analysis," *Global Environmental Change*, vol. 23, no. 5, pp. 1028–1038, Oct. 2013, doi: 10.1016/J.GLOENVCHA.2013.05.014.

[177] C. A. Klöckner and A. Blöbaum, "A comprehensive action determination model: Toward a broader understanding of ecological behaviour using the example of travel mode choice," *J. Environ. Psychol.*, vol. 30, no. 4, pp. 574–586, Dec. 2010, doi: 10.1016/J.JENVP.2010.03.001.

[178] A. Bandura, "Human agency in social cognitive theory," *American Psychologist*, vol. 44, no. 9, pp. 1175–1184, Sep. 1989, doi: https://doi.org/10.1037/0003-066X.44.9.1175.

[179] M. Moezzi and L. Lutzenhiser, “What’s missing in theories of the residential energy user,” 2010.

[180] W. H. Greene, D. A. Hensher, and J. M. Rose, Eds., “Experimental design and choice experiments,” in *Applied Choice Analysis*, 2nd ed., Cambridge: Cambridge University Press, 2015, pp. 189–319. doi: DOI: 10.1017/CBO9781316136232.008.

[181] J. Louviere and H. Timmermans, “Stated preference and choice models applied to recreation research: a review,” *Leis. Sci.*, vol. 12, no. 1, pp. 9–32, 1990.

[182] G. Tusset, “Manual of Political Economy: A Critical and Variorum Edition,” *History of Economics Review*, vol. 79, no. 1, pp. 84–86, Jan. 2021, doi: 10.1080/10370196.2021.1926107.

[183] D. A. Hensher, J. M. Rose, and W. H. Greene, “Choice and utility,” in *Applied Choice Analysis*, 2nd ed., D. A. Hensher, J. M. Rose, and W. H. Greene, Eds., Cambridge: Cambridge University Press, 2015, pp. 30–79. doi: 10.1017/cbo9781316136232.005.

[184] D. Campbell, W. G. Hutchinson, and R. Scarpa, “Incorporating Discontinuous Preferences into the Analysis of Discrete Choice Experiments,” *Environ. Resour. Econ. (Dordr).*, vol. 41, no. 3, pp. 401–417, 2008, doi: 10.1007/s10640-008-9198-8.

[185] P. Sinha, C. S. Calfee, and K. L. Delucchi, “Practitioner’s Guide to Latent Class Analysis: Methodological Considerations and Common Pitfalls,” *Crit. Care Med.*, vol. 49, no. 1, 2021, [Online]. Available: https://journals.lww.com/ccmjournal/fulltext/2021/01000/practitioner_s_guide_to_latent_class_analysis_.26.aspx

[186] R. De Dear and G. S. Brager, “Developing an adaptive model of thermal comfort and preference,” 1998.

[187] A. Auliciems, “Towards a psycho-physiological model of thermal perception,” *Int. J. Biometeorol.*, vol. 25, no. 2, pp. 109–122, 1981, doi: 10.1007/BF02184458.

[188] D. Xie, “Two-Process Theory of Perceived Control: Changing the workspace and changing the self,” in *A Handbook of Theories on Designing Alignment between People and the Office Environment*, Routledge, 2021, pp. 124–131.

[189] F. Rothbaum, J. R. Weisz, and S. S. Snyder, “Changing the world and changing the self: A two-process model of perceived control.,” *J. Pers. Soc. Psychol.*, vol. 42, no. 1, p. 5, 1982.

[190] D. Yan *et al.*, “IEA EBC Annex 66: Definition and simulation of occupant behavior in buildings,” *Energy Build.*, vol. 156, pp. 258–270, 2017, doi: https://doi.org/10.1016/j.enbuild.2017.09.084.

[191] C. Chun, A. Kwok, T. Mitamura, N. Miwa, and A. Tamura, “Thermal diary: Connecting temperature history to indoor comfort,” *Build. Environ.*, vol. 43, no. 5, pp. 877–885, May 2008, doi: 10.1016/J.BUILDENV.2007.01.031.

[192] M. Schweiker, C. Berger, J. Day, and A. Mahdavi, “Fundamentals of IEQ and Occupant Needs,” in *Occupant-Centric Simulation-Aided Building Design*, Routledge, 2023, pp. 10–33.

[193] A. K. Raue, A. C. Boestra, A. C. Van der Linden, and S. R. Kurvers, “NATVENT buildings versus HVAC buildings. A new Dutch thermal comfort guideline,” in *25th AIVC Conference, Prague, Czech Republic*, 2004.

[194] G. Torriani, S. Torresin, I. Lara-Ibeas, R. Albatici, and F. Babich, “Perceived air quality (PAQ) assessment methods in office buildings: A systematic review towards an indoor smellscape approach,” *Build. Environ.*, vol. 258, p. 111645, Jun. 2024, doi: 10.1016/J.BUILDENV.2024.111645.

[195] F. Felgueiras, Z. Mourão, A. Moreira, and M. F. Gabriel, “Characterizing indoor environmental quality in Portuguese office buildings for designing an intervention program,” *Build. Environ.*, vol. 254, p. 111393, Apr. 2024, doi: 10.1016/J.BUILDENV.2024.111393.

[196] M. A. Ortiz and P. M. Bluyssen, “Profiling office workers based on their self-reported preferences of indoor environmental quality and psychosocial comfort at their workplace during COVID-19,” *Build. Environ.*, vol. 211, p. 108742, Mar. 2022, doi: 10.1016/J.BUILDENV.2021.108742.

[197] Choice Metrics, *Ngene 1.1.1 User Manual & Reference Guide*. Australia, 2012. Accessed: Aug. 26, 2024. [Online]. Available: chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://choice-metrics.com/NgeneManual120.pdf

[198] J. Kim, R. de Dear, C. Cândido, H. Zhang, and E. Arens, “Gender differences in office occupant perception of indoor environmental quality (IEQ),” *Build. Environ.*, vol. 70, pp. 245–256, Dec. 2013, doi: 10.1016/J.BUILDENV.2013.08.022.

[199] D. H. Kim and P. M. Bluyssen, “Clustering of office workers from the OFFICAIR study in The Netherlands based on their self-reported health and comfort,” *Build. Environ.*, vol. 176, p. 106860, Jun. 2020, doi: 10.1016/J.BUILDENV.2020.106860.

[200] C. B. Danielsson and L. Bodin, “Office Type in Relation to Health, Well-Being, and Job Satisfaction Among Employees,” *Environ. Behav.*, vol. 40, no. 5, pp. 636–668, Jan. 2008, doi: 10.1177/0013916507307459.

[201] H. Zafar, J. A. Ho, J. Cheah, and R. Mohamed, “Promoting pro-environmental behavior through organizational identity and green organizational climate,” *Asia Pacific Journal of Human Resources*, vol. 61, no. 2, pp. 483–506, 2023.

[202] T. Hong, “Occupant Behavior: impact on energy use of private offices,” *ASim 2012 - 1st Asia conference of International Building Performance Simulation Association*, no. January, p. 8, Jun. 2012, [Online]. Available: https://escholarship.org/uc/item/6jp5w8kn#page-11

[203] R. W. Motl *et al.*, “Factorial Validity and Invariance of Questionnaires Measuring Social-Cognitive Determinants of Physical Activity among Adolescent Girls,” *Prev. Med. (Baltim).*, vol. 31, no. 5, pp. 584–594, 2000, doi: https://doi.org/10.1006/pmed.2000.0735.

[204] L. Steg and A. Nordlund, “Theories to explain environmental behaviour,” *Environmental Psychology: an introduction*, pp. 217–227, 2018.

[205] A. Rivis and P. Sheeran, “Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis,” *Current psychology*, vol. 22, pp. 218–233, 2003.

[206] S. D. Gosling, P. J. Rentfrow, and W. B. Swann, “A very brief measure of the Big-Five personality domains,” *J. Res. Pers.*, vol. 37, no. 6, pp. 504–528, Dec. 2003, doi: 10.1016/S0092-6566(03)00046-1.

[207] K. Cherry, “What Are the Big 5 Personality Traits?,” *Verywellmind*, p. 1, 2023, [Online]. Available: https://www.verywellmind.com/the-big-five-personality-dimensions-2795422

[208] K. Nylund-Gibson and A. Y. Choi, “Ten frequently asked questions about latent class analysis.,” *Transl. Issues Psychol. Sci.*, vol. 4, no. 4, pp. 440–461, 2018, doi: 10.1037/tps0000176.

[209] L. M. Collins and S. T. Lanza, *Latent Class and Latent Transition Analysis: With Applications in the Social, Behavioral, and Health Sciences*. 2010. doi: 10.1002/9780470567333.

[210] K. E. Masyn, “Latent class analysis and finite mixture modeling.,” in *The Oxford handbook of quantitative methods: Statistical analysis, Vol. 2*, in Oxford library of psychology. , New York, NY, US: Oxford University Press, 2013, pp. 551–611.

[211] K. Genjo *et al.*, “Development of Adaptive Model and Occupant Behavior Model in Four Office Buildings in Nagasaki, Japan,” *Energies (Basel).*, vol. 16, no. 16, p. 6060, 2023.

[212] D. A. Hensher, J. M. Rose, and W. H. Greene, Eds., “Mixed logit estimation,” in *Applied Choice Analysis*, 2nd ed., Cambridge: Cambridge University Press, 2015, pp. 601–705. doi: DOI: 10.1017/CBO9781316136232.019.

[213] M. Kompier, K. Smolders, and Y. de Kort, “Effects of light and ambient temperature on visual and thermal appraisals,” in *Routledge Handbook of Resilient Thermal Comfort*, Routledge, 2022, pp. 347–362.

[214] C. Andrews, J. Day, P. Agee, R. Wener, Q. Jin, and J. Senick, “4 Methods to Obtain the Occupant Perspective,” *Occupant-Centric Simulation-Aided Building Design*, p. 60, 2023.

[215] D. A. Hensher, J. M. Rose, and W. H. Greene, *Applied Choice Analysis*, 2nd ed. Cambridge: Cambridge University Press, 2015. doi: DOI: 10.1017/CBO9781316136232.

[216] A. S. Weerasinghe, E. O. Rasheed, and J. O. B. Rotimi, “Environmental and socio-psychological drivers of building users’ behaviours: a case study of tertiary institutional offices in Auckland,” *Journal of Facilities Management*, vol. 22, no. 4, pp. 564–587, Jan. 2024, doi: 10.1108/JFM-01-2022-0011.

[217] H. Akaike, “A new look at the statistical model identification,” *IEEE Trans. Automat. Contr.*, vol. 19, no. 6, pp. 716–723, 1974, doi: 10.1109/TAC.1974.1100705.

[218] G. Schwarz, “Estimating the Dimension of a Model,” *The Annals of Statistics*, vol. 6, no. 2, pp. 461–464, Mar. 1978, doi: 10.1214/aos/1176344136.

[219] S. Clark and B. O. Muthén, “Relating Latent Class Analysis Results to Variables not Included in the Analysis,” *StatisticalInnovations.com*, pp. 1–55, 2009.

[220] D. NAGIN, *Group-Based Modeling of Development*. Harvard University Press, 2015. doi: 10.4159/9780674041318.

[221] T. Hong, C.-F. Chen, Z. Wang, and X. Xu, “Linking human-building interactions in shared offices with personality traits,” *Build. Environ.*, vol. 170, 2020, doi: 10.1016/j.buildenv.2019.106602.

[222] A. Eijkelenboom and P. M. Bluyssen, “Profiling outpatient staff based on their self-reported comfort and preferences of indoor environmental quality and social comfort in six hospitals,” *Build. Environ.*, vol. 184, p. 107220, Oct. 2020, doi: 10.1016/J.BUILDENV.2020.107220.

[223] Á. Bognár, P.-J. Hoes, T. van Hooff, and M. G. L. C. Loomans, “Practical experiences from the implementation of extensive sensoring in a modern building,” *CLIMA 2022 conference*, May 2022, doi: 10.34641/clima.2022.308.

[224] F. Stazi, F. Naspi, and M. D’Orazio, “A literature review on driving factors and contextual events influencing occupants’ behaviours in buildings,” *Build. Environ.*, vol. 118, pp. 40–66, 2017, doi: 10.1016/j.buildenv.2017.03.021.

Curriculum vitae

Han Li studied Management of the Built Environment at Politecnico di Milano and subsequently pursued his PhD at Eindhoven University of Technology, the results of which are presented in this dissertation. His research focuses on heterogeneous occupant behaviour in office buildings, combining discrete choice experiments, econometric modelling, latent class analysis, agent-based modelling, and building performance simulation. He also has a professional background in construction management, building services, green-building assessment, and building sustainability.

Publications

Han Li, Rianne Appel-Meulenbroek, Theo A. Arentze, Pieter-Jan Hoes, Conceptualizing sustainable occupant behaviour in offices from an interdisciplinary point of view: A systematic review, Energy and Built Environment, (2026), https://doi.org/10.1016/j.enbenv.2024.08.004

Han Li, Rianne Appel-Meulenbroek, Theo A. Arentze, Pieter-Jan Hoes, Revealing and modelling occupants' preferences for comfort adaptive actions in open-plan offices with the inclusion of contextual and social-psychological aspects, Building and Environment, 285 (2025) 113681, https://doi.org/10.1016/j.buildenv.2025.113681

Han Li, Rianne Appel-Meulenbroek, Theo Arentze, Pieter-Jan Hoes, Profiling office workers' comfort-related adaptive actions: a latent class analysis, Journal of Environmental Psychology,111 (2026) 102979, https://doi.org/10.1016/j.jenvp.2026.102979

Li, H., Appel-Meulenbroek, R., Arentze, T., Hoes, PJ. (2026). Occupant-Centric Interdisciplinary Approach to Obtain Occupants' Preferences on Comfort Adaptative Behaviours in Office Environments. Lecture Notes in Civil Engineering, vol 762. Springer, Cham. https://doi.org/10.1007/978-3-032-06806-4_23

Appendix A – Latent class model results

Table 21 Summary of the latent class model

	Model		*MNL model*		*Class 1*		*Class2*		*Class 3*	
	Attributes	Level	*β*	*P*	*β*	*P*	*β*	*P*	*β*	*P*
Behaviours	Constant	Window	.068**	0.032	.688***	0.000	.154	0.117	-.662***	0.000
		Blinds	-.220***	0.000	.117**	0.042	-.316***	0.000	-.525***	0.000
		Thermostat	-.170***	0.000	.088	0.108	-.811***	0.000	-.268***	0.000
		Lighting	-.852***	0.000	-.764***	0.000	-.807***	0.000	-1.101***	0.000
		Secondary	-.502***	0.000	-1.148***	0.000	-.617***	0.000	.425***	0.000
Window	Location and tasks	Individual concentration work in Con. area	-.069	0.217	.202	0.132	.409**	0.016	-.629***	0.000

		Formal meeting in MR	.084	0.129	-.217*	0.056	.586***	0.000	-.045	0.700
		Informal meeting in a Col. area	.020	0.691	.380***	0.001	-1.653***	0.000	.860***	0.000
		Informal meeting in a MR	-.035	0	-.365	0	.658	0	-.186	0
	Season	Summer	.004	0.930	-.052	0.541	.083	0.465	.087	0.301
		Winter	-.114**	0.010	-.265***	0.002	-.060	0.609	-.109	0.218
		Fall/Spring	.110	0	.317	0	-.023	0	.022	0
	Weather	Sunny	-.015	0.730	-.032	0.702	.032	0.792	-.020	0.813
		Windy	-.001	0.974	-.134	0.126	.163	0.194	-.005	0.956
		Rainy	.016	0.000	.166	0.000	-.195	0.000	.025	0.000
		2 to 3 people	-.005	0.918	-.065	0.442	.125	0.304	.003	0.973

	Occupancy level	10 to 15 people	.013	0.761	.118	0.185	-.144	0.260	-4.60E-04	0.996
		4 to 9 people	-.008	0.000	-.053	0.000	.019	0.000	-2.54E-03	0.000
	IEQ - temperature	Temperature is below 18°C	-.311***	0.000	-.542***	0.000	-.278**	0.019	-.221**	0.012
		Temperature is higher than 24°C	.172***	0.000	.425***	0.000	-.021	0.859	.072	0.393
		Temperature is 18 to 24°C	.139	0.000	.117	0.000	.299	0.000	.149	0.000
	IEQ – Air quality	Odour air	.723***	0.000	1.203***	0.000	.691***	0.000	.384***	0.000
		Stuffy air	.588***	0.000	1.047***	0.000	.629***	0.000	.095	0.274
		Air quality is fine	-1.311	0.000	-2.250	0.000	-1.320	0.000	-.479	0.000

