EXPLORING ENERGY-RELATED OCCUPANT BEHAVIOR IN OFFICE BUILDINGS: AN INTERDISCIPLINARY STUDY IN THE CONTEXT OF BUILDING PHYSICS AND SOCIAL PSYCHOLOGY

A Ph.D. Dissertation

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December 2024

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Bilkent University 2024

To my family…

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The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

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In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN INTERIOR ARCHITECTURE AND ENVIRONMENTAL DESIGN

THE DEPARTMENT OF
INTERIOR ARCHITECTURE AND ENVIRONMENTAL DESIGN
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
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By İrem Çağlayan

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Interior Architecture and Environmental Design.

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ABSTRACT

EXPLORING ENERGY-RELATED OCCUPANT BEHAVIOR IN OFFICE BUILDINGS: AN INTERDISCIPLINARY STUDY IN THE CONTEXT OF BUILDING PHYSICS AND SOCIAL PSYCHOLOGY

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December 2024

This thesis presents a novel approach to occupant behavior (OB) modeling in office buildings by integrating psycho-social behavioral clusters with environmental parameters through fuzzy logic modeling. Traditional building performance simulations often rely on static and generalized assumptions, which fail to capture the dynamic and complex nature of human behavior in energy use, contributing to the energy performance gap. This research addresses this challenge through a three-step methodology: (1) online study, (2) field study, and (3) fuzzy logic modeling. Each step informs the next, culminating in a holistic framework for more accurate energy performance predictions.

In Step 01, three distinct behavioral clusters were developed using the Theory of Planned Behavior, Self-Determination Theory, and habit and comfort constructs, capturing different energy-saving tendencies, motivation, and comfort needs. Step 02 mapped these clusters against environmental parameters—outdoor and indoor temperature, humidity, and CO_2 levels—to create a dynamic, context-responsive model of occupant actions. Finally, Step 03 implemented a fuzzy logic system in MATLAB, designed to integrate with EnergyPlus™ via its Energy Management System (EMS). This integration enables real-time simulation of occupant responses to environmental shifts, incorporating psycho-social influences and seasonal variations, thereby improving the precision and adaptability of energy consumption forecasts.

Keywords: Building Simulation Tools, Energy Efficiency, Environmental Parameters, Energy Performance Gap, Occupant Behavior

ÖZET

OFİS BİNALARINDA ENERJİ İLE İLGİLİ KULLANICI DAVRANIŞLARININ ARAŞTIRILMASI: BİNA FİZİĞİ VE SOSYAL PSİKOLOJİ BAĞLAMINDA DİSİPLİNLER ARASI BİR ÇALIŞMA

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Bu tez, ofis binalarında kullanıcı davranışı (OB) modellemesine yenilikçi bir yaklaşım sunarak, psikososyal davranış kümelerini çevresel parametrelerle bulanık mantık modelleme aracılığıyla entegre etmektedir. Geleneksel bina performansı simülasyonları, enerji kullanımındaki insan davranışının dinamik ve karmaşık doğasını yakalayamayan statik ve genelleştirilmiş varsayımlara dayanır; bu da enerji performans boşluğuna katkıda bulunur. Bu araştırma, bu sorunu üç adımlı bir metodoloji ile ele almaktadır: (1) çevrimiçi çalışma, (2) saha çalışması ve (3) bulanık mantık modelleme. Her adım bir sonraki adımı bilgilendirerek, daha doğru enerji performansı tahminleri için bütüncül bir çerçeve oluşturmaktadır.

Adım 01'de, Planlı Davranış Teorisi, Öz-Belirleme Teorisi ile alışkanlık ve konfor unsurlarına dayalı üç farklı davranış kümesi geliştirilmiştir. Bu kümeler, enerji tasarrufu eğilimleri, motivasyon ve konfor ihtiyaçlarındaki farklılıkları ortaya koymaktadır. Adım 02' de, bu kümeler çevresel parametreler — dış ve iç sıcaklık, nem ve CO_2 seviyeleri — ile eşleştirilerek, bağlama duyarlı ve dinamik bir kullanıcı davranışı modeli oluşturulmuştur. Son olarak, Adım 03’ te, MATLAB'de geliştirilmiş bir bulanık mantık sistemi, EnergyPlus™'ın Enerji Yönetim Sistemi (EMS) aracılığıyla entegre edilmiştir. Bu entegrasyon, psikososyal etkileri ve mevsimsel değişiklikleri yansıtarak çevresel değişimlere karşı kullanıcı tepkilerinin gerçek zamanlı simülasyonunu mümkün kılmakta ve enerji tüketimi tahminlerinin hassasiyetini ve uyarlanabilirliğini artırmaktadır.

Anahtar Kelimeler: Bina Simülasyon Araçları, Çevresel Parametreler, Enerji Performans Boşluğu, Enerji Verimliliği, Kullanıcı Davranışı

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CHAPTER 1

INTRODUCTION

The rapid pace of urbanization and the expansion of the building sector have heightened global awareness of environmental issues in both practice and research (Chuai, Lu, Huang, & Zhao, 2021). With people spending most of their time indoors, conserving energy within buildings is crucial. The built environment accounts for one-third of primary energy use, 40% of global energy consumption, and 30% of energy-related greenhouse emissions (Li, Zhang, Zhang, & Jha, 2021). Therefore, enhancing energy efficiency in buildings is a cornerstone of energy and climate strategies to reduce carbon emissions (Paone & Bacher, 2018). While there have been substantial efforts to develop innovative building systems to lower energy consumption, further improvements are essential. Physical characteristics, indoor environmental conditions, operations, maintenance, and—crucially—occupant behavior (OB) all shape building energy performance (Zhang, Bai, Mills, & Pezzey, 2018). As Janda (2011) noted, “Buildings do not use energy: people do.” Occupant behavior significantly impacts building energy performance, with OB-related factors accounting for substantial variations in energy use. According to Bottaccioli et al. (2017), OB can lead to up to 30% of energy waste in buildings, underscoring the importance of considering OB in energy consumption analysis.

Despite the significant role of OB in influencing energy use—through actions related to ventilation, cooling, heating, and lighting—our understanding of energy-related human-building interactions remains limited (Hong, Yan, D’Oca, & Chen, 2017). Interest in OB has grown notably since the early 2000s, with increasing academic research examining OB and its impacts (Harputlugil & de Wilde, 2021). Because OB in buildings is inherently subjective, involving individual behaviors and movement, it is often assessed with assumptions rather than measured behavioral data. These assumptions introduce limitations to current tools that measure behavioral impacts on building energy efficiency (Hong et al., 2017). Therefore, reliable models are needed to analyze building-occupant interactions and predict energy use patterns accurately.

Given the randomness and unpredictability of OB, understanding the complex interactions between buildings, the environment, and human behavior requires robust methodologies and techniques. Such approaches are essential to effectively model and simulate OB for accurate energy performance assessment across the building life cycle (Hong, D'Oca, Turner, & Taylor-Lange, 2015). The IEA EBC Annex 66, "Definition and Simulation of Occupant Behavior in Buildings," seeks to advance this area by developing new tools, methodologies, and datasets to simulate OB in buildings (International Energy Agency, 2018). While technology is instrumental in enhancing our understanding of OB, it alone cannot guarantee reduced energy consumption (Zhang et al., 2018).

1.1 Problem Statement

The "energy performance gap" presents a significant challenge arising from the difficulty in accurately measuring occupant behavior (OB). This gap reflects the difference between the actual and predicted energy usage in buildings (Hong, Chen, Belafi, & D'Oca, 2018). Building simulation tools are widely used to estimate energy consumption, assuming predicted and actual energy use should closely align (Hong et al., 2015). Despite the maturity of these simulation tools and algorithms, there is still limited understanding of how occupant behavior impacts simulated energy use (He, Hong, & Chou, 2021). A deeper understanding and accurate modeling of OB are essential to narrow the gap between designed and actual energy performance. Therefore, effectively integrating OB modeling into simulation tools is crucial to closing this gap and achieving more reliable energy consumption predictions.

1.2 Thesis Aim

Within this context, the study aims to identify occupants' energy-related behavioral actions in office buildings to develop OB models by integrating social psychology and building physics. Herein, more realistic and representative behavioral algorithms can support the building design and reduce the energy performance gap in building simulations. By focusing on socio-technical data interchange and co-learning in the disciplines of building science and social psychology, the study has the following objectives:

1) To identify clusters of energy-related behaviors in office buildings through a psycho-social online survey.
2) To investigate the interrelationship between behavioral clusters of energy-related behaviors, occupant actions (window operation, blind operation, solar shading operation, door operation, thermostat adjustment, and clothing adjustment), indoor stimuli (temperature, relative humidity, and CO_2), and outdoor stimuli (temperature).
3) To develop behavioral models by providing a more accurate description of the relationship between occupant behavior and influencing factors at different levels.
4) To implement the generated behavioral models into building simulation software.

To achieve these objectives, the study seeks to answer the following research questions:

RQ_1: What are the different groups of office occupants categorized based on psycho-social behavioral data?

RQ_2: What is the relationship between identified behavioral clusters related to occupant behavior and their behavioral actions?

RQ_3: How do behavioral actions correlate with indoor and outdoor environmental parameters?

> **RQ_{3a}:** How do window operation correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?
>
> **RQ_{3b}:** How do door operations correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?
>
> **RQ_{3c}:** How do solar shading operations correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?
>
> **RQ_{3d}:** How do thermostats correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?
>
> **RQ_{3e}:** How do clothing adjustments correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?
>
> **RQ_{3f}:** How does drink intake correlate with outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2?

This thesis substantially contributes to studying energy-related occupant behavior (OB) in office buildings through a structured, interdisciplinary approach. First, it introduces a clustering-based method to profile occupants using psycho-social data, revealing distinct groups of energy-saving behaviors informed by social psychology theories. Second, the thesis emphasizes the importance of understanding individual motivations and actions within the workplace, addressing challenges such as the "public good dilemma," where employees may not feel responsible for energy use (Perrow & Olson, 1973). By exploring the interactions between intentional drivers, habits, comfort, and environmental factors, this work provides a comprehensive framework for designing energy-efficient policies and workplace strategies that align with actual occupant behavior.

Third, the study advances OB research by integrating behavioral clusters with environmental parameters, uncovering correlations between specific occupant actions (e.g., window operation, thermostat adjustments) and indoor and outdoor conditions.

Furthermore, the thesis develops a fuzzy logic model to predict occupant actions in real time, capturing OB's complex and adaptive nature. This model addresses a critical gap in energy behavior modeling by combining psycho-social theories with dynamic environmental data, offering a holistic tool for more precise building performance simulations.

Overall, this approach fills an essential gap in OB research by integrating multiple aspects of occupant behavior—including psycho-social characteristics and environmental factors—into a cohesive dataset. This interdisciplinary framework aligns with the holistic approach recommended by Harputlugil and de Wilde (2021), providing valuable insights for future studies and applications in building design and energy management.

CHAPTER 2

OCCUPANT BEHAVIOR (OB)

2.1 OB in buildings

Shi et al. (2019) defined occupant behavior (OB) as the actions and responses of occupants to various stimuli. Similarly, Hong et al. (2015) described OB as actions or reactions to environmental conditions such as temperature, indoor air quality (IAQ), or lighting, while Deng and Chen (2019) defined OB in terms of occupant movements and interactions with building systems like windows, blinds, lights, or thermostats. Most definitions of OB center on occupant actions and controls within building systems (e.g., lighting, windows, HVAC). These actions and responses can be classified into physiological, environmental, spatial, and individual adjustments (Arslan, Cruz & Ginhac, 2019), highlighting human reactions to buildings through different behaviors.

In most buildings, occupants have various options for interacting with their environment, including entering or leaving a room, adjusting indoor environmental quality (IEQ) conditions (such as windows, doors, or blinds), and using other devices. These interactions can result in a change of state (active interaction) or maintain the current state (no interaction), as illustrated in Figure 1 (Wagner et al., 2017). Occupants engage in both adaptive and non-adaptive behaviors in buildings. Adaptive triggers prompt behaviors that help occupants adjust to indoor conditions—for example, opening a window to reduce CO_2 concentration. Non-adaptive behaviors, however, are driven by triggers unrelated to environmental adaptation, such as switching on lights when entering a room, regardless of lighting needs (Wagner et al., 2017).

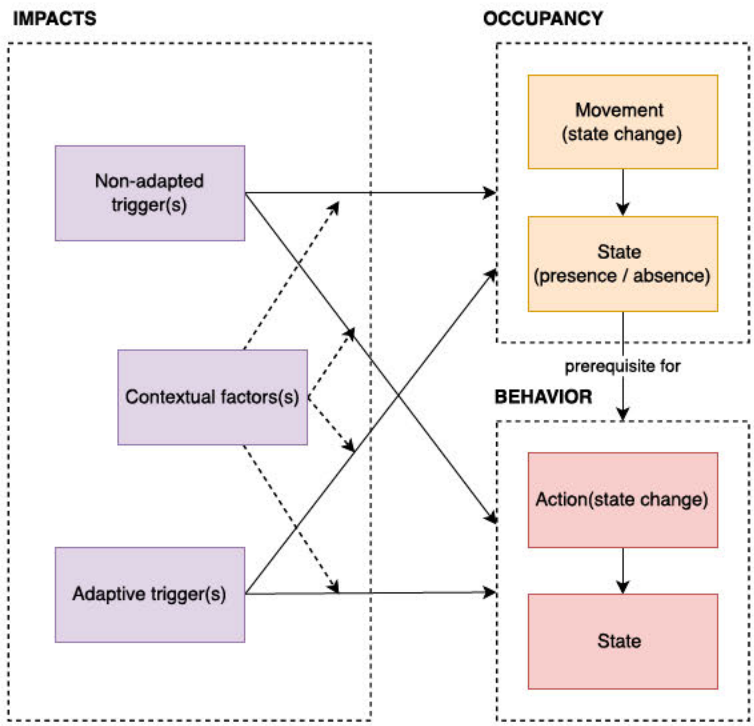


Figure 1. The ontology of occupant behavior (Wagner & Brien, 2018).

Human interactions with building systems to adjust indoor environmental conditions play an essential role in the energy use and performance of the buildings (Zhang et al., 2018). Studies show that OB significantly impacts energy consumption, waste, and CO_2 emissions in buildings (Csoknyai et al., 2019; Vogiatzi et al., 2018). A deeper understanding of OB is crucial for robustly predicting building energy use (Ali, Thaheem, Ullah & Sepasgozar, 2020). However, since numerous variables may drive their actions, occupants do not always act systematically (Harputlugil & de Wilde, 2021).

Existing studies specified different aspects of OB. For example, D'Oca et al. (2018) and Gkargkavouzi et al. (2019) examine human dimensions, while Stazi et al. (2017a) focus on the driving factors behind OB. Other researchers, like Naylor et al. (2018) and Deng et al. (2021), study occupant-centric control systems. Amasyali and El-Gohary (2018) provide a review of data-driven OB studies related to energy consumption prediction, while Delzendeh et al. (2017) examine factors influencing energy-related OB, and Khosrowpour et al. (2018) categorize research by data analysis methods. De Bakker et al. (2017) concentrate on OB related to lighting, and Guyot et al. (2018) focus on ventilation. Technical issues remain a predominant theme in OB research (Franceschini & Neves, 2022; Khosrowpour et al., 2018). According to Li et al. (2018), residences and offices are the most common contexts for OB studies, with surveying and indoor monitoring being popular data-gathering methods.

To predict building energy consumption, prior studies have used models such as statistical (Sun & Hong, 2017), linear regression (Andersen, Olesen & Toftum, 2011), logistical regression (Fabi, Andersen & Corgnati, 2013), stochastic (Feng, Yan, & Wang, 2017) and agent-based (Papadopoulos & Azar, 2016). Despite these advancements, current OB models often lack a comprehensive integration of psycho-social and environmental factors, which limits their accuracy. Many models also overlook the variability and adaptability of human behavior, oversimplifying complex interactions. Further research is needed to develop more nuanced OB models that better capture occupant behavior and improve predictive reliability, narrowing the gap between predicted and actual building energy performance.

2.2 Effects of OB on the building energy performance gap

According to Merriam-Webster, “performance” is defined as “the ability to perform” (Merriam-Webster, n.d.). In the built environment context, performance refers to qualities like energy efficiency and indoor environmental quality (IEQ) (Shi et al., 2019). Of these aspects, building energy performance has received the most attention in the building sector and academia, mainly because energy metering is more accessible than other forms of measurement (De Wilde, 2014). The term “gap” is commonly defined as a “difference” or “discrepancy” (Shi et al., 2019), and the “performance gap” specifically refers to the difference between predicted (designed, calculated) and actual (measured, achieved) building performance (Ali et al., 2020).

The “energy performance gap” highlights the discrepancy between predicted and actual energy use, and despite a rise in energy-efficient buildings, actual savings often fall short of expectations (Ali et al., 2020). This gap results from poor communication between designers and building managers, design errors, limitations in modeling tools, construction quality, and occupant behavior (OB) (Shi et al., 2019). While technological improvements require substantial investment, human behavior is more adaptable to changes in attitudes, lifestyles, and technologies, offering significant potential for energy savings (Harputlugil & de Wilde, 2021). Previous studies demonstrated occupants' influence on energy performance through their presence, actions, and interactions, such as opening windows or switching lights (Chen, Ding, Bai & Sun, 2020; Hong et al., 2017; Wagner & Brien, 2018). Encouraging responsible OB can greatly enhance building energy efficiency.

The difference between the predicted and actual energy use of the buildings is illustrated in Figure 2. In many countries, building performance is modeled using standardized operating conditions, which, while helpful in meeting baseline requirements, risks overlooking unregulated loads and varying occupant patterns (van Dronkelaar et al., 2016). To improve accuracy, energy simulation tools must account for regulated and unregulated uses, aligning predictions with actual energy use.

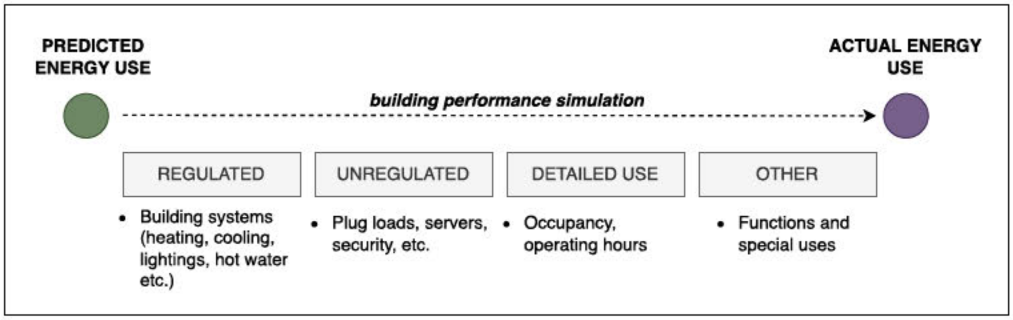


Figure 2. Representation of building performance simulation through different end-uses in energy calculations (Adapted from van Dronkelaar et al., 2016).

Today, technologies like eQuest® and DesignBuilder® support early design simulations, yet they assume fixed occupant behaviors and energy use (Ali et al., 2020). Although tools like EnergyPlus™ have started incorporating behavioral modules, they still rely on standard schedules rather than fully capturing OB dynamics (Gunay & O'Brien, 2018). Ali et al. (2020) emphasize that no current commercial tools effectively capture occupants' variable energy use patterns. This underscores the need for detailed research into OB's complexity to close the simulation performance gap, leading to more robust energy predictions and reduced building consumption.

2.3 Theoretical background of energy-related OB

Various social and environmental psychology approaches have been applied to gain a comprehensive understanding of energy-related occupant behavior (OB). For example, the Motivation-Opportunity-Ability (MOA) theory has explored attitudes and intentions around energy-saving behaviors (Li, Xu, Chen, Fei & Menassa, 2019). The Theory of Planned Behavior (TPB) examines factors influencing energy-related behavioral intentions (Ajzen, 1991). Perceptual Control Theory (PCT) has been employed to understand comfort-driven OB (Langevin et al., 2015), while the Values-Beliefs-Norms (VBN) framework investigates pro-environmental behavior (PEB) through a causal chain of variables. The Drivers-Needs-Actions-Systems (DNAS) framework analyzes energy use in buildings by examining four key components (D'Oca et al., 2017). Lastly, the Self-Determination Theory (SDT) framework has studied pro-environmental behavior, focusing on different motivation forms (Baxter & Pelletier, 2020).

TPB, proposed by Ajzen (1991), is widely used and well-cited in behavioral studies and has been particularly influential in research on energy-saving and pro-environmental behaviors (Li et al., 2019; Wolske et al., 2017). However, earlier studies revealed that the TPB variables could only explain 46% to 81% of the variance in behavioral intention (Greaves et al., 2013; Steg et al., 2015), leaving a substantial gap in understanding OB. SDT, on the other hand, is a newer, widely adopted theory for understanding pro-environmental behavior, distinguishing between motivation (why people act) and goals (what people aim to achieve) (Baxter & Pelletier, 2020). Given this study's goal of accurately analyzing energy-related OB in office settings, combining TPB and SDT could significantly strengthen the study's model.

Recognizing the role of motivation in shaping behavioral intentions, a deeper understanding of how motivations influence the formation of these intentions is essential. Therefore, this study integrates SDT to provide insight into energy-related OB, specifically by focusing on SDT's basic psychological needs that may mediate pro-environmental intentions in office buildings. To our knowledge, no prior research has combined TPB and SDT to investigate pro-environmental behavior in built environments. Few studies have merged these models to explore OB in other contexts, such as exercise participation (Cho et al., 2020), lecture attendance (Hollett, Gignac, Milligan, & Chang, 2020), health promotions (Brooks et al., 2018), and consumer purchase intention (Widyarini & Gunawan, 2018). This study is, therefore, the first to integrate intentional and motivational constructs with additional factors such as habit and comfort, aiming to improve our understanding of energy-related behavior in office buildings and its impact on building energy use.

2.3.1 The theory of planned behavior (TPB)

The theory of planned behavior (TPB) proposed by Ajzen (1991), is one of the most popular frameworks for studying occupant behavior, particularly in environmental behavior research (Gao et al., 2017). According to TPB, an individual's behavioral intention is influenced by three main factors: attitude toward the behavior (the person's feelings about the behavior), subjective norms (the perceived social pressure from essential people), and perceived behavioral control (the perceived ease or difficulty of performing the behavior). When someone has a positive attitude toward a behavior, they are more likely to form an intention to perform it (Gao et al., 2017) (See Figure 3). For example, in the context of energy-saving behavior, if someone holds a positive attitude toward reducing carbon emissions, they are more likely to intend to engage in energy-saving practices.

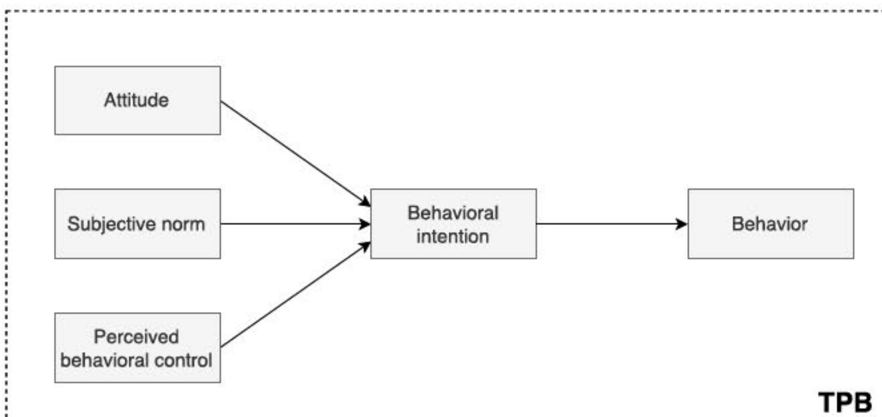


Figure 3. The theory of planned behavior (Ajzen, 1991).

Subjective norms, the second component of TPB, are associated with the expectations and opinions of people important to the individual. This means that an individual's intention to perform a behavior can be influenced by the approval or disapproval of others who matter to them (Ajzen, 1991). For instance, if students perceive that their classmates expect them to save energy, they may feel social pressure to act accordingly. The third component, perceived behavioral control, relates to an individual's perceived control over performing the behavior. When people think they have the necessary knowledge and resources, they are likelier to engage in that behavior (Gao et al., 2017). For example, if workers feel confident and well-informed about energy-saving practices, they are more likely to intend to save energy at work

The TPB has been widely adapted in energy and social science research to explore various environmental behaviors, including pro-environmental behavior (Correia et al., 2021), low-carbon travel (Hu, Wu, & Chen, 2021), walking (Seles & Afacan, 2019), green buying behaviors (Li et al., 2021), and recycling (Cheung, Chan, & Wong, 1999). Among existing studies, pro-environmental behavior is one of the most commonly used behaviors investigated through TPB. For instance, Kaiser and Gutscher (2003) demonstrated that the TPB components could predict up to 81% of residents' intentions to perform energy-saving behaviors. Similarly, Greaves et al. (2013) studied energy-related behaviors in office settings, finding that TPB explained between 46%-61% of the variance in employees' pro-environmental behaviors, such as turning off computers when leaving their desks and recycling at work.

2.3.2 The self-determination theory (SDT)

Self-determination theory, developed by Ryan and Deci (2000), is a comprehensive framework for understanding human motivation and one of social psychology's most widely used theories. SDT distinguishes intrinsic and extrinsic motivation as essential to occupant behavior (OB). These motivations fall along a continuum based on how self-determined or autonomous an individual feels about performing the behavior, as shown in Table 1 (Budzanowska-Drzewiecka & Tutko, 2021). In SDT, behaviors arise from specific motives that reflect an individual's level of self-determination.

Table 1. The self-determination continuum (Ryan & Deci, 2000).

Type of behavior	***Non-self-determined***					***Self-determined***
Type of motivation	**Amotivation**	**Extrinsic motivation**				**Intrinsic motivation**
	Amotivation	**Controlled**	**Controlled**	**Autonomous**	**Autonomous**	**Autonomous**
Type of regulation	Amotivation	External regulation	Introjected regulation	Identified regulation	Integrated motivation	Intrinsic motivation
Locus of causality	Impersonal	External	Somewhat external	Somewhat internal	Internal	Internal

In the self-determination continuum, the least self-determined type is amotivation, which can be related to the absence of behavioral modifications and incorporation. In amotivation, there is a lack of behavioral intention to act (Baxter & Pelletier, 2020). When people don't recognize how to adopt certain behaviors or achieve the desired outcome, they may have amotivation. Introjected regulation is the first motive where behavioral internalization starts. Herein, behaviors are mainly accomplished to prevent negative feelings of shame or guilt. Thus, introjected regulation is derived from human behaviors to avoid experiencing guilt (Baxter & Pelletier, 2020).

Moreover, identified regulation refers to the behaviors performed by people because they are essential to someone or to accomplish personal goals. For instance, when individuals adopt a behavior as they perceive its importance (Ryan & Deci, 2000). Next, integrated regulation is a more self-determined type of motivation, where individuals adapt behaviors as they are fully internalized and consistent with their various attributes. For example, people act in some behaviors because they embrace them as part of their identity. Lastly, intrinsic regulation is the most self-determined type of motivation where satisfaction and pleasure are the reasons for the behaviors. When an individual is intrinsically motivated, behaving in a certain way brings pleasure to the field (Baxter & Pelletier, 2020). Overall, people's motivation on this continuum is detected in how behaviors are internalized into self.

The SDT has been studied mainly in pro-environmental behavior by looking at the impacts of self-determined and non-self-determined motives on pro-environmental behavior. Previous studies showed that an individual with higher self-determined forms of motivation tends to perform a higher frequency of PEB than non-self-determined forms of motivation (Budzanowska-Drzewiecka & Tutko, 2021; Pelletier & Aitken, 2014). Herein, pro-environmental behavior refers to activities that profit the natural environment (e.g., recycling) and neglect the activities that may damage it (e.g., avoiding car travel) (Lange & Dewitte, 2019). The SDT has been utilized to understand various kinds of pro-environmental behavior as recycling (Huffman et al., 2014), purchasing (Gao, Liu, Liu, & Li, 2018), household energy-saving (Dave, Tim, & Patricia, 2013), green employee behaviors (Zhang et al., 2021), and green information technology (Koo & Chung, 2014). Previous studies have also been performed in a variety of settings, including the office (Brunelle & Fortin, 2021), home (Dave et al., 2013), and classroom (Niemiec & Ryan, 2009). These pro-environmental behavior studies mainly focused on environmental concerns in various fields. To our knowledge, no previous studies have utilized SDT with an integrated framework to investigate the pro-environmental behavior in building energy efficiency. In this manner, pro-environmental behavior in office buildings were examined in depth with a consideration of IEQ through the combination of subjective and objective measurements.

2.3.3 Habit

Habits, automatic actions performed without conscious effort, are recognized as crucial factors in comprehending energy-saving behaviors (Rubinstein, 1984). In our daily lives, we develop habits by repeating actions in familiar situations. These habits then become efficient and automatic responses that persist without much conscious guidance or deliberate thought (Wood & Rünger, 2016). A study analyzing hourly self-reported behavior records suggests that around 40% of our daily behaviors are guided by habits without conscious deliberation (Wood, Quinn, & Kashy, 2002). However, this estimate is likely lower since self-reported measures struggle to capture automatic behaviors fully. Due to the challenging nature of measuring habits and other automated processes, they have often been understudied, mainly because they require expensive long-term analysis (Rebar, Gardner, Thodes, & Verplanken, 2018). While it's difficult to determine the extent to which habits influence our behavior precisely, it's safe to say that they significantly shape many of our daily actions.

Habits exhibit specific characteristics, including occurring in stable situations, not requiring much cognitive effort, helping us achieve particular goals, and happening frequently. When it comes to energy-related behaviors, many tend to be habitual, as energy consumption serves a purpose. It often occurs in stable environments like homes and workplaces, can be performed automatically, and appears regularly (Maréchal, 2010). A study by Macey and Brown (1983) found that past experiences are better predictors of frequent energy behaviors, whereas intentions play a more substantial role in predicting less frequent energy behaviors. It is important to note that strong habits, characterized by automatic responses to contextual cues, can hinder the adoption of new intentions (Maréchal, 2010). This suggests that habits have a significant impact on our energy-related behaviors.

However, despite its importance, habits are often overlooked in studies on pro-environmental behavior, focusing instead on values, norms, attitudes, intentions, and motivation (Schultz & Kaiser, 2012). Interventions for sustainable transformations prioritize intrinsic motivation, but these approaches may not effectively break habits and drive long-term behavioral change (Verplanken & Sui, 2019). Popular behavior models, such as the theory of planned behavior and value belief norm theory, explain some pro-environmental behavior but fail to capture the complete picture. People struggle to align their knowledge and motivations with sustainable actions, resulting in a value/attitude-action gap (Steg & Vlek, 2009).

Despite their potential significance, habits have been largely neglected in sustainability science. They have been identified as potential barriers to aligning intrinsic motivation with sustainable behavior changes and as factors that influence the validity of attitude-behavior models (Jackson, 2005; Kollmuss & Agyeman, 2002; Verplanken & Aarts, 1999). A Scopus search revealed that habits are mentioned in less than 0.5% of sustainability research articles and only about 3% of articles specifically addressing pro-environmental behavior (Linder, Giusti, Samuelsson, & Barthel, 2022). While some efforts have been made to integrate habits into attitude-behavior models, yielding improved predictive power, there is a need for further research on habits and their role as barriers or motivators for pro-environmental behavior. Some studies have incorporated habit theory into the design of behavior-specific interventions. Still, there is limited scientific interest in exploring the role of habits concerning sustainable actions (White, Habib, & Hardisty, 2019).

2.3.4 Comfort

Comfort is generally described as the absence of unpleasant sensations contributing to a sense of well-being. The factors that lead to discomfort are subjective and vary from person to person. However, most individuals commonly perceive certain aspects as unpleasant (Feige, Wallbaum, Janser, & Windlinger, 2013). The comfort conditions in a given environment directly impact individuals, affecting them both physically and psychologically and ultimately influencing their performance in various activities. Environmental comfort encompasses functionality, temperature, lighting, and acoustic conditions. Unfavorable comfort conditions, including high temperatures, excessive noise, inadequate lighting, crowded classrooms, and mismatched equipment for different age groups, can harm occupants' well-being, satisfaction, health, and productivity (Rasheed & Byrd, 2018). The design of a building plays a significant role in determining these comfort conditions, which are also influenced by user activities and clothing choices. Achieving optimal comfort requires individuals to consider their behavior with the environment and make spontaneous adjustments to enhance their comfort experience (Bernardi & Kowaltowski, 2006).

Occupant comfort plays a vital role not just during the usage phase but also during the design and construction phases, especially when dealing with building energy efficiency (Djamila, Chu, & Kumaresan, 2013). It is influenced by various factors, such as indoor and outdoor environmental conditions, occupant characteristics, and building-related factors (Andargie, Touchie & O'Brien, 2019). When assessing occupant comfort, four key aspects come into play: thermal comfort, visual comfort, acoustic comfort, and indoor air quality (IAQ) satisfaction, with thermal comfort being the most prominent factor. These aspects were explained in detail in Chapter 3, Section 3.2. Moreover, the comfort literature highlights the importance of adaptive opportunities in building design. A building that offers flexibility for occupants to adjust to the indoor environment will likely provide a higher level of comfort than one with limited control (Baker & Standeven, 1997; Humphreys, 1996). Access to tools such as thermostats, windows, or lights allows users to customize their indoor experience, increasing satisfaction (Brager & Baker, 2009). Studies have shown that perceptions of reasonable control are closely associated with improved comfort and satisfaction. Furthermore, environmental control systems that are responsive, accessible, simple, and user-friendly contribute to higher user satisfaction (Shahzad et al., 2017). It is important to note that individuals have varying perceptions and expectations of comfort in a controlled and refined indoor environment, emphasizing the need for tailored solutions (Moezzi, 2009).

CHAPTER 3

INDOOR ENVIRONMENTAL QUALITY

As people spend nearly 90% of their time indoors, indoor environmental quality (IEQ) significantly affects health, comfort, productivity, and energy use (Rasheed & Byrd, 2018). In office settings, key components of IEQ include thermal comfort, air quality, lighting, and acoustics. The design of these spaces—incorporating architectural elements, furniture, conditioning systems, and occupants' adaptive behaviors—further influences how individuals feel and function within them, ultimately impacting their overall well-being and work performance (Hwang & Kim, 2013).

Research has increasingly focused on establishing standardized indoor conditions that promote both productivity and well-being, recognizing the close link between IEQ and work outcomes. For instance, studies compare private and open-plan offices (Rasheed, Khoshbakht & Baird, 2019) and naturally vs. mechanically ventilated spaces (Rasheed & Byrd, 2018). Findings consistently indicate that a well-designed IEQ in office environments plays a crucial role in supporting employees' health, comfort, and productivity, making it a priority in modern workplace design (Bluyssen et al., 2016; Rasheed et al., 2019; Rasheed & Byrd, 2018).

Office layout directly affects employee performance and behavior. For example, open-plan layouts encourage communication but can reduce workspace size, compromise visual privacy, and increase noise (Kupritz, 2003). Workspace comfort, flexibility, and individual space allocation are essential for employee satisfaction and productivity (Kim & de Dear, 2013). Research highlights that well-designed open-plan offices can support occupant comfort and productivity, with considerations for furniture comfort, spatial allocation per person, and equipment flexibility (Kim & de Dear, 2013. Additional studies show that a suitable open-plan office layout is influenced by task complexity (Maher & von Hippel, 2005), work patterns (Haynes, 2008), and work processes (al Horr et al., 2016).

Thermal comfort is a critical factor influencing satisfaction and productivity in office environments. Humphreys (2005) surveyed 26 European open-plan offices, revealing that satisfaction with indoor temperature was the most crucial aspect of overall IEQ satisfaction. Similarly, a study in Hong Kong found that temperature comfort is closely linked to productivity (Mak & Lui, 2012). Studies also indicate that task performance declines if the temperature deviates from a neutral range (e.g., 21-25 °C) and that high temperatures can negatively affect motivation, concentration, and mood (Hygge & Knez, 2001).

Based on heat balance theory, the Predicted Mean Vote (PMV) index is widely used to predict thermal comfort. It considers four physical parameters (air temperature, humidity, air velocity, and radiant temperature) and two human factors (metabolic rate and clothing insulation) (International Organization for Standardization, 2005). This model is incorporated into significant standards like ISO 7730, BS EN ISO 7730, and ASHRAE 55 (International Organization for Standardization, 2005), BS EN ISO 7730 (British Standards Institution, 2005), and the American Society of Heating, Refrigerating and Air-Conditioning

Engineers (ASHRAE) 55 (ASHRAE, 2013). However, a more comprehensive thermal comfort analysis should include physical, physiological, and psychological aspects, as factors such as age, sex, location, and task type also affect thermal perceptions (al Horr et al., 2016).

Indoor air quality (IAQ) is another critical environmental aspect that significantly impacts occupant comfort and work productivity. Poor IAQ can reduce productivity and lead to sick-building syndrome (SBS), causing fatigue, headaches, and lethargy (Wargocki, 1999). IAQ is primarily determined by ventilation rate and emissions from materials and equipment. Research shows that higher ventilation rates can decrease health symptoms, reduce IAQ dissatisfaction, and improve productivity (Sundell, 2011; Wargocki, 1999). Xue et al. (2016) further observed that perceived air freshness correlates with IAQ satisfaction, while unpleasant odors negatively impact mood, task performance, and health (Danuser, Moser, Vitale-Sethre, Hirsig & Krueger, 2003; Michael, Jacquot, Millot, & Brand, 2005).

Lighting is fundamental to office design, impacting comfort, health, and productivity (Mills, 2018). Lighting sources are generally divided into natural and artificial lighting (Winchip, 2017), and office lighting is provided in forms such as general, localized, and task-specific lighting (Knoop, 2012). Office lighting systems should create comfortable physical, psychological, and visual conditions that support occupant activities (Mills, 2018). High-quality lighting environments help reduce fatigue, motivational issues, and eye strain (Haapakangas, Keranen, Nyman & Hongisto, 2012). Studies indicate that daylight is generally preferred for visual comfort (Xue, 2014), although artificial lighting is necessary when natural light is insufficient (Hamedani et al., 2019). Office activity types also influence occupant satisfaction with the lighting environment. For example, employees working with their computers may prefer lower light levels than those not working with their computers (Escuyer & Fontoynont, 2001).

Acoustics in the office environment are essential in protecting occupants from noise (Rocca, 2017), defined as unwanted sound that causes disturbance (Freihoefer, Guerin, Martin, Kim, & Brigham, 2015). Studies show poor acoustics negatively impact job satisfaction, productivity, and health (Freihoefer et al., 2015; Lee et al., 2016). Noise levels and sound privacy are significant in open-plan offices (Haapakangas et al., 2012). Quietness is one essential criterion for satisfying the acoustic environment in the offices (Kim & de Dear, 2012). However, various noise types in offices, such as traffic noise, speech, machine noise, or human activity noise, are widespread. These noise sources cause dissatisfaction, annoyance, and lower work productivity (Freihoefer et al., 2015; Haapakangas et al., 2012). Conversation noise is the most unmanageable among the noise sources in open-plan offices (Roelofsen, 2008). Speech privacy is considered to be one of the essential aspects of offices. It has been adopted by well-known standards such as ISO 3382-3 (International Organization for Standardization, 2012), BS EN ISO 3382-3 (British Standards Institution, 2012), and ASTM E1130 (the World Trade Organization Technical Barriers to Trade (TBT) Committee, 2016).

3.1 Evaluation of indoor environmental quality

IEQ is commonly assessed through both subjective and objective methods. Studies typically involve participants in (1) sharing their perceptions of the environment, (2) recording physiological responses, or (3) performing specific tasks. These evaluations aim to determine how each IEQ factor impacts occupants' health, satisfaction, and productivity.

3.1.1 Subjective evaluation of indoor environmental quality

Building occupants are essential sources for designers, architects, and building owners to supply feedback about the building's performance (Zhang et al., 2018a). Subjective evaluation of IEQ involves building occupants using surveys (Kim & de Dear, 2012), interviews (Xuan, 2018), focus groups (Nix et al., 2015), walkthroughs (Fadeyi et al., 2014), observations (Kamaruzzaman & Azmal, 2019), cohort studies (Pantelic et al., 2018), self-assessed surveys (Sadick et al., 2020) or task performance tests (Wang et al., 2021). Surveys are prevalent due to their simplicity and cost-effectiveness. For example, post-occupancy evaluation (POE) surveys are widely used to collect occupant perceptions of IEQ (Freihoefer et al., 2015). To obtain occupant perceptions about the IEQ, several POE surveys have been developed, and they were mainly applied online to automatically administer surveys and gather responses from the participants (Freihoefer et al., 2015).

The most commonly used ones are the Building Use Studies (BUS) advanced in the UK (Leaman & Bordass, 2001) and the Centre for the Built Environment survey developed in the US (Candido, Kim, de Dear, & Thomas, 2016). In addition, the Building Assessment Survey and Evaluation Study (USEPA, 2003), the Cost-effective Open-Plan Environments (Veitch et al., 2002), and the Health Optimization Protocol for Energy-efficient Buildings Project (Bluyssen, 2002) are the other developed tools to evaluate IEQ subjectively. Although several instruments have been advanced and validated over the years, challenges persist with subjective evaluations, such as selecting representative questions, timing the surveys appropriately, and interpreting results effectively (Nicol & Humphreys, 2002).

3.1.2 Objective evaluation of indoor environmental quality

Objective evaluation of IEQ mainly refers to physical measurements and is considered under three categories: (1) indoor environmental quality in-situ measurements, (2) energy, and (3) water (Li et al., 2018). IEQ in-situ measurements are generally divided into four: thermal comfort, lighting, air quality, and acoustical quality (Bluyssen et al., 2016). Previous studies measured thermal comfort through infrared thermal imaging (Zuhaib et al., 2018) and sensors for temperature, relative humidity, air velocity, etc. (Berquist et al., 2019). Lighting was assessed with high dynamic range (HDR) imaging cameras (Konis, 2014) and illuminance and luminance meters (Yang & Mak, 2020). Air quality was measured through CO_2 sensors (Kanal & Tamas, 2020), formaldehyde (Gunschera, Mentese, Salthammer & Andersen, 2013), TVOC (Stamatelopoulou et al., 2019), and respirable particles (Madureira et al., 2009). In addition to in-situ measurements, energy was assessed through sensors (Chen et al., 2017), simulation (Lee et al., 2016), meters (Sharmin et al., 2014), or bills (Fumo, Mago & Luck, 2010), while water was measured via bills (Mora et al., 2018) or meters (Clifford, Mulligan, Comer, & Hannon, 2018). Lastly, few studies utilized GPS-enabled mobility tracking (Koehler, Ziebart, Mankoff & Dey, 2013) and window-opening sensors (Chen et al., 2020) to monitor OB. The measurements were analyzed based on some standards, such as ASHRAE Standard 70 (ANSI/ASHRAE Standard 70, 2006) and ISO 7726 (ISO 7726, 1998), wherein the measured IEQ parameters were compared to the recommended values in standards.

Moreover, to objectively measure each indoor environmental quality factor, different standards, such as ASHRAE Standard 55 related to thermal comfort and indoor air quality (ANSI/ASHRAE 55, 2017), were considered during the measurements. Besides, during the experimental studies, indoor environmental conditions generally controlled or isolated individual parameters instead of embracing the complex multi-modal relationships that influence indoor environmental quality (Mui & Chan, 2005). As a formula, findings are frequently incorporated into indoor environmental quality models or indices that unify the impacts of the component areas by applying weighting coefficients (Mendell, 2003). The output was a single and summative indoor environmental quality evaluation. Nevertheless, the measurement instruments are expensive, hard to use, and complex to perform these evaluations. Some sensors require regular calibration to maintain accuracy (Berquist et al., 2019). There are also some difficulties in objectively evaluating the time, cost, and effort needed while implementing these measurement instruments across large buildings and analyzing vast data (Reynolds et al., 2001). In this manner, there is a need to obtain easy-to-use but accurate tools for data collection, where a combination of subjective and objective methods can be utilized for indoor environmental quality assessments. Table 2 briefly reviews the subjective and objective studies that evaluated indoor environmental quality.

Table 2. Summary of indoor environmental quality studies.