	IEQ – Lighting conditions	Dimmed lighting	.052	0.238	.249***	0.008	-.087	0.473	.040	0.654
		Glare from the lighting	-.033	0.462	-.127	0.126	.035	0.780	-.026	0.761
		Adequate lighting	-.019	0.000	-.122	0.000	.052	0.000	-.014	0.000
	IEQ – Indoor daylight conditions	Glare from the Sun	-.113**	0.011	-.040	0.661	-.329***	0.005	.009	0.918
		Minimum daylight	.220***	0.000	.156*	0.084	.580***	0.000	.071	0.432
		Soft daylight	-.107	0.000	-.116	0.000	-.251	0.000	-.080	0.000
Blinds	Location and tasks	Individual concentration work in Con. area	-.161***	0.006	.093	0.368	-.607***	0.000	-.190*	0.096

		Formal meeting in MR	.021	0.696	.075	0.445	.150	0.283	-.136	0.222
		Informal meeting in a Col. area	-.072	0.166	-.216**	0.023	-.731***	0.000	.472***	0.000
		Informal meeting in a MR	.212	0.000	.048	0.000	1.188	0.000	-.146	0.000
	Season	Summer	.208***	0.000	.276***	0.000	.137	0.232	.264***	0.001
		Winter	-.057	0.199	-.063	0.392	-.058	0.603	-.150*	0.070
		Fall/Spring	-.151	0.000	-.213	0.000	-.079	0.000	-.114	0.000
	Weather	Sunny	.223***	0.000	.296***	0.000	.147	0.181	.300***	0.000
		Windy	-.083*	0.064	-.060	0.431	-.056	0.642	-.155*	0.074
		Rainy	-.140	0.000	-.236	0.000	-.091	0.000	-.145	0.000
		2 to 3 people	-.031	0.494	-.109	0.145	-.165	0.147	.156*	0.060

	Occupancy level	10 to 15 people	.103**	0.021	.091	0.219	.257**	0.025	.022	0.795
		4 to 9 people	-.072	0.000	.018	0.000	-.092	0.000	-.178	0.000
	IEQ - Temperature	Temperature is below 18°C	-.156***	0.001	-.104	0.168	-.378***	0.001	-.107	0.208
		Temperature is higher than 24°C	.301***	0.000	.368***	0.000	.405***	0.000	.222***	0.008
		Temperature is 18 to 24°C	-.145	0.000	-.264	0.000	-.027	0.000	-.115	0.000
	IEQ – Air quality	Odour air	-.106**	0.018	-.130*	0.084	-.043	0.687	-.152*	0.068
		Stuffy air	-.030	0.506	-.059	0.431	-.100	0.376	.020	0.817
		Air quality is fine	.136	0.000	.189	0.000	.143	0.000	.132	0.000
		Dimmed lighting	-.277***	0.000	-.326***	0.000	-.358***	0.001	-.191**	0.024

	IEQ – Lighting conditions	Glare from the lighting	.430***	0.000	.672***	0.000	.335***	0.003	.256***	0.002
		Adequate lighting	-.153	0.000	-.346	0.000	.023	0.000	-.065	0.000
	IEQ – Indoor daylight conditions	Glare from the Sun	1.237***	0.000	2.010***	0.000	1.201***	0.000	.588***	0.000
		Minimum daylight	-.364***	0.000	-.573***	0.000	-.370***	0.001	-.290***	0.001
		Soft daylight	-.873	0.000	-1.437	0.000	-.831	0.000	-.298	0.000
Thermostat	Location and tasks	Individual concentration work in Con. area	-.038	0.471	.262***	0.005	-1.591***	0.000	.097	0.371
		Formal meeting in MR	-.109**	0.039	.247**	0.020	-.729***	0.000	.001	0.991

	Informal meeting in a Col. area	.028	0.569	-.384***	0.000	.601***	0.000	.315***	0.002
	Informal meeting in a MR	.119	0.000	-.125	0.000	1.719	0.000	-.413	0.000
Season	Summer	-.219***	0.000	-.187***	0.008	-.115	0.350	-.294***	0.000
	Winter	.209***	0.000	.174**	0.011	.247**	0.034	.224***	0.006
	Fall/Spring	.010	0.000	.013	0.000	-.132	0.000	.070	0.000
Weather	Sunny	-.079*	0.062	-.141**	0.039	-.008	0.949	-.018	0.824
	Windy	.107**	0.010	.176***	0.009	-.002	0.989	.102	0.208
	Rainy	-.028	0.000	-.035	0.000	.010	0.000	-.084	0.000
Occupancy level	2 to 3 people	-.043	0.314	-.102	0.150	.033	0.790	-.034	0.676
	10 to 15 people	.023	0.589	.017	0.808	-.083	0.491	.099	0.218
	4 to 9 people	.020	0.000	.085	0.000	.050	0.000	-.065	0.000

IEQ - Temperature	Temperature is below 18°C	.481***	0.000	.839***	0.000	.319**	0.013	.217***	0.008
	Temperature is higher than 24°C	.497***	0.000	.676***	0.000	.553***	0.000	.257***	0.002
	Temperature is 18 to 24°C	-.978	0.000	-1.515	0.000	-.872	0.000	-.474	0.000
IEQ – Air quality	Odour air	.011	0.788	.009	0.892	-.019	0.867	.079	0.311
	Stuffy air	.152***	0.000	.232***	0.001	.111	0.356	.085	0.298
	Air quality is fine	-.163	0.000	-.241	0.000	-.092	0.000	-.164	0.000
IEQ – Lighting conditions	Dimmed lighting	-.008	0.855	-.008	0.904	.174	0.168	-.060	0.469
	Glare from the lighting	-.015	0.717	-.054	0.426	-.217*	0.083	.080	0.320

		Adequate lighting	.023	0.000	.062	0.000	.043	0.000	-.020	0.000
	IEQ – Indoor daylight conditions	Glare from the Sun	.011	0.793	.029	0.682	.005	0.966	-.006	0.943
		Minimum daylight	.041	0.336	.055	0.435	-.023	0.851	.064	0.436
		Soft daylight	-.052	0.000	-.084	0.000	.018	0.000	-.058	0.000
Lighting	Location and tasks	Individual concentration work in Con. area	.046	0.415	.030	0.737	-.383**	0.017	.289**	0.013
		Formal meeting in MR	-.231***	0.000	.047	0.652	-.882***	0.000	-.136	0.359
		Informal meeting in a Col. area	.098*	0.061	.018	0.846	.134	0.316	.258**	0.022

		Informal meeting in a MR	.087	0.000	-.095	0.000	1.131	0.000	-.411	0.000
	Season	Summer	-.006	0.894	.025	0.730	.129	0.234	-.150	0.106
		Winter	.042	0.351	.015	0.827	-.099	0.373	.161*	0.072
		Fall/Spring	-.036	0.000	-.040	0.000	-.030	0.000	-.011	0.000
	Weather	Sunny	-.036	0.421	-.092	0.181	.045	0.684	.058	0.512
		Windy	.016	0.724	.030	0.674	.168	0.138	-.050	0.594
		Rainy	.020	0.000	.062	0.000	-.213	0.000	-.008	0.000
	Occupancy level	2 to 3 people	.074	0.103	2.40E-02	0.729	.255**	0.027	.041	0.648
		10 to 15 people	-.052	0.251	-2.38E-02	0.731	-.096	0.393	-.072	0.432
		4 to 9 people	-.022	0.000	-1.30E-04	0.000	-.159	0.000	.031	0.000
	IEQ - Temperature	Temperature is below 18°C	-.057	0.220	-.065	0.363	.153	0.177	-.200**	0.040

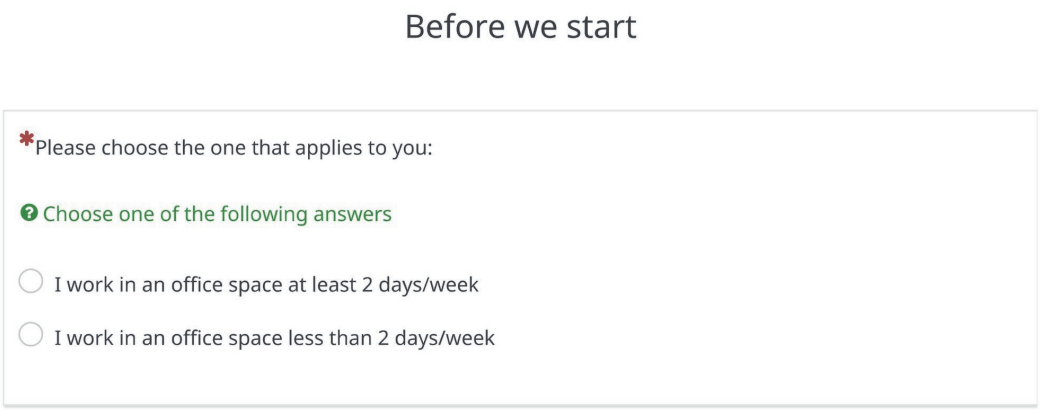
		Temperature is higher than 24°C	-.059	0.197	-.029	0.674	-.426***	0.000	.094	0.290
		Temperature is 18 to 24°C	.116	0.000	.094	0.000	.273	0.000	.106	0.000
	IEQ – Air quality	Odour air	-.003	0.949	.154**	0.027	-.217**	0.050	-.066	0.468
		Stuffy air	.094**	0.039	-.030	0.674	.300***	0.009	.179**	0.046
		Air quality is fine	-.091	0.000	-.124	0.000	-.083	0.000	-.113	0.000
	IEQ – Lighting conditions	Dimmed lighting	.077*	0.087	.081	0.232	.186	0.110	.085	0.351
		Glare from the lighting	.778***	0.000	1.134***	0.000	.685***	0.000	.330***	0.000
		Adequate lighting	-.855	0.000	-1.215	0.000	-.871	0.000	-.415	0.000
	IEQ – Indoor	Glare from the Sun	-.204***	0.000	-.217***	0.002	-.298***	0.009	-.234**	0.013

	daylight conditions	Minimum daylight	.392***	0.000	.528***	0.000	.528***	0.000	.222**	0.015
		Soft daylight	-.188	0.000	-.311	0.000	-.230	0.000	.012	0.000
Secondary	Location and tasks	Individual concentration work in Con. area	.227***	0.000	.841***	0.000	.258	0.123	-.616***	0.000
		Formal meeting in MR	-.477***	0.000	-.142	0.176	-1.720***	0.000	-.363***	0.005
		Informal meeting in a Col. area	.041	0.392	-.148	0.146	-.748***	0.000	.688***	0.000
		Informal meeting in a MR	.209	0.000	-.551	0.000	2.210	0.000	.291	0.000
	Season	Summer	.028	0.497	.061	0.396	.104	0.408	-.091	0.273

	Winter	.020	0.623	.017	0.811	-.128	0.304	.120	0.181
	Fall/Spring	-.048	0.000	-.078	0.000	.024	0.000	-.029	0.000
Weather	Sunny	-.026	0.538	-.010	0.890	-.039	0.752	-.050	0.544
	Windy	-.014	0.742	-.060	0.401	-.015	0.904	.048	0.568
	Rainy	.040	0.000	.070	0.000	.054	0.000	.002	0.000
Occupancy level	2 to 3 people	-.024	0.572	-.097	0.190	.109	0.387	-.005	0.954
	10 to 15 people	.060	0.144	.052	0.462	-.130	0.289	.103	0.224
	4 to 9 people	-.036	0.000	.045	0.000	.021	0.000	-.098	0.000
IEQ - Temperature	Temperature is below 18°C	.207***	0.000	.415***	0.000	-.013	0.922	.179**	0.039
	Temperature is higher than 24°C	.188***	0.000	.271***	0.000	.602***	0.000	.070	0.422
	Temperature is 18 to 24°C	-.395	0.000	-.686	0.000	-.589	0.000	-.249	0.000

IEQ – Air quality	Odour air	.041	0.324	.060	0.397	.085	0.502	.081	0.334
	Stuffy air	.126***	0.003	.142**	0.046	.141	0.284	.170**	0.045
	Air quality is fine	-.167	0.000	-.202	0.000	-.226	0.000	-.251	0.000
IEQ – Lighting conditions	Dimmed lighting	.006	0.880	.053	0.454	-.033	0.799	-.062	0.454
	Glare from the lighting	-.014	0.744	-.065	0.365	-.014	0.915	-.012	0.890
	Adequate lighting	.008	0.000	.012	0.000	.047	0.000	.074	0.000
IEQ – Indoor daylight conditions	Glare from the Sun	-.037	0.381	.007	0.928	-.208	0.114	-.135	0.103
	Minimum daylight	.025	0.548	-.105	0.160	.118	0.356	.054	0.514
	Soft daylight	.012	0.000	.098	0.000	.090	0.000	.081	0.000
***, **, * ==> Significance at 1%, 5%, 10% level.									

Appendix B – Survey



Employee & Current workplace

*What is your gender identity?

Choose one of the following answers

- ○ Female
- ○ Male
- ○ Others

*What is your age?

Your answer must be between 18 and 75
Only an integer value may be entered in this field.

*What is your field of occupation?

Choose one of the following answers

- ○ Business and finance
- ○ Engineering and Technology
- ○ Healthcare and Medicine

- Education and Research
- Legal and Law Enforcement
- Social Sciences and Humanities
- Trade and Services
- Science and Research
- Information Technoligy
- Other:

*What is your education level?

Choose one of the following answers

- Primary education
- Secondary education (VMBO, HAVO, VWO)
- Bachelor's degree (HBO)
- Master's degree (WO)
- Doctorate (PhD)
- Other:

*How long have you been working in the current office building?

Choose one of the following answers

- Less than 1 Year
- Equal to or more than 1 Year

*Which type of workspace do you most often use?

Choose one of the following answers

Private (single) room (1 person).

Shared room (2-3 person).

Small open-plan work area (4-9 persons).

Medium-sized open-plan work area (10-24 persons).

Large open-plan work area (More than 25 persons).

*Do you have an assigned desk/workstation in the office or choose from flexible workstations?

Choose one of the following answers

Assigned desk/workstation

Flexible use of desk/workstation

*Please indicate the amount of hours you work in the following places in a typical week (In percentage):

The sum must equal 100
Only integer values may be entered in these fields.

Office
%

Home
%

Others
%

Total:
0

*What percentage of your time do you spend on the following activities?

The sum must equal 100
Only integer values may be entered in these fields.

Formal meeting

%

Informal meeting

%

Individual concentration work

%

Total:

0

Scenario 1

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Winter and Rainy	
Social community:	
4 to 9 people work in this space	
Indoor Environmental Quality:	
Temperature is below 18 degrees	**Air quality is Fine**
Dimmed artificial lights	**Soft daylight**

1. Please select any building systems that you would propose to the others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Note:

1. **Your colleague propose to adjust the window**.

   Selecting this proposed option indicates your acceptance of others' suggestion.

   Not selecting it indicates your intention to propose something else (reflected by the other choice(s) you make.)

Select all that apply

- [ ] Adjust Window (Proposed)
- [ ] Adjust Blinds
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of personal fan
- [ ] Use of personal heater
- [ ] Do nothing

Scenario 2

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Summer and Rainy	
Social community:	
4 to 9 people work in this space	
Indoor Environmental Quality:	
Temperature is higher than 24 degrees	**Air quality is fine**
Glare from aritificial lighitng	**Glare from the Sun**

1. Please select any building systems that you would propose to others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater
- [ ] Do nothing

Scenario 3

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Fall/Spring and Windy	
Social community:	
2 to 3 people work in this space	
Indoor Environmental Quality:	
Temperature is below 18 degrees	**Stuffy air**
Glare from artificial lighting	**Minimum daylight**

1. Please select any building systems that you would propose to others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater
- [ ] Do nothing

Scenario 4

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Fall/Spring and rainy	
Social community:	
2 to 3 people work in this space	
Indoor Environmental Quality:	
Temperature is higher than 24 degrees	**Air quality is fine**
Adequate lighting	**Glare of the Sun**

1. Please select any building systems that you would propose to others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater
- [ ] Do nothing

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Winter and Windy	
Social community:	
2 to 3 people work in this space	
Indoor Environmental Quality:	
Temperature is below 18 degrees	**Air quality is fine**
Adequate lighting	**Minimum daylight**

1. Please select any building systems that you would propose to the others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Note:

1. **Your colleague propose to adjust the thermostat**.

   Selecting this proposed option indicates your acceptance of others' suggestion.

   Not selecting it indicates your intention to propose something else (reflected by the other choice(s) you make.)

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust thermostat (Proposed)
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater
- [ ] Do nothing

Scenario 6

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Winter and windy	
Social community:	
4 to 9 people work in this space	
Indoor Environmental Quality:	
Temperature is 18 to 24 degrees	**Stuffy air**
Glare from artificial lighting	**Soft daylight**

1. Please select any building systems that you would propose to others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater
- [ ] Do nothing

Scenario 7

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Summer and windy	
Social community:	
10 to 15 people work in this space	
Indoor Environmental Quality:	
Temperature is higher than 24 degrees	**Stuffy air**
Adequate lighting	**Minimum daylight**

1. Please select any building systems that you would propose to the others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Note:

1. **Your colleague propose to adjust the thermostat**.

Selecting this proposed option indicates your acceptance of others' suggestion.

Not selecting it indicates your intention to propose something else (reflected by the other choice(s) you make.)

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds
- [ ] Adjust Thermostat (Proposed)
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater

Scenario 8

*Imagine you are experiencing the following situation while doing **individual work** in a **concentration area**:

Season and weather:	
Summer and Windy	
Social community:	
2 to 3 people work in this space	
Indoor Environmental Quality:	
Temperature is higher than 24 degrees	**Odour in the air**
Dimmed artificial lights	**Glare from the Sun**

1. Please select any building systems that you would propose to the others to improve the indoor environment comfort.
2. In addition, you can choose any personal control measures that you believe would improve your indoor comfort the most.

Note:

1. **Your colleague propose to adjust the blinds**.

   Selecting this proposed option indicates your acceptance of others' suggestion.

   Not selecting it indicates your intention to propose something else (reflected by the other choice(s) you make.)

Select all that apply

- [ ] Adjust Window
- [ ] Adjust Blinds (Proposed)
- [ ] Adjust Thermostat
- [ ] Adjust Lighting
- [ ] Adjust amount of clothing
- [ ] Drinking a cold or hot beverage
- [ ] Use of Personal Fan
- [ ] Use of Personal Heater

General Information

Kindly respond to the following brief general questions, envisioning yourself within your usual workplace setting.

*Which comfort adaptive control options do you have in your office? Select all that applies.

	Yes	No	I do not know.
I can open/close the window	○	○	○
I can adjust the blinds/shades	○	○	○
I can adjust the lighting	○	○	○
I can adjust the thermostat	○	○	○

*To what extent do you agree with the following statement:

	1. Totally disagree	2	3	4	5. Totally agree
I can easily (or am able to) reach any of the building control system to change the indoor environment according to my preference.	○	○	○	○	○

*To what extent do you agree with the following statement?

	1. Totally disagree	2	3	4	5. Totally agree
My organization/company is interested in supporting environmental policies.	○	○	○	○	○
My organization/company believes it is important to protect the environment.	○	○	○	○	○
My organization/company emphasizes the use of less paper, energy and disposable products.	○	○	○	○	○

*What is you attitude towards energy usage in office environments?

Choose one of the following answers

- ○ I am actively focused on energy saving.
- ○ I am neutral towards energy conservation.
- ○ I am less inclined (mindful) towards energy conservation.

	disagree	2	3	4	5. Totally agree
I believe it is easy to use the building control system in my office to regulate the indoor environmental quality:	○	○	○	○	○

*How often do your colleagues/boss perform energy-related adaptive behaviours while in the office?

	1. Rarely	2	3	4	5. Very often	I do not know.
For instance: Open window for fresh air, Turn on air-conditioning to cool down the room, Lower the blinds to stop the Sun glare.	○	○	○	○	○	○

*Do you feel morally obliged to conserve energy in your office environment?

	1. Not at all	2	3	4	5. Extremely Yes
	○	○	○	○	○

*Please indicate the level of agreement for the following statement: I see myself as

	1. Totally disagree	2	3	4. Neutral	5	6	7. Totally agree
Extraverted, enthusiastic.	○	○	○	○	○	○	○
Critical, quarrelsome.	○	○	○	○	○	○	○
Dependable, self-disciplined.	○	○	○	○	○	○	○
Anxious, easily upset.	○	○	○	○	○	○	○
Open to new experiences, complex.	○	○	○	○	○	○	○
Reserved, quiet.	○	○	○	○	○	○	○
Sympathetic, warm.	○	○	○	○	○	○	○
Disorganized, careless.	○	○	○	○	○	○	○
Calm, emotionally stable.	○	○	○	○	○	○	○
Conventional, uncreative.	○	○	○	○	○	○	○

Appendix C – Comfort and energy trade-off data

Table 22 Distribution of cooling-prone commands during cooling period

zone	Cooling increase	Mean c_cmd	Median c_cmd	p75 c_cmd	Share c_cmd ≤ 24
FLOORX10:10XZ04AB4	393.60	24.06	24	24	0.92
FLOORX10:10XZ0303	268.91	23.99	24	24	0.92
FLOORX10:10XZ0310	251.22	23.85	24	24	0.92
FLOORX10:10XZ010	246.26	24.07	24	24	0.92
FLOORX10:10XZ0308	243.60	23.98	24	24	0.92
FLOORX10:10XZ08	217.14	24.04	24	24	0.92
FLOORX10:10XZ05	199.36	24.09	24	24	0.92
FLOORX10:10X335	197.41	23.87	24	24	0.92
FLOORX10:10XZ0312	192.95	24.06	24	24	0.92
FLOORX10:10XZ0306	192.01	24.01	24	24	0.92
FLOORX10:10X121	191.32	24.02	24	24	0.92
FLOORX10:10XZ0309	169.79	24.07	24	24	0.92
FLOORX10:10X301	169.50	23.97	24	24	0.92
FLOORX10:10XZ012	155.11	24.11	24	24	0.92
FLOORX10:10X410	146.50	23.84	24	24	0.92
FLOORX10:10X123	137.76	23.86	24	24	0.92
FLOORX10:10X124	134.04	23.92	24	24	0.92
FLOORX10:10X406	127.76	23.93	24	24	0.92
FLOORX10:10XZ013	127.10	24.02	24	24	0.92
FLOORX10:10XZ014	123.47	24.03	24	24	0.92

Table 23 Ranking of zones by highest increase in cooling demand

Zone	Zone type	Area (m2)	Occupancy capacity (max)	Advanced model cooling demand (kWh)	Baseline model cooling demand (kWh)	Difference	% Change	Warm hours advanced model	Warm hours baseline model	Warm hour reduction %	Energy-comfort trade-off (kWh)
FLOORX10:10XZ04AB4	Open office	138.4	16	5909	5515	394	7.14	110.25	312.25	64.69	1.95
FLOORX10:10XZ0303	Open office	84.6	8	3234	2965	269	9.07	193.25	384.25	49.71	1.41
FLOORX10:10XZ0310	Open office	58.3	8	2302	2051	251	12.25	153.25	357.75	57.16	1.23

FLOORX10:10XZ010	Open office	93.4	8	2623	2377	246	10.36	125.5	238.25	47.32	2.18
FLOORX10:10XZ0308	Open office	84.9	8	3222	2979	244	8.18	188.5	376	49.87	1.3
FLOORX10:10XZ08	Open office	86.1	8	2646	2429	217	8.94	111.25	227	50.99	1.88
FLOORX10:10XZ05	Open office	79.2	8	2751	2552	199	7.81	113.25	251.5	54.97	1.44
FLOORX10:10X335	Meeting room	37.8	8	1933	1735	197	11.38	330	519	36.42	1.04
FLOORX10:10XZ0312	Open office	66.1	8	2534	2341	193	8.24	195.5	366	46.58	1.13
FLOORX10:10XZ0306	Open office	75.1	8	2849	2657	192	7.23	185	385.75	52.04	0.96
FLOORX10:10X121	Open office	63.8	8	3575	3384	191	5.65	331.25	552.25	40.02	0.87

FLOORX10:10XZ0309	Open office	77.8	8	3374	3204	170	5.3	223.75	403.75	44.58	0.94
FLOORX10:10X301	Meeting room	37.8	8	1509	1339	170	12.66	104.5	265.5	60.64	1.05
FLOORX10:10XZ012	Open office	75.5	8	2292	2137	155	7.26	109.25	233	53.11	1.25
FLOORX10:10X410	Meeting room	25.2	8	990	843	147	17.37	99.75	242.5	58.87	1.03
FLOORX10:10X123	Meeting room	25.1	4	1309	1171	138	11.76	327	538.75	39.3	0.65
FLOORX10:10X124	Meeting room	25.5	4	1318	1184	134	11.32	333.75	537.75	37.94	0.66
FLOORX10:10X406	Meeting room	25.2	4	1009	881	128	14.49	93.5	237.25	60.59	0.89
FLOORX10:10XZ013	Open office	76.8	8	4473	4346	127	2.92	544.75	738.5	26.24	0.66

FLOORX10:10XZ014	Open office	79.1	8	4069	3945	123	3.13	290.25	476.5	39.09	0.66
FLOORX10:10XZ0313	Open office	25.4	4	1158	1041	117	11.22	44.5	247.5	82.02	0.58
FLOORX10:10X407	Meeting room	25.4	4	985	875	111	12.68	101.5	252.5	59.8	0.73
FLOORX10:10XZ0315	Open office	24.9	4	1140	1029	111	10.75	54.75	241.25	77.31	0.59
FLOORX10:10X220	Meeting room	18.9	4	962	853	108	12.68	318	526.5	39.6	0.52
FLOORX10:10XZ0311	Open office	26.5	4	1183	1079	104	9.64	57.5	244.5	76.48	0.56
FLOORX10:10XZ04AB	Open office	25	4	1470	1368	101	7.4	235	455.5	48.41	0.46
FLOORX10:10X306	Single office	19	2	738	639	99	15.57	88.25	255.25	65.43	0.6

FLOORX10:10X221	Meeting room	18.9	4	945	847	99	11.64	325	521.25	37.65	0.5
FLOORX10:10XZ06	Open office	24.9	4	1344	1246	98	7.86	330	571.75	42.28	0.41
FLOORX10:10XZ0304	Open office	24.9	4	1130	1035	95	9.22	54.25	236.25	77.04	0.52
FLOORX10:10XZ04AB3	Open office	25.1	4	1405	1310	94	7.19	228.25	439.75	48.1	0.45
FLOORX10:10XZ0307	Open office	63.3	8	2666	2579	87	3.37	92.25	275.25	66.49	0.47
FLOORX10:10XZ04AB2	Open office	24.2	4	1344	1262	83	6.54	225.25	423	46.75	0.42
FLOORX10:10X305	Single office	19	2	709	639	71	11.07	100	262.25	61.87	0.44
FLOORX10:10X310	Single office	12.6	1	462	407	56	13.76	101.25	231.75	56.31	0.43

FLOORX10:10X225	Single office	13.1	1	634	580	54	9.25	306.25	494	38.01	0.29
FLOORX10:10X127	Single office	12.7	1	634	582	51	8.78	338.75	514.25	34.13	0.29
FLOORX10:10X128	Single office	12.7	1	635	586	49	8.32	349.75	516.5	32.28	0.29
FLOORX10:10X224	Single office	13.1	1	626	579	47	8.12	343.5	485.25	29.21	0.33
FLOORX10:10X309	Single office	12.6	1	448	410	38	9.17	94.75	232.75	59.29	0.27
FLOORX10:10XZ03	Open office	20.2	4	540	524	16	3.09	156	329.5	52.66	0.09
FLOORX10:10X140	Meeting room	14.3	4	187	171	16	9.28	217	404.5	46.35	0.08
FLOORX10:10X240	Meeting room	14	4	147	136	11	8.46	207	289.25	28.44	0.14

FLOORX10:10X445	Meeting room	14.6	4	165	156	9	5.88	236	364.25	35.21	0.07
FLOORX10:10XZ04AB1	Corridor	260.8	0.04 person/m2	1451	1465	-13	-0.91	47	104.25	54.92	-0.23
FLOORX10:10XZ0305	Corridor	208.7	0.04 person/m2	1132	1149	-17	-1.44	44.5	84.5	47.34	-0.41
FLOORX10:10XZ09	Corridor	200.2	0.04 person/m2	1219	1238	-19	-1.51	56.75	107	46.96	-0.37
FLOORX10:10X330	Classroom	98.8	0.04 person/m2	2380	2401	-21	-0.87	211.5	374.75	43.56	-0.13
FLOORX10:10XZ0314	Corridor	258.4	0.04 person/m2	1514	1537	-22	-1.45	51.75	100.75	48.64	-0.46

FLOORX10:10XZ 0301	Open office	68	8	2481	2578	-97	-3.76	86	324.75	73.52	-0.41
FLOORX10:10XZ 0302	Open office	67.6	8	2947	3065	-118	-3.85	216.75	432.25	49.86	-0.55

Appendix D – Use case 1 extra material

Use Case 1 Heatmap

Following the annual and zone-level energy comparison, three-month heatmap diagnostics were generated for two selected ABM-controlled meeting zones. Their purpose was to examine the temporal mechanism behind the increased cooling demand, particularly the interaction between indoor temperature, outdoor–indoor temperature difference, CO_2 concentration, and natural-ventilation commands. The heatmaps show that occupant-driven window actions were not activated continuously or solely in response to high indoor temperature. Instead, they occurred during specific occupied periods and could also be triggered by relatively high CO_2 concentrations.

The CO_2 heatmaps show clear occupancy-related patterns, with higher concentrations occurring mainly during working hours and lower concentrations during unoccupied periods. The indoor-temperature heatmaps show the expected seasonal variation, with higher values during summer and lower values during winter and transition periods.

The third panel presents the outdoor–indoor temperature difference as ΔT [K], delta-t was calculated as outdoor dry-bulb temperature minus indoor air temperature. Negative values indicate that outdoor air was cooler than indoor air, suggesting potential for natural ventilation to provide cooling. Near-zero or positive delta-t values indicate that outdoor air was similar to or warmer than indoor air, meaning that window opening would provide little thermal benefit and could increase the cooling load. This panel therefore indicates whether a natural-ventilation command was thermally favourable at a particular moment.

When the four panels are considered together, they show that natural ventilation was sometimes activated even when it was not thermally advantageous. During

parts of the third week of July, for example, natural-ventilation commands reached approximately 0.5 or 1 while indoor temperature was already close to 24 °C and outdoor air was substantially warmer than indoor air. At the same moments, CO_2 concentrations were relatively high compared with adjacent periods. This suggests that the window action was likely driven by air-quality conditions rather than by a need for additional cooling. The resulting inflow of warmer outdoor air would then have increased the load on the mechanical cooling system, which continued operating to maintain the indoor cooling setpoint. Based on the data, for meeting zone 301, the total simulated hours were 2,208 hours, with 858 occupied hours (e.g., Occ > 0), and 308 occupied hours with delta t above zero. Hence, 35.9 % of the occupied hours with the natural ventilation command were active while the outdoor air was warmer than the indoor air. With the same simulated hours and occupied hours, 313 occupied hours and approximately 36.5% of occupied hours the natural ventilation was active while the outdoor air was warmer than the indoor air, for meeting room 335.

The heatmaps therefore provide temporal evidence of a multi-domain trade-off in the advanced model. Window opening could improve indoor air quality while simultaneously increasing cooling demand. This helps explain why the advanced

model reduced warm occupied hours but consumed more cooling energy than the baseline model.