Study	Indoor environmental quality factor	Method	Population	Building type	Parameter	Data analysis
(Berquist et al., 2019)	Thermal comfort	On-site measurements of the indoor thermal environment, Electronic occupant survey	Not mentioned	Gymnastics center	Temperature, RH, thermal comfort	Kruskal-Wallis H test, pair-wise comparison, Mann-Whitney U test
(Freihoefer et al., 2015)	Thermal comfort, lighting, acoustics	Questionnaire	N= 70	Office	Satisfaction with thermal, acoustic, and lighting conditions	paired t-test, linear regression analyses, ANOVA
(Kang et al., 2017)	Thermal comfort	On-site measurements of the indoor thermal environment, Questionnaire	N= 21	Office	Comfort and thermal environment perception, air temperature, globe temperature, relative humidity, carbon dioxide concentration, illuminance, and background noise level	Shapiro-Wilk test, t-test, ANOVA, the Spearman or Pearson correlation coefficient
(Rasheed, Khoshbakht, & Baird, 2021)	Thermal comfort, air quality, lighting, acoustics	Questionnaire	N= 5149	Office	IEQ perception, comfort, productivity, and health	ANOVA, Pearson's correlation, multiple regression analyses
(Choi, Loftness, & Aziz, 2012)	Thermal comfort, air quality, lighting, acoustics	On-site measurements of the indoor thermal environment, Questionnaire	N= 402	Office	IEQ satisfaction, relative humidity, carbon dioxide (CO2) and carbon monoxide (CO) concentrations, total particulates, and volatile organic compounds (VOCs)	two-sample t-test, ANOVA, ordinal logistic regression analysis
(Nimlyat, 2018)	Thermal comfort, air quality, lighting, acoustics	Case study, questionnaire	N= 990	Hospital	IEQ performance	Structural Equation Modelling

Table 2 (cont'd)

Study	Indoor environmental quality factor	Method	Population	Building type	Parameter	Data analysis
(Zhan et al., 2021)	Thermal comfort, air quality, lighting, acoustics	On-site measurements of the indoor thermal environment, Questionnaire	N= 25	Nursing home	Older adults' acceptance of the IEQ, air temperature, relative humidity, CO2 concentration, illuminance level, and noise level	χ2-test, Spearman correlation, t-test, batch gradient-descent algorithm
(Yang & Moon, 2019)	Thermal comfort, lighting, acoustics	Questionnaire	N= 60	Test laboratory	Temperature, humidity, illuminance level, sound level, sound type	ANOVA, Bonferroni's posthoc test, factor analysis
(Korsavi, Montazami, & Mumovic, 2020)	Thermal comfort, air quality, lighting	On-site measurements of the indoor thermal environment, Questionnaire	N= 805	Classrooms	Comfort votes in thermal, air quality, lighting, operative temperature, humidity	Multilinear regression model; Binary logistic regression
(Tahsildoost & Zomorodian, 2018)	Thermal comfort, air quality, lighting, acoustics	On-site measurements of the indoor thermal environment, Questionnaire	N= 842	Educational building	IEQ satisfaction, air temperature, relative humidity, air velocity, globe temperature, background noise level, CO_2 concentration, illuminance levels	Regression, correlation
(Ghita & Catalina, 2015)	Thermal comfort	On-site measurements, Questionnaire	N= 708	School	Thermal comfort, CO2, relative humidity and air temperature, consumption recordings for electric, hot water, and heating	Mean

The reviewed studies highlight the vital role of assessing indoor environmental quality (IEQ) using both subjective and objective methods, each contributing unique perspectives on occupant comfort and productivity. Combining these approaches has proven effective in providing a comprehensive understanding of IEQ performance across diverse building types, as detailed in Table 2. These findings emphasize the importance of integrative strategies that blend subjective feedback with objective measurements to address cost, complexity, and accuracy challenges in IEQ assessments. The insights from these studies lay a solid foundation for developing advanced methodologies that evaluate and improve IEQ, aligning with occupant needs and energy efficiency objectives.

CHAPTER 4

OCCUPANT BEHAVIOR MODELLING

Occupant behavior modeling (OBM) simulates how occupants are present, move, and interact with building systems (Franceschini & Neves, 2022). It encompasses occupants' behavior related to energy use, including their interactions with electrical appliances, lighting systems, thermostat settings, and other building energy systems (Carlucci et al., 2020). Extensive research OB has resulted in the development of deterministic and stochastic models to predict interactions with window openings, shading devices, heating set-point preferences, and electrical lighting. These models have been reviewed in studies by Fabi et al. (2012), Günay et al. (2014), Haldi et al. (2017), and Reinhart (2004).

Additionally, it has been acknowledged that buildings may fall short of desired standards, posing a risk of missed opportunities for optimizing design and control to enhance occupant comfort and energy efficiency (O'Brien et al., 2017). Modeling OB can play a vital role in understanding and bridging the gap between design intentions and actual building energy performance. However, it's crucial to recognize that occupant models are often context-specific (Mahdavi & Tahmasebi, 2016). Merely predicting or simulating occupant behavior in one setting presents inherent challenges when transferring that knowledge to more complex scenarios.

4.1 Modeling Occupant Actions

4.1.1 Window/door operation

The operation of windows and doors plays a key role in enabling occupants to control their indoor environments and maintain a connection with the outdoors (Carlucci et al., 2020). Predicting window and door operation behaviors is challenging due to their dependence on physical conditions and the inherently random nature of these actions. Limited research has been done on using door openings specifically for adaptive comfort, although this approach is valuable for naturally ventilated buildings as it enhances cross-ventilation (Yan et al., 2015).

Researchers commonly use logit models and logistic regression to model window operations, which estimate the probability of a window being opened or closed (Pan et al., 2018, 2019; Stazi et al., 2017b). Binary logistic regression is especially popular due to its clear physical interpretation and reliable accuracy (Andersen, Fabi, Toftum, Corgnati & Olesen, 2013; Andersen, Toftum, Andersen, & Olesen, 2009; Cao et al., 2022). When the angle of the window opening is not considered, this behavior is simplified into two categories: “opened” or “closed.” This binary approach disregards the dynamic processes behind occupants’ actions. To address this, some models apply a Markov process, where future states depend on current conditions and probabilities of change (Fabi, Andersen & Corgnati, 2015; Wei et al., 2019). However, integrating such methods into conventional building performance tools can limit temporal resolution, as these tools rely on fixed time steps and may overlook brief openings. Predicting exact timings for actions like window closure also remains a challenge. To enhance accuracy, Haldi and Robinson (2009) proposed a hybrid approach combining Markov processes for state transitions and continuous-time survival analysis to estimate reversal times.

Neural networks (NNs) and deep learning (DL) methods are increasingly applied to window operation modeling (Markovic, Grintal, Wölki, Frisch & van Treeck, 2018). NNs can learn relationships between variables through training with historical data and offer advantages like fault tolerance, robustness, and noise immunity (Abiodun et al., 2018; Jamil, Sharma & Singh, 2015). However, selecting the NN architecture and tuning hyperparameters often require a trial-and-error approach, making these models case-specific (Kalogirou & Bojic, 2000). Each application needs tailored design and validation for effective results.

When examining window opening models, the majority have been developed for temperate climate zones based on the Köppen classification, specifically Cfb (43%), Cfa (23%), and Csa (2%). A smaller percentage of models are designed for continental climates, namely Dwa (16%) and Dfb (16%). Most studies investigating occupant window behavior have also focused on European countries (Calì et al., 2018; Haldi & Robinson, 2009; Schweiker et al., 2012). Given that window and door operations are influenced by atmospheric conditions, personal routines, and individual preferences, there is a strong need for research on these behaviors across diverse climates. While statistical models are widely used in this field, further exploration of data-driven and deep-learning approaches would advance our understanding and predictive accuracy of window and door operations in different contexts (Markovic et al., 2018).

4.1.2 Solar shading operation

Solar shading devices and electric lighting ensure indoor thermal and visual comfort. Solar shading controls internal daylight levels and influences solar heat gains. It serves a dual purpose: allowing solar radiation to passively heat the indoor space while affecting the operation of electric lighting, contributing gains. Additionally, solar shading provides privacy by obstructing views from the outside.

The operation of solar shading is typically modeled by predicting the state of the shading device, either as open or closed (binary), or by estimating multiple states. Occupant-controlled shading devices have attracted significant attention in building performance simulation for various reasons. The selection of predictor variables is vital in occupant-controlled shading models. Analysis of relevant literature reveals that commonly used predictors include indoor and outdoor air temperatures (Haldi & Robinson, 2009), work plane daylight levels (Yeon et al., 2019), indoor illuminance (Haldi & Robinson, 2010), external radiation (Trobec Lah et al., 2006), and rainfall (Haldi et al., 2017). The climatic conditions during data collection for model development are exciting as most models rely on external conditions as predictors. The majority of analyzed shading operation models come from temperate (Hunt, 1979; Schweiker & Wagner, 2016) and continental climates (Haldi et al., 2017; Haldi & Robinson, 2008, 2010), with Kurian et al. (2008) being the exception, who worked in the tropics. Moreover, except for Andersen et al. (2009) predicting shading movements in residential buildings, the models primarily focus on offices (Haldi et al., 2017; Haldi & Robinson, 2008; Schweiker & Wagner, 2016).

Since 2000, data-driven methods have been increasingly used to accurately predict occupant-driven solar shading, with fuzzy logic and regularized logistic regression being the most prevalent techniques. NNs have been applied to optimize energy consumption for lighting, space heating, and cooling by controlling the slat angle of Venetian blinds (Yeon et al., 2019). Reinforced learning has also been employed to develop a controller that adjusts electric lighting and blind position (Cheng et al., 2016). In summary, there is a lack of models reflecting solar shading operations in tropical and arid climates. Furthermore, further investigations should encompass residential and other building types to provide broader support for building energy modeling.

4.1.3 Thermostat adjustment

Thermostat adjustment behavior is a critical factor in building performance modeling as it directly influences the energy consumption of HVAC systems. Thermostats act as control devices determining when to apply space heating, cooling, or ventilation to a building's thermal zone. They rely on sensors to measure the air temperature or humidity within the area and trigger the HVAC systems based on predefined set-point values. Building occupants interact with thermostats by adjusting temperature and humidity settings and creating schedules for HVAC activation and deactivation (Carlucci et al., 2020). Therefore, occupant behavior, including set points and schedules, plays a significant role in determining HVAC system operation and other factors like building envelope properties, internal heat gains, and HVAC capacity.

The decisions made by building simulation modelers regarding thermostat set points and schedules substantially impact predictions and occupants' thermal comfort. This aspect contributes significantly to the performance gap since international and national building performance standards often assume simplified and constant occupant behavior in thermostat control. However, occupants frequently adjust set points and schedules based on their presence at home or work, external weather conditions, and special occasions such as holidays. This disparity between assumptions and actual behavior introduces considerable uncertainty in predicting building energy use (De Wilde, 2014).

The most commonly used methods for modeling thermostat set points include the General/Generalized Linear Model (Ren et al, 2014), Markov chain models (Baetens & Saelens, 2016), and logit analysis (Haldi & Robinson, 2008). The studies encompass various building types, with residential buildings comprising 54%, offices comprising 26%, commercial buildings comprising 7%, and educational buildings comprising 6% (Carlucci et al., 2020). Measurement campaigns are conducted to collect data for training and calibrating models, including variables such as set-point and indoor air temperature, occupancy, heating/cooling/ventilation energy demand, and outdoor weather. In residential applications, directly measuring thermostat set points and schedules can be challenging, so indirect measurements, like estimating settings based on air temperature, are often used as proxies (Gouda, Danaher & Underwood, 2002), adding further uncertainty to the predictions.

Despite numerous studies in this field, there is no consensus on the necessary measurement variables for constructing occupant behavior models or the choice of evaluation metrics for validating models. In addition to set-point adjustments, the interaction between occupants and HVAC systems has been explored in residential (Fabi et al., 2013), office, and commercial contexts (Langevin et al., 2015). Researchers have employed Markov transfer probabilities (Ren et al., 2014) and descriptive statistics (Fabi et al., 2013; Schweiker & Shukuya, 2009) to model HVAC usage in residential buildings, while logistic regression and rule-based agent models have shown promise for modeling HVAC usage in commercial buildings (Langevin et al., 2015). A study evaluating different machine learning algorithms, including neural networks (NN), reported energy consumption reductions of temperature set points in an office and commercial building setting (Peng et al., 2019).

Further significant research is needed in thermostat set-point modeling. Developing a transparent data collection methodology, standardized model testing framework, and defined reporting criteria and evaluation metrics is crucial. To harness the full potential of existing and future datasets, creating a common data collection vocabulary or ontology would facilitate data reuse and meta-analysis across various building types, sample sizes, and countries of origin.

4.1.4 Clothing adjustment

The choice of clothing is crucial in how humans interact with their environment (Deng & Chen, 2018) and plays a significant role in thermal comfort models. Age, gender, and relative humidity have been found to have minimal impact on individuals' selection of clothing insulation levels (Lu & Hameen, 2018). However, it is emphasized that the daily mean outdoor temperature is the primary factor influencing clothing insulation levels (Lu & Hameen, 2018). Previous studies on clothing insulation predominantly relied on linear regression methods. However, Deng and Chen (2018) argued that the relationship between clothing and its influencing factors might not be linear. To address this, they developed clothing prediction models using ordinal logistic regression and neural networks based on data collected in office environments. The neural network model demonstrated high training accuracies, ranging from 87.3% to 91.2%, for different actions related to adjusting set points and clothing, providing an accurate tool for predicting occupants' clothing behavior in office settings (Carlucci et al., 2020).

The literature commonly employs various predictors to estimate clothing adaptation, including indoor air and operative temperature, relative humidity, CO2 levels, air velocity, outdoor air temperature, skin temperature, human activities, and time of the day (Schiavon & Lee, 2013). Many existing methods for estimating clothing insulation assume fixed values based on in-situ estimation and thermal models or rely on outdoor and indoor temperature conditions (Chaudhuri, Zhai, Soh, Li, & Xie 2018; Rana et al., 2013). Additionally, data-driven approaches such as neural networks, support vector machines, and regression models have been employed to capture occupants' responses and interactions with building utilities and management systems, contributing to the establishment of thermal comfort in built environments (Chaudhuri et al., 2018; Deng & Chen, 2018). Machine learning and deep learning models have recently gained attention in predicting indoor clothing levels (Chaudhuri et al., 2018; Deng & Chen, 2018). Literature suggests that clothing adaptation is influenced by three factors: occupant behavioral adjustment, physiological, and psychological factors (Chaudhuri et al., 2018; Deng & Chen, 2018). Future research directions should explore the intricate relationships and correlations between these influencing factors in building types that have not been extensively studied, considering various individual conditions such as different levels of metabolic activity.

4.1.5 Combined occupant actions

Researchers have explored models that integrate the actions of multiple users to analyze different aspects of comfort and energy consumption in buildings. Lighting operation, in particular, has taken significant attention due to its impact on visual comfort, thermal comfort, and electricity demand. Various studies have combined lighting operation with shading control using schedules/profiles, stochastic OPA modeling techniques, and data-driven models (Cheng et al., 2016; Mahdavi, Mohammadi, Kabir & Lambeva, 2008). Regression models have also been utilized to capture combined actions, including scenarios such as light switching with window operation (Naspi et al., 2018), window and solar shading operation (Schweiker & Wagner, 2016), and light switching with both window and solar shading operations (Haldi et al., 2017). Data-driven techniques have been employed to model lighting switches with blind operation and changes in space heating set-point temperature to assess visual discomfort (Lindelöf & Morel, 2008).

Moreover, the combined operation of light switching, window operation, and space heating and cooling has been modeled using schedule/profile and stochastic OPA models (Brackney & Shoureshi, 1994). Furthermore, data-driven models (Candanedo, Feldheim & Deramaix, 2017) and stochastic OPA models (Widén & Wäckelgård, 2010) have been developed to predict energy consumption by considering lighting and appliance usage. In a study by Haldi et al. (2017), the combined operation of windows, solar shading, and light switching was investigated, and logit models were developed for residential buildings and offices. These models incorporated random effects to account for inter-individual variability in occupant behavior, thus addressing the challenge of modeling average behavior and explicitly considering diversity and variability. Modeling combined actions offers a comprehensive approach that provides valuable insights into human actions and their impact on energy consumption and occupants’ comfort. However, there are still gaps in the existing literature, and further interdisciplinary studies are needed to bridge these gaps (Haldi et al., 2017).

4.2 Drivers of occupant actions

Various drivers influence OB during modeling, known as triggers, predictors, or controlling variables (Balvedi, Ghisi & Lamberts, 2018; Carlucci et al., 2020; Fabi et al., 2012). These drivers can be categorized into two primary groups: external and internal (Yan et al., 2017). External drivers encompass environmental, time-related, and contextual factors, while internal drivers include physiological, psychological, and social factors (Yan et al., 2017). Some authors also consider random factors when classifying energy-related drivers (Laaroussi, Bahrar, El Mankibi, Draoui & Si-Larbi, 2020).

External factors are objective and relatively more straightforward to measure and compare (Stazi et al., 2017a). They encompass indoor and outdoor conditions such as air temperature, relative humidity, illuminance, and CO2 concentration (Stazi et al., 2017a). Time-related factors consider variables like the time of day (e.g., morning, noon), day of the week, season, and occupant routines (e.g., arrival and departure) (Laaroussi et al., 2020). Contextual factors consider building characteristics, location, solar orientation, and other relevant aspects (Fabi et al., 2012).

On the other hand, internal factors pose more challenges regarding collection, quantification, and analysis (Stazi et al., 2017a). Physiological factors are related to an occupant’s physiological condition, including age, gender, health status, clothing, activity level, sensitivity to brightness, and other variables (Stazi et al., 2017a). Psychological factors involve individual perception, expectations, habits, and lifestyle (Fabi et al., 2012). Social factors pertain to interactions among occupants and may include organizational policies (Fabi et al., 2012). Random factors are uncertain and unquantifiable variables seldom considered in

OB modeling as they cannot be synthesized with association rules (Stazi et al., 2017a).

4.3 Fuzzy logic modelling

Zadeh introduced the concept of fuzzy logic in 1964 (Zadeh, 1965), which involves mapping input data nonlinearly to obtain scalar output data. It's a machine learning technique that simplifies and categorizes real-world problems into manageable tasks. This idea led to the development of the Theory of Fuzzy Subsets, recognizing the common occurrence of parameters that defy easy classification and cannot fit neatly into predefined sets. This approach combines verbal statements with algorithms, allowing numerical values to be assigned to imprecise linguistic terms like “large,” “small,” “hot,” or “cold.” Fuzzy logic is particularly useful when data are incomplete, unavailable, or when processes are highly complex. It deals in partial and multivalued truths, making it suitable for problems that resist straightforward mathematical modeling (Zadeh, 1965).

4.3.1 Steps of the fuzzy system

The fuzzy system's essence lies in allowing partial membership of an object to different subsets of a universal set rather than belonging entirely to a single set. This principle is structured into four fundamental steps: Fuzzification, Decision Making Unit, Rule Base, and Defuzzification (Kazanasmaz & Tayfur, 2012). These steps are shown in Figure 20. In the initial step, Fuzzification, a fuzzy set's membership functions transform inputs into membership ranks, assigning fuzzy variables to values between 0 and 1. These membership functions use linguistic terms like “high,” “medium,” or “low” to guide the conversion process (Kunduracı & Kazanasmaz, 2019). A fuzzy number, a specific instance of a fuzzy set, has a continuous, convex membership function defined over a closed interval of real numbers. These membership functions can take various shapes, such as triangular or trapezoidal, favored for their simplicity and linearity, although Gaussian or generalized bell shapes are common (Kunduracı & Kazanasmaz, 2019).

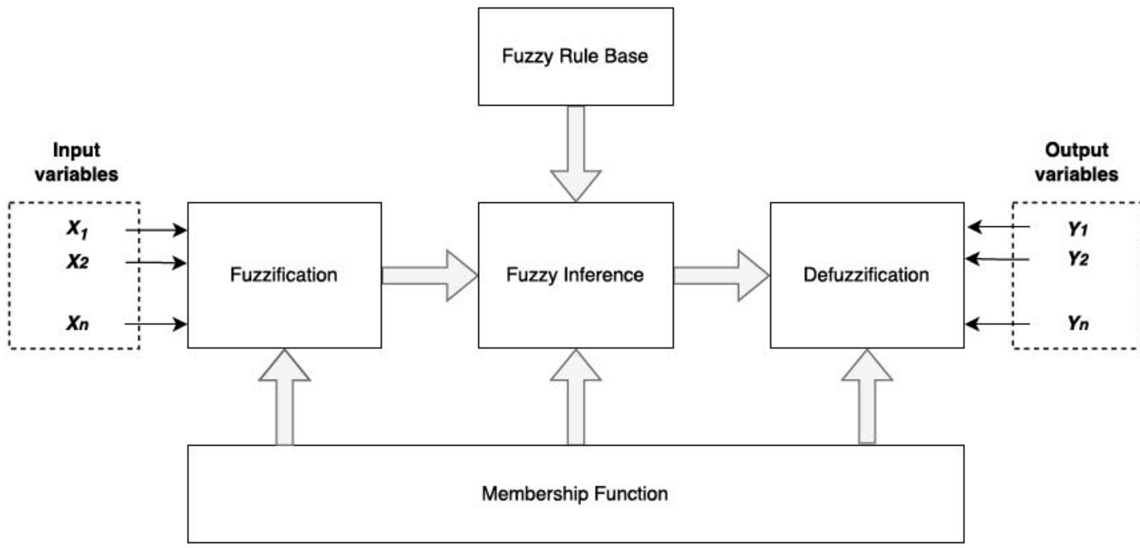


Figure 4. Steps of the fuzzy system.

The Rule Base, the second step, entails applying fuzzy inference through mathematical interpretations of linguistic expressions. Rules are established to establish relationships between input (x1, x2, ...) and output data (y1), describing non-linear relationships or uncertainties using IF-THEN or AND/OR rules without relying on numerical equations or models (Kunduracı & Kazanasmaz, 2019). This forms the foundation of the fuzzy model application, where IF defines the antecedent part of the rule statement with AND/OR connectors. In contrast, the consequent part comprises THEN statements. Researchers construct these rules by analyzing input data or based on intuitive understanding gleaned from existing literature on the subject matter (Gravani et al., 2007).

The fuzzy inference engine harnesses all fuzzy rules and learns to adjust inputs to corresponding outputs using activation operators within the Decision-Making Unit. Defuzzification then translates these fuzzified outputs into concrete values. Various defuzzification methodologies can be found in the literature(Şen, 1998). For example, the maximum membership principle and mean of maxima are two methods that disregard the shape of the fuzzy set and are applicable in specific scenarios (Sivanandam, Sumathi, & Deepa, 2007). Conversely, the weighted average method is suitable only for symmetric rival output membership functions. Another method, the bisector of area, determines the abscissa of the vertical line, dividing the area of the combined output fuzzy subset into two halves (Azizi et al., 2020).

The centroid (COG) method, which calculates the output value as the abscissa under the center of gravity of the combined output fuzzy subset, is the most commonly used (Kazanasmaz & Tayfur, 2012). It is considered a fundamental approach that offers a practical characterization of continuity (Van Leekwijck & Kerre, 1999). Hence, the COG method was selected for this study. Alternatively, the middle of maxima (MOM) method, one of the maxima methods, is employed to compare results during the validation process. The literature notes these methods' superior performance compared to more basic defuzzification criteria (Van Leekwijck & Kerre, 1999). The verbally structured relations are transformed into single numerical values following the Rule Base and Defuzzification phases, which involve additional computations.

4.3.2 Mamdani's fuzzy inference method

This study used Mamdani's inference approach because of its intuitive nature and compatibility with human involvement (Yusoff, Mutalib, Rahman & Mohammed, 2007). It is especially fitting for depicting energy-related behaviors relying on human intuition and behavioral patterns. Rules are combined using a logical OR operator, denoted by the mathematical symbol $\vee$and. Within each rule, logical AND and THEN operations are represented by the minimum operator ∧ (Pedrycz & Gomide, 1998). The method is illustrated as follows:

R: IF x is A_1 AND y is B_1, THEN z is C_1

where Ai, Bi, and C_i represent fuzzy sets.

Mamdani's Inference Method (1974) starts by utilizing the AND operator. It combines fuzzy input numbers, represented by membership sets A_i and B_i, using the minimum operator, which matches the AND connector according to fuzzy intersection rules. This step, called aggregation, chooses input values for x and y on the horizontal axis. Following rule R_2, vertical lines are drawn by intersecting the input values, defining functions $\mu A_1(x)$ and $\mu B_1(y)$. Then, horizontal lines are added, with the first one passing through $\mu A1(x)$ and $\mu B1(y)$.

The AND connector involves identifying the minimum value and extending a horizontal line over the successive fuzzy set C_1. This is achieved by computing w_{C1}= min$\{\mu_{A1}(x), \mu_{B1}(y)\}$. This action truncates set C_1, facilitating the formation of a new C_1 set with a membership function described by $\mu_{C1}(z)$ = min$\{w_{C1}, \mu_{C1}(z)\}$ for all z. Similar steps are taken for rule R_2, creating fuzzy set C_2 (Mamdani, 1974).

The second phase of Mamdani's Inference Method also employs the AND operator. In the composition process, the fuzzy sets corresponding to C_1 and C_2 are merged using the maximum operator, aligning with the OR connector based on fuzzy union rules. This operator establishes the shared boundary for fuzzy sets C. A comparable approach is undertaken for systems with n rules, with each rule contributing independently to derive the output (Mamdani, 1974). During defuzzification, the input linguistic variable's inferred value from fuzzy rules is converted into a real value to yield a single number representing the input linguistic variable's inferred fuzzy values. The selection of the appropriate method can be guided by the centroid method or the occurrence of maximum values in the resulting membership function (Mamdani, 1974).

4.4 Literature Review Summary: Basis for Methodology

The literature review underscores the pivotal role of occupant behavior (OB) in influencing building energy performance, emphasizing its contribution to the energy performance gap between predicted and actual energy use It examines various theoretical frameworks, including the Theory of Planned Behavior (TPB) and Self-Determination Theory (SDT), to explore the psycho-social and motivational factors that influence energy-related behaviors. Additionally, it highlights the role of habitual actions, which occur automatically and significantly affect energy use patterns, and comfort-related factors—such as thermal, visual, and acoustic preferences—that shape occupants' satisfaction and adaptive responses in building environments. The review also highlights key indoor environmental quality (IEQ) aspects, including thermal comfort, air quality, lighting, and acoustics, and their interaction with occupant behavior. Furthermore, it examines existing occupant behavior models and identifies limitations, such as oversimplified assumptions and the lack of integration of psycho-social and environmental factors.

To address these gaps, the review advocates for advanced approaches, including data-driven methods and fuzzy logic modeling, to capture the complexity and variability of occupant actions. By integrating subjective and objective data, the study aims to develop dynamic and context-sensitive models that better align with real-world scenarios. These insights lay the groundwork for the methodological framework, which is designed to operationalize the theoretical concepts and develop predictive models for occupant behavior in office buildings. The methodology chapter will build upon these foundations to present a structured approach for addressing the identified research gaps.

CHAPTER 5

METHOD OF THE STUDY

5.1 Research hypotheses

Specific hypotheses have been developed to systematically investigate the research questions and achieve the study objectives. These hypotheses are a foundation for analyzing the relationships between psycho-social behavioral clusters, occupant actions, and environmental variables. The study has six hypotheses. Table 3 explains each research question, hypothesis-related instrument, data analysis, and outcome. Table 3 explains each research question (see Section 1.2), hypothesis-related instrument, data analysis, and outcome. The hypotheses of the study are:

H_1: There is a statistical relationship between behavioral clusters of office occupants and the psycho-social data.

H_{2a}: There are statistically significant differences within behavioral clusters regarding their behavioral actions.

H_{2b}: A statistically significant correlation exists between the identified clusters and their behavioral actions.

H_3: A statistically significant correlation exists between behavioral actions and environmental variables (temperature, RH, CO_2).

Table 3. *Research questions of the study and related hypotheses, instruments, data analysis method, and outcome.*

Research Question	Hypothesis	Instrument	Data analysis	Outcome
RQ_1	H_1	Online study: -A structured questionnaire	Principal component analysis Two-step cluster analysis	Behavioral clusters
RQ_2	H_{2a}, H_{2b}	Field study: -Daily study	ANOVA	Behavioral differences within clusters
RQ_3	H_3	Field study: -Daily study -IEQ monitoring	Logistic regression	Action probabilities for each cluster

5.2 Study design

The proposed method can detect probabilities of occupant actions in office buildings concerning their identified psycho-social behavioral clusters. This study uses a method to collect subjective and objective data series. Accordingly, the proposed methodology was applied in compliance with the following assumptions: Collecting psycho-social behavioral data in the online survey allows for creating energy-related behavioral clusters in office buildings. Using a set of monitored data and information in the daily surveys concerning the identified behavioral clusters allows for obtaining behavioral models to simulate occupant behavior in office buildings.

Application of the method was achieved in three steps: 01) online study, 02) field study, and 03) implementation. Figure 4 illustrates the process diagram of the study.

Step 01 represents a specialized online questionnaire administered to a sample of office occupants in Turkey. The questionnaire was designed to be similar to the previously developed questionnaires by integrating the TPB (Ajzen, 1991) and the Motivation toward the Environment scale (Correia, Sousa, Viseu & Leite, 2021), adding variables like habit and comfort. The results of the online questionnaire were analyzed through two-step cluster analyses. Subsequently, behavioral clusters were determined from a psycho-social perspective.

Step 02 is the field study conducted in one selected office building that participated in the online study in Step 01. Based on the responses of the selected office occupants to the online questionnaire, they were considered representative occupants of the identified clusters. Data was collected through self-assessed behaviors of the representative occupants in the selected office and through extra dimensions by collecting building data by monitoring indoor environmental conditions (temperature, humidity, and CO_2). Herein, action probabilities were obtained separately for each cluster during the summer and winter periods.

Step 03 corresponds to the software implementation of the occupant actions by using a fuzzy logic modeling approach. This model integrates the behavioral clusters with environmental parameters to simulate the probability of specific occupant actions through a set of IF-THEN rules.

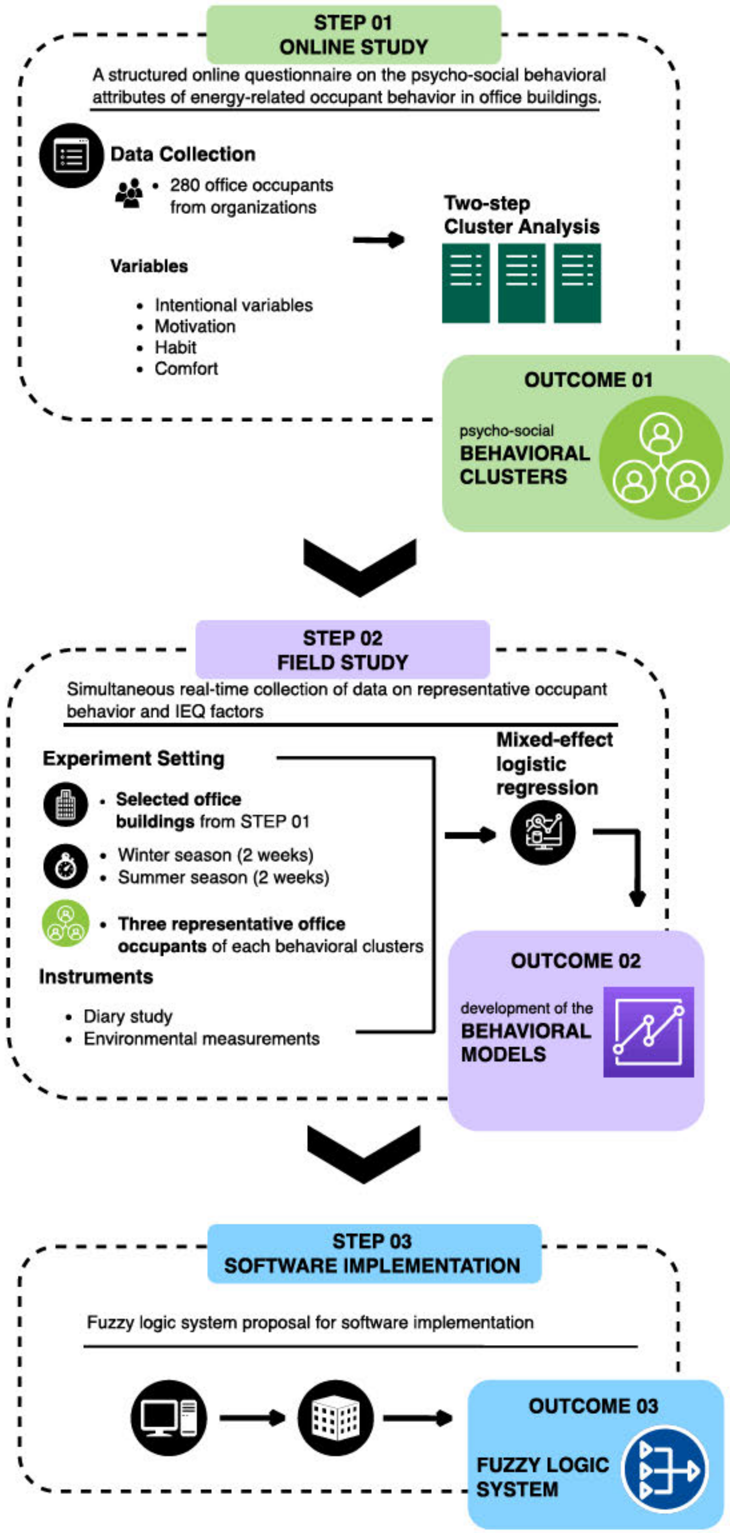


Figure 5. Conceptual flow diagram of the study.

5.3 Step 01 – Online Study

5.3.1 Participants

This study recruited participants from the general population of full-time employees in private sector office settings in three major cities in Turkey: Ankara, Istanbul, and Muğla. The selection of participants was purposeful. According to the Köppen-Geiger climate classification, Ankara is classified as a Csb Climate zone, characterized by significant temperature fluctuations between hot, dry summers and cold, snowy winters (Kottek, Grieser, Beck, Rudolf & Rubel, 2006). Istanbul has a transitional climate, encompassing temperate, subtropical (Cfa), Mediterranean (Csa), and oceanic climate types (Cfb). This results in hot and humid summers and cold, rainy, and occasionally snowy winters (Kottek et al., 2006). Lastly, Muğla belongs to the Csa Climate Zone, characterized by hot and dry summers and warm and rainy winters (Kottek et al., 2006).

The study included a total of 280 participants, ranging in age from 21 to 67 years. G*Power is a widely employed statistical software tool for power analysis concerning hypothesis testing and determining sample sizes. Nevertheless, G*Power lacks specific functionality for determining sample sizes in two-step cluster analysis (Kang, Ou & Mak, 2021). In this manner, the sample size was determined by referring to previous behavioral studies that utilized clustering-based approaches in different areas, including home occupants' energy behavior (n=316) (Ortiz & Bluyssen, 2018), coffee consumption (n=210) (Carvalho et al., 2015), academic and behavioral risk profiles (n=146) (Hagaman et al., 2010), academic performance and lifestyle behaviors (n=248) (Dumuid et al., 2017), and sport participation (n=303) (Chian & Wang, 2008). These studies were used as references to determine the appropriate sample size for the current study.

Office buildings were selected to be included in the sample based on three main criteria: having a minimum of 20 occupants, operating mixed-mode heating and cooling systems, and being no more than 25 years old. To gather the data, organizations affiliated with chambers of industry and commerce in Ankara and Istanbul were invited to participate through an online email survey outlining the specific inclusion criteria. One invited organization also extended its participation by including its sub-company in Muğla, affiliated with the Muğla Chamber of Commerce. Ultimately, the study included office buildings that agreed to participate and met the criteria. As seen in Table 4, the participating organizations represented a range of private sectors, including machines, business and management, food, finance, communication, transportation and logistics, hotel management, electrical and electronics, chemistry, automotive, and transportation and logistics. The goal was to obtain a diverse sample that captured sector variations, participant demographics (age and gender), office layout and size, and climate.

Table 4. Participant distribution by office building affiliation and sector.

	Sectors	n (%)
Ankara Chamber of Industry		
	Machine	40 (14.3)
	Business and Management	62 (22.1)
	Food	11 (3.9)
	Other	5 (1.7)
Ankara Chamber of Commerce		
	Finance	37 (13.2)
	Communication	15 (5.4)
	Transportation and Logistics	14 (5.0)
	Food	13 (4.6)
	Hotel Management	29 (10.4)
	Other	5 (1.7)
İstanbul Chamber of Industry		
	Electrical and Electronics	9 (3.2)
	Chemistry	13 (4.6)
İstanbul Chamber of Commerce		
	Finance	2 (0.7)
	Automotive	8 (2.9)
Muğla Chamber of Commerce		
	Transportation and Logistics	17 (6.0)
Total		(100)

5.3.2 Data Collection

The data collection was conducted online using the SurveyMonkey platform, involving organizations that willingly agreed to participate in the study. The study obtained ethical approval from the Bilkent University Ethics Committee to protect participants' rights and privacy. Before proceeding with the survey, participants were provided with detailed information about the research and allowed to provide their consent to participate voluntarily, following ethical guidelines. The research process, depicted in Figure 5, provides a concise summary of the sequential process of Step 01.

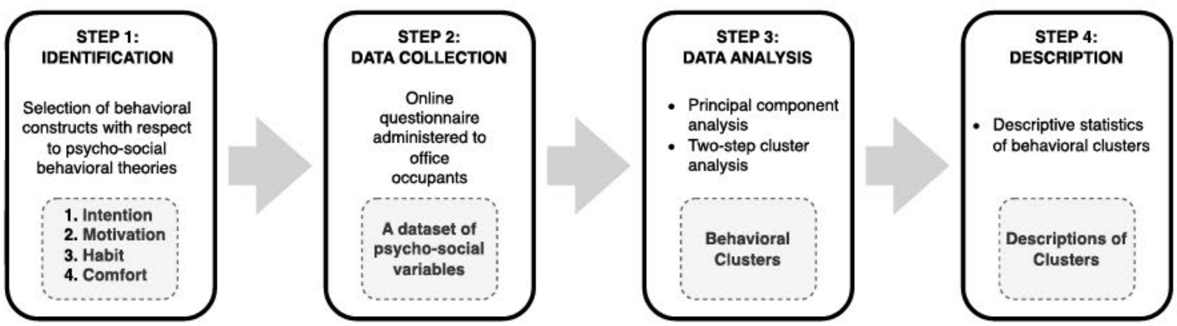


Figure 6. Process diagram of Step 01.

5.3.3 Measures

Psycho-social behavioral data were collected through an online survey using a questionnaire that incorporated constructs from two theories: the Theory of Planned Behavior (TPB) (Ajzen, 1991; Gao, Liu, Liu & Li, 2017) and the Self-Determination Theory (SDT) (Budzanowska-Drzewiecka & Tutko, 2021; Ryan & Deci, 2000). The questionnaire was expanded by adding two additional variables: habit (Verplanken & Sui, 2019) and comfort (Agyekum et al., 2021; Lee, 2019). Its purpose was to assess factors relevant to energy-saving behavior and provide valuable insights for building energy efficiency solutions and simulation modeling. The online format allowed for a diverse and extensive participant sample.

The survey consisted of five parts. The first part collected background information, including demographic details, office layout, size, location, and organization name, as seen in Table 5. The second part focused on TPB constructs: attitude (ATT) - 3 items, subjective norm (SN) - 3 items, and perceived behavioral control (PBC) - 3 items (Ajzen, 1991; Gao et al., 2017). The third part consisted of the original SDT constructs: integrated regulation (INTEG) - 4 items, identified regulation (IDEN) - 3 items, introjected regulation (INTRO) - 4 items, and external regulation (ER) - 4 items (Budzanowska-Drzewiecka & Tutko, 2021; Ryan & Deci, 2000). The fourth part assessed the habit construct (H) with six items, using a self-report habit index developed by Verplanken and Orbell (Verplanken & Sui, 2019). The fifth part focused on comfort (C) and comprised six items. Participants rated their general perception of indoor environmental quality parameters in their offices, such as temperature, air quality, natural lighting, and artificial lighting (Agyekum, Hammond & Salgin, 2021; Lee, 2019). The questionnaire did not include the acoustic environment, as occupant behavior does not influence it.

All constructs were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). It's important to note that the questionnaire was translated from English to Turkish, following a rigorous process that involved translation into Turkish, back-translation into English for accuracy verification, and evaluation by three content experts specializing in social psychology and human behavior. Based on their feedback, certain measurement items were modified in the Turkish version of the questionnaire to enhance its validity. For a detailed explanation of each construct's operational definition and measurement items, please refer to Table 6.

Table 5. Background survey questions in the online study.

Category	Answer option
Demographic information	Age (Open-ended) Gender (Male/Female) Education level (Senior high school or below, college or bachelor's degree, master's degree or above)
Office layout	Open-plan, shared enclosed, individual office
Office size/occupant number	Large office room (10+ occupants), Middle office room (5-10 occupants), Small office room (1-4 occupants)
Office location	Open-ended
Organization name	Open-ended

Table 6. Constructs and measurement items in the online study.

Key references	Construct	Operational definition	Items for measurement
Theory of Planned Behavior (Ajzen, 1991; Gao et al., 2017)	Attitude (ATT)	An individual's overall assessment of regarding energy conservation in their workplace.	ATT1: I think that saving energy in my workplace is helpful for protecting the environment ATT2: I think energy-saving behaviors in my workplace are a wise action ATT3: I think energy-saving behaviors in my workplace are valuable for alleviating energy shortages.
Theory of Planned Behavior (Ajzen, 1991; Gao et al., 2017)	Subjective norm (SN)	An individual's perception of how significant individuals view their responsibility to engage in energy-saving behavior within their workplace.	SN1: My colleagues think that I should save energy in my workplace. SN2: My managers want me to save energy in my workplace. SN3: People who are important to me want me to save energy in my workplace.
Theory of Planned Behavior (Ajzen, 1991; Gao et al., 2017)	Perceived behavioral control (PBC)	An individual's belief in their own resources and abilities to effectively engage in energy-saving behavior within their workplace.	PBC1: I think that I am capable of saving energy in my company. PBC2: I have the knowledge and skills to save energy in my company. PBC3: Whether or not saving energy is entirely up to me.
Self Determination Theory (Budzanowska-Drzewiecka & Tutko, 2021; Ryan & Deci, 2000)	Intrinsic motivation (IM)	An individual's internal motivation and belief in their own ability to perform energy-saving behavior in their workplace.	IM1: I derive pleasure from mastering new ways of helping. IM2: I derive pleasure from improving the quality of the environment. IM3: I derive pleasure from doing things for the environment. IM4: I derive pleasure from contributing to the environment.

Table 6 (cont'd)

Self Determination Theory (Budzanowska-Drzewiecka & Tutko, 2021; Ryan & Deci, 2000)	Extrinsic motivation (EM): - Integrated regulation (INTEG) - Identified regulation (IDEN) - Introjected regulation (INTRO) - External regulation (ER)	An individual's motivation influenced by external factors and external reasons to perform energy-saving behavior in their workplace.	INTEG1: It is an integral part of my life INTEG 2: It is inseparably linked with self-care INTEG 3: It is my way of life INTEG 4: It is a fundamental part of me IDEN1: It is a sensible action IDEN2: It is a way to contribute to the environment IDEN3: It is an excellent idea to do something about the environment INTRO1: I would regret it if I did nothing. INTRO2: I would feel guilty if I did nothing. INTRO3: I would feel bad if I did nothing. INTRO4: I would be ashamed of my inactivity. ER1: To avoid upsetting others ER2: To gain approval ER3: My friends insist ER4: To avoid being criticized
Self-report habit index (Verplanken & Sui, 2019)	Habit (H)	An individual's spontaneous or automatic behavioral response to engage in energy-saving behavior in their workplace.	H1: Saving energy in my workplace is something that gives me a strange feeling when I don't do it H2: Saving energy in my workplace is something that I do automatically H3: Saving energy in my workplace is something that I do without thinking about it H4: Saving energy in my workplace is something that is part of my routine H5: Saving energy in my workplace is something that is typical for me H6: Saving energy in my workplace is something that does not require any active thought
Comfort Perception (Agyekum et al., 2021; Lee, 2019)	Comfort (C)	An individual's subjective satisfaction with the indoor environmental conditions in their workplace.	C1: I am satisfied with the temperature in my workplace C2: I am satisfied with the humidity in my workplace C3: I am satisfied with the air quality in my workplace C4: I am satisfied with the ventilation in my workplace C5: I am satisfied with the amount of daylight in my workplace C6: I am satisfied with the comfort of artificial lighting

5.3.4 Data Analysis

The data analysis was performed using IBM SPSS Statistics 24. Initially, 354 responses were collected, incomplete or missing data were excluded, and responses with a standard deviation below 0.25 were eliminated. The remaining 280 valid responses were used for further analysis.

Described statistics were conducted to understand the characteristics of the study participants. Then, Principal Component Analysis (PCA) was employed to decrease the psycho-social, motivational, habitual, and comfort constructs into smaller independent components, minimizing information loss. The suitability of PCA was assessed using the Kayser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity (BTS). A p-value below 0.001 indicated that the data were appropriate for analysis. The number of components was detected based on eigenvalues greater than 1, KMO values exceeding 0.7, Varimax orthogonal rotation, and significant factor loadings of 0.4 or higher.

Next, a Two-step cluster analysis was carried out using the variables identified from the PCA to categorize office workers based on their self-reported responses. Two-step cluster analysis was selected because it can handle categorical and continuous data simultaneously, automatically determine the optimal number of clusters, and needs minimal data preparation. This method was appropriate to analyze demographic, intentional, motivational, habitual, and comfort data relevant to the study. Akaike's Information Criterion and the log-likelihood distance measure were utilized for the analysis.

The validation of the final model involved four steps. First, the silhouette measure coefficient was examined, with a recommended value above 0.0 and preferably above 0.2. Second, cluster differences were assessed using a p-value threshold of less than 0.05. Third, the predictor importance of variables was controlled, with a recommended threshold of greater than 0.02. Finally, the model's outcomes on two randomly split datasets were compared. Lastly, descriptive statistics for each cluster were performed to specify and label the resulting behavioral clusters.