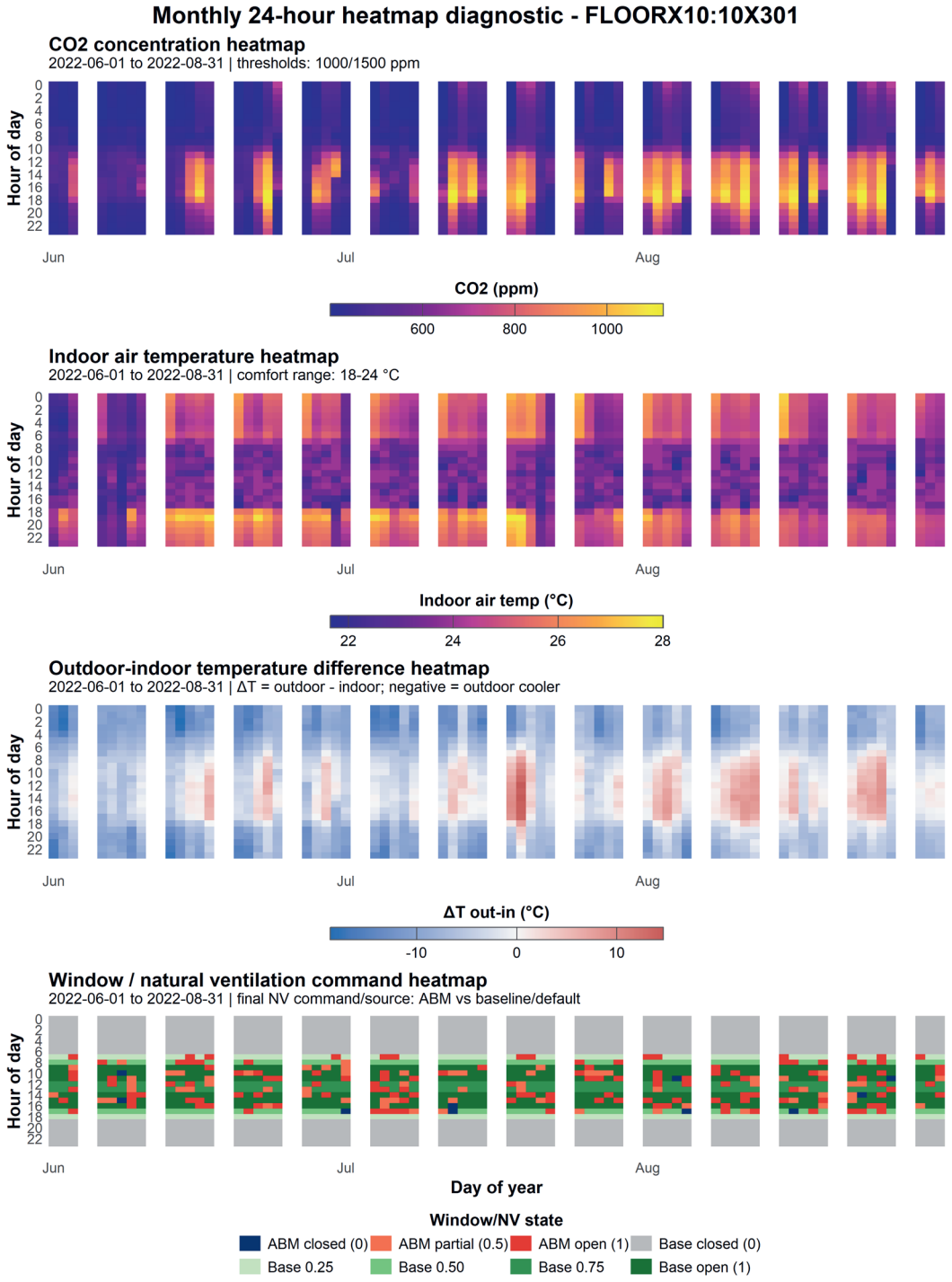


Figure 27 Three months heatmap for meeting room 301, including CO2, indoor air temperature, delta t, and natural-ventilation command state

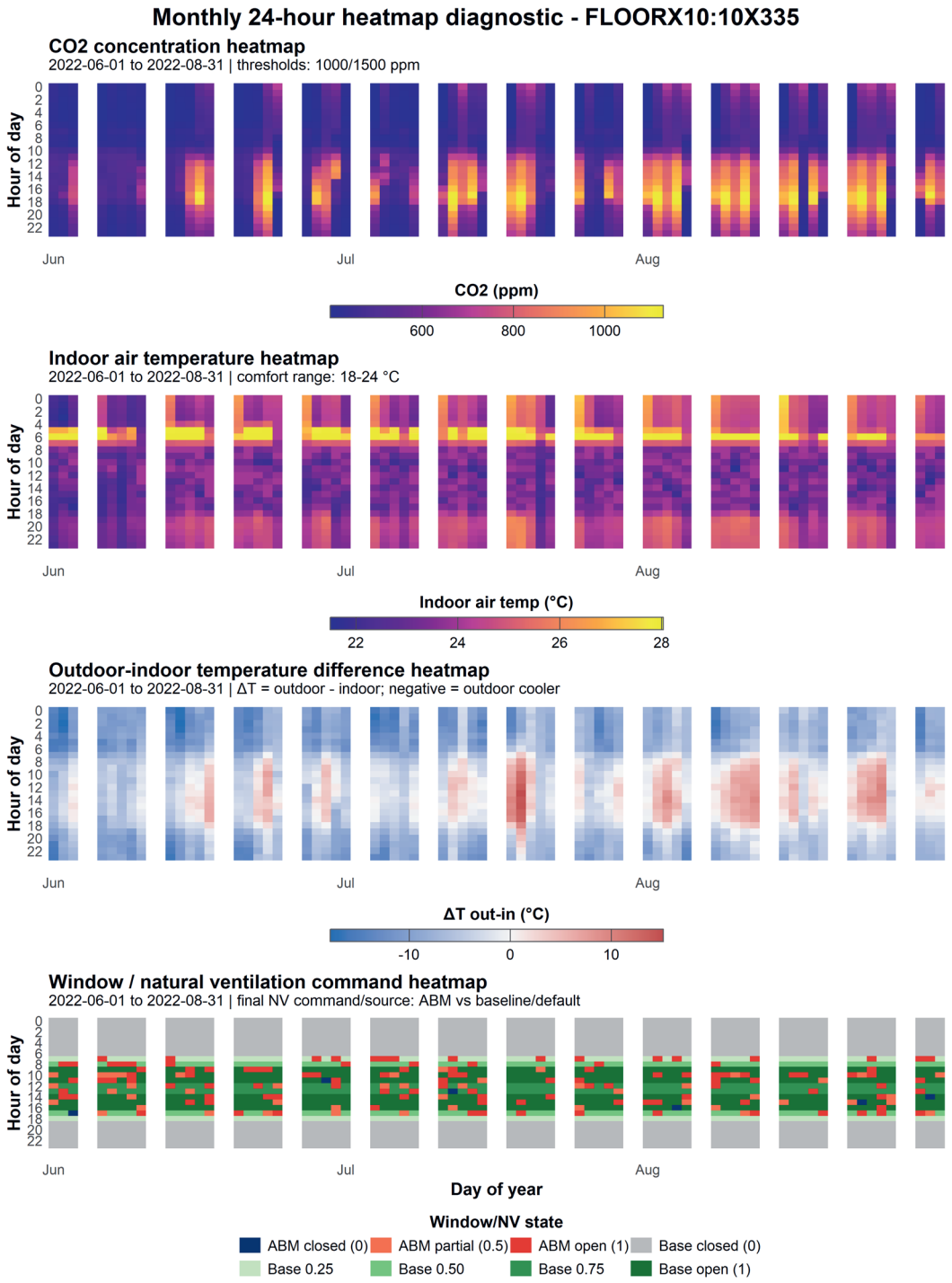


Figure 28 Three months heatmap diagnostic for meeting room 335, including CO2, indoor air temperature, delta t, and natural-ventilation command state

Use Case 1 KPIs

Figure 29 compares indoor air quality using CO_2 exceedance thresholds. The results show that most occupied zone-hours in both models remain within the acceptable CO_2 range. The baseline model shows slightly more hours in the moderate CO_2 range, while the advanced model reduces the number of hours with elevated CO_2 concentration. This indicates that occupant-driven window actions (changes in natural ventilation flow rate) can improve air quality conditions to a certain extent. However, the difference between the two models is not as strong as the thermal comfort difference. This suggests that CO_2 concentration is still mainly shaped by occupancy patterns and the underlying ventilation settings, while the advanced model adds behavioural variation through occupant choice commands.



Figure 29 CO_2 exceedance thresholds

Figure 30 presents the whole-building distribution of occupied daylight conditions. The two models show similar distribution across three context categories. This suggests that the advanced model does not fundamentally change the overall annual daylight availability of the building. The result is expected because daylight

conditions are strongly determined by building geometry, window orientation, weather, and solar exposure. Though the advanced model can influence shading commands, it does not change the physical daylight condition of the building. Therefore, at the whole building level, the difference between the baseline and advanced models remains relatively limited for daylight availability.

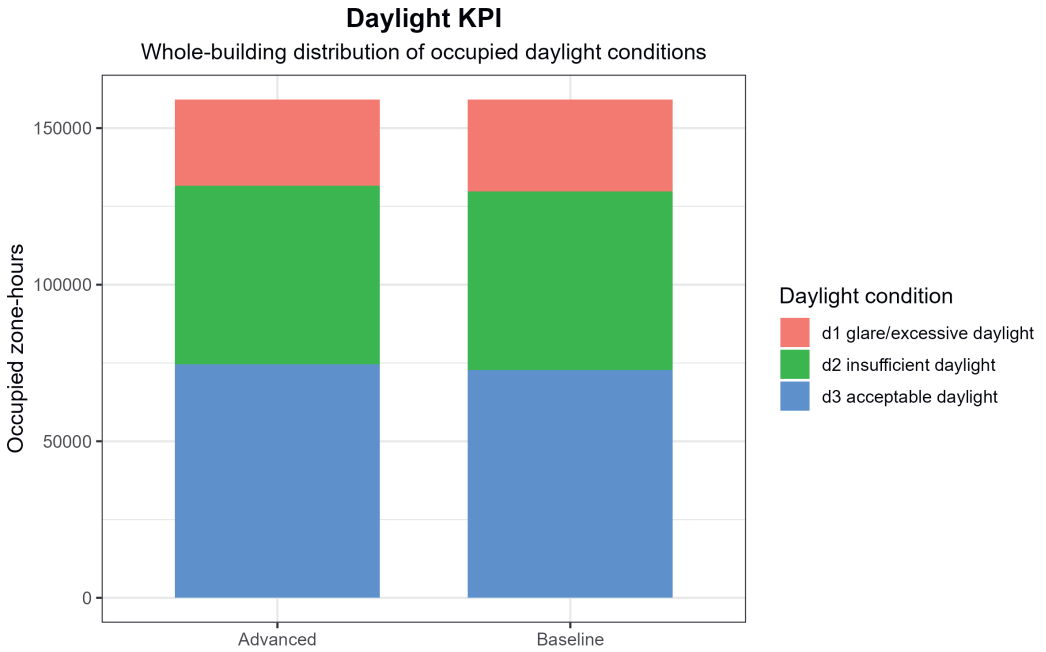


Figure 30 whole building daylighting conditions

Figure 31 further explored the excessive daylight and glare conditions (d1) by orientation. The results show that excessive daylight and glare are not evenly distributed across orientations. South-facing zones show the highest number of occupied zone-hours with excessive conditions, while east-facing zones show lower values. The difference between the two models is relatively small compared with the difference between orientation. This confirms that orientation and solar exposure are the main drivers of excessive daylight conditions. The advanced model adds occupant-responsive shading behaviour, but the overall daylight discomfort pattern is still dominated by the physical condition of the zones.

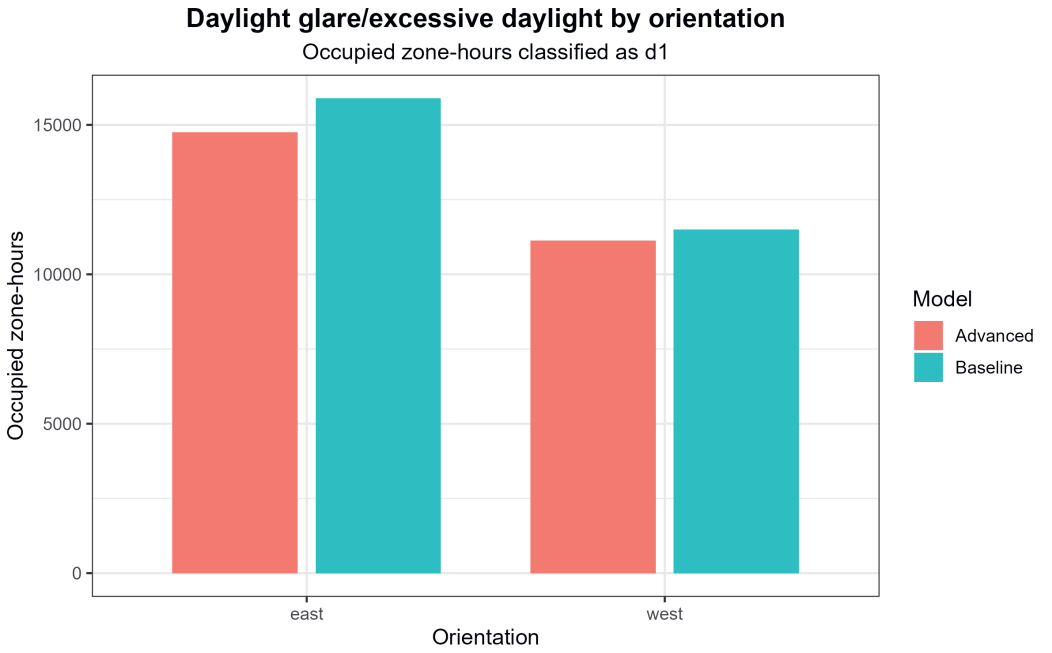


Figure 31 Excessive daylight/glare conditions by orientation

Figure 32 compares artificial lighting conditions at the whole-building level. The distribution of three context categories is similar between two models. This suggests that the advanced model does not necessarily change the annual lighting conditions. Though lighting-related ABM actions are observed during occupied periods, the final lighting conditions are still dominated by the lighting schedule and daylighting dimming logic. Therefore, the behavioural lighting control introduces variation at the control level, but its effect on the whole building remains limited.

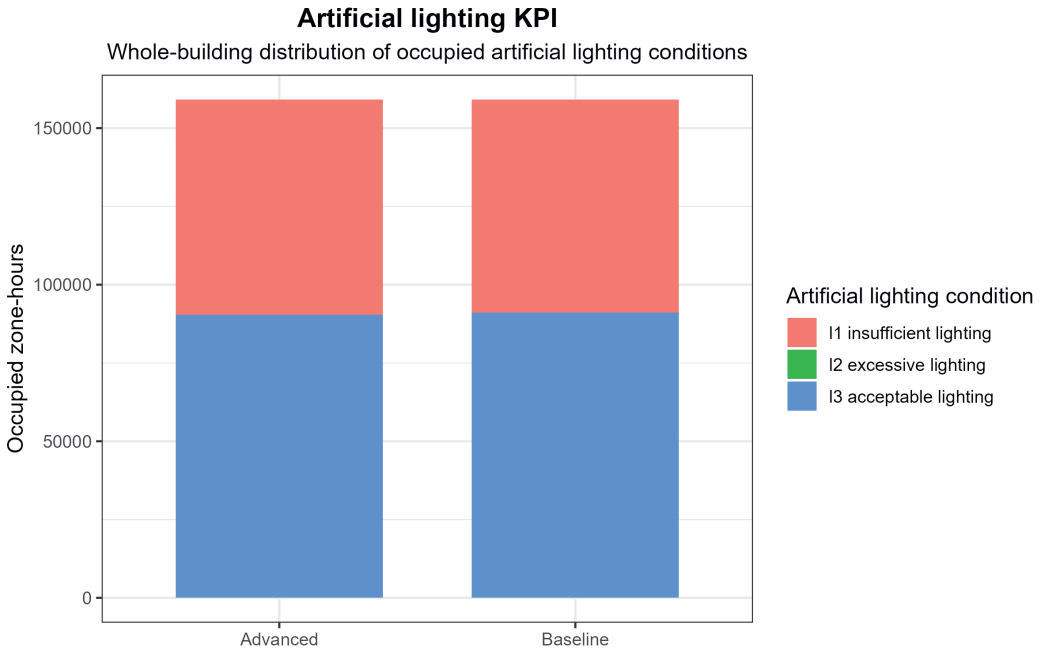


Figure 32 Artificial lighting KPI

Figure 33 shows artificial lighting discomfort by orientation. The results also show a variation across orientations, with east-facing zones showing higher discomfort. The difference between the two models remains small. This suggests that the advanced model does not substantially change the lighting outcomes at the annual whole-building scale.

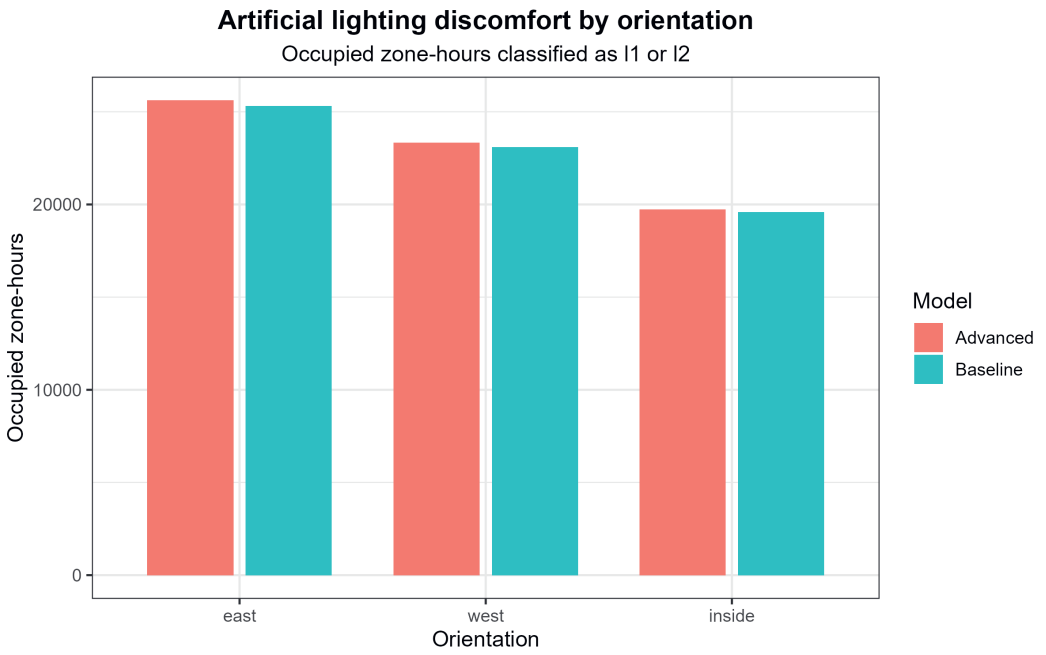


Figure 33 Artificial lighting discomfort by orientation

Appendix E – Use case 2 extra materials

Figure 34 Weekly lighting and shading setpoint for west-facing meeting zone

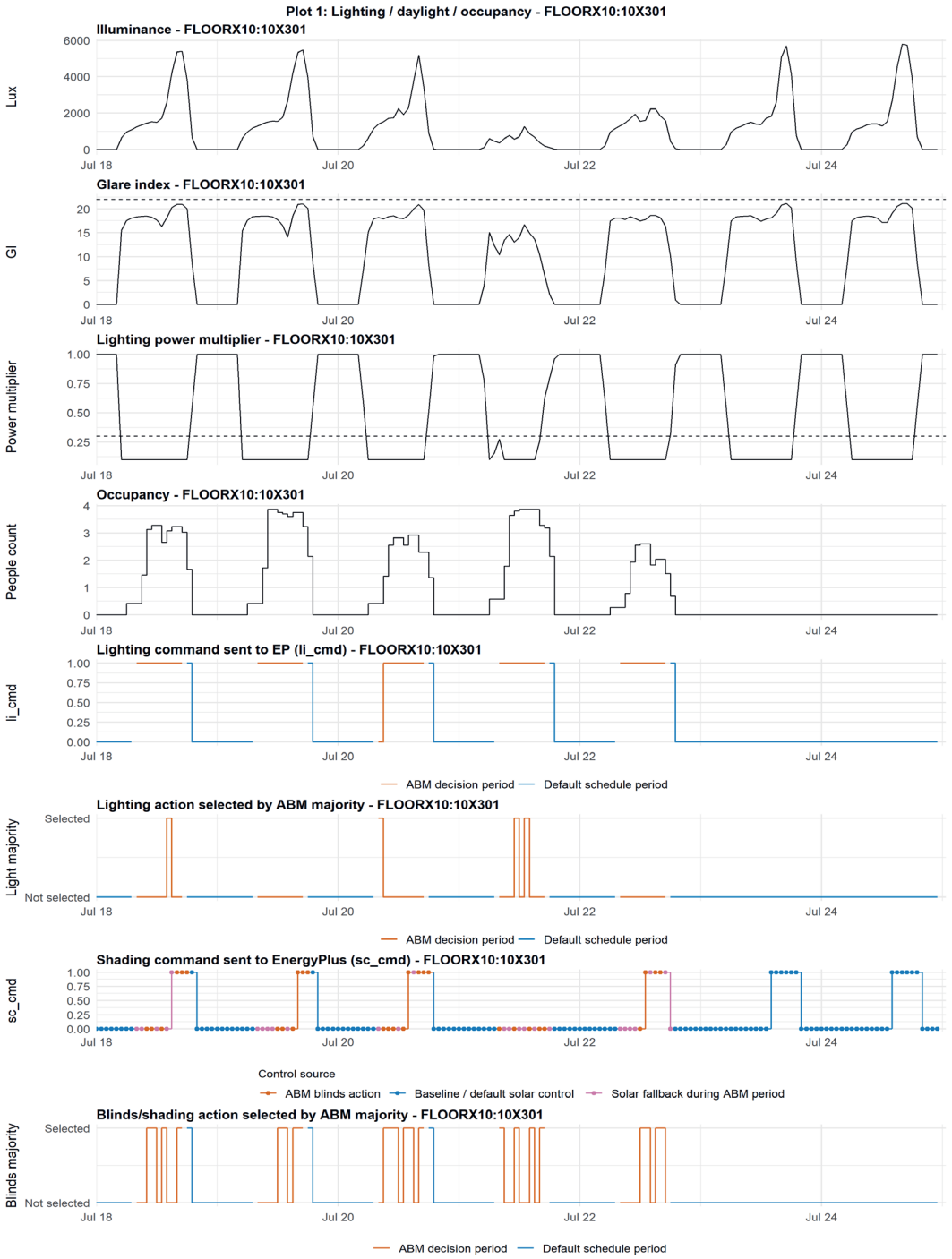
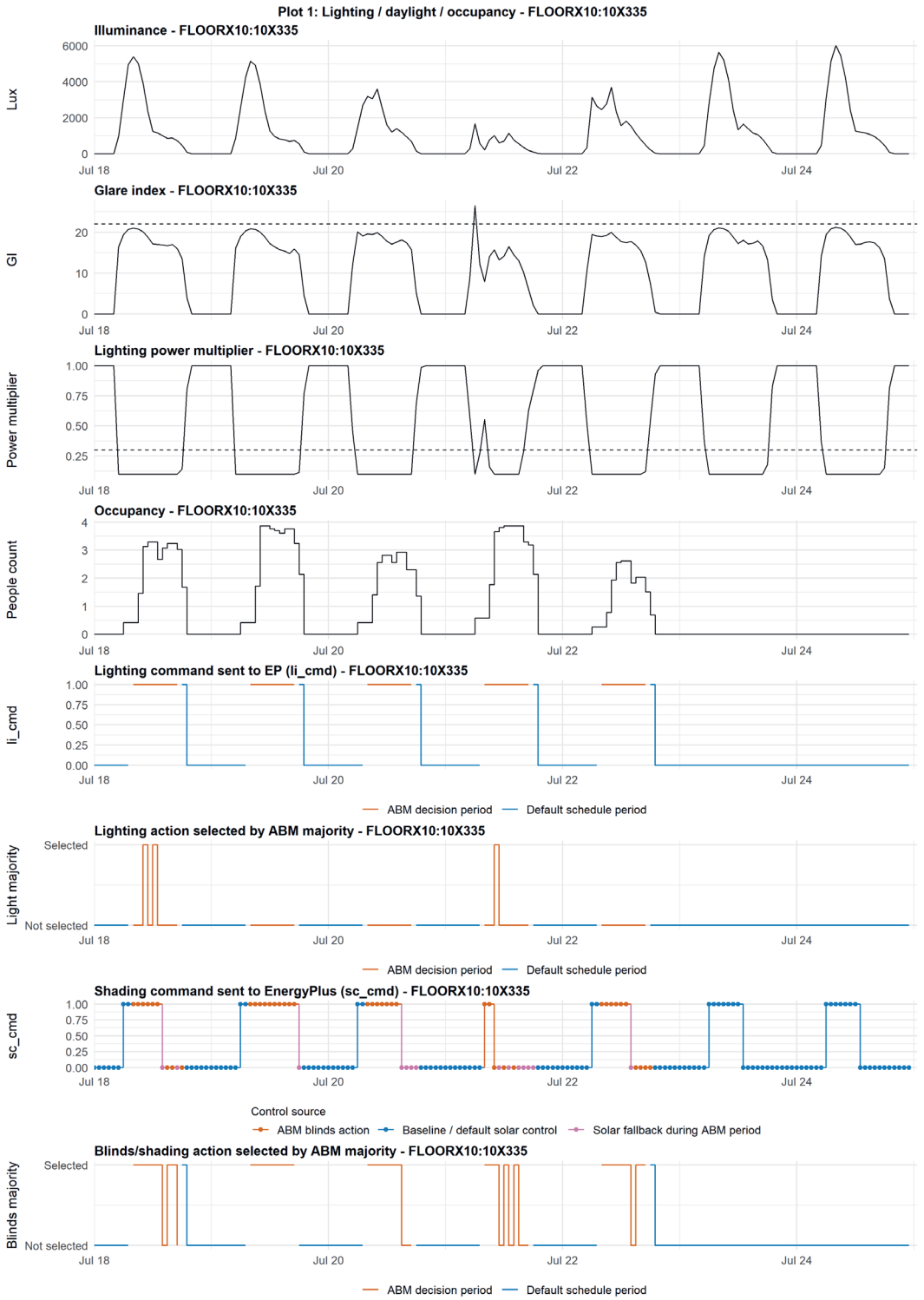


Figure 35 Weekly lighting and shading setpoint for east-facing meeting zone



Bouwstenen is een publicatiereeks
van de Faculteit Bouwkunde,
Technische Universiteit Eindhoven.
Zij presenteert resultaten van
onderzoek en andere activiteiten op
het vakgebied der Bouwkunde,
uitgevoerd in het kader van deze
Faculteit.

Bouwstenen en andere proefschriften van de
TU/e zijn online beschikbaar via:
https://research.tue.nl/

Reeds verschenen in de serie
Bouwstenen

nr 1
Elan: A Computer Model for Building Energy Design: Theory and Validation
Martin H. de Wit
H.H. Driessen
R.M.M. van der Velden

nr 2
Kwaliteit, Keuzevrijheid en Kosten: Evaluatie van Experiment Klarendal, Arnhem
J. Smeets
C. le Nobel
M. Broos
J. Frenken
A. v.d. Sanden

nr 3
Crooswijk: Van 'Bijzonder' naar 'Gewoon'
Vincent Smit
Kees Noort

nr 4
Staal in de Woningbouw
Edwin J.F. Delsing

nr 5
Mathematical Theory of Stressed Skin Action in Profiled Sheeting with Various Edge Conditions
Andre W.A.M.J. van den Bogaard

nr 6
Hoe Berekenbaar en Betrouwbaar is de Coëfficiënt k in x-ksigma en x-ks?
K.B. Lub
A.J. Bosch

nr 7
Het Typologisch Gereedschap: Een Verkennende Studie Omtrent Typologie en Omtrent de Aanpak van Typologisch Onderzoek
J.H. Luiten

nr 8
Informatievoorziening en Beheerprocessen
A. Nauta
Jos Smeets (red.)
Helga Fassbinder (projectleider)
Adrie Proveniers
J. v.d. Moosdijk

nr 9
Strukturering en Verwerking van Tijdgegevens voor de Uitvoering van Bouwwerken
ir. W.F. Schaefer
P.A. Erkelens

nr 10
Stedebouw en de Vorming van een Speciale Wetenschap
K. Doevendans

nr 11
Informatica en Ondersteuning van Ruimtelijke Besluitvorming
G.G. van der Meulen

nr 12
Staal in de Woningbouw, Korrosie-Bescherming van de Begane Grondvloer
Edwin J.F. Delsing

nr 13
Een Thermisch Model voor de Berekening van Staalplaatbetonvloeren onder Brandomstandigheden
A.F. Hamerlinck

nr 14
De Wijkgedachte in Nederland: Gemeenschapsstreven in een Stedebouwkundige Context
K. Doevendans
R. Stolzenburg

nr 15
Diaphragm Effect of Trapezoidally Profiled Steel Sheets: Experimental Research into the Influence of Force Application
Andre W.A.M.J. van den Bogaard

nr 16
Versterken met Spuit-Ferrocement: Het Mechanische Gedrag van met Spuit-Ferrocement Versterkte Gewapend Betonbalken
K.B. Lubir
M.C.G. van Wanroy

nr 17
De Tractaten van Jean Nicolas Louis Durand
G. van Zeyl

nr 18
Wonen onder een Plat Dak: Drie Opstellen over Enkele Vooronderstellingen van de Stedebouw
K. Doevendans

nr 19
Supporting Decision Making Processes: A Graphical and Interactive Analysis of Multivariate Data
W. Adams

nr 20
Self-Help Building Productivity: A Method for Improving House Building by Low-Income Groups Applied to Kenya 1990-2000
P. A. Erkelens

nr 21
De Verdeling van Woningen: Een Kwestie van Onderhandelen
Vincent Smit

nr 22
Flexibiliteit en Kosten in het Ontwerpproces: Een Besluitvormingondersteunend Model
M. Prins

nr 23
Spontane Nederzettingen Begeleid: Voorwaarden en Criteria in Sri Lanka
Po Hin Thung

nr 24
Fundamentals of the Design of Bamboo Structures
Oscar Arce-Villalobos

nr 25
Concepten van de Bouwkunde
M.F.Th. Bax (red.)
H.M.G.J. Trum (red.)

nr 26
Meaning of the Site
Xiaodong Li

nr 27
Het Woonmilieu op Begrip Gebracht: Een Speurtocht naar de Betekenis van het Begrip 'Woonmilieu'
Jaap Ketelaar

nr 28
Urban Environment in Developing Countries
editors: Peter A. Erkelens
George G. van der Meulen (red.)

nr 29
Stategische Plannen voor de Stad: Onderzoek en Planning in Drie Steden
prof.dr. H. Fassbinder (red.)
H. Rikhof (red.)

nr 30
Stedebouwkunde en Stadsbestuur
Piet Beekman

nr 31
De Architectuur van Djenné: Een Onderzoek naar de Historische Stad
P.C.M. Maas

nr 32
Conjoint Experiments and Retail Planning
Harmen Oppewal

nr 33
Strukturformen Indonesischer Bautechnik: Entwicklung Methodischer Grundlagen für eine 'Konstruktive Pattern Language' in Indonesien
Heinz Frick arch. SIA

nr 34
Styles of Architectural Designing: Empirical Research on Working Styles and Personality Dispositions
Anton P.M. van Bakel

nr 35
Conjoint Choice Models for Urban Tourism Planning and Marketing
Benedict Dellaert

nr 36
Stedelijke Planvorming als Co-Produktie
Helga Fassbinder (red.)

nr 37
Design Research in the Netherlands
editors: R.M. Oxman
M.F.Th. Bax
H.H. Achten

nr 38
Communication in the Building Industry
Bauke de Vries

nr 39
Optimaal Dimensioneren van Gelaste Plaatliggers
J.B.W. Stark
F. van Pelt
L.F.M. van Gorp
B.W.E.M. van Hove

nr 40
Huisvesting en Overwinning van Armoede
P.H. Thung
P. Beekman (red.)