5.4 Step 02 – Field Study

Fabi et al. (2011) explained that a comprehensive database should encompass all parameters related to the potential driving forces behind occupant behavior. This includes external parameters, such as physical, environmental, and contextual variables, and internal parameters, such as social, psychological, and physiological variables. While most existing studies have primarily focused on monitoring activities using measurements, it is crucial to highlight that surveys and questionnaires addressed to occupants are vital tools for accurately characterizing user behavior.

Yan et al. (2015) mentioned that traditional methods of manual observation, such as using photographs or handwritten recordings, had limitations regarding the sample group size. These limitations included the number of individuals observed and the duration of the observations. Furthermore, these methods were not well-suited for developing statistical models that could be used in building simulations. In early research on occupant behavior, surveys significantly gained insights into critical behavioral characteristics and motivators influencing interactions with building systems (Andersen et al., 2009). While surveys and interviews provide valuable insights, they come with particular challenges. Firstly, participants may knowingly or unknowingly misrepresent their behavior (Lutzenhiser, 1993). Secondly, they may struggle to recall their behaviors accurately or gauge the severity of discomfort they experienced (Gunay et al., 2014). Lastly, participants may feel compelled to respond in ways they believe align with expectations. To overcome these issues, one potential solution is to employ frequent computer-based surveys. This approach involves regularly prompting occupants to report their recent comfort levels and behaviors, partially offering a means to address the concerns mentioned above (Yan et al., 2015).

In this study, considering respective behavioral clusters, occupant actions were observed, and environmental parameters were monitored with a field study. At the same time, occupants' perceptions and preferences about the indoor environment were collected. When the field study concluded, the complete data was analyzed to identify relationships between occupant actions and the measured environmental parameters. In this manner, the causal relationships between the dependent variable, occupant actions, and the independent variables, environmental parameters, indoor environmental satisfaction, and comfort preference, were investigated for each cluster. Consequently, statistical models were created to predict occupant behavior of different clusters concerning occupant actions in an office building.

For Step 02 of the study, a representative sample office building was carefully chosen, along with individual office rooms equipped with mixed-mode building systems. The selection criteria included several factors:

1. Ensuring the presence of at least three representatives from each behavioral cluster.
2. Having adjustable control elements such as windows, doors, thermostats, and, if possible, solar shading.
3. Being small-sized office spaces with a maximum of 1-4 occupants to minimize the influence of external factors like other co-workers.

The adequate sample size for Step 02 was determined by seeking response saturation, ensuring comprehensive data collection without introducing bias. In this manner, references were made to insights from prior field studies in the field to determine the adequate sample size. This approach aimed to strike a balance, optimizing the richness of responses while staying within the project budget and time frame constraints. In this context, Ortiz and Bluyssen (2019) conducted a qualitative data collection field study through interviews with 15 participants. Building data, including indoor environmental parameters (temperature, humidity, and CO2) and energy readings, were monitored using a building characteristics checklist. In another study, Pisello et al. (2016) explored the influence of peers' attitudes on building thermal energy, lighting performance, and opening schedules. This research involved 12 office occupants and covered spring, summer, and winter, with daily surveys conducted for one week each. Li et al. (2015) observed window opening behaviors for natural ventilation in an office building during the transition seasons involving 15 occupants over two months. Rafsanjani et al. (2018) tracked the energy-use behaviors of 12 occupants in two office buildings over four months, focusing on entry and departure events. Peng et al. (2012) conducted a quantitative study describing human behavior in residential buildings. This research involved five participants and incorporated objective and subjective measurements for ten days in the summer and one month in the winter. Du and Pan (2021) applied mixed methods, including a questionnaire survey of 137 students, in-situ monitoring of adaptive behaviors using noninvasive sensors in 12 rooms with 12 participants, building energy simulation validated by full-season metered energy use data, and scenario analysis considering multifaceted factors. Lastly, Langevin et al. (2015) conducted a longitudinal case study on occupant thermal comfort and related behavioral adaptations in an air-conditioned office building, with 24 participants filling out daily surveys over two weeks.

In Step 01, occupants from offices of varying sizes were recruited for the online study. The offices were categorized as small (1-4 occupants), medium (5-9 occupants), and large (+10 occupants). However, research suggests that having more people in the same room reduces the perceived control of occupants (Schweiker & Wagner, 2016). This could potentially affect the energy-related behavior of participants during the field study. Therefore, for Step 02, only participants from small offices with a maximum of four people were recruited. The selected office occupants were free to control building systems related to indoor air quality. This approach aims to gather the necessary information for analyzing different behavioral actions among representative office occupants within their specific clusters and office environments. The field study was conducted for both the summer and winter seasons. The variables selected for monitoring the real-time data were (i) occupant behavior through their actions and (ii) IEQ factors. These variables were measured simultaneously, and collected data were used for further analysis. Thereby, the field study protocol consists of the following:

- A two-week summer and winter study (start survey, daily survey, and end survey),
- A two-week summer and winter continuous IEQ monitoring (outdoor temperature, indoor temperature, relative humidity, and CO_2).

5.4.1 Case building and offices

The field study was conducted on the office floor of a high-rise hotel building located in Ankara, Türkiye (39°56'51.5 “N 32°46'11.7" E). Figure 6 shows the façade of the hotel building. The construction of the building was finished in 2022. According to the Köppen-Geiger classification, the building is part of the Csb Climate zone with notable variations in temperature, with hot and arid summers contrasting sharply with cold, snow-filled winters (Kottek et al., 2006). The building has a centralized heating and cooling system with operable thermostats in each office. Natural ventilation was also possible with operable windows and doors for air exchange.

Figure 7. Façade of the case hotel building where the offices were selected (photograph taken by the author, 2023).

A total of six offices were selected and investigated. Figure 7 illustrates the office floor layout, indicating the chosen office rooms, the placement of sensors, and the gateway utilized for the investigation. Table 7 provides an overview of the designated offices and their occupants. The office floor consisted of one general manager's office, two administrative offices, three private offices, and three shared enclosed offices. All offices were equipped with A/C systems, windows, and doors. Some offices were also equipped with solar shading. Occupants typically used the offices on weekdays, from Monday to Friday, from 8:30 a.m. to 6:30 p.m.

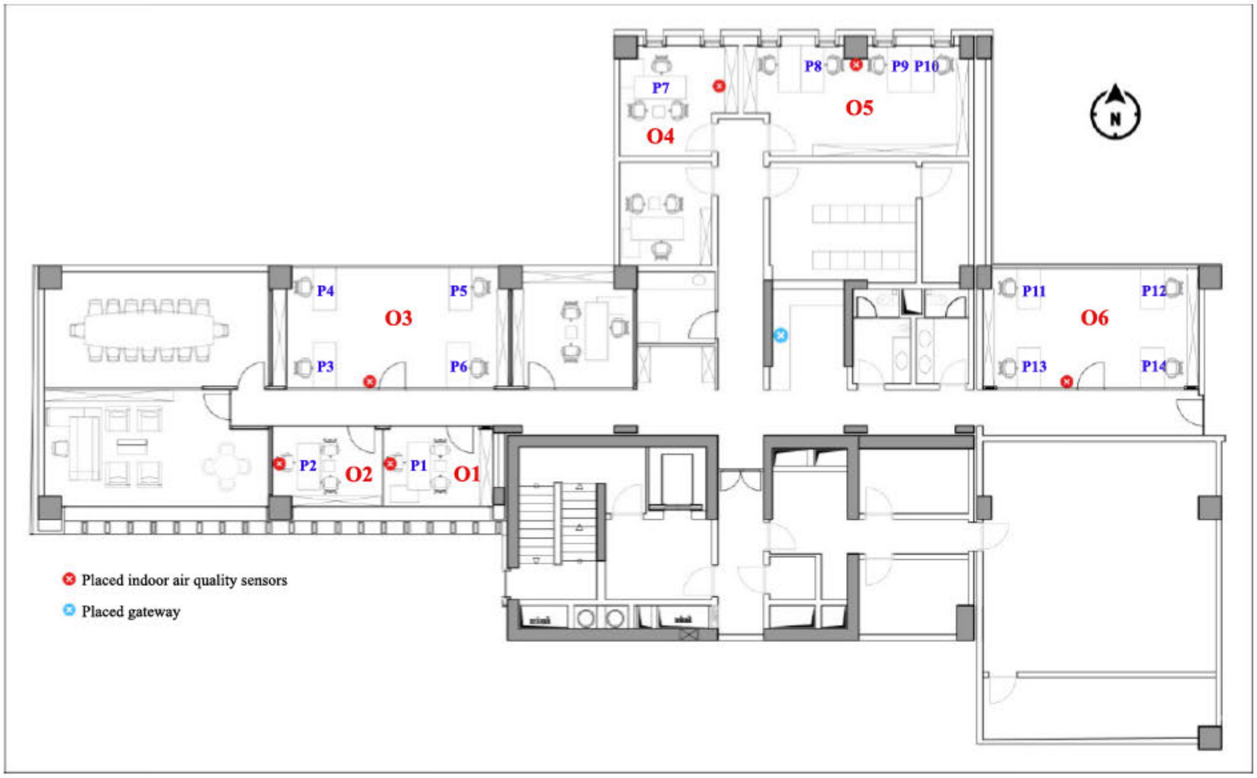


Figure 8. The layout of the investigated office floor.

Table 7. Summary of the investigated building and participants.

Participant ID	Office ID	Office type	No. of occupants	Available physical controls	Façade
P1	O1	Private	1-4	Windows, doors, solar shading, thermostat	South
P2	O2	Private	1-4	Windows, doors, solar shading, thermostat	South
P3	O3	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P4	O3	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P5	O3	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P6*	O3	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P7	O4	Private	1-4	Windows, doors, thermostat	North
P8	O5	Shared-enclosed	1-4	Windows, doors, thermostat	North
P9	O5	Shared-enclosed	1-4	Windows, doors, thermostat	North
P10*	O5	Shared-enclosed	1-4	Windows, doors, thermostat	North
P11	O6	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P12	O6	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P13	O6	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North
P14	06	Shared-enclosed	1-4	Windows, doors, solar shading, thermostat	North

*Participants who only took part in the winter field study.

5.4.2 Participants

The study included participants from the selected office building who participated in Step 01. Initially, a meeting was held with the organization manager to explain the recruitment process for the office rooms. A final list of employees and their email addresses was obtained, considering the recruitment criteria detailed in Section 5.4. Participants who expressed their willingness to take part in the daily study were subsequently enrolled.

To initiate the recruitment process, an email was sent to employees of the selected office building, providing them with a clear outline of the field campaign's procedure. The research obtained ethical approval from the Bilkent University Ethics Committee to protect participants' rights and privacy. Before starting the daily study, a face-to-face meeting was arranged with the participants. This meeting provided comprehensive information about the research, ensuring transparency and adherence to ethical guidelines. During this meeting, participants were allowed to provide voluntary consent, empowering them to make informed decisions regarding their participation in the study.

Throughout the field study, participants were free to modify the environmental conditions of their office spaces, including adjustments to windows, doors, solar shadings, and thermostats. They were also free to choose their clothing and drink intake based on their preferences. Importantly, no restrictions were imposed on the participants, allowing them to act following their regular daily routines.

5.4.3 Subjective measurements

As part of a field study, a daily study was conducted to monitor changes in representative occupants' comfort perceptions, preferences, and behavioral actions during the summer and winter seasons. This study analyzes the dynamic relationship between occupant actions and the indoor environment, specifically focusing on thermal environments. To this end, occupant actions and measured environmental conditions were explicitly selected. The field study consists of three parts: a start survey, a daily survey, and an end survey. A WhatsApp group was created with the participants during the face-to-face meeting to ensure effective communication and facilitate the survey distribution during the field study.

The start survey includes questions about the occupants' overall assessment of the indoor environment, their perception of various factors related to indoor air quality (thermal comfort, humidity, and air quality), and the frequency of their physical and personal adjustments in their office rooms as seen in Table C1 in Appendix C. Then, for a continuous two-week period in both the summer (completed) and winter seasons (scheduled for the following January), the occupant sample filled out the daily (right-now) survey one time a day (late afternoon). The daily (right-now) survey is based on ASHRAE Standard 55 (ASHRAE, 2013), and the parameters were quantified on multi-point scales, as seen in Table C2 in Appendix C. These surveys were sent through the WhatsApp group every working day, one hour before the end of the working hour. The participants rated their satisfaction with overall indoor climate, temperature, humidity, and air quality on ASHRAE seven-point scale (1: very dissatisfied, 2: dissatisfied, 3: slightly dissatisfied, 4: neutral, 5: slightly satisfied, 6: satisfied, 7: very satisfied). Additionally, thermal preference (-2: much warmer, -1: a bit warmer, 0: no change, 1: a bit cooler, 2: much cooler) and humidity preference (-2: much humid, -1: a bit humid, 0= no change, 1: a bit drier, 2: much direr) were recorded on an ASHRAE five-point scale.

Occupant actions with the building systems (windows, doors, solar shading, and thermostat), clothing adjustments, and drink intake were collected in binary form. The frequency of these actions was recorded using four options: 1-3 times, 4-6 times, 7-9 times, and 10 or more times (see Table C2 in Appendix C). Besides, although clothing level and drink intake do not directly influence energy use but affect occupant comfort (Yan et al., 2015), they were considered in this study as influencing factors of occupants' adaptive behaviors. Clothing insulation values were evaluated based on the ASHRAE Standard-55, considering the participants sat for 15-20 minutes while completing the daily survey. The metabolic rate was assumed to be 1.2 MET, as specified by the ASHRAE Standard-55 (ASHRAE, 2013).

At the end of two weeks, an end retrospective survey was administered to collect participants' overall comfort and experience during the survey period. As seen in Table C3 in Appendix C, participants could also provide feedback on their satisfaction with the questionnaire.

Therefore, the representative office occupants were analyzed for both winter and summer from three approaches:

- Daily subjective assessment of indoor environmental conditions
- Observation of occupant actions during the day
- Tracking the number of occupant actions per day

5.4.4 Objective measurements

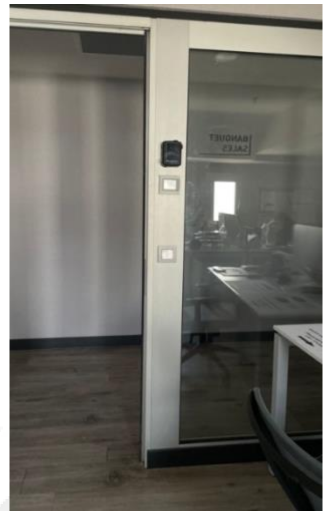
Outdoor temperature, indoor temperature, relative humidity (RH), and carbon dioxide (CO_2) measurements were taken through Sensgreen Air Quality Sensors (Sensgreen, 2023). The photographs of the instruments are shown in Figure 8. Measurements were collected for two weeks each summer (completed) and winter (scheduled for the following January) season simultaneously with the daily study. Following ASHRAE Standard 55-2020 (ASHRAE, 2020), placing IEQ monitoring sensors is essential to ensure accurate and representative measurements of indoor environmental conditions. The standard recommends that sensors be positioned in areas where occupants typically spend most of their time or engage in activities. However, if it is challenging to estimate the occupancy distribution, a practical approach is to place the sensors at the center of the room. Since occupants in office environments are usually seated during their daily activities, specific guidelines are provided for placing sensors to measure temperature, humidity, and CO2 levels. For temperature and humidity measurements, sensors should be positioned at different heights: 0.1m, 0.6m, or 1.1m. These heights account for variations in indoor climate to varying levels within the room, enabling a comprehensive assessment.

(a) Indoor air quality sensor (b) Gateway of the indoor air quality sensors

Figure 9. The instruments used during the field study (photographs taken by the author, 2023).

On the other hand, for measuring CO2, it is recommended to place sensors at a height of 1.8m, corresponding to the typical breathing zone of seated occupants. This placement ensures that CO2 measurements accurately represent the air quality experienced by individuals during their regular working conditions. The sensors placed in the selected offices are shown in Figure 9.

(a) Sensor placed in office



(b) Sensor placed in office

(c) Sensor placed in office

(d) Sensor placed in office

Figure 10. Some sensors were placed at the selected offices during the field study (photographs taken by the author, 2023).

In this study, the Sensgreen sensors (Sensgreen, 2023) proved to be highly versatile and capable of effectively measuring all of these parameters. Therefore, an average height of 1.5m above the floor was selected as the installation point for the IEQ sensors. Placing the sensors at this central height within the office allowed for a representative and balanced indoor environmental quality assessment. By adhering to ASHRAE guidelines and employing the

Sensgreen sensors at the specified heights, the study obtained comprehensive and reliable data on temperature, humidity, and CO2 levels, enabling a thorough analysis of the indoor environmental conditions in the selected office setting.

Special care was taken to ensure the sensors were shielded from direct sunlight and kept from heating/cooling sources. There are no universal standards for the time interval of data recording regarding sensors. However, for energy modeling purposes, it is suggested to use a five-minute time interval for frequently occurring occupant behaviors, while a time interval of 15 minutes to 1 hour is considered acceptable (Du et al., 2020). In this study, the environmental parameters were recorded in 15-minute intervals. Data was collected considering the working hours and days of the selected building. Accordingly, the indoor environmental conditions were analyzed through the:

- Daily outdoor/indoor environmental conditions regarding air temperature, relative humidity (RH), and carbon dioxide (CO_2) (daily mean values)
- The effect of season, weather, and indoor conditions on occupants' actions with the building systems, clothing, and drink intake.

5.4.5 Data Analysis

During the field study, the environmental parameters and occupant actions were collected. Additionally, the participants' comfort perceptions and comfort preferences were also gathered. As a result, there were two distinct types of data: one related to the subjective responses of the participants and another to environmental parameters measured through sensors– factors that may influence these actions were to be investigated in this study. A series of statistical analyses were conducted to understand occupants' behavior of different behavioral clusters.

The subjective responses obtained from the participants during (1) start survey, (2) daily survey, and (3) end survey were analyzed separately. The dataset included responses related to occupant actions, satisfaction with indoor environmental quality, and comfort preferences. First, the dataset was subjected to descriptive analysis. Then, one-way ANOVA analyses were performed to compare the differences among the three clusters in terms of their frequencies of occupant actions, satisfaction with indoor environmental quality, and comfort preferences.

To explore occupants' actions, including window operation (WO), solar shading operation (SO), door operation (DO), thermostat adjustment (TA), clothing adjustment (CA), and drink intake (DI) concerning the environmental parameters, a logistic regression analysis was conducted. The logistic regression analysis has been the most frequently employed method to predict the probability of an adaptive action (Carlucci et al., 2020). This statistical method is suitable for scenarios with only two categorical outcome variables, such as yes/no or binary measurements, for dependent variables (Sperandei, 2014). It is commonly employed to estimate the likelihood of specific actions, like opening windows, based on environmental factors (Haldi & Robinson, 2008; Rijal et al., 2007).

The study analyzed these actions through binary logistic regression to understand their likelihood. Before applying the logistic regression, the assumptions of this method were tested to ensure its appropriateness for the study. The dependent variables (WO: closing/opening, SO: lowering/raising, DO: closing/opening, TA: switching off/on, CA: adding/removing, and DI: hot/cold) were measured using binary levels (yes/no), while environmental parameters (outdoor temperature, indoor temperature, humidity, and CO2) and behavioral clusters served as independent variables in the study. The outcome variables of the model are illustrated in Table 8. Lastly, to further understand the rules governing the occupant actions in an office building during the day, the frequency of each action was statistically analyzed.

Table 8. Outcome variables of the model

Outcome variable	Outcome
Behavioral cluster	1 – Cluster 1 2 – Cluster 2 3 – Cluster 3
Comfort perception	ASHRAE seven-point scale
Comfort preference	ASHRAE five-point scale
Adaptive actions (mixed effect models)	**Binary Outcome**
Probability of windows opening	0 – no window changing 1 – open windows
Probability of windows closing	0 – no window changing 1 – close windows
Probability of raising solar shading	0 – no solar shading changing 1 – raise solar shading
Probability of raising solar shading	0 – no solar shading changing 1 – lower solar shading
Probability of switching on the thermostat	0 – no thermostat changing 1 – switch on the thermostat
Probability of switching off the thermostat	0 – no thermostat changing 1 – switch off the thermostat
Probability of adding a garment	0 – no clothes changing 1 – add a piece of clothes
Probability of removing a garment	0 – no clothes changing 1 – remove a piece of clothes
Probability of drinking a hot beverage	0 – drank nothing 1 – drank a hot beverage
Probability of drinking a hot beverage	0 – drank nothing 1 – drank a cold beverage
Environmental parameters	Indoor temperature – daily mean Outdoor temperature – daily mean Humidity – daily mean CO_2 – daily mean

A correlation approach was utilized, referring to the study of Pan et al. (2018) in analyzing the correlation between occupants' actions and their influential factors. This study explored the influence of environmental factors on occupants' actions. The significance probability of the correlation coefficient plays a crucial role in determining the relationship between two variables. When p is less than 0.05, it indicates a significant correlation between the variables. If p is less than 0.01, the correlation becomes even more critical. Conversely, when p is higher than 0.05, it suggests no significant correlation between the two variables, and p merely represents the probability value (Pan et al., 2018b).

The datasets were prepared and analyzed separately for both summer and winter data. First, correlation analyses were performed to explore the relationships between different variables, as explained in Section 5.3.4, to prepare the dataset for regression analysis. Collinearity statistics, as suggested by Weerasinghe (2022), were then used to detect multicollinearity among predictor variables. Typically, tolerance values below 0.1 and variance inflation factor (VIF) values above 10 are indicators of significant multicollinearity. In this study, a stable logistic regression model required the absence of multicollinearity among predictors and the identification of potential outliers. High-correlated variables were identified and removed based on collinearity statistics to address this. Additionally, potential outliers in the independent variables were checked using box plots of Z-score values (Sperandei, 2014).

Following the correlation analysis, environmental variables that were not statistically related to the corresponding occupant actions were removed from further analysis. Collinearity statistics were performed separately for each behavioral cluster (WO: opening/closing, SO: lowering/raising, DO: opening/closing, TA: switching off/on, CA: removing/adding, and DI: hot/cold). Next, outliers were checked using box plots of Z-score values.

The goodness of fit statistics determines how well the model describes the data. To evaluate this, a chi-square (χ^2) analysis is conducted for each behavioral cluster separately. If there is a significant outcome, this suggests that the model fits the data well and demonstrates a considerable improvement compared to the null model. After considering the p-value (<0.05), the models that did not sufficiently fit the data were removed from further analysis.

Lastly, the Wald statistic was used to assess the statistical significance of each B coefficient in the logistic regression models, indicating the individual impact of each predictor variable on the outcome. Since logistic models were employed, interpreting the regression coefficients was best understood through the odds ratio (OR), representing the exponential of the B coefficient. The odds ratio estimates the change in odds resulting from a unit change in the predictor variable. Finally, the Nagelkerke R-squared value was calculated to assess the goodness of fit of the logistic regression models, indicating how well the models fit the observed data.

CHAPTER 6

RESULTS – STEP 01 ONLINE STUDY

6.1 Descriptive analysis

A total of 354 participants accepted and participated in the online survey study. Among the 354 respondents, 280 completed questionnaires were received, which means a completion rate of 79%. The gender ratio was almost identical, with 139 (49.6%) females and 141 (50.4%) males. The mean age of the participants was 36.44 years (SD=8.496). Concerning education, most declared (n=185, 66.1%) graduated from college or had a bachelor's degree, whereas 44 (15.7%) participants graduated from senior high school or below, and 49 (17.5%) graduated with a master's degree or above. Considering the office layout, the number of participants working in shared enclosed (n=113, 40.4%) and open-plan (n=112, 40.0%) was almost identical, where 55 (19.6%) participants worked in individual offices. The most common office size was small office rooms (1-4 occupants) (n=125, 44.6%), followed by large office rooms (10+ occupants) (n=95, 33.9%) and middle office rooms (5-10 occupants) (n=60, 21.4%).

6.2 Principal component analysis

Based on the sample of 280 participants, the KMO measure and BTS test support the feasibility of PCA (KMO=0.899, $p<0.001$). The PCA resulted in 7 components, which accounted for 73.188% of the total variance. Table 9 shows the result of the rotated component matrix.

Component 1 contains a total of ten items: perceived behavioral control, intrinsic motivation, integrated regulation, and identified regulation. These items include statements like "Whether or not saving energy is entirely up to me," "I derive pleasure from mastering new ways of helping," and "It is a sensible action." This component is labeled as inherent motivation (Cronbach's alpha = 0.941).Considering its elements, the study named this component *inherent motivation (INHER)*.

Component 2 expresses all six items of habit, such as "Saving energy in my workplace is something that gives me a strange feeling when I don't do it," "Saving energy in my workplace is something that I do automatically," "Saving energy in my workplace is something that I do without thinking about it," "Saving energy in my workplace is something that is part of my routine," "Saving energy in my workplace is something that is typical for me," and "Saving energy in my workplace is something that does not require any active thought" (Cronbach's alpha=0.879).

Component 3 includes all six items of comfort perception as "The temperature in your workspace," "The humidity in your workplace," "The air quality in your workspace," "The ventilation in your workspace," "The amount of daylight in your workspace," and "The comfort of artificial lighting" (Cronbach's alpha=0.870). Component 4 describes all four items of introjected regulation as "I would regret it if I did nothing," "I would feel guilty if I did nothing," "I would feel bad if I did nothing," and "I would be ashamed of my inactivity" (Cronbach's alpha=0.914). Component 5 contains all four items of external regulation: "To avoid upsetting others," "To gain approval," "My friends insist," and "To avoid being criticized" (Cronbach's alpha=0.913). Component 6 expresses all three items of the attitude (Cronbach's alpha=0.927). Lastly, Component 7 represents all three items of the subjective norm (Cronbach's alpha=0.826). These findings provide a robust basis for analyzing and modeling energy-related actions in office environments.

Table 9. Results of the rotated component matrix

Rotated Component Matrix[a]							
	Component						
	1 (Inherent motivation)	2 (Habit)	3 (Comfort)	4 (Introjected regulation)	5 (External regulation)	6 (Attitude)	7 (Subjective norm)
ATT1						.847	
ATT2						.889	
ATT3						.827	
SN1							.782
SN2							.858
SN3							.813
PBC3	.856						
IM1	.877						
IM2	.897						
IM3	.887						
INTEG2	.614						
INTEG3	.530						
INTEG4	.527						
IDEN1	.699						
IDEN2	.741						
IDEN3	.731						
INTRO1				.722			
INTRO2				.814			
INTRO3				.799			
INTRO4				.775			
ER1					.743		
ER2					.926		
ER3					.920		
ER4					.913		
C1			.737				
C2			.806				
C3			.869				
C4			.852				
C5			.577				
C6			.669				
H1		.459					
H2		.700					
H3		.768					
H4		.794					
H5		.787					
H6		.683					

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

Table 10 shows the correlation between the obtained components and the respondents' socio-demographic characteristics, office type, and office size. The components with p-value (sig2-taled) <0.05 were strongly correlated with the related social-demographic variable.

Table 10. The correlations of identified components.

Correlations								
		ATT	SN	INHER	INTRO	ER	H	C
Age	Pearson Correlation	.047	.003	-.070	-.126*	-.016	-.009	.003
	Sig. (2-tailed)	.436	.966	.253	.038	.792	.878	.963
	N	272	272	272	272	272	272	272
Gender	Pearson Correlation	.119*	.073	-.012	-.094	-.011	.026	.139*
	Sig. (2-tailed)	.046	.224	.835	.116	.855	.671	.020
	N	280	280	280	280	280	280	280
Education	Pearson Correlation	-.196**	-.123*	.039	.022	-.092	-.069	-.100
	Sig. (2-tailed)	.001	.039	.512	.711	.123	.251	.096
	N	280	280	280	280	280	280	280
Office layout	Pearson Correlation	-.209**	-.005	.089	.118*	.013	-.040	-.114
	Sig. (2-tailed)	.000	.928	.138	.049	.828	.504	.056
	N	280	280	280	280	280	280	280
Office size	Pearson Correlation	.182**	.034	.097	.105	.026	.188**	.200**
	Sig. (2-tailed)	.002	.567	.104	.080	.667	.002	<001
	N	280	280	280	280	280	280	280

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

6.3 Two-step cluster analysis

A two-step cluster analysis was conducted using the new variables (n=36) generated by the PCA to categorize office occupants. Demographic variables, office type, and office size were not used to produce clusters since the clusters need to be based on the participants' intentional, motivational, habitual, and comfort expressions. Three clusters were made for 280 office employees. The size of the Cluster 1 is 93 (33.2%), Cluster 2 is 60 (21.4%), and Cluster 3 is 127

(45.4%). The silhouette measure of cohesion and separation of the clusters in the final model was 0.2, indicating a fair separation between the clusters (Tkaczynski, 2016). The variable with the lowest score of predictor importance was subjective norm 2 (SN2), with a rating of 0.27, well above the recommended 0.02. The highest score of predictor importance was 1.00 and belonged to habit 3 (H3). The result of the ANOVA showed that the final 36 variables were statistically significant ($p<0.001$), and hence, they all varied between the three identified clusters. Finally, the database was split into two, and the result of the final solution was compared, where minor changes were determined (Table 11). All of these showed that the constituted cluster solution was justified (Norušis et al., 2011).

Table 11. Final solution variables and prediction importance

Predictor Importance	Final Solution	First half solution	Second half solution
0.8-1.0	Habit 3 (1.00) Habit 4 (0.87) Habit 2 (0.84) Introjected regulation 3 (0.83) Identified regulation 3 (0.80)	Habit 3 (1.00) Habit 4 (0.86) Habit 2 (0.85)	Habit 5 (1.00) Habit 4 (0.81)
0.6-0.79	Introjected regulation 2 (0.79) Habit 5 (0.78) Identified regulation 2 (0.76) Introjected regulation 4 (0.72) Integrated regulation 4 (0.71) Integrated regulation 2 (0.70) Introjected regulation 1 (0.68) Intrinsic motivation 3 (0.67) Identified regulation 1 (0.63) Integrated regulation 3 (0.63) Intrinsic motivation 1 (0.62)	Identified regulation 3 (0.79) Identified regulation 2 (0.77) Introjected regulation 2 (0.70) Introjected regulation 3 (0.63) Habit 5 (0.63) Intrinsic motivation 3 (0.62)	Habit 3 (0.72) Habit 1 (0.71) Habit 2 (0.70) Habit 6 (0.69) Integrated regulation 2 (0.67) Identified regulation 1 (0.67) Identified regulation 3 (0.66) Integrated regulation 4 (0.66) External regulation 3 (0.65) External regulation 4 (0.61) Identified regulation 2 (0.60)
0.4-0.59	Attitude 2 (0.58) Habit 1 (0.57) Intrinsic motivation 2 (0.56) Comfort 1 (0.56) Subjective norm 3 (0.54) Habit 6 (0.54) Comfort 4 (0.54) Comfort 3 (0.51) Perceived behavioral control 3 (0.51) Subjective norm 1 (0.49) Attitude 1 (0.46) External regulation 1 (0.45) External regulation 3 (0.45) Attitude 3 (0.43) Comfort 5 (0.43)	Integrated regulation 4 (0.59) Attitude 2 (0.59) Identified regulation 1 (0.59) Intrinsic motivation 2 (0.58) Introjected regulation 4 (0.56) Integrated regulation 2 (0.53) Introjected regulation 1 (0.51) Intrinsic motivation 1 (0.50) Integrated regulation 3 (0.49) Comfort 4 (0.49) Perceived behavioral control 3 (0.48) Habit 1 (0.47)	Introjected regulation 2 (0.58) Introjected regulation 1 (0.57) Intrinsic motivation 3 (0.57) Intrinsic motivation 2 (0.57) Intrinsic motivation 1 (0.57) Introjected regulation 3 (0.55) Comfort 6 (0.52) Integrated regulation 3 (0.52) Perceived behavioral control 3 (0.51) Subjective norm 3 (0.48) Introjected regulation 4 (0.46)

Table 11 (cont'd)

Predictor Importance	Final Solution	First half solution	Second half solution
0.4-0.59	External regulation 4 (0.42)	Subjective norm 3 (0.47) Habit 6 (0.44) Subjective norm 1 (0.43) Attitude 3 (0.43) Attitude 1 (0.41) Comfort 1 (0.40)	Subjective norm 1 (0.45) External regulation 2 (0.45)
0.2-0.39	External regulation 2 (0.39) Comfort 2 (0.34) Comfort 6 (0.34) Subjective norm 2 (0.27)	External regulation 1 (0.37) Comfort 5 (0.37) External regulation 3 (0.33) External regulation 2 (0.32) Comfort 6 (0.31) Subjective norm 2 (0.31) Comfort 3 (0.29) Comfort 2 (0.23)	External regulation 1 (0.36) Comfort 2 (0.36) Comfort 4 (0.36) Comfort 1 (0.32) Attitude 2 (0.31) Comfort 3 (0.31) Comfort 5 (0.29) Attitude 3 (0.23) Attitude 1 (0.21)
0.00-0.19			Subjective norm 2 (0.16)

6.4 Description of clusters

In this study, these clusters represent office occupants that embody the most salient psycho-social, motivational, habitual, and comfort-related responses of that specific segment to the office buildings and energy-saving behavior. Traditional clustering studies suggest that members of each cluster hold similar subconscious cognitive processes (Ortiz & Bluyssen, 2018). That means members of a segment – in this case, the office occupants – respond similarly to certain stimuli in their environment. Table 12 presents the descriptive results of each cluster concerning office occupants' background information, psycho-social, motivational, habitual characteristics, and comfort perceptions. Figure 10 illustrates the process diagram of the two-step cluster analysis.

Table 12. Characteristics of office occupants in different clusters.

	Cluster 1 (n= 93, 33.2%)	Cluster 2 (n= 60, 21.4%)	Cluster 3 (n= 127, 45.7%)	Total (n=280, 100%)
Background information				
Gender (%)				
· Female	53,8	51,7	45,7	100
· Male	46,2	48,3	54,3	100
Age (mean)	37,77	36,28	35,54	36,44
Education (%)				
· Master's degree or above	7,5	30	18,9	17,5
· College or bachelor's degree	71	55	68,5	66,8
· Senior high school or below	20,4	15	12,6	17,5
Office layout (%)				
· Individual office	24,7	11,7	19,7	19,6
· Shared enclosed	36,6	48,3	39,4	40,2
· Open-plan	38,7	40	40,9	40,2
Office size (%)				
· Large office room (10+ occupants)	41,9	30	53,5	34,4
· Middle office room (5-10 occupants)	28	23,3	15,7	21,4
· Small office room (1-4 occupants)	30,1	46,7	30,7	44,2
Psycho-social characteristics (mean)				
Attitude	4,2	3,4	4,5	4,2
Subjective norm	3,7	2,9	3,9	3,6
Motivational characteristics (mean)				
Inherent motivation	4	3,9	4,7	4,3
· Perceived behavioral control	4,1	4,1	4,8	4,4
· Intrinsic motivation	4,1	4,1	4,8	4
· Integrated regulation	3,8	3,4	4,5	4
· Identified regulation	4,1	4,1	4,9	4,4
Introjected regulation	3,9	3,4	4,6	4,1
External regulation	2,4	1,6	2	2,1
Habitual characteristics (mean)				
· Energy-saving habit	3,8	3,1	4,4	3,9
Comfort (mean)				
· Perceived satisfaction with the indoor air quality of the office	3,6	2,4	3,6	3,3

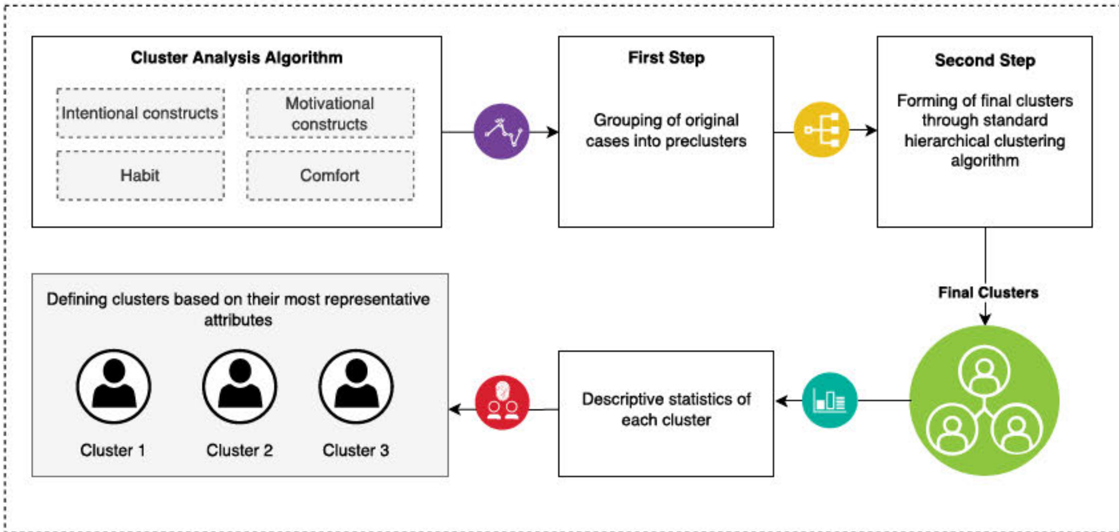


Figure 11. Flow diagram of two-step cluster analysis.

In line with the cumulative means of each cluster, as shown in Figure 11, clusters were ranked according to their energy-saving levels. Cluster 3, with a cumulative mean of 46.7, demonstrated the highest energy-saving behavior, followed by Cluster 1, with a mean of 41.7, and lastly, Cluster 2, with a mean of 36.4, showing the lowest energy-saving tendency. To enhance clarity throughout the thesis, clusters are labeled as follows: Cluster 3 – H (high energy-saving behavior), Cluster 1 – M (medium energy-saving behavior), and Cluster 2 – L (low energy-saving behavior).

Clusters	Attitude	Subjective norm	Inherent motivation	Perceived behavioral control	Intrinsic motivation	Integrated regulation	Identified regulation	Introjected regulation	External regulation	Habit	Comfort	**Cumulative mans**
Cluster 1	4,2	3,7	4	4,1	4,1	3,8	4,1	3,9	2,4	3,8	3,6	**41,7**
Cluster 2	3,4	2,9	3,9	4,1	4,1	3,4	4,1	3,4	1,6	3,1	2,4	**36,4**
Cluster 3	4,5	3,9	4,7	4,8	4,8	4,5	4,9	4,6	2	4,4	3,6	**46,7**

Figure 12. Characteristics of the behavioral clusters.

6.4.1 Cluster 1 – M

Cluster 1 – M comprised 93 (33.2%) participants, including a relatively balanced gender distribution, with 51 (53.8%) female and 43 (46.2%) male participants. The average age of Cluster 1 – M was 37.77 years (SD=9.041). The majority (n= 66, 71.0%) of the participants graduated from college or had a bachelor's degree, whereas 19 occupants (20.4%) graduated from senior high school or below, and seven participants (7.5%) graduated with a master's degree or above. Thirty-six participants (38.7%) were working in open-plan offices, whereas 34 participants (36.6%) were working in shared enclosed offices, and 23 participants (24.7%) were working in individual offices. Lastly, the majority (n=39, 41.9%) of participants were working in large office rooms (10+ occupants), whereas 28 participants (30.1%) were working in small office rooms (1-4 occupants), and 26 participants (28.0%) were working in middle office rooms.

In terms of **psycho-social characteristics**, participants in this cluster exhibited a positive attitude (average score of 4.2) and a moderate subjective norm (3.7) toward energy-saving in their office environments. They demonstrated high levels of **motivation**, including strong intrinsic motivation (4.1) and perceived behavioral control (4.1). Identified regulation (4.1) was also strong, reflecting their alignment with energy-saving behaviors, complemented by moderate identified regulation (3.8) and strong introjected regulation (4.1). Regarding **habits**, Cluster 1 – M showed a moderate level of energy-saving habits, scoring 3.8 on average. **Comfort perceptions** regarding indoor air quality in their offices were moderate, with an average satisfaction score of 3.6. These characteristics highlight a group that is moderately engaged in energy-saving practices with balanced psycho-social and motivational traits.

6.4.2 Cluster 2 – L

Cluster 2 – L consisted of 60 (21.4%) participants. Like Cluster 1 – M, the gender distribution in Cluster 2 – L was relatively balanced, with 31 (51.7%) female and 29 (48.3%) male participants. The average age of the participants in Cluster 2 was 36.28 (SD=7.464). Educational level varied, with n (55.0%) participants graduating from college or having a bachelor's degree, 9 (15.0%) participants having graduated from senior high school or below, and 18 (30%) participants having a master's degree or above. Participants in Cluster 2 predominantly worked in shared enclosed offices (n=29, 48.3%), followed by open-plan offices (n=24, 40.0%) and individual offices (n=7, 11.7%). The majority (n=28, 46.7%) of the participants were working in small office rooms (1-4 occupants), 18 (30.0%) were working in large office rooms (10+ occupants), and 14 (23.3%) were working in middle office rooms (5-10 occupants).

Participants in Cluster 2 – L exhibited relatively lower **psycho-social characteristics**, with an average attitude score of 3.4 and a subjective norm of 2.9 towards energy-saving behaviors in their office environments. Despite this, their **motivational characteristics** were relatively high, as they scored 4.1 for both intrinsic motivation and perceived behavioral control, indicating a strong internal drive and sense of autonomy. Identified regulation was also high (4.1), reflecting a clear understanding of their goals and motivations, although introjected regulation was moderate (3.4).

In terms of **habitual characteristics**, Cluster 2 – L reported a lower energy-saving habit, with an average score of 3.1. **Comfort perceptions** were notably lower in this cluster, with an average score of 2.4 for satisfaction with indoor air quality, reflecting less contentment compared to other clusters. These traits suggest a group with strong internal motivation but weaker habitual engagement and lower satisfaction with their office environment.

6.4.3 Cluster 3 – H

Cluster 3 – H is the largest cluster, with 127 (45.7%) participants. Gender distribution in Cluster 3 – H was skewed towards males, with 69 (54.3%) male and 58 (45.7%) female participants. The average age of Cluster 3 – H was 35.54 (SD=8.477). The educational level in this cluster was diverse, with 87 (68.5%) participants holding a college or bachelor's degree, 16 (12.6%) participants having senior high school or below, and 24 (18.9%) participants possessing a master's degree or above. Office layouts were distributed across open-plan offices (n=52, 40.9%), shared enclosed offices (n=50, 39.4%), and individual offices (n=25, 19.7%). The majority (n=68, 53,5%) of the participants were working in large office rooms (10+ occupants), 39 (30.7%) were working in small office rooms (1-4 occupants), and 20 (15.7%) were working in middle office rooms (5-10 occupants).

Cluster 3 – H participants exhibited highly **positive psycho-social characteristics**, with an attitude score of 4.5 and a moderate subjective norm of 3.9 toward energy-saving behaviors in their office environments. **Motivationally**, this cluster showed exceptional levels, with inherent motivation (4.7), perceived behavioral control (4.8), and identified regulation (4.9), all reflecting a strong internal drive, self-confidence, and precise alignment with energy-saving practices.

Regarding **habitual characteristics**, Cluster 3 – H demonstrated a high energy-saving habit, scoring 4.4 on average. **Comfort perceptions** of indoor air quality were moderate, with an average satisfaction score of 3.6. Overall, this cluster reflects highly motivated individuals, habitually engaged in energy-saving practices, and moderately satisfied with their office environment.

6.4.4 Summary

Analyzing the three clusters based on psycho-social, motivational, habitual characteristics, and comfort reveals similarities and differences, as seen in Figure 11. Regarding similarities, all clusters demonstrate a generally positive attitude towards sustainable practices. This is evident in their mean scores, which range from 4.2 to 4.5, indicating a favorable disposition towards environmental concerns. Additionally, subjective norms across all clusters reflect a moderate level of social influence, ranging from 3.6 to 3.9, suggesting that individuals within each cluster perceive a certain level of pressure or encouragement from their social circles to engage in sustainable behaviors.

However, notable differences emerge when examining motivational characteristics. Cluster 1 – M exhibits a balanced mix of motivational factors, with relatively high scores across inherent motivation (mean=4), perceived behavioral control (mean=4.1), intrinsic motivation (mean=4.1), and identified regulation (mean=4.1). In contrast, Cluster 2 – L shows lower scores in introjected regulation (mean=3.4) and external regulation (mean=1.6), indicating a weaker sense of internalized and externally imposed motivation than the other clusters. Cluster 3 – H, on the other hand, stands out with consistently high scores across all motivational factors, particularly in inherent motivation (mean=4.7), perceived behavioral control (mean=4.8), intrinsic motivation (mean=4.8), and identified regulation (mean=4.9), suggesting a strong internal drive and perceived ability to engage in sustainable behaviors.

Habitual characteristics also vary among the clusters. Cluster 1 – M and 3 – H demonstrate relatively strong energy-saving habits, with mean scores of 3.8 and 4.4, respectively. In contrast, Cluster 2 – L displays a weaker energy-saving habit with a mean score of 3.1. This discrepancy suggests differing levels of ingrained behaviors related to sustainability practices among the clusters.

Regarding comfort, there are noticeable differences in the perceived satisfaction with the office's indoor air quality. Cluster 1 – M and Cluster 3 – H exhibit moderate levels of comfort, with mean scores of 3.6 and 3.6, respectively. However, Cluster 2 – L shows the lowest satisfaction level, with a mean score of 2.4, indicating a less favorable perception of comfort in the office environment.