nr 41
Urban Habitat: The Environment of Tomorrow
George G. van der Meulen
Peter A. Erkelens

nr 42
A Typology of Joints
John C.M. Olie

nr 43
Modeling Constraints-Based Choices for Leisure Mobility Planning
Marcus P. Stemerding

nr 44
Activity-Based Travel Demand Modeling
Dick Ettema

nr 45
Wind-Induced Pressure Fluctuations on Building Facades
Chris Geurts

nr 46
Generic Representations
Henri Achten

nr 47
Johann Santini Aichel: Architectuur en Ambiguiteit
Dirk De Meyer

nr 48
Concrete Behaviour in Multiaxial Compression
Erik van Geel

nr 49
Modelling Site Selection
Frank Witlox

nr 50
Ecolemma Model
Ferdinand Beetstra

nr 51
Conjoint Approaches to Developing Activity-Based Models
Donggen Wang

nr 52
On the Effectiveness of Ventilation
Ad Roos

nr 53
Conjoint Modeling Approaches for Residential Group preferences
Eric Molin

nr 54
Modelling Architectural Design Information by Features
Jos van Leeuwen

nr 55
A Spatial Decision Support System for the Planning of Retail and Service Facilities
Theo Arentze

nr 56
Integrated Lighting System Assistant
Ellie de Groot

nr 57
Ontwerpend Leren, Leren Ontwerpen
J.T. Boekholt

nr 58
Temporal Aspects of Theme Park Choice Behavior
Astrid Kemperman

nr 59
Ontwerp van een Geïndustrialiseerde Funderingswijze
Faas Moonen

nr 60
Merlin: A Decision Support System for Outdoor Leisure Planning
Manon van Middelkoop

nr 61
The Aura of Modernity
Jos Bosman

nr 62
Urban Form and Activity-Travel Patterns
Daniëlle Snellen

nr 63
Design Research in the Netherlands 2000
Henri Achten

nr 64
Computer Aided Dimensional Control in Building Construction
Rui Wu

nr 65
Beyond Sustainable Building
editors: Peter A. Erkelens
Sander de Jonge
August A.M. van Vliet
co-editor: Ruth J.G. Verhagen

nr 66
Das Globalrecyclingfähige Haus
Hans Löfflad

nr 67
Cool Schools for Hot Suburbs
René J. Dierkx

nr 68
A Bamboo Building Design Decision Support Tool
Fitri Mardjono

nr 69
Driving Rain on Building Envelopes
Fabien van Mook

nr 70
Heating Monumental Churches
Henk Schellen

nr 71
Van Woningverhuurder naar Aanbieder van Woongenot
Patrick Dogge

nr 72
Moisture Transfer Properties of Coated Gypsum
Emile Goossens

nr 73
Plybamboo Wall-Panels for Housing
Guillermo E. González-Beltrán

nr 74
The Future Site-Proceedings
Ger Maas
Frans van Gassel

nr 75
Radon transport in Autoclaved Aerated Concrete
Michel van der Pal

nr 76
The Reliability and Validity of Interactive Virtual Reality Computer Experiments
Amy Tan

nr 77
Measuring Housing Preferences Using Virtual Reality and Belief Networks
Maciej A. Orzechowski

nr 78
Computational Representations of Words and Associations in Architectural Design
Nicole Segers

nr 79
Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns
Chang-Hyeon Joh

nr 80
Strategic Briefing
Fayez Al Hassan

nr 81
Well Being in Hospitals
Simona Di Cicco

nr 82
Solares Bauen: Implementierungs- und Umsetzungs-Aspekte in der Hochschulausbildung in Österreich
Gerhard Schuster

nr 83
Supporting Strategic Design of Workplace Environments with Case-Based Reasoning
Shauna Mallory-Hill

nr 84
ACCEL: A Tool for Supporting Concept Generation in the Early Design Phase
Maxim Ivashkov

nr 85
Brick-Mortar Interaction in Masonry under Compression
Ad Vermeltfoort

nr 86
Zelfredzaam Wonen
Guus van Vliet

nr 87
Een Ensemble met Grootstedelijke Allure
Jos Bosman
Hans Schippers

nr 88
On the Computation of Well-Structured Graphic Representations in Architectural Design
Henri Achten

nr 89
De Evolutie van een West-Afrikaanse Vernaculaire Architectuur
Wolf Schijns

nr 90
ROMBO Tactiek
Christoph Maria Ravesloot

nr 91
External Coupling between Building Energy Simulation and Computational Fluid Dynamics
Ery Djunaedy

nr 92
Design Research in the Netherlands 2005
editors: Henri Achten
Kees Dorst
Pieter Jan Stappers
Bauke de Vries

nr 93
Ein Modell zur Baulichen Transformation
Jalil H. Saber Zaimian

nr 94
Human Lighting Demands: Healthy Lighting in an Office Environment
Myriam Aries

nr 95
A Spatial Decision Support System for the Provision and Monitoring of Urban Greenspace
Claudia Pelizaro

nr 96
Leren Creëren
Adri Proveniers

nr 97
Simlandscape
Rob de Waard

nr 98
Design Team Communication
Ad den Otter

nr 99
Humaan-Ecologisch Georiënteerde Woningbouw
Juri Czabanowski

nr 100
Hambase
Martin de Wit

nr 101
Sound Transmission through Pipe Systems and into Building Structures
Susanne Bron-van der Jagt

nr 102
Het Bouwkundig Contrapunt
Jan Francis Boelen

nr 103
A Framework for a Multi-Agent Planning Support System
Dick Saarloos

nr 104
Bracing Steel Frames with Calcium Silicate Element Walls
Bright Mweene Ng'andu

nr 105
Naar een Nieuwe Houtskeletbouw
F.N.G. De Medts

nr 106 and 107
Niet gepubliceerd

nr 108
Geborgenheid
T.E.L. van Pinxteren

nr 109
Modelling Strategic Behaviour in Anticipation of Congestion
Qi Han

nr 110
Reflecties op het Woondomein
Fred Sanders

nr 111
On Assessment of Wind Comfort by Sand Erosion
Gábor Dezsö

nr 112
Bench Heating in Monumental Churches
Dionne Limpens-Neilen

nr 113
RE. Architecture
Ana Pereira Roders

nr 114
Toward Applicable Green Architecture
Usama El Fiky

nr 115
Knowledge Representation under Inherent Uncertainty in a Multi-Agent System for Land Use Planning
Liying Ma

nr 116
Integrated Heat Air and Moisture Modeling and Simulation
Jos van Schijndel

nr 117
Concrete Behaviour in Multiaxial Compression
J.P.W. Bongers

nr 118
The Image of the Urban Landscape
Ana Moya Pellitero

nr 119
The Self-Organizing City in Vietnam
Stephanie Geertman

nr 120
A Multi-Agent Planning Support System for Assessing Externalities of Urban Form Scenarios
Rachel Katoshevski-Cavari

nr 121
Den Schulbau Neu Denken, Fühlen und Wollen
Urs Christian Maurer-Dietrich

nr 122
Peter Eisenman Theories and Practices
Bernhard Kormoss

nr 123
User Simulation of Space Utilisation
Vincent Tabak

nr 125
In Search of a Complex System Model
Oswald Devisch

nr 126
Lighting at Work: Environmental Study of Direct Effects of Lighting Level and Spectrum on Psycho-Physiological Variables
Grazyna Górnicka

nr 127
Flanking Sound Transmission through Lightweight Framed Double Leaf Walls
Stefan Schoenwald

nr 128
Bounded Rationality and Spatio-Temporal Pedestrian Shopping Behavior
Wei Zhu

nr 129
Travel Information: Impact on Activity Travel Pattern
Zhongwei Sun

nr 130
Co-Simulation for Performance Prediction of Innovative Integrated Mechanical Energy Systems in Buildings
Marija Trčka

nr 131
Niet gepubliceerd

nr 132
Architectural Cue Model in Evacuation Simulation for Underground Space Design
Chengyu Sun

nr 133
Uncertainty and Sensitivity Analysis in Building Performance Simulation for Decision Support and Design Optimization
Christina Hopfe

nr 134
Facilitating Distributed Collaboration in the AEC/FM Sector Using Semantic Web Technologies
Jacob Beetz

nr 135
Circumferentially Adhesive Bonded Glass Panes for Bracing Steel Frame in Façades
Edwin Huveners

nr 136
Influence of Temperature on Concrete Beams Strengthened in Flexure with CFRP
Ernst-Lucas Klamer

nr 137
Sturen op Klantwaarde
Jos Smeets

nr 139
Lateral Behavior of Steel Frames with Discretely Connected Precast Concrete Infill Panels
Paul Teewen

nr 140
Integral Design Method in the Context of Sustainable Building Design
Perica Savanović

nr 141
Household Activity-Travel Behavior: Implementation of Within-Household Interactions
Renni Anggraini

nr 142
Design Research in the Netherlands 2010
Henri Achten

nr 143
Modelling Life Trajectories and Transport Mode Choice Using Bayesian Belief Networks
Marloes Verhoeven

nr 144
Assessing Construction Project Performance in Ghana
William Gyadu-Asiedu

nr 145
Empowering Seniors through Domotic Homes
Masi Mohammadi

nr 146
An Integral Design Concept for Ecological Self-Compacting Concrete
Martin Hunger

nr 147
Governing Multi-Actor Decision Processes in Dutch Industrial Area Redevelopment
Erik Blokhuis

nr 148
A Multifunctional Design Approach for Sustainable Concrete
Götz Hüsken

nr 149
Quality Monitoring in Infrastructural Design-Build Projects
Ruben Favié

nr 150
Assessment Matrix for Conservation of Valuable Timber Structures
Michael Abels

nr 151
Co-simulation of Building Energy Simulation and Computational Fluid Dynamics for Whole-Building Heat, Air and Moisture Engineering
Mohammad Mirsadeghi

nr 152
External Coupling of Building Energy Simulation and Building Element Heat, Air and Moisture Simulation
Daniel Cóstola

nr 153
Adaptive Decision Making In Multi-Stakeholder Retail Planning
Ingrid Janssen

nr 154
Landscape Generator
Kymo Slager

nr 155
Constraint Specification in Architecture
Remco Niemeijer

nr 156
A Need-Based Approach to Dynamic Activity Generation
Linda Nijland

nr 157
Modeling Office Firm Dynamics in an Agent-Based Micro Simulation Framework
Gustavo Garcia Manzato

nr 158
Lightweight Floor System for Vibration Comfort
Sander Zegers

nr 159
Aanpasbaarheid van de Draagstructuur
Roel Gijsbers

nr 160
'Village in the City' in Guangzhou, China
Yanliu Lin

nr 161
Climate Risk Assessment in Museums
Marco Martens

nr 162
Social Activity-Travel Patterns
Pauline van den Berg

nr 163
Sound Concentration Caused by Curved Surfaces
Martijn Vercammen

nr 164
Design of Environmentally Friendly Calcium Sulfate-Based Building Materials: Towards an Improved Indoor Air Quality
Qingliang Yu

nr 165
Beyond Uniform Thermal Comfort on the Effects of Non-Uniformity and Individual Physiology
Lisje Schellen

nr 166
Sustainable Residential Districts
Gaby Abdalla

nr 167
Towards a Performance Assessment Methodology using Computational Simulation for Air Distribution System Designs in Operating Rooms
Mônica do Amaral Melhado

nr 168
Strategic Decision Modeling in Brownfield Redevelopment
Brano Glumac

nr 169
Pamela: A Parking Analysis Model for Predicting Effects in Local Areas
Peter van der Waerden

nr 170
A Vision Driven Wayfinding Simulation-System Based on the Architectural Features Perceived in the Office Environment
Qunli Chen

nr 171
Measuring Mental Representations Underlying Activity-Travel Choices
Oliver Horeni

nr 172
Modelling the Effects of Social Networks on Activity and Travel Behaviour
Nicole Ronald

nr 173
Uncertainty Propagation and Sensitivity Analysis Techniques in Building Performance Simulation to Support Conceptual Building and System Design
Christian Struck

nr 174
Numerical Modeling of Micro-Scale Wind-Induced Pollutant Dispersion in the Built Environment
Pierre Gousseau

nr 175
Modeling Recreation Choices over the Family Lifecycle
Anna Beatriz Grigolon

nr 176
Experimental and Numerical Analysis of Mixing Ventilation at Laminar, Transitional and Turbulent Slot Reynolds Numbers
Twan van Hooff

nr 177
Collaborative Design Support: Workshops to Stimulate Interaction and Knowledge Exchange Between Practitioners
Emile M.C.J. Quanjel

nr 178
Future-Proof Platforms for Aging-in-Place
Michiel Brink

nr 179
Motivate: A Context-Aware Mobile Application for Physical Activity Promotion
Yuzhong Lin

nr 180
Experience the City: Analysis of Space-Time Behaviour and Spatial Learning
Anastasia Moiseeva

nr 181
Unbonded Post-Tensioned Shear Walls of Calcium Silicate Element Masonry
Lex van der Meer

nr 182
Construction and Demolition Waste Recycling into Innovative Building Materials for Sustainable Construction in Tanzania
Mwita M. Sabai

nr 183
Durability of Concrete with Emphasis on Chloride Migration
Przemysław Spiesz

nr 184
Computational Modeling of Urban Wind Flow and Natural Ventilation Potential of Buildings
Rubina Ramponi

nr 185
A Distributed Dynamic Simulation Mechanism for Buildings Automation and Control Systems
Azzedine Yahiaoui

nr 186
Modeling Cognitive Learning of Urban Networks in Daily Activity-Travel Behavior
Şehnaz Cenani Durmazoğlu

nr 187
Functionality and Adaptability of Design Solutions for Public Apartment Buildings in Ghana
Stephen Agyefi-Mensah

nr 188
A Construction Waste Generation Model for Developing Countries
Lilliana Abarca-Guerrero

nr 189
Synchronizing Networks: The Modeling of Supernetworks for Activity-Travel Behavior
Feixiong Liao

nr 190
Time and Money Allocation Decisions in Out-of-Home Leisure Activity Choices
Gamze Zeynep Dane

nr 191
How to Measure Added Value of CRE and Building Design
Rianne Appel-Meulenbroek

nr 192
Secondary Materials in Cement-Based Products: Treatment, Modeling and Environmental Interaction
Miruna Florea

nr 193
Concepts for the Robustness Improvement of Self-Compacting Concrete: Effects of Admixtures and Mixture Components on the Rheology and Early Hydration at Varying Temperatures
Wolfram Schmidt

nr 194
Modelling and Simulation of Virtual Natural Lighting Solutions in Buildings
Rizki A. Mangkuto

nr 195
Nano-Silica Production at Low Temperatures from the Dissolution of Olivine - Synthesis, Tailoring and Modelling
Alberto Lazaro Garcia

nr 196
Building Energy Simulation Based Assessment of Industrial Halls for Design Support
Bruno Lee

nr 197
Computational Performance Prediction of the Potential of Hybrid Adaptable Thermal Storage Concepts for Lightweight Low-Energy Houses
Pieter-Jan Hoes

nr 198
Application of Nano-Silica in Concrete
George Quercia Bianchi

nr 199
Dynamics of Social Networks and Activity Travel Behaviour
Fariya Sharmeen

nr 200
Building Structural Design Generation and Optimisation including Spatial Modification
Juan Manuel Davila Delgado

nr 201
Hydration and Thermal Decomposition of Cement/Calcium-Sulphate Based Materials
Ariën de Korte

nr 202
Republiek van Beelden:
De Politieke Werkingen van het Ontwerp in Regionale Planvorming
Bart de Zwart

nr 203
Effects of Energy Price Increases on Individual Activity-Travel Repertoires and Energy Consumption
Dujuan Yang

nr 204
Geometry and Ventilation:
Evaluation of the Leeward Sawtooth Roof Potential in the Natural Ventilation of Buildings
Jorge Isaac Perén Montero

nr 205
Computational Modelling of Evaporative Cooling as a Climate Change Adaptation Measure at the Spatial Scale of Buildings and Streets
Hamid Montazeri

nr 206
Local Buckling of Aluminium Beams in Fire Conditions
Ronald van der Meulen

nr 207
Historic Urban Landscapes:
Framing the Integration of Urban and Heritage Planning in Multilevel Governance
Loes Veldpaus

nr 208
Sustainable Transformation of the Cities:
Urban Design Pragmatics to Achieve a Sustainable City
Ernesto Antonio Zumelzu Scheel

nr 209
Development of Sustainable Protective Ultra-High Performance Fibre Reinforced Concrete (UHPFRC):
Design, Assessment and Modeling
Rui Yu

nr 210
Uncertainty in Modeling Activity-Travel Demand in Complex Uban Systems
Soora Rasouli

nr 211
Simulation-based Performance Assessment of Climate Adaptive Greenhouse Shells
Chul-sung Lee

nr 212
Green Cities:
Modelling the Spatial Transformation of the Urban Environment using Renewable Energy Technologies
Saleh Mohammadi

nr 213
A Bounded Rationality Model of Short and Long-Term Dynamics of Activity-Travel Behavior
Ifigeneia Psarra

nr 214
Effects of Pricing Strategies on Dynamic Repertoires of Activity-Travel Behaviour
Elaheh Khademi

nr 215
Handstorm Principles for Creative and Collaborative Working
Frans van Gassel

nr 216
Light Conditions in Nursing Homes: Visual Comfort and Visual Functioning of Residents
Marianne M. Sinoo

nr 217
Woonsporen: De Sociale en Ruimtelijke Biografie van een Stedelijk Bouwblok in de Amsterdamse Transvaalbuurt
Hüseyin Hüsnü Yegenoglu

nr 218
Studies on User Control in Ambient Intelligent Systems
Berent Willem Meerbeek

nr 219
Daily Livings in a Smart Home: Users' Living Preference Modeling of Smart Homes
Erfaneh Allameh

nr 220
Smart Home Design: Spatial Preference Modeling of Smart Homes
Mohammadali Heidari Jozam

nr 221
Wonen: Discoursen, Praktijken, Perspectieven
Jos Smeets

nr 222
Personal Control over Indoor Climate in Offices: Impact on Comfort, Health and Productivity
Atze Christiaan Boerstra

nr 223
Personalized Route Finding in Multimodal Transportation Networks
Jianwe Zhang

nr 224
The Design of an Adaptive Healing Room for Stroke Patients
Elke Daemen

nr 225
Experimental and Numerical Analysis of Climate Change Induced Risks to Historic Buildings and Collections
Zara Huijbregts

nr 226
Wind Flow Modeling in Urban Areas Through Experimental and Numerical Techniques
Alessio Ricci

nr 227
Clever Climate Control for Culture: Energy Efficient Indoor Climate Control Strategies for Museums Respecting Collection Preservation and Thermal Comfort of Visitors
Rick Kramer

nr 228
Fatigue Life Estimation of Metal Structures Based on Damage Modeling
Sarmediran Silitonga

nr 229
A multi-agents and occupancy based strategy for energy management and process control on the room-level
Timilehin Moses Labeodan

nr 230
Environmental assessment of Building Integrated Photovoltaics: Numerical and Experimental Carrying Capacity Based Approach
Michiel Ritzen

nr 231
Performance of Admixture and Secondary Minerals in Alkali Activated Concrete: Sustaining a Concrete Future
Arno Keulen

nr 232
World Heritage Cities and Sustainable Urban Development:
Bridging Global and Local Levels in Monitoring the Sustainable Urban Development of World Heritage Cities
Paloma C. Guzman Molina

nr 233
Stage Acoustics and Sound Exposure in Performance and Rehearsal Spaces for Orchestras:
Methods for Physical Measurements
Remy Wenmaekers

nr 234
Municipal Solid Waste Incineration (MSWI) Bottom Ash:
From Waste to Value Characterization, Treatments and Application
Pei Tang

nr 235
Large Eddy Simulations Applied to Wind Loading and Pollutant Dispersion
Mattia Ricci

nr 236
Alkali Activated Slag-Fly Ash Binders: Design, Modeling and Application
Xu Gao

nr 237
Sodium Carbonate Activated Slag: Reaction Analysis, Microstructural Modification & Engineering Application
Bo Yuan

nr 238
Shopping Behavior in Malls
Widiyani

nr 239
Smart Grid-Building Energy Interactions: Demand Side Power Flexibility in Office Buildings
Kennedy Otieno Aduda

nr 240
Modeling Taxis Dynamic Behavior in Uncertain Urban Environments
Zheng Zhong

nr 241
Gap-Theoretical Analyses of Residential Satisfaction and Intention to Move
Wen Jiang

nr 242
Travel Satisfaction and Subjective Well-Being: A Behavioral Modeling Perspective
Yanan Gao

nr 243
Building Energy Modelling to Support the Commissioning of Holistic Data Centre Operation
Vojtech Zavrel

nr 244
Regret-Based Travel Behavior Modeling: An Extended Framework
Sunghoon Jang

nr 245
Towards Robust Low-Energy Houses: A Computational Approach for Performance Robustness Assessment using Scenario Analysis
Rajesh Reddy Kotireddy

nr 246
Development of sustainable and functionalized inorganic binder-biofiber composites
Guillaume Doudart de la Grée

nr 247
A Multiscale Analysis of the Urban Heat Island Effect: From City Averaged Temperatures to the Energy Demand of Individual Buildings
Yasin Toparlar

nr 248
Design Method for Adaptive Daylight Systems for buildings covered by large (span) roofs
Florian Heinzelmann

nr 249
Hardening, high-temperature resistance and acid resistance of one-part geopolymers
Patrick Sturm

nr 250
Effects of the built environment on dynamic repertoires of activity-travel behaviour
Aida Pontes de Aquino

nr 251
Modeling for auralization of urban environments: Incorporation of directivity in sound propagation and analysis of a framework for auralizing a car pass-by
Fotis Georgiou

nr 252
Wind Loads on Heliostats and Photovoltaic Trackers
Andreas Pfahl

nr 253
Approaches for computational performance optimization of innovative adaptive façade concepts
Roel Loonen

nr 254
Multi-scale FEM-DEM Model for Granular Materials: Micro-scale boundary conditions, Statics, and Dynamics
Jiadun Liu

nr 255
Bending Moment - Shear Force Interaction of Rolled I-Shaped Steel Sections
Rianne Willie Adriana Dekker

nr 256
Paralympic tandem cycling and handcycling: Computational and wind tunnel analysis of aerodynamic performance
Paul Fionn Mannion

nr 257
Experimental characterization and numerical modelling of 3D printed concrete: Controlling structural behaviour in the fresh and hardened state
Robert Johannes Maria Wolfs

nr 258
Requirement checking in the building industry: Enabling modularized and extensible requirement checking systems based on semantic web technologies
Chi Zhang

nr 259
A Sustainable Industrial Site Redevelopment Planning Support System
Tong Wang

nr 260
Efficient storage and retrieval of detailed building models: Multi-disciplinary and long-term use of geometric and semantic construction information
Thomas Ferdinand Krijnen

nr 261
The users' value of business center concepts for knowledge sharing and networking behavior within and between organizations
Minou Weijs-Perrée

nr 262
Characterization and improvement of aerodynamic performance of vertical axis wind turbines using computational fluid dynamics (CFD)
Abdolrahim Rezaeiha

nr 263
In-situ characterization of the acoustic impedance of vegetated roofs
Chang Liu

nr 264
Occupancy-based lighting control: Developing an energy saving strategy that ensures office workers' comfort
Christel de Bakker

nr 265
Stakeholders-Oriented Spatial Decision Support System
Cahyono Susetyo

nr 266
Climate-induced damage in oak museum objects
Rianne Aleida Luimes

nr 267
Towards individual thermal comfort: Model predictive personalized control of heating systems
Katarina Katic

nr 268
Modelling and Measuring Quality of Urban Life: Housing, Neighborhood, Transport and Job
Lida Aminian

nr 269
Optimization of an aquifer thermal energy storage system through integrated modelling of aquifer, HVAC systems and building
Basar Bozkaya

nr 270
Numerical modeling for urban sound propagation: developments in wave-based and energy-based methods
Raúl Pagán Muñoz

nr 271
Lighting in multi-user office environments: improving employee wellbeing through personal control
Sanae van der Vleuten-Chraibi

nr 272
A strategy for fit-for-purpose occupant behavior modelling in building energy and comfort performance simulation
Isabella I. Gaetani dell'Aquila d'Aragona

nr 273
Een architectuurhistorische waardestelling van naoorlogse woonwijken in Nederland: Het voorbeeld van de Westelijke Tuinsteden in Amsterdam
Eleonore Henriette Marie Mens

nr 274
Job-Housing Co-Dependent Mobility Decisions in Life Trajectories
Jia Guo

nr 275
A user-oriented focus to create healthcare facilities: decision making on strategic values
Emilia Rosalia Catharina Maria Huisman

nr 276
Dynamics of plane impinging jets at moderate Reynolds numbers – with applications to air curtains
Adelya Khayrullina

nr 277
Valorization of Municipal Solid Waste Incineration Bottom Ash - Chemical Nature, Leachability and Treatments of Hazardous Elements
Qadeer Alam

nr 278
Treatments and valorization of MSWI bottom ash - application in cement-based materials
Veronica Caprai

nr 279
Personal lighting conditions of office workers - input for intelligent systems to optimize subjective alertness
Juliëtte van Duijnhoven

nr 280
Social influence effects in tourism travel: air trip itinerary and destination choices
Xiaofeng Pan

nr 281
Advancing Post-War Housing: Integrating Heritage Impact, Environmental Impact, Hygrothermal Risk and Costs in Renovation Design Decisions
Lisanne Claartje Havinga

nr 282
Impact resistant ultra-high performance fibre reinforced concrete: materials, components and properties
Peipeng Li

nr 283
Demand-driven Science Parks: The Perceived Benefits and Trade-offs of Tenant Firms with regard to Science Park Attributes
Wei Keat Benny Ng

nr 284
Raise the lantern; how light can help to maintain a healthy and safe hospital environment focusing on nurses
Maria Petronella Johanna Aarts

nr 285
Modelling Learning and Dynamic Route and Parking Choice Behaviour under Uncertainty
Elaine Cristina Schneider de Carvalho

nr 286
Identifying indoor local microclimates for safekeeping of cultural heritage
Karin Kompatscher

nr 287
Probabilistic modeling of fatigue resistance for welded and riveted bridge details. Resistance models and estimation of uncertainty.
Davide Leonetti

nr 288
Performance of Layered UHPFRC under Static and Dynamic Loads: Effects of steel fibers, coarse aggregates and layered structures
Yangyueye Cao

nr 289
Photocatalytic abatement of the nitrogen oxide pollution: synthesis, application and long-term evaluation of titania-silica composites
Yuri Hendrix

nr 290
Assessing knowledge adoption in post-disaster reconstruction: Understanding the impact of hazard-resistant construction knowledge on reconstruction processes of self-recovering communities in Nepal and the Philippines
Eefje Hendriks

nr 291
Locating electric vehicle charging stations: A multi-agent based dynamic simulation
Seheon Kim

nr 292
De invloed van Lean Management op de beheersing van het bouwproces
Wim van den Bouwhuijsen

nr 293
Neighborhood Environment and Physical Activity of Older Adults
Zhengying Liu

nr 294
Practical and continuous luminance distribution measurements for lighting quality
Thijs Willem Kruisselbrink

nr 295
Auditory Distraction in Open-Plan Study Environments in Higher Education
Pieternella Elizabeth Braat-Eggen

nr 296
Exploring the effect of the sound environment on nurses' task performance: an applied approach focusing on prospective memory
Jikke Reinten

nr 297
Design and performance of water resistant cementitious materials– Mechanisms, evaluation and applications
Zhengyao Qu

nr 298
Design Optimization of Seasonal Thermal Energy Storage Integrated District Heating and Cooling System: A Modeling and Simulation Approach
Luyi Xu

nr 299
Land use and transport: Integrated approaches for planning and management
Zhongqi Wang

nr 300
Multi-disciplinary optimization of building spatial designs: co-evolutionary design process simulations, evolutionary algorithms, hybrid approaches
Sjonnie Boonstra

nr 301
Modeling the spatial and temporal relation between urban land use, temperature, and energy demand
Hung-Chu Chen

nr 302
Seismic retrofitting of masonry walls with flexible deep mounted CFRP strips
Ömer Serhat Türkmen

nr 303
Coupled Aerostructural Shape and Topology Optimization of Horizontal-Axis Wind Turbine Rotor Blades
Zhijun Wang

nr 304
Valorization of Recycled Waste Glass and Converter Steel Slag as Ingredients for Building Materials: Hydration and Carbonation Studies
Gang Liu

nr 305
Low-Carbon City Development based on Land Use Planning
Gengzhe Wang

nr 306
Sustainable energy transition scenario analysis for buildings and neighborhoods - Data driven optimization
Shalika Saubhagya Wickramarachchi Walker

nr 307
In-between living and manufactured: an exploratory study on biobuilding components for building design
Berrak Kirbas Akyurek

nr 308
Development of alternative cementitious binders and functionalized materials: design, performance and durability
Anna Monika Kaja

nr 309
Development a morphological approach for interactive kinetic façade design: Improving multiple occupants' visual comfort
Seyed Morteza Hosseini

nr 310
PV in urban context: modeling and simulation strategies for analyzing the performance of shaded PV systems
Ádám Bognár

nr 311
Life Trajectory, Household Car Ownership Dynamics and Home Renewable Energy Equipment Adoption
Gaofeng Gu

nr 312
Impact of Street-Scale Built Environment on Walking/Cycling around Metro Stations
Yanan Liu

nr 313
Advances in Urban Traffic Network Equilibrium Models and Algorithms
Dong Wang

nr 314
Development of an uncertainty analysis framework for model-based consequential life cycle assessment: application to activity-based modelling and life cycle assessment of multimodal mobility
Paul Martin Baustert

nr 315
Variable stiffness and damping structural joints for semi-active vibration control
Qinyu Wang

nr 316
Understanding Carsharing-Facilitating Neighborhood Preferences
Juan Wang

nr 317
Dynamic alignment of Corporate Real Estate to business strategies: An empirical analysis using historical data and in-depth modelling of decision making
Howard Cooke

nr 318
Local People Matter: Towards participatory governance of cultural heritage in China
Ji Li

nr 319
Walkability and Walkable Healthy Neighborhoods
Bojing Liao

nr 320
Light directionality in design of healthy offices: exploration of two methods
Parisa Khademagha

nr 321
Room acoustic modeling with the time-domain discontinuous Galerkin method
Huiqing Wang

nr 322
Sustainable insulating lightweight materials for enhancing indoor building performance: miscanthus, aerogel and nano-silica
Yuxuan Chen

nr 323
Computational analysis of the impact of façade geometrical details on wind flow and pollutant dispersion
Xing Zheng

nr 324
Analysis of urban wind energy potential around high-rise buildings in close proximity using computational fluid dynamics
Yu-Hsuan Jang

nr 325
A new approach to automated energy performance and fault detection and diagnosis of HVAC systems: Development of the 4S3F method
Arie Taal

nr 326
Innovative Admixtures for Modifying Viscosity and Volume Change of Cement Composites
Hossein Karimi

nr 327
Towards houses with low grid dependency: A simulation-based design optimization approach
Zahra Mohammadi

nr 328
Activation of demand flexibility for heating systems in buildings: Real-life demonstration of optimal control for power-to-heat and thermal energy storage
Christian Finck

nr 329
A computational framework for analysis and optimisation of automated solar shading systems
Samuel B. de Vries

nr 330
Challenges and potential solutions for cultural heritage adaptive reuse: a comparative study employing the Historic Urban Landscape approach
Nadia Pintossi

nr 331
Shared control in office lighting systems
Tatiana Aleksandrovna Lashina

nr 332
Comfort in Urban Public Spaces
You Peng

nr 333
Numerical modelling of metal soap formation in historical oil paintings
Gerardus Johannes Anna Maria Eumelen

nr 334
A transdisciplinary decision-making approach to food-water-energy nexus: A guide towards sustainable development
Maryam Ghodsvali

nr 335
Numerical modelling of transient low-frequency sound propagation and vibration in buildings
Indra Sihar

nr 336
Characterization of impact sound from lightweight joist floors
Yi Qin

nr 337
Cities for Children: Supporting Children and Caregivers in Participatory Urban Planning
Özlemnur Ataol

nr 338
Engaging the unengaged: Exploring citizen participation in nature-based solutions in China
Li Dai

nr 339
Municipal Solid Waste Incineration Residues: analysis, treatments, and applications
Ekaterina Loginova

nr 340
Enhancing the Uptake of Nature-Based Solutions in Urban Settings: An Information Systems Approach
Shahryar Ershad Sarabi

nr 341
Work Schedule Arrangements in Two-Adult Households with Children
Bilin Han

nr 342
Increasing awareness of urban cultural heritage using digital technologies: empirical design and analysis of a new multi-media web platform
Benshuo Wang

nr 343
Mechanical and physical properties of fibre-cement composites using alternative natural fibres
Katerina Kochova

nr 344
Numerical and experimental investigation of urban microclimate in a real compact heterogeneous urban area
Nestoras Antoniou

nr 345
Examining in-class activities to facilitate academic achievement in higher education: A framework for optimal indoor environmental conditions
Henk W. Brink

nr 346
High-temperature resistant geopolymers: composition, microstructure and performance
Kinga Malgorzata Klima

nr 347
Individual and household decision-making in shared parking
Qianqian Yan

nr 348
In-situ formation of LDHs in Alkali activated binders
Tao Liu

nr 349
Condition assessment of concrete sewer pipes through an integrated experimental-numerical approach
Irene C. Scheperboer

nr 350
In situ PU-based characterization of sound absorbing materials for room acoustic modeling purposes
Baltazar Briere de La Hosseraye

nr 351
Uncertainty analysis and management in building energy data mining: A bottom-up approach considering the temporal and spatial aspect of data
Waqas Khan

nr 352
Personalized Heating Control Systems to improve thermal comfort and reduce energy consumption
Michal Veselý

nr 353
Restorative value of the urban greenscape: Urban residential streets as restorative environments
Robert P. van Dongen

nr 354
Urban ventilation and the compact Mediterranean city: numerical investigations of the dynamic relationships between density, morphology and wind flow
Olga Palusci

nr 355
Data science for buildings: a multi-scale approach bridging occupants to smart-city energy planning
Julien Leprince

nr 356
Class Association Rule Models for Predicting Transportation Mode Choice
Jiajia Zhang

nr 357
Acceptance and use of autonomous vehicles
Zhihui Tian

nr 358
Consumer Acceptance of Crowdshipping Services
Chenyu Wang

nr 359
Determinants of habitual participation in leisure-time physical activity and active travel in life trajectories
Xiaoyue Chen