In summary, while all clusters share a positive attitude towards sustainability, they differ in the strength of their motivational factors, habitual behaviors, and comfort levels. Cluster 3 – H emerges as the most motivated and habitually inclined towards sustainable practices, potentially making it a key target for sustainable initiatives

CHAPTER 7

RESULTS – STEP 02 FIELD STUDY

7.1 Summer results

7.1.1 Start survey

Descriptive analysis

A total of 12 participants were involved in the field study. Among them, Cluster 1 – M included five participants (41.7%), Cluster 2 – L included three participants (25.0%), and Cluster 3 – H had four participants (33.3%). Most participants were female, accounting for 91.7% (n=11), while only one participant (8.3%) was male. The average age of the participants was 36.93 years (SD=6.067). Regarding education, most participants (83.3%, n=10) had graduated from college or held a bachelor's degree. One participant (8.3%) had a senior high school education or below, and the other (8.3%) had a master's degree or above. Regarding office layout, three participants (25.0%) worked in individual offices, and nine (75.0%) worked in shared enclosed spaces. In line with the recruitment criteria, all participants (n=12, 100%) worked in small office rooms (1-4 occupants). These findings provide an overview of the participant distribution across clusters, gender, age, education, office layout, and office size.

Frequency of use of occupant actions within each behavioral cluster

During the start survey, participants were asked about the frequency at which they made physical and personal adjustments within their offices to maintain their environmental comfort. The frequencies of these adjustments were recorded and analyzed, and the descriptive statistics are presented in Table 13. The results of the ANOVA test indicated that there were no statistically significant differences between clusters when it came to individual control elements such as windows ($p= 0.073$), solar shading ($p= 0.104$), air conditioning ($p-= 0.947$), doors ($p= 0.344$), clothing ($p= 0.728$), and drinking ($p= 0.261$). However, a significant difference was observed between clusters regarding the overall frequency of adjustments ($p= 0.003$).

Cluster 1 – M demonstrated a higher environmental adjustment than the other clusters, particularly in actions like opening windows (mean of 3). In contrast, Cluster 2 – L exhibited a moderate level of environmental adjustment, which is evident in their choice of window adjustment (mean of 2.33) and A/C adjustments (mean of 2.33). Cluster 3 – H generally opted for more minor to medium-sized adjustments, as their responses indicated less extensive window adjustments (mean of 2.25) and door openings (mean of 2.50). The overall patterns highlight preferences, ranging from more substantial adjustments in Cluster 1 – M to moderate and minor adjustments in Clusters 2- L and 3 – H, respectively.

Table 13. Environmental adjustments frequencies in the start survey.

Descriptives									
						95% Confidence Interval for Mean			
Adjustment	Cluster	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Window	1	5	3.40	.894	.400	2.29	4.51	2	4
	2	3	2.33	.577	.333	.90	3.77	2	3
	3	4	2.25	.500	.250	1.45	3.05	2	3
	Total	12	2.75	.866	.250	2.20	3.30	2	4
Solar shading	1	5	2.80	1.304	.583	1.18	4.42	1	4
	2	3	1.33	.577	.333	-.10	2.77	1	2
	3	4	1.50	.577	.289	.58	2.42	1	2
	Total	12	2.00	1.128	.326	1.28	2.72	1	4
A/C	1	5	2.60	1.517	.678	.72	4.48	1	5
	2	3	2.33	.577	.333	.90	3.77	2	3
	3	4	2.50	.577	.289	1.58	3.42	2	3
	Total	12	2.50	1.000	.289	1.86	3.14	1	5
Door	1	5	3.20	1.095	.490	1.84	4.56	2	4
	2	2	2.00	.000	.000	2.00	2.00	2	2
	3	4	2.50	1.000	.500	.91	4.09	2	4
	Total	11	2.73	1.009	.304	2.05	3.41	2	4
Clothing	1	5	3.00	1.225	.548	1.48	4.52	2	5
	2	3	2.33	1.528	.882	-1.46	6.13	1	4
	3	4	2.75	.500	.250	1.95	3.55	2	3
	Total	12	2.75	1.055	.305	2.08	3.42	1	5
Drinking	1	5	3.40	.894	.400	2.29	4.51	2	4
	2	3	2.33	.577	.333	.90	3.77	2	3
	3	4	2.75	.957	.479	1.23	4.27	2	4
	Total	12	2.92	.900	.260	2.34	3.49	2	4

7.1.2 Daily survey

The data collected during the daily survey comprised 111 records, including subjective and objective measurements. Over two weeks, each day's subjective responses from each participant were matched with the daily mean of environmental variables measured in their offices. Daily responses and environmental data obtained from one participant formed a single record. This means a time-series dataset for each participant and their respective offices was collected over two weeks. This dataset included the time-series data for behavioral actions and the corresponding environmental factors. The behavioral actions were represented as ‘1’ for ‘change’ and ‘0’ for ‘no change.’ The daily mean values of outdoor temperature, indoor temperature, indoor humidity, and indoor CO2 were assigned to the measured behavioral actions for each day accordingly. The dataset was further enhanced by combining IEQ satisfaction and comfort preferences. This compilation resulted in the total dataset for analysis. In this study, the dependent variable is represented by the probability of each behavioral action. Before conducting the regression analysis, the environmental predictors were appropriately scaled and centered to ensure accurate and meaningful results.

Indoor environmental quality satisfaction of behavioral clusters

Participants in the selected building were asked to rate their comfort in indoor climate, temperature, humidity, and air quality at the end of every working day during the two weeks of the field study period. The frequency of participants’ responses on the given Likert scale of occupants’ satisfaction with each behavioral cluster with environmental parameters is shown in Table 14.

Table 14. IEQ satisfaction of behavioral clusters over two weeks.

	Frequency	%	Cumulative (%)	Frequency	%	Cumulative (%)	Frequency	%	Cumulative (%)
		Cluster 1 – M			Cluster 2 – L			Cluster 3 – H	
Indoor climate									
Very dissatisfied	10	21.7	21.7	0	0	0	4	10.5	10.5
Dissatisfied	6	13.0	34.8	4	14.8	14.8	1	2.6	13.2
Slightly dissatisfied	7	15.2	50.0	8	29.6	44.4	5	13.2	26.3
Neutral	14	0	50.0	4	14.8	59.3	0	0	26.3
Slightly satisfied	9	30.4	80.4	9	33.3	92.6	9	23.7	50.0
Satisfied	46	19.6	100.0	2	7.4	100.0	14	36.8	86.8
Very satisfied	0	0	100.0	0	0	100.0	5	13.2	100.0
Temperature									
Very dissatisfied	15	32.6	32.6	0	0	0	5	13.2	13.2
Dissatisfied	6	13.0	45.7	4	14.8	14.8	1	2.6	15.8
Slightly dissatisfied	3	6.5	52.2	8	29.6	29.6	5	13.2	28.9
Neutral	0	0	52.2	6	22.2	22.2	1	2.6	31.6
Slightly satisfied	13	28.3	80.4	7	25.9	25.9	10	26.3	57.9
Satisfied	9	19.6	100.0	2	7.4	7.4	11	28.9	86.8
Very satisfied	0	0	100.0	0	0	100.0	5	13.2	100.0
Humidity									
Very dissatisfied	11	23.9	23.9	0	0	0	2	5.3	5.3
Dissatisfied	6	13.0	37.0	4	14.8	14.8	0	0	5.3
Slightly dissatisfied	6	13.0	50.0	5	18.5	33.3	5	13.2	18.4
Neutral	12	0	50.0	8	29.6	63.0	1	2.6	21.1
Slightly satisfied	11	26.1	76.1	8	29.6	92.6	5	13.2	34.2
Satisfied	0	23.9	100.0	2	7.4	100.0	20	52.6	86.8
Very satisfied	0	0	100.000	0	0	100.0	5	13.2	100.0

Table 14 (cont'd)

	Frequency	%	Cumulative (%)	Frequency	%	Cumulative (%)	Frequency	%	Cumulative (%)
	Cluster 1 – M			Cluster 2 – L			Cluster 3 – H		
Indoor Air Quality									
Very dissatisfied	14	30.4	32.6	0	0	0	5	13.2	13.2
Dissatisfied	7	15.2	45.7	4	14.8	14.8	2	5.3	18.4
Slightly dissatisfied	5	10.9	52.2	10	37.0	51.9	3	7.9	26.3
Neutral	0	0	52.2	7	25.9	77.8	8	21.1	47.4
Slightly satisfied	11	23.9	80.4	6	22.2	100.0	6	15.8	63.2
Satisfied	9	19.6	100.0	0	0	100.0	9	23.7	86.8
Very satisfied	0	0	100.0	0	0	100.0	5	13.2	100.0

Concerning indoor climate, Cluster 1 – M participants exhibited a mix of responses, with 21.7% being very dissatisfied, but the majority, 19.6%, were satisfied. For Cluster 2 – L, no participants expressed dissatisfaction; the highest portion, 33.3%, was slightly satisfied. Cluster 3 – H had 10.5% of its participants very dissatisfied, with the most significant proportion, 36.8%, indicating they were satisfied. Regarding indoor temperature, in Cluster 1 – M, 32.6% were very dissatisfied, which was the highest. Conversely, 19.6% were satisfied. Cluster 2 – L had 29.6% of its participants slightly dissatisfied, while 25.9% were slightly satisfied. For Cluster 3 – H, 28.9% of the participants felt satisfied, and 13.2% were very dissatisfied.

For humidity, in Cluster 1 – M, 23.9% of participants were very dissatisfied, while 26.1% were slightly satisfied. Cluster 2 – L had its most considerable portion, 29.6%, feeling neutral and slightly satisfied, respectively. For Cluster 3 – H, over half, or 52.6%, expressed satisfaction, while only 5.3% were very dissatisfied. Lastly, regarding indoor air quality, 30.4% of Cluster 1 – M's participants were very dissatisfied, whereas 23.9% felt slightly satisfied. Cluster 2 – L saw its highest portion, 37%, being slightly dissatisfied, while 22.2% were slightly satisfied. In Cluster 3 – H, 23.7% of participants felt satisfied, while 13.2% were very dissatisfied.

Cluster 2 – L predominantly showed neutral to slightly satisfied sentiments across the various categories. Cluster 1 – M showcased many sentiments, from high dissatisfaction to satisfaction. Meanwhile, Cluster 3 – H had a significant proportion of its participants feeling satisfied in most categories.

The results of the one-way ANOVA revealed that there is a statistically significant difference between the behavioral clusters and IEQ satisfaction for indoor climate ($p=0.005$), temperature ($p=0.007$), humidity ($p=0.000$), and indoor air quality (0.014). Table 15 illustrates the results of the one-way ANOVA for environmental satisfaction and behavioral clusters.

Table 15. One-way ANOVA results for environmental satisfaction and behavioral clusters.

ANOVA		Sum of Squares	df	Mean Square	F	Sig.
Climate Satisfaction	Between Groups	33.751	2	16.876	5.494	.005
	Within Groups	331.726	108	3.072		
	Total	365.477	110			
Temperature Satisfaction	Between Groups	34.926	2	17.463	5.134	.007
	Within Groups	367.344	108	3.401		
	Total	402.270	110			
Humidity Satisfaction	Between Groups	60.846	2	30.423	10.755	.000
	Within Groups	305.496	108	2.829		
	Total	366.342	110			
Indoor Air Quality Satisfaction	Between Groups	28.632	2	14.316	4.471	.014
	Within Groups	345.801	108	3.202		
	Total	374.432	110			

* *Significance level = p<0.05*

Comfort preferences of behavioral clusters

Participants in the selected building were asked to rate their comfort preferences for temperature and humidity at the end of every working day during the two weeks of the field study period. The frequency of participants' responses on the given Likert scale of occupants' preferences with each behavioral cluster is shown in the Appendix in Table E1. The one-way ANOVA results revealed no statistically significant difference between the behavioral clusters and comfort preferences for temperature (p=0.874) and humidity (p=0.287). Table 16 illustrates the results of the one-way ANOVA for comfort preferences and behavioral clusters.

Table 16. One-way ANOVA results for comfort preferences and behavioral clusters.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Temperature preference	Between Groups	.211	2	.106	.135	.874
	Within Groups	84.455	108	.782		
	Total	84.667	110			
Humidity preference	Between Groups	1.759	2	.880	1.281	.282
	Within Groups	74.151	108	.687		
	Total	75.910	110			

[*] *Significance level = p<0.05*

Correlation analysis between environmental variables and occupant actions

The results of the correlation analysis showed that for the “Closing Windows” action, indoor humidity and indoor CO_2 have weak positive correlations with the probability of window closure (r = 0.328, p = 0.026 and r = 0.304, p = 0.045, respectively). On the other hand, indoor temperature exhibits a moderate negative correlation with the probability of closing windows (r = -0.497, p = 0.000). Regarding “Opening Windows,” no statistically significant correlations were observed with any of the environmental variables (all p > 0.05).

For the action “Switching off Thermostats,” there is a strong negative correlation between indoor temperature and the probability of switching off thermostats (r = -0.705, p = 0.000). Additionally, indoor humidity and indoor CO_2 show weak positive correlations with the likelihood of this action (r = 0.443, p = 0.002 and r = 0.639, p = 0.000, respectively). Regarding “Lowering Solar Shading,” indoor temperature exhibits a weak positive correlation with the probability of this action (r = 0.314, p = 0.034), while indoor CO2 shows a moderate negative correlation (r = -0.319, p = 0.035). No statistically significant correlations were found for the action “Raising Solar Shading” and any of the environmental variables (all p > 0.05).

For the action “Closing Doors,” there is a strong negative correlation between indoor temperature and the probability of closing doors ($r = -0.836$, $p = 0.000$). Additionally, indoor humidity and indoor CO_2 show moderate positive correlations with the likelihood of this action ($r = 0.538$, $p = 0.000$ and $r = 0.665$, $p = 0.000$, respectively). Regarding “Opening Doors,” outdoor temperature has a weak positive correlation with the probability of this action ($r = 0.239$, $p = 0.019$). Indoor temperature, on the other hand, exhibits a moderate negative correlation ($r = -0.515$, $p = 0.003$).

For the action “Drinking Hot Beverage,” indoor temperature has a moderate negative correlation with the probability of this action ($r = -0.515$, $p = 0.003$). Indoor CO_2, however, shows a weak positive correlation ($r = 0.466$, $p = 0.000$). Regarding “Drinking Cold Beverages,” indoor temperature has a moderate positive correlation with the probability of this action ($r = 0.427$, $p = 0.003$), while indoor CO_2 exhibits a moderate negative correlation ($r = -0.529$, $p = 0.000$).

Based on the correlation analysis, environmental predictors that did not show a significant correlation ($p < 0.05$) with behavioral actions were excluded from the dataset for further analysis. Additionally, any behavioral actions that did not exhibit substantial correlations with environmental parameters were removed entirely from the dataset. The list of removed predictors and behavioral actions is provided in Table 17. By eliminating these non-significant variables, the dataset was refined to focus on the most relevant and influential factors for the subsequent analyses.

Table 17. Correlation between the occupants' actions and environmental variables.

	Pearson Correlation	Sig. (2-tailed)		Pearson Correlation	Sig. (2-tailed)
Closing windows			***Switching off thermostats***		
Outdoor temperature*	0.123	0.414	Outdoor temperature*	0.108	0.477
Indoor temperature	-0.497	0.000	Indoor temperature	-0.705	0.000
Indoor humidity	0.328	0.026	Indoor humidity	0.443	0.002
Indoor CO_2	0.304	0.045	Indoor CO_2	0.639	0.000
Opening windows*			***Switching on thermostats****		
Outdoor temperature*	0.024	0.877	Outdoor temperature*	0.022	0.882
Indoor temperature*	-0.015	0.919	Indoor temperature*	0.107	0.481
Indoor humidity*	-0.022	0.886	Indoor humidity*	0.010	0.946
Indoor CO_2*	-0.160	0.299	Indoor CO_2*	0.026	0.868
Lowering solar shading			***Adding clothes****		
Outdoor temperature*	0.125	0.408	Outdoor temperature*	0.188	0.211
Indoor temperature	0.314	0.034	Indoor temperature*	0.021	0.892
Indoor humidity*	-0.217	0.148	Indoor humidity*	-0.115	0.445
Indoor CO_2	-0.319	0.035	Indoor CO_2*	-0.109	0.481
Raising solar shading*			***Removing clothes****		
Outdoor temperature*	0.202	0.179	Outdoor temperature*	0.155	0.304
Indoor temperature*	-0.013	0.932	Indoor temperature*	-0.095	0.530
Indoor humidity*	-0.048	0.753	Indoor humidity*	0.103	0.497
Indoor CO_2*	-0.026	0.866	Indoor CO_2*	-0.063	0.684
Closing doors			**Drinking hot beverage**		
Outdoor temperature*	-0.037	0.806	Outdoor temperature*	0.045	0.109
Indoor temperature	-0.836	0.000	Indoor temperature	-0.515	0.003
Indoor humidity	0.538	0.000	Indoor humidity*	0.288	0.249
Indoor CO_2	0.665	0.000	Indoor CO_2	0.466	0.000
Opening doors			***Drinking cold beverage***		
Outdoor temperature*	-0.008	0.960	Outdoor temperature	0.239	0.019
Indoor temperature*	-0.131	0.387	Indoor temperature	0.427	0.003
Indoor humidity*	0.153	0.311	Indoor humidity*	-0.173	0.2249
Indoor CO_2	0.033	0.033	Indoor CO_2	-0.529	0.000

*Removed variables from the dataset.

** Significance level = $p<0.05$

Following the correlation analysis, environmental variables that were not statistically related to the corresponding occupant actions were removed from further analysis. The results indicated that the selected predictors had tolerances greater than 0.1 and VIF values less than 10, suggesting a moderate correlation with each predictor (1 < VIF < 5) and no significant multicollinearity. Next, outliers were checked using box plots of Z-score values, which led to the identification of three outliers for CO2 values. These outliers were removed from the dataset to ensure data integrity.

The goodness of fit statistics determines how well the model describes the data. A chi-square (2) analysis is conducted for each behavioral cluster separately to evaluate this. If there is a significant outcome, this suggests that the model fits the data well and demonstrates a considerable improvement compared to the null model. After considering the p-value (<0.05), the models that did not sufficiently fit the data were removed from further analysis. Additionally, the analysis of lowering solar shading for Cluster 2 – L could not be conducted due to the number of factors not being two. Consequently, this model was also removed from the subsequent analysis. These test results for each occupant's actions and removed models are summarized in Table 18. In this manner, to limit the complexity of the model, the final model included occupant actions that resulted in a p-value < 0.05.

Table 18. Omnibus tests of model coefficients.

	Model Item	χ^2	df	Sig.	Nagelkerke R^2
Cluster 1	Closing windows	14.194	40	0.003	0.392
	Lowering solar shading	6.521	41	0.038	0.200
	Closing doors	41.677	40	<.001	0.831
	Opening doors*	0.047	42	0.828	0.001
	Switching off thermostats	26.921	40	<.001	0.651
	Drinking hot beverage	15.548	41	<.001	0.397
	Drinking cold beverage	15.922	40	0.001	0.405
Cluster 2	Closing windows	14.954	23	0.002	0.574
	Lowering solar shading*				
	Closing doors	11.086	23	0.011	0.479
	Opening doors*	2.185	25	0.139	0.114
	Switching off thermostats	9.529	23	0.023	0.397
	Drinking hot beverages*	0.743	24	0.690	0.037
	Drinking cold beverages*	2.325	23	0.508	0.164
Cluster 3	Closing windows*	6.007	33	0.111	0.213
	Lowering solar shading*	1.557	34	0.459	0.120
	Closing doors*	6.729	33	0.081	0.232
	Opening doors*	0.332	35	0.565	0.013
	Switching off thermostats	12.657	33	0.005	0.391
	Drinking hot beverage	32.758	34	<.001	0.853
	Drinking cold beverage	15.277	33	0.002	0.457

*Models removed from further analysis.
** *Significance level = $p<0.05$*

The Wald statistic was used to assess the statistical significance of each B coefficient in the logistic regression models, indicating the individual impact of each predictor variable on the outcome. Since logistic models were employed, interpreting the regression coefficients was best understood through the odds ratio (OR), representing the exponential of the B coefficient. The odds ratio estimates the change in odds resulting from a unit change in the predictor variable. Finally, the Nagelkerke R-squared value was calculated to assess the goodness of fit of the logistic regression models, indicating how well the models fit the observed data. The Nagelkerke values for each behavioral action can be found in Table 18.

For Cluster 1 – M, the analysis shows that “Closing Windows” and “Switching off Thermostats” actions have a statistically significant relationship with the environmental predictors. The χ^2 statistic for “Closing Windows” is 14.194 with 40 degrees of freedom, and the p-value is 0.003, suggesting a significant association. The Nagelkerke R^2 value of 0.392 indicates that the model accounts for approximately 39.2% of the variance in the closing windows behavior. Similarly, the χ^2 statistic for “Switching off Thermostats” is 26.921 with 40 degrees of freedom, and the p-value is less than 0.001, indicating a highly significant relationship. The Nagelkerke R^2 value of 0.651 suggests that the model explains around 65.1% of the variation in the behavior of the switching-off thermostat.

For the other actions in Cluster 1 – M, including “Lowering Solar Shading,” “Opening Doors,” “Drinking Hot Beverage,” and “Drinking Cold Beverage,” the chi-square statistics and p-values vary. “Lowering Solar Shading” is significant with a χ^2 of 6.521 and p-value of 0.038, while “Opening Doors” shows no significant association with the predictors, as indicated by a p-value of 0.828. Regarding beverage-related actions, “Drinking Hot Beverage” and “Drinking Cold Beverage” display significant relationships with the predictors, with p-values of less than 0.001 and 0.001, respectively. The corresponding Nagelkerke R^2 values for these actions are 0.200, 0.001, 0.397, and 0.405, respectively.

Moving to Cluster 2 – L, the analysis reveals significant associations for “Closing Windows” and “Closing Doors” with p-values of 0.002 and 0.011, respectively. The χ^2 statistics for these actions are 14.954 and 11.086, while the corresponding Nagelkerke R^2 values are 0.574 and 0.479. However, “Lowering Solar Shading,” “Opening Doors,” “Switching off Thermostats,” “Drinking Hot Beverages,” and “Drinking Cold Beverages” in Cluster 2 – L did not exhibit statistically significant relationships with the environmental predictors.

In Cluster 3, “Drinking Hot Beverage” displays a highly significant association with the predictors, with a χ^2 statistic of 32.758 and a p-value less than 0.001. The Nagelkerke R^2 value for this action is 0.853, indicating that the model explains approximately 85.3% of the variation in the drinking hot beverage behavior. On the other hand, “Opening Doors” did not show a significant association, as evidenced by a p-value of 0.565. The remaining actions in Cluster 3 – H, including “Closing Windows,” “Lowering Solar Shading,” “Closing Doors,” “Switching off Thermostats,” and “Drinking Cold Beverages,” exhibit varying levels of significance with p-values ranging from 0.002 to 0.111, and Nagelkerke R^2 values ranging from 0.213 to 0.232.

In conclusion, the logistic regression analysis provides valuable insights into the relationships between occupants' behavioral actions and the environmental predictors in each cluster. The results indicate that specific actions, such as “Closing Windows” and “Switching off Thermostats” in Cluster 1 – M, are significantly influenced by environmental factors. In Cluster 2 – L, while “Closing Windows” and “Closing Doors” show significance, other actions lack statistically significant relationships with environmental predictors. Cluster 3 – H, notably, exhibits a highly significant association for “Drinking Hot Beverages,” with less consistent significance across other actions. These findings emphasize the nuanced nature of the relationships between environmental predictors and occupants' actions within distinct clusters, contributing to a comprehensive understanding of behavioral patterns in response to environmental conditions and offering valuable implications for further logistic regression models in this study.

Occupant actions within each behavioral cluster

Cluster 1 – M

Following the initial data preparation, the model items considered for Cluster 1 – M were closing windows, lowering solar shading, closing doors, switching off thermostats, drinking hot beverages, and drinking cold beverages. Subsequently, logistic regression models were developed for these actions, considering environmental variables such as outdoor temperature, indoor temperature, indoor humidity, and indoor CO2. These environmental variables were selected for each model based on the correlation analysis between occupant actions and environmental variables. The result of the logistic regression for Cluster 1 – M is illustrated in Table 19.

Table 19. Logistic regression coefficients for Cluster 1 – M.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B)		Model Accuracy (%)
							Lower	Upper	
Closing windows									
Indoor temperature	-.1.147	0.507	5.115	1	0.024	0.318	0.118	0.858	
Indoor humidity	0.086	0.163	0.277	1	0.598	1.090	0.792	1.500	72.7
Indoor CO_2	-0.007	0.009	0.743	1	0.389	0.993	0.976	1.009	
Lowering solar shading									
Indoor temperature	0.249	0.430	0.337	1	0.562	1.283	0.553	2.978	70.5
Indoor CO_2	-0.019	0.014	1.793	1	0.181	0.982	0.955	1.009	
Closing doors									
Indoor temperature	-3.664	1.480	6.130	1	0.013	-2.476	-6.564	-0.763	0.932
Indoor humidity	-0.411	0.308	1.777	1	0.183	-1.333	-1.015	0.193	
Indoor CO_2	0.011	0.019	0.359	1	0.549	0.599	-0.025	0.048	
Switching off thermostats									
Indoor temperature	-1.636	0.744	4.839	1	0.028	0.195	0.045	0.837	
Indoor humidity	-0.149	0.211	0.499	1	0.480	0.862	0.570	1.302	86.4
Indoor CO_2	0.012	0.011	1.188	1	0.276	1.012	0.991	1.034	
Drinking hot beverage									
Indoor temperature	-0.759	0.429	3.132	1	0.077	0.468	0.202	1.085	75.0
Indoor CO_2	0.013	0.012	1.257	1	0.262	1.013	0.990	1.037	
Drinking cold beverage									
Outdoor temperature	0.429	0.175	6.030	1	0.014	1.535	1.090	2.162	
Indoor temperature	0.138	0.457	0.092	1	0.762	1.148	0.469	2.813	86.4
Indoor CO_2	-0.030	0.014	4.271	1	0.039	0.971	0.944	0.998	

For the action “Closing Windows,” the indoor temperature variable shows a statistically significant negative correlation (B = -1.147, SE = 0.507, p = 0.024), indicating that the likelihood of occupants closing windows decreases as indoor temperature increases. The odds ratio (Exp(B)) of 0.318 suggests that for each unit increase in indoor temperature, the odds of closing windows decrease by approximately 68.2%. However, indoor humidity and indoor CO_2 do not exhibit significant correlations with the probability of closing windows ($p > 0.05$).

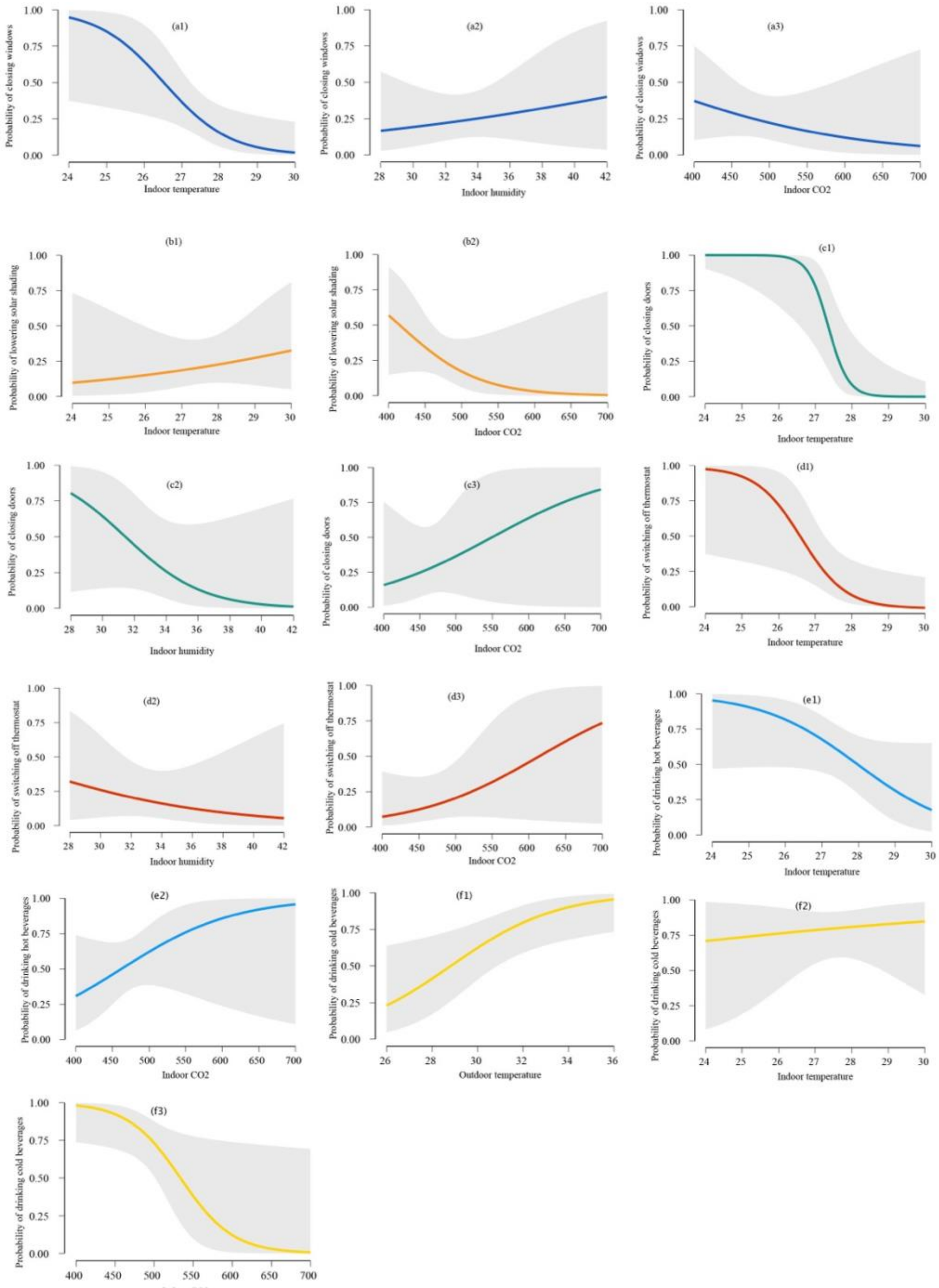
Regarding “Lowering Solar Shading,” indoor temperature has a positive and non-significant relationship with the probability of this action ($B = 0.249$, $SE = 0.430$, $p = 0.562$). In contrast, indoor CO_2 shows a non-significant negative correlation ($B = -0.019$, $SE = 0.014$, $p = 0.181$). The model accuracy for this action is 70.5%.

For “Closing Doors,” indoor temperature has a substantial negative correlation ($B = -3.664$, $SE = 1.480$, $p = 0.013$). The odds ratio of 0.086 implies that for each unit increase in indoor temperature, the odds of closing doors decrease by approximately 91.4%. Indoor humidity and indoor CO_2, however, do not exhibit significant correlations ($p > 0.05$).

Moving to “Switching off Thermostats,” indoor temperature exhibits a significant negative correlation ($B = -1.636$, $SE = 0.744$, $p = 0.028$). The odds ratio of 0.195 implies that for each unit increase in indoor temperature, the odds of occupants switching off thermostats decrease by approximately 80.5%. However, indoor humidity and indoor CO_2 do not display significant associations with the probability of this action ($p > 0.05$). The model accuracy for "Switching off Thermostats" is 86.4%.

For “Drinking Hot Beverages,” indoor temperature has a non-significant negative correlation ($B = -0.759$, $SE = 0.429$, $p = 0.077$). Likewise, indoor CO_2 shows a non-significant positive correlation ($B = 0.013$, $SE = 0.012$, $p = 0.262$). The model accuracy for this action is 75.0%. Finally, for “Drinking Cold Beverages,” outdoor temperature exhibits a statistically significant positive correlation ($B = 0.429$, $SE = 0.175$, $p = 0.014$). The odds ratio of 1.535 indicates that each unit's outdoor temperature increases the odds of occupants drinking cold beverages by approximately 53.5%. In contrast, indoor temperature and indoor CO_2 both have non-significant correlations with the probability of this action ($p > 0.05$). The model accuracy for "Drinking Cold Beverage" is 86.4%.

The logistic regression analysis provides valuable insights into the relationships between occupant actions and environmental variables. The results suggest that indoor temperature and outdoor temperature play significant roles in influencing specific occupant actions such as “Closing Windows,” “Switching off Thermostats,” and “Drinking Cold Beverages.” However, other environmental variables, including indoor humidity and indoor CO_2, do not consistently exhibit significant associations with occupant actions. Referring to these results, the action probabilities of Cluster 1 are shown in Figure 12.



*(a1, a2, a3) probability of closing windows , (b1, b2) probability of lowering solar shading, (c1, c2, c3) probability of closing doors, (d1, d2, d3) probability of switching off the thermostat, (e1, e2) probability of drinking hot beverages, and (f1, f2, f3) probability of drinking cold beverages.

Figure 13. Action probabilities of Cluster 1 – M.

Cluster 2 – L

The model items considered for Cluster 2 – L were closing windows, closing doors, and switching off thermostats. For the occupant action “Closing Windows,” the logistic regression model examined the predictors of indoor temperature, indoor humidity, and indoor CO_2. The odds ratio (Exp(B)) for each predictor indicates the change in the odds of occupants closing windows with a one-unit increase in the predictor while holding other variables constant. The odds of closing windows decrease by 8.0% (Exp(B) = 0.920, p = 0.895) for each one-unit increase in indoor temperature. Indoor humidity has an odds ratio of 1.182 (p = 0.358), suggesting that a one-unit increase in indoor humidity results in an 18.2% increase in the odds of closing windows. However, this change is not statistically significant. Similarly, the odds of closing windows increase by 3.2% (Exp(B) = 1.032, p = 0.108) for each one-unit increase in indoor CO_2, but the effect is not statistically significant. The model accuracy for predicting this action is 85.2%, indicating that the model correctly classifies 85.2% of the closing window actions.

Moving to the occupant action of “Closing Doors,” the logistic regression model considered indoor temperature, indoor humidity, and indoor CO_2 as predictors. The odds ratio for indoor temperature is 0.516 (p = 0.510), indicating that a one-unit increase in indoor temperature decreases the odds of closing doors by 48.4%. Indoor humidity has an odds ratio of 1.310 (p = 0.181), suggesting that a one-unit increase in indoor humidity increases the odds of closing doors by 31.0%. However, this change is not statistically significant. Similarly, the odds of closing doors increase by 1.2% (Exp(B) = 1.012, p = 0.308) for each one-unit increase in indoor CO_2, but the effect is not statistically significant. The model accuracy for this action is 77.8%.

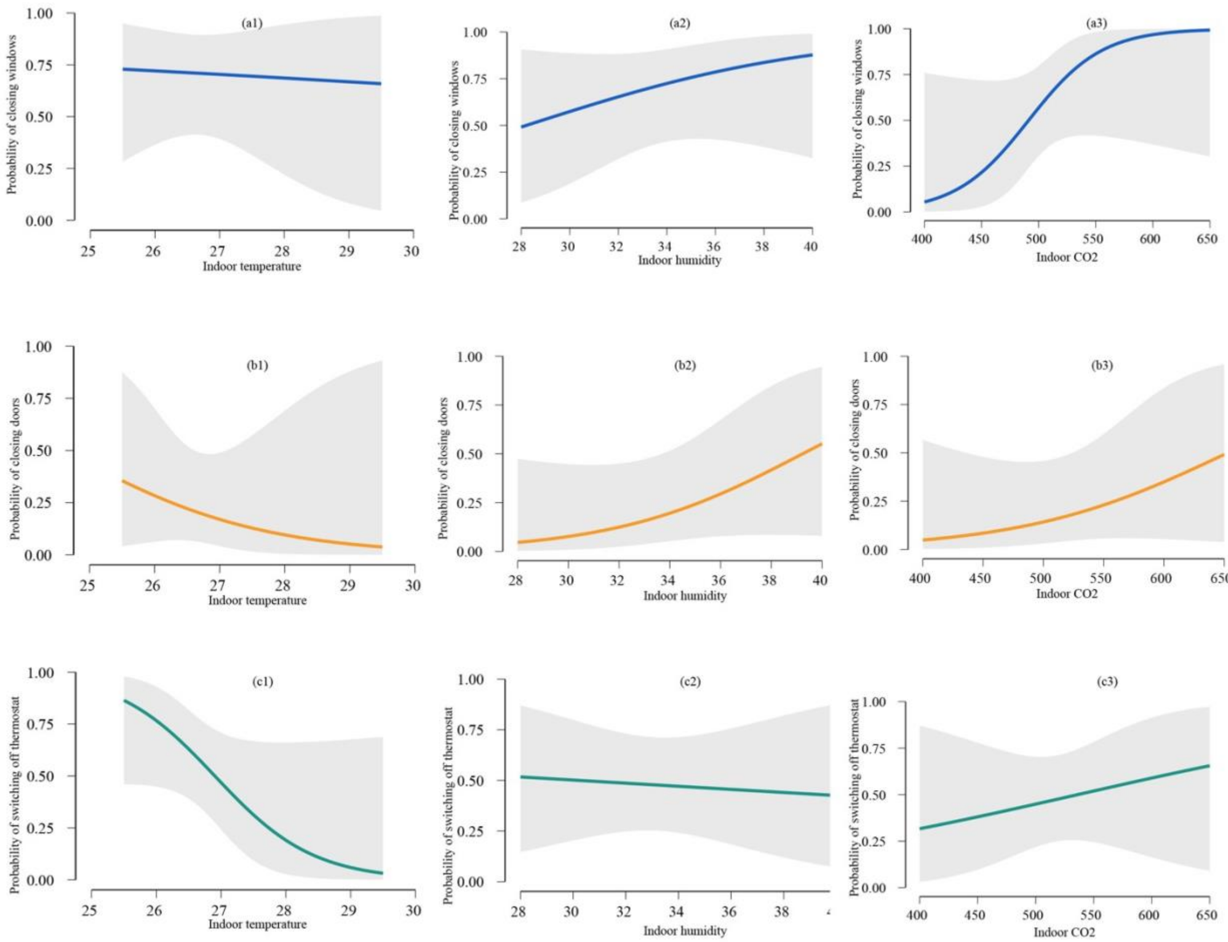
Regarding the occupant action of “Switching off Thermostats,” the logistic regression model examined indoor temperature, indoor humidity, and indoor

CO_2 as predictors. The odds ratio for indoor temperature is 0.268 ($p = 0.080$), indicating that a one-unit indoor temperature increases the odds of occupants switching off thermostats by 73.2%. Indoor humidity has an odds ratio of 0.970 ($p = 0.840$), suggesting that a one-unit increase in indoor humidity results in a 3.0% decrease in the odds of switching off thermostats. However, this effect is not statistically significant. Similarly, the odds of switching off thermostats increase by 0.6% (Exp(B) = 1.006, $p = 0.598$) for each one-unit increase in indoor CO_2, but the effect is not statistically significant. The model accuracy for predicting this action is 77.8%.

In summary, the logistic regression analysis results for Cluster 2 – L regarding occupant actions of "Closing Windows," "Closing Doors," and "Switching off Thermostats" indicate that the considered environmental predictors (indoor temperature, indoor humidity, and indoor CO_2) do not show significant influences on these behaviors (all $p > 0.05$) as seen in Table 20. The odds ratios and corresponding p-values reveal these relationships' magnitude and statistical significance. Although the predictors do not have statistically significant effects, the model accuracies ranging from 77.8% to 85.2% suggest that the model can still reasonably predict these actions based on the given predictors. Referring to these results, the action probabilities of Cluster 2 – L are shown in Figure 13.

Table 20. Logistic regression coefficients for Cluster 2 – L.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B) Lower	95% CI for EXP(B) Upper	Model Accuracy (%)
Closing windows									
Indoor temperature	-0.083	0.629	0.017	1	0.895	0.920	0.268	3.160	85.2
Indoor humidity	0.167	0.182	0.844	1	0.358	1.182	0.828	1.687	
Indoor CO_2	0.031	0.020	2.581	1	0.108	1.032	0.993	1.072	
Closing doors									
Indoor temperature	-0.661	1.002	0.435	1	0.510	0.516	0.072	3.682	77.8
Indoor humidity	0.270	0.202	1.310	1	0.181	1.310	0.882	1.945	
Indoor CO_2	0.012	0.012	1.037	1	0.308	1.012	0.989	1.035	
Switching off thermostats									
Indoor temperature	-1.317	0.752	3.066	1	0.080	0.268	0.061	1.170	77.8
Indoor humidity	-0.031	0.152	0.041	1	0.840	0.970	0.720	1.306	
Indoor CO_2	0.006	0.011	0.277	1	0.598	1.006	0.985	1.027	



*(a1, a2, a3) probability of closing windows, (b1, b2, b3) probability of closing doors, (c1, c2, c3) probability of switching off the thermostat.

Figure 14. Action probabilities of Cluster 2 – L.

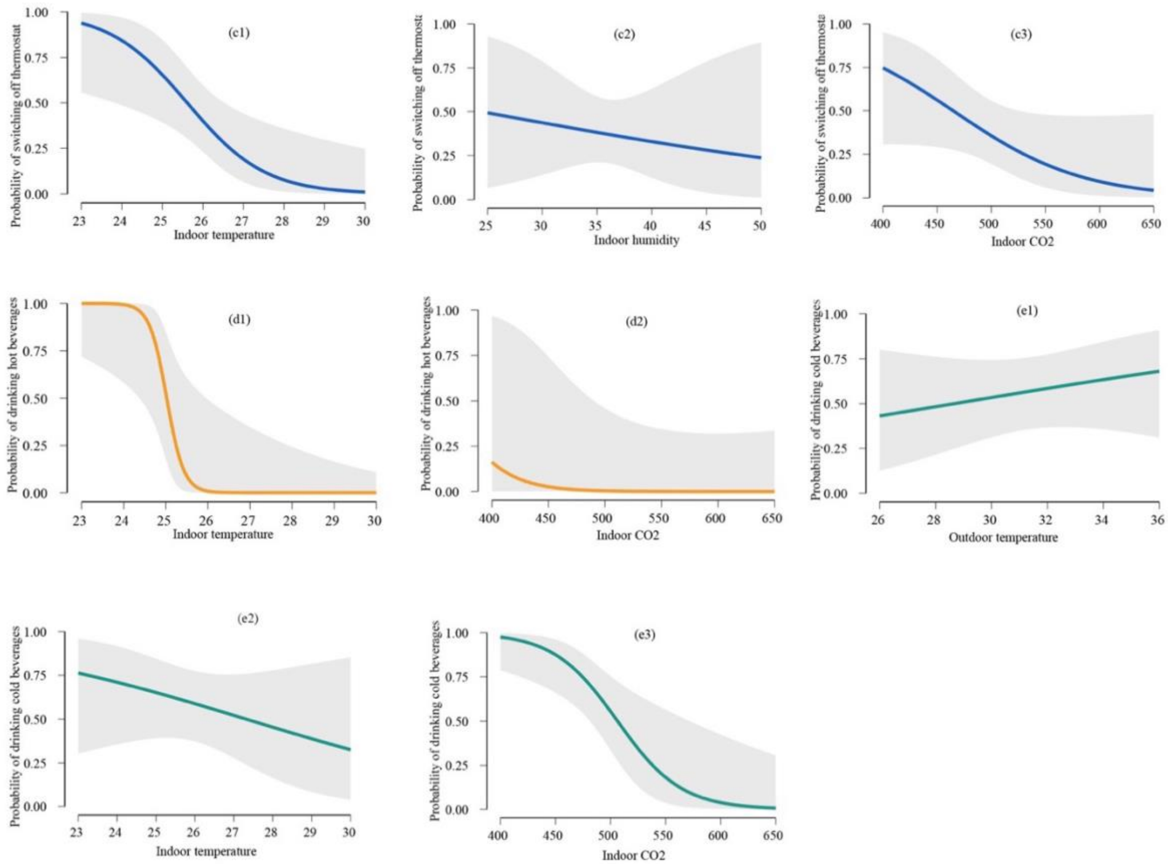
Cluster 3 – H

The model items considered for Cluster 3 – H were switching off thermostats, drinking hot beverages, and drinking cold beverages. For the occupant action of "Switching off Thermostats," the logistic regression model examined indoor temperature, indoor humidity, and indoor CO2 as predictors. The odds ratio for indoor temperature was 0.268 ($p = 0.080$), indicating that a one-unit increase in indoor temperature led to a 73.2% decrease in the odds of occupants switching off thermostats. However, this decrease was not statistically significant. For indoor humidity, the odds ratio was 0.970 ($p = 0.840$), suggesting that a one-unit increase in indoor humidity resulted in a 3.0% decrease in the odds of switching off thermostats, but this effect was not statistically significant. The odds ratio for indoor CO2 was 1.006 ($p = 0.598$), indicating that a one-unit increase in indoor CO2 increased the odds of switching off thermostats by 0.6%, but this change was not statistically significant. The model accuracy for predicting the "Switching off Thermostats" action was 77.8%.

In summary, the logistic regression analysis results for the occupant action of "Switching off Thermostats" revealed that the included environmental predictors (indoor temperature, indoor humidity, and indoor CO2) did not show significant influences on these behaviors (all $p > 0.05$) as seen in Table 21. Although the predictors did not have statistically significant effects, the model accuracies ranging from 77.8% to 85.2% suggest that the model can still reasonably predict these actions based on the given predictors. Referring to these results, the action probabilities of Cluster 3 are shown in Figure 14.

Table 21. Logistic regression coefficients for Cluster 3 – H.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B) Lower	95% CI for EXP(B) Upper	Model Accuracy (%)
Switching off thermostats									
Indoor temperature	-1.041	0.417	6.225	1	0.013	0.353	0.156	0.800	81.1
Indoor humidity	-0.045	0.116	0.153	1	0.695	0.965	0.761	1.200	
Indoor CO_2	-0.017	0.009	3.147	1	0.076	0.983	0.965	1.002	
Drinking hot beverage									
Indoor temperature	-4.933	2.280	4.683	1	0.030	0.007	0.000	0.628	94.6
Indoor CO_2	-0.039	0.024	2.756	1	0.097	0.961	0.917	1.007	
Drinking cold beverage									
Outdoor temperature	0.103	0.138	0.557	1	0.456	1.108	0.846	1.452	75.7
Indoor temperature	-0.270	0.300	0.367	1	0.367	0.763	0.424	1.373	
Indoor CO_2	-0.034	0.013	7.308	1	0.007	0.966	0.942	0.991	



* (a1, a2, a3) probability of switching off the thermostat, (b1, b2) probability of drinking hot beverages, and (c1, c2, c3) probability of cold beverages.

Figure 15. Action probabilities of Cluster 3 – H.

Summary of regression analysis

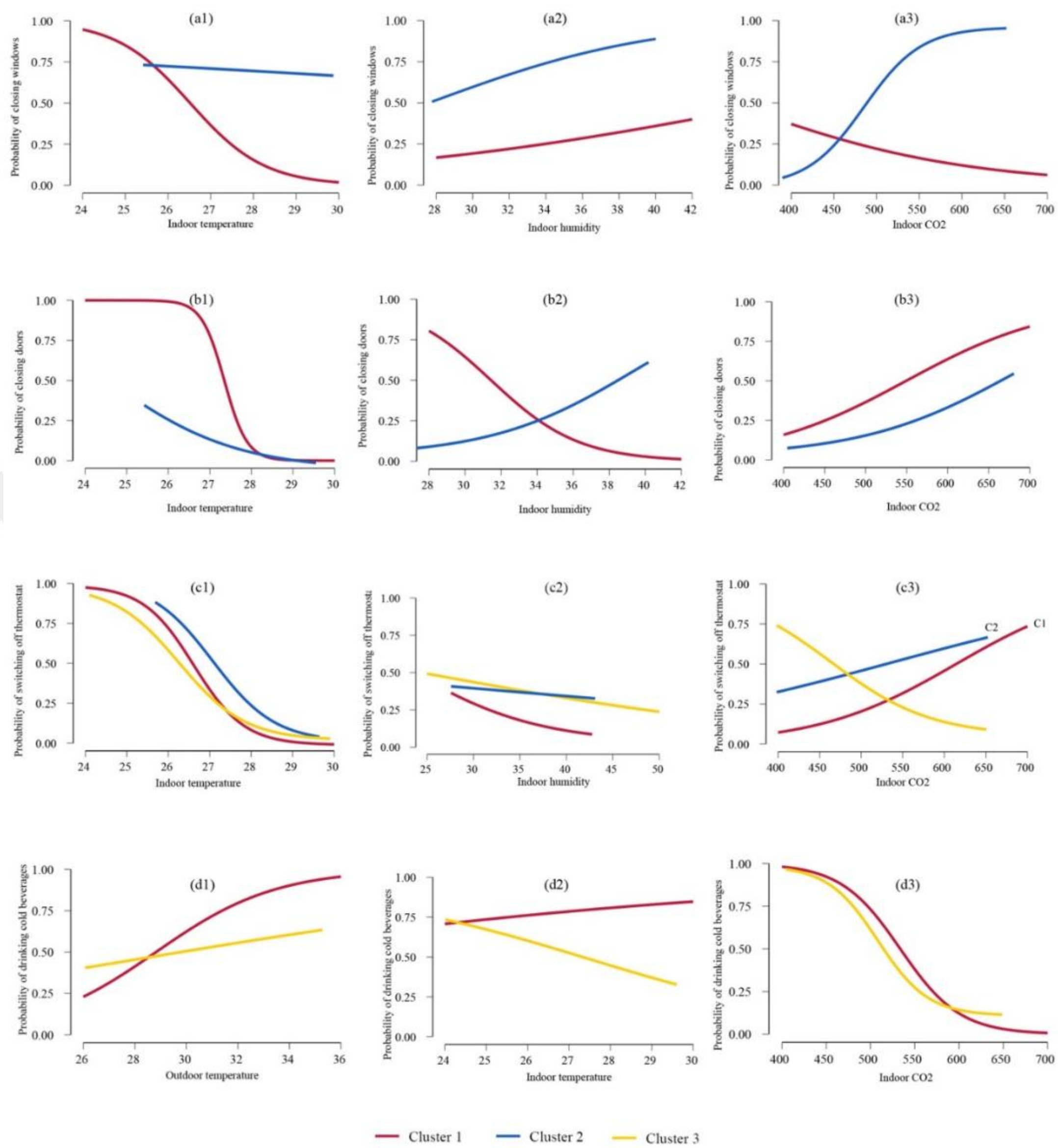
Across all three clusters, indoor temperature, humidity, and CO2 were consistently considered predictors for various occupant actions, suggesting their universal relevance in modeling such behaviors. In all three clusters, there are occupant actions whose likelihoods are not significantly influenced by these environmental predictors (all with $p > 0.05$). Moreover, the model accuracies across the clusters generally indicate that despite some non-significant associations, the models can predict occupant actions with reasonable accuracy, ranging from 59.1% to 86.4% in Cluster 1 – M and 77.8% to 85.2% in Clusters 2 – L and 3 – H.

Cluster 1 – M presents a broader range of occupant actions, including actions related to beverages, which are absent from Clusters 2 – L and 3 – H. The actions unique to Cluster 1 – M, like “Drinking Cold Beverages,” demonstrated significant associations with environmental variables, such as outdoor temperature. Additionally, in Cluster 1 – M, specific occupant actions like “Closing Windows” and “Switching off Thermostats” showed statistically significant correlations with indoor temperature. However, most Clusters 2 – L and 3 – H actions lacked substantial associations with the chosen predictors. Notably, Cluster 2 – M and Cluster 3 – H seem nearly identical in their presented data, focusing on the same actions (“Closing Windows,” “Closing Doors,” and “Switching off Thermostats”) and showing similar outcomes in logistic regression analyses. The only apparent discrepancy between them is that Cluster 3 – H mentions additional actions like “lowering solar shading,” but details regarding these actions were not provided.

In conclusion, while the three clusters bear significant resemblances in their approach and outcomes, there are key differences, primarily in the range of occupant actions analyzed and the significant associations found in Cluster 1 – M compared to Clusters 2 – L and 3 – H.

Common action probabilities among the behavioral clusters

The analysis involved a comparison of common actions across the three clusters. Notably, closing windows and closing doors were shared between Cluster 1 and Cluster 2. Drinking cold beverages was common between Cluster 1 and Cluster 3. Switching off the thermostat was prevalent across all three behavioral clusters. This exploration of commonalities extends to evaluating the differences in action probabilities between the clusters, as illustrated in Figure 15.



*(a1, a2, a3) probability of closing windows, (b1, b2, b3) probability of closing doors, (c1, c2, c3) probability of switching off thermostat, and (d1, d2, d3) probability of drinking cold beverages

Figure 16 Common action probabilities among three clusters

Frequency analysis

The frequency of occupants' actions with a consideration of behavioral clusters was also analyzed. Table 22 presents the distribution of different occupant actions within each behavioral cluster. In Cluster 1 – M, the most common occupant actions include “Closing Windows” (63.04%), “Lowering Solar

Shading” (73.91%), and “Closing Doors” (56.52%). A significant portion of occupants in this cluster prefers to close windows, accounting for 63.04% of their actions, which suggests a preference for maintaining indoor thermal comfort. They also frequently lower solar shading, with 73.91% of occupants in this cluster choosing this action, likely to reduce direct sunlight and solar heat gain, contributing to a more pleasant indoor environment. Moreover, occupants in Cluster 1 – M tend to close doors, representing 56.52% of their actions, indicating a preference for thermal isolation between indoor areas. Compared to the other clusters, Cluster 1 – M has a relatively balanced distribution of actions, meaning a moderate range of choices among its occupants.

Table 22. Frequencies and percentages of occupants actions in summer.

WO	Closing Windows n (%)					Opening Windows n (%)				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	29 (63.04%)	16 (34.78%)	1 (2.17%)	0 (0.00%)	0 (0.00%)	24 (52.17%)	18 (39.13%)	4 (8.69%)	0 (0.00%)	0 (0.00%)
C2	11 (40.74%)	16 (59.25%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	5 (19.235)	16 (61.53%)	5 (19.23)	0 (0.00%)	0 (0.00%)
C3	26 (68.42 %)	10 (26.31%)	2 (5.26%)	0 (0.00%)	0 (0.00%)	28 (73.68%)	8 (21.05%)	2 (5.26%)	0 (0.00%)	0 (0.00%)
SO	**Lowering solar shading n (%)**					**Raising solar shading n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	34 (73.91%)	10 (21.73%)	2 (4.34%)	0 (0.00%)	0 (0.00%)	43 (93.47%)	3 (6.52%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
C2	27 (100.0%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	23 (85.18%)	2 (7.40%)	2 (7.40%)	0 (0.00%)	0 (0.00%)
C3	36 (94.73%)	1 (2.63%)	1 (2.63%)	0 (0.00%)	0 (0.00%)	36 (94.73%)	2 (5.26%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
DO	**Closing doors n (%)**					**Opening doors n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	26 (56.52%)	17 (36.95%)	2 (4.34%)	1 (2.174%)	0 (0.00%)	25 (54.34%)	15 (32.60%)	3 (6.52%)	2 (4.34%)	1 (2.174%)
C2	18 (66.66%)	9 (33.33%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	7 (25.92%)	16 (59.25%)	1 (3.70%)	0 (0.00%)	3 (11.111%)
C3	25 (65.78%)	5 (13.15%)	3 (7.89%)	4 (10.52%)	1 (2.63%)	59 (53.15%)	38 (34.23%)	7 (6.30%)	2 (1.80%)	5 (4.50%)
TA	**Switching off thermostats n (%)**					**Switching on thermostats n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	32 (69.56%)	12 (26.08%)	2 (4.34%)	0 (0.00%)	0 (0.00%)	17 (36.95%)	20 (43.47%)	9 (19.56%)	0 (0.00%)	0 (0.00%)
C2	13 (48.14%)	13 (48.14%)	1 (3.70%)	0 (0.00%)	0 (0.00%)	8 (29.63%)	16 (59.25%)	0 (0.00%)	0 (0.00%)	3 (11.11%)
C3	23 (60.52%)	14 (36.84%)	1 (2.63%)	0 (0.00%)	0 (0.00%)	13 (34.21%)	4 (10.52%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
CA	**Adding clothes n (%)**					**Removing clothes n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	42 (91.30%)	4 (8.69%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	41 (89.13%)	4 (8.69%)	1 (2.17%)	0 (0.00%)	0 (0.00%)
C2	26 896.29%)	1 (3.70%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	18 (66.66%)	9 (33.33%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
C3	30 (78.94%)	8 (21.05%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	28 (73.68%)	4 (10.52%)	6 (15.78%)	0 (0.00%)	0 (0.00%)
DI	**Drinking hot beverages n (%)**					**Drinking cold beverages n (%)**				
C1	22 (47.82%)	22 (47.82%)	2 (4.34%)	0 (0.00%)	0 (0.00%)	15 (32.60%)	22 (47.82%)	4 (8.69%)	2 (4.34%)	3 (6.52%)
C2	11 (40.74%)	10 (37.03%)	5 (18.51%)	1 (3.70%)	0 (0.00%)	3 (11.11%)	8 (29.63%)	10 (37.03%)	6 (22.22%)	0 (0.00%)
C3	26 (68.42%)	11 (28.94%)	1 (2.63%)	0 (0.00%)	0 (0.00%)	16 (42.10%)	18 (47.36%)	3 (7.89%)	1 (2.63%)	0 (0.00%)

*C1: Cluster 1, C2: Cluster 2, C3: Cluster 3, WO: Window operation, SO: Solar shading operation, DO: Door operation, TA: Thermostat adjustment, CA: Clothing adjustment

In Cluster 2 – L, the most common occupant actions include “Opening Windows” (59.25%), “Lowering Solar Shading” (100%), and “Opening Doors” (59.25%). A substantial percentage of occupants in Cluster 2 – L, accounting for 59.25% of their actions, prefer to open windows, suggesting a preference for increased natural ventilation and fresh air circulation. Additionally, all occupants in this cluster, representing 100% of actions, lower solar shading, indicating a strong preference for reducing direct sunlight and solar heat gain. Moreover, occupants in Cluster 2 – L frequently open doors, with 59.25% of their actions involving door opening, emphasizing a preference for spatial connectivity and unrestricted movement between indoor areas. Compared to the other clusters, Cluster 2 – L has a dominant choice for lowering solar shading and opening windows, indicating a clear preference for controlling daylight and ventilation.

Lastly, in Cluster 3 – H, the most common occupant actions include “Closing Windows” (68.42%), “Lowering Solar Shading” (94.73%), and “Closing Doors” (65.78%). A considerable percentage of occupants in Cluster 3 – H, accounting for 68.42% of their actions, prefer to close windows, likely to maintain indoor thermal comfort and control outdoor noise and pollutants. They also frequently lower solar shading, with 94.73% of occupants in this cluster choosing this action, indicating a preference for reducing direct sunlight and associated heat gain. Moreover, occupants in Cluster 3 – H tend to close doors, representing 65.78% of their actions, suggesting a preference for privacy and thermal isolation between indoor areas. Compared to the other clusters, Cluster 3 – H has a higher prevalence of actions related to solar shading, emphasizing a stronger preference for controlling daylight and solar heat gain.

Cluster 1 – M demonstrates a more balanced distribution of occupant actions among the three clusters, with moderate preferences for different behaviors. Cluster 2 – L exhibits a distinct preference for actions related to controlling solar shading and opening windows for ventilation. In contrast, Cluster 3 – H has a higher prevalence of actions focused on solar shading and indoor environmental control. Understanding these differences in occupant actions among the clusters can help inform building design and energy management strategies and tailor indoor environments to meet the specific preferences and needs of occupants in each cluster.

7.1.3 End survey

Following the conclusion of the 2-week daily study period, participants were administered an end survey. Out of the 12 participants, 11 filled out the survey, and the subsequent analysis is based on these 11 responses.

Frequency of use of occupant actions within each behavioral cluster

During the end survey, participants were asked about the frequency at which they made physical and personal adjustments within their offices to maintain their environmental comfort for the last two weeks. The frequencies of these adjustments were recorded and analyzed, and the descriptive statistics are presented in Table E2 in the Appendix E. The ANOVA test results indicated no statistically significant differences between clusters regarding the frequencies of their behavioral actions, as seen in Table 23.

Table 23. ANOVA results from the end survey.

		Sum of Squares	df	Mean Square	F	Sig.
Window Operation	Between Groups	2.795	2	1.398	1.443	.292
	Within Groups	7.750	8	.969		
	Total	10.545	10			
Solar shading Operation	Between Groups	1.400	2	.700	.980	.421
	Within Groups	5.000	7	.714		
	Total	6.400	9			
Thermostat Adjustment	Between Groups	.159	2	.080	.038	.963
	Within Groups	16.750	8	2.094		
	Total	16.909	10			
Door Operation	Between Groups	.311	2	.155	.076	.928
	Within Groups	16.417	8	2.052		
	Total	16.727	10			
Clothing Adjustment	Between Groups	1.583	2	.792	.752	.502
	Within Groups	8.417	8	1.052		
	Total	10.000	10			
Drink Intake	Between Groups	2.000	2	1.000	1.333	.316
	Within Groups	6.000	8	.750		
	Total	8.000	10			

* *Significance level = p<0.05*

Differences between the start survey and end survey

The occupants' responses based on their environmental satisfaction and comfort preferences during the start and end surveys were compared to determine whether there were any statistically significant differences after two weeks of the daily survey period. Results showed that there are no statistically significant differences between environmental satisfaction ($p_{indoor\ climate}$=0.82, $p_{temperature}$= 0.132, $p_{humidity}$=0.052, $p_{indoorairquality}$=0.420) and comfort preferences ($p_{temperature}$=1.000, $p_{humidity}$=0.341). The results of the paired samples test are shown in Table 24.

Table 24. Paired samples test results.

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	Indoor climate satisfaction	.091	1.300	.392	-.783	.964	.232	10	.821
Pair 2	Temperature satisfaction	.636	1.286	.388	-.228	1.501	1.641	10	.132
Pair 3	Humidity satisfaction	1.182	1.779	.536	-.013	2.377	2.204	10	.052
Pair 4	Indoor Air Quality satisfaction	.364	1.433	.432	-.599	1.327	.841	10	.420
Pair 5	Temperature preference	.000	1.000	.302	-.672	.672	.000	10	1.000
Pair 6	Humidity preference	-.091	.302	.091	-.293	.112	-1.000	10	.341

* *Significance level = $p<0.05$*

7.2 Winter results

7.2.1 Start survey

Descriptive analysis

The winter season field study involved 14 participants, with 12 participants included in the summer measurements. Two additional volunteers from Step 01 were recruited for the winter season data collection, supplementing the original participants from the summer measurements. The participant distribution across clusters revealed that Cluster 1 – M comprised five participants (35.7%), Cluster 2 – L included four participants (28.6%), and Cluster 3 – H had five participants (35.7%).

Most participants were female, constituting 85.7% (n=12), while only two (14.3%) were male. The average age of the participants was 39.71 years (SD=9.211). Regarding education, most participants (71.4%, n=10) had graduated from college or held a bachelor's degree. Three participants (21.4%) had a senior high school education or below, and one (7.1%) had a master's degree or above.

Regarding office layout, three participants (21.4%) worked in individual offices, while 11 (78.6%) worked in shared enclosed spaces. All participants (n=12, 100%) met the recruitment criteria by working in small office rooms with 1-4 occupants. These findings offer an insightful overview of participant distribution across clusters, gender, age, education, office layout, and office size.

Frequency of use of occupant actions within each behavioral cluster

Table 25 explains participants' preferences for various adjustments, encompassing factors like window adjustment, solar shading, air conditioning, door, cloth, and drink adjustments. Notable findings include Cluster 3 displaying the highest mean rating for window adjustment at 2.20, while Cluster 1 exhibited the highest mean ratings for solar shading (1.50), air conditioning (3.60), door (3.40), cloth (3.00), and drink (3.50) adjustments. Overall, the combined mean rating for these adjustments ranges from 1.25 to 3.29 across all clusters. The provided insights shed light on the variability and tendencies within participant preferences, offering a comprehensive overview of the adjustment factors. However, the results of the ANOVA test indicated that there were no statistically significant differences between clusters for control elements as windows (p= 0.947), solar shading (p= 0.323), air conditioning (p= 0.526), doors (p= 0.581), clothing (p= 0.293), and drinking (p= 0.206).

Table 25. Environmental adjustments in the winter start survey.

Descriptives

	Cluster	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Window adjustment	1	5	2.00	1.225	.548	.48	3.52	1	4
	2	4	2.00	1.155	.577	.16	3.84	1	3
	3	5	2.20	.837	.374	1.16	3.24	1	3
	Total	14	2.07	.997	.267	1.50	2.65	1	4
Solar shading adjustment	1	4	1.50	.577	.289	.58	2.42	1	2
	2	4	1.00	.000	.000	1.00	1.00	1	1
	3	4	1.25	.500	.250	.45	2.05	1	2
	Total	12	1.25	.452	.131	.96	1.54	1	2
A/C adjustment	1	5	3.60	1.140	.510	2.18	5.02	2	5
	2	4	3.50	1.000	.500	1.91	5.09	3	5
	3	5	2.80	1.304	.583	1.18	4.42	2	5
	Total	14	3.29	1.139	.304	2.63	3.94	2	5
Door adjustment	1	5	3.40	1.342	.600	1.73	5.07	2	5
	2	4	2.75	.500	.250	1.95	3.55	2	3
	3	5	2.60	1.517	.678	.72	4.48	1	5
	Total	14	2.93	1.207	.322	2.23	3.63	1	5
Cloth adjustment	1	5	2.60	.894	.400	1.49	3.71	2	4
	2	4	3.00	1.155	.577	1.16	4.84	2	4
	3	5	2.00	.707	.316	1.12	2.88	1	3
	Total	14	2.50	.941	.251	1.96	3.04	1	4
Drink intake	1	5	3.00	.707	.316	2.12	3.88	2	4
	2	4	3.50	.577	.289	2.58	4.42	3	4
	3	5	2.40	1.140	.510	.98	3.82	1	4
	Total	14	2.93	.917	.245	2.40	3.46	1	4

7.2.2 Daily survey

The winter-daily survey gathered 134 records, encompassing both subjective and objective measurements. Across two weeks, each participant's daily subjective responses were paired with the daily mean of environmental variables in their offices, creating individual records. As in the summer period, the dependent variable is the probability of each behavioral action. Before delving into regression analysis, the environmental predictors underwent suitable scaling and centering to guarantee precise and meaningful results.

Indoor environmental quality satisfaction of behavioral clusters

Participants in the selected building were asked to rate their comfort in indoor climate, temperature, humidity, and air quality at the end of every working day during the two weeks of the winter field study. The frequency of participants' responses on the given Likert scale of occupants' satisfaction of each behavioral cluster with environmental parameters is shown in Table C3 of the Appendix C.

In terms of indoor climate, Cluster 1 – M displays the highest percentage of participants expressing "Very dissatisfied" sentiments (17.0%), while Cluster 3 – H has the highest proportion of participants indicating "Satisfied" feelings (37.0%). Overall, the majority of participants fall into the "Slightly satisfied" category (25.6%). Regarding temperature, Cluster 2 – L has the highest percentage of participants expressing "Very dissatisfied" sentiments (37.5%), whereas Cluster 3 – H reports the highest proportion of participants indicating "Satisfied" feelings (32.6%). The prevailing satisfaction level across all clusters is "Slightly satisfied" (22.6%). For humidity, Cluster 3 – H records the highest percentage of participants expressing "Slightly dissatisfied" sentiments (28.3%), while Cluster 1 – M has the highest proportion of participants indicating "Slightly satisfied" feelings (40.4%). The predominant satisfaction level across all clusters is "Slightly satisfied" (23.3%). Lastly, concerning indoor air quality, Cluster 1 – M leads in the percentage of participants reporting "Very dissatisfied" sentiments (38.3%), whereas Cluster 3 has the highest proportion of participants indicating "Slightly satisfied" feelings (27.7%). The prevailing satisfaction level is "Very dissatisfied" (28.6%).

In summary, participants within different clusters exhibit diverse satisfaction levels across indoor climate, temperature, humidity, and indoor air quality, providing valuable insights into their preferences and experiences within the built environment.

The results of the one-way ANOVA revealed that there is a statistically significant difference between the behavioral clusters and IEQ satisfaction for indoor climate (p=0.000), temperature (p=0.000), humidity (p=0.000), and indoor air quality (0.000). Table 26 illustrates the results of the one-way ANOVA for environmental satisfaction and behavioral clusters.

Table 26. One-way ANOVA for environmental satisfaction and clusters.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Climate Satisfaction	Between Groups	80.358	2	40.179	14.859	.000
	Within Groups	351.522	130	2.704		
	Total	431.880	132			
Temperature Satisfaction	Between Groups	81.545	2	40.772	13.888	.000
	Within Groups	381.658	130	2.936		
	Total	463.203	132			
Humidity Satisfaction	Between Groups	63.517	2	31.758	14.627	.000
	Within Groups	282.258	130	2.171		
	Total	345.774	132			
Indoor Air Quality Satisfaction	Between Groups	81.739	2	40.870	14.246	.000
	Within Groups	372.938	130	2.869		
	Total	454.677	132			

* *Significance level = p<0.05*

Comfort preferences of behavioral clusters

Participants in the selected building were surveyed about their comfort preferences regarding temperature and humidity after each working day throughout the two-week winter field study. The Likert scale responses, reflecting occupants' preferences within each behavioral cluster, are detailed in Table E4 of the Appendix E. This table illustrates the distribution of participants' temperature and humidity preferences across the distinct behavioral clusters.

Regarding temperature preference, Cluster 2 – L stands out with the highest percentage of participants expressing a desire for “Much warmer” conditions (42.5%), while Cluster 3 – H leads in those preferring “A bit warmer” (26.1%). Most participants across all clusters commonly choose “No change” in temperature (33.1%). Clusters 1 – M and 2 – L exhibit a minor percentage indicating a desire for “A bit cooler” or “Much cooler” conditions. Shifting to humidity preference, Cluster 2 – L emerges with the highest rate of participants favoring “A bit humid” conditions (72.5%), whereas Cluster 3 – H leads in those expressing a preference for “Much humid” conditions (6.5%). The predominant choice across all clusters is “No change” in humidity (40.6%). Clusters 1 – M and 2 – L show a modest percentage, indicating a preference for “A bit drier” or “Much drier” conditions. In summary, the diverse preferences for temperature and humidity among participants in different clusters offer valuable insights into their expectations and comfort preferences within the indoor environment.

Moreover, the one-way ANOVA results revealed statistically significant differences between the behavioral clusters and comfort preferences for temperature (p=0.008) and humidity (p=0.041). Table 27 illustrates the results of the one-way ANOVA for comfort preferences and behavioral clusters.

Table 27. One-way ANOVA for winter comfort preferences and clusters.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Temperature preference	Between Groups	8.931	2	4.466	4.973	.008
	Within Groups	116.738	130	.898		
	Total	125.669	132			
Humidity preference	Between Groups	2.615	2	1.307	3.263	.041
	Within Groups	52.092	130	.401		
	Total	54.707	132			

* *Significance level = p<0.05*

Correlation analysis between environmental variables and behavioral clusters

A correlation approach inspired by the methodology outlined in Pan et al.'s (2018) study was employed to investigate the relationship between occupants' actions and their influencing factors. A significance level of p-value 0.005 was considered to assess the impact of environmental factors on occupants' actions.

Table 28 presents Pearson correlation coefficients and associated significance levels (p= 0.005) for different environmental factors concerning occupants' actions in the indoor setting during the winter period. For closing windows and switching off thermostats, the outdoor temperature shows a minimal and insignificant correlation ($r = 0.014$, $p = 0.876$) with closing windows but a significant positive correlation ($r = 0.175$, $p = 0.044$) with switching off thermostats. Indoor temperature exhibits a strong positive correlation ($r = 0.494$, $p = 0.000$) with closing windows but a nonsignificant correlation ($r = -0.033$, $p = 0.073$) with switching off thermostats. Indoor humidity is significantly negatively correlated ($r = -0.509$, $p = 0.000$) with closing windows and weakly positively correlated ($r = 0.073$, $p = 0.405$) with switching off thermostats. Indoor CO2 demonstrates a significant negative correlation ($r = -0.345$, $p = 0.000$) with closing windows and an insignificant correlation ($r = -0.009$, $p = 0.921$) with switching off thermostats.

Table 28. Winter correlations between occupant actions and environmental variables.

	Pearson Correlation	Sig. (2-tailed)		Pearson Correlation	Sig. (2-tailed)
Closing windows			***Switching off thermostats***		
Outdoor temperature*	0.014	0.876	Outdoor temperature	0.175	0.044
Indoor temperature	0.494	0.000	Indoor temperature*	-0.033	0.073
Indoor humidity	-0.509	0.000	Indoor humidity*	0.073	0.405
Indoor CO_2	-0.345	0.000	Indoor CO_2*	-0.009	0.921
Opening windows			***Switching on thermostats***		
Outdoor temperature	0.219	0.011	Outdoor temperature*	0.048	0.584
Indoor temperature	0.306	0.000	Indoor temperature	0.394	0.000
Indoor humidity	-0.239	0.006	Indoor humidity	-0.359	0.000
Indoor CO_2	-0.241	0.005	Indoor CO_2	-0.101	0.249
Lowering solar shading			***Adding clothes***		
Outdoor temperature*	-0.013	0.882	Outdoor temperature*	-0.048	0.584
Indoor temperature	0.179	0.039	Indoor temperature	-0.331	0.000
Indoor humidity*	-0.157	0.070	Indoor humidity	0.288	0.001
Indoor CO_2	-0.197	0.023	Indoor CO_2	0.231	0.008
Raising solar shading			***Removing clothes***		
Outdoor temperature*	-0.007	0.933	Outdoor temperature	0.199	0.022
Indoor temperature*	0.160	0.065	Indoor temperature*	0.025	0.777
Indoor humidity*	-0.114	0.191	Indoor humidity	0.054	0.535
Indoor CO_2	-0.239	0.006	Indoor CO_2	0.083	0.346
Closing doors			**Drinking hot beverages***		
Outdoor temperature	0.011	0.904	Outdoor temperature*	0.024	0.787
Indoor temperature*	0.478	0.000	Indoor temperature*	0.046	0.602
Indoor humidity	-0.433	0.000	Indoor humidity*	-0.011	0.897
Indoor CO_2	-0.261	0.002	Indoor CO_2*	0.093	0.288
Opening doors			***Drinking cold beverages***		
Outdoor temperature*	0.130	0.135	Outdoor temperature*	-0.057	0.516
Indoor temperature	0.388	0.000	Indoor temperature	0.375	0.000
Indoor humidity	-0.380	0.000	Indoor humidity	-0.433	0.000
Indoor CO_2	-0.400	0.000	Indoor CO_2	-0.446	0.000

* *Removed variables from the dataset.*

** *Significance level = $p<0.05$ (2-tailed).*

With both actions, the outdoor temperature for opening windows and switching on thermostats is significantly positively correlated ($r = 0.219$, $p = 0.011$). Indoor temperature shows significant positive correlations ($r = 0.306$, $p = 0.000$) with opening windows and switching on thermostats. Indoor humidity is significantly negatively correlated ($r = -0.239$, $p = 0.006$) with opening windows and positively correlated ($r = -0.359$, $p = 0.000$) with switching on thermostats. Indoor CO_2 is significantly negatively correlated ($r = -0.241$, $p = 0.005$) with both actions.

Regarding adjusting solar shading, the outdoor temperature does not significantly correlate with either lowering ($r = -0.013$, $p = 0.882$) or raising ($r = -0.007$, $p = 0.933$) solar shading. Indoor temperature positively correlates ($r = 0.179$, $p = 0.039$) with lowering solar shading but not significantly ($r = -0.331$, $p = 0.000$) with raising solar shading. Indoor humidity exhibits a significantly negative correlation ($r = -0.157$, $p = 0.070$) with lowering solar shading and a significant positive correlation ($r = 0.288$, $p = 0.001$) with raising solar shading. Indoor CO_2 is significantly negatively correlated ($r = -0.197$, $p = 0.023$) with lowering solar shading and positively correlated ($r = 0.231$, $p = 0.008$) with raising solar shading.

For closing and opening doors, the outdoor temperature does not show a significant correlation with either closing ($r = 0.011$, $p = 0.904$) or opening ($r = 0.130$, $p = 0.135$) doors. Indoor temperature is positively correlated ($r = 0.478$, $p = 0.000$) with closing doors and not significantly correlated ($r = 0.046$, $p = 0.602$) with opening doors. Indoor humidity is significantly negatively correlated ($r = -0.433$, $p = 0.000$) with closing doors and not significantly correlated ($r = -0.011$, $p = 0.897$) with opening doors. Indoor CO_2 is significantly negatively correlated ($r = -0.261$, $p = 0.002$) with closing doors and weakly positively correlated ($r = 0.093$, $p = 0.288$) with opening doors.

Lastly, for drinking hot and cold beverages, the outdoor temperature does not show a significant correlation with either drinking hot ($r = 0.024$, $p = 0.787$) or cold ($r = -0.057$, $p = 0.516$) beverages. Indoor temperature is positively correlated (r = 0.388, p = 0.000) with drinking hot beverages and similarly correlated (r = 0.375, p = 0.000) with drinking cold beverages. Indoor humidity is significantly negatively correlated (r = -0.380, p = 0.000) with drinking hot beverages and significantly negatively correlated (r = -0.433, p = 0.000) with drinking cold beverages. Indoor CO_2 is significantly negatively correlated (r = -0.400, p = 0.000) with drinking hot beverages and similarly correlated (r = -0.446, p = 0.000) with drinking cold beverages.

In summary, the correlation coefficients and p-values provide valuable insights into the strength and significance of the relationships between environmental factors and occupants' actions in the indoor environment, offering a nuanced understanding of the factors influencing various behaviors related to thermal comfort and activities within the space.

As in summer period analyses, environmental predictors lacking significant correlations ($p < 0.05$) with behavioral actions were eliminated from the dataset for subsequent analysis after the correlation analysis. Moreover, any behavioral actions that did not display significant correlations with environmental parameters were entirely removed from the dataset. The excluded predictors and behavioral actions are detailed in Table 28. This refinement process aimed to streamline the dataset by excluding non-significant variables, emphasizing the most pertinent and influential factors for subsequent analyses.

Initial correlation analyses were conducted to prepare the dataset for regression analysis to examine the associations among different variables. Subsequently, collinearity statistics, recommended by Weerasinghe (2022), were employed to identify multicollinearity among predictor variables. Typically, tolerance values below 0.1 and variance inflation factor (VIF) values above 10 indicate significant multicollinearity. In this study, establishing a robust logistic regression model necessitated the absence of multicollinearity among predictors and the identification of potential outliers. High-correlated variables were pinpointed and eliminated based on collinearity statistics to address this. Moreover, box plots of

Z-score values (Sperandei, 2014) were employed to scrutinize potential outliers in the independent variables.

Following the correlation analysis, environmental factors lacking statistically significant associations with corresponding occupant actions were excluded from subsequent analyses. The results revealed that the chosen predictors exhibited tolerances greater than 0.1 and VIF values less than 10, indicating a strong correlation with each predictor (1 < VIF < 10) and no significant multicollinearity. Subsequently, outliers were examined using box plots of Z-score values, and no outliers were identified.

A chi-square (χ2) analysis is performed individually for each behavioral cluster. Models that did not adequately fit the data, as indicated by a p-value (<0.05), were excluded from further analysis. The results of these tests for each occupant action and the models removed are outlined in Table X. This approach ensures that the final model comprises only occupant actions with a p-value < 0.05, simplifying the overall model complexity. A chi-square (χ2) analysis was conducted separately for each behavioral cluster. Models with a p-value (<0.05) were excluded from further analysis, indicating inadequate fit to the data. The results of these tests for each occupant action and the excluded models are summarized in Table 29. This approach ensures that the final model consists only of occupant actions with a p-value < 0.05, simplifying the overall model complexity.

However, some actions in certain clusters could not be analyzed due to specific constraints. For instance, in Cluster 1 – M, raising solar shading and switching off thermostats couldn't be analyzed due to the number of models not being equal to two. Additionally, removing clothes in Cluster 1 – M couldn't be analyzed for the same reason. Similarly, in Cluster 2 – L, actions related to lowering and raising solar shading and switching off thermostats faced the same constraint. In Cluster 3 – H, raising solar shading and switching off the thermostat couldn't be analyzed due to the model's unequal factor levels and insufficient terms. Consequently, these models were also removed from subsequent analysis.

Table 29. Omnibus tests of model coefficients.

	Model Item	χ^2	df	Sig.	Nagelkerke R^2
Cluster 1	Closing windows	29.703	43	<.001	0.706
	Opening windows	15.643	42	0.004	0.642
	Lowering solar shading*	5.904	44	0.052	0.267
	Raising solar shading*				
	Closing doors	16.395	43	<.001	0.400
	Opening doors*	4.756	43	0.191	0.218
	Switching off thermostats*				
	Switching on thermostats	40.687	43	<.001	0.773
	Adding clothes	9.997	43	0.019	0.282
	Removing clothes*				
	Drinking cold beverages*	5.860	43	0.119	0.630
Cluster 2	Closing windows	31.642	36	<.001	0.731
	Opening windows*	6.580	35	0.160	0.728
	Lowering solar shading*				
	Raising solar shading*				
	Closing doors	13.466	36	0.004	0.423
	Opening doors	14.087	36	0.003	0.453
	Switching off thermostats*				
	Adding clothes*	2.361	36	0.501	0.077
	Removing clothes*	6.580	36	0.087	0.728
	Drinking cold beverages	35.667	36	<.001	0.793
Cluster 3	Closing windows	10.131	42	0.017	0.276
	Opening windows	22.305	41	<.001	0.773
	Lowering solar shading*	3.885	43	0.143	0.141
	Raising solar shading*				
	Closing doors*	6.199	42	0.102	0.169
	Opening doors*	7.487	42	0.058	0.209
	Switching off thermostats*				
	Adding clothes	27.362	42	<.001	0.644
	Removing clothes*	4.148	42	0.246	0.193
	Drinking cold beverages	1.545	42	0.672	0.175

*Models removed from further analysis.

** *Significance level = p<0.05*

The chi-square (χ2) analysis was applied to each behavioral cluster, examining the relationship between environmental factors and specific occupant actions. In Cluster 1 – M, significant associations were found for various actions. Closing windows demonstrated a substantial χ2 value of 29.703 (df = 43, p < .001), with a Nagelkerke R2 of 0.706, indicating a strong relationship. Similarly, opening windows showed a significant χ2 of 15.643 (df = 42, p = 0.004) with a Nagelkerke R2 of 0.642. Closing doors exhibited a highly significant χ2 of

16.395 (df = 43, $p < .001$) with a Nagelkerke R2 of 0.400. Switching on thermostats had the highest χ2 value of 40.687 (df = 43, $p < .001$) and a Nagelkerke R2 of 0.773, indicating a robust relationship. Adding clothes also displayed a significant association (χ2 = 9.997, df = 43, p = 0.019) with a Nagelkerke R2 of 0.282. For drinking cold beverages, the χ2 was 5.860 (df = 43, p = 0.119), and the Nagelkerke R2 was 0.630.

In Cluster 2 – L, closing windows exhibited a substantial χ2 of 31.642 (df = 36, $p < .001$) with a Nagelkerke R2 of 0.731. Closing doors (χ2 = 13.466, df = 36, p = 0.004) and opening doors (χ2 = 14.087, df = 36, p = 0.003) also revealed significant associations with Nagelkerke R2 values of 0.423 and 0.453, respectively. Drinking cold beverages in this cluster had a highly substantial χ2 of 35.667 (df = 36, $p < .001$) and a Nagelkerke R2 of 0.793.

In Cluster 3 – H, opening windows demonstrated a significant χ2 of 22.305 (df = 41, $p < .001$) with a Nagelkerke R2 of 0.773, indicating a strong relationship. Adding clothes had a highly significant χ2 of 27.362 (df = 42, $p < .001$) and a Nagelkerke R2 of 0.644. Other actions in this cluster, such as closing windows and doors and drinking cold beverages, also showed significant associations. The χ2 values, degrees of freedom (df), and associated significance levels (p-values) provide insights into the strength and significance of relationships between environmental factors and occupant actions in each behavioral cluster. The Nagelkerke R2 values further quantify the proportion of variance explained by these relationships.

Occupant actions within each behavioral cluster

Cluster 1 – M

Following the initial data preparation, the model items considered for Cluster 1 – M were closing windows, opening windows, closing doors, switching on thermostats, and adding clothes. Subsequently, logistic regression models were developed for these actions, considering environmental variables such as outdoor temperature, indoor temperature, humidity, and CO2. The correlation analysis between occupant actions and environmental factors guided each model's selection of these environmental variables. The outcome of the logistic regression analysis for Cluster 1 – M is presented in Table 30.

Table 30. Winter logistic regression coefficients for Cluster 1 - M actions.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B)		Model Accuracy (%)
							Lower	Upper	
Closing windows									
Indoor temperature	-0.049	0.566	0.007	1	0.931	0.952	-1.158	1.060	0.957
Indoor humidity	-0.520	0.306	2.887	1	0.089	0.595	-1.119	0.080	
Indoor CO_2	0.011	0.004	7.201	1	0.009	1.001	0.003	0.019	
Opening windows									
Outdoor temperature	1.047	1.148	0.832	1	0.362	2.849	-1.203	3.297	0.936
Indoor temperature	-0.440	1.050	0.176	1	0.675	0.644	-2.497	1.617	
Indoor humidity	-0.659	0.508	1.680	1	0.195	0.518	-1.655	0.337	
Indoor CO_2	-0.013	0.012	1.137	1	0.286	0.988	-0.036	0.011	
Closing doors									
Outdoor temperature	-0.133	0.571	0.055	1	0.815	0.875	-1.252	0.985	0.723
Indoor humidity	-0.291	0.094	9.509	1	0.002	0.748	-0.475	-0.106	
Indoor CO_2	0.000	0.002	0.010	1	0.921	1.000	-0.004	0.004	
Switching on thermostats									
Indoor temperature	-0.011	0.268	8.513×10^{-4}	1	0.977	0.989	-0.731	0.710	0.894
Indoor humidity	0.108	0.215	0.252	1	0.615	1.114	-0.313	0.529	
Indoor CO_2	-0.003	0.003	0.998	1	0.318	0.997	-0.010	0.003	
Adding cloths									
Indoor temperature	-0.237	0.322	0.542	1	0.462	0.789	-0.867	0.394	0.723
Indoor humidity	0.182	0.191	0.913	1	0.339	1.200	-0.192	0.556	
Indoor CO_2	-0.003	0.003	1.223	1	0.269	0.997	-0.010	0.003	

* *Significance level = $p<0.05$*

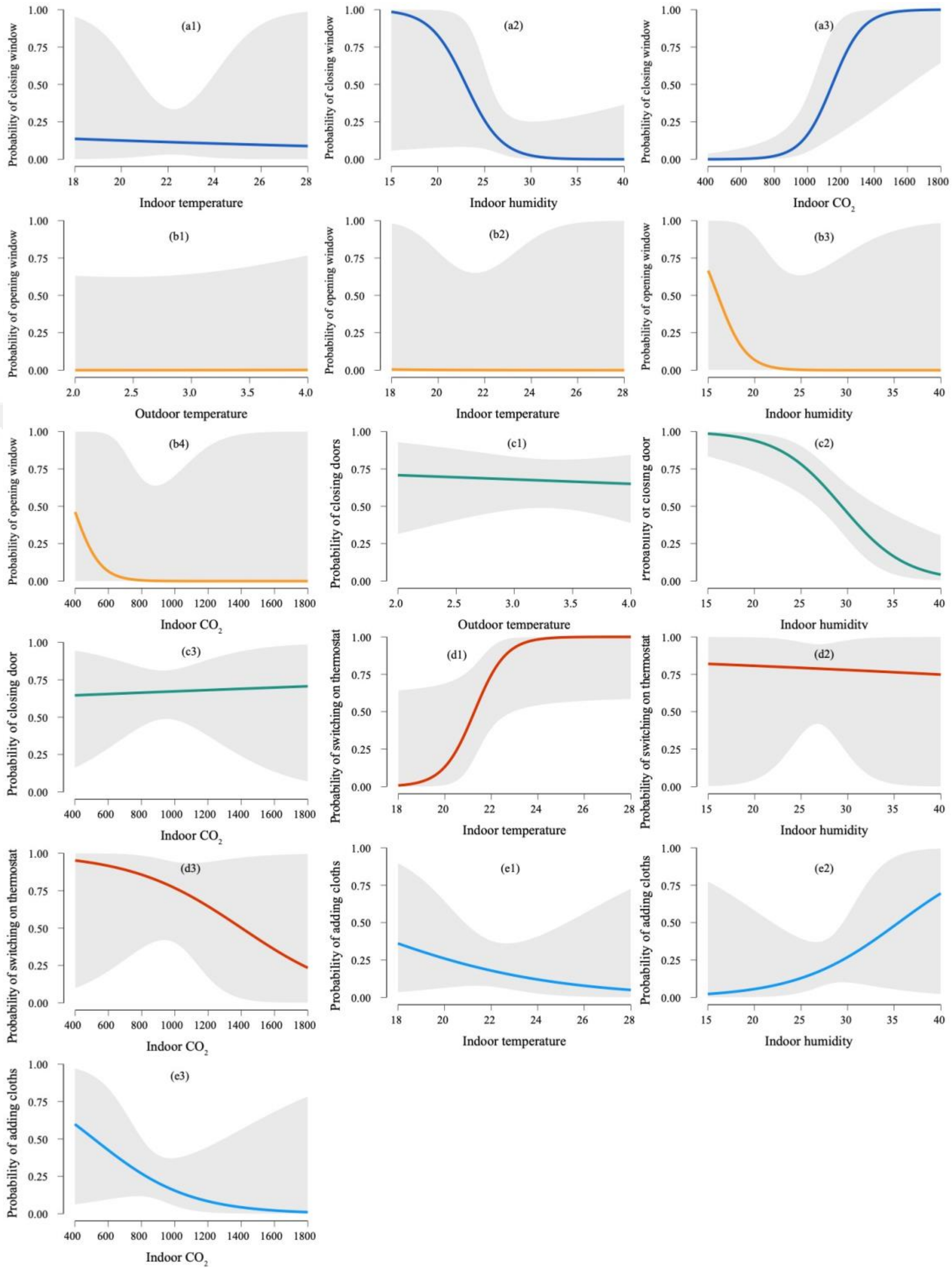
For the occupant action of “Closing Windows” in Cluster 1 – M, indoor temperature exhibits a non-significant negative association ($B = -0.049$, $SE = 0.566$, $p = 0.931$), suggesting that variations in indoor temperature are not significantly linked to the likelihood of closing windows. Indoor humidity, on the other hand, shows a marginally significant negative correlation ($B = -0.520$, $SE = 0.306$, $p = 0.089$), indicating a potential but weak association. Indoor CO_2 significantly and positively correlates with the probability of closing windows ($B = 0.011$, $SE = 0.004$, $p = 0.009$). The model accuracy for this action is 95.7%, signifying a robust fit.

For “Opening Windows,” none of the environmental variables, including outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2, show statistically significant correlations with the action (all $p > 0.05$). The model accuracy percentage for this action is 93.6%, indicating a high fit of the logistic regression model to the observed data.

In the case of “Closing Doors,” the environmental variables, namely outdoor temperature, indoor humidity, and indoor CO_2, do not exhibit statistically significant correlations with the action (all $p > 0.05$). The model accuracy for this action is 72.3%, suggesting a reasonable fit of the model.

“Switching on Thermostats” in Cluster 1 – M shows non-significant associations with indoor temperature, indoor humidity, and indoor CO_2 (all $p > 0.05$). The model accuracy percentage for this action is 89.4%, indicating a strong fit.

Finally, for “Adding Clothes,” none of the environmental variables, including indoor temperature, indoor humidity, and indoor CO_2, display statistically significant correlations with the action (all $p > 0.05$). The model accuracy for this action is 72.3%, suggesting an adequate fit of the model to the observed data. Referring to these results, the action probabilities of Cluster 1 during winter are shown in Figure 16.



**(a1,a2,a3): probability of closing window,(b1, b2, b3, b4): probability of opening window, (c1, c2, c3): probability of closing doors, (d1, d2, d3): probability of switching on thermostat, (e1, e2, e3): probability of adding cloths*

Figure 17. Action probabilities of Cluster 1 – M during winter.

Cluster 2 – L

The winter model items considered for Cluster 2 – L are closing windows, closing doors, opening doors, and drinking cold beverages. For the “Closing Windows” action, the logistic regression model indicates that indoor temperature has a positive but non-significant relationship with the likelihood of this action (B = 0.651, SE = 0.583, p = 0.264). Similarly, indoor humidity and indoor CO2 exhibit non-significant correlations (B = 0.089, SE = 0.338, p = 0.792; B = -0.005, SE = 0.007, p = 0.437, respectively). The model achieves a high accuracy of 90.0%, suggesting a good fit to the observed data.

Moving to “Closing Doors,” the logistic regression results reveal that outdoor temperature, indoor humidity, and indoor CO2 do not show statistically significant correlations with the action (B = 0.082, SE = 0.762, p = 0.914; B = -0.0249, SE = 0.197, p = 0.205; B = 0.000, SE = 0.005, p = 0.934, respectively). The model accuracy for this action is 75.0%, indicating a reasonable fit.

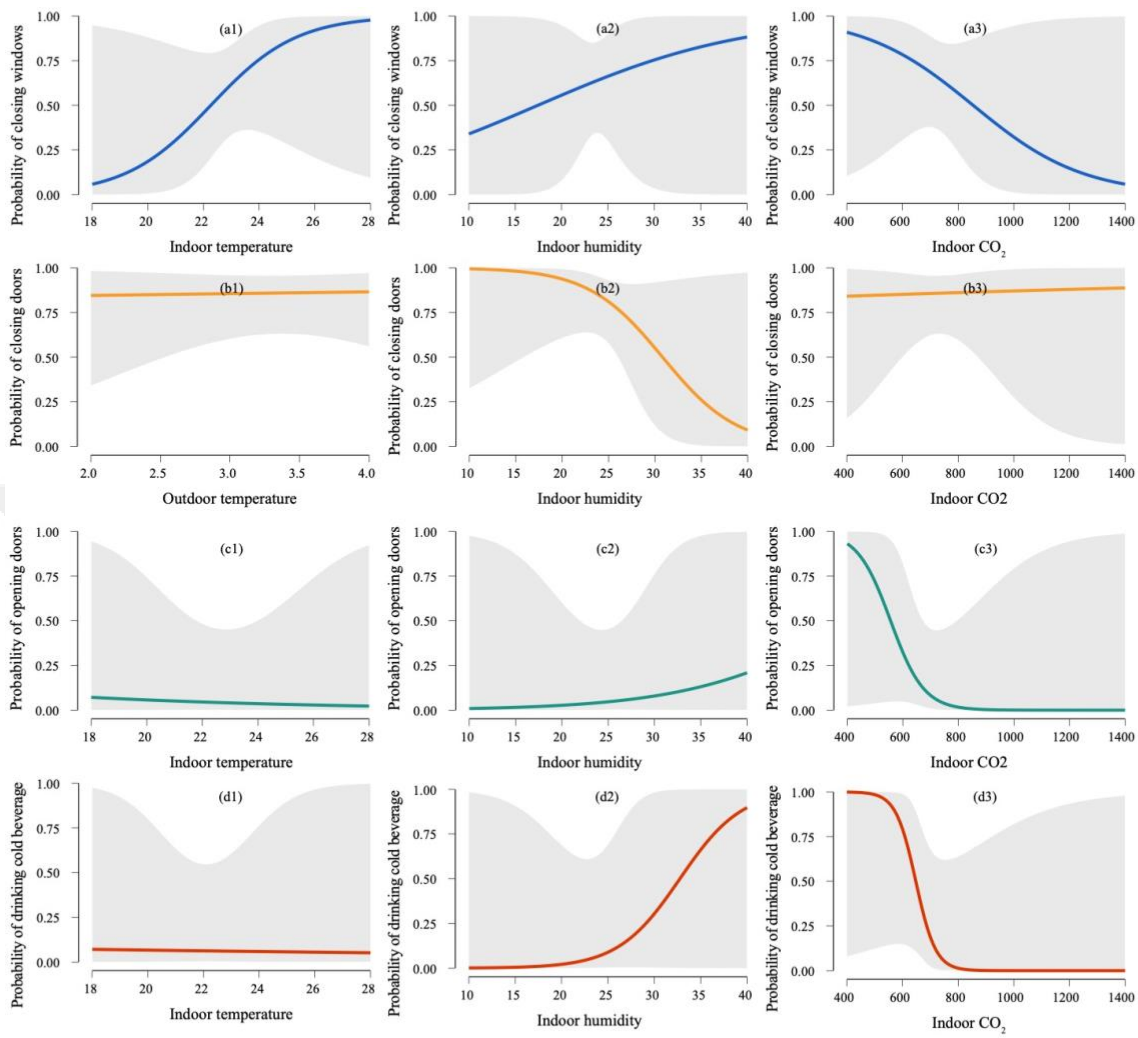
For the “Opening Doors” action, none of the environmental variables—indoor temperature, indoor humidity, and indoor CO2—demonstrate statistically significant correlations (B = -0.119, SE = 0.512, p = 0.816; B = 0.112, SE = 0.260, p = 0.666; B = -0.017, SE = 0.013, p = 0.181, respectively). The model accuracy percentage is 77.5%, suggesting a good fit to the observed data.

Finally, in the case of “Drinking Cold Beverages,” indoor temperature, indoor humidity, and indoor CO2 do not exhibit statistically significant correlations with the action (B = -0.034, SE = 0.698, p = 0.962; B = 0.300, SE = 0.361, p = 0.407; B = -0.028, SE = 0.017, p = 0.206, respectively). The model accuracy for this action is notably high at 92.5%, indicating a robust fit to the observed data. Referring to these results, the result of the logistic regression for Cluster 2 is illustrated in Table 31, and the action probabilities of Cluster 2 during winter are shown in Figure 17.

Table 31. Winter logistic regression coefficients for Cluster 2 - L actions.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B)		Model Accuracy (%)
							Lower	Upper	
Closing windows									
Indoor temperature	0.651	0.583	1.246	1	0.264	1.917	-0.492	1.794	0.900
Indoor humidity	0.089	0.338	0.070	1	0.792	1.093	-0.573	0.751	
Indoor CO_2	-0.005	0.007	0.604	1	0.437	0.995	-0.018	0.008	
Closing doors									
Outdoor temperature	0.082	0.762	0.012	1	0.914	1.086	-1.412	1.576	0.750
Indoor humidity	-0.0249	0.197	1.606	1	0.205	0.779	-0.635	0.136	
Indoor CO_2	0.000	0.005	0.007	1	0.934	1.000	-0.009	0.010	
Opening doors									
Indoor temperature	-0.119	0.512	0.054	1	0.816	0.887	-1.123	0.884	0.775
Indoor humidity	0.112	0.260	0.186	1	0.666	1.119	-0.397	0.621	
Indoor CO_2	-0.017	0.013	1.786	1	0.181	0.983	-0.041	0.008	
Drinking cold beverages									
Indoor temperature	-0.034	0.698	0.002	1	0.962	0.967	-1.402	1.334	0.925
Indoor humidity	0.300	0.361	0.689	1	0.407	1.349	-0.408	1.008	
Indoor CO_2	-0.028	0.017	2.614	1	0.206	0.972	-0.062	0.006	

* *Significance level = $p<0.05$*



(a1,a2,a3): probability of closing window,(b1, b2, b3): probability of closing doors, (c1, c2, c3): probability of opening doors, (d1, d2, d3): probability of drinking cold beverages, (e1, e2, e3)

Figure 18. Action probabilities of Cluster 2 – L during winter.

Cluster 3 – H

The model items considered for Cluster 3 – H were closing windows, opening windows, adding clothes, and drinking cold beverages. For the "Closing Windows" action, the logistic regression model indicates that indoor temperature has a non-significant negative relationship with the probability of this action (B = -0.159, SE = 0.356, p = 0.654). Indoor humidity and indoor CO2 also show non-significant correlations (B = 0.021, SE = 0.152, p = 0.889; B = -0.006, SE =

0.003, p = 0.059, respectively). The model accuracy for this action is 65.2%, suggesting a moderate fit to the observed data.

Turning to "Opening Windows," the results reveal that outdoor temperature, indoor temperature, indoor humidity, and indoor CO_2 do not exhibit statistically significant correlations with the action ($B = 21.300$, $SE = 3753.948$, $p = 0.995$; $B = 1.998$, $SE = 1.191$, $p = 0.093$; $B = 0.533$, $SE = 0.481$, $p = 0.268$; $B = -0.010$, $SE = 0.008$, $p = 0.203$, respectively). The model accuracy for this action is 95.7%, indicating a solid fit for the observed data.

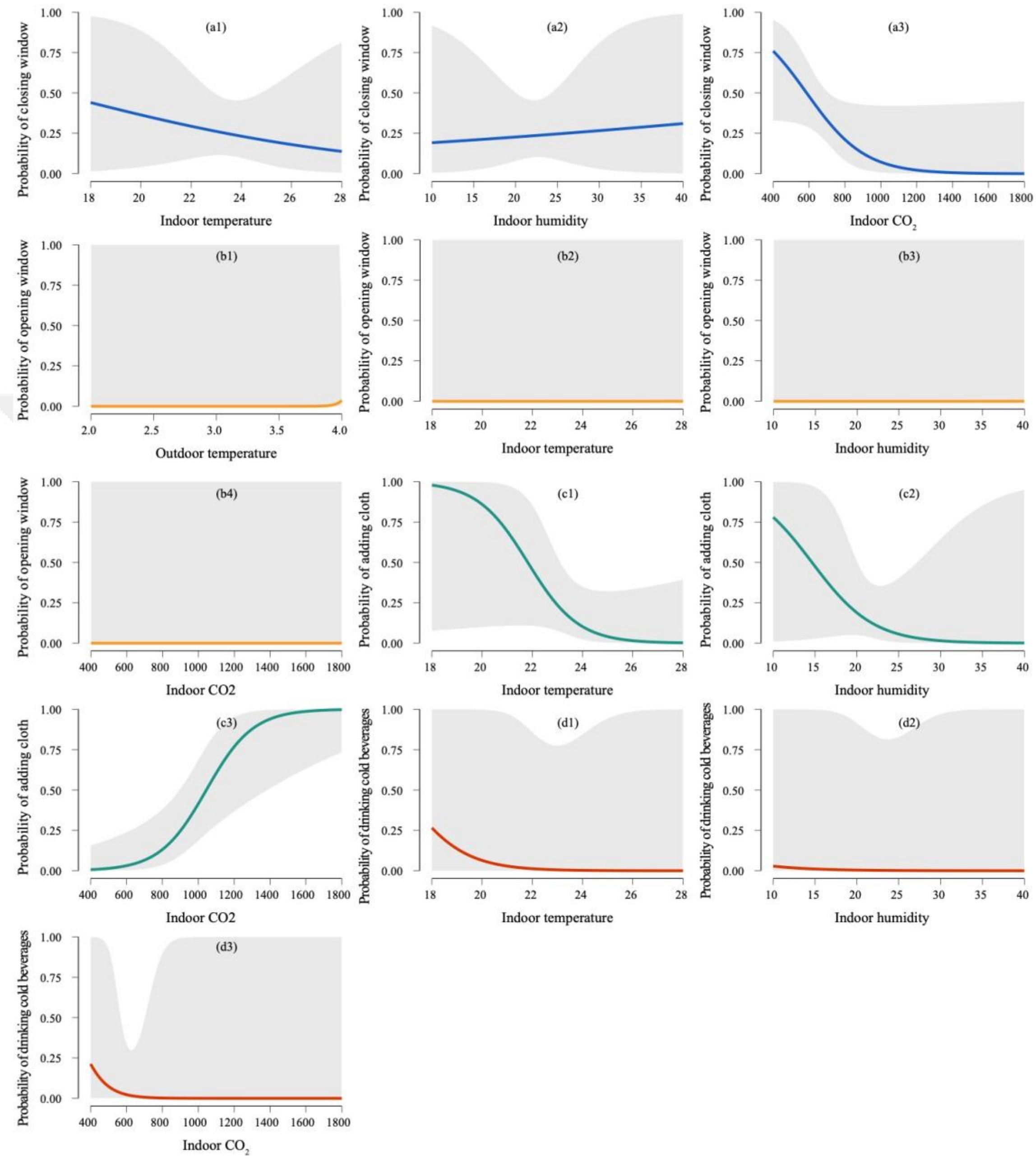
For "Adding Clothes," the logistic regression model suggests that indoor temperature has a non-significant negative relationship with the likelihood of this action ($B = -0.994$, $SE = 0.598$, $p = 0.096$). Indoor humidity and indoor CO_2 also show non-significant correlations ($B = -0.272$, $SE = 0.263$, $p = 0.301$; $B = 0.008$, $SE = 0.003$, $p = 0.007$, respectively). The model accuracy for this action is 87.0%, reflecting a reasonably good fit to the observed data.

Finally, in the case of "Drinking Cold Beverages," indoor temperature, indoor humidity, and indoor CO_2 do not demonstrate statistically significant correlations with the action ($B = -0.831$, $SE = 1.395$, $p = 0.551$; $B = -0.196$, $SE = 0.514$, $p = 0.703$; $B = -0.012$, $SE = 0.020$, $p = 0.541$, respectively). The model accuracy for this action is 97.8%, indicating a robust fit to the observed data. Referring to these results, the result of the logistic regression for Cluster 3 – H is illustrated in Table 32, and the action probabilities of Cluster 3 – H during winter are shown in Figure 18.

Table 32. Winter logistic regression coefficients for Cluster 3 - H actions.

Model predictors	B	SE	Wald	df	Sig.	Exp(B)	95% CI for EXP(B) Lower	Upper	Model Accuracy (%)
Closing windows									
Indoor temperature	-0.159	0.356	0.201	1	0.654	0.654	-0.856	0.538	0.652
Indoor humidity	0.021	0.152	0.020	1	0.889	0.889	-0.277	0.320	
Indoor CO_2	-0.006	0.003	3.568	1	0.059	0.059	-0.013	0.000	
Opening windows									
Outdoor temperature	21.300	3753.948	3.220×10^{-5}	1	0.995	$1.781 \times 10^{+9}$	-7336.303	7378.904	0.957
Indoor temperature	1.998	1.191	2.813	1	0.093	7.373	-0.337	4.332	
Indoor humidity	0.533	0.481	1.229	1	0.268	1.705	-0.410	1.476	
Indoor CO_2	-0.010	0.008	1.620	1	0.203	0.990	-0.025	0.005	
Adding cloths									
Indoor temperature	-0.994	0.598	2.766	1	0.096	0.370	-2.166	0.177	0.870
Indoor humidity	-0.272	0.263	1.071	1	0.301	0.762	-0.788	0.243	
Indoor CO_2	0.008	0.003	7.401	1	0.007	1.008	0.002	0.013	
Drinking cold beverages									
Indoor temperature	-0.831	1.395	0.355	1	0.551	0.436	-3.566	1.903	0.978
Indoor humidity	-0.196	0.514	0.145	1	0.703	0.822	-1.204	0.812	
Indoor CO_2	-0.012	0.020	0.373	1	0.541	0.988	-0.051	0.027	

* *Significance level = $p<0.05$*



(a1,a2,a3): probability of closing window,(b1, b2, b3, b4): probability of opening windows, (c1, c2, c3): probability of adding cloths, (d1, d2, d3): probability of drinking cold beverages, (e1, e2, e3)

Figure 19. Action probabilities of Cluster 3 – H during winter.

Summary of regression analysis

In Cluster 1 – M, the most representative results indicate a significant association between indoor CO_2 levels and the likelihood of “Closing Windows,” with a positive correlation found ($B = 0.011$, $p = 0.009$). This suggests that higher indoor CO_2 concentrations are linked to an increased probability of closing windows, highlighting the importance of indoor air quality in influencing occupant behavior. Conversely, for “Opening Windows” in the same cluster, none of the environmental variables show significant correlations with the action, indicating that factors like outdoor temperature, indoor temperature, humidity, and CO_2 levels do not significantly influence the decision to open windows. Despite this, the logistic regression model exhibits a high accuracy of 93.6%, suggesting a reliable fit to the observed data.

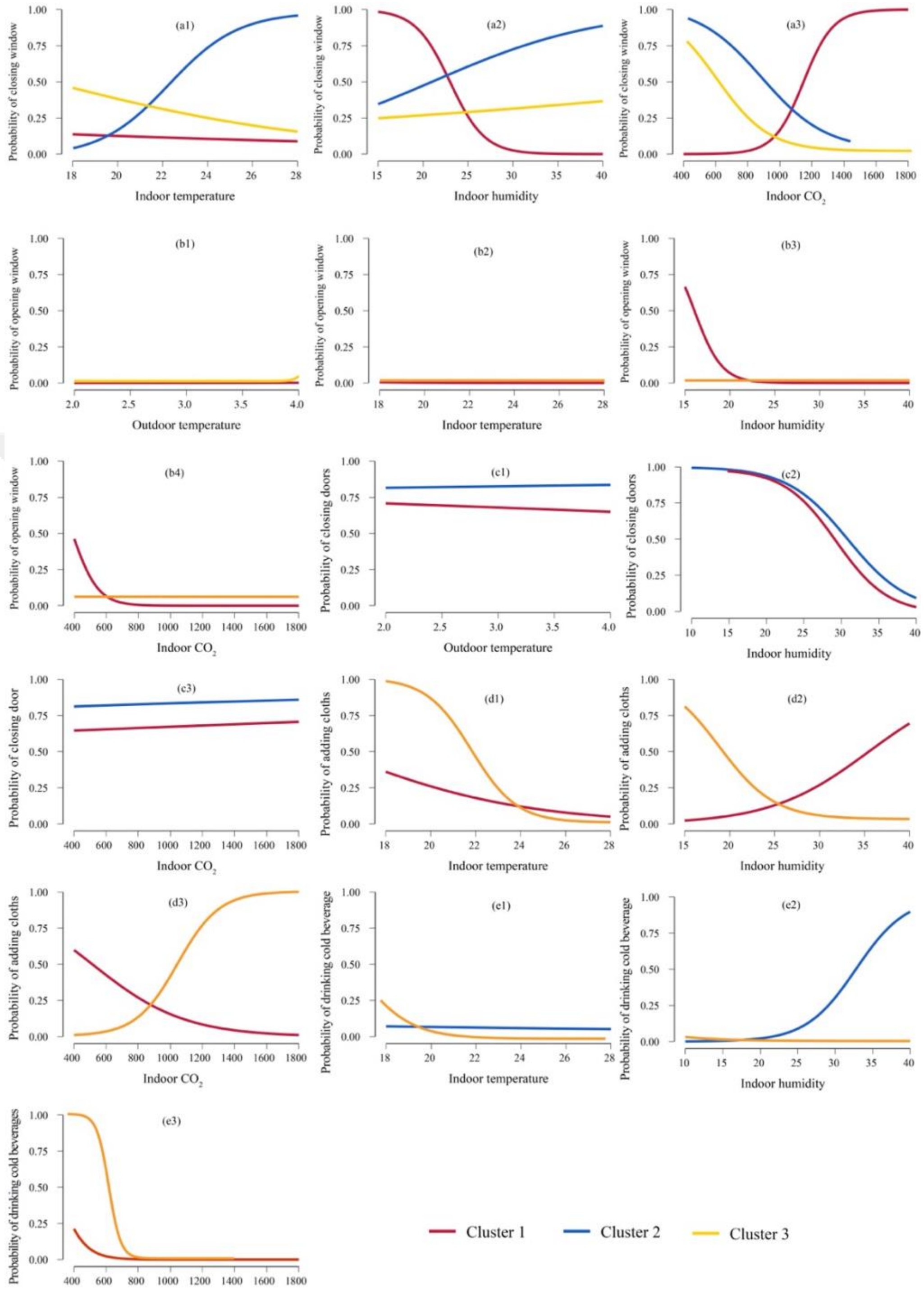
In Cluster 2 – L, the focus is on actions such as “Closing Windows,” “Closing Doors,” “Opening Doors,” and “Drinking Cold Beverages.” Notably, for “Drinking Cold Beverages,” the model demonstrates a notably high accuracy of 92.5% despite no environmental variables showing significant correlations with the action. This indicates that factors like indoor temperature, humidity, and CO_2 levels do not significantly impact this cluster's likelihood of drinking cold beverages. Similarly, for actions like “Closing Doors” and “Opening Doors,” none of the environmental variables exhibit statistically significant correlations. Yet, the models achieve reasonable accuracies of 75.0% and 77.5%, respectively, suggesting adequate fits to the observed data.

In Cluster 3 – H, the logistic regression analysis highlights the action of “Opening Windows” as the most representative. Despite including predictors like outdoor temperature, indoor temperature, humidity, and CO_2 levels, none of these variables show significant correlations with the action. However, the model accuracy remains notably high at 95.7%, indicating a solid fit for the observed data. This suggests that in Cluster 3 – H, environmental factors do not significantly influence occupant decisions regarding opening windows. Similarly, for actions like "Closing Windows" and "Adding Clothes," none of the environmental variables exhibit significant associations. Yet, the models achieve moderate to good accuracies, ranging from 65.2% to 87.0%, implying reasonable fits to the observed data.

Overall, these findings underscore the varying influences of environmental factors on occupant actions across different clusters. While factors like indoor CO2 levels may significantly influence some actions, others may exhibit minimal correlations with the considered predictors, indicating the complex nature of human behavior in response to environmental conditions.

Common action probabilities among the three behavioral clusters

Common actions were assessed and compared across the three clusters. The shared practice of closing windows was observed in all three clusters. Additionally, opening windows and adding cloth were common among Clusters 1 – M and 3 – H. Closing doors showed commonality between Cluster 1 – M and Cluster 2 – L. Furthermore, drinking cold beverages was noted among Cluster 2 – L and Cluster 3 – H. This exploration is illustrated in Figure 19.



* (a1, a2, a3) probability of closing windows, (b1, b2, b3, b4) probability of opening window, (c1, c2, c3) probability of closing doors, (d1, d2, d3) probability of adding cloths, and (e1, e2, e3) probability of drinking cold beverages

Figure 20. Common action probabilities among three clusters

Frequency analysis

The analysis included an examination of the frequency of actions performed by occupants, taking into account the identified behavioral clusters. The analysis of occupant actions, categorized into behavioral clusters, is elucidated in Table 33. Cluster 1 – M manifests distinctive preferences in occupant behaviors, with prevalent actions including “Closing Windows” (76.60%), “Lowering Solar Shading” (91.49%), and “Closing Doors” (63.04%). Within this cluster, closing windows is a predominant action, constituting 76.60% of observed behaviors, highlighting a collective inclination to regulate indoor thermal conditions. Moreover, a significant majority, 91.49%, engages in lowering solar shading, indicating a proactive approach to mitigating direct sunlight and solar heat gain, thereby enhancing indoor comfort.

Table 33. Frequencies and percentages of occupants' actions in winter.

WO	**Closing Windows n (%)**					**Opening Windows n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	36 (76.596%)	10 (21.277%)	0 (0.000%)	0 (0.000%)	1 (2.128%)	43 (91.489%)	4 (8.511%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
C2	18 (45.00%)	21 (52.500%)	0 (0.000%)	0 (0.000%)	1 (2.500%)	39 (97.500%)	1 (2.500%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C3	31 (67.391%)	7 (15.217%)	0 (0.000%)	6 (13.043%)	1 (2.174%)	41 (89.130%)	5 (10.870%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
SO	**Lowering solar shading n (%)**					**Raising solar shading n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	43 (91.489%)	4 (8.511%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	43 (91.489%)	4 (8.511%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C2	40 (10.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	40 (10.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C3	39 (84.783%)	7 (15.217%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	37 (80.435%)	0 (0.000%)	2 (4.348%)	5 (10.870%)	0 (0.000%)
DO	**Closing doors n (%)**					**Opening doors n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	17 (36.170%)	17 (36.170%)	1 (2.128%)	2 (4.255%)	10 (21.277)	43 (91.489%)	2 (4.255%)	0 (0.000%)	2 (4.255%)	0 (0.000%)
C2	10 (25.000%)	20 (50.000%)	6 (15.000%)	4 (10.000%)	0 (0.000%)	31 (77.500%)	9 (22.500%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C3	20 (43.478%)	10 (21.739%)	2 (4.348%)	12 (26.087%)	1 (2.174%)	31 (67.391%)	13 (28.261%)	(2.174%)	(2.174%)	0 (0.000%)
TA	**Switching off thermostats n (%)**					**Switching on thermostats n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	42 (89.362%)	4 (8.511%)	1 (2.128%)	0 (0.000%)	0 (0.000%)	22 (46.809%)	11 (23.404%)	3 (6.383%)	1 (2.128%)	10 (21.277%)
C2	40 (10.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	10 (25.000%)	19 (47.500%)	7 (17.500%)	3 (7.500%)	1 (2.500%)
C3	43 (93.478%)	3 (6.522%)	0 (0.000%)	0 (0.000%)	0 (0.000%)	11 (23.912%)	29 (63.043%)	2 (4.438%)	1 (2.174%)	2 (4.348%)
CA	**Adding clothes n (%)**					**Removing clothes n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	36 (76.596%)	8 (17.021%)	1 (2.128%)	1 (2.128%)	1 (2.128%)	45 (95.745)	2 (4.255%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C2	22 (55.000%)	10 (25.000%)	8 (20.000%)	0 (0.000%)	0 (0.000%)	39 (97.500%)	1 (2.500%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C3	33 (71.739%)	11 (23.912%)	2 (4.348%)	0 (0.000%)	0 (0.000%)	42 (91.304%)	3 (6.522%)	1 (2.174%)	0 (0.000%)	0 (0.000%)
DI	**Drinking hot beverages n (%)**					**Drinking cold beverages n (%)**				
	0	1-3	4-6	7-9	10≥	0	1-3	4-6	7-9	10≥
C1	2 (4.255%)	24 (51.064%)	16 (34.043%)	4 (8.511%)	1 (2.128%)	46 (97.872%)	1 (2.128%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C2	7 (17.500%)	20 (50.000%)	7 (17.500%)	5 (12.500%)	1 (2.500%)	23 (57.500%)	17 (42.500%)	0 (0.000%)	0 (0.000%)	0 (0.000%)
C3	10 (21.739%)	24 (52.174%)	12 (26.087%)	0 (0.000%)	0 (0.000%)	45 (97.826)	1 (2.174%)	0 (0.000%)	0 (0.000%)	0 (0.000%)

Notably, the preference for closing doors is also evident, with 63.04% of actions underscoring a desire for thermal isolation between distinct indoor spaces. The distribution of actions in Cluster 1 – M reflects a balanced and moderate range of preferences among its occupants, distinguishing it from the other clusters.

Moving to Cluster 2 – L, notable actions include “Closing Windows” (45.00%), “Opening Windows” (97.50%), and “Closing Doors” (25.00%). In Cluster 2, closing windows remains a common action, representing 45.00% of observed behaviors. Opening windows, however, emerges as a predominant choice, constituting 97.50% of actions, suggesting a collective preference for increased natural ventilation. Closing doors, representing 25.00%, signifies a partial inclination toward thermal isolation.

Cluster 3 – H exhibits distinct patterns, with predominant actions such as “Closing Windows” (67.39%), “Opening Windows” (89.13%), and “Closing Doors” (43.48%). Closing windows is a prevailing choice in this cluster, constituting 67.39% of actions, indicating a shared tendency among occupants to regulate indoor thermal conditions. Opening windows emerges as a prominent action, representing 89.13% of observed behaviors, underlining a strong preference for increased natural ventilation. The choice to close doors, representing 43.48%, signifies a moderate inclination toward thermal isolation.

In summary, the detailed analysis reveals nuanced preferences within each cluster, with distinct concentrations of actions shaping the behavioral dynamics of occupants in response to environmental conditions.

7.2.3 End survey

Participants were sent an end survey after two weeks of winter daily study. Of the 14 participants, 13 filled out the end survey. The results were analyzed according to these 13 answers.

Frequency of use of occupant actions within each behavioral cluster

During the end survey, participants were asked about the frequency at which they made physical and personal adjustments within their offices to maintain their environmental comfort for the last two weeks of winter study. The frequencies of these adjustments were recorded and analyzed, and the descriptive statistics are presented in Table E 5 in Appendix E. The ANOVA test results indicated no statistically significant differences between clusters regarding the frequencies of their behavioral actions, as seen in Table 34.

Table 34. ANOVA results from the winter-end survey.

		Sum of Squares	df	Mean Square	F	Sig.
Window Operation	Between Groups	.033	2	.017	.036	.965
	Within Groups	4.217	9	.469		
	Total	4.250	11			
Solar shading Operation	Between Groups	.300	2	.150	.692	.525
	Within Groups	1.950	9	.217		
	Total	2.250	11			
Thermostat Adjustment	Between Groups	1.973	2	.987	.762	.492
	Within Groups	12.950	10	1.295		
	Total	14.923	12			
Door Operation	Between Groups	2.327	2	1.163	.695	.522
	Within Groups	16.750	10	1.675		
	Total	19.077	12			
Clothing Adjustment	Between Groups	3.681	2	1.840	1.049	.386
	Within Groups	17.550	10	1.755		
	Total	21.231	12			
Drink Intake	Between Groups	1.142	2	.571	.872	.448
	Within Groups	6.550	10	.655		
	Total	7.692	12			

* *Significance level = $p<0.05$*

Differences between the start survey and end survey

The occupants' responses based on their environmental satisfaction and comfort preferences during the start and end surveys were compared to determine whether there were any statistically significant differences after two weeks of the winter-daily survey period. Results showed that there are no statistically significant differences between environmental satisfaction ($p_{indoor\ climate}$=0.776, $p_{temperature}$= 0.851, $p_{humidity}$=0.367, $p_{indoorairquality}$=0.472) and comfort preferences ($p_{temperature}$=0.436, $p_{humidity}$=1.000). The results of the paired samples test are shown in Table 35.

Table 35. Paired samples test results in winter.

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	Indoor climate satisfaction	.077	.954	.265	-.500	.653	.291	12	.776
Pair 2	Temperature satisfaction	-.077	1.441	.400	-.948	.794	-.192	12	.851
Pair 3	Humidity satisfaction	.308	1.182	.328	-.407	1.022	.938	12	.367
Pair 4	Indoor air quality satisfaction	.308	1.494	.414	-.595	1.210	.743	12	.472
Pair 5	Temperature preference	-.154	.689	.191	-.570	.262	-.805	12	.436
Pair 6	Humidity preference	.000	.577	.160	-.349	.349	.000	12	1.000

7.3 Summary

After conducting logistic regression analyses on occupant actions in the summer, in Cluster 1 – M, significant associations were found between environmental predictors and actions like “Closing Windows” (negatively correlated with indoor temperature) and “Switching off Thermostats” (negatively correlated with indoor temperature). Drink intake actions (“Drinking Hot Beverage” and “Drinking Cold Beverage”) demonstrated significant relationships with predictors. Model accuracies ranged from 70.5% to 86.4%, highlighting the role of indoor temperature in shaping occupant behavior.

In Cluster 2 – L, “Closing Windows” and “Closing Doors” displayed significant associations ($p = 0.002$ and 0.011, respectively), with the indoor temperature being a significant predictor for both actions. Other actions in Cluster 2 – L did not exhibit significant relationships with environmental predictors. The model accuracies ranged from 75.0% to 85.2%, suggesting reasonable predictive capabilities despite some non-significant associations.

In Cluster 3 – H, significant associations were found for “Drinking Hot Beverages” ($p < 0.001$), with the indoor temperature being a significant predictor ($B = -0.759$). Other actions in Cluster 3 – H displayed varying levels of significance. Overall model accuracies ranged from 65.2% to 95.7%, highlighting the diversity in associations across different occupant behaviors.

Across all clusters, indoor temperature consistently played a significant role in shaping occupant behavior, particularly in actions like “Closing Windows,” “Switching off Thermostats,” and “Drinking Cold Beverages.” However, indoor humidity and indoor CO_2 did not consistently exhibit significant associations. While some occupant actions showed strong correlations, others displayed more nuanced relationships, emphasizing the complex interplay between environmental factors and behavior.

Referring to winter results, in Cluster 1 – M, “Closing Windows” demonstrated a significant positive correlation with indoor CO_2 ($B = 0.011$, $p = 0.009$), highlighting the impact of indoor air quality on occupant behavior. However, “Opening Windows” did not show significant correlations with environmental variables, yet the model exhibited high accuracy (93.6%). Actions like “Closing Doors” and “Switching on Thermostats” also demonstrated non-significant associations.

Cluster 2 – L focused on actions like “Closing Windows,” “Closing Doors,” “Opening Doors,” and “Drinking Cold Beverages.” Despite non-significant correlations with environmental predictors, the models achieved reasonable accuracies (75.0% to 92.5%). Notably, “Drinking Cold Beverages” showed high accuracy despite lacking significant associations.

In Cluster 3 – H, “Opening Windows” did not show significant correlations with environmental variables, yet the model accuracy was high (95.7%). Other actions like “Closing Windows,” “Adding Clothes,” and “Drinking Cold Beverages” demonstrated moderate to good accuracies despite lacking significant associations.

The winter results reinforced the complex nature of occupant behavior, with some actions significantly influenced by environmental factors (e.g., indoor CO2 in “Closing Windows” in Cluster 1 – M), while others displayed minimal correlations. The models maintained reasonable predictive capabilities, indicating the intricate balance between environmental influences and human responses.

CHAPTER 8

FUZZY LOGIC MODEL DEVELOPMENT

In the last section of this study, a data-driven fuzzy logic system based on occupant behavior was carried out. The objective of this fuzzy logic system is to predict occupant actions in an office building in line with the environmental parameters. Numerous problems necessitate a degree of ambiguity in their definition and examination. Traditional methods fail to adequately account for linguistic nuances and intuitive elements (Zúñiga, Castilla & Aguilar, 2014). Fuzzy logic enables the advancement of genetic algorithms, which can imitate some aspects of human reasoning. These techniques are constructed by developing a computer program that relies on rules derived from fuzzy logic principles. This results in what is known as a system based on fuzzy rules (Zúñiga et al., 2014). In this study, fuzzy logic is a methodological tool to integrate knowledge, intuition, and experience to simulate occupant behavior in office buildings.

A fuzzy logic model was constructed to incorporate behavioral actions into simulation tools, addressing occupants' tendencies to adapt to their environment. This model employs a fuzzy algorithm to discern behavioral patterns and interpret relations among non-linear input data. This model makes it feasible to predict and categorize occupants' behavioral actions based on their behavioral clusters for environment control. The model establishes connections between various inputs through a set of rules, which determines the behavioral actions of office occupants. Fuzzification is employed to translate input values into linguistic terms using fuzzy sets with defined membership functions. Lastly, defuzzification converts the linguistic output into a precise value. Figure 21 illustrates the fuzzy model of this study.

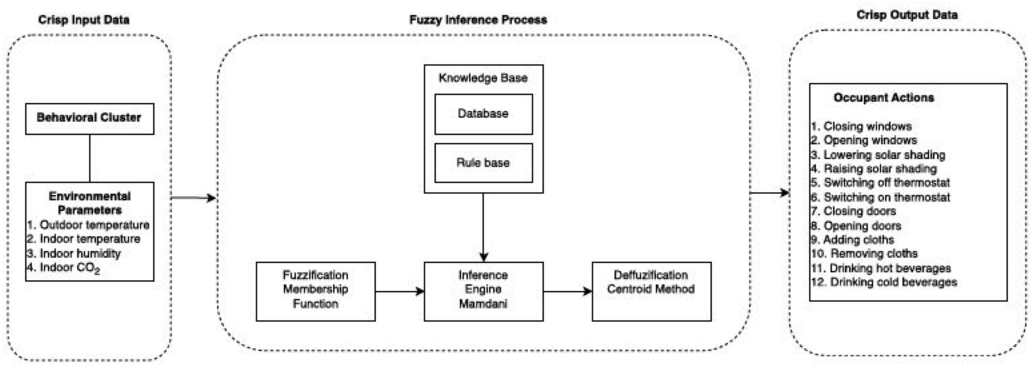


Figure 21. Fuzzy inference system of this study (drawn by the author, 2024).

MATLAB Version R2024a Fuzzy Logic Designer was utilized to implement the fuzzy logic model, employing a dataset obtained from field studies. The fuzzy rules and membership functions were developed separately for the summer (the cooling season) and winter (the heating season) periods, aligning with environmental data collected during the field studies. Mamdani inference was chosen due to its reputation for being intuitive and well-suited to human input (Yusoff et al., 2007). It is particularly suitable for modeling energy-related behaviors based on human intuition and behavioral clusters. Figure 22 shows the fuzzy inference system plot of this study.

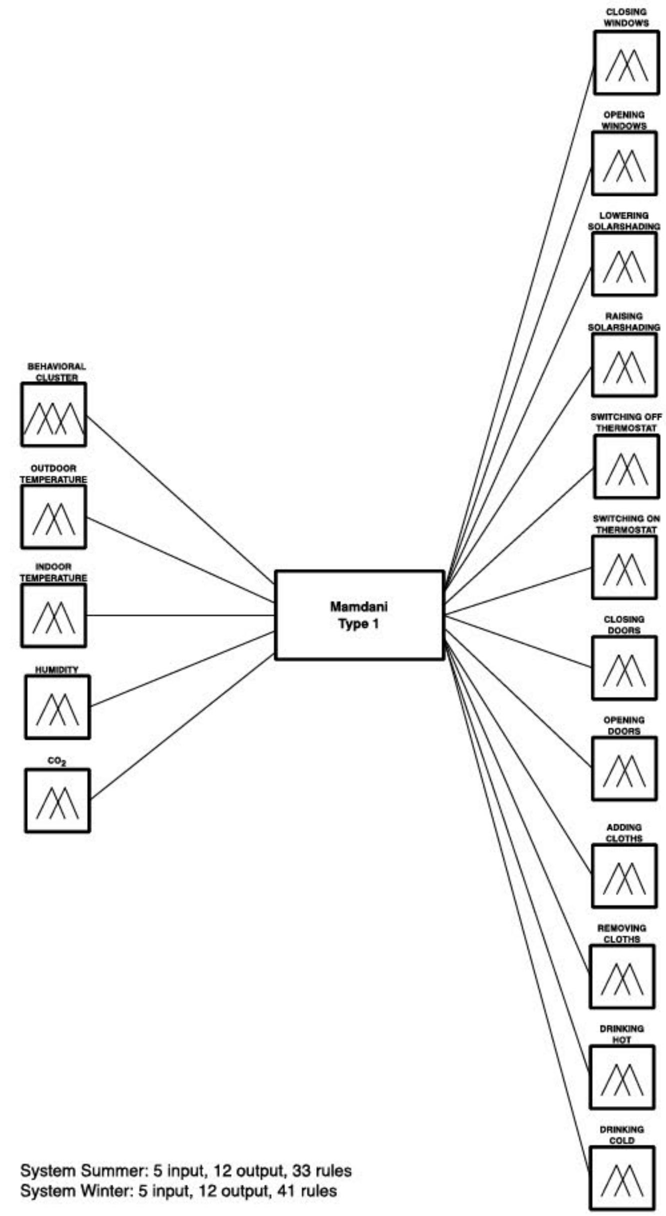


Figure 22. Fuzzy inference system plot of this study (drawn by the author, 2024).

For the defuzzification, the Centroid Method was used, which is the most common defuzzification technique used commonly, and it allows us to obtain the point where a vertical line divides in the middle of an aggregate set. With the help of MATLAB's fuzzy logic designer, a computational system was developed using fuzzy rules to generate three-dimensional charts or surfaces and outline maps of the associated function, representing the system and conducting fuzzy system simulations. Therefore, following the definition of fuzzy rules using the Mamdani method, the indicators' values were combined. Subsequently, the results were defuzzified using the Centroid method to derive a qualification value representing the level of occupant actions.

8.1.1 Input variables

For this study, five input variables were fuzzified: behavioral cluster (BC), outdoor temperature (OT), indoor temperature (IT), indoor humidity (H), and indoor CO_2 levels (CO_2). The fuzzy value of BC was determined based on the cumulative means of the obtained behavioral clusters in Step 01, reflecting their energy-saving behavior. For instance, Cluster 1 – M had a cumulative mean of 41.9, Cluster 2 – L had 38.2, and Cluster 3 – H had 47.7. These behavioral clusters were then de-fuzzified using triangular membership functions into three linguistic values: Cluster 2 as "L" (low), Cluster 1 as "M" (medium), and Cluster 3 as "H" (high).

Furthermore, environmental parameters such as OT, IT, H, and CO2 were fuzzified using triangular membership functions into two linguistic values: "L" (low) and "H" (high). These environmental inputs were created based on the analysis results in Chapter 7. The range for these environmental variables was derived from field study data, separately considering summer and winter datasets. The decision to use two linguistic values rather than three (e.g., "low," "medium," and "high") was based on the results of the correlation analysis presented in Chapter 7. Correlation analysis inherently identifies positive or negative relationships between variables, reflecting a binary outcome. As such, only two categories— "low" and "high"—were used to capture these relationships effectively. Introducing a third category, such as "medium," would not align with the binary nature of the relationships observed, and would add unnecessary complexity without improving the accuracy of the model.

Moreover, this approach enhances the model's simplicity and computational efficiency. In fuzzy logic systems, the number of linguistic values should reflect the granularity of the data and the nature of the relationships being modeled. By using two linguistic values, the model avoids overfitting and provides a clear, robust framework for translating environmental inputs into actionable outputs. This approach also ensures that the fuzzy model remains adaptable across different scenarios, such as varying building contexts and climatic conditions.

The range was defined by each environmental parameter's minimum and maximum values during the measurement periods. Table 36 shows the data that is used to determine the range. Finally, different kinds of relevant functions are available (Martínez et al., 2020). However, this study selected a triangular discrete function for its operational advantages. In this model, triangular-type membership functions were defined for all input variables (BC, OT, IT, H, and CO2). The membership functions described for the fuzzy sets of input variables are evenly distributed and shown in Figures 23 and 24.

Table 36. Dataset for fuzzifying environmental parameters.

Season	**Parameters**	**Min**	**Max**	**Denomination**
Summer	Outdoor temperature	26	36	°C
	Indoor temperature	23.50	29.20	°C
	Humidity	28	45.6	%
	CO_2	400.30	661.00	ppm
Winter	Outdoor temperature	2	4	°C
	Indoor temperature	19	27.6	°C
	Humidity	14.2	37.4	%
	CO_2	438.30	1630.40	ppm

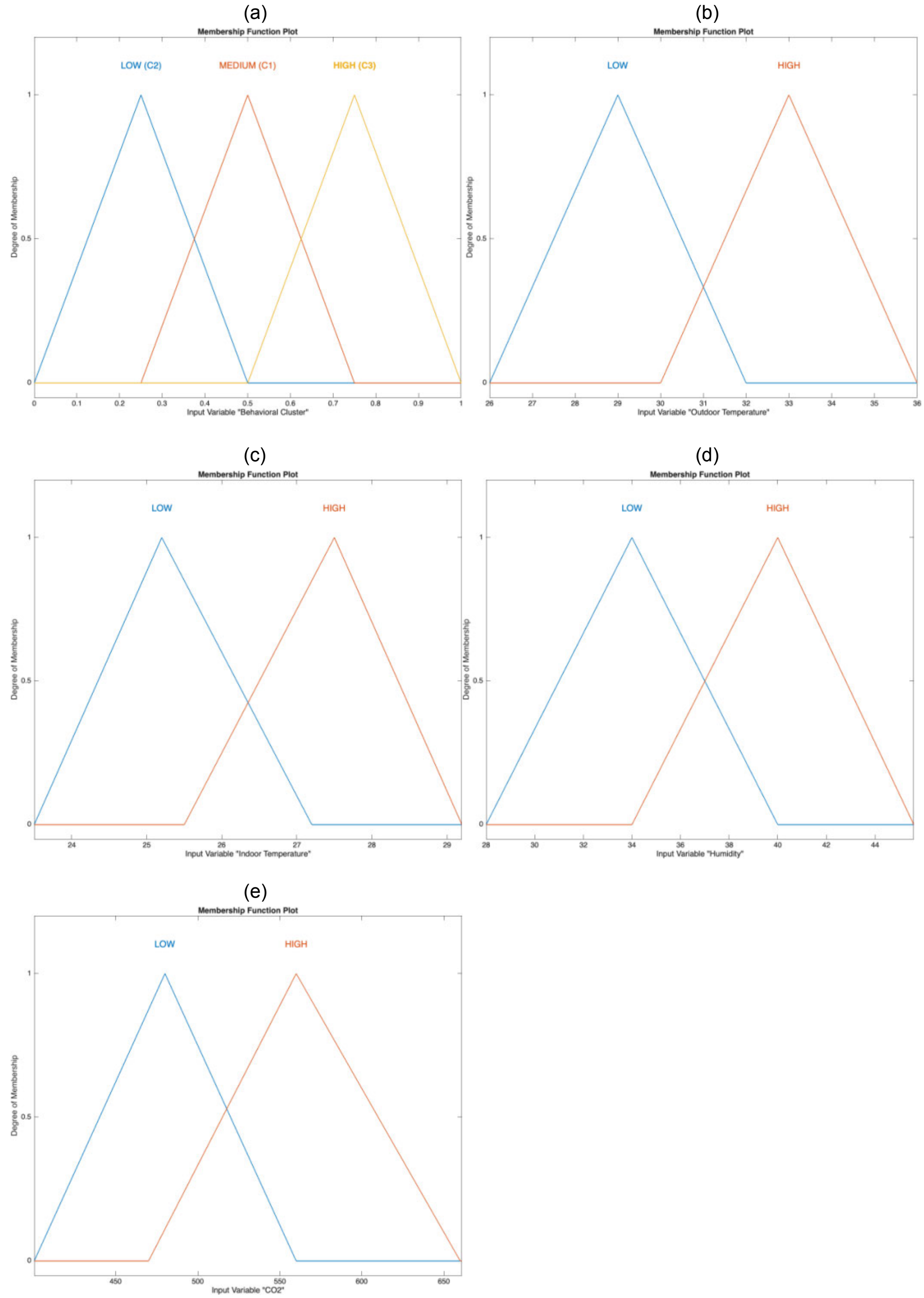


Figure 23. Membership functions for the fuzzy input variables during the summer season: a) Behavioral Cluster, b) Outdoor temperature, c) Indoor temperature, d) Humidity, and d) CO2.

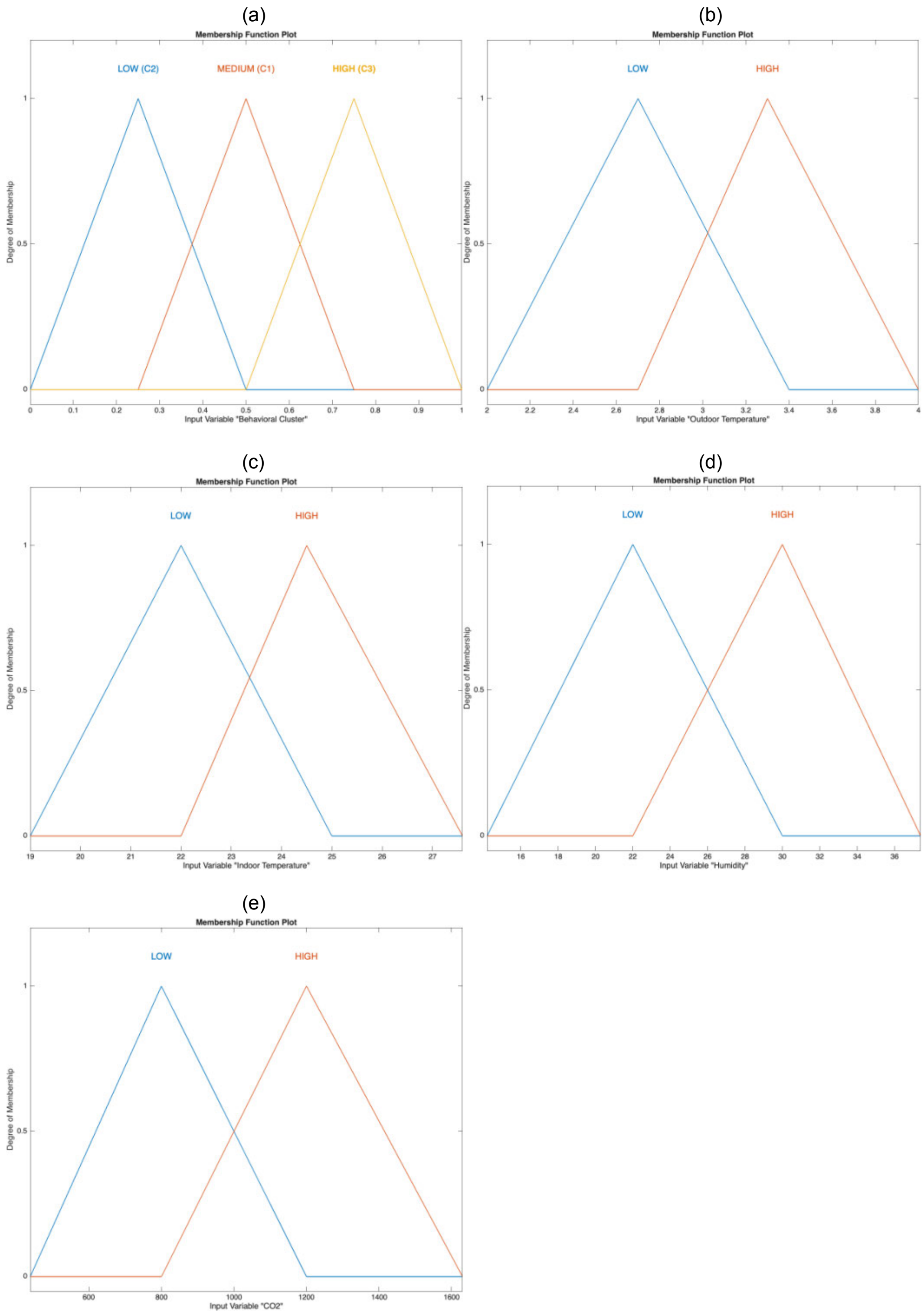


Figure 24. Membership functions for fuzzy input variables during the winter season: a) Behavioral Cluster, b) Outdoor temperature, c) Indoor temperature, d) Humidity, and d) CO2.

8.1.2 Fuzzy rules

The transition from inputs to output relies on fuzzy rules. Fuzzy rules were intuitively applied by taking into account the measured and analyzed data of the field study. These rules were derived from correlation and regression analyses conducted between occupant actions and environmental variables, as outlined in Section 7.1.2 for summer and Section 7.2.2. for winter models.

Referring to the results of the correlation analysis, the rules were developed by considering only those environmental variables that correlated with the corresponding occupant actions. Similarly, following the chi-square analysis, certain occupant actions were excluded from the fuzzy inference system rules. This decision was made carefully considering behavioral clusters and regression models that adequately fit the data. In this study, a total of 33 rules for the summer season and 41 rules for the winter season were employed to optimize the performance of the fuzzy inference system. Figure 25 illustrates the rule editor interface used in this system and a selection of randomly chosen examples of these rules. In developing the mathematical model, it was crucial to establish the relationships between input and output variables, resembling those within an intelligent system. The input variables were classified using Mamdani's method to ascertain the values linked to a membership degree of 1. This approach allows for implementing rule structures such as "IF ... THEN ..." to translate fuzzy input sets into output sets based on fuzzy logic principles (Martínez et al., 2020). This means the antecedent part of a rule begins with IF, up to THEN, which includes a statement on the cluster, outdoor temperature, indoor humidity, and indoor CO_2. In contrast, the consequent part, beginning with THEN, up to the end, included a statement on occupant action. For example, ‘IF the cluster is ‘Medium,’ the indoor temperature is ‘High,’ THEN the closing door is ‘Low.’

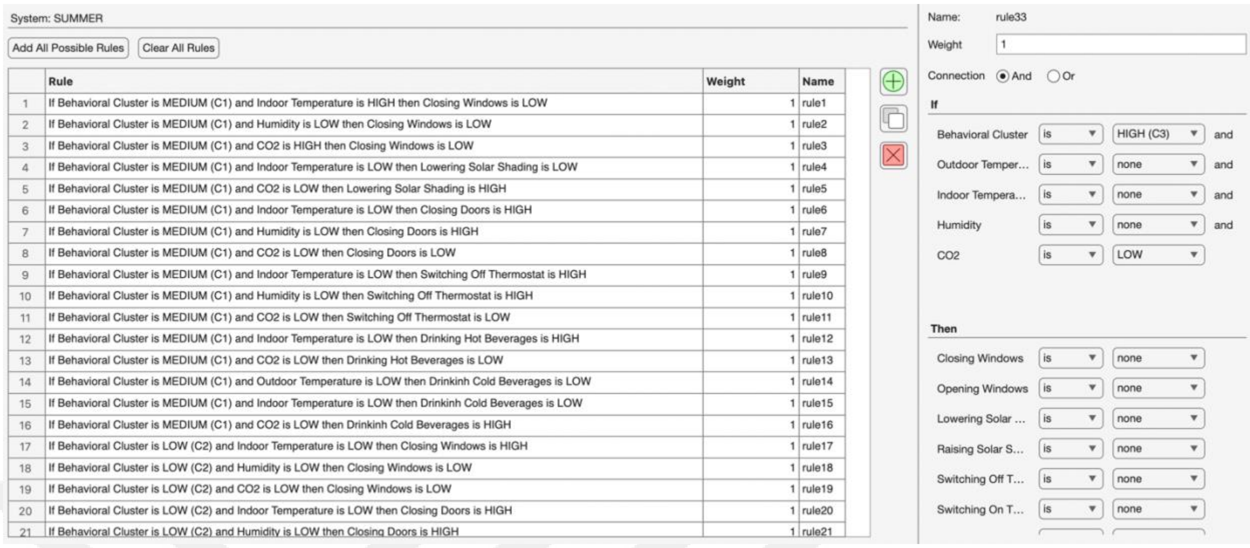


Figure 25. Examples of the rules implemented in MATLAB.

8.1.3 Output variables

In the study, twelve output variables were identified and fuzzified into fuzzy subsets. These variables included closing and opening windows, adjusting solar shading, manipulating thermostats, operating doors, changing clothing, and consuming beverages. Their selection was guided by data collected during daily surveys, which recorded occupants' responses to environmental conditions. These actions were chosen because they represent tangible behaviors through which occupants adapt to their surroundings.

The study employed fuzzy subsets to capture the nuanced nature of these actions. These subsets allowed for the recognition of behavioral patterns and the interpretation of relationships among non-linear input data. By leveraging this model, the study aimed to predict and classify occupants' behavioral actions based on their behavioral clusters, thus enabling control over their environment.

The output variables were fuzzified using triangular membership functions, categorizing them into “low” (L) and “high” (H) linguistic values. These membership functions were evenly distributed and considered most suitable for the model based on the study's data and nature. Across all cases, these functions were triangular and ranged between zero and one [0,1].

8.1.4 The developed fuzzy logic models and implications for architectural design

As a result of the generated models, it was possible to create a comprehensive simulation of occupant behaviors. Two sets of designs were built for the summer (cooling season) and winter (heating season) periods. Figures 26 and 27 display randomly selected relationships between behavioral clusters, corresponding environmental parameters, and occupant actions converted using MATLAB software, presenting three-dimensional surfaces for decision analysis. These representations showcase the fuzzy system solution obtained through Mamdani's Inference Method, with each surface described accordingly. As mentioned, behavioral clusters are categorized based on their energy-saving behavior level using three linguistic variables (low, medium, high).

In comparison, environmental parameters and occupant actions are represented using two linguistic variables denoting low and high levels. The colored contours displayed in the figure aid in grasping the behavior of the input-output relationship and delineating the regions of minimum and maximum probability of the corresponding occupant action. The surface provides a visual and uninterrupted representation of how inputs influence the output. Additionally, the contours offer insights into the output level within specific input ranges. Notably, the color spectrum transitions smoothly from dark blue (indicating the lowest output values) to orange (signifying the highest output values).

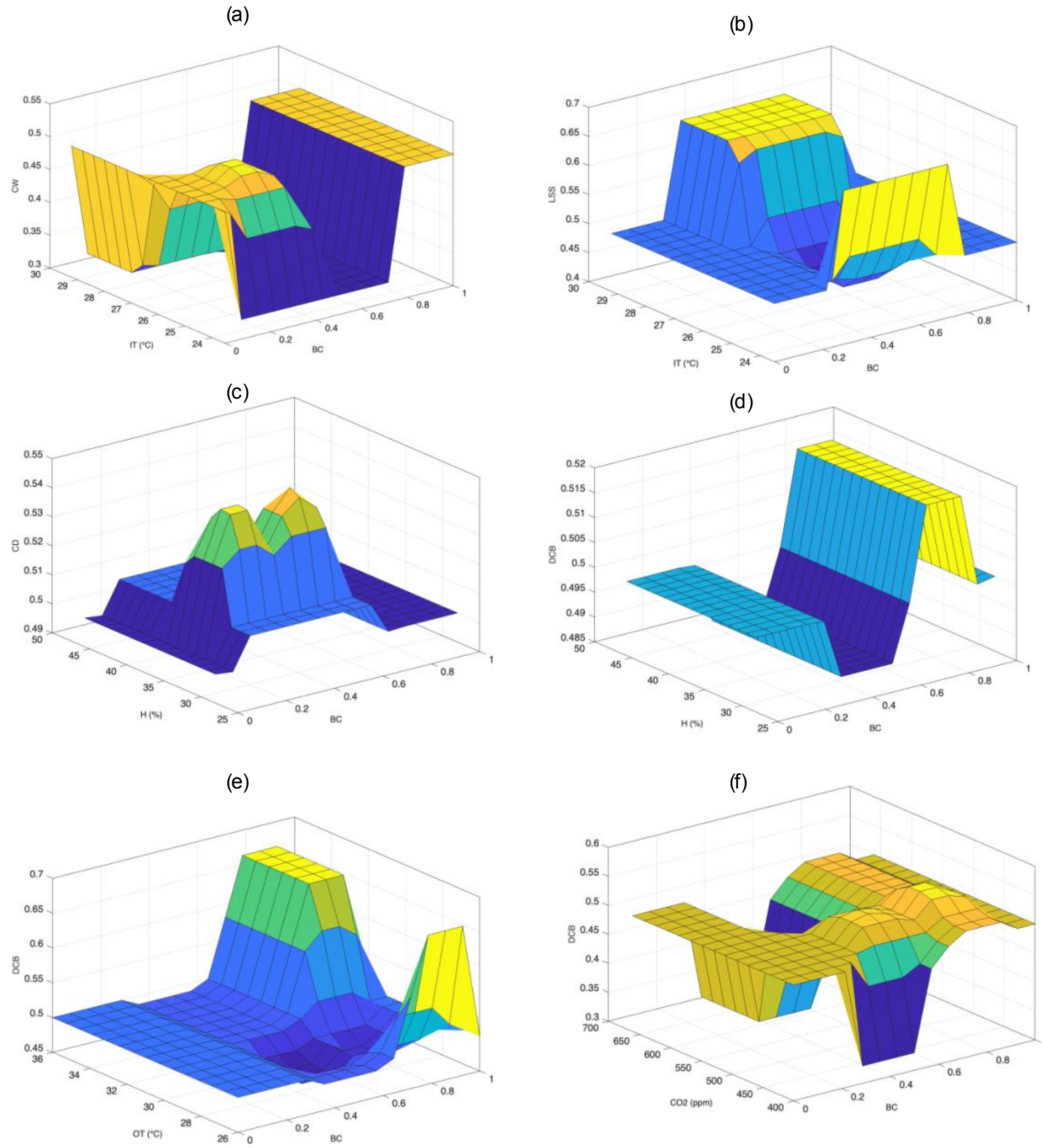


Figure 26. The 3D fuzzy control surfaces during summer for the relationship between (a) indoor temperature (IT) and closing windows (CW), (b) indoor temperature (IT) and lowering solar shading (LSS), (c) humidity and closing door (CD), (d): humidity (H) and drinking cold beverages (DCB), (e) outdoor temperature (OT) and drinking cold beverages (DCB), and (f) CO2 and drinking cold beverages (DCB).

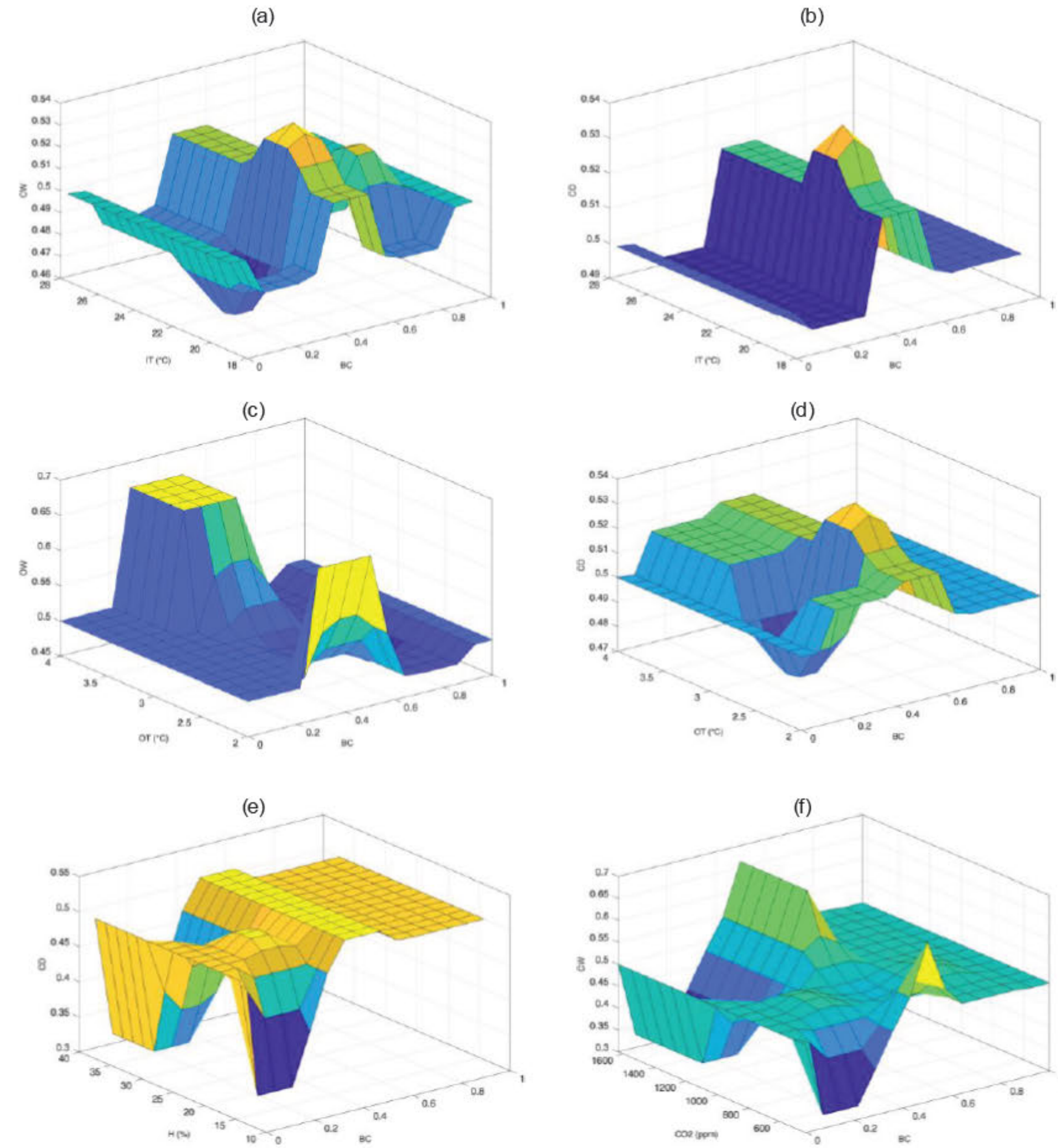


Figure 27. The 3D fuzzy control surfaces for the relationship between during winter (a): indoor temperature (IT) and closing window (CW), (b): indoor temperature (IT) and closing door (CD), (c): outdoor temperature (OT) and closing window (CW), (d): outdoor temperature (OT) and closing door (CD), (e): humidity (H) and closing door (CD), and (f): CO_2 and closing window (CW).

The three-dimensional surfaces generated through MATLAB may offer architects and building professionals a visual means to analyze the intricate relationships between input variables, such as behavioral clusters and environmental parameters fuzzified through triangular membership functions with defined ranges and output variables representing occupant actions. These visualizations enable the exploration of correlations and trends in occupant actions across different environmental conditions and behavioral clusters, aiding in optimizing building designs for enhanced occupant comfort and energy efficiency. Architects can identify optimal solutions that balance occupant needs with energy conservation goals by simulating various design scenarios and comparing the surfaces generated for different design alternatives. Additionally, these visualizations serve as effective communication tools for stakeholders, facilitating discussions and informed decision-making processes related to building design and operation.

Figure 28 represents a rule inference mechanism for simulating occupant behavior using fuzzy logic. The first five columns illustrate the input variables: Behavioral Cluster (BC), Outdoor Temperature (OT), Indoor Temperature (IT), Humidity (H), and CO_2 levels. Each input value is shown as a red vertical strip within its corresponding membership shape, categorizing the input values into fuzzy sets such as low, medium (only for BC), or high. These input variables feed into a set of 33 fuzzy rules, where each row corresponds to an individual rule. The rules are conditional statements combining specific inputs to generate outputs, such as "IF BC is medium AND OT is high, THEN closing windows HIGH."

The remaining twelve columns display the possible occupant actions. The outputs of these actions are depicted as blue areas within their respective membership shapes, which indicate the degree to which each action is triggered by the given input conditions. The size and position of the blue areas provide visual insight into the likelihood of each action under the specific environmental and behavioral inputs.

The fuzzy outputs (blue areas) are translated into numerical probability levels for each occupant action using the centroid defuzzification method. For example, a larger blue area in the "Closing Windows" (CW) column indicates a higher probability of performing that action under the given conditions. This allows for a clear interpretation of how strongly a particular action is activated by the rule system. Furthermore, the figure demonstrates the dynamic nature of fuzzy logic modeling. As the input values, such as temperature or humidity, change, the red vertical strips shift within the membership shapes, and the corresponding fuzzy outputs in the action columns adjust accordingly. This dynamic relationship enables the model to adapt to changing environmental and behavioral conditions, producing a context-sensitive prediction of occupant actions.

As a result, the constructed fuzzy logic model presents a powerful tool for integrating human behavior into building simulation tools, offering detailed insights into occupant actions in response to environmental conditions. This model can be seamlessly incorporated into building performance simulation software, such as EnergyPlus™ or DesignBuilder®, enhancing their predictive capabilities and enabling architects and designers to optimize building designs for energy efficiency and occupant comfort.

One of the key outcomes of this model is its ability to predict and categorize occupants' behavioral actions based on their behavioral clusters, thus enabling more accurate simulations of occupant behavior. By considering factors such as behavioral clusters, outdoor and indoor temperatures, humidity, and CO2 levels, the model provides insights into how occupants may adjust elements within their environment, such as opening or closing windows and doors, adjusting thermostats, or even modifying clothing choices and beverage consumption.

From an architectural perspective, these outcomes have profound implications for building design strategies to enhance occupant comfort and energy efficiency. Architects can utilize the insights from the fuzzy logic model to inform the design of building envelopes, HVAC systems, and interior layouts. For instance, understanding the propensity of occupants to open or close windows in response to outdoor temperature fluctuations can influence the placement and design of operable windows to optimize natural ventilation while minimizing energy consumption for heating or cooling.

Similarly, insights into occupant behavior related to solar shading can inform the design of shading devices, such as blinds or louvers, to mitigate glare and solar heat gain, thereby reducing the need for artificial lighting and cooling. Moreover, knowledge of occupants' preferences for thermostat adjustments can guide the selection and placement of HVAC controls to provide personalized comfort settings while maximizing energy savings.

Interior designers can also leverage the findings of the fuzzy logic model to create interior environments that support occupants' comfort and productivity. For example, knowledge of occupants' tendencies to adjust clothing or beverage consumption in response to thermal conditions can inform the selection of furniture and finishes that promote thermal comfort and create inviting spaces conducive to various activities.

Overall, the outcomes of this model underscore the importance of considering human behavior as a critical factor in architectural and interior design sustainable decision-making processes. By integrating behavioral insights into design strategies, architects and designers can create more responsive, energy-efficient, and user-centric built environments that foster occupant well-being and satisfaction.

8.1.5 The integration proposal of the fuzzy logic model with EnergyPlus

This section explains how this study's proposed fuzzy logic model can be integrated with building simulation tools. In this study, we explain the integration of our model with EnergyPlus™ as it offers an Energy Management System (EMS), a feature allowing for custom control logic that can incorporate external data (Gunay & O'Brien, 2018). The fuzzy logic model's integration with

EnergyPlus™ comprises five main steps. These steps are illustrated in Figure 29. In Step 1, occupant action predictions are generated in MATLAB using the fuzzy logic model, based on environmental inputs like temperature and humidity, which represent potential adjustments occupants may make in their environment, such as opening windows or modifying thermostat settings. These predictions are then exported from MATLAB in a data-friendly format, such as a CSV file, capturing the occupant behavior outcomes for various environmental conditions.

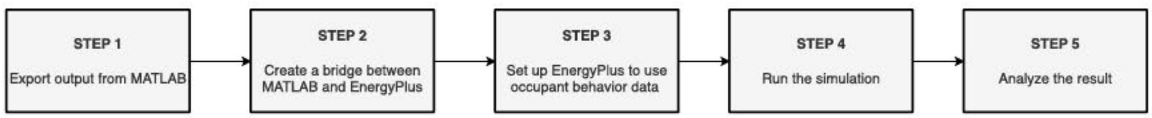


Figure 29. Integration of the fuzzy model into EnergyPlus

Step 2 involves creating a bridge script in either Python or MATLAB to facilitate data exchange between MATLAB and EnergyPlus™. This bridge script functions as an intermediary, pulling in environmental data from EnergyPlus™ at each simulation timestep, running the data through the fuzzy logic model in MATLAB, and retrieving the predicted occupant actions. For each timestep, the script reads environmental conditions from EnergyPlus™, feeds these inputs into the fuzzy logic model, and gathers output predictions of occupant behavior.

In Step 3, the occupant behavior data is configured in EnergyPlus™ using the Energy Management System (EMS) feature, which allows the software to dynamically adjust building parameters based on external inputs. EnergyPlus™ is set up through EMS to accept data from the bridge script, enabling it to adjust building elements such as window openings and thermostat settings according to the occupant actions predicted by the fuzzy model.

Step 4 encompasses the actual running of the simulation. As EnergyPlus™ progresses through each timestep, the bridge script continuously exchanges data, sending updated environmental inputs from EnergyPlus™ to MATLAB, running the fuzzy logic model, and passing the occupant action outputs back to EnergyPlus™. This continuous exchange ensures that the simulation dynamically reflects occupant behavior's influence on building energy consumption, as environmental data prompts corresponding occupant actions in real-time.

Finally, in Step 5, the simulation results are analyzed. Comparing energy usage with and without the fuzzy logic model reveals the impact of occupant behavior on energy performance. This step highlights how the integration improves the accuracy of energy consumption predictions by accounting for dynamic occupant actions, ultimately creating a more behavior-sensitive and realistic building simulation environment. This five-step process enables the fuzzy logic model to interact seamlessly with EnergyPlus™, enhancing predictions of building performance based on occupant influences.

CHAPTER 9

DISCUSSION

This study integrated behavioral and environmental data to develop a predictive fuzzy logic model for occupant actions in office environments. The research was structured around three key steps: Step 01, which focused on occupant behavioral profiling based on psycho-social data; Step 02, which combined behavioral clusters with environmental parameters for predictive modeling; and Step 03, developing a fuzzy logic system to predict occupant actions. Through these three steps, the study addressed three research questions and tested three hypotheses of this thesis (Table 37). Each step contributes significantly to understanding energy-related occupant behavior (OB) and its application in building performance models.

Table 37. Research questions of the study and their outcomes.

ID		Result
RQ_1	What are the different groups of office occupants categorized based on psycho-social behavioral data?	Supported
RQ_2	What are the relationship between identified behavioral clusters related to occupant behavior and their behavioral actions?	Supported
RQ_3	How do behavioral actions correlate with indoor and outdoor environmental parameters?	Supported

9.1 Behavioral profiling and clustering

Step 01 aimed to address RQ1 by collecting psycho-social data through an online questionnaire based on social psychology theories such as the Theory of Planned Behavior (Ajzen, 1991) and Self-Determination Theory (Ryan & Deci, 2000). The aim was to identify distinct behavioral clusters of office occupants based on their energy-related behaviors. The results revealed three main clusters: low, medium, and high energy-saving behavior groups. This approach confirmed that there are statistically significant relationships between behavioral clusters and the psycho-social data, aligning with studies like those by Delzendeh et al. (2017) and Gkargkavouzi et al. (2019), which similarly emphasized behavioral heterogeneity.

Integrating multiple behavioral theories distinguishes this study from conventional linear models, which often presume a consistent link between intention and behavior. Previous studies, such as Greaves et al. (2013), noted that TPB explained a significant portion of energy-saving behavior, yet limitations remained, with TPB accounting for only 46-67% of behavioral variance. In contrast, our study achieved a 73.2% explanation of variance by expanding the model to incorporate SDT and additional factors like habit and comfort. This approach enabled a broader, more nuanced perspective, capturing intentional actions and subconscious behaviors that traditional models might overlook.

A notable contribution of this study is the inclusion of habit, reflecting findings by Wood and Rünger (2016) that much of daily behavior is habitual, often occurring without conscious decision-making. Actions like adjusting blinds or turning off lights are frequently performed out of routine rather than active energy-saving intention, and by recognizing this, the study adds realism to the predictive model. However, measuring and changing ingrained habits remains challenging, introducing potential unpredictability into occupant behavior modeling. Although habits enhance the model's accuracy by representing everyday occupant actions, they also complicate behavior prediction, which could be a limitation for long-term energy-saving interventions.

Similarly, adding comfort as a factor acknowledges that occupants often prioritize personal comfort, such as thermal, visual, or acoustic satisfaction, over energy-saving goals (Brager & Baker, 2009). While integrating comfort into the behavioral model offers a more comprehensive view of occupant motivations, it highlights an inherent tension. While vital for satisfaction, comfort-driven behaviors may conflict with energy-saving efforts. This issue is corroborated by Harputlugil and de Wilde (2021), who similarly observed that comfort often outweighs energy concerns in occupants' priorities, presenting an unresolved challenge in sustainable building management.

In addition, the results of the two-step cluster analysis showed that Cluster 3 - H, with high levels of energy-saving behavior, is the largest group. This may partly reflect social desirability bias, where participants responded in line with perceived workplace expectations, perhaps influenced by managerial or company values favoring sustainability. In office settings, individuals may adjust their responses to align with organizational goals, like energy efficiency, especially if they believe such actions are valued by their employers. This limitation suggests that the high energy-saving behaviors in Cluster 3 – H may not fully reflect genuine habits but rather a response to social norms, underscoring the need for objective data collection methods to better capture actual behavior.

Lastly, a critical aspect of Step 01 is its recognition that OB is not static. Instead of treating occupants as "energy savers" or "energy consumers," the study enriched the data by identifying patterns in behavior over time, adding depth to the clusters that previous studies might have overlooked. This approach helped to capture the behavioral preferences and frequencies within each group, addressing RQ2 and offering a more dynamic view of OB. Therefore, the study moved beyond simple categorization and contributed a novel understanding of how different psycho-social factors shape real-world behaviors across time, providing a critical improvement over more rigid, one-time behavioral classifications found in earlier research (Csoknyai et al., 2019).

9.2 Integration of Behavioral Clusters and Environmental Parameters

Step 02 involved integrating the behavioral clusters from Step 01 with environmental parameters such as indoor and outdoor temperature, humidity, and CO_2 levels, addressing RQ2 and RQ3. While Step 01 allowed for more generalized assumptions about the energy-saving behaviors of each cluster based on their energy-saver levels, Step 02 moved beyond these assumptions by adopting a more detailed approach. This approach aligns with studies like those by Fabi et al. (2012) and Balvedi et al. (2018), which emphasize the importance of contextually detailed OB modeling to capture dynamic occupant responses in real-world environments. Moreover, by integrating behavioral clusters with environmental factors, the model was refined to reveal significant correlations between environmental parameters and occupant actions (RQ3).

The study's seasonal analysis, performed across both summer and winter, revealed distinct occupant interactions with building systems (e.g., window and door operation) based on environmental changes, reflecting findings by Deng and Chen (2019) and adding to the growing body of research underscoring seasonal behavior variability. Earlier studies, such as those by Haldi & Robinson (2009), found that factors like CO_2 levels and temperature can trigger specific occupant behaviors, emphasizing the need for models that adapt to occupants' situational and temporal contexts. This analysis aligns with the work of Langevin et al. (2015) and Mahdavi & Tahmasebi (2016), who highlighted the limitations of static models and advocated for adaptive systems that capture how behavior shifts according to fluctuating environmental stimuli.

Seasonal analysis has been shown in studies such as those by Reinhart (2004) and Stazi et al. (2017) to enhance model realism, capturing behaviors like seasonal shifts in heating or cooling preferences and window usage. This study's seasonal coding approach aligns with Brager & Baker (2009) and Baker & Standeven (1997), who advocated for models incorporating seasonal adaptations to achieve accurate occupant comfort and energy predictions. This seasonal approach illustrates that OB is influenced by environmental stimuli and varying psycho-social motivations across seasons. This finding is consistent with D'Oca et al. (2017) and Pan et al. (2018), who argued that external conditions and personal comfort goals interact to shape behavior. The alignment of psycho-social factors with seasonal environmental changes provides a comprehensive understanding of OB, suggesting the importance of flexible, contextually aware models for predicting occupant behavior in dynamic building environments.

In addition to capturing responses to environmental changes, integrating behavioral clusters with environmental parameters highlights a clear relationship between energy-saving levels and specific occupant actions. Higher energy-saving clusters, such as Cluster 3, demonstrate more consistent and proactive adjustments to environmental shifts (e.g., frequently opening windows or regulating thermostat settings) and exhibit heightened sensitivity to indoor air quality indicators like CO_2 levels. This proactive behavior aligns with findings by Schweiker et al. (2012) and Wagner et al. (2017), which underscore that energy-conscious occupants are more likely to adjust their surroundings in response to comfort cues that impact energy use.

In contrast, lower energy-saving clusters, such as Cluster 2, tend to exhibit a more passive approach, where actions such as window adjustments are less frequent, even under similar conditions of high CO_2 levels or discomfort. This variance underscores the psychological and habitual differences across clusters. At the same time, high energy-savers are motivated by intrinsic and regulatory factors aligned with sustainability goals, and lower energy-saving groups might prioritize immediate comfort over energy-saving behaviors. This finding parallels the observations of Mahdavi & Tahmasebi (2016) and D' Oca et al. (2018), who argued that internal motivations, or lack thereof, play a significant role in the degree of interaction with building systems.

These distinctions indicate that energy-saving behaviors are not solely a reaction to environmental parameters but are also shaped by intrinsic motivations and habitual inclinations tied to each cluster. Consequently, the model's integration of behavioral clusters enhances the predictive accuracy for energy-related actions, as occupants with different energy-saving levels respond in varied ways to identical environmental cues. This reinforces the importance of incorporating psycho-social dimensions within OB modeling, as highlighted by Fabi et al. (2012) and Langevin et al. (2015), enabling more nuanced and actionable insights for building energy management and occupant comfort optimization.

9.3 Development of the fuzzy logic model

In Step 03, a fuzzy logic model was constructed to predict occupant actions by integrating behavioral clusters with environmental parameters, offering a robust tool for simulating occupant behavior (OB) in building environments. This approach leverages fuzzy logic's capacity to handle ambiguity and uncertainty in OB, often shaped by nuanced factors beyond straightforward, linear relationships (Zadeh, 1965; Mamdani, 1974). Unlike traditional static models, fuzzy logic allows for a rule-based structure that adapts to dynamic, real-time stimuli. It is particularly suited for applications that involve occupant-driven changes in building environments, such as window operation or thermostat adjustments (Gunay & O'Brien, 2017).

One of the notable contributions of this study is the model's capacity to integrate psycho-socially derived behavioral clusters, which represent varied energy-saving tendencies, with environmental inputs such as indoor temperature and CO_2 levels. This integration reflects the behavioral complexity in buildings, where the immediate environment and individual psychological and habitual profiles influence actions. Unlike the conventional reliance on fixed occupancy schedules (Andersen et al., 2013), this model provides a framework that accommodates different motivations and habits, thus offering insights into how varied occupant types might engage with energy-related systems. Other behavioral studies have explored similar approaches, which emphasize the importance of contextually adaptive models (Lee & Malkawi, 2014).

The fuzzy logic model's seasonal coding, applied separately for summer and winter, further strengthens its predictive power by acknowledging seasonal variations in occupant behavior. This choice enhances model adaptability, capturing different comfort needs and responses that fluctuate seasonally, highlighted as essential in studies exploring thermal comfort and adaptive behavior in diverse climates (Schiavon & Lee, 2013; D'Oca et al., 2017). Seasonal coding allows the model to distinguish, for instance, the increased likelihood of window opening in summer to reduce indoor temperature versus thermostat adjustments in winter to maintain warmth. This dual coding approach aligns with work by Carlucci et al. (2020) on seasonal occupant behavior adaptations, emphasizing the need for dynamic models to simulate these shifts accurately.

The decision to use two linguistic values ("low" and "high") for environmental parameters, combined with three levels for behavioral clusters, provides a balanced yet computationally efficient approach. This two-tiered linguistic structure allows the model to avoid overfitting while capturing the essential interactions between environment and behavior. Fuzzy logic research emphasizes that the granularity of linguistic values should reflect the data structure and nature of the modeled relationships (Martínez et al., 2020). In this case, a more straightforward binary approach for environmental parameters paired with a three-tiered structure for behavioral clusters strikes this balance. This structure prevents unnecessary complexity and mirrors the findings by

Rana et al. (2013), who found that simplified fuzzy models often perform robustly without excessive detail.

Furthermore, integrating the fuzzy model with EnergyPlus™ through its Energy Management System (EMS) provides a pathway for implementing real-time occupant actions within a widely used building simulation environment. This study's integration involves five key steps: generating occupant action predictions in MATLAB, exchanging data via a bridge script, and dynamically adjusting building parameters within EnergyPlus™ (Gunay & O'Brien, 2018). This continuous data exchange at each simulation timestep enables real-time adaptation of energy-related parameters in response to occupant actions, offering a highly responsive simulation environment.

Such integration with EnergyPlus™ is particularly advantageous for practitioners seeking behavior-sensitive simulations that align with real-world building operations, as underscored by Lee et al. (2016) and Schweiker et al. (2012). By accounting for OB in real-time, the model helps reduce discrepancies between expected and actual energy performance. This integration marks a step forward in OB modeling by offering facility managers and building designers a tool that simulates energy use with improved accuracy and reflects the actual influence of dynamic occupant behavior on building systems.

The fuzzy logic model presents a unique combination of psycho-social insights and environmental adaptability, reinforced by its seamless integration with EnergyPlus™. This approach captures the complexity of OB and addresses the need for adaptive, seasonally responsive models, providing actionable insights for building energy management and occupant comfort.

CHAPTER 10

CONCLUSION

The model operationalizes behavioral clusters, linking them to environmental parameters such as indoor temperature, humidity, and CO_2 levels, allowing for more accurate predictions of energy-related occupant actions. By integrating human behavior theories with building physics and embedding this model within the EnergyPlus™ simulation environment, this research provides a more holistic approach to improving energy efficiency and occupant comfort in office buildings. Figure 30 presents a comprehensive roadmap of the study, highlighting its timeline and key milestones. The following sections summarize the key implications, limitations, and future directions for research.

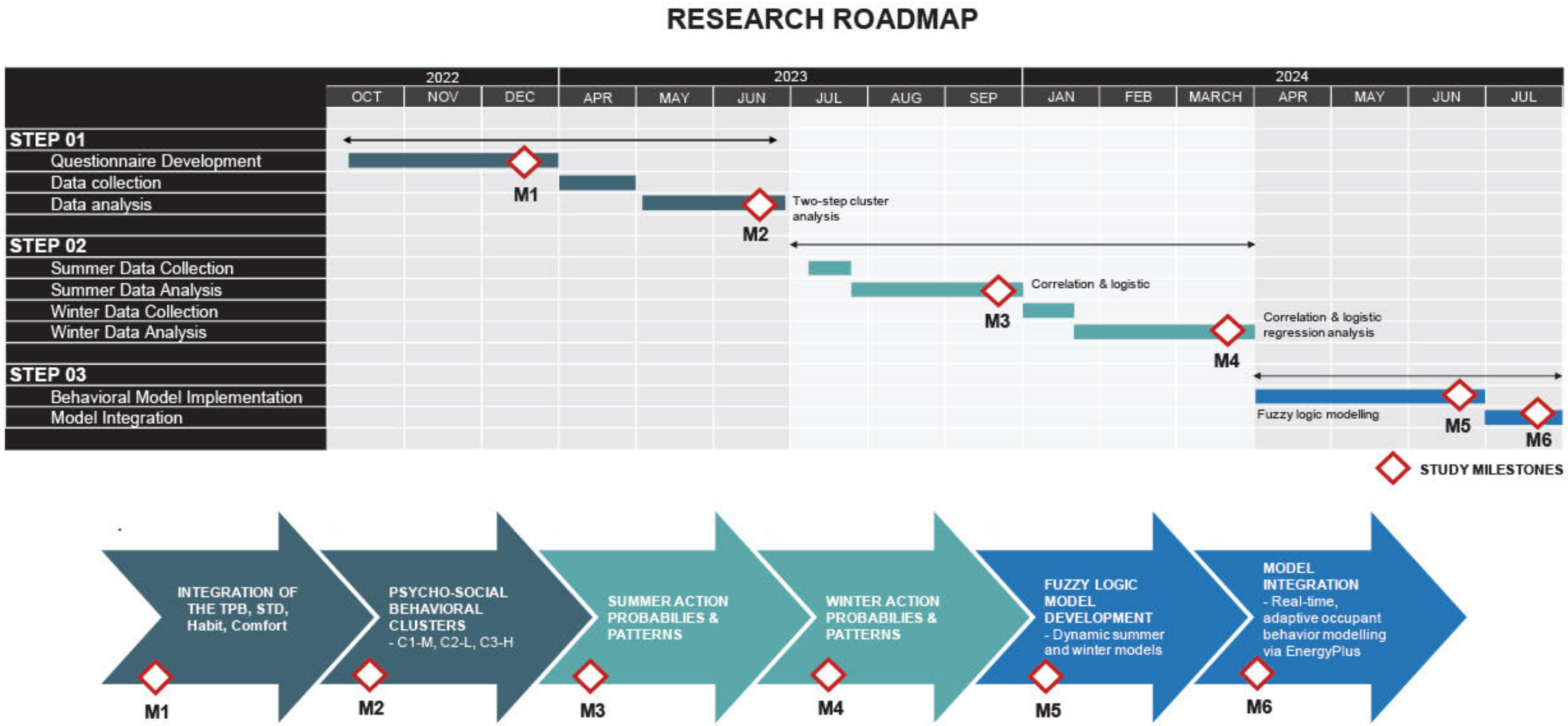


Figure 30. Research roadmap of the study

10.1 Implications

This research holds important implications for both the theoretical and practical understanding of OB, particularly in the context of energy efficiency in office environments. By combining psycho-social theories with environmental parameters and fuzzy logic, the study provides a holistic framework that bridges the gap between behavioral science and building performance modeling. This section outlines the study's implications for both theoretical knowledge and practical applications, highlighting its contribution to the ongoing discourse in architecture, environmental psychology, and building performance modeling.

10.1.1 Theoretical Implications

The thesis contributes in several ways to the theoretical discourse on occupant behavior (OB). By integrating the Theory of Planned Behavior (TPB) (Ajzen, 1991) and Self-Determination Theory (SDT) (Ryan & Deci, 2000), it explores the motivations behind energy-related occupant behavior in greater depth than prior studies. This hybrid theoretical approach broadens the understanding of how intrinsic and extrinsic motivations shape energy-saving behaviors in office settings, advancing over the TPB's traditional focus on intention and attitude alone.

Additionally, the study introduces two underexplored constructs—habit and comfort—into the behavioral profiling model. Habits often operate below conscious awareness and play a substantial role in shaping energy-related workplace actions. By accounting for habitual actions, the study acknowledges the challenge of behavior change, providing a more realistic portrayal of how energy-related actions are embedded in everyday routines. Similarly, the inclusion of comfort in the model highlights how office occupants often prioritize their personal comfort over energy-saving goals, adding complexity to existing OB theories.

Incorporating fuzzy logic provides a methodological advance, as it accounts for the variability in how occupants respond to environmental conditions. This flexible, rule-based approach addresses the challenge of accurately capturing OB in dynamic building environments, aligning with prior studies emphasizing adaptive, real-time modeling to reduce performance gaps in energy predictions (Harputlugil & de Wilde, 2021). Integrating these theories into EnergyPlus™ through the Energy Management System (EMS) allows for customized control logic, bridging theory, and practical simulation, which has been limited in OB research.

10.1.2 Practical Implications

The practical implications of this study are multifaceted, particularly in how they can inform the design and operation of energy-efficient office buildings. Five different practical implications can be explained for architectural design, facility management, occupant-centric building control systems, user satisfaction and space use, and energy auditing and retrofitting.

- *Architectural Design:* Insights into behavioral differences across clusters enable architects to design more adaptive spaces. For instance, understanding that high energy-saving occupants actively adjust windows or thermostats can guide the strategic placement of operable windows, shading devices, and user-controlled HVAC systems. This model integration with EnergyPlus™ ensures that architectural features are tested under varied simulated conditions, optimizing for comfort and efficiency.
- *Facility Management:* The model allows facility managers to anticipate how occupant behaviors vary seasonally, enabling adaptive strategies for HVAC and shading, which aligns with demand fluctuations and minimizes energy waste. By integrating behavior-based simulations, facility

managers can make more proactive decisions, responding to predicted occupant needs and improving building management’s overall efficiency.

- *Occupant-Centric Building Controls:* This model enhances building control systems by enabling real-time adjustments based on occupant behavior predictions. Integrating the fuzzy logic model with EnergyPlus™’s EMS enables dynamic building management that adjusts lighting, HVAC, and shading systems based on predicted occupant actions, thus enhancing energy savings and comfort.
- *User Satisfaction and Space Use:* Predicting how different clusters respond to environmental cues enables better alignment of space designs with occupant comfort needs. For instance, companies can implement flexible work zones tailored to occupants’ comfort and environmental preferences, potentially improving well-being and productivity.
- *Energy Auditing and Retrofitting:* This model provides valuable insights into energy consumption patterns, identifying areas with the most potential for energy savings. By simulating occupant behavior and energy use, facility managers can prioritize retrofitting efforts to optimize comfort and energy efficiency, yielding maximum impact from energy conservation measures.

10.1.3 Limitations

While this study offers significant contributions to both theoretical and practical fields, it is essential to acknowledge its limitations. First, the geographical and contextual limitations of this research are notable. The data collection was confined to office environments in specific regions, which may limit the model’s applicability to other building types, such as residential or educational buildings, or to regions with different climatic conditions. The behavioral clustering method also presents certain limitations. The clusters were derived from psycho-social data collected via an online survey, which, while insightful, relies on self-reported behaviors that may not always align with actual occupant actions. This introduces potential biases and limits the ability to capture more spontaneous or unconscious behaviors that might occur in real-world settings.

In addition, the study considered only a limited set of environmental variables, explicitly focusing on temperature, humidity, and CO2. While these parameters are critical to understanding occupant behavior, they do not encompass all aspects of indoor environmental quality. Other factors, such as lighting or acoustics, may influence occupant actions and were not addressed in this model. For example, participants might have opened doors in response to noise disturbances or closed solar shading to reduce glare from sunlight—actions unrelated to the measured parameters of temperature, humidity, or CO2. This limitation suggests that not all occupant actions observed during the field study can be entirely attributed to the environmental factors measured, highlighting the need for a broader set of monitored variables. Including lighting and acoustical factors in future studies would allow for a more comprehensive investigation into the drivers of occupant behavior.

Another limitation is the seasonal scope of the data, as the study examined behavior only during summer and winter, omitting transitional seasons like spring and fall. This leaves an incomplete picture of how occupant behavior might vary throughout the year. Including data from these transitional periods could provide a more holistic view of seasonal influences on occupant actions.

Finally, there is a limitation related to the computational complexity of the fuzzy logic model. Although the model balances simplicity and accuracy, applying it to larger, more complex environments with additional variables and linguistic categories may present computational challenges. Further refinement may be necessary to ensure seamless integration of the model into large-scale building management systems.

10.1.4 Future research

This study opens several avenues for future research to enhance the model's scope, accuracy, and applicability.

- *Energy-Efficient Behavioral Interventions:* Future studies could explore the model's capacity to support interventions that promote sustainable occupant behaviors, such as feedback systems or incentives. Testing these interventions in natural settings would allow researchers to evaluate the model's effectiveness in fostering sustainable habits.
- *Longitudinal Habit Studies:* The influence of habit in shaping energy-related behavior suggests that future longitudinal studies could explore how these behaviors change over time and in response to intervention efforts. Such insights would be valuable for encouraging energy-efficient habits in building occupants.
- *Comprehensive Seasonal Data Collection:* Including data from all seasons, especially transitional ones like spring and fall, would help capture a complete view of OB variations throughout the year, enhancing model accuracy and predictive capability.
- *Expanding Environmental Variables:* Adding factors such as lighting quality, noise levels, and overall indoor air quality could deepen the understanding of occupant-environment interactions, thus refining the model's precision and broadening its relevance to various indoor conditions.

- *Application in Diverse Building Types:* Testing the model in different building types, such as residential or educational buildings and varied geographic locations, would provide a more comprehensive evaluation of the model's adaptability and generalizability.
- *Real-Time Monitoring and Validation:* Future work could integrate real-time monitoring systems within smart buildings to validate the fuzzy logic model with actual occupant behavior data. This real-time validation would

improve model reliability and enable immediate adjustments to optimize building performance.

This study underscores the importance of integrating behavioral insights with environmental data to create adaptive, occupant-centered building models. By combining fuzzy logic with EnergyPlus™, this research advances the field of OB modeling and offers a versatile tool for optimizing building energy performance and occupant comfort. Future research can build on these foundations to improve model accuracy and extend its applicability across building types and climates.

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APPENDIX

Appendix A. Online Study Questionnaire (Turkish)

ADIM 01 – ÇEVRİMİÇİ ÇALIŞMA SORULARI

1. **Kişisel Bilgiler**

1.1.	Çalışılan kuruluş adı	*[Açık uçlu soru]*
1.2.	Cinsiyet	*[Erkek / Kadın]*
1.3.	Yaş	*[Açık uçlu soru]*
1.4.	Eğitim seviyesi	*[Lise ve altı / Lisans / Yüksek lisans / Doktora]*
1.5.	Ofis tipi	*[Bireysel kapalı / Paylaşımlı kapalı / Açık ofis]*
1.6.	Ofisinizin bulunduğu şehir	*[Açık uçlu soru]*
1.7.	Ofis büyüklüğü / kişi sayısı	*[Büyük ofis odası (10+ kişi) / Orta ofis odası (5-10 kişi) / Küçük ofis odası (1-4 kişi)]*

2. **Ofislerde Enerji Tasarrufu**

		[1: Kesinlikle katılmıyorum / 2: Katılmıyorum / 3: Kararsızım / 4: Katılıyorum / 5: Kesinlikle katılıyorum]
2.1.	Ofisimde enerji tasarrufunun çevreyi korumak için faydalı olduğunu düşünüyorum.	[1 / 2 / 3 / 4 / 5]
2.2.	Ofisimdeki enerji tasarrufu davranışlarının akıllıca bir davranış olduğunu düşünüyorum.	[1 / 2 / 3 / 4 / 5]
2.3.	Ofisimdeki enerji tasarrufu davranışlarının enerji kıtlığını azaltmak için değerli olduğunu düşünüyorum.	[1 / 2 / 3 / 4 / 5]
2.4.	Meslektaşlarım ofisimde enerji tasarrufu yapmam gerektiğini düşünüyor.	[1 / 2 / 3 / 4 / 5]
2.5.	Yöneticilerim ofisimde enerji tasarrufu yapmamı istiyor.	[1 / 2 / 3 / 4 / 5]
2.6.	Benim için önemli olan insanlar ofisimde enerji tasarrufu yapmamı isterler.	[1 / 2 / 3 / 4 / 5]

2.7.	Ofisimde enerji tasarrufu yapabileceğimi düşünüyorum.	[1 / 2 / 3 / 4 / 5]
2.8.	Ofisimde enerji tasarrufu sağlayacak bilgi ve becerilere sahibim.	[1 / 2 / 3 / 4 / 5]
2.9.	Çevreye yardım etmenin yeni yollarını öğrenmekten zevk alıyorum.	[1 / 2 / 3 / 4 / 5]
2.10.	Çevrenin kalitesini iyileştirmekten zevk alıyorum.	[1 / 2 / 3 / 4 / 5]
2.11.	Çevre için bir şeyler yapmaktan zevk alıyorum.	[1 / 2 / 3 / 4 / 5]
2.12.	Çevreye katkıda bulunmaktan zevk alıyorum.	[1 / 2 / 3 / 4 / 5]
2.13.	Çevreye faydalı bir şeyler yapmak hayatımın ayrılmaz bir parçası	[1 / 2 / 3 / 4 / 5]
2.14.	Çevre faydalı bir şeyler yapmak kişisel gelişim ile ayrılmaz bir şekilde bağlantılıdır.	[1 / 2 / 3 / 4 / 5]
2.15.	Çevreye faydalı bir şeyler yapmak benim yaşam tarzım.	[1 / 2 / 3 / 4 / 5]
2.16.	Çevreye faydalı bir şeyler yapmak benim temel bir parçam.	[1 / 2 / 3 / 4 / 5]
2.17.	Çevreye faydalı bir şeyler yapmak mantıklı bir eylemdir.	[1 / 2 / 3 / 4 / 5]
2.18.	Çevreye faydalı bir şeyler yaparak ona katkıda bulunabilirim.	[1 / 2 / 3 / 4 / 5]
2.19.	Çevreye faydalı bir şeyler yapmak iyi bir fikirdir.	[1 / 2 / 3 / 4 / 5]
2.20.	Çevreye faydalı bir şeyler yapmasaydım pişman olurdum.	[1 / 2 / 3 / 4 / 5]
2.21.	Çevreye faydalı bir şeyler yapmasaydım kendimi suçlu hissederdim.	[1 / 2 / 3 / 4 / 5]
2.22.	Çevreye faydalı bir şeyler yapmasaydım kendimi kötü hissederdim.	[1 / 2 / 3 / 4 / 5]
2.23.	Çevreye faydalı bir şeyler yapmasaydım utanırdım.	[1 / 2 / 3 / 4 / 5]
2.24.	Başkalarını üzmemek adına çevreye faydalı bir şeyler yapıyorum.	[1 / 2 / 3 / 4 / 5]
2.25.	Başkalarından onay almak adına çevreye faydalı bir şeyler yapıyorum.	[1 / 2 / 3 / 4 / 5]
2.26.	Arkadaşlarım ısrar ettiği için çevreye faydalı bir şeyler yapıyorum.	[1 / 2 / 3 / 4 / 5]
2.27.	Eleştirilmekten kaçınmak için çevreye faydalı bir şeyler yapıyorum.	[1 / 2 / 3 / 4 / 5]
2.28.	Ofisimde enerji tasarrufu yapmaya istekliyim.	[1 / 2 / 3 / 4 / 5]
2.29.	Ofisimde enerji tasarrufu sağlayan faaliyetlerde bulunmak istiyorum.	[1 / 2 / 3 / 4 / 5]

2.30.	Ofisimde enerji tasarrufu için çaba göstereceğim.	[1 / 2 / 3 / 4 / 5]
2.31.	Ofisimde enerji tasarrufu yapmamak bana garip bir his verir.	[1 / 2 / 3 / 4 / 5]
2.32.	Ofisimde enerji tasarrufu yapmak otomatik olarak yaptığım bir şeydir	[1 / 2 / 3 / 4 / 5]
2.33.	Ofisimde enerji tasarrufu, hiç düşünmeden yaptığım bir şey.	[1 / 2 / 3 / 4 / 5]
2.34.	Ofisimde enerji tasarrufu yapmak rutinimin bir parçası	[1 / 2 / 3 / 4 / 5]
2.35.	Ofisimde enerji tasarrufu benim için tipik bir şey	[1 / 2 / 3 / 4 / 5]
2.36.	Ofisimde enerji tasarrufu yapmak, herhangi bir aktif düşünce gerektirmeyen bir şeydir.	[1 / 2 / 3 / 4 / 5]
2.37.	Bilgisayarımı kullanmadığım zamanlarda kapatırım.	[1 / 2 / 3 / 4 / 5]
2.38.	Ofiste son çıkan ben olduğumda, ışıkları kapatırım.	[1 / 2 / 3 / 4 / 5]
2.39.	Ofiste yazın klimayı daha düşük bir sıcaklığa ayarlamak için kullanırım.	[1 / 2 / 3 / 4 / 5]
2.40.	Ofiste klima çalışırken uzun süre camları açarım.	[1 / 2 / 3 / 4 / 5]
2.41.	Ofiste başkalarının enerjiyi boşa harcamasını engellerim.	[1 / 2 / 3 / 4 / 5]
2.42.	Ofiste başka şekillerde de enerji tasarrufu yaparım.	[1 / 2 / 3 / 4 / 5]
2.43.	Ofisimdeki sıcaklıktan memnunum	[1 / 2 / 3 / 4 / 5]
2.44.	Ofisimdeki nemden memnunum	[1 / 2 / 3 / 4 / 5]
2.45.	Ofisimdeki hava kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]
2.46.	Ofisimdeki havalandırmadan memnunum	[1 / 2 / 3 / 4 / 5]
2.47.	Ofisimdeki gün ışığı miktarından memnunum	[1 / 2 / 3 / 4 / 5]
2.48.	Ofisimdeki yapay aydınlatmanın rahatlığından memnunum	[1 / 2 / 3 / 4 / 5]

Appendix B. Field Study Questionnaire (Turkish)

ADIM 02 - ÇEVRİMİÇİ SAHA ÇALIŞMASI

1. **Başlangıç Anketi**

		[1: Kesinlikle katılmıyorum / 2: Katılmıyorum / 3: Kararsızım / 4: Katılıyorum / 5: Kesinlikle katılıyorum]
1.1.	Ofisimdeki genel iç mekan kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]
1.2.	Ofisimdeki sıcaklıktan memnunum	[1 / 2 / 3 / 4 / 5]
1.3.	Ofisimdeki nemden memnunum	[1 / 2 / 3 / 4 / 5]
1.4.	Ofisimdeki hava kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]
1.5.	Ofisimdeki hava kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]

2. **Günlük Anket**

2.1.	Bugün ofisinizdeki genel iç mekan iklimini nasıl değerlendiriyorsunuz?	[çok konforsuz, konforsuz, nötr, konforlu, çok konforlu]
2.2.	Bugün ofisinizdeki sıcaklığı nasıl değerlendiriyorsunuz?	[çok konforsuz, konforsuz, nötr, konforlu, çok konforlu]
2.3.	Bugün ofisinizdeki hava kalitesini nasıl değerlendiriyorsunuz?	[çok konforsuz, konforsuz, nötr, konforlu, çok konforlu]
2.4.	Bugün pencerelerde herhangi bir ayar yaptınız mı?	[evet, hayır]
2.5.	Cevabınız evet ise, pencereleri ne sıklıkla ayarladınız?	1,2,3,4,5,6,7,8,9,10, >10
2.6.	Cevabınız evet ise, lütfen ayarlamanızın ana nedenlerini belirtiniz. Birden fazla seçenek seçilebilir.	Pencereleri açtım: [temiz hava almak, ofise varmak/çıkmak, enerji tasarrufu için, iç ortam sıcaklığı çok soğuk/sıcak, iş arkadaşımın/yöneticimin isteği için, dış mekan sesini dinlemek, diğer] Pencereleri kapattım: [ofise gelme/bırakma, dış gürültüyü azaltmak, dış ortam sıcaklığı çok soğuk/sıcak, güvenlik nedenleri,

		kirleticileri/böcekleri önlemek, enerji tasarrufu yapmak, iş arkadaşının/yöneticinin talebi üzerine, diğer]
2.7.	Bugün perde / gölgeliklerde herhangi bir ayarlama yaptınız mı?	[evet, hayır]
2.8.	Cevabınız evet ise, perde / gölgelikleri ne sıklıkla ayarladınız?	1,2,3,4,5,6,7,8,9,10, >10
2.9.	Cevabınız evet ise, lütfen ayarlamanızın ana nedenlerini belirtiniz. Birden fazla seçenek seçilebilir.	Perde / gölgelikleri açtım: [daha fazla gün ışığı almak, dışarıyı görmek veya ofise gelip/çıkmak, enerji tasarrufu yapmak, ofisi güneş ışığı ile ısıtmak, bir iş arkadaşının/yöneticinin talebi için, diğer] Perde / gölgelikleri kapattım: [ekranımdaki/çalışma alanımdaki parlamayı azaltmak, ofise varmak/bırakmak, aşırı ısınmayı azaltmak, dışarıdan görüşü engellemek (gizlilik), bir iş arkadaşının/yöneticinin talebi için, diğer]
2.10.	Bugün termostat / klima ayarlarında herhangi bir değişiklik yaptınız mı?	[evet, hayır]
2.11.	Cevabınız evet ise, termostat / klimayı ne sıklıkla ayarladınız?	1,2,3,4,5,6,7,8,9,10, >10
2.12.	Cevabınız evet ise, lütfen ayarlamanızın ana nedenlerini belirtiniz. Birden fazla seçenek seçilebilir.	[iç ortam sıcaklığı çok sıcak, bir iş arkadaşının/yöneticinin isteği için, iç ortam sıcaklığı çok soğuk, enerji tasarrufu için, ofise varmak/bırakmak, diğer]

3. Bitiş Anketi

		[1: Kesinlikle katılmıyorum / 2: Katılmıyorum / 3: Kararsızım / 4: Katılıyorum / 5: Kesinlikle katılıyorum]
1.1.	Geçtiğimiz iki haftada göz önünde bulundurduğumda, ofisimdeki genel iç mekan kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]

1.2.	Geçtiğimiz iki haftada göz önünde bulundurduğumda, ofisimdeki sıcaklıktan memnunum	[1 / 2 / 3 / 4 / 5]
1.3.	Geçtiğimiz iki haftada göz önünde bulundurduğumda, ofisimdeki nemden memnunum	[1 / 2 / 3 / 4 / 5]
1.4.	Geçtiğimiz iki haftada göz önünde bulundurduğumda, ofisimdeki hava kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]
1.5.	Geçtiğimiz iki haftada göz önünde bulundurduğumda, ofisimdeki hava kalitesinden memnunum	[1 / 2 / 3 / 4 / 5]
		[1: Hiçbir zaman / 2: Nadiren / 3: Bazen / 4: Sıklıkla / 5: Sürekli]
1.6.	Geçtiğimiz iki haftada göz önünde bulundurduğunuzda, pencereleri ne sıklıkla ayarladınız?	[1 / 2 / 3 / 4 / 5]
1.7.	Geçtiğimiz iki haftada göz önünde bulundurduğunuzda, perde / gölgelikleri ne sıklıkla ayarladınız?	[1 / 2 / 3 / 4 / 5]
1.8.	Geçtiğimiz iki haftada göz önünde bulundurduğunuzda, termostat / klima ayarlarında herhangi bir değişiklik yaptınız mı?	[1 / 2 / 3 / 4 / 5]
1.9.	Lütfen son iki hafta boyunca doldurmuş olduğunuz günlük anket ile ilgili görüş ve önerilerinizi paylaşınız.	*[Açık uçlu soru]*

Appendix C. Field Study Questionnaire (English)

Table C 1. Questions of the start survey

Aspects	Question	Answer option
Overall IAQ Satisfaction (Environmental factors)	1. How satisfied are you with the indoor climate in your office in general?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	2. How satisfied are you with the temperature in your office in general?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	3. How satisfied are you with the humidity in your office in general?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	4. How satisfied are you with the air quality in your office in general?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
Overall IAQ Preference (Environmental factors)	5. How would you prefer the thermal environment in your office in general?	Much warmer, a bit warmer, no change, a bit cooler, much cooler
	6. How would you prefer the humidity in your office in general?	Much humid, a bit humid, no change, a bit drier, much drier
Occupant control	7. To maintain your comfort, how often do you adjust the windows in your office in general?	Never, rarely, sometimes, always, often

Table C1. Questions of the start survey (continued).

Aspects	Question	Answer option
	8. To maintain your comfort, how often do you adjust the solar shading in your office in general?	Never, rarely, sometimes, always, often
	9. To maintain your comfort, how often do you adjust the thermostat in your office in general?	Never, rarely, sometimes, always, often
	10. To maintain your comfort, how often do you adjust your clothing in your office in general?	Never, rarely, sometimes, always, often
	11. To maintain your comfort, how often do you drink some beverage in your office in general?	Never, rarely, sometimes, always, often
Feedback	11. Please share your thoughts and suggestions regarding the daily survey you will complete in the following two weeks.	Open-ended

Table C 2. Questions in the daily study.

Aspects		**Question**	**Answer option**
Satisfaction (Environmental factors)		1. How satisfied were you with the indoor climate in your office today?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
		2. How satisfied were you with the temperature in your office today?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
		3. How satisfied were you with the humidity in your office today?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
		4. How satisfied were you with the air quality in your office today	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
Preference (Environmental factors)		5. How would you prefer the thermal environment in your office today?	Much warmer, a bit warmer, no change, a bit cooler, much cooler
		6. How would you prefer the humidity in your office today?	Much humid, a bit humid, no change, a bit drier, much drier
Physical adjustment	Window adjustment	7. Have you opened the windows today?	yes, no
		8. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
		9. Have you closed the windows today?	yes, no
		10. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
	Solar shading adjustment	11. Have you raised the solar shading today?	yes, no
		12. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
		13. Have you lowered the solar shading today?	yes, no
		14. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
	Thermostat adjustment	15. Have you switched on the thermostat today?	yes, no

Table C 2. Questions in the daily study (continued).

		16. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
		17. Have you switched off the thermostat today?	yes, no
		18. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
Personal adjustment	Clothing adjustment	19. Have you added any garments today?	yes, no
		20. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
		21. Have you removed any garments today?	yes, no
		22. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
	Drink intake	23. Have you drunk a hot beverage today?	yes, no
		24. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10
		24. Have you drunk a cold beverage today?	yes, no
		25. If yes, please indicate your action frequency today.	1-3, 4-6, 7-9, ≥10

Table C 3. Questions of the end survey

Aspects	Question	Answer option
IAQ Satisfaction considering the past two weeks (Environmental factors)	1. Considering the past two weeks, how satisfied are you with the indoor climate in your office?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	2. Considering the past two weeks, how satisfied are you with the temperature in your office?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	3. Considering the past two weeks, how satisfied are you with the humidity in your office?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
	4. Considering the past two weeks, how satisfied are you with the air quality in your office?	Very dissatisfied, dissatisfied, slightly dissatisfied, neutral, slightly satisfied, satisfied, very satisfied
IAQ Preference considering the past two weeks (Environmental factors)	5. Considering the past two weeks, how would you prefer the thermal environment in your office?	Much warmer, a bit warmer, no change, a bit cooler, much cooler
	6. Considering the past two weeks, how would you prefer the humidity in your office?	Much humid, a bit humid, no change, a bit drier, much drier
Occupant control	7. Considering the past two weeks, how often did you adjust the windows?	Never, rarely, sometimes, always, often
	8. Considering the past two weeks, how often did you adjust the solar shading?	Never, rarely, sometimes, always, often
	9. Considering the past two weeks, how often did you adjust the thermostat?	Never, rarely, sometimes, always, often
	10. Considering the past two weeks, how often did you adjust your clothing?	Never, rarely, sometimes, always, often
Feedback	11. Please share your thoughts and suggestions regarding the daily survey you completed in the last two weeks.	Open-ended

Appendix D. Bilkent University Ethics Committee Approval

Bilkent Üniversitesi
Akademik İşler Rektör Yardımcılığı

Tarih : 17 Ekim 2022

Gönderilen : İrem Çağlayan

Danışman : Yasemin Afacan

Gönderen : H. Altay Güvenir
İnsan Araştırmaları Etik Kurulu Başkanı [redacted]

Konu : "*Exploring* ..." çalışması etik kurul onay [redacted]

Üniversitemiz İnsan Araştırmaları Etik Kurulu, 17 Ekim 2022 tarihli görüşme sonucu, "*Exploring energy-related occupant behavior in office buildings: An interdisciplinary study in the context of the building physics and social psychology.*" isimli çalışmanız kapsamında yapmayı önerdiğiniz etkinlik için etik onay vermiş bulunmaktadır. Onay, ekte verilmiş olan çalışma önerisi, çalışma yürütücüleri ve bilgilendirme formu için geçerlidir.

Bu onay, yapmayı önerdiğiniz çalışmanın genel bilim etiği açısından bir değerlendirmedir. Çalışmanızda, kurulumuzun değerlendirmesi dışında kalabilen özel etik ve yasal sınırlamalara uymakla ayrıca yükümlüsünüz.

Kovid-19 salgını nedeniyle konulmuş olan kısıtlamaların yürürlükte olduğu süre içinde, tüm komite toplantıları elektronik ortamda yapılmaktadır; aşağıda isimleri bulunan Bilkent Üniversitesi Etik Kurulu Üyeleri adına bu yazıyı imzalama yetkisi kurul başkanındadır.

Etik Kurul Üyeleri:

Ünvan / İsim	Bölüm / Uzmanlık	
Prof.Dr. H. Altay Güvenir	Bilgisayar Mühendisliği	Başkan
Prof.Dr. Erdal Onar	Hukuk	Üye
Prof.Dr. Haldun Özaktaş	Elektrik ve Elektronik Müh.	Üye
Doç.Dr. Işık Yuluğ	Moleküler Biyoloji ve Genetik	Üye
Dr. Öğr. Üyesi Burcu Ayşen Ürgen	Psikoloji	Üye
Dr. Öğr. Üyesi Didem Özkul McGeoch	İletişim ve Tasarımı	Yedek Üye
Dr. Öğr. Üyesi A.Barış Özbilen	Hukuk	Yedek Üye

Kurul karar/toplantı No: 2022_10_17_01

Bilkent Üniversitesi, 06800 Bilkent, Ankara • Telefon: (312) 290 12 13 • (312) 290 12 14 • Faks: (312) 266 41 52

(Form Staff_EN[*])

Staff Application Form for Experiments with Human Participants

(A separate application form must be completed for each experiment and staff member.)

Please check one: __x__ ***I need a formal approval letter for an external agency (TÜBİTAK, etc.)***

___ ***An internal communication letter informing me of the approval will be sufficient***

1. Name of applicant (graduate students should indicate their supervisors)

Graduate student: İrem Çağlayan, Supervisor: Assoc. Prof. Dr. Yasemin Afacan

2. Funder of grant/studentship if any:

None

3. Full title of experiment/project

Exploring energy-related occupant behavior in office buildings: An interdisciplinary study in the context of the building physics and social psychology

4. When do you wish to start data collection: ___**15.10.2022**________

5. Aims of project:

This study aims to identify occupants' energy-related behavioral patterns in office buildings and to develop OB algorithms by focusing on to help socio-technical data interchange and co-learning regarding the disciplines of building science and social psychology.

6. What will the participants have to do? (Provide a brief outline of procedure, *for survey work, a copy of the survey should be attached to this form.*) Please indicate if the participants may be exposed to stimuli which may upset them:

Application of the method will be achieved in four steps as follows: 01) online study, 02) identification of behavioral categories, 03) field study, and 04) implementation. Step 01 represents a specialized online questionnaire that will be administered to a sample of office occupants in Turkey to collect their subjective assessments related to energy-related occupant behavior from a psycho-social perspective. In Step 02 behavior categories will be developed based on the statistical calculation through cluster analysis. Step 03 is the field study. The field study protocol will consist of: (1) a two-week winter and summer diary study and (2) a two-week winter and summer continuous IEQ monitoring. During the diary study, participants will make judgements about perceived indoor environmental quality and will indicate the adjustments that they made with the building systems. Herein, behavioral patterns will be achieved for each behavioral categories with a consideration of measured environmental data. Step 04 corresponds to the implementation phase of the method, where the finalized behavioral archetypes and their energy-related behavioral patterns will be coded into BIM as a plug-in. See the end of this documents for the type of questions that will be asked.

7. What sort of people will the participants be and how will they be recruited? In the case of children state age range. *(Any participant who has not lived through his/her 18th birthday is considered to be a child!)*

The participants will be occupants of the mixed-mode office buildings (N=150-200), who are over 18 years old, with manually controlled building systems. An e-mail will be sent to organizations to invite them to participate in an online questionnaire about the occupants' energy-related behaviors in their offices. Participants will be recruited in the study from the office buildings who accept to participate in the study. In the Step 01, the volunteer participants in the offices are asked to fill out the energy-related behavior questionnaire. In the Step 03, three participants from each behavior group that are calculated based on the first step's data analysis will randomly selected to fill out the diary study.

I have CRB[**] clearance yes / no

8. Arrangements for consent and debriefing (attach information sheet and consent form)

Participants will be briefed about the study prior to the two phases (Step 01 and Step 03) of the data collection. Then, each participant will be asked to read and sign a consent form. The consent form and the debriefing form are at the end of this document.

9. How will you guarantee confidentiality of participants?

The questionnaire will not include any questions related to personal information such as names or contact information that might identify a participant. Only some demographics including age, gender and education will be asked in Step 01. The

[*] Adapted from www.york.ac.uk/depts/psych/www/research/ethics/StaffPGEthicsForm.doc

[**] Criminal Records Bureau – clearance is required for non-university personnel, including students, for experiments involving children. Please attach relevant documentation.

18/10/22

[redacted]

10. Please upload an electronic version of this word processed form (without signatures) along with other application material. Paper copies of all application material, (properly signed where indicated, and initialled on all other pages) should be sent after possible modifications suggested by the committee are finalized.

Signature(s):

Person carrying out the work

..İrem Çağlayan..

Supervisor, grant holder, or Principal Investigator: I am satisfied that that the procedures adopted will ensure the dignity, welfare and safety of all participants in this work.

Assoc. Prof. Dr. Yasemin Afacan......[redacted]...

The signature above signifies that researchers will conform to the accepted ethical principles endorsed by relevant professional bodies, in particular to

Declaration of Helsinki (WMA):
https://www.wma.net/policies-post/wma-declaration-of-helsinki-ethical-principles-for-medical-research-involving-human-subjects/

Ethical Principles of Psychologists and Code of Conduct (APA):
http://www.apa.org/ethics/code2002.html

Ethical Standards for Research with Children (SCRD):
http://www.srcd.org/about-us/ethical-standards-research

Bilkent University does not allow the use of students of research investigators as participants. Students who have the potential of being graded by the investigators during or following the semester(s) in which the study is being carried out should not participate in the study. Students may not receive any credit for any university course, with the exception of the GE250/GE251 courses, for their participation. The GE250 and GE251 (Collegiate Activities I and II) courses include an optional activity which encompasses volunteering as a participant in a research project.

18/10/22

[redacted]

(vi) **Consent** Informed consent must be obtained for all participants before they take part in your project. The form should clearly state what they will be doing, drawing attention to anything they could conceivably object to subsequently. It should be in language that the person signing it will understand. It should also state that they can withdraw from the study at any time and the measures you are taking to ensure the confidentiality of data. If children are recruited from schools, you will require the permission of the head teacher, and of parents. Children over 14 years should also sign an individual consent form themselves. When testing children, you will also need Criminal Records Bureau clearance. Testing to be carried out in any institution (prison, hospital, etc.) will require permission from the appropriate authority. (Please include documentation for such permission.)

Who will you seek permission from?

Participants own permission will be obtained prior to the two phases (Step 01 and Step 03) of the data collection.

Please attach the consent form you will use. Write the "brief description of study" in the words that you will use to inform the participants here.

This study investigates energy-related occupant behaviour in office buildings. In the first step, energy-related occupant behaviour in office buildings will be examined through subjective assessment of office occupants through an online survey with a consideration of psycho-social variables. The online survey data will be processed and behavioural categories will be developed at the second step. In the third step, a longitudinal field study will be conducted in the office buildings who participated in the first step. Three participants from each behavior group that are calculated based on the first step's data analysis will randomly selected to be recruited in the field study. The field study will consist of a diary study and environmental measurements. Herein, occupant control behaviour with building systems will be analysed in relation with the environmental parameters for a two weeks period for both summer and winter. There won't be any personal Information that can identify a person such as names and contact information. Participants' answers will be held in confidence in the researchers' database and accessed only by the research personnel.

(vii) **Debriefing - how and when will participants be informed about the experiment, and what information you intend to provide? If there is any chance that a participant will be 'upset' by taking part in the experiment what measures will you take to mitigate this?**

Each participant who takes part both in the online study and field study will be asked to sign a consent form to satisfy ethical procedures (See attached consent form). Before starting the data collection in the two phases (Step 01and Step 03) of the study, a brief explanation will be also given as to how data from their responses will be used.

(viii) **What procedures will you follow in order to guarantee the confidentiality of participants' data?** Personal data (name, addresses etc.) should only be stored if absolutely necessary and then only in such a way that they cannot be associated with the participant's experimental data.

Each participant, who takes part in the in the online study and field study, will be asked to sign a consent form to satisfy ethical procedures (See attached consent form). All personal information of participants supplied during the research will be held in confidence in the researchers' database and accessed only by the research personnel. The participants will be coded into the numbers as labels.

In the information consent form, there is a statement which is signed by the graduate student and the supervisor that "we confirm that the confidentiality and anonymity will be maintained and the participant will not be identified from any publications".

(vii) **Give brief details of other special issues the ethics committee should be aware of.**

None

(viii) **Tick any of the following that apply to your project**

[x] it uses Bilkent facilities;

[ ] it uses stimuli designed to be emotive or aversive;

[ ] it requires participants to ingest substances (e.g., alcohol);

[ ] it require participants to give information of a personal nature;

18/10/22

[redacted]

Student's signature: [redacted] date: 18/10/22
(all students must sign if this is a group project, please initial all other pages)

The signatures here signify that researchers will conform to the accepted ethical principles endorsed by relevant professional bodies, in particular to

Declaration of Helsinki (WMA):
http://www.wma.net/en/30publications/10policies/b3/index.html

Ethical Principles of Psychologists and Code of Conduct (APA):
http://www.apa.org/ethics/code2002.html

Ethical Standards for Research with Children (SCRD):
http://www.srcd.org/about-us/ethical-standards-research

2. Supervisor's assessment (supervisor to complete - circle yes or no)

Yes/No - I confirm that I have secured the resources required by this project, including any workshop time, equipment, or space that are additional to those already allocated to me.

Yes/No - The design of this study ensures that the dignity, welfare and safety of the participants will be ensured and that if children or other vulnerable individuals are involved, they will be afforded the necessary protection.

Yes/No - All statutory, legislative and other formal requirements of the research have been addressed (e.g., permissions, police checks)

Yes/No - I am confident that the participants will be provided with all necessary information before the study, in the consent form, and after the study in debriefing.

Yes/No - I am confident the participant's confidentiality will be preserved.

Yes/No - I confirm that students involved have sufficient professional competency for this project.

Yes/No - I consider that the risks involved to the student, the participants and any third party are insignificant and carry no special supervisory considerations. If you circle "no" please attach an explanatory note.

No/Yes - I would like the ethics committee to give this proposal particular attention. (Please state why below)

Supervisor's signature: [redacted] date: 18/10/22

Please e-mail an electronic version of this word processed form (without signatures) along with other application material to the committee to start the evaluation process. Paper copies of all application material, (properly signed where indicated, and initialed on all other pages) should be sent after possible modifications suggested by the committee are finalized.

Bilkent University does not allow the use of students of research investigators as participants. Students who have the potential of being graded by the investigators during or following the semester(s) in which the study is being carried out should not participate in the study. Students may not receive any credit for any university course, with the exception of the GE250/GE251 courses, for their participation. The GE250 and GE251 (Collegiate Activities I and II) courses include an optional activity which encompasses volunteering as a participant in a research project.

18/10/22

[redacted]

Appendix E. Results from field study

Table E 1. Comfort preferences of the behavioral clusters during two weeks of field measurements.

	Cluster 1			Cluster 2			Cluster 3		
Temperature Preference									
	Frequency	**%**	**Cumulative (%)**	**Frequency**	**%**	**Cumulative (%)**	**Frequency**	**%**	**Cumulative (%)**
Much warmer	4	8.7	8.7	0	0	0	0	0	0
A bit warmer	3	6.5	15.2	0	0	0	0	0	0
No change	10	21.7	37.0	7	25.9	25.9	17	44.7	44.7
A bit cooler	18	39.1	76.1	20	74.1	100.0	17	44.7	89.5
Much cooler	11	23.9	100.0	0	0	100.0	4	10.5	100.0
Humidity Preference									
Much humid	6	13.0	13.0	0	0	0	0	0	0
A bit humid	6	13.0	26.1	9	33.3	33.3	8	21.1	21.1
No change	17	37.0	63.0	16	59.3	92.6	28	73.7	94.7
A bit drier	14	30.4	93.5	2	7.4	100.0	2	5.3	100.0
Much drier	3	6.5	100.0	0	0	100.0	0	0	100.0

Table E 2. Descriptive statistics for frequency of occupant actions in the end survey.

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Window operation	C1	4	2.50	1.291	.645	.45	4.55	1	4
	C2	3	3.00	.000	.000	3.00	3.00	3	3
	C3	4	1.75	.957	.479	.23	3.27	1	3
	Total	11	2.36	1.027	.310	1.67	3.05	1	4
Solar shading operation	C1	4	1.50	1.000	.500	-.09	3.09	1	3
	C2	2	2.00	1.414	1.000	-10.71	14.71	1	3
	C3	4	1.00	.000	.000	1.00	1.00	1	1
	Total	10	1.40	.843	.267	.80	2.00	1	3
Thermostat adjustment	C1	4	3.25	1.708	.854	.53	5.97	1	5
	C2	3	3.00	.000	.000	3.00	3.00	3	3
	C3	4	3.00	1.633	.816	.40	5.60	1	5
	Total	11	3.09	1.300	.392	2.22	3.96	1	5
Door Operation	C1	4	2.25	1.258	.629	.25	4.25	1	4
	C2	3	2.67	.577	.333	1.23	4.10	2	3
	C3	4	2.50	1.915	.957	-.55	5.55	1	5
	Total	11	2.45	1.293	.390	1.59	3.32	1	5
Clothing Adjustment	C1	4	1.50	.577	.289	.58	2.42	1	2
	C2	3	2.33	1.155	.667	-.54	5.20	1	3
	C3	4	2.25	1.258	.629	.25	4.25	1	4
	Total	11	2.00	1.000	.302	1.33	2.67	1	4
Drink Intake	C1	4	3.50	.577	.289	2.58	4.42	3	4
	C2	3	3.00	.000	.000	3.00	3.00	3	3
	C3	4	2.50	1.291	.645	.45	4.55	1	4
	Total	11	3.00	.894	.270	2.40	3.60	1	4

*C1: Cluster 1, C2: Cluster 2, C3: Cluster 3

Table E 3. IEQ satisfaction level of the behavioral clusters during two weeks of field measurements.

			Cluster 1	Cluster 2	Cluster 3	Total
Indoor climate	Very dissatisfied	Count	8	13	3	24
		% within Cluster	17.0%	32.5%	6.5%	18.0%
	Dissatisfied	Count	12	5	2	19
		% within Cluster	25.5%	12.5%	4.3%	14.3%
	Slightly dissatisfied	Count	8	10	7	25
		% within Cluster	17.0%	25.0%	15.2%	18.8%
	Neutral	Count	0	2	6	8
		% within Cluster	0.0%	5.0%	13.0%	6.0%
	Slightly satisfied	Count	15	10	9	34
		% within Cluster	31.9%	25.0%	19.6%	25.6%
	Satisfied	Count	4	0	17	21
		% within Cluster	8.5%	0.0%	37.0%	15.8%
	Very satisfied	Count	0	0	2	2
		% within Cluster	0.0%	0.0%	4.3%	1.5%
Temperature	Very dissatisfied	Count	16	15	3	34
		% within Cluster	34.0%	37.5%	6.5%	25.6%
	Dissatisfied	Count	8	5	2	15
		% within Cluster	17.0%	12.5%	4.3%	11.3%
	Slightly dissatisfied	Count	5	10	10	25
		% within Cluster	10.6%	25.0%	21.7%	18.8%
	Neutral	Count	0	1	7	8
		% within Cluster	0.0%	2.5%	15.2%	6.0%
	Slightly satisfied	Count	15	8	7	30
		% within Cluster	31.9%	20.0%	15.2%	22.6%
	Satisfied	Count	3	1	15	19
		% within Cluster	6.4%	2.5%	32.6%	14.3%
	Very satisfied	Count	0	0	2	2
		% within Cluster	0.0%	0.0%	4.3%	1.5%
Humidity	Very dissatisfied	Count	9	3	2	14
		% within Cluster	19.1%	7.5%	4.3%	10.5%
	Dissatisfied	Count	4	14	1	19
		% within Cluster	8.5%	35.0%	2.2%	14.3%
	Slightly dissatisfied	Count	10	15	13	38
		% within Cluster	21.3%	37.5%	28.3%	28.6%
	Neutral	Count	4	2	5	11
		% within Cluster	8.5%	5.0%	10.9%	8.3%
	Slightly satisfied	Count	19	6	6	31
		% within Cluster	40.4%	15.0%	13.0%	23.3%
	Satisfied	Count	1	0	17	18
		% within Cluster	2.1%	0.0%	37.0%	13.5%
	Very satisfied	Count	0	0	2	2
		% within Cluster	0.0%	0.0%	4.3%	1.5%
Indoor air quality	Very dissatisfied	Count	18	13	7	38
		% within Cluster	38.3%	32.5%	15.2%	28.6%
	Dissatisfied	Count	4	6	1	11
		% within Cluster	8.5%	15.0%	2.2%	8.3%
	Slightly dissatisfied	Count	7	17	10	34
		% within Cluster	14.9%	42.5%	21.7%	25.6%
	Neutral	Count	3	0	4	7
		% within Cluster	6.4%	0.0%	8.7%	5.3%
	Slightly satisfied	Count	13	4	5	22
		% within Cluster	27.7%	10.0%	10.9%	16.5%
	Satisfied	Count	2	0	17	19
		% within Cluster	4.3%	0.0%	37.0%	14.3%
	Very satisfied	Count	0	0	2	2
		% within Cluster	0.0%	0.0%	4.3%	1.5%

Table E 4. Comfort preferences of the behavioral clusters during two weeks of winter field measurements.

			Cluster			
			1	2	3	Total
Temperature preference	Much warmer	Count	16	17	7	40
		% within Cluster	34.0%	42.5%	15.2%	30.1%
	A bit warmer	Count	15	13	12	40
		% within Cluster	31.9%	32.5%	26.1%	30.1%
	No change	Count	13	8	23	44
		% within Cluster	27.7%	20.0%	50.0%	33.1%
	A bit cooler	Count	2	1	4	7
		% within Cluster	4.3%	2.5%	8.7%	5.3%
	Much cooler	Count	1	1	0	2
		% within Cluster	2.1%	2.5%	0.0%	1.5%
Humidity preference	Much humid	Count	0	2	3	5
		% within Cluster	0.0%	5.0%	6.5%	3.8%
	A bit humid	Count	24	29	17	70
		% within Cluster	51.1%	72.5%	37.0%	52.6%
	No change	Count	21	7	26	54
		% within Cluster	44.7%	17.5%	56.5%	40.6%
	A bit drier	Count	1	2	0	3
		% within Cluster	2.1%	5.0%	0.0%	2.3%
	Much drier	Count	1	0	0	1
		% within Cluster	2.1%	0.0%	0.0%	0.8%

Table E 5. Descriptive statistics for frequency of occupant actions in the winter-end survey.

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Window Operation	1	5	1.80	.447	.200	1.24	2.36	1	2
	2	3	1.67	1.155	.667	-1.20	4.54	1	3
	3	4	1.75	.500	.250	.95	2.55	1	2
	Total	12	1.75	.622	.179	1.36	2.14	1	3
Solar shading Operation	1	5	1.40	.548	.245	.72	2.08	1	2
	2	3	1.00	.000	.000	1.00	1.00	1	1
	3	4	1.25	.500	.250	.45	2.05	1	2
	Total	12	1.25	.452	.131	.96	1.54	1	2
Thermostat Adjustment	1	5	3.40	1.140	.510	1.98	4.82	2	5
	2	4	2.50	1.291	.645	.45	4.55	1	4
	3	4	2.75	.957	.479	1.23	4.27	2	4
	Total	13	2.92	1.115	.309	2.25	3.60	1	5
Door Operation	1	5	3.00	1.414	.632	1.24	4.76	2	5
	2	4	2.75	1.500	.750	.36	5.14	1	4
	3	4	2.00	.816	.408	.70	3.30	1	3
	Total	13	2.62	1.261	.350	1.85	3.38	1	5
Clothing Adjustment	1	5	2.20	1.095	.490	.84	3.56	1	4
	2	4	3.25	1.500	.750	.86	5.64	1	4
	3	4	2.00	1.414	.707	-.25	4.25	1	4
	Total	13	2.46	1.330	.369	1.66	3.27	1	4
Drink Intake	1	5	2.80	.837	.374	1.76	3.84	2	4
	2	4	3.25	.957	.479	1.73	4.77	2	4
	3	4	2.50	.577	.289	1.58	3.42	2	3
	Total	13	2.85	.801	.222	2.36	3.33	2	4

*C1: Cluster 1, C2: Cluster 2, C3: Cluster 3