nr 360
Analysis of Citizens' Motivation and Intention Using Modern Information Technology in Urban Planning Public Participation
Wenshu Li

nr 361
Linking smart and physical port cities. Port-city interface areas: from obsolete/isolated to smart environments.
Mercè de Miguel Capdevila

nr 362
Assessment and improvement of indoor thermal comfort and energy demand of Chinese heritage apartment buildings under climate change
Muxi Lei

nr 363
Indoor airflow and heat transfer in a cross-ventilated generic building: wind tunnel experiments and computational fluid dynamics analyses
Katarina Kosutova

nr 364
A Robotic Construction Simulation Platform for Light-weight Prefabricated Structures.
Aiyu Zhu

nr 365
Lifetime prediction of vertical-axis wind turbines based on CFD simulations and high-cycle fatigue modeling
Feiyu Geng

nr 366
Computational modeling of convective heat transfer at building surfaces
Samy Iousef

nr 367
Numerical simulation of the atmospheric boundary layer with application to natural ventilation
Raffaele Vasaturo

nr 368
Bouwen zonder scrupules. De Nederlandse bouwnijverheid tijdens de bezetting en de eerste jaren van wederopbouw (1940-1950)
Geert-Jan Mellink

nr 369
Factors Promoting a Positive Experienced Neighborhood Public Space--A Virtual Environment-based analysis.
Yuwen Zhao

nr 370
Place quality making in high-speed railway station areas: Devising place quality indicators for urban design, beyond the transport-land use divide
Jinglun Du

nr 371
Sustainable Bio-based Adsorptive Concrete for Phosphorus Removal
Fan Wu

nr 372
The physical workplace as a resource for mental health: A salutogenic approach to a mentally healthy workplace design at home and at the office
Lisanne Bergefurt

nr 373
High-end application of basic oxygen furnace steel slag as sustainable building materials
Muhammad Jawad Ahmed

nr 374
Energy-Efficient Urban Rail Transit Operations: Models, Algorithms, and Applications
Kang Huang

nr 375
Household Energy Efficiency Adoption: Influencing Factors and Diffusion Interventions
Hua Du

nr 376
High-temperature resistant geopolymer-based materials out of industrial residuals.
Yan Luo

nr 377
A Simulation Approach Exploring the Impacts of Land Use Variables on Travel Behavior.
Xiaoming Lyu

nr 378
Understanding and modelling individual preferences for Mobility as a Service
Valeria Caiati

nr 379
Linking the physical and digital built environment - Enabling occupant-centric decision-making using cross-domain semantic digital twins
Alex Donkers

nr 380
Indoor Air Quality in Daycare Centers: Assessing and Mitigating Indoor Exposure on Young Children
Hailin Zheng

nr 381
A Data-Driven Approach to Understanding Visitors' Behavior to Reduce the Negative Effects of Tourism in Historical Cities
Sezi Karayazi

nr 382
Wind effects on internal depressurization for asbestos abatement
Anjali Radhakrishnan Jayakumari

nr 383
Spatiotemporal Graph Convolutional Neural Network for Robust and Accurate Traffic Flow Prediction
Yutian Liu

nr 384
Photo-responsive functional aluminosilicate cementitious materials - Design, Performance and Durability
Daoru Liu

nr 385
High-end applications of basic oxygen furnace slag as a cementitious binder. Phase Assemblage, Mechanical & Chemical Activation, Composites Application
Winnie Franco Santos

nr 386
Towards improved performance modelling of distributed PV systems in the built environment
Bin Meng

nr 387
Development of sustainable insulation materials. Design, performance and applications
Alex Koh Chuen Hon

nr 388
Simulations of Sandwich Panel Systems under Fire: Two-Scale Methods for Connections, Pyrolysis for Insulation, Experimental Validations
Qingfeng Xu

nr 389
Long-term Mechanical Performance of the Flax Fiber Reinforced Polymer Composites Considering the Environmental Effects
Bowen Xu

nr 390
Quality engineering and control for digital fabrication with concrete
Derk Bos

nr 391
Structural Engineering of 3D Printed Strain Hardening Cementitious Composites. From micro-scale analysis to application
Karsten Nefs

nr 392
Children's Outdoor Play in the Digital Age; The Role of Digital Interventions in Stimulating Children's Outdoor Play Behavior
Avin Khalilollahi

nr 393
Biophilic design and integrating nature in architecture: Guidelines for three-dimensional green spaces to innovate architectural typologies and create impact for sustainability
Weijie Zhong

nr 394
Crafting Smart Homes: Innovative Design Strategies to Enhance Housing Quality for Ageing Well
Chuan Ma

nr 395
Valorization of Natural Fibers and Municipal Solid Waste Incineration (MSWI) Bottom Ash in Building Composite
Helong Song

nr 396
Digital Placemaking and Healthy Ageing. A user-centric approach for empowering senior citizens in inclusive decision-making of future healthy ageing neighbourhoods
Peyman Najafi

nr 397
Optimizing aerodynamic performance in cycling. - Analyses of drafting strategies and skinsuit design through computational simulations and wind tunnel experiments
Thijs Druenen

nr 398
A simulation-based analytical framework for heat battery in residential use cases.
Shuwei Wang

nr 399
Design and performance of alternative cementitious materials using industrial solid wastes - carbonation and chemical activation
Yanjie Tang

nr 400
Valorization of industrial solid wastes as ingredients for construction materials: Design, Performance and Durability
Xuan Ling

nr 401
Towards Healthy Neighborhoods for Children –Analysis of Parental Perception of Child Friendliness and Children's Physical Activity
Xiaoli Gong

nr 402
Simultaneous large-scale modeling of individual and household life events
Yajie Yang

nr 403
Helical reinforcement in 3D printed concrete: Development and characterization of a novel reinforcement technique
Lauri Hass

nr 404
Advancing Sustainable Built Environment: Insights from stakeholder perspectives and decision support models
Pei-Hsuan Lee

nr 405
Children and urban green infrastructure in the digital age: children's perception and desires, and parents' attitudes, towards digitally-enabled interactions with urban green infrastructure
Shengchen Yin

nr 406
Exhibition Entanglements. The Department of Architecture at the Museo de Arte Moderno de Bogotá, 1983-1995
Michael Forero Parra

nr 407
Outdoor-to-indoor sound propagation models for noise exposure studies
Michail Evangelos Terzakis

nr 408
Conceptualising the relationship between the psychosocial and the physical learning environment. Towards an overarching theory, methodology and exploration of practices in innovative physical learning environments at a university of applied sciences
Siebren Baars

nr 409
Nano TiO2 hydrosols-based photocatalytic self-cleaning cementitious materials: FUNCTIONAL PERFORMANCES AND APPLICATIONS
Zixiao Wang

nr 410
Multi-Physics and Multi-Scale Investigations of the Temperature-Induced Response of Flax Fiber Reinforced Sandwich Footbridges with laboratory and field monitoring validation
Marco Manconi

nr 411
Flax Fiber Polyester Resin in Bridge Construction: Design, Modeling, and Long-Term Performance
Ali Shahmirzaloo

nr 412
Children's Mental Health and the Environment
Examining the role of activity patterns and environmental noise exposure
Maud Dohmen

nr 413
Heterogeneous Human Mobility Analysis using Big DataCFD modeling of air pollution in an urban street canyon by car traffic emissions - Sensitivity analyses and recommendations
Bin Zhang

nr 414
CFD modeling of air pollution in an urban street canyon by car traffic emissions - Sensitivity analyses and recommendations
Pen Qin

nr 415
The spatial planning of urban green space – an empirical analysis and land-use modeling approach
Jianfei Li

nr 416
3D-printed mortars with carbon nanotubes for self-sensing applications
Albanela Dulaj

nr 417
A Framework for Modeling and Simulating Pedestrians' Affective Experiences, Perceptions, and Activities in Public Spaces
Senqi Yang

nr 418
High-rise living - Stimulating social interaction in high-rise apartment buildings
Linh Nguyen

nr 419
Enhancing activity-based models: dynamic scheduling and trip chain modeling
Pim Labee

nr 420
Built Environment, Active Travel, and Location-Based Outdoor Activity: Spatial and Temporal Perspectives
Ting Zhou

nr 421
In the Interplay of Acceptance of Crowd-Sourced Delivery and Transportation Mode Choice within a MaaS Service
Qiang Qi

nr 422
Spatial-Temporal Effects of Land-use on Food-Water Energy Nexus: A Case Study of Beijing-Tian Urban Agglomeration
Ke Yang

nr 423
Engaging Youth with Cultural Heritage in the Digital Age An Integrated Framework for Youth Digital Participation in Cultural Heritage Management
Yingxin Zhang

nr 424
E-bikes and the Built Environment. Cross-Sectional and Longitudinal Explorations of the Determinants of E-Bike Ownership and Use in the Netherlands
Yushan Zhang

nr 425
The fault-free case of low delta-T syndrome
Alet van den Brink

nr 426
The role of viewing behavior in simulating personal light conditions
Myrta Gkaintatzi Masouti

nr 427
Multi-scale analysis of the hygro-mechanical behaviour of oak wood. A numerical and experimental study
Amin Livani

nr 428
Ceiling and attic ventilation to improve the indoor thermal environment of residential buildings in hot-humid climates
Mutmainnah

nr 429
A multiscale approach to sustainable silica aerogels. Optimizing synthesis, waste valorization, and environmental analysis
Marina Borzova

nr 430
Smart and Hybrid Workplaces from the Perspective of Municipal Employees: Preferences and Experiences in Office- and Home-Workplaces
Deniz Tuzcuoglu

nr 431
High-temperature resistant sprayed UHPC based on PC-CAC-C$ system
Jia He

nr 432
Semantics for Smart Building Systems: Towards Portable Demand Side Management Applications in Buildings
Rathnayaka Mudiyanselag

nr 433
Salt Hydrate Phase Change Materials: Material Behaviour and Thermal Energy Storage Applications
Charles Wesemann

nr 434
A hybrid computational framework for room-acoustic prediction and assessment: Room impulse response based parameter analysis and HRTF-based auralization
Wouter Wittebol

nr 435
Evaluating Peer Effects in the Transition to Energy Neutral Homes - An Econometric Approach
Tije van Casteren

nr 436
Analysis and Modeling of Aggregated Sound Scattering Effects in Enclosures
Xie Dingding

nr 437
High-Resolution Modeling of Distributed Photovoltaic Systems in Cities: Development, Validation and Applications
Tian Bouwen

nr 438
Semantic integration for urban energy transition. Linked data for cross sector interaction
Xuan Liu

nr 439
Local composition control in 3D concrete printing. Experimental and theoretical foundation for informed system design
Aart Harmen Deetman

nr 440
Simulation-based design optimization of local energy communities with coordinated building demand flexibility and distributed energy resources
Seyedeh Farzaneh Mousavi Motlagh

nr 441
Restorative environments in later life. (Design) guidelines for restorative neighbourhood open spaces to support mental health of older adults.
Anne Grave

nr 442
Theorizing Archivology: A Multisite Inquiry into the Convergence of Archival and Curatorial Practices in Architecture after the Archival Turn
Emilie Banville

nr 443
Prefiguring resilient futures: practices and infrastructures of care, experimentation and collective agency in neighborhood living rooms
Louwrens Botha

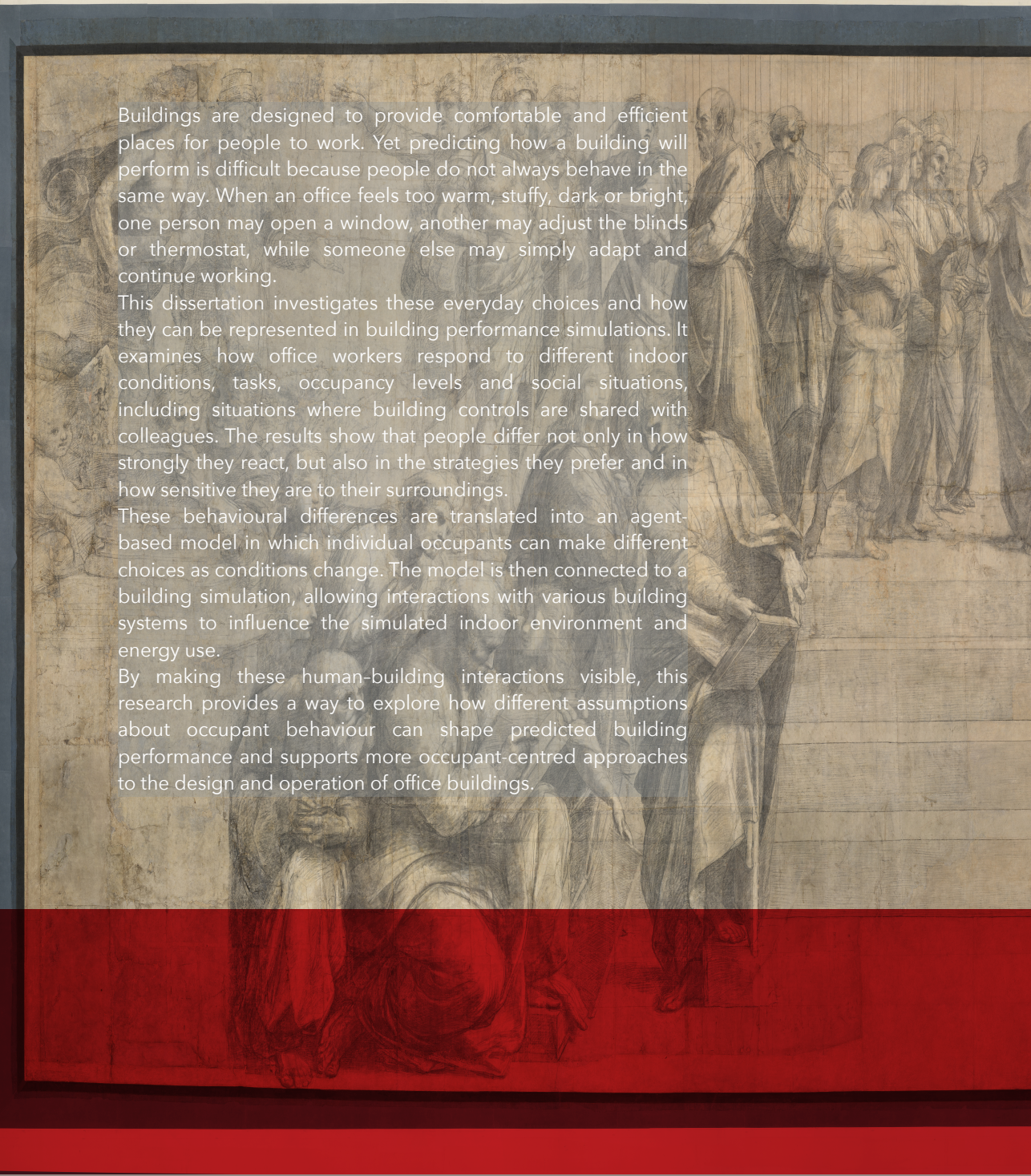
nr 444
Augmented Urban Planning: A Systematic Framework for Sociotechnical Integration of Digital Representations in Urban Planning
Shervin Azadi

nr 445
Understanding and Enabling Occupant Comfort in Smart Buildings
Nitant Upasani

nr 446
A Lens Toward Healthy Aging - Associations Between Environments, Daily Activity Patterns, and Loneliness
Yongchen Zou

nr 447
Sleep and technology: exploring non-pharmacological interventions for people with dementia and their caregivers living at home
Chantal Huisman

nr 448
Particle–airflow interactions in built environments: Modeling and experimental investigation of outdoor spray cooling and indoor aerosol control
Lili Xia



Buildings are designed to provide comfortable and efficient places for people to work. Yet predicting how a building will perform is difficult because people do not always behave in the same way. When an office feels too warm, stuffy, dark or bright, one person may open a window, another may adjust the blinds or thermostat, while someone else may simply adapt and continue working.

This dissertation investigates these everyday choices and how they can be represented in building performance simulations. It examines how office workers respond to different indoor conditions, tasks, occupancy levels and social situations, including situations where building controls are shared with colleagues. The results show that people differ not only in how strongly they react, but also in the strategies they prefer and in how sensitive they are to their surroundings.

These behavioural differences are translated into an agent-based model in which individual occupants can make different choices as conditions change. The model is then connected to a building simulation, allowing interactions with various building systems to influence the simulated indoor environment and energy use.

By making these human–building interactions visible, this research provides a way to explore how different assumptions about occupant behaviour can shape predicted building performance and supports more occupant-centred approaches to the design and operation of office buildings.

DEPARTMENT OF THE BUILT ENVIRONMENT

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY