Simulating energy use in Office Buildings by Modeling the Relationship between Psychological Factors and Occupants' Behavior in Japan

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Simulating energy use in Office Buildings by Modeling the Relationship between Psychological Factors and Occupants' Behavior in Japan

心理的要因と行動の関係のモデル化によるオフィスのエネルギー

使用行動シミュレーション

Kyushu University
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Chapter-1
Introduction

1.1. Background
1.2. Objectives and Significance
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Chapter 1. Introduction

1.1. Background

In Japan, carbon dioxide emissions from residential and building use in fiscal year 2022 amounted to 179 million tons (17.3%) in the "corporate and other sectors" such as commercial and service industries, and 159 million tons (15.3%) in the "household sector." Together, these two sectors account for 33% of the total emissions, or one-third of the total [1], as shown in Figure 1.1. Human culture, lifestyles, and behaviors significantly impact global issues such as climate change and greenhouse gas emissions[2]. Studies have further demonstrated that occupant behavior substantially influences energy use in private office spaces. Conservative working practices, for example, can save up to 50% of energy compared to standard practices, while wasteful practices can increase energy consumption by as much as 89%[3]. These findings underscore the crucial role occupant behavior plays in building energy efficiency. By strategically targeting occupant behavior modifications, significant energy

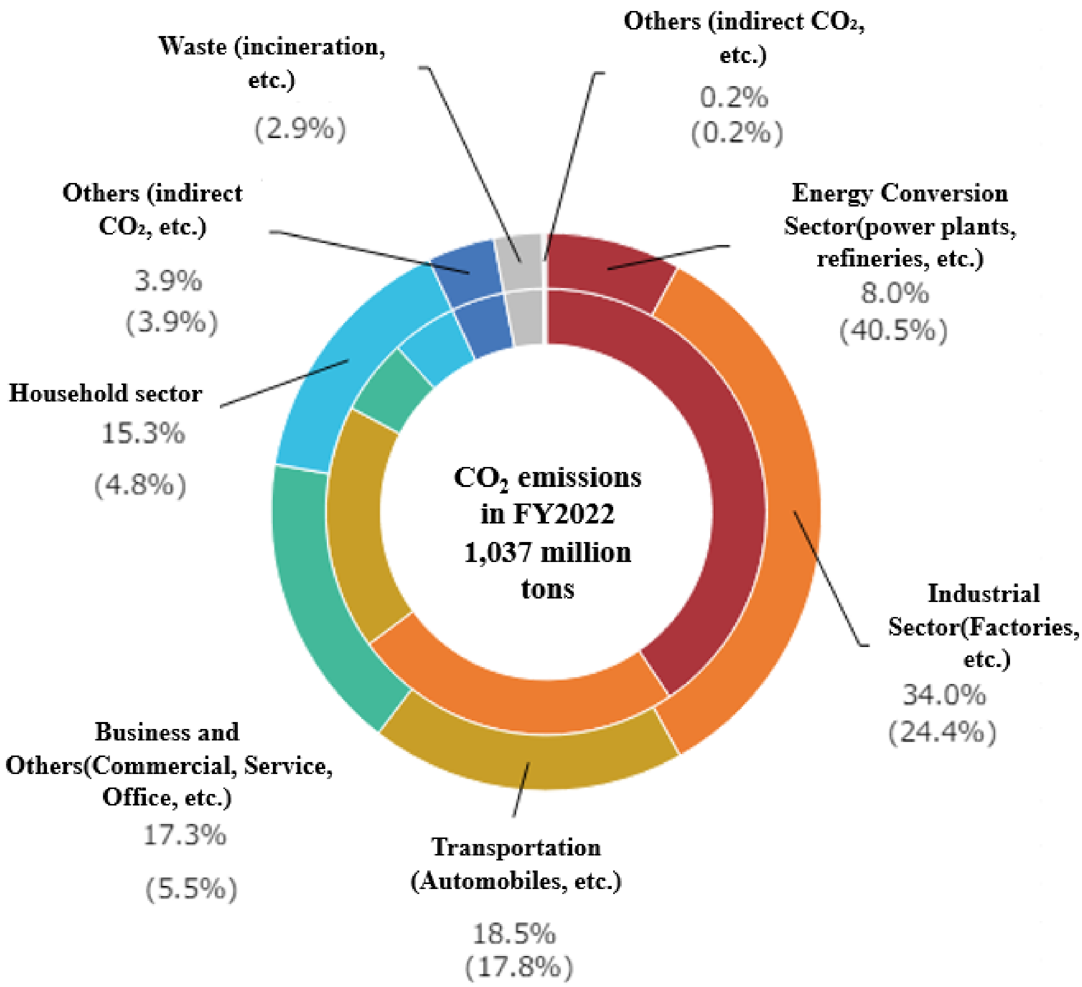

Figure 1.1 Japan Breakdown of emissions by sector and entity (FY2022)

savings can be achieved, contributing to sustainable development goals and reducing environmental impact [4,5]. To address these concerns, it is essential to consider how human behavior can be altered to become more environmentally friendly. Various intervention strategies are currently in place to influence building energy conservation, such as goal-setting, information provision, and commitment techniques. For policymakers and scholars to effectively craft energy-saving policies and interventions, a deeper exploration and understanding of the relationship between people's energy-saving awareness and their intentions is essential.

In recent years, comprehensive assessments of occupants' energy-related behaviors from a socio-psychological perspective have garnered significant attention[6,7]. Social psychological frameworks emphasize the influence of attitudes, personal norms, subjective norms, perceived behavioral control (PBC), and knowledge on energy consumption in residential and commercial buildings. Recognizing the value of these factors, researchers are exploring models that connect individuals' psychological tendencies with tangible energy-saving behaviors[8].

Many studies have also focused on modeling the impact of occupant behavior on building energy consumption. For example, Lee et al. developed an innovative agent-based modeling approach to simulate various occupant behaviors in commercial buildings[9]. This approach seeks to replicate real-world autonomous interactions between occupants, their environment, and other agents, allowing occupants to make decisions based on thermal comfort considerations.

Expanding on these findings, researchers argue that integrating psychological factors into building energy modeling could offer greater accuracy in predicting energy use and could enhance building management practices. By adopting a multi-faceted approach that includes behavioral, cultural, and psychological perspectives, policymakers can develop more effective strategies to encourage energy-efficient behavior, thereby making substantial contributions to global climate targets.

1.2. Objectives and Significance

To date, there has been limited research on how environmental awareness influences behavior and, subsequently, how such behavior impacts energy consumption in buildings. Environmental awareness plays a crucial role in determining whether individuals adopt energy-saving behaviors, making it essential to understand how this awareness affects energy-use behavior within buildings. This understanding could serve as an important reference for implementing energy-saving measures in built environments.

The primary objective of this study is to explore the relationship between environmental awareness, behavior, and building energy consumption to identify methods for reducing carbon emissions associated with buildings. To quantify the extent of awareness's impact on both behavior and energy use, this research will develop a model that simulates the influence of awareness on behavior, along with a tool to simulate these interactions.

By examining the relationship between environmental awareness and energy-related behaviors within buildings and by creating tools to model these behaviors and energy consumption, this study helps to fill a gap in the research field. The findings could provide theoretical support for future energy-saving policies, educational campaigns on energy conservation, and the development of targeted strategies to encourage sustainable behaviors in building environments. This research, therefore, contributes valuable insights for policymakers, environmental educators, and building managers, offering a foundation upon which more effective energy-saving initiatives can be designed and implemented.

1.3. Methodology

1.3.1. Conceptual Model

To understand the relationship between environmental awareness and energy consumption behavior, it is essential to explore this topic from a social psychology perspective. Several theoretical frameworks are commonly employed to investigate individuals' energy-saving intentions, including the Drivers-Needs-Actions-Systems (DNAs) framework, Norm Activation Theory (NAT), and the Theory of Planned Behavior (TPB)[10]. Among these, TPB is widely regarded as one of the most effective models for understanding personal energy-saving intentions and behaviors. In areas such as green purchasing, water conservation, and waste management, TPB has been broadly accepted as a robust model. Studies have shown that TPB constructs explain a substantial portion of the variance in employees' behavioral intentions[11].

The DNAs framework, initially proposed by Turner and Hong[12], offers another approach by examining the determinants of energy use behavior among building occupants. According to this theory, occupant behavior's influence on building energy consumption can be described using four core components: drivers, needs, actions, and systems. These components exist within two distinct "worlds": the "external world" (representing the physical building environment) and the "internal world" (encompassing the cognitive processes of individuals). In this model, the actions of occupants serve as a link between internal needs and external environmental factors, demonstrating how personal needs and environmental contexts interact to influence behavior.

Building upon these theoretical foundations, this study will develop a model framework as the basis of its research methodology. The model aims to incorporate insights from TPB, DNAs, and other relevant theories to examine how environmental awareness shapes energy-saving intentions and actions within building environments.

A comprehensive literature review and detailed description of this model framework will be presented in Chapter 2, outlining the theoretical foundations and components that inform the study's approach. This conceptual foundation not only guides the development of the simulation tool but also establishes a basis for interpreting the interactions between awareness, intention, and energy consumption behavior in the context of building environments.

1.3.2. Awareness and Behavior Data Collected Through Questionnaires

This study quantifies environmental awareness primarily through a questionnaire based on a Likert scale. The questionnaire, designed according to the conceptual model of this research, gathers data on both awareness and behavior. Statistical analysis methods are then applied to these data to identify the relationship between environmental awareness and energy consumption behavior.

To obtain data on environmental awareness and behavior across various demographics in Japan—including different regions, types of offices, and work roles—the questionnaire was distributed online through a specialized survey platform in Japan. In addition, the questionnaire seeks to measure specific factors such as individual attitudes toward energy conservation, perceived behavioral control, and personal norms, which have been identified as key indicators of energy-saving behavior. By analyzing these variables across different workplace contexts, the study aims to determine how variations in awareness impact energy usage within different office settings.

A detailed description of the questionnaire structure, the collected data, and the analysis of survey results will be presented in Chapter 3, providing a foundation for understanding the behavioral patterns and awareness levels among different demographic groups in Japan. These insights are instrumental in shaping strategies that cater to specific needs and attitudes in workplace energy-saving initiatives.

1.3.3. Introduction of the Simulation Tool and Development of the Simulation System

After establishing the relationship between environmental awareness and energy consumption behavior, the next step is to simulate the impact of environmental awareness on energy consumption behavior and overall building energy use. This study utilizes NetLogo to develop an Agent-Based Model (ABM). ABM is a computational simulation method designed to examine the interactions among individuals, objects, locations, and time. As a bottom-up, stochastic model, ABM assigns specific attributes to individual agents, allowing them to act autonomously within a simulated environment.

NetLogo is a specialized programming language and integrated development environment (IDE) for agent-based modeling. It features various types of agents—such as turtles, patches, links, and observers—that facilitate programming concepts in an accessible way. NetLogo is especially useful for studying interactions between individuals, as well as between individuals and their environment, making it an ideal tool for this research. The simulation system built in NetLogo can adjust input parameters—such as levels of environmental awareness, environmental conditions, and other relevant data—to simulate different behavioral choices individuals might make in varying scenarios. By analyzing the energy consumption resulting from these choices, the system helps predict how environmental awareness influences energy use.

A detailed explanation of the system's architecture, parameter settings, and the specific steps used to build the simulation will be provided in Chapter 4, where the setup and functioning of the simulation tool are discussed in depth. This approach enables the model to adapt to various scenarios and provides a flexible platform for exploring the complex dynamics between environmental awareness and energy consumption behavior in office environments.

1.4. Research Process

Figure 1.2 illustrates the research process of this study. Based on the theoretical model, a questionnaire was designed to obtain data on environmental awareness and energy consumption behavior. This data was used to create a mathematical model of behavior and awareness, forming the foundation for a simulation system that models behavior and energy consumption. The contents of each chapter are as follows:

Chapter 1 introduces the research background, objectives, methodology, and structure of the thesis. This chapter discusses the necessity of studying awareness and behavior related to building energy consumption, and the approach taken, including the software used to simulate behavior and building energy use.

Chapter 2 provides a detailed review and synthesis of previous research to establish the study's theoretical framework. By analyzing studies related to environmental awareness and energy-saving behaviors, as well as factors influencing building energy consumption behavior, this chapter builds a behavioral theory framework that underpins the research.

Chapter 3 explains how this study explores the relationship between environmental awareness and energy consumption behavior through a questionnaire. Based on the behavior model developed in Chapter 2, an online questionnaire was designed and validated through experiments to check for any significant discrepancies between the questionnaire results and actual behaviors. The data collected from the questionnaire are then used to construct a mathematical model that represents the relationship between environmental awareness and energy consumption behavior.

Chapter 4, building on the findings from previous chapters, develops a simulation system capable of modeling the impact of awareness on energy consumption and energy-saving behaviors. This system is built upon the mathematical models of environmental awareness and energy consumption behavior and incorporates the energy use habits gathered through the questionnaire. To evaluate the system's applicability, practical experiments are conducted in real office settings to verify whether the simulation system can be widely used.

Chapter 5 summarizes and synthesizes the key findings from each chapter, providing an overview of the study's contributions and implications for future research and practical applications in energy conservation policy.

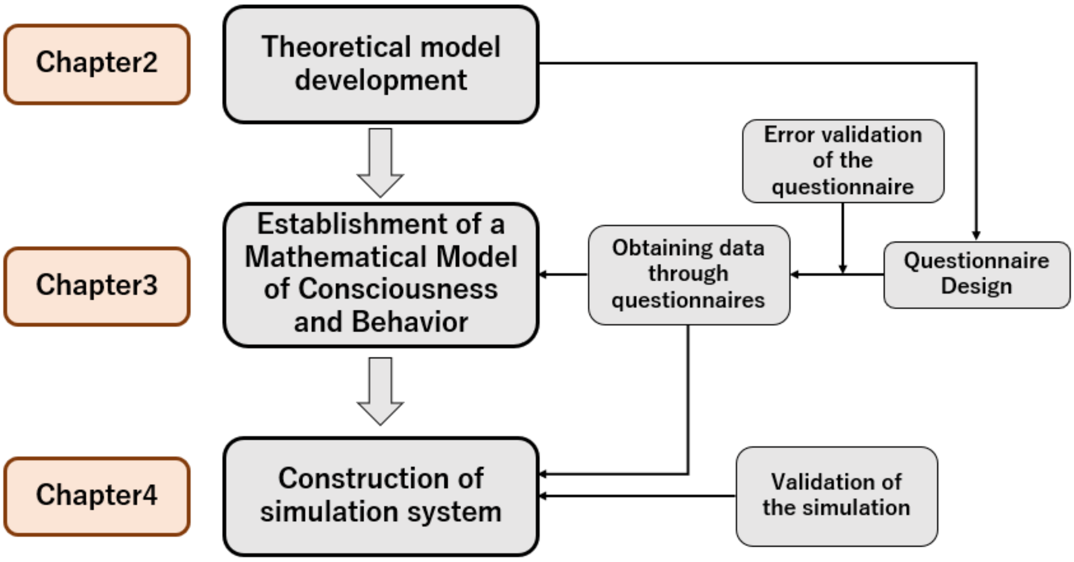

Figure 1.2 Research Process

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Chapter-2

Literature Review and Theoretical Model

2.1. Simulation of Energy Consumption Behavior in Existing Studies
2.2. Behavioral models
2.3. Theoretical Model

Chapter 2. Literature Review and Theoretical Model

This chapter primarily provides a review of previous research and introduces the theoretical model that serves as the foundation of this study. It begins with an introduction to Agent-Based Modeling (ABM), which is widely used in behavior simulation, along with an overview of how it has been applied in past studies. The chapter also discusses theories related to environmental behavior. Finally, based on prior research, this chapter establishes the theoretical model for this study.

2.1. Simulation of Energy Consumption Behavior in Existing Studies

When simulating behavior, Agent-Based Modeling (ABM) is widely recognized as a suitable approach for modeling complex human behaviors. As shown in Figure 2.1, ABM's unique advantage lies in its use of autonomous decision-making entities, or "agents," which can assess their own situations and make decisions based on individual behavioral rules[1]. This agent-centered paradigm has become increasingly popular as a method for occupant modeling in buildings, as it allows for the representation of intricate and dynamic processes associated with occupant-related interactions[2].In recent years, ABM has been frequently applied to explore the relationship between low-carbon transition scenarios and consumer behavior, offering insights into how individual actions can collectively influence environmental outcomes[3,4]. By enabling each agent to interact with both their environment and other agents, ABM facilitates a detailed understanding of the factors driving energy-related behaviors and supports the development of realistic scenarios for evaluating potential energy-

Figure 2.1 ABM Schematic Diagram

saving strategies.

Many recent studies have used ABM to model human behavior within buildings. For example, Yu [5] applied ABM in the field of workplace design to simulate individual activity patterns and interactions. The goal was to test various office layouts for spatial planning, customizing them with real data collected from online surveys to reflect actual usage patterns.

Lee et al. [6] developed an innovative ABM approach to simulate occupant behavior in commercial buildings, aiming to replicate real-world, autonomous interactions between occupants, the environment, and other agents. This model incorporates decision-making based on thermal comfort, thereby enhancing the simulation's realism and relevance for energy management in commercial spaces.

Similarly, Azar et al. [7] proposed a novel ABM-based method to simulate energy use in commercial buildings. By accounting for the diversity and dynamism of energy consumption behaviors resulting from interactions among occupants and with the building environment, this model aims to provide more accurate predictions of building energy performance. The study's emphasis on behavior-driven energy variations contributes valuable insights into optimizing energy use.

Zhang et al. [8] took a broader approach by integrating four essential elements—organizational energy management policies/regulations, energy management technologies, appliances, and human behavior—into an agent-based model to simulate electricity consumption in office buildings. By testing different electricity management strategies through case studies, their model addresses real-world office energy challenges. This study demonstrates the practical utility of ABM as a method for integrating multiple energy consumption factors in office buildings, highlighting its value in energy management strategies.

These studies underscore ABM's potential as a powerful tool for analyzing and optimizing energy use within building environments, enabling more accurate, context-specific simulations that capture the complexities of occupant behavior and environmental interactions.

In addition to modeling human behavior within buildings, ABM has also been applied to study the relationship between social and psychological factors and consumer behavior. For example, Tong et al. [9] proposed an ABM framework based on the Theory of Planned Behavior to simulate how different business models impact household participation rates in a community recycling program in Beijing. Their study examines the potential of post-consumption recycling to reduce carbon emissions, emphasizing the importance of shifting from facility-oriented strategies to behavior-oriented community norms. Through scenario analysis, the study compares the effects of introducing two new business models against the current baseline, offering insights into the role of behavioral approaches in encouraging sustainable practices.

Zhang et al. [10]utilized a combination of social psychology theories and agent-based modeling to investigate the impact of government policies on the adoption of smart meters. Their model demonstrates how different policy options can manage and guide the process of technology diffusion, providing a framework for evaluating and managing the spread of smart meters within the UK electricity market. This research not only supports the direct integration of social psychology theory with agent-based computational modeling but also presents a practical approach for assessing and guiding the adoption of smart meters through targeted policy interventions.

These studies highlight ABM's versatility in examining consumer behavior influenced by social and psychological factors. By integrating behavioral theories with agent-based simulations, ABM can provide actionable insights for policymakers and stakeholders on managing technology adoption, promoting sustainable community practices, and optimizing consumer behavior interventions to achieve environmental goals.

In summary, ABM is frequently applied in simulating occupant behavior in buildings, as well as in studying the relationship between social factors and low-carbon consumer behaviors. ABM offers several advantages that make it particularly suitable for these applications. First, it enables modelers to build on both practical insights and established theoretical knowledge. Second, ABM is adept at representing the complexities of energy demand, such as social interactions and the impact of behavioral diversity on energy use. Additionally, ABM is especially valuable for managing various agents with differing behaviors, allowing a nuanced simulation of diverse scenarios and interactions[3].

This study also seeks to model building energy consumption based on existing theoretical knowledge, particularly in the context of environmental awareness and behavioral influences. Given ABM’s capacity to handle complex interactions and varying agent behaviors, it provides an effective and suitable approach for this research.

2.2. Behavioral models

Several theoretical frameworks are used to explore individual energy-saving intentions, including the Drivers-Needs-Actions-Systems (DNAs) framework, Norm Activation Theory (NAT), and the Theory of Planned Behavior (TPB). TPB, developed by Ajzen [11], as shown in Figure 2.2, is a theoretical framework used to predict and explain individual behavioral intentions, making it particularly suitable for studying the relationship between human behavior and psychology. As shown in Table 2.1, previous research based on the TPB model is presented. These studies indicate that TPB is widely recognized as an effective model for understanding individual environmental behaviors, such as green purchasing, recycling, and energy-saving behaviors, and has been extensively applied in studies related to environmental behaviors. Additionally, TPB is considered capable of explaining a significant portion of the variance in employees' behavioral intentions [12]. Furthermore, in the study by Tong et al., the TPB model was utilized along with an Agent-Based Modeling (ABM) framework to simulate the impact of business models on household participation rates in recycling programs. Similarly, this study employs ABM for behavioral simulation to analyze the complexity of individual behaviors in office environments. Therefore, it can be concluded that compared to other theoretical models, the TPB model serves as a theoretical foundation supporting the behavioral simulations in this study.

However, TPB has faced criticism for its limitations, particularly its lack of comprehensiveness. To enhance TPB's explanatory power, some studies advocate adding supplementary factors to the model. For example, Gao et al. found that an extended TPB model, which includes additional variables, demonstrated improved explanatory capacity compared to the original TPB framework[12]. In this study, we will expand TPB by incorporating three additional factors — personal moral norms, descriptive norms, and environmental knowledge—to better capture the complexities of energy-saving behavior within buildings.

In addition to psychological influences, building energy consumption behaviors are shaped by a variety of other factors. According to Hong et al.'s theory[13], the impact of occupant behavior on

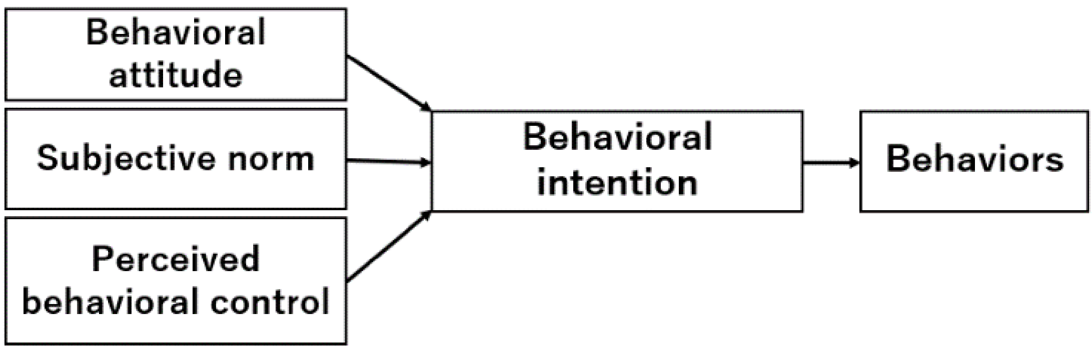

Figure 2.2 Theory of Planned Behavior (TPB) model.

building energy use can be described using four primary components: drivers, needs, actions, and systems. This DNAs framework emphasizes that occupant behavior results from an interaction between internal needs and external environmental factors, shaping energy consumption in unique and dynamic ways.

The theoretical model developed in this study will therefore build upon these frameworks—primarily TPB, and the DNAs framework. By integrating these theories, the model will provide a more comprehensive foundation for analyzing the relationship between environmental awareness, behavior, and energy consumption in building settings.

Table 2.1 Previous research using TPB model

Author (Year)	Research methods	Object of study
Donald et al. (2014)[14]	Extended TPB model, Regression analysis	Commuters' transport mode
Gao et al. (2017) [12]	Extended TPB model, Questionnaire survey	Energy saving intentions in the workplace
Lizin et al. (2017) [15]	TPB model, Questionnaire survey, Path analysis	Battery pack recycling Intentions
Yadav et al. (2017) [16]	TPB model, Questionnaire survey	Consumers' Green Purchase Behavior
Wang et al. (2014) [17]	Extended TPB model, Questionnaire survey, Structural equation model	Energy-saving behavioral intention among
Ru et al. (2018) [18]	Extended TPB model, Questionnaire survey, Regression analysis	Individual's energy-saving intention
Botetzagias et al. (2015) [19]	Extended TPB model, Questionnaire survey, Structural equation model	Intention to recycle
Abrahamse et al. (2009) [20]	TPB model, Norm Activation Theory (NAT)	Energy saving behaviors
Wang et al. (2016) [21]	Extended TPB model, Questionnaire survey	Consumers' intention to adopt hybrid electric vehicles
Shi et al. (2016) [22]	TPB model, Norm Activation Theory (NAT), Questionnaire survey	Household PM2.5-reduction behavior
Kaiser et al. (2006) [23]	TPB model, Questionnaire survey	Ecological Behavior
Greaves et al. (2013) [24]	TPB model, Questionnaire survey	Environmental behavioral intentions in the workplace
Tong et al. (2023) [9]	Agent-based modelling (ABM), TPB model	Post-consumer recycling infrastructures

2.2.1. Extended TPB Model

(1) Attitude

Extensive research has shown that an individual’s positive attitude toward environmental protection is a critical driving force in promoting energy-saving behavior. This attitude is often reflected through people’s concern for environmental issues and their recognition of sustainable behaviors, with its significance widely acknowledged and supported in the fields of environmental psychology and behavioral economics[25].

According to existing literature, environmental attitude is commonly used as a metric to assess pro-environmental behavior. For instance, in studies on environmental intention, researchers measure individuals' views and attitudes toward environmental conservation to predict potential actions. These attitudes not only shape personal environmental intentions but also influence actual behavior. Previous research on pro-environmental behavior (such as attitudes, values, and beliefs) indicates that individuals with a positive attitude and environmentally friendly mindset are more likely to develop strong environmental intentions and convert them into practical actions [26]. For example, in their study, Ek and Söderholm Patrik found that residents' attitudes toward the environment significantly influenced their energy-saving behaviors. Their findings revealed that individuals with positive environmental attitudes are more inclined to adopt energy-saving measures in their daily lives, such as using energy-efficient lighting and water-saving equipment[27].

Moreover, research by Zografakis et al. further emphasizes the role of information and awareness. They argue that individuals exposed to more information on energy-saving practices and with a deeper understanding of climate change are more likely to purchase energy-saving products and participate in conservation activities. This highlights the critical role that education and information dissemination play in fostering environmentally friendly behavior[28]. Similarly, Wells et al. pointed out that attitudes specifically linked to certain environmental actions—such as attitudes toward recycling or the use of energy-saving appliances—can significantly influence behavior patterns at home and in the workplace. Their research underscores that changing individuals' attitudes toward specific environmental measures can substantially increase the implementation rates of eco-friendly practices [25].

Collectively, these studies stress that education, information provision, and attitude shifts can effectively motivate individuals and communities to adopt more energy-saving and environmentally friendly practices. Understanding and shaping environmental attitudes not only form a foundation for theoretical research but also provide a basis for designing practical environmental policies and behavioral intervention strategies. By further exploring and leveraging these relationships, we can promote the achievement of sustainable development goals more effectively.

(2) Subjective Norms

Subjective norms are a crucial concept for understanding and predicting human behavior, particularly in the fields of environmental and social psychology. Originally introduced by psychologists, this concept describes the influence of others' expectations on an individual's behavioral choices. Specifically, subjective norms refer to an individual's perception of whether significant others—such as peers and important figures within their social circle—believe they should engage in a particular behavior. This perceived social pressure can greatly impact an individual's decision-making process [29].

Ajzen, a prominent social psychologist, highlighted in his theory that an individual's behavior is primarily determined by two factors: personal behavioral intention and the level of approval received from others [11]. This suggests that even if an individual has a clear intention to act, if they perceive disapproval from significant others, they may be less likely to carry out the behavior. Numerous studies support the significant role of subjective norms in behavior adoption. For instance, Ek and Söderholm Patrik found that individuals who are more closely connected to social networks are more likely to have their environmental attitudes and behaviors influenced by those around them, especially in the context of adopting energy-saving practices. This indicates that attitudes and behaviors within one's social network can have a strong impact on individual energy-saving actions[27].

Similarly, Greaves et al. demonstrated that when individuals perceive stronger expectations from significant others regarding participation in certain behaviors, they are more likely to engage in those behaviors. This highlights the powerful social motivation behind individual actions, particularly concerning environmental and energy-saving behaviors [30].

Energy-saving models developed within social psychology further emphasize the role of social influence, communication, and reference groups (including friends, family, and other members of one's social network) in promoting and sustaining energy-saving behaviors. Effective communication and social support can significantly reinforce pro-environmental behaviors, helping individuals establish more enduring and consistent energy-saving habits. These models illustrate that social environment and group dynamics, in addition to personal cognition and attitudes, are essential drivers of pro-environmental behavioral change.In conclusion, subjective norms and social influence play a decisive role in the adoption of environmentally friendly and energy-saving behaviors. Understanding and leveraging these social psychological factors can not only aid in designing more effective behavioral intervention strategies but also facilitate the broader social diffusion and sustainability of environmental actions on a larger scale.

(3) Perceived Behavioral Control

Perceived behavioral control is an important concept in psychology that describes an individual's expectations and beliefs about their ability to perform a particular behavior. Introduced by Ajzen in the Theory of Planned Behavior (TPB), this concept has been widely applied in predicting and understanding various environmental behaviors. According to TPB, a person's behavioral intention is influenced not only by their attitude and subjective norms but also by their perceived behavioral control—namely, the extent to which they believe they can successfully execute the behavior.

In environmental behavior research, many scholars have identified perceived behavioral control as a key factor in predicting whether individuals will engage in eco-friendly actions. For example, if people believe they can easily engage in energy-saving actions, such as turning off unnecessary lights or adjusting air conditioning settings, they are more likely to exhibit these behaviors. However, perceived behavioral control can be constrained by various external factors, such as the availability of facilities, time limitations, and cost considerations. While these factors may be outside an individual's direct control, they can significantly impact one's willingness and capacity to participate in specific environmental behaviors.

In the study by Oikonomou et al.[31], it was found that higher levels of perceived behavioral control related to energy conservation correlated with a more positive response to energy-saving actions among residents. This suggests that increasing individuals' confidence in their ability to effectively conserve energy is an effective strategy for promoting energy-saving behaviors. The study recommended that educating and training residents to improve their energy-saving skills and knowledge could significantly enhance their sense of perceived behavioral control, thereby motivating them to engage more actively in conservation activities.

Similarly, Gao et al. noted that this phenomenon also applies to energy-saving behaviors in the workplace. In a work environment, if individuals feel at ease and are equipped with relevant knowledge and skills for energy conservation, they are more likely to develop a strong intention to save energy. This emphasizes the importance of creating a supportive and resource-rich environment in the workplace, such as providing access to energy-efficient equipment, organizing energy-saving training programs, and fostering a company culture that encourages conservation. These measures not only enhance employees' perceived behavioral control but also stimulate their intention to save energy, ultimately leading to actual energy-saving behaviors [12].

In conclusion, perceived behavioral control plays a crucial role in predicting and understanding environmental and energy-saving behaviors. By enhancing individuals' confidence and abilities and reducing external barriers, the likelihood of adopting eco-friendly and energy-saving actions can be significantly increased. Therefore, developing and implementing strategies aimed at strengthening perceived behavioral control is an essential direction for promoting changes in environmental and energy-saving behaviors.

(4) Personal Moral Norms

To more comprehensively assess the effectiveness of the Theory of Planned Behavior (TPB), many scholars have conducted in-depth research, attempting to extend the framework by introducing additional factors. Among these, personal moral norms have gained significant attention as an important extension factor. Personal moral norms refer to an individual's moral judgment about a specific behavior—namely, their belief that a behavior is right or wrong. These norms are often deeply rooted in an individual's system of moral beliefs and play a crucial role in their decision-making process [32].

In a study by Botetzagias et al., the research team explored the role of personal moral norms within the TPB framework and proposed that it serves as an important supplement to the standard TPB model[21]. They argued that personal moral norms not only provide a necessary addition to the TPB framework but also conceptually differ from the original TPB structure, offering independent explanatory power. By incorporating personal moral norms into the TPB model, Botetzagias et al. conducted a study on the intention to purchase green vehicles. The results indicated that personal moral norms significantly influenced people's purchase intentions, suggesting that personal moral norms can play a crucial role in predicting individual pro-environmental behaviors. Their findings support the inclusion of personal moral norms as a valuable factor in the extended TPB framework, providing empirical evidence for further theoretical development.

(5) Descriptive Norms

Descriptive norms refer to the tendency of individuals to believe they should behave in the same way when they observe significant people or members of their social group engaging in a particular behavior. These norms are based on individuals' observations and imitation of others' actions, reflecting the role of social influence in decision-making processes. Descriptive norms differ from subjective norms, which focus more on an individual's perception of others' expectations—specifically, what others think they should do or how they should act. These expectations are internalized perceptions that may shape an individual's behavioral choices.

Manning, in his meta-analysis, examined the role of descriptive norms within the Theory of Planned Behavior (TPB) in detail. He noted that incorporating descriptive norms into the TPB model significantly enhanced the model's explanatory power, particularly in predicting behavioral intentions. As a key variable, descriptive norms demonstrated strong predictive abilities in Manning's study, showing that they are not only an important addition to the TPB model but also effective in explaining how individuals form behavioral intentions in social contexts [33].

Further empirical research supports Manning's findings, showing a significant correlation between descriptive norms and behavioral intentions. This suggests that when individuals see important people or group members engaging in a certain behavior, this observation profoundly impacts their own intentions, making them more likely to mimic that behavior [34]. Including descriptive norms in behavior prediction models not only strengthens the model's explanatory capacity but also offers a more comprehensive perspective on the mechanisms behind the formation of behavioral intentions. This insight holds substantial theoretical and practical value for research in social psychology and behavioral science.

(6) Environmental Knowledge

It is commonly assumed that there is a positive correlation between knowledge and behavior—meaning that the more knowledge individuals possess, the more likely their behavior will align with that knowledge [35]. This assumption is particularly supported in the fields of environmental and energy studies. For example, Wang et al. confirmed a significant positive correlation between energy knowledge and personal attitudes, indicating that the more knowledge individuals have about energy, the more positive and proactive their attitudes toward energy use and conservation [17].

Additionally, Vicente-Molina et al. explored the crucial role of knowledge in environmental behavior [36]. They pointed out that for those who already have a positive environmental attitude, a lack of relevant knowledge often significantly hinders the transformation of that attitude into actual environmental behavior. This finding suggests that knowledge not only influences the formation of attitudes but is also essential in the implementation of behaviors. In other words, even if a person has a strong positive attitude toward environmental conservation, their likelihood of putting these ideals into practice in daily life is greatly reduced if they lack the necessary knowledge to guide specific actions.

Thus, the positive relationship between knowledge and behavior is evident not only in attitude formation but also in the actual execution of behaviors. Enhancing individuals' environmental and energy knowledge through education not only fosters positive attitudes but also increases the likelihood that these attitudes will translate into concrete actions, thereby promoting broader implementation of environmentally friendly behaviors. This insight provides essential guidance for policymakers and educators, highlighting that knowledge dissemination is an indispensable element in encouraging pro-environmental behavior.

(7) Extended TPB Model

Based on the assumptions of the Theory of Planned Behavior (TPB) and the literature discussed above, this study has developed an extended TPB model, as shown in Figure 2.3. In addition to the original three factors—attitude, subjective norms, and perceived behavioral control—this model incorporates three additional factors: personal moral norms, descriptive norms, and environmental knowledge.

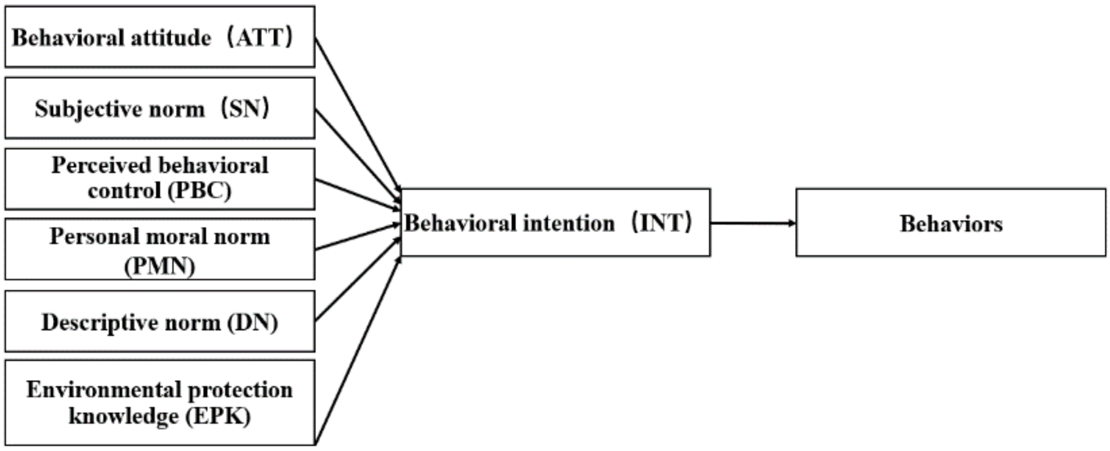

Figure 2.3 Extended TPB model.

2.2.2. DNAs Framework

The study by Hong et al. presents a critical viewpoint: relying solely on technological measures does not fully guarantee high performance in buildings[13]. In modern building design, construction, and operation, the influence of human behavior is often simplified or even overlooked. However, research shows that energy-conscious human behaviors play an essential role in improving indoor environmental quality and reducing building energy consumption. Energy awareness not only reduces energy use effectively but also enhances the overall performance of buildings.

Based on this understanding, Hong et al. proposed an innovative framework to systematically describe energy-related human behaviors in buildings, known as the DNAs (Drivers, Needs, Actions, Systems) Framework. This framework aims to capture and understand the influence of human behavior on building energy efficiency more comprehensively. The DNAs framework consists of four key components: drivers of energy behavior, occupant needs, actions, and interactive systems.

Drivers of Energy Behavior: This component examines the various internal and external factors that motivate individuals or groups to engage in specific energy behaviors, including personal motivation, cultural background, social norms, and policy incentives.

Occupant Needs: This section focuses on the needs and preferences of occupants when using building spaces, covering multiple dimensions such as comfort, safety, and convenience.

Actions: This component describes the actual behaviors that occupants take within building spaces,

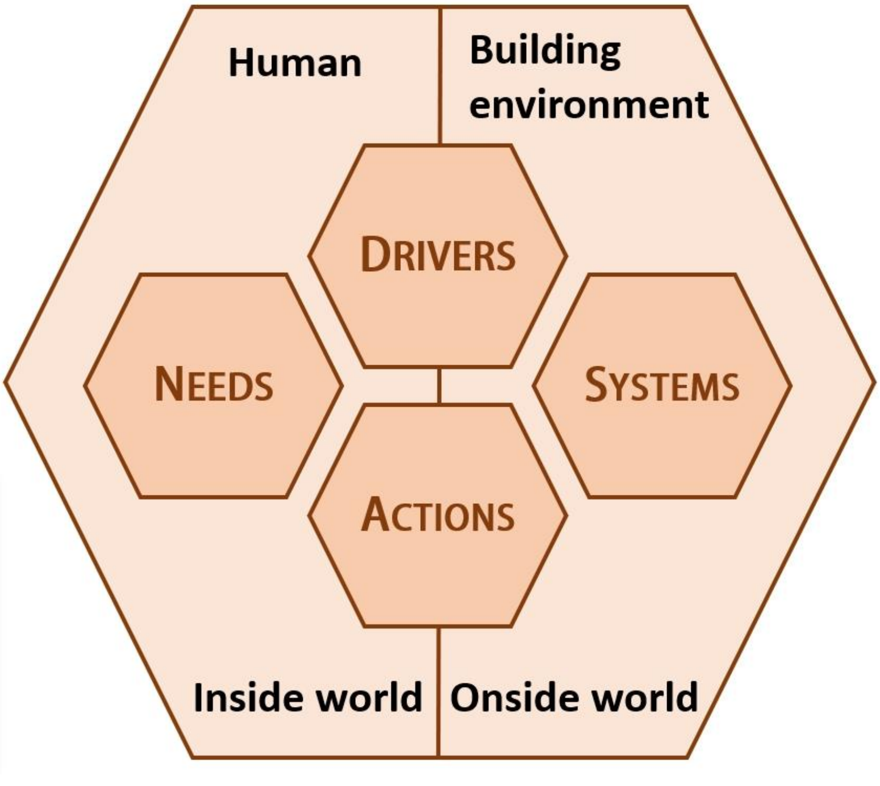

Figure 2.4 Four key components of the DNAS framework

such as adjusting temperature, turning lights on and off, and using appliances, which directly impact building energy consumption.

Interactive Systems: This section emphasizes the interaction between building systems and occupant behavior, such as how smart building systems respond to occupants' needs and adjust their operational states to achieve optimal energy efficiency.

As shown in Figure 2.5 and Figure 2.6, these are examples of window operation behavior and lighting control behavior described using the DNAs framework. Changes in building ventilation rates due to window-opening behavior have a significant impact on thermal comfort, indoor air quality (IAQ), and building energy consumption. Therefore, identifying the main drivers that prompt occupants to interact with windows to restore their personal comfort is crucial for better predicting building performance. An example of window-opening behavior in the DNAs format is as follows: Driver: Outdoor air temperature; Need: Thermal comfort; Action: Open the window; System: Window.

In the control of lighting behavior, occupants can interact with building lighting systems by manually switching on, off, or dimming the lights to maintain visual comfort. However, this interaction is driven not only by physical and visual comfort requirements but also by non-physical factors, such as social dynamics, organizational policy, individual habits, and even a sense of "luminosity

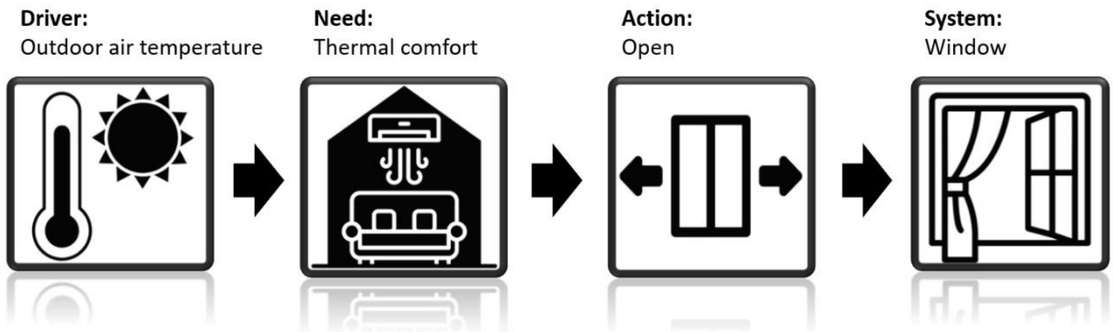

Figure 2.5 Window opening and closing adaptation mechanisms described according to the DNAS framework

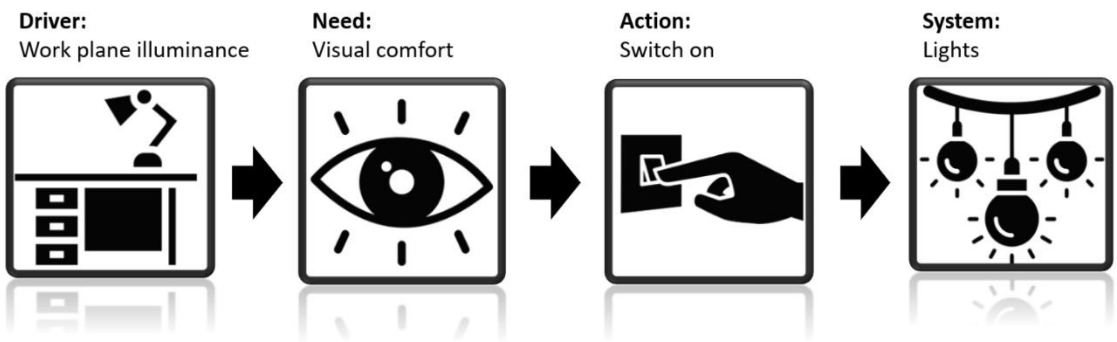

Figure 2.6 Lighting system control adaptation mechanisms described according to the DNAS framework

ownership." Clearly, a more energy-conscious use of lighting systems by building occupants can provide a low-impact method to reduce global electricity consumption, offering a highly replicable source of potential energy savings. An example of turning on the lights when indoor illuminance is too low in the DNAs format is as follows: Driver: Work plane illuminance; Need: Visual comfort; Action: Switch on; System: Lights.

Hong et al. highlight that the DNAs framework has broad applications, including building energy modeling and simulation, building design, energy benchmarking and performance rating, as well as standard setting and policy decision-making [37]. Through this framework, energy efficiency analysis can become more precise, enhancing building energy performance at various stages of the building lifecycle, such as design, operation, management, and retrofitting.

Ultimately, the DNAs framework aims to improve building energy efficiency through more accurate behavioral models, achieving advancements not only on a technical level but also in understanding and optimizing human behavior. This framework provides building professionals with a systematic tool that better incorporates the complexity of human behavior in energy efficiency optimization processes, leading to more sustainable and efficient building environments.

2.3. Theoretical Model

Building on Sections 2.1 and 2.2, this study further develops and constructs a theoretical model as shown in Figure 2.7. This model integrates the extended TPB with the DNAs framework, aiming to provide a more comprehensive and multidimensional tool for analyzing the impact of human behavior on building energy consumption.

Specifically, the extended TPB theory introduces additional variables to the original model to better capture the complexity of individual decision-making, particularly in contexts related to building energy efficiency. By incorporating factors such as personal moral norms and descriptive norms, the model's explanatory power is enhanced. At the same time, the DNAs framework adds a detailed classification of energy-related human behaviors to the model, with a particular focus on behavioral drivers, occupant needs, actions, and interactions with building systems. This integrated theoretical model not only explains individual behavioral intentions but also simulates how these behaviors impact building energy consumption.

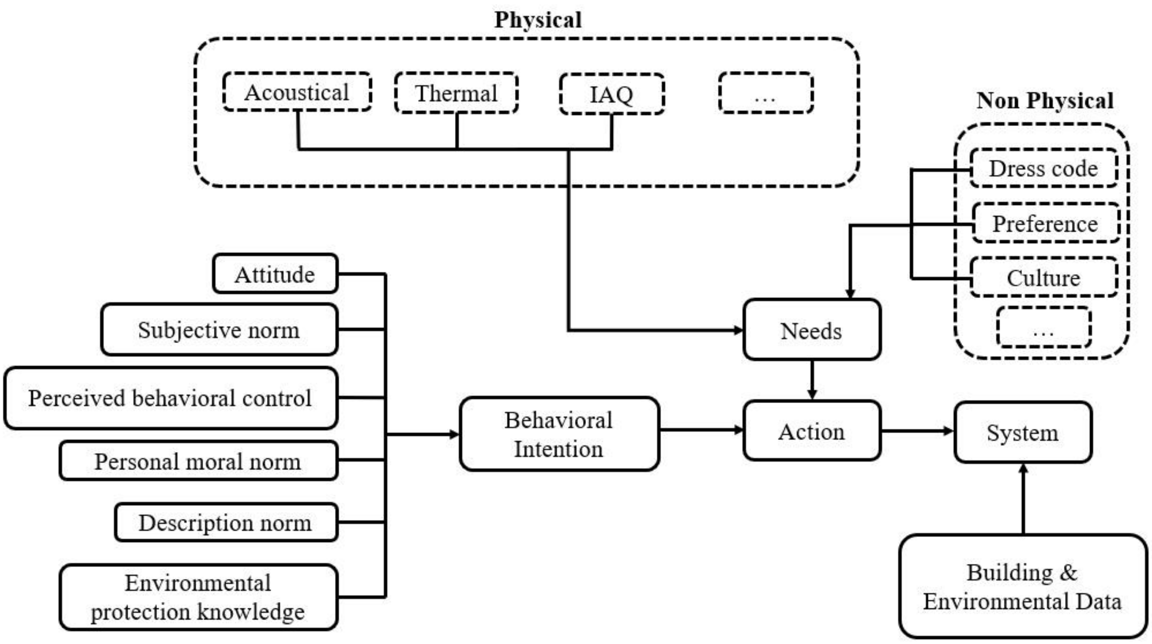

Figure 2.7 Conceptual model of this study

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Chapter-3

Study on Environmental Psychology and Energy Consumption Behavior

3.1. Research Hypotheses
3.2. Questionnaire Design
3.3. Validation Experiment
3.4. Data Collection for the Questionnaire
3.5. Questionnaire Results
3.6. Discussion
3.7. Conclusion

Chapter 3. Study on Environmental Psychology and Energy Consumption Behavior

This study seeks to explore the relationship between energy-saving behaviors and environmental awareness by developing a mathematical model based on data gathered through extensive online surveys. According to the theoretical model established in Chapter 2, human behavior is influenced by internal environmental awareness as well as external environmental factors, such as building characteristics and cultural context. Since data for the awareness-related components of the extended TPB model cannot be directly measured, they are collected through questionnaires. Therefore, this portion of the model serves as the theoretical basis for this section, guiding the questionnaire design to obtain the necessary data.

3.1. Research Hypotheses

To explore the relationship between environmental psychology and energy consumption behavior, this study proposes the following hypotheses based on the TPB assumptions and the literature discussed in **Chapter 2**:

Hypothesis 1. Attitude positively influences individuals' intention to save energy in office buildings.

Hypothesis 2. Subjective norm positively influences individuals' intention to save energy in office buildings.

Hypothesis 3. Perceived behavioral control positively influences individuals' intention to save energy in office buildings.

Hypothesis 4. Personal moral norm influences individuals' intention to save energy positively in office buildings.

Hypothesis 5. In office buildings, people's intention to engage in energy-saving behavior is positively influenced by their personal moral norm.

Hypothesis 6. In office buildings, people's intention to engage in energy-saving behavior is positively influenced by their environmental protection knowledge.

Hypothesis 7. Intention to save energy positively influences people's energy-saving behaviors.

3.2. Questionnaire Design

The questionnaire was meticulously designed based on the theoretical model and hypotheses outlined in Chapter 2 of this study. It aims to examine various aspects of energy-saving psychology and behaviors within office environments. The questionnaire includes items that assess participants' attitudes, subjective norms, perceived behavioral control, personal moral norms, descriptive norms, environmental knowledge, as well as intentions related to energy-saving behaviors and actual energy-saving behaviors. In addition to these psychological and behavioral components, the questionnaire also includes demographic items such as age, gender, and other relevant background information.

Since the questionnaire referenced English literature, it was initially translated from English to Japanese. The distribution of the questionnaire occurred in multiple rounds and through various methods to ensure clarity and cultural relevance. In the initial rounds, the survey was distributed on a small scale within campus research labs, which closely resemble office environments. Feedback on the language and phrasing was collected through brief interviews with respondents, including professors, students, and office workers. Based on their feedback, a revised version of the questionnaire was prepared in Japanese to better fit the nuances of the Japanese context.

In subsequent rounds, to gather a larger sample size and increase the reach, the study used an online survey platform to collect responses. To ensure that respondents were indeed working in office environments, a preliminary screening step was added before the main survey. This screening was designed to confirm the primary work environment of respondents, with a particular focus on verifying whether they worked in office buildings.

The screening question asked, "Which of the following best describes your work environment?" and provided four options: a. I work in the office almost every day; b. Although I also work from home or work remotely, my office hours are the longest; c. I work from home most of the time; d. I primarily work outside the office. Respondents who selected options (a) or (b) were chosen to participate in the main survey. This approach ensured that the survey focused on individuals whose primary work environment is within office buildings in Japan, aligning with the study's objectives and target demographic.

This structured, multi-phase distribution process not only allowed for careful refinement of the survey language but also ensured that the data collected accurately represented the office-based work environments necessary for the research goals.

Most items in the questionnaire were measured using a Likert scale ranging from 1 to 5. For items related to environmental psychology, a scale of 1 (strongly disagree) to 5 (strongly agree) was used. For items assessing behavioral intention, responses were measured on a scale from 1 (almost never) to 5 (always). The questionnaire items were adapted from several research papers, including works by Ru et al. [1], Gao et al. [2], and other relevant sources. Each item was carefully selected and modified to align with the objectives of this study.

The constructs and measurement items are detailed in Table 3.1. Because the questionnaire referenced English literature, it was initially translated from English to Japanese before the first validation experiment. Based on the feedback received, the language of the second version was refined to better suit the Japanese context. The items in Table 3.1 represent the Japanese-adapted version, translated back into English, and therefore may differ slightly from the original English references to ensure cultural and contextual relevance for Japanese respondents.

This adaptation process ensured that the questionnaire was culturally appropriate while maintaining the integrity and comparability of the measurement items, making the survey results more reliable and relevant for the study's focus on Japanese office environments.

Table 3.1 Constructs and measurement items in questionnaire

	Items	Source
Attitude (ATT)	ATT1. The continuously increasing energy demand is a serious issue for society. ATT2. I also bear some responsibility for issues such as global warming and the depletion of fossil fuels. ATT3. I believe that energy conservation in daily life is useful for environmental preservation.	Adapted from Ru et al. [1], Gao et al. [2]
Subjective Norm (SN)	SN1. The managers (executives, officers, etc.) of your company are considering the request to turn off the office lighting and air conditioning when not in use. SN2. People who are significant in my life think that I should conserve energy wherever possible. SN3. I value the opinion of people who are significant in my life when it comes to making decision on energy conservation.	Adapted from Ru et al [1], Lee and Tanusia [3]
Perceived Behavioral Control (PBC)	PBC1. I have knowledge and know-how to implement energy-saving practices in my daily life. PBC2. Convenience without compromising energy efficiency is also an important factor for me when promoting energy conservation. PBC3. Whether or not saving energy is completely up to me.	Adapted from Ru et al. [1], Gao et al. [2]
Personal Moral Norm (PMN)	PMN1. There is a moral responsibility to engage in energy-saving practices in everyday life. PMN2. I use electricity, gas, and other forms of energy in my daily life, and I feel that my actions have an impact on climate change. PMN3. Save energy in my daily life is depending on my own moral obligation.	Adapted from Ru et al. [1], Gao et al. [2], Wang et al. [4]
Descriptive Norm (DN)	DN1. A number of employees in my company I know have participated in energy saving behavior. DN2. Others who are important to me have participated in energy saving behavior. DN3. My manager and the high-level management team have	Adapted from Ru et al. [1], Gao et al. [2]

	participated in energy saving behavior.	
Environmental Protection Knowledge (EPK)	EPK1. Greenhouse gases have the effect of suppressing the thermal radiation emitted by the Earth. EPK2. The increase in greenhouse gases in the atmosphere over the past 150 years is primarily attributed to human activities. EPK3. I know much about the energy-saving tips of daily life.	Adapted from Wang et al. [4], Park and Kwon [5]
Behavioral Intention (INT)	INT1. I will pay more attention and accumulate energy-saving knowledge and tips in the future. INT2. I am going to behave pro-environmentally in the coming month to reduce my impact on the environment (e.g. by turning off the computer, printing less, using a mug etc.) INT3. I intend to engage in energy-saving activities in the future.	Adapted from Park and Kwon [5], Lee and Tanusia [3]
Behavior	B1. Set office automation equipment (computers, monitors, printers, etc.) to ener-gy-saving mode. B2. To save energy, the air conditioner is adjusted upwards during heating and downwards during cooling.	Adapted from Lee and Tanusia [3], Kang et al. [6]
Options:5.Strongly agree;4.Somewhat agree;3.Neither agree nor disagree;2.Somewhat disagree;1.Strongly disagree		

3.3. Validation Experiment

To ensure the accuracy of the study’s findings and minimize potential errors, a two-stage research process was designed. First, a preliminary questionnaire survey was conducted in an office building to gather environmental psychology data on employees' daily behaviors. Following this, a validation experiment was carried out in the same office building to test the reliability of the self-reported data from the survey. In this experiment, employees participating in the study were asked to record their actual energy consumption behaviors, allowing for a comparison between the questionnaire data and observed behaviors to assess whether there were any significant discrepancies.

This validation helps to determine the trustworthiness of the questionnaire results. If the observed behaviors show trends similar to those reported in the questionnaire, it indicates that the questionnaire data are highly reliable and can serve as a solid basis for subsequent research. Conversely, if significant differences are found between the two, it may be necessary to reconsider the questionnaire design or survey method to ensure the collection of more accurate data.

Once the reliability of the questionnaire data is confirmed, the study moves into the second phase, which involves a large-scale distribution of the questionnaire and extensive data analysis. In this phase, the survey is distributed to more office employees, and a substantial amount of data is collected for in-depth analysis. This approach aims to gain a comprehensive understanding of the behavior patterns of office employees and explore the potential factors influencing these behaviors.

In summary, this two-stage research design not only validates the reliability of the data but also provides a strong foundation for further analysis and understanding of office employees' behaviors. The methodological rigor of this approach is essential for reaching effective and applicable research conclusions.

3.3.1. Introduction to the Validation Experiment

To accurately assess the consistency between the actual environmental energy-saving behaviors of office employees and their stated intentions in the questionnaire, a validation experiment was designed. This experiment was conducted in November 2022 in two office buildings of the same company located in Fukuoka and Osaka, Japan. Before the experiment, a detailed questionnaire was distributed to participating employees to gain an initial understanding of their environmental awareness and energy-saving behavior intentions. A total of 98 employees participated in the survey. The questionnaire included multiple items measuring energy-saving behavioral intentions, such as turning off lights and adjusting air conditioning temperatures. Each behavior was rated on a five-point scale ranging from 1 (never perform this behavior) to 5 (always perform this behavior), as shown in Table 3.1. This design aimed to capture participants' self-assessments of various energy-saving behaviors, providing baseline data for subsequent behavioral observations.

Following the completion of the questionnaire, the experimental phase began. Participants were asked to use a specially developed mobile application that provided reminders for energy-saving actions. The app included a specific "Energy-Saving Action Button," which participants were required to press each time they performed an energy-saving action. This process allowed us to record the daily frequency of energy-saving actions for each participant, as illustrated in Figure 3.1.

The mobile app was originally developed for other studies aimed at encouraging energy-saving behaviors through app-based interventions. Since the data it collected aligned well with the objectives of this study, its results were utilized to validate the questionnaire. The mobile app provided prompts and incentives, encouraging participants to record their energy-saving behaviors by pressing the designated button within the app daily, as shown in Figure 2. In this experiment, material rewards, such as stationery and towels, were offered as incentives. However, participants were informed about these rewards only after the experiment was completed. While the phrase "Something good might happen if you win the bingo game..." may have influenced participants' behavior, the delayed notification of rewards is believed to have minimized its impact.

After the experiment concluded, the data collected through the mobile app was compared in detail with the initial questionnaire data. The primary objective of this analysis was to examine the degree of discrepancy between the energy-saving intentions expressed in the questionnaire and the actual energy-saving behaviors recorded by the app. Special attention was given to participants who reported "always exhibiting energy-saving behaviors" in the questionnaire, analyzing whether they maintained a high frequency of these behaviors in real life. Similarly, participants who reported lower intentions in the questionnaire were analyzed to see if they demonstrated correspondingly lower behavior frequencies.

Through this approach, we aimed to reveal the consistency and discrepancies between the questionnaire data and actual behavior data, thereby evaluating the validity of our questionnaire design and energy-saving behavior monitoring methods. This analysis not only strengthens the methodological foundation for future research but also enhances our understanding of how energy-saving intentions translate into actual behaviors in office environments. Furthermore, these insights will support the development of more effective energy-saving policies and interventions.

Figure 3.1 Schematic diagram of the verification experiment mobile

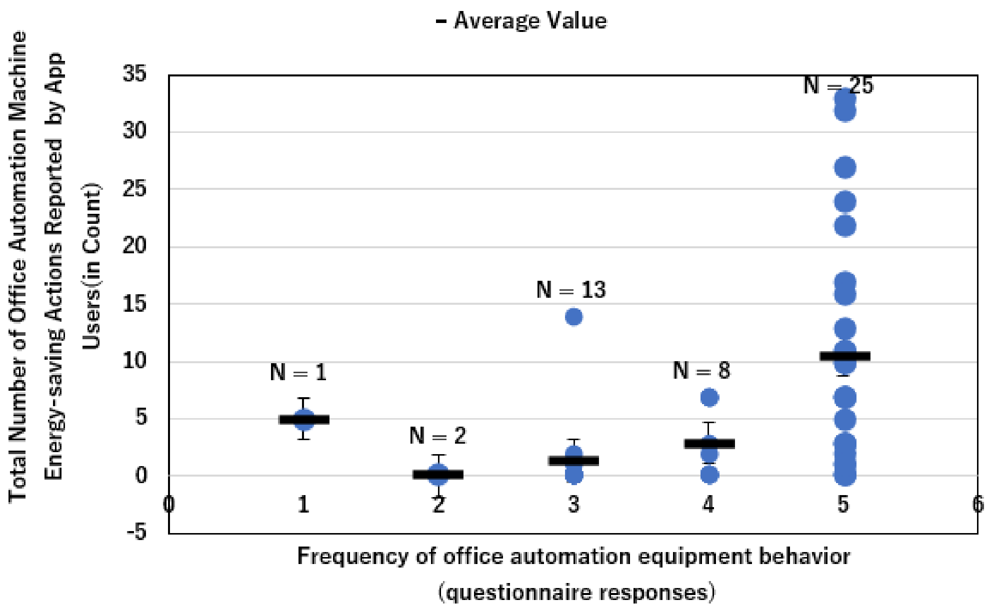
3.3.2. Validation Experiment Results

During data processing and analysis, we first focused on energy-saving behavioral intentions and environmental awareness related to the use of various appliances, as reported in the questionnaire survey. Through initial data screening and correlation analysis, we identified two behaviors that were significantly associated with energy consumption and demonstrated the highest correlation and potential for energy savings. Specifically, these behaviors pertain to air conditioning use and energy efficiency management of office automation equipment, corresponding to the questionnaire items: "Set office automation equipment (computers, monitors, printers, etc.) to energy-saving mode" and "To save energy, the air conditioner is adjusted upwards during heating and downwards during cooling."

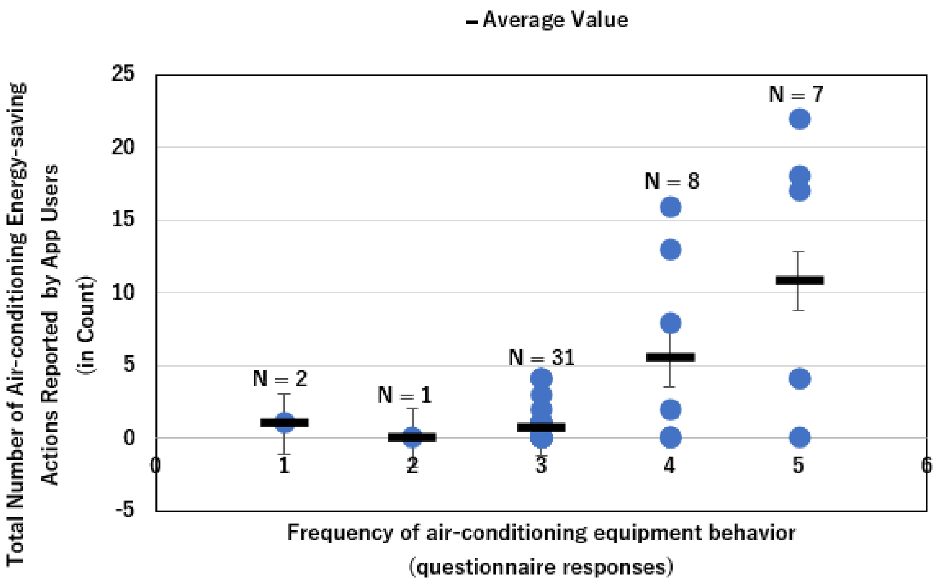
Since the participants in the questionnaire survey and those in the mobile app experiment were not identical, and given some invalid data from the experiment, we conducted thorough data cleaning to ensure the accuracy and validity of further analyses. During this process, we excluded erroneous records, such as incorrect timestamps and duplicate entries. Additionally, we removed data from participants who completed the questionnaire but failed to effectively record behaviors in the mobile app experiment.

After this series of screening and validation steps, we finalized 49 valid samples for in-depth analysis. These samples included participants who provided complete questionnaire data alongside valid behavioral records in the app. This selected sample allows us to more accurately evaluate the relationship between energy-saving behavioral intentions and actual energy-saving behaviors, specifically focusing on the behaviors related to air conditioning use and energy-saving settings for office automation equipment.

To further explore the relationship between participants' self-reported energy-saving intentions in the questionnaire and the actual number of energy-saving actions recorded via the mobile app, we created a scatter plot, shown in Figure 3.2. In this plot, each data point represents a participant, providing a clear visual distribution of the data and potential trends. On the x-axis, we display the level of energy-saving behavioral intention as reported in the questionnaire, based on responses to intention-related items rated from 1 (never perform energy-saving behaviors) to 5 (always perform energy-saving behaviors). The y-axis represents the frequency of energy-saving actions recorded by participants in the mobile app.



a) Scatter plot showing the relationship analysis about office automation machine



b) Scatter plot showing the relationship analysis about air-conditioning

Figure 3.2 Relationship between self-reported energy-saving behaviors (from questionnaire) and reported energy-saving behaviors

The scatter plot reveals a noticeable positive trend. While participants at intention level "1" were relatively few, potentially impacting data accuracy, there is a gradual increase in average values from intention level “2” to “5,” indicating a clear positive trend. This suggests that as participants’ reported level of energy-saving intention increases, the frequency of energy-saving actions they recorded in the app also rises.

To further validate the statistical significance of this trend and assess the correlation between energy-saving behavioral intentions and actual energy-saving actions, we conducted a correlation analysis. By calculating the correlation coefficient, we quantified the strength of association between these two variables. Preliminary analysis supports our hypothesis: there is a significant positive correlation between higher levels of energy-saving intention and the frequency of actual energy-saving actions.

In this study, data were collected on a five-point scale, with questionnaire responses ranging from 1 to 5. Since these data are ordinal rather than continuous, traditional Pearson correlation analysis may not be suitable, as Pearson's method requires continuous and normally distributed data. Therefore, to accurately handle this ordinal data, we used Spearman's rank correlation analysis, a non-parametric method ideal for evaluating the correlation between ranked variables, especially when dealing with ordinal data.

According to our analysis, shown in Table 3.2, the results reveal a significant and robust correlation between the studied variables. Specifically, there is a strong positive correlation between energy-saving intention related to air conditioning use and the frequency of energy-saving actions recorded in the app, with a Spearman correlation coefficient of 0.608. This indicates that participants who reported higher energy-saving intentions in the questionnaire also tended to record more frequent energy-saving actions in real life through the app. Additionally, we found a moderate positive correlation between energy-saving intention related to office automation equipment and the frequency of energy-saving actions recorded in the app, with a correlation coefficient of 0.489. Although this correlation is slightly lower than that for air conditioning-related behaviors, it still shows a notable positive relationship, suggesting that an increase in energy-saving awareness related to office automation equipment can similarly promote the execution of energy-saving behaviors.

The statistical significance of these results is confirmed by p-values of less than 0.01, indicating that the observed correlations are highly unlikely to be due to random variation. This finding provides strong support for our research hypothesis: in office environments, enhancing energy-saving intentions can effectively increase the frequency of actual energy-saving behaviors.

Overall, these findings not only reinforce the positive link between energy-saving behavioral intentions and actual energy-saving actions but also provide data support for designing future interventions. They suggest that by strengthening energy-saving awareness and intentions, the actual execution of energy-saving behaviors can be significantly increased, thereby contributing to improved overall energy efficiency.

Table 3.2 Spearman correlation analysis: energy-saving behavioral-intentions in the questionnaire and reported energy-saving behaviors

	B1 (from questionnaire) and numbers of B2 reported by app	B2 (from questionnaire) and numbers of B2 reported by app
Corr. Coef.	.608**	.489**
N	49	49

Note. B1 = Energy-saving behavior about Air-conditioning; B2 = Energy-saving behavior about office automation machine
**p < .01

In this study, the analysis results reveal a notable trend: there is a significant positive correlation between participants' expressed energy-saving intentions in the questionnaire and their actual energy-saving behaviors recorded through the mobile app. This finding holds important implications for understanding the motivations behind energy-saving behaviors and their actual performance.

It is important to note, however, that while these energy-saving behavior data were collected via a mobile application, there may be certain limitations. For example, the data may not fully capture all participants' energy-saving actions, as they rely on participants actively recording each instance. Some energy-saving behaviors may have gone unrecorded, particularly those considered habitual or less noticeable. Additionally, the usage environment and user interface of the mobile app may influence participants' frequency and motivation for recording their actions. Despite these potential data biases, we tend to believe that individuals who record energy-saving behaviors in the app are likely to be actively engaged in such actions. This assumption is based on a logical inference: participants willing to take the time to record specific behaviors are generally more aware of and attentive to these behaviors and are thus more likely to practice them in their daily lives.

Based on this analysis and reasoning, we plan to expand future research by utilizing online survey tools to collect broader data and examine intention items more closely linked to actual behaviors. Such online surveys not only provide more diverse data but also help us assess and understand participants' behavioral intentions more accurately. In doing so, we aim to better represent and predict actual energy-saving behaviors, offering stronger data support for developing related energy-saving policies and interventions.

In summary, while there are limitations to behavior data collected through mobile apps, they remain a valuable tool for assessing and understanding the relationship between energy-saving intentions and behaviors. By improving data collection methods and expanding the scope of our research, we can further deepen our understanding of the motivations and patterns of energy-saving behaviors, providing a scientific basis for promoting more effective energy-saving practices.

3.4. Data Collection for the Questionnaire

To enhance the effectiveness of the questionnaire survey and improve participant experience, this study utilized the professional online survey platform Surveroid [7]. The platform, with its well-designed user interface, ensured a smooth and user-friendly experience during the March 2023 survey, thereby increasing participant response rates. To ensure the reliability of the survey and the authenticity of the data, significant effort was invested in the design phase of the questionnaire to make sure that all questions included clear instructions, guiding participants to correctly interpret each question's intent. Additionally, to protect participant privacy and data security, all responses were collected anonymously, which helped build trust and encouraged participants to provide honest and accurate answers.

After data collection and initial screening, a rigorous data cleaning process was conducted to exclude invalid or incomplete responses, resulting in a final sample of 1,069 individuals working in office buildings in Japan. This sample size was selected based on statistical considerations, aiming to ensure sufficient statistical power for the study's results, while also providing a sample that is representative of the target population. Detailed demographic information about the sample, including age, gender, occupation, and other basic details, is presented in Table 3.3.

Table 3.3 Profile of the respondents participating in the survey

Characteristics		Frequency	Percent(%)
Sex	Male	537	50
	Female	532	50
Age group	20~29	93	9
	30~39	231	22
	40~49	308	29
	50~59	265	25
	60~	172	16
Region	Hokkaido	52	5
	Tohoku region	53	5
	Kanto region	429	40
	Chubu region	145	14
	Kinki region	223	21
	Chugoku region	60	6
	Shikoku region	32	3
	Kyushu region	75	7
Job	Civil servant	54	5
	Manager/Executive	31	3
	Company employee(administrative)	306	29
	Company employee(technical)	152	14
	Company employee(other)	212	20
	Self-employed	40	4
	Freelancer	14	1
	Part-time/Temporary worker	215	20
	Others	45	4
Total		1069	100

Regarding demographic variables, correlation analysis indicated a weak relationship between these variables and environmental psychology. To further explore the impact of demographic variables such as gender, occupation, region, and age on environmental psychology, independent t-tests (Table 3.4) and one-way ANOVA (Table 3.5) were conducted. The results showed no significant differences in environmental psychology concerning gender, occupation, or region ($P > 0.05$), suggesting these factors do not significantly influence individuals' environmental awareness, attitudes, or behavioral intentions. However, age was found to have a significant effect on several environmental psychology factors ($P < 0.05$). Older groups tended to exhibit higher levels of environmental awareness and energy-saving intentions, particularly regarding environmental attitudes, energy-saving intentions, and behavior habits.

Although this study considered multiple demographic variables, gender, occupation, and region did not demonstrate statistically significant differences, while age had a relatively more pronounced effect on environmental psychology. As a result, the study does not discuss other demographic variables in further detail. Additionally, the primary aim of this research is to explore the relationship between environmental awareness, behavioral intention, and actual behavior. Therefore, although age was the only variable showing a significant impact, it is treated as a background variable rather than a primary focus.

Future research could delve deeper into the variations in environmental awareness across different age groups, especially examining the potential causal relationship between age and environmental behaviors. The correlation analysis conducted in this study found a weak association between these

Table 3.4 Independent samples T-test results for gender and environmental psychology

	ATT	SN	PBC	PMN	DN	EPK	INT	B1	B2
F-value	0.198	0.004**	0.255	0.414	2.276	4.178	0.611	0.095	0.018*
p-value	0.656	0.950	0.614	0.520	0.132	0.041	0.434	0.758	0.892
Note:*. Correlation is significant at the 0.05 level.; **. Correlation is significant at the 0.01 level.									

Table 3.5 ANOVA results for other demographic variables and environmental psychology

		ATT	SN	PBC	PMN	DN	EPK	INT	B1	B2
Region	F-value	1.589	1.532	1.240	1.775	1.178	2.748	1.681	0.850	1.613
	p-value	0.135	0.152	0.277	0.089	0.312	0.008**	0.110	0.545	0.128
Job	F-value	1.583	1.620	1.533	1.490	1.652	1.335	1.386	1.478	0.578
	p-value	0.115	0.105	0.131	0.147	0.096	0.214	0.189	0.151	0.816
Age group	F-value	16.945	13.210	12.022	12.844	7.417	11.662	14.479	4.058	2.939
	p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.003**	0.020**
Note: *. Correlation is significant at the 0.05 level.; **. Correlation is significant at the 0.01 level.; ***. Correlation is significant at the 0.001 level										

demographic variables and environmental psychology. Based on this finding, we decided to disregard the impact of demographic variables in further analysis, allowing us to concentrate more on investigating the influence of environmental psychology factors on energy-saving behaviors.

3.5. Questionnaire Results

3.5.1. Validation of the Extended TPB Measurement Model

In this study, to conduct an in-depth analysis and validate the proposed theoretical model, we utilized SPSS 23.0 and Amos 23.0 for all statistical tests. These software tools are widely used in social science research and are particularly suited for complex statistical analyses, such as Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA).

First, to ensure the validity and reliability of our measurement model, we conducted Confirmatory Factor Analysis (CFA). This step is crucial, as it helps us confirm whether the constructed measurement tools accurately represent the research variables. In CFA, we focused on model fit indices such as Chi-square statistic, Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and Root Mean Square Error of Approximation (RMSEA) to evaluate the degree of fit between the model and the actual data.

Next, to assess construct reliability, we calculated Composite Reliability (CR) and Cronbach's alpha values. These indices are commonly used to evaluate the internal consistency of questionnaires or measurement tools. A CR value above 0.7 is generally considered acceptable, indicating good internal consistency. Similarly, Cronbach's alpha is a standard measure of reliability for questionnaires or measurement tools, and values above 0.7 confirm high reliability [8].

In addition, we evaluated convergent validity of the constructs by analyzing Average Variance Extracted (AVE) and the factor loadings of individual items. AVE provides a quantitative measure of how well a set of items represents their underlying construct, with values above 0.5 generally indicating good convergent validity. Likewise, each item's factor loading should ideally be significant and above 0.5 to ensure that each item effectively reflects its respective construct [9].

After thoroughly validating the measurement model, we further applied Structural Equation Modeling (SEM) to test the six hypotheses proposed in this study. SEM is a powerful statistical technique that simultaneously considers the relationships among multiple dependent and independent variables, allowing us to precisely analyze both direct and indirect effects between variables. This analysis is the core of this study, as it not only helps us understand the relationships between variables but also validates the overall validity of the theoretical model [10].

Through this detailed series of statistical analyses, this study aims to ensure that the proposed theoretical model and related hypotheses are thoroughly validated, thereby providing deep insights and reliable conclusions regarding the research topic.

(1) Evaluation of the Measurement Model

This study conducted CFA (Confirmatory Factor Analysis), as shown in Figure 3.3, to assess the reliability and validity of the model. The CFA results indicate an acceptable fit between the measurement model and the dataset. The fit indices for the model are as follows: Chi-square to degrees of freedom ratio (χ^2/df) is 3.972, Comparative Fit Index (CFI) is 0.973, Goodness of Fit Index (GFI) is 0.953, Normed Fit Index (NFI) is 0.965, Incremental Fit Index (IFI) is 0.974, and Root Mean Square Error of Approximation (RMSEA) is 0.053.

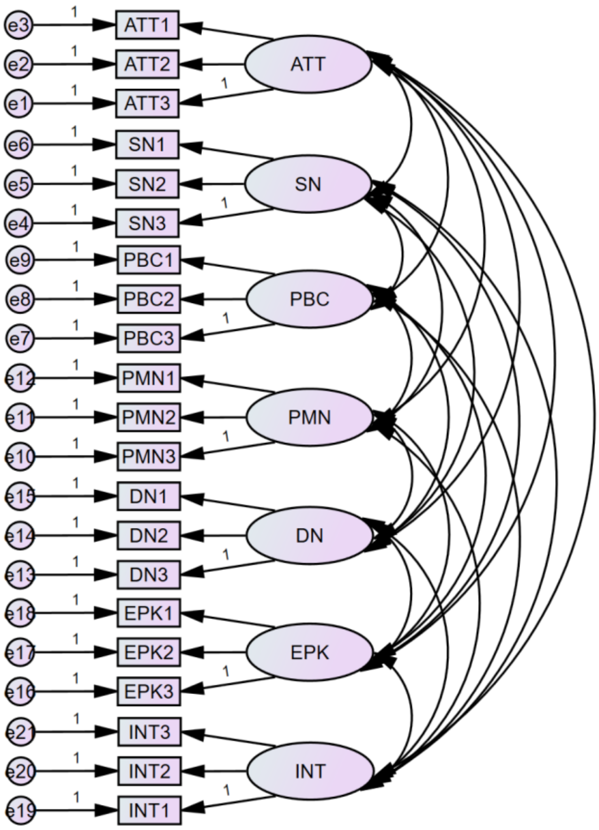


Figure 3.3 CFA (Confirmatory Factor Analysis) Structural Diagram

As shown in Table 3.4, the Cronbach's alpha coefficients for the scales used in this study are all above 0.8, exceeding the recommended threshold of 0.70, indicating good internal consistency among items. This demonstrates that the questionnaire items reliably measure the same underlying constructs. The Composite Reliability (CR) values for all latent constructs in the model are consistently above 0.8, also exceeding the 0.70 threshold, indicating good internal consistency and reliability. This suggests that the observed variables reliably measure their respective constructs [11].

The standardized factor loadings for the observed variables in the model consistently remain around

0.8, indicating a strong and significant relationship between the measurement items and their respective latent constructs [8]. The Average Variance Extracted (AVE) for each construct in the model was calculated, with all values exceeding 0.5 [9]. This demonstrates good convergent validity, meaning that a substantial portion of the variance in the observed variables is explained by their respective latent constructs. Overall, these findings strongly support the robustness and validity of the measurement model used to assess the relationship between environmental psychology and energy-saving behavioral intentions. The high factor loadings, satisfactory internal consistency, and reliable measurement attributes for these constructs validate the questionnaire-based analysis.

Additionally, discriminant validity was tested by comparing the Average Variance Extracted (AVE) values with the shared variance among the constructs. Table 3.7 displays the bolded diagonal values, representing the square root of the AVE for each construct. The table also shows the correlations between different constructs. Notably, the correlations between constructs in the same row and column are lower than the square root of their respective AVE values, indicating relatively low shared variance and supporting discriminant validity [12]. Thus, based on these results, it can be concluded that the measurement model has sufficient reliability, convergent validity, and discriminant validity.

Table 3.6 Results of confirmatory factor analysis.

Constructs	Items	Standardized factor Loading	Cronbach's Alpha	CR	AVE
Attitude	ATT1	0.814	0.851	0.851	0.656
	ATT2	0.821			
	ATT3	0.795			
Subjective norm	SN1	0.814	0.860	0.860	0.672
	SN2	0.820			
	SN3	0.825			
Perceived behavioral control	PBC1	0.829	0.873	0.872	0.695
	PBC2	0.852			
	PBC3	0.820			
Personal moral norm	PMN1	0.689	0.877	0.855	0.665
	PMN2	0.876			
	PMN3	0.868			
Descriptive norm	DN1	0.931	0.951	0.951	0.866
	DN2	0.932			
	DN3	0.929			
Environmental protection knowledge	EPK1	0.815	0.855	0.856	0.664
	EPK2	0.811			
	EPK3	0.819			
Behavioral intention	INT1	0.846	0.871	0.871	0.693
	INT2	0.827			
	INT3	0.824			

Table 3.7 Descriptive statistics and correlations (n = 1069)

Constructs	Means	SD	ATT	SN	PBC	EPK	DN	PMN	INT
ATT	3.389	1.142	**0.810**						
SN	3.340	1.170	0.546**	**0.820**					
PBC	3.418	1.186	0.586**	0.591**	**0.834**				
EPK	3.343	1.147	0.545**	0.571**	0.617**	**0.815**			
DN	3.394	1.275	0.569**	0.581**	0.582**	0.582**	**0.931**		
PMN	3.389	1.195	0.576**	0.599**	0.612**	0.606**	0.949**	**0.815**	
INT	3.345	1.173	0.573**	0.517**	0.579**	0.565**	0.556**	0.573**	**0.832**
B1			0.392**	0.390**	0.420**	0.380**	0.452**	0.443**	0.420**
B2			0.411**	0.411**	0.440**	0.393**	0.445**	0.448**	0.397**

Note. Diagonal values in bold are the square root of the average variance extracted (AVE).
**. Correlation is significant at the 0.01 level (2-tailed).

(2) Structural Model and Hypothesis Testing Results

In this study, since air conditioning and office automation equipment behaviors were validated during the experimental phase, the primary focus is on analyzing the environmental psychological factors and hypotheses associated with these two behaviors, as shown in Table 2. To facilitate the analysis, the model hypotheses were divided into two independent models: Model 1 (Air Conditioning) and Model 2 (Office Automation Equipment), each examining the relationship between awareness and these behaviors.

To test these hypotheses, we conducted a structural analysis, as illustrated in Figure 3.4. Table 3.8 presents the fit indices for Model 1 and Model 2, demonstrating a good fit between the proposed theoretical framework and the data, including Model 1 (χ^2/df=3.799, RMR=0.05, GFI=0.954, CFI=0.974, NFI=0.965, IFI=0.974, RMSEA=0.051) and Model 2 (χ^2/df=3.823, RMR=0.05, GFI=0.953, CFI=0.974, NFI=0.965, IFI=0.974, RMSEA=0.051). The observed Root Mean Square Error of Approximation (RMSEA) was 0.051, below the recommended threshold of 0.08 suggested by Browne and Cudeck [13]. Additionally, other fit indices, including GFI, TLI, CFI, and IFI, all met or exceeded the recommended standards, closely approaching or surpassing the threshold of 0.9 [14].

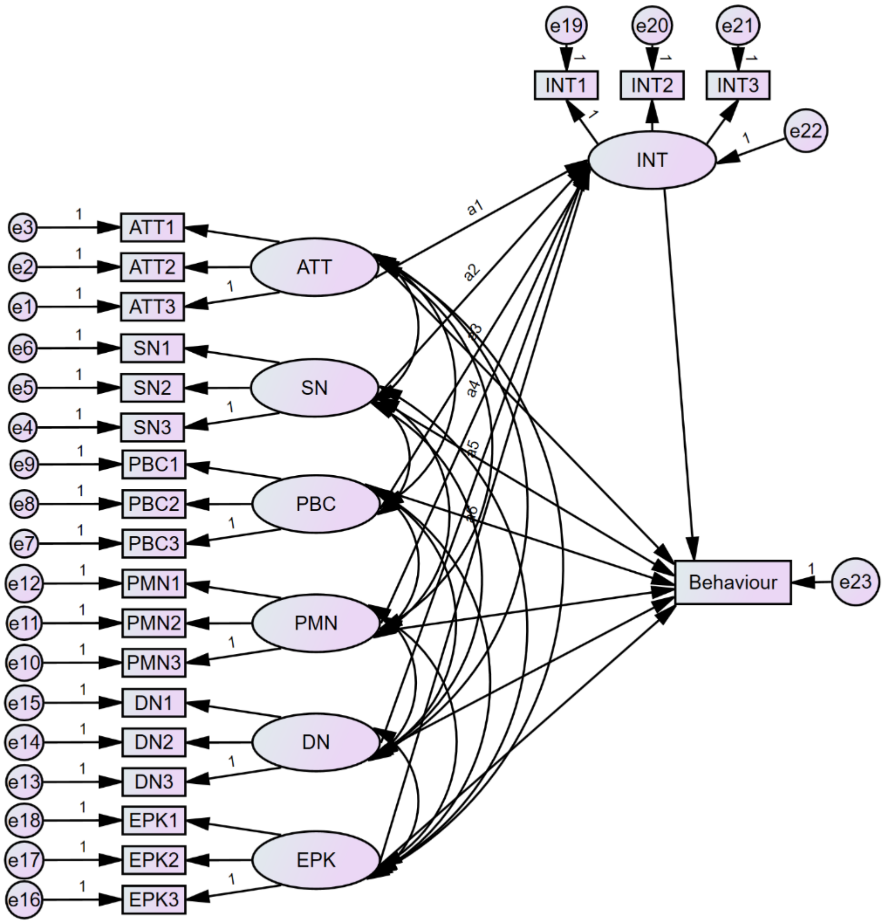


Figure 3.4 Structural Model Diagram

Table 3.9 provides the results of hypothesis testing. It can be seen that the results for Model 1 and Model 2 are highly consistent. In Model 1, individual energy-saving attitude ($\beta = 0.265$, $p < 0.001$), perceived behavioral control ($\beta = 0.199$, $p < 0.001$), and environmental knowledge ($\beta = 0.217$, $p < 0.001$) are significantly positively correlated with individual workplace energy-saving intentions. Similarly, in Model 2, personal energy-saving attitude ($\beta = 0.265$, $p < 0.001$), perceived behavioral control ($\beta = 0.199$, $p < 0.001$), and environmental knowledge ($\beta = 0.031$, $p < 0.001$) also show a significant positive correlation with individual workplace energy-saving intentions, thus supporting Hypotheses 1, 3, and 5.

Descriptive norms in Model 1 ($\beta = 0.097$, $p < 0.05$) and Model 2 ($\beta = 0.096$, $p < 0.05$) also have a significant positive effect on individual workplace energy-saving intentions, supporting Hypothesis 6. Furthermore, individual workplace energy-saving intentions in Model 1 ($\beta = 0.162$, $p < 0.001$) are significantly positively correlated with workplace energy-saving behaviors, and in Model 2, individual workplace energy-saving intentions ($\beta = 0.115$, $p < 0.05$) are also significantly positively correlated with workplace energy-saving behaviors, supporting Hypothesis 7.However, the effects of subjective norms and personal moral norms on workplace energy-saving intentions were not statistically significant, providing no support for Hypotheses 2 and 4.

Table 3.8 Fit indices for Model 1 and Model 2

	Criteria	Parameter	
		Model1	Model2
χ^2/df	1~5	3.799	3.823
RMR	<0.05	0.05	0.05
GFI	>0.9	0.954	0.953
CFI	>0.9	0.974	0.974
NFI	>0.9	0.965	0.965
IFI	>0.9	0.974	0.974
RMSEA	<0.1	0.051	0.051

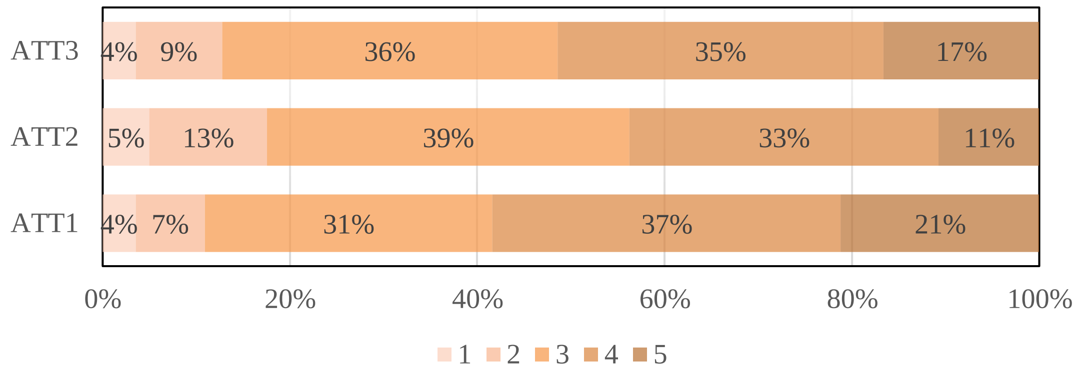
Table3.9 Path relationship among the constructs.

	Path	Hypotheses	β	t-value	95% CI	Test results
Model1	ATT ---> INT	H1	0.265	5.925***	0.163,0.376	supported
	SN ---> INT	H2	0.061	1.372	-0.017,0.139	Not supported
	PBC ---> INT	H3	0.199	4.186***	0.112,0.301	supported
	PMN ---> INT	H4	0.03	0.493	-0.084,0.136	Not supported
	EPK ---> INT	H5	0.217	4.46***	0.135,0.3	supported
	DN ---> INT	H6	0.097	1.989*	0,0.235	supported
	INT --->Behavior	H7	0.182	3.87***	0.082,0.24	supported
Model2	ATT ---> INT	H1	0.265	5.921***	0.162,0.376	supported
	SN ---> INT	H2	0.061	1.366	-0.017,0.138	Not supported
	PBC ---> INT	H3	0.199	4.189***	0.113,0.301	supported
	PMN ---> INT	H4	0.031	0.5	-0.084,0.136	Not supported
	EPK ---> INT	H5	0.217	4.463***	0.136,0.3	supported
	DN ---> INT	H6	0.096	1.983*	0,0.235	supported
	INT --->Behavior	H7	0.115	2.463*	0.025,0.173	supported
Note. *p<0.05, ***p<0.001; Model1: Behavior1 Air-conditioner; Model2: Behavior2 OA machine.						

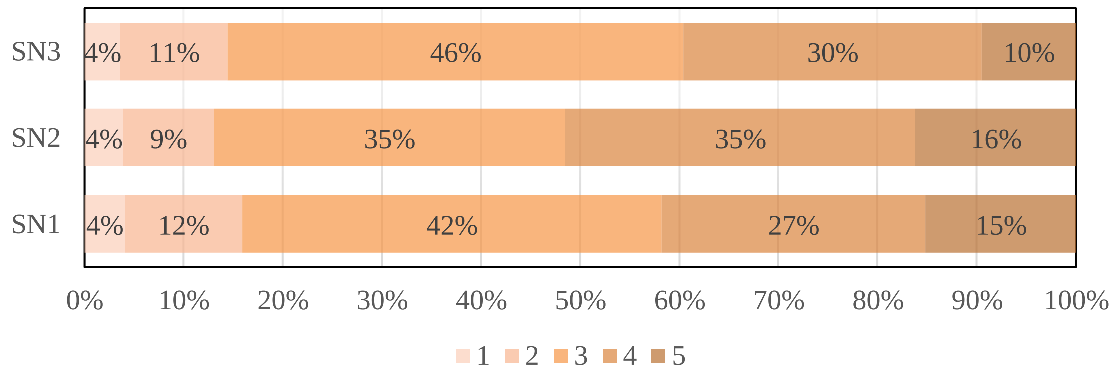
3.5.2. Others Questionnaire Analysis

(1) Frequency Distribution Analysis

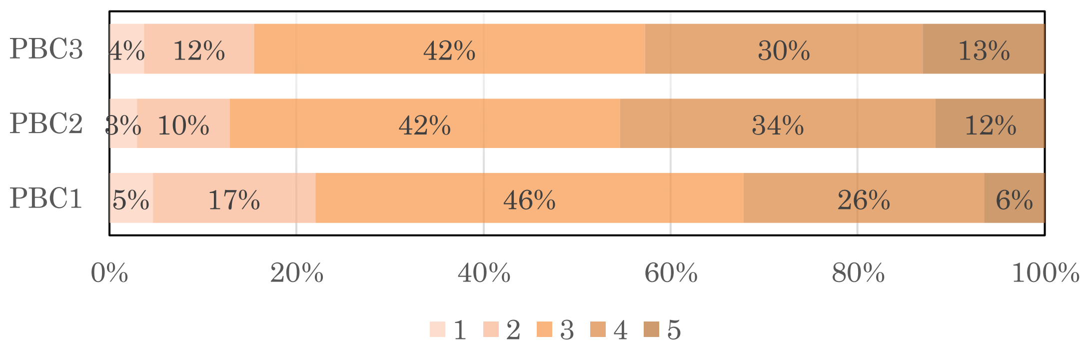
To understand the frequency distribution results of each environmental awareness factor and behavior of the questionnaire, this study generated frequency distribution charts for each behavior and awareness factor. Figure3.5 shows the score frequency distribution of the seven environmental psychological factors. As previously mentioned, the response options for awareness-related questions ranged from 1 to 5. In the chart, different colors represent the percentage of each response option. It can be observed that for responses from ATT to INT, option 3 has the highest percentage, with options 4 and 5 significantly higher in proportion than options 1 and 2.



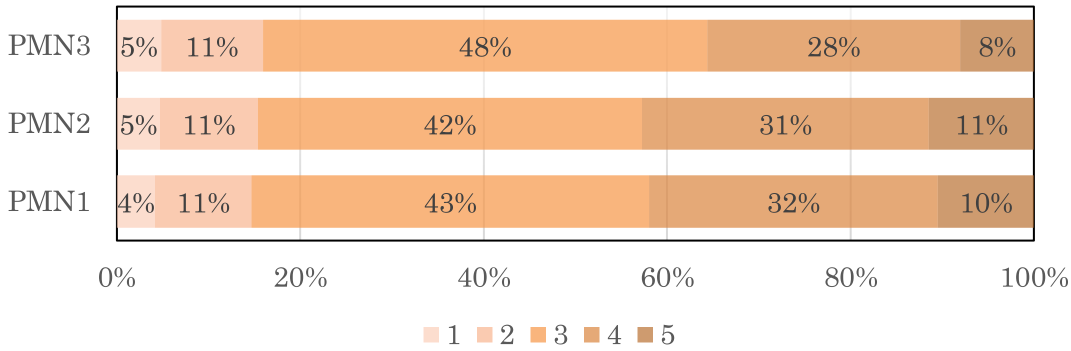
(a) Frequency distribution of attitude (ATT)



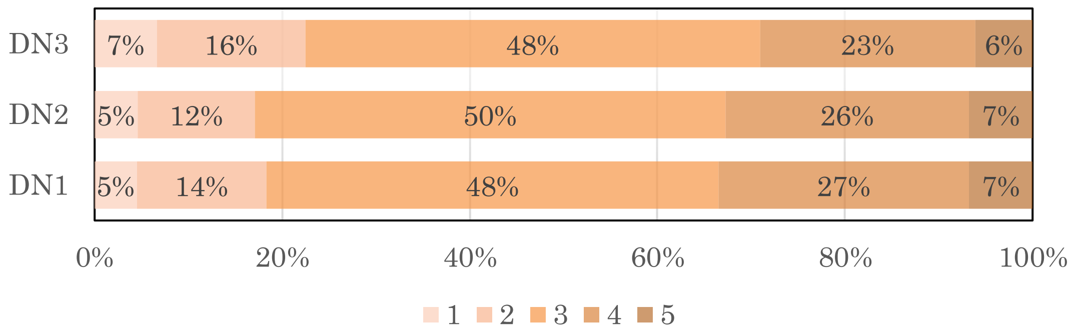
(b) Frequency distribution of subjective norm (SN)



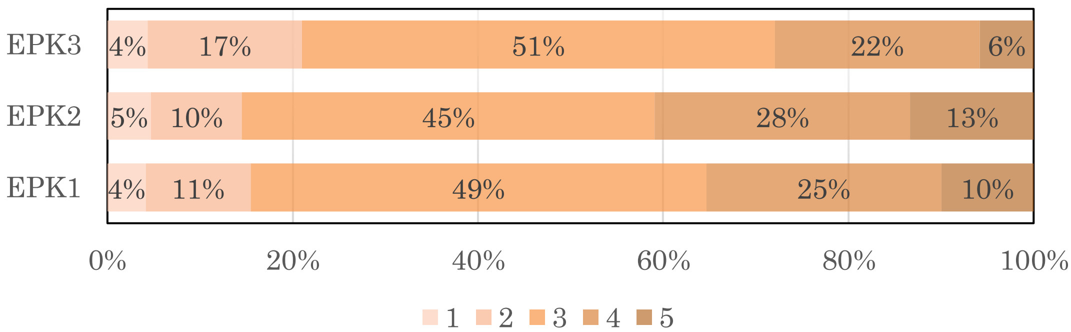
(c) Frequency distribution of perceived behavioral control (PBC)



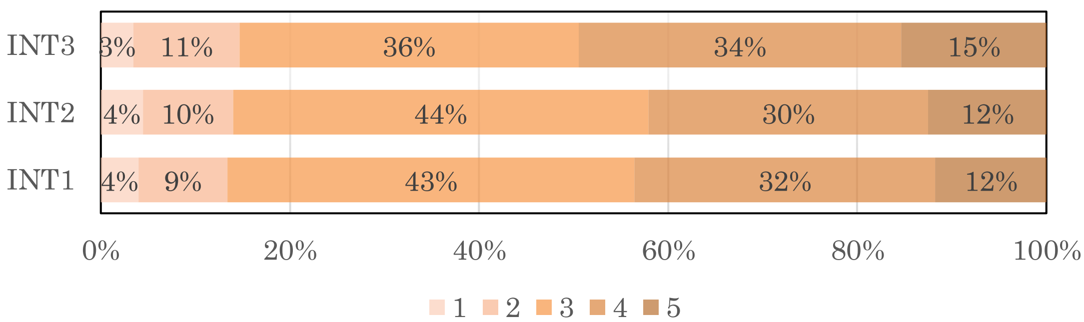
(d) Frequency distribution of personal moral norm (PMN)



(e) Frequency distribution of descriptive norm (DN)



(f) Frequency distribution of environmental protection knowledge (EPK)



(g) Frequency distribution of intention (INT)

Figure 3.5 Frequency distribution of each environmental awareness factor

As shown in the figure 3.6, the chart presents the average scores of seven environmental awareness dimensions, ranging from ATT to INT. It is evident that the mean values for all seven awareness dimensions fall between 3 and 4, indicating a generally neutral-to-positive inclination among respondents in these areas. Specifically, ATT (attitude) displays the highest average score across all awareness dimensions, suggesting a relatively strong and positive awareness among respondents in this regard. Conversely, DN (descriptive norm) shows a comparatively lower average score, indicating that respondents are less aligned with this dimension of awareness.

This distribution highlights an overall trend where respondents demonstrate a moderate to favorable level of environmental awareness, with the strongest emphasis on attitude and a lower tendency toward responsibility.

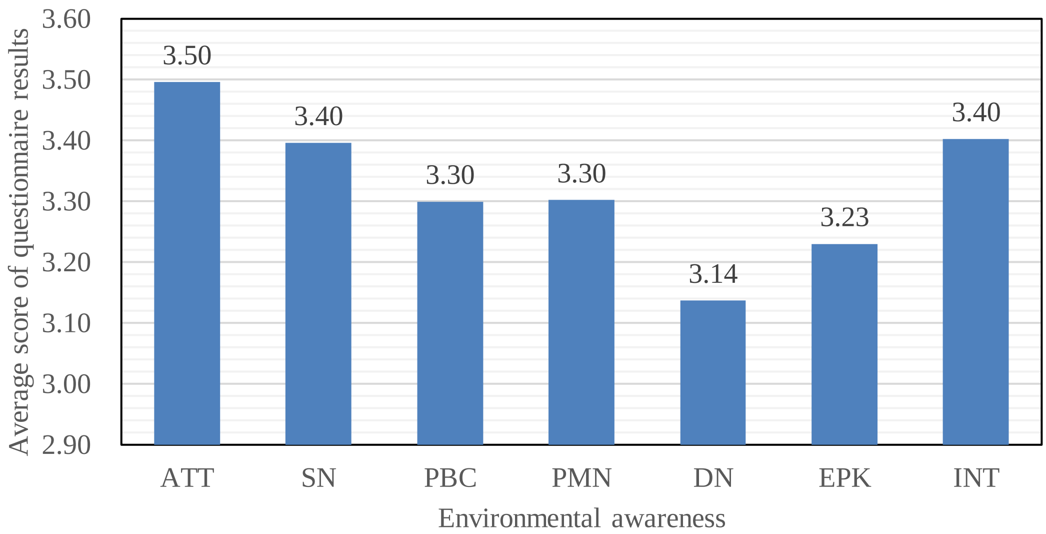


Figure 3.6 Average score of each environmental awareness factor of questionnaire results

In the questionnaire mentioned earlier, certain behaviors did not exhibit significant correlations in the SEM (Structural Equation Modeling) analysis and were thus excluded from subsequent model analysis. However, these behaviors did show significant correlations in the preliminary analysis, suggesting that they still hold some association with other variables. Therefore, this study will not only focus on behaviors with significant correlations but will also further discuss these excluded behaviors to comprehensively analyze their representation and frequency distribution in the questionnaire data.

Specifically, in addition to the two retained behaviors previously mentioned, there are six excluded behaviors that still demonstrate some statistical correlation in certain aspects. To fully understand how these behaviors perform within the dataset, this section will provide a detailed discussion of the frequency distribution of all eight behaviors and analyze their distribution characteristics within the sample.

Table 3.10 lists the specific content of these eight behaviors, with their frequency distribution illustrated in figure 3.7. These charts visually display the frequency of each behavior choice among respondents, providing data support for subsequent discussions on the potential impact of these behaviors.

As shown, similar to the awareness dimensions, the distribution of responses for behaviors is also concentrated between 3 and 4 on the scale. For B1 ("Turn off the lights when you are the last to leave the room"), the proportion of respondents selecting option 5 even surpasses those choosing 3 or 4. As illustrated, the distribution of behavior choices resembles that of the awareness dimensions, with most response frequencies concentrated between 3 and 4. This reflects that the actual execution frequency of these behaviors among respondents generally falls within a moderate-to-high range. However, for

B1 (i.e., "When you are the last person to leave the room, do you always turn off the lights?"), the proportion selecting 5 ("always do so") is significantly higher than those choosing 3 ("sometimes do

so") or 4 ("often do so"). This suggests that many respondents demonstrate a high level of consistency in this behavior, frequently turning off the lights when they are the last to leave.

Table 3.10 All energy consumption-related behaviors in the questionnaire

Behavior	Questionnaire content
B1	Turn off the lights when you are the last to leave the room.
B2	In the office, turned on lights in areas where people are present.
B3	To save energy, the temperature is increased during heating and decreased during cooling.
B4	If you feel hot or cold in the office, adjust your clothing before changing the air conditioner settings.
B5	Even when there are many people in the room, actively manage the air conditioning temperature settings.
B6	Setting office appliances (PCs, monitors, printers, etc.) to energy-saving mode.
B7	Use the stairs instead of the elevator if going up two floors or down three floors.
B8	Turn off the PC or put it in sleep mode when leaving your seat for more than an hour.

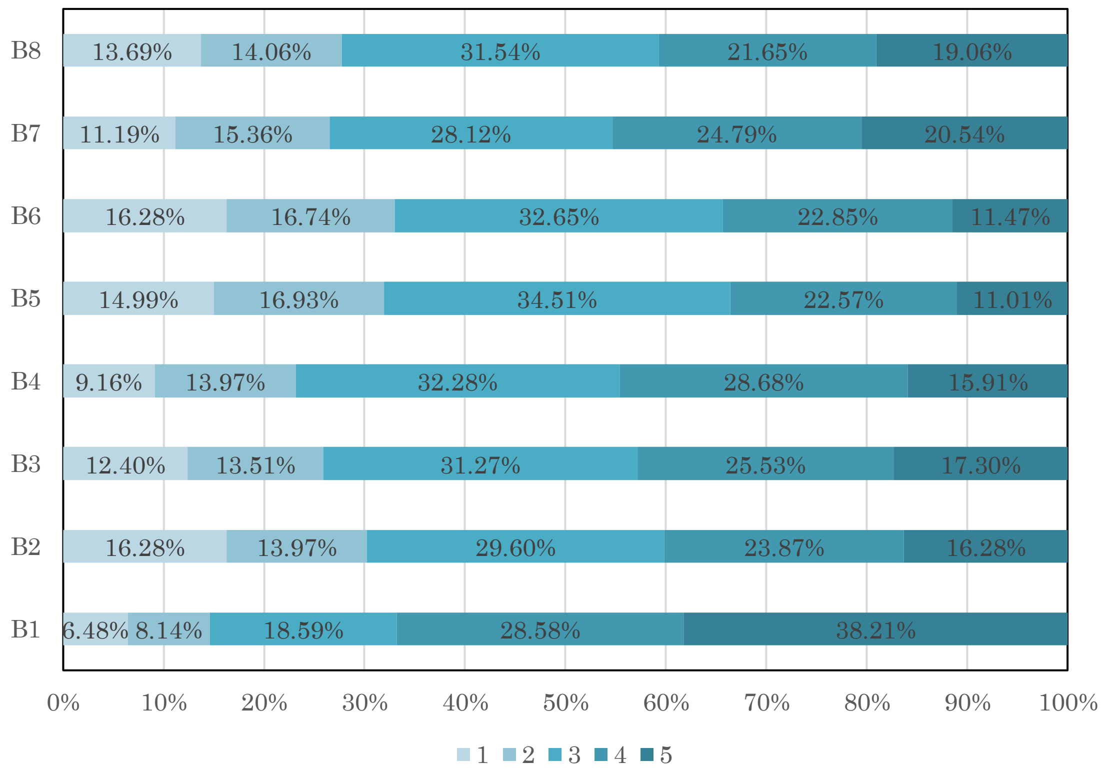


Figure 3.7 Frequency distribution of each behaviours of questionnaire results

(2) Spearman Correlation Analysis

In the previous tables, the correlations between behavior and awareness were analyzed in detail. This section will further explore the correlations between other variables—specifically age and income—and environmental awareness and behavior. The Spearman correlation coefficients for these variables with environmental awareness and behavior are shown in the Table 3.11 and Table 3.12.

The results indicate a significant positive correlation between age and both environmental awareness and behavior, suggesting that as age increases, respondents demonstrate higher levels of environmental awareness and a greater frequency of related behaviors. This may reflect an increased sense of responsibility or greater concern for environmental issues as people age.

On the other hand, income shows a somewhat different pattern of correlation with environmental awareness and behavior. Specifically, income is significantly positively correlated only with ATT (Attitude), DN (descriptive norm), and INT (Intention), indicating that higher-income groups exhibit greater alignment with or willingness to act on these specific dimensions of awareness. However, income's correlation with actual behavior is relatively weak, with significant positive correlations observed only with B1 (turning off lights when leaving). This suggests that higher-income individuals may be more inclined to take energy-saving actions in specific instances, such as turning off lights when leaving a room, though this tendency does not extend uniformly across all behaviors.

Table 3.11 Spearman correlation analysis of environmental awareness with age and income

			ATT	SN	PBC	PMN	DN	EPK	INT
Spearman's rho	Age	Correlation Coefficient	.252**	.219**	.201**	.221**	.156**	.211**	.238**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
		N	1069	1069	1069	1069	1069	1069	1069
	Income	Correlation Coefficient	-.070*	-.057	-.028	-.052	.067*	-.051	-.081**
		Sig. (2-tailed)	.022	.059	.349	.086	.028	.096	.008
		N	1069	1069	1069	1069	1069	1069	1069
**. Correlation is significant at the 0.01 level (2-tailed).									
*. Correlation is significant at the 0.05 level (2-tailed).									

Table 3.12 Spearman correlation analysis of behaviors with age and income

			B1	B2	B3	B4	B5	B	B7	B8
Spearman's rho	Age	Correlation Coefficient	.144**	.124**	.121**	.101**	.102**	.100**	.098**	.130**
		Sig. (2-tailed)	.000	.000	.000	.001	.001	.001	.001	.000
		N	1081	1081	1081	1081	1081	1081	1081	1081
	Income	Correlation Coefficient	-.072*	-.035	-.047	-.043	-.029	-.058	-.053	-.058
		Sig. (2-tailed)	.018	.254	.124	.156	.338	.055	.083	.057
		N	1081	1081	1081	1081	1081	1081	1081	1081
**. Correlation is significant at the 0.01 level (2-tailed).										
*. Correlation is significant at the 0.05 level (2-tailed).										

Table 3.13 presents the correlation analysis between all energy consumption behaviors and environmental awareness factors. While previous analyses indicated that only air conditioning and office automation (OA) behaviors showed significant correlations in the SEM analysis, and Chapter 3.5.1 further found that subjective norms (SN) and personal moral norms (PMN) were not significantly correlated with behavioral intentions, the Spearman correlation analysis reveals a broader relationship. Specifically, all environmental psychological factors demonstrate a significant positive correlation with energy consumption behaviors ($p<0.01$).

This suggests that, although SEM analysis identified only specific significant associations, a general positive correlation exists across all environmental awareness factors and energy-saving behaviors, highlighting the potential influence of environmental psychology on a wide range of energy consumption actions.

Table 3.13 Spearman correlation analysis between all energy consumption behaviors and environmental awareness

			B1	B2	B3	B4	B5	B6	B7	B8
Spearman's rho	ATT	Correlation Coefficient	.378**	.345**	.337**	.443**	.282**	.346**	.422**	.379**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	SN	Correlation Coefficient	.355**	.405**	.354**	.435**	.340**	.425**	.440**	.400**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	PBC	Correlation Coefficient	.330**	.317**	.331**	.383**	.288**	.323**	.378**	.373**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	PMN	Correlation Coefficient	.296**	.298**	.324**	.406**	.316**	.349**	.365**	.340**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	DN	Correlation Coefficient	.230**	.316**	.315**	.350**	.331**	.401**	.340**	.338**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	EPK	Correlation Coefficient	.298**	.316**	.369**	.395**	.347**	.370**	.386**	.372**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
	INT	Correlation Coefficient	.373**	.367**	.365**	.462**	.326**	.382**	.430**	.407**
		Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000
**. Correlation is significant at the 0.01 level (2-tailed).										

3.6. Discussion

This study developed the current questionnaire (Table 3.1) based on previous research. However, the original version of the questionnaire was in English, while a translated Japanese version was used for the survey conducted in Japan. Due to time constraints and other factors, a thorough analysis of the adequacy of the Japanese translation could not be performed. To ensure the rigor of questionnaire analysis, future research should further investigate the potential differences caused by language translation and the impact of cultural differences on questionnaire results.

According to the results presented in Chapter 3.5, the components of the extended TPB model used in this study—including energy-saving attitude, perceived behavioral control, descriptive norms, and environmental knowledge—all demonstrate predictive effects on individuals' energy-saving intentions within office buildings. These findings are consistent with previous research outcomes. However, contrary to Hypotheses 2 and 4, although subjective norms and personal moral norms show significant correlations with various psychological factors and behaviors at the 0.01 level in the correlation analysis (as shown in Table 3.4), they do not show significant correlations with behavioral intention according to the SEM analysis results (as shown in Table 3.7). This observation aligns with findings from Gao et al., where subjective norms also did not significantly impact behavioral intention [2].

It can therefore be inferred that to enhance individuals' energy-saving intentions within office buildings, focusing on energy-saving attitude, perceived behavioral control, descriptive norms, and environmental knowledge may be more effective. Unlike Gao et al.'s study, however, this research employs a more comprehensive TPB model, specifically verifying the relationship between intention and behavior (Hypothesis 7). Unlike prior studies, such as Manning's study [15] which explored the intention-behavior relationship, this study introduces additional psychological factors, including personal moral norms, descriptive norms, and environmental knowledge. These additions strengthen the model's predictive power by providing a deeper understanding of the psychological mechanisms driving energy-saving behaviors. This part of the analysis enriches the existing literature by offering empirical evidence on the transition from intention to behavior, demonstrating the significant influence of these additional factors.

However, this study differs from previous research in that it specifically examines energy-saving intentions related to different devices, namely air conditioning and office automation (OA) equipment, and incorporates validation experiments conducted prior to the extensive online survey described in Chapter 3. The findings reveal that the predictive power of environmental intention varies across different energy-saving behaviors. The analysis indicates significant differences between energy-saving behaviors associated with different types of equipment. As shown in Table 3.9, behavioral intention has a significant impact on air conditioning-related energy-saving behavior (Model 1) at the 0.001 level ($\beta = 0.182$, $p < 0.001$), demonstrating a substantial effect on air conditioning energy-saving actions. In contrast, the influence of behavioral intention on energy-saving behavior related to office automation equipment (Model 2) is only significant at the 0.05 level, indicating a lesser impact compared to air conditioning energy-saving behavior. These findings suggest that the influence of environmental awareness and intention on energy-saving behaviors is not consistent across all behaviors, emphasizing the importance of considering the specific context of different devices when promoting energy-saving initiatives.

Moreover, these findings hold significant practical implications for promoting energy-saving intentions across the office environment. For example, as shown in Table 3.9, attitudes toward environmental conservation ($\beta = 0.265$, $p < 0.001$) and environmental knowledge ($\beta = 0.217$, $p < 0.001$) significantly influence behavioral intention, indicating that environmental awareness seminars and energy-saving training programs could prove effective at the company or office building level. Perceived behavioral control ($\beta = 0.199$, $p < 0.001$) also has a considerable effect on behavioral intention, making efforts to increase the feasibility of energy-saving actions within the office building a promising approach. Additionally, descriptive norms ($\beta = 0.097$, $p < 0.05$) influence behavioral intention, implying that guidance for commonly accepted or rejected energy consumption behaviors could start at the management level. By incorporating psychological factors such as personal moral norms, descriptive norms, and environmental knowledge into the extended TPB model, this study provides new insights and empirical support for encouraging energy-saving actions within buildings. Given the differing impact of intention on various devices, it may be more effective to prioritize changing energy-saving intentions related to air conditioning rather than office automation equipment.

Nevertheless, this study primarily focuses on air conditioning and office automation (OA) equipment because, in the preliminary analyses conducted using SEM structural modeling and regression analysis, models for other behaviors exhibited poor fit (e.g., CFI < 0.9) and failed to yield statistically significant correlations. Although the psychological factors in the TPB model showed significant correlations with other behaviors in the correlation analysis, the model's complexity—due to the inclusion of numerous psychological factors—may have contributed to the low fit for those behaviors. Future research could improve model fit by optimizing the selection of psychological factors or considering additional factors.

Additionally, for certain behaviors, an insufficient sample size may have reduced the statistical power of the analysis, leading to non-significant findings. Therefore, this study focuses on behaviors with higher model fit, particularly assessing the likelihood of implementing energy-saving behaviors through the TPB model. Future research should consider revising or re-evaluating the psychological factors used in the TPB model to enhance its applicability to a broader range of behaviors. While the characteristics of specific devices may influence results, predicting model fit based solely on these characteristics is challenging. Future work should continue to focus on the precise selection of psychological factors within the TPB model to improve its overall accuracy and applicability.

As shown in the correlation analysis in Table 3.13, all environmental psychological factors display significant correlations with energy consumption behaviors. This indicates that, although the TPB model may not be ideally suited to explain all types of energy-related behaviors within the scope of this study, the influence of environmental psychology on these behaviors is both substantial and consistent. In other words, while the structural limitations of the TPB model might restrict its ability to fully capture the complexities of certain behaviors, the data still reveal a clear and significant relationship between environmental awareness, attitudes, norms, and energy-saving actions. This underscores that environmental psychological factors indeed play a meaningful role in shaping energy-saving behaviors, even if their predictive power may vary across different types of behaviors. Consequently, these findings emphasize the value of integrating environmental psychology perspectives into the study and promotion of energy conservation actions, as these factors exert a real impact on individuals' behavioral choices regarding energy use.

3.7. Conclusions

This chapter explores the relationship between energy-saving behavioral intentions and influencing factors in office buildings from the perspectives of environmental psychology and environmental behavior. Based on a literature review, this study develops an extended model grounded in the TPB. Questionnaires were distributed and validation experiments conducted within actual office buildings in Japan to ascertain the relationship between behavioral intentions from the questionnaire and actual behaviors. Following this, an online survey platform was used to disseminate the questionnaire, with statistical methods applied to analyze the responses and validate the model assumptions. The study results confirm the effectiveness of the extended TPB model in predicting individuals' energy-saving intentions and behaviors within office buildings. The findings of this chapter carry significant implications for energy management across various office buildings. Given the applicability of the TPB model in predicting energy-saving intentions in office settings, managers can utilize multi-level environmental psychology interventions to reinforce employees' attitudes toward energy-saving behaviors, thereby positively influencing their actual energy-saving actions.

Despite the robust reliability demonstrated through validation experiments and various analytical methods, this study has certain limitations. First, the validation experiment was conducted within a single company with a relatively small sample size. To enhance the generalizability of the findings, it is recommended that similar studies be replicated with larger sample sizes and across office buildings with diverse backgrounds. Second, this study did not consider factors beyond environmental psychology, such as income levels and educational backgrounds. Future studies should incorporate a broader range of influencing factors and employ segmentation methods to yield more precise models. Moving forward, the research will integrate environmental awareness, behavior, and building energy consumption to explore more effective methods for reducing energy consumption in buildings. Furthermore, this study primarily focused on air-conditioning and office automation equipment, whereas results for other equipment, such as printers and copiers, were relatively weaker. Future research should aim to improve measurement accuracy, increase sample sizes, and broaden the range of equipment studied. Investigating how the characteristics of specific devices affect the transition from intention to action will enhance the robustness of findings and offer targeted energy-saving strategies.

Following this chapter's verification of the TPB model's predictive capability for energy-saving behaviors, the next chapter will further the research by developing a simulation tool to model the effects of various levels of environmental awareness on behavioral choices and building energy consumption. This simulation tool will not only quantify the impact of awareness on individual energy-saving behaviors but also predict overall building energy consumption changes across different scenarios. By establishing this simulation system, the study aims to provide data-driven support and theoretical foundations for designing targeted energy-saving policies and interventions while offering a practical modeling framework for future research in this field.

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Chapter-4

Simulation of Human Behavior and Building Energy Consumption

4.1. Simulation of Air Conditioner Usage Behavior

4.2. Validation Experiments for Behavioral Simulation

4.3. Simulation of Lighting Behavior and Energy Consumption

4.4. Summer Office Cooling Load Simulation

4.5. Discussion and conclusion

Chapter 4. Simulation of Human Behavior and Building Energy Consumption

4.1. Simulation of Air Conditioner Usage Behavior

In Chapter 3, this study provides a detailed explanation of how the extended TPB model is used to predict the influence of environmental psychological factors on energy-saving behaviors. This study specifically focuses on energy-saving behaviors. The findings show that these behaviors have a significant impact in the model, indicating that the respondents' decisions regarding energy-saving behaviors are notably influenced by environmental psychological factors.

This chapter will delve into the influencing factors of air conditioner energy-saving behaviors through empirical data and model analysis, providing relevant analysis results and recommendations by integrating behavior patterns and building energy consumption simulations. This will offer theoretical support and empirical evidence for future improvements in building energy efficiency and the formulation of energy-saving strategies.

4.1.1. Questionnaire on Air Conditioner Usage Behavior

Although the previous questionnaire covered some energy-saving behaviors related to air conditioning, the information remains insufficient for simulation purposes. To build a more precise simulation model, we need not only to understand the respondents' environmental awareness but also to collect more detailed data about their daily air conditioner usage habits. This includes specific information such as the duration of air conditioner usage, temperature settings, and usage frequency across different seasons. Therefore, this chapter will introduce a specially designed questionnaire that covers not only respondents' environmental awareness but also focuses specifically on air conditioner usage habits. This will provide a more comprehensive data foundation for subsequent simulations, leading to more accurate and realistic results.

The environmental psychology section of this questionnaire is largely consistent with the previous one, covering respondents' attitudes towards environmental behaviors, subjective norms, and perceived behavioral control. However, unlike the previous questionnaire, this one includes more specific content, particularly related to air conditioner usage habits and temperature preferences.

The questionnaire content is shown in Table 4.1. The section related to air conditioning includes assessing respondents' preferred temperature settings for summer and winter (T1 and T2). Additionally, there is a section on the frequency of adjusting air conditioner settings, where respondents report how often they adjust the temperature when feeling too hot or too cold in the office (P6: summer/winter). Next, the questionnaire gathers basic information such as age group, job position, and the number of people in the office. It also inquires about dress code, whether formal, semi-formal, casual, or other, as these factors may influence their comfort with air conditioner usage. Finally, respondents are asked to consider the most important factors influencing their decisions when adjusting air conditioner settings. The listed factors include energy costs, the number of people in the office, others' comfort, company policies, personal comfort, and environmental awareness.

Table 4.1 Questionnaire questions & options

Categories	**Items**	
Psychological Factors	**ATT1:** The continuously increasing energy demand is a serious issue for society.	**Options** 5.Strongly agree 4.Somewhat agree 3.Neither agree nor disagree 2.Somewhat disagree 1.Strongly disagree
	ATT2: I believe that energy conservation in daily life is useful for environmental preservation.	
	ATT3: I also bear some responsibility for issues such as global warming and the depletion of fossil fuels.	
	SN1: People who are significant in my life think that I should conserve energy wherever possible.	
	SN2: I value the opinion of people who are significant in my life when it comes to making decision on energy conservation.	
	SN3: The managers (executives, officers, etc.) of your company are considering the request to turn off the office lighting and air conditioning when not in use.	
	PBC1: Convenience without compromising energy efficiency is also an important factor for me when promoting energy conservation.	
	PBC2: Whether or not saving energy is completely up to me.	
	PBC3: I have knowledge and know-how to implement energy-saving practices in my daily life.	
	PMN1: There is a moral responsibility to engage in energy-saving practices in everyday life.	
	PMN2: Save energy in my daily life is depending on my own moral obligation.	
	PMN3: I use electricity, gas, and other forms of energy in my daily life, and I feel that my actions have an impact on climate change.	
	DN1: A number of employees in my company I know have participated in energy saving behavior.	
	DN2: My manager and the high-level management team have participated in energy saving behavior.	
	DN3: Others who are important to me have participated in energy saving behavior.	
	EPK1: The increase in greenhouse gases in the atmosphere over the past 150 years is primarily attributed to human activities.	
	EPK2: I know much about the energy-saving tips of daily life.	
	EPK3: The increase in greenhouse gases in the atmosphere over the past 150 years is primarily attributed to human activities.	
	INT1: I intend to engage in energy-saving activities in the future.	
	INT2: I will pay more attention and accumulate energy-saving knowledge and tips in the future.	
	INT3: I am going to behave pro-environmentally in the coming month to reduce my impact on the environment (e.g. by turning off the computer, printing less, using a mug etc.)	
Temperature preference	**T1(summer)/T2(winter):** What temperature setting do you find most comfortable in your office during summer and winter?	
Probability of	**P1** Endure **(summer/ winter)**	If you felt hot (cold) in your office 10 times
	P2 Adjust clothes **(summer/ winter)**	

<table>
<tr><td rowspan="4">thermal adaptative behaviors when feel hot (cold) (summer/ winter)</td><td>P3 Drink water (ice/hot) (summer/ winter)</td><td rowspan="4">during the summer, how many times out of 10 would you take the following actions? Please give the approximate number of times for changing air conditioning setting temperature. Options(Times): 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10</td></tr>
<tr><td>P4 Summer: Use an electric fan or fan. / Winter: Use equipment such as underfoot heaters and chair carpets.</td></tr>
<tr><td>P5 Summer: Open the window. / Winter: Use thermal items such as blankets and hand warmers.</td></tr>
<tr><td>P6 Change the temperature setting of the air conditioner.(summer/ winter)</td></tr>
<tr><td rowspan="5">Other basic information</td><td colspan="2">Age: Please select your age group. Options :20~29, 30~39, 40~49,50~59, 60 and over</td></tr>
<tr><td colspan="2">Position: Please select your position. Options: Part-time job, No position or position with no subordinates, section chief, section manager</td></tr>
<tr><td colspan="2">Number of people in office room: In the office where you work, how many people are in the room you are in?
Options: only for me, 2 people,3~4 people,5~9 people,10~19 people,20~49 people,50 and more than 50</td></tr>
<tr><td colspan="2">If you are considering adjusting the temperature settings or air volume of your office air conditioner, the factors that will have the greatest impact on your behavior are: Energy cost, Number of people in the office, Comfort of others, Company policies and regulations, My own comfort, Environmental awareness</td></tr>
<tr><td colspan="2">Dress code: Tell us about the dress code in the office where you work
Options: Formal (including uniforms), Semi-formal, Casual, Work clothes, Clothing varies widely from person to person, Other</td></tr>
</table>

4.1.2. Results of the Air Conditioner Questionnaire

In January 2024, we conducted an online survey primarily in Japanese to understand the perspectives and behavioral habits of individuals working in office buildings in Japan regarding air conditioner usage, lighting habits, and environmental awareness. This survey targeted a broad group of office workers, with participants from various industries and job levels. After data screening and cleaning, a total of 906 valid responses were collected.

(1) Demographic Data

The demographic data of the survey respondents, as shown in Table 4.2, illustrate the distribution by gender, age group, and region. In terms of gender, 62.0% of the respondents were male (562 individuals), while females accounted for 38.0% (344 individuals). This proportion reflects the basic gender distribution within the survey sample and provides a foundation for analyzing gender differences in air conditioner usage and environmental awareness.

Regarding age groups, the largest proportion of respondents was in the 30-39 age group, accounting for 21.3%, indicating high participation from this age group among office employees. The 40-49 and 50-59 age groups followed closely, representing 21.2% and 21.4%, respectively, highlighting the significant representation of middle-aged respondents. Those aged 60 and above made up 21.3%, while the youngest group, aged 20-29, comprised 14.8%.

In terms of regional distribution, the majority of respondents were from the Kanto region, making up 38.1%, likely reflecting the high density of office buildings in this area. The Kinki and Chubu regions followed with 22.2% and 15.2%, respectively, representing other major economic and office hubs in Japan. The proportion of respondents from other regions was relatively smaller, with Hokkaido at 3.2%, Tohoku at 6.3%, Chugoku at 4.4%, Shikoku at 3.0%, and Kyushu at 7.6%.

Table 4.2 Profile of the respondents

		Frequency	Percent	Valid Percent	Cumulative Percent
Sex	Male	562	62.0	62.0	62.0
	Famle	344	38.0	38.0	100.0
Gender	20~29	134	14.8	14.8	14.8
	30~39	193	21.3	21.3	36.1
	40~49	192	21.2	21.2	57.3
	50~59	194	21.4	21.4	78.7
	60~	193	21.3	21.3	100.0
Aare	Hokkaido	29	3.2	3.2	3.2
	Tohoku Region	57	6.3	6.3	9.5
	Kanto Region	345	38.1	38.1	47.6
	Chubu Region	138	15.2	15.2	62.8
	Kinki Region	201	22.2	22.2	85.0
	Chugoku Region	40	4.4	4.4	89.4
	Shikoku Region	27	3.0	3.0	92.4
	Kyushu Region	69	7.6	7.6	100.0
Total		906	100.0	100.0	

(2) Correlation Analysis

This table presents the correlation analysis between environmental awareness and temperature adaptation behavior, examining temperature preferences (within the 16~30°C range) and the likelihood of adjusting air conditioner settings for both summer and winter.

In summer, there is a strong correlation between environmental awareness and temperature preference. For instance, the correlation coefficient between attitude (ATT) and summer temperature preference is 0.206, reaching a significant level ($p<0.01$), indicating that individuals with higher environmental awareness are more likely to choose appropriate temperature settings during summer. Subjective norm (SN) and perceived behavioral control (PBC) also show significant positive correlations in summer, suggesting that temperature preferences are strongly influenced by environmental awareness. In other words, individuals with stronger environmental awareness are more inclined to make energy-saving choices in air conditioner usage during summer.

However, in winter, the correlation between environmental awareness and temperature preference is minimal or nonexistent. For example, the correlation coefficient for attitude (ATT) in winter is only 0.073, not reaching a significant level. Other psychological factors, such as subjective norm (SN) and perceived behavioral control (PBC), also show no significant correlation in winter. This phenomenon may be due to the complexity of temperature regulation in winter and the higher demands directly linked to physical comfort. Additionally, external factors such as heating methods and clothing thickness may weaken the impact of environmental awareness on air conditioner usage behavior in winter. Additionally, the significant climate differences across regions in Japan, such as the stark contrast in air conditioning usage during winter between Hokkaido and Okinawa, may have influenced the results. Since the questionnaire covered respondents from all over Japan, this regional variation could be one of the reasons why no significant correlation was observed between environmental awareness and air conditioning temperature preferences during winter.

In this analysis, demographic factors such as age, position, and office size were also considered alongside environmental awareness. Age showed a certain influence on correlations in both summer and winter. Specifically, in summer, the correlation coefficient between age and temperature preference is 0.231 ($p<0.01$), indicating that older respondents are more inclined to choose specific temperature settings. In winter, while age did not show a significant correlation with temperature preference, it had a positive correlation with the behavior of adjusting air conditioner settings ($r=.150$, $p<0.01$).

Previous studies have shown that gender differences and clothing thickness have a notable impact on thermal comfort in winter. For example, women often prefer higher indoor temperatures and wear thicker clothing in winter, directly affecting their perception of indoor temperature [1]. These factors may explain why the correlation between environmental awareness and temperature preference is not significant in winter.

Position also shows a significant positive correlation with air conditioner adjustment behavior ($r=0.128$, $p<0.01$), suggesting that individuals in higher positions are more likely to adjust air conditioner settings. This may be because higher-positioned employees typically have greater control over the office environment and prioritize personal comfort, making them more proactive in adjusting the air conditioning. However, since position is challenging to simulate, it will not be considered in the subsequent simulations.

Office size shows a negative correlation ($r=-0.118$, $p<0.01$), indicating that the more people there are in an office, the less likely individuals are to adjust air conditioner settings. This could be because, in shared work environments, individuals have less control over the environment or are more considerate of others' comfort, thus reducing their likelihood of adjusting the air conditioning.

Based on these findings, this study chooses summer as the primary scenario for behavioral simulation, as the stronger correlation between environmental awareness and temperature preference during summer better reflects the influence of environmental awareness on air conditioner usage behavior.

Table 4.3 Correlation analysis of environmental awareness and thermal adaptation-related behavior

		Temperature preference(16~30℃)		Probability (Change AC set temperature)	
		summer	winter	summer	winter
ATT	Corr. Coef.	.206**	.073*	-.161**	-.128**
SN	Corr. Coef.	.200**	.064	-.173**	-.137**
PBC	Corr. Coef.	.165**	.050	-.166**	-.138**
PMN	Corr. Coef.	.158**	.039	-.120**	-.093**
DN	Corr. Coef.	.204**	.024	-.140**	-.104**
EPK	Corr. Coef.	.166**	.021	-.146**	-.118**
INT	Corr. Coef.	.225**	.012	-.150**	-.108**
Age	Corr. Coef.	.231**	.049	.150**	.151**
Position	Corr. Coef.	.025	-.050	.128**	.151**
Number of people	Corr. Coef.	-.001	.020	-.118**	-.142**
**. Correlation is significant at the 0.01 level (2-tailed).; *. Correlation is significant at the 0.05 level (2-tailed).					

(3) Gender Analysis

In this study, in addition to analyzing psychological factors related to temperature preference and behavioral adaptation, gender was also considered. To assess the potential impact of gender on the simulation, we conducted an independent samples T-test to examine gender differences. Specifically, we compared the scores of males and females on various thermal adaptation behaviors and temperature preferences reported in the questionnaire to determine whether gender significantly influences these behaviors. The purpose of this analysis was to decide whether gender needs to be controlled as an independent variable in the simulation or if its impact on behavior and temperature preference is minimal and thus not significant for the simulation outcomes.

As shown in Table 4.4, the results of the independent samples T-test between gender and temperature adaptation behaviors are presented. The goal was to compare males and females in terms of temperature preferences and air conditioner adjustment behaviors.

Firstly, in terms of summer temperature preferences, the average score for males was 8.40, while for females it was 8.16. The T-test result showed a significance level of 0.824, indicating no significant difference in summer temperature preferences between genders. For winter temperature preferences, the average scores were 7.54 for males and 8.01 for females, with a significance level of 0.919, similarly indicating no significant gender difference.

Regarding the behavior of adjusting air conditioner settings, the average adjustment frequency for males in summer was 4.18, compared to 3.91 for females, with a significance level of 0.378, showing no significant difference between genders. In winter, the average adjustment frequency was 4.12 for males and 3.86 for females, with a significance level of 0.342, also indicating no significant impact of gender on air conditioner adjustment behavior.

In summary, gender did not show a significant impact on temperature preferences or air conditioner adjustment behaviors in either summer or winter. Therefore, gender differences will not be considered as a variable in the subsequent simulation.

Table 4.4 T-test of gender and thermal adaptation-related behavior

		Temperature preference(16~30°C)		Probability (Change AC set temperature)	
		Summer	Winter	Summer	Winter
Male	Mean	8.40	7.54	4.18	4.12
	SD	3.187	2.747	3.258	3.281
Famale	Mean	8.16	8.01	3.91	3.86
	SD	3.106	2.784	3.214	3.253
F		.050	.010	.778	.904
Sig.		.824	.919	.378	.342
**. Correlation is significant at the 0.01 level (2-tailed).; *. Correlation is significant at the 0.05 level (2-tailed).					

4.1.3. Development of the Behavioral Simulation System

Based on the questionnaire data discussed earlier, this study further developed a simulation system to analyze air conditioner usage behavior. First, through the survey, we collected detailed data related to individual environmental awareness, temperature preferences, and air conditioner usage behavior. Using this data, we constructed a simulation system that models individual air conditioner temperature adjustment behaviors under different levels of awareness and behavioral habits.

(1) Behavioral Decision Framework

This study employs a multiple regression model to predict the likelihood of individuals adjusting air conditioner settings under varying levels of environmental awareness. Based on the collected questionnaire data, environmental awareness is used as the independent variable, while air conditioner behaviors (such as temperature adjustment or the frequency of adjusting air conditioner settings) serve as the dependent variable. The regression model quantifies the relationship between these factors and provides probability estimates for behavioral occurrences, helping us better understand the impact of environmental awareness on energy-saving behaviors. Regression models are widely used in behavioral predictions, and existing studies have demonstrated a significant positive relationship between environmental awareness and energy-saving behaviors, which can be effectively quantified using regression models [2].

In this study, we collected data on environmental awareness and air conditioner usage behaviors through a questionnaire and then analyzed these data using linear regression models. Specifically, these regression models helped us identify how environmental awareness influences individuals' air conditioner temperature adjustment behaviors. In the regression model, environmental awareness is set as the independent variable, and the behavior of adjusting air conditioner settings is the dependent variable. The equations (1) and (2) in the model show the probability calculation for individuals adjusting air conditioner temperatures under different levels of awareness.

$$Y_{\mathrm{INT}} = \beta_1 + aX_{\mathrm{ATT}} + bX_{\mathrm{SN}} + cX_{\mathrm{PBC}} + dX_{\mathrm{PMN}} + eX_{\mathrm{DN}} + fX_{\mathrm{EPK}} \tag{1}$$

$$P = \beta_2 + gY_{\mathrm{INT}} + hX_{\mathrm{Age}} + iX_{\mathrm{People}} \tag{2}$$

In this study, we used two regression equations to analyze the decision-making process of individuals under different levels of environmental awareness. Equation (1) primarily describes how behavioral intention (Y_{INT}) is influenced by various environmental psychological factors. By incorporating variables such as attitude (X_{ATT}), subjective norm (X_{SN}), perceived behavioral control (X_{PBC}), personal moral norm (X_{PMN}), descriptive norm (X_{DN}), and environmental knowledge (X_{EPK}) into the model, we can quantify their impact on energy-saving behavioral intentions. β_1 is a constant term used to adjust the baseline value of the model, ensuring the accuracy of the regression equation. In equation (2), P represents the probability of an individual adjusting air conditioner settings, influenced by factors including behavioral intention (Y_{INT}), age (X_{Age}), and the number of people in the office (X_{People}). These variables allow the model to predict the likelihood of individuals adjusting air conditioner temperatures under different environments and situations. β_2 is another constant term that helps the model better fit the data.

The coefficients in equations (1) and (2) are calculated through regression analysis of the questionnaire data, reflecting the quantitative relationships between different environmental awareness variables and individual behavioral intentions. In the simulation system, the variables X_{ATT} to X_{EPK} describe the input for environmental awareness levels, while X_{Age} and X_{People} represent demographic characteristics in the office environment. By inputting these data into the NetLogo platform, the model can calculate behavioral decision probabilities in real-time.

During the simulation process, the system starts at the beginning of working hours and takes into account the time required for air conditioner temperature adjustments and individual response times. To better simulate air conditioner usage behavior, the system is designed to make decisions every half hour, determining whether to adjust the set temperature of air conditioner. This decision is primarily based on whether the current temperature setting aligns with the individual's perceived comfort level. Through this method, the system dynamically adjusts the temperature settings to closely match individual needs.

Additionally, based on the results of the previous questionnaire analysis, the simulation considers the impact of environmental awareness on the decision-making process. Since individuals have varying comfort temperatures, and this study mainly relies on questionnaire data, we use the personal temperature preferences collected from the questionnaire as the standard for measuring satisfaction. In indoor thermal comfort simulation studies, using a normal distribution model to describe preferences for air conditioner settings has a solid theoretical foundation. Relevant literature indicates that the PMV (Predicted Mean Vote) model's error distribution in predicting thermal comfort typically approximates a normal distribution, with a standard deviation of 1.22. This suggests that individual responses to temperature may fluctuate around a central value under different environments [3].

Based on this, we constructed a normal distribution for comfort based on the percentage of each temperature preference from the questionnaire to reflect satisfaction levels at different temperature settings. Specifically, the probability density function (PDF) of the normal distribution is as follows:

$$f(T) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(X-\mu)^2}{2\sigma^2}} \tag{3}$$

In this formula, $f(T)$ represents satisfaction; T denotes the air conditioner's set temperature, ranging from 16°C to 30°C; σ (standard deviation) depends on the range of T. When T exceeds 25°C, σ=3.5, and when T is below 25°C, σ=1.5.

Studies have shown that when indoor temperatures exceed an individual's comfort range, employees tend to adjust the air conditioner settings to maintain comfort. This implies that if the current temperature is within the individual's comfort range, their willingness to adjust the air conditioner decreases. Therefore, in designing the simulation system, the current temperature is evaluated at each decision point.

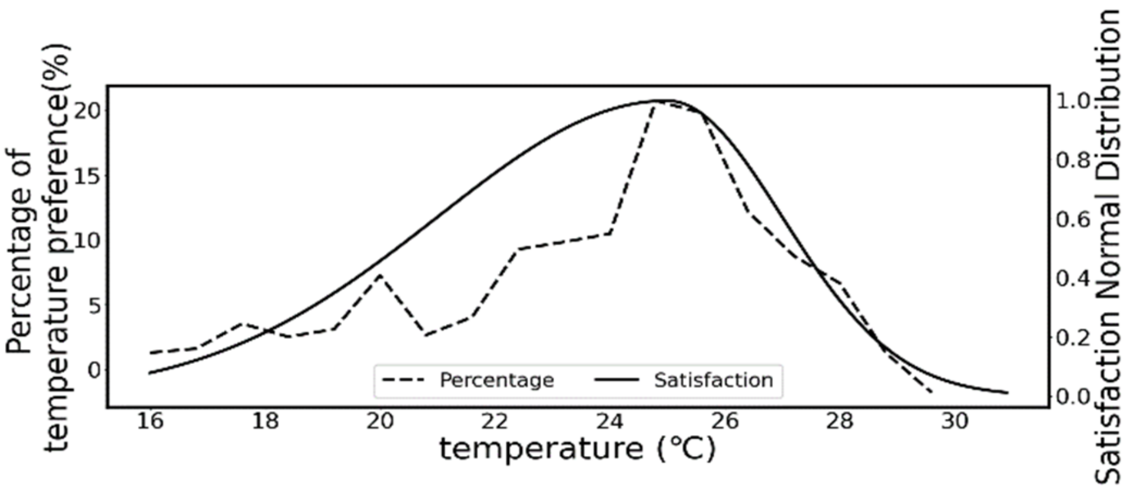


Figure 4.1 Percentage of Preferred Temperatures and Normal Distribution of Satisfaction

(2) Simulation Process

Figure 4.2 details the simulation process used in this study, illustrating how individuals make air conditioning setting decisions under different conditions. By integrating actual data and psychological factors into the simulation, the study can more accurately predict individual behavioral responses, optimizing air conditioning usage strategies for efficient energy management.

As shown in the process, if a temperature change is detected, the system calculates and outputs a new setting temperature based on the current temperature input, then continues the simulation. If no temperature change is detected, the current temperature setting is maintained, and the result is output. This evaluation process continues until the end of the working hours.

After the working hours, all data recorded during the simulation, including temperature changes, adjustment frequency, and individual responses, are thoroughly analyzed. This analysis provides detailed feedback, revealing behavioral patterns and responses to comfort under different temperature conditions. Through this analysis, researchers can gain deeper insights into the factors influencing air conditioning setting adjustments, providing scientific evidence for air conditioning management and energy-saving strategies in office environments.

The flowchart describes the simulation process for air conditioning temperature settings in detail. The simulation starts with initialization and activation. Each time step (Time step +1) represents the progression of simulation time. At each time step, the system calculates user satisfaction based on the current air conditioning setting and ambient temperature. This step uses the satisfaction distribution formula mentioned earlier, influencing whether the air conditioning setting needs adjustment.

Next, the system calculates the probability of changing the air conditioning temperature. This step primarily depends on the user's satisfaction with the current temperature. If the system determines that the user is dissatisfied with the current temperature and requires adjustment, the next step is to calculate the new setting temperature. This step predicts the new temperature setting based on preset rules or models.

If a temperature change is necessary, the system outputs the new setting temperature and records it in the exported data. If no adjustment is needed, the current setting temperature is directly output.

Finally, the system checks whether the current time is within working hours (Time < Working time). If it is, the simulation continues; if it is beyond working hours, the air conditioning is turned off, and all relevant data are exported for further analysis.

This flowchart illustrates the entire simulation process, from temperature perception to adjustment decisions and temperature output.

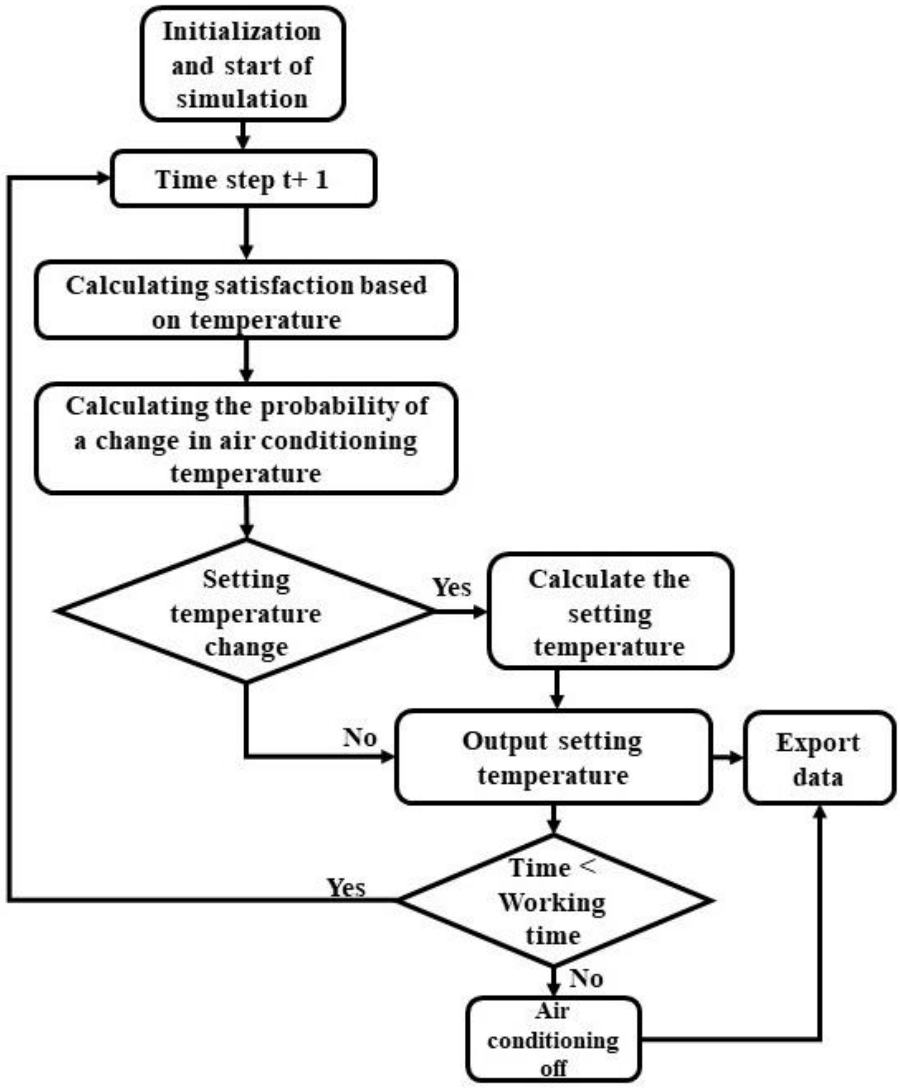


Figure 4.2 Process of simulating people's air conditioning decision behavior

(3) Development of the Simulation System

As mentioned earlier, this study constructs a simulation of air conditioning usage behavior using an Agent-Based Model (ABM). To implement this model, NetLogo was adopted as the primary modeling tool. NetLogo is a programming language and integrated development environment specifically designed for simulating complex dynamic systems and is widely used in research fields involving individual interactions. Its agent-based framework allows researchers to define decision-making processes, behavior patterns, and interactions with the external environment at multiple levels, effectively capturing dynamic relationships between multiple variables.

The initial interface of NetLogo is a blank workspace where users can design and build simulation systems according to their research needs. Using the interface editor, users can add sliders, switches, buttons, and other interactive elements to control input variables and parameter settings in the simulation. To simulate the behavior of individuals or groups, users need to write code in NetLogo’s programming language, defining the behavior rules of each agent and interaction mechanisms within the environment. By writing setup and go functions, users can initialize the simulation environment and control the simulation process. Once the model is launched, users can adjust parameters through sliders and other components, observe the simulation in real-time, and monitor and record data changes using graphs for further analysis.

Figure 4.3 presents the simulation system developed in NetLogo for this study, designed to integrate physical and psychological factors in individual behavior to better simulate human air conditioning usage behavior in office environments.

1. The view section provides real-time visualization of individual movement behaviors. Users can intuitively observe each agent’s location, movement paths, and interactions with the environment, helping researchers better understand individual behavior and group dynamics.
2. The simulation setup and start buttons control the initialization and operation of the simulation. When input parameters change, users can click the "Setup" button to update configurations, ensuring parameter synchronization, and click the "Start" button to launch the simulation. These functions allow researchers to flexibly adjust experimental conditions and observe behavior patterns under different conditions.
3. Based on questionnaire data analysis, this study found that the number of people in the office significantly affects the probability of adjusting air conditioner temperature settings. Through T-test analysis, we categorized occupant numbers into three groups: 1-2 people, 3-20 people, and more than 20 people, representing the most significant probability differences under different occupancy conditions. This categorization helps accurately simulate behavioral responses in environments with varying numbers of people.
4. To enhance the simulation's applicability and adapt to different types of office buildings, this study added work time sliders and initial air conditioning temperature sliders to the user

interface. Users can adjust the work start and end time sliders to change the duration of the workday in the simulation, observing the impact of varying workday lengths on behavior patterns. The initial temperature slider allows adjustment of the default air conditioning temperature at the start of the workday, simulating temperature changes under different initial environmental conditions.

5. **The temperature change chart on the interface provides users with a real-time monitoring tool**, visually displaying the trend of air conditioning temperature changes over time. This helps researchers analyze the relationship between air conditioning adjustment behaviors and environmental conditions, providing data support for subsequent energy-saving optimizations.

According to research by Elie Azar et al., occupants in commercial and public buildings can be classified into high energy consumers (HEC), medium energy consumers (MEC), and low energy consumers (LEC) based on their energy consumption levels [4]. Based on this, the study also classifies respondents into high, medium, and low groups according to their environmental awareness levels, representing different levels of environmental consciousness. Each group's psychological input includes six environmental psychological factors from the extended TPB theory to reflect behavioral differences across various awareness levels.

Moreover, given that the questionnaire analysis showed a significant correlation between age and

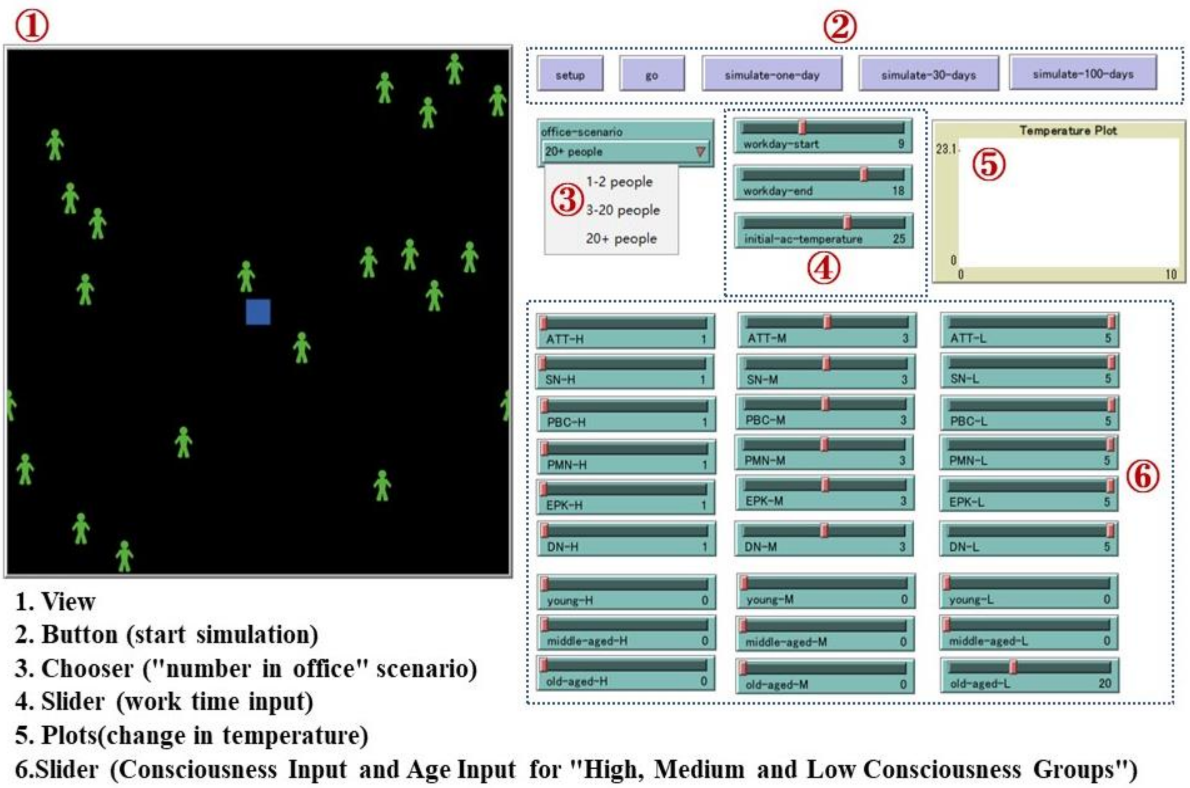


Figure 4.3 The view of simulation system using NetLogo

air conditioning adjustment behavior, the study further subdivides each awareness level group into young, middle-aged, and elderly subgroups. Researchers can use interface sliders to set the number of participants in different age groups and conduct simulations. To facilitate comparison of energy consumption differences across awareness levels, all participants in each simulation are set to the same age and environmental awareness level.

In addition to the primary components in the interface, the study also integrates the aforementioned regression models. All data and information are imported into NetLogo's coding environment to ensure the model's accuracy and flexibility. During the simulation, the system dynamically adjusts behavioral decisions based on the input parameters of different groups, observing air conditioning adjustment behaviors and energy consumption changes under various environmental awareness and age levels. This method not only provides an opportunity to deeply understand individual decision-making mechanisms but also helps identify key drivers of energy-saving behavior.

4.1.4. Simulation Results

In this study, the simulation of summer office air conditioner usage is divided into two different scenarios, with each scenario further analyzed under three different room occupancy conditions. Each scenario features a distinct initial set temperature, which refers to the default temperature setting when the air conditioner is turned on at the start of the workday.

The initial set temperature for the first scenario is 28°C, which is the ideal summer office temperature recommended by the Japanese Ministry of the Environment [5]. This temperature is considered both energy-efficient and comfortable, helping to reduce excessive air conditioner usage while ensuring basic comfort for staff. The initial set temperature for the second scenario is 25°C, based on the most preferred air conditioner setting temperature reported by respondents in the questionnaire survey.

The simulation input data include the number of office users, the initial air conditioner set temperature, working hours, user age, and environmental awareness level. The specific formats of these input variables and detailed settings for each simulation scenario are shown in Table 4.5. All input data calculations are based on the mathematical models presented earlier, specifically the derivations from equations 1, 2, and 3.

To ensure the stability and reproducibility of the simulation results, each scenario was simulated 400 times, equivalent to simulating 400 days of air conditioner usage. After each simulation, the system outputs the daily average of key indicators: the daily average number of air conditioner temperature adjustments in the office, the average number of temperature adjustments per employee per day, and the average change in air conditioner set temperature. These simulation results provide an in-depth analysis of air conditioner usage habits, revealing behavioral differences under varying input conditions.

The simulation is primarily divided into two scenarios based on initial temperatures of 28°C and 25°C at the start of work. Each scenario is simulated under three different conditions. The following are the simulation results.

Table 4.5 Input data types and setting conditions of simulated cases

Input data	Type and range of input data	Setting of case 1 **Fig 5.** (a)~(c)	Setting of case2 **Fig 5.** (d)(e)
Number of people in office	Optional scenarios: 1~2 people, 3~19 people, above 20 people	(1) 2 people; (2)10 people; (3)20people	(1) 2 people; (2)10 people; (3)20people
Initial temperature Setpoint	16~30℃	28℃	25℃
Work time	Start: 0:00~24:00; End: 0:00~24:00	Start: 9:00; end: 18:00	Start: 9:00; end: 18:00
Age	Young, middle-aged, old-aged	Young (average 30); middle-aged (average 40); old-aged (average 60)	Young (average 30); middle-aged (average 40); old-aged (average 60)
Awareness	ATT, SN, PBC, PMN, DN, EPK (range 1~5)	Low group: average 1 Middle group: average 3 High group: average 5	Low group: average 1 Middle group: average 3 High group: average 5

a. Average Daily Changes in Air Conditioner Set Temperature (Initial Set Temperature of 28°C)

As shown in Figure 4.4, when the initial air conditioner set temperature is 28°C, the average daily number of temperature adjustments increases with the number of people in the office. This indicates that higher occupant density leads to more frequent air conditioner use and adjustments. Notably, apart from the exception of the elderly group in a 20-person office, groups with lower awareness tend to change the air conditioner set temperature more frequently. This may be because individuals with lower awareness of energy-saving behaviors are more inclined to frequently adjust the air conditioner temperature for immediate comfort.

Additionally, from an age perspective, the middle-aged group shows the highest frequency of air conditioner adjustments across all room sizes, with the highest average number of daily changes. This phenomenon may be related to the more demanding work pace and higher comfort requirements of middle-aged individuals, prompting them to adjust the air conditioner temperature more often to maintain a suitable working environment.

These results indicate that age and awareness levels significantly affect air conditioner usage behaviors, especially in office environments with varying occupant densities.

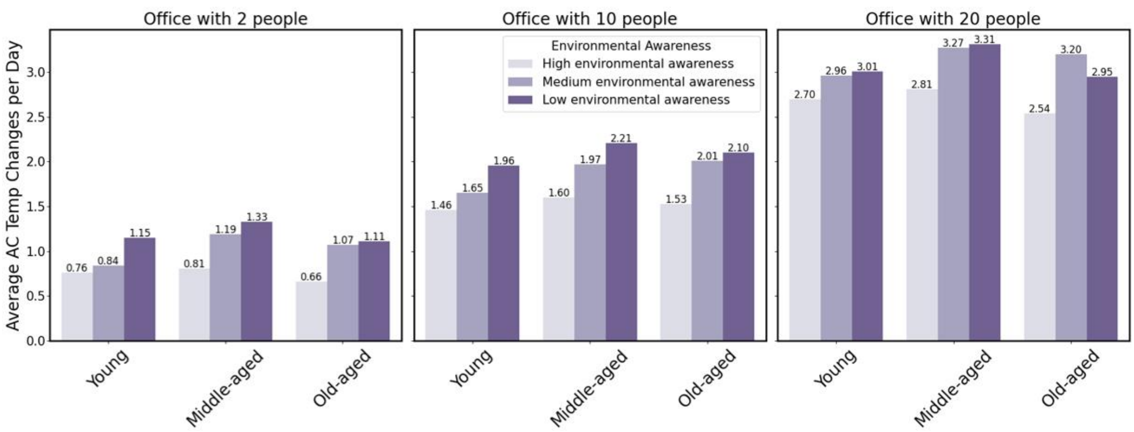


Figure 4.4 Average number of times per day the air conditioner setpoint was changed

b. Average Daily Air Conditioner Temperature Adjustments per Person (Initial Set Temperature of 28°C)

Figure 4.5 illustrates the average number of air conditioner temperature adjustments per person per day. When the initial set temperature is 28°C, the number of occupants in the room significantly influences the frequency of temperature adjustments. Specifically, as the number of occupants increases, the frequency of individual temperature adjustments decreases. This difference is particularly noticeable in the scenarios with 2 and 10 occupants. This may be because, in less crowded environments, each person has greater control over the temperature and is more sensitive to temperature changes, making them more likely to adjust the air conditioner settings based on personal needs. Conversely, in more crowded rooms, the frequency of individual temperature adjustments decreases. This could be due to the distribution of control in shared office spaces, where individuals must coordinate or compromise to maintain a relatively comfortable environment, reducing the need for each person to adjust the temperature settings. Additionally, as the number of occupants increases, the effectiveness of temperature adjustments becomes less noticeable, which may also reduce the motivation for individuals to adjust the temperature. This trend suggests that room density significantly impacts individual air conditioner usage behavior: the higher the density, the more dispersed the control over temperature, leading to fewer individual adjustments.

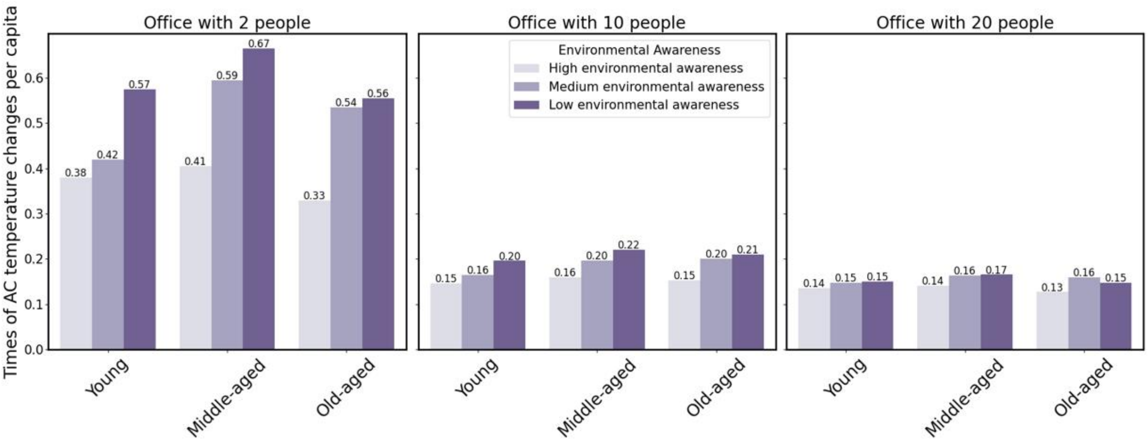


Figure 4.5 Number of air conditioning temperature changes per capita per day

c. Average Change in Air Conditioner Temperature (Initial Set Temperature of 28°C)

Figure 4.6 illustrates the average change in air conditioner temperature. Under the initial set temperature of 28°C, the study found no significant correlation between awareness levels and adjustments in air conditioner temperature settings. In other words, regardless of individuals' levels of environmental awareness, the overall magnitude of temperature adjustments was similar.

However, when comparing different age groups, it was observed that the elderly group showed a slightly higher average magnitude of temperature adjustments than the young and middle-aged groups. Although this trend is not highly significant, it is noteworthy. Elderly individuals may, due to physiological reasons—particularly as sensitivity to temperature changes decreases with age—or higher demands for environmental comfort, tend to make more frequent or larger adjustments to air conditioner settings. This behavioral pattern may reflect the unique needs of the elderly when dealing with environmental changes and their greater reliance on external temperature control to maintain comfortable working conditions. These findings suggest that age may play a role in temperature adjustment behaviors in office environments.

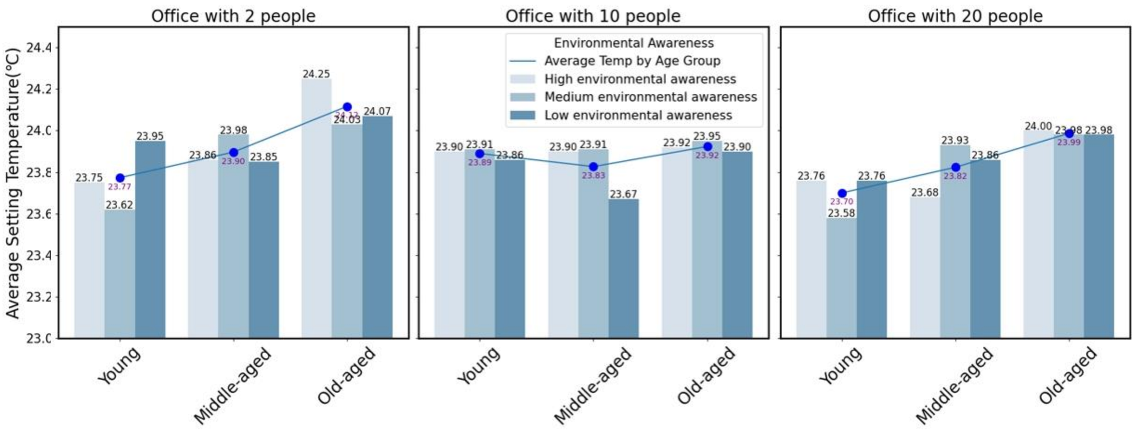


Figure 4.6 Changing average temperature of air conditioners

d. Average Daily Air Conditioner Adjustments (Initial Set Temperature of 25°C)

Figure 4.7 illustrates the average daily changes in air conditioner temperature settings when the initial temperature is set at 25°C. It is clear from the figure that, compared to the initial temperature of 28°C, the frequency of temperature adjustments significantly decreases under the 25°C setting. This is because 25°C is closer to most people's comfort range, leading to higher satisfaction with the temperature settings and reducing the need for frequent adjustments.

Although the overall number of adjustments decreases, the influence of age and environmental awareness levels on air conditioner adjustment behavior remains consistent with the 28°C scenario. The high-awareness group and the middle-aged population continue to show higher frequencies of air conditioner adjustments. This indicates that individuals with high environmental awareness still tend to adjust the air conditioner settings based on actual conditions to achieve optimal comfort, even when the temperature is closer to their comfort range. Similarly, the middle-aged group continues to adjust the temperature more frequently, possibly due to their higher sensitivity to environmental changes or their greater focus on balancing energy-saving awareness and comfort.

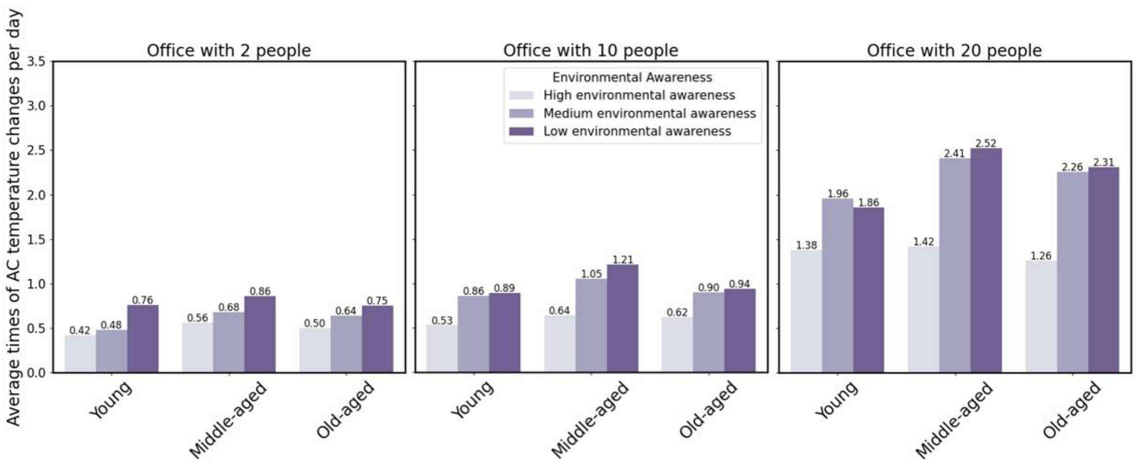


Figure 4.7 Average number of times per day the air conditioner was changed

e. Average Daily Air Conditioner Adjustments per Person (Initial Set Temperature of 25°C)

Figure 4.8 shows the average number of air conditioner temperature adjustments per person per day when the initial temperature is set at 25°C. Similar to the scenario with an initial temperature of 28°C, the more people in the room, the fewer the temperature adjustments per person, particularly in the 2-person and 10-person scenarios, where this trend is especially evident. However, compared to the 28°C initial setting, the overall number of temperature adjustments per person is lower under the 25°C initial setting. This is likely because 25°C is closer to the comfort range for most individuals, reducing the need for frequent temperature adjustments. Nevertheless, changes in the number of people in the room still have a significant impact on the frequency of temperature adjustments per person, especially in scenarios with fewer people, where individual sensitivity to temperature and the need for adjustments are more pronounced.

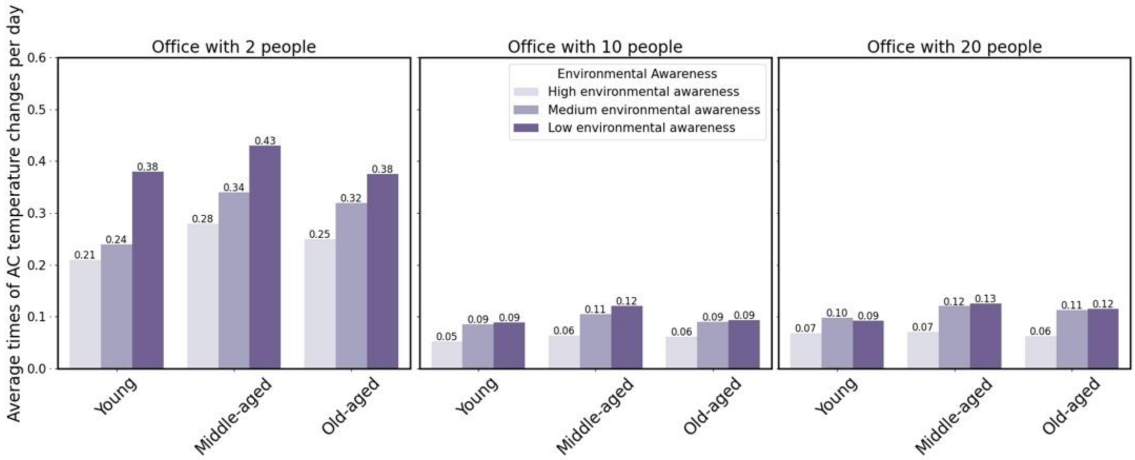


Figure 4.8 Average number of times per day the air conditioner was changed

f. Average Change in Air Conditioner Temperature (Initial Set Temperature of 25°C)

Figure 4.9 shows the average change in air conditioner temperature when the initial set temperature is 25°C. As illustrated, the average temperature change is not significantly different from the scenario with an initial set temperature of 28°C. Similarly, there is no significant correlation between awareness levels and changes in temperature settings. However, compared to the young and middle-aged groups, the elderly group shows a slightly higher average temperature change, reflecting their preference for adjusting air conditioner temperature. This trend suggests that differences in air conditioner adjustment behavior across age groups may be influenced by physiological factors or habits. Overall, temperature adjustment behavior remains relatively stable under the 25°C set temperature.

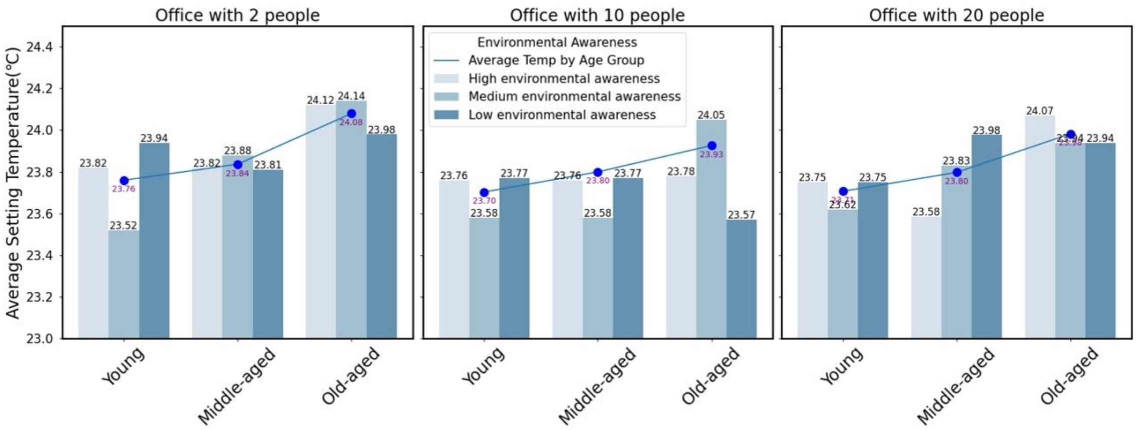


Figure 4.9 Changing average temperature of air conditioners

4.2. Validation Experiments for Behavioral Simulation

4.2.1. Questionnaire Design for Validation Experiment

To validate the accuracy of the simulation results, this study plans to collect behavioral and physical data in an actual office environment. Specifically, we will distribute periodic questionnaires to record employees' air conditioner usage behaviors, temperature preferences, and related physical conditions of the office environment. The questionnaire aims to capture long-term trends in individual behavior changes and external environmental factors.

To ensure the representativeness and consistency of the data, we will adopt a longitudinal study approach. This method involves multiple observations and data collections from the same group over an extended period, effectively revealing changes in behavior over time. Therefore, the study will regularly distribute questionnaires with consistent content in the same office, continuously monitoring employees' changes in air conditioner usage behaviors and their adaptation to environmental temperatures. Through long-term data accumulation and analysis, we can gain a more comprehensive understanding of the relationship between behavior and environmental factors.

As shown in Table 4.6, the questionnaire for the validation experiment includes feedback on thermal comfort and thermal satisfaction in the office environment. Participants are asked to rate their perceived thermal comfort in the current environment based on their subjective feelings. This not only helps in understanding individual reactions to office temperatures but also aids in further analyzing their specific needs for temperature adjustments and air conditioner settings.

The questionnaire also asks participants whether they have engaged in adaptive behaviors in the office environment, such as adjusting air conditioner settings, wiping sweat, or drinking water. These questions aim to understand the specific measures taken by participants to enhance their comfort under varying environmental conditions, particularly during temperature changes.

Additionally, the questionnaire records the air conditioner temperature settings before and after adjustments by the participants. In the previous simulation, we focused not only on the frequency of air conditioner adjustments but also simulated the temperature settings after adjustments made by office personnel. By recording and analyzing these temperature changes, we can effectively validate the accuracy of the simulation results. The actual data from the questionnaire allow for an in-depth exploration of air conditioner temperature adjustment behavior patterns and a comparison of the simulated temperature settings with real-world user behaviors, thereby verifying whether the simulation assumptions align with actual conditions.

Table 4.6 Content of the validation questionnaire

Questions	Options
How do you feel about the thermal environment of the current laboratory? (If you are in the laboratory within the next hour, please provide your feedback based on that time.)	-3: Cold; -2: Cool; -1: Slightly cool; 0: Just right; 1: Slightly warm; 2: Warm; 3: Hot
How satisfied are you with the current thermal environment in the laboratory? (If you will be in the laboratory within the next hour, please write your impression at that time.)	Very dissatisfied; Dissatisfied; Neutral; Satisfied; Very satisfied.
Have you performed any of the following actions? If so, how many times did you perform them to improve your comfort?	Wiping sweat/fanning yourself with your hand or paper; Rubbing your hands/blowing warm air on your hands; Taking off clothes (such as a jacket); Putting on clothes (such as a jacket); Using electrical devices such as a fan; Drinking cold beverages; Drinking warm beverages; Increasing the air conditioner temperature; Lowering the air conditioner temperature
If you adjusted the air conditioner temperature, please tell us the temperature settings before and after the adjustment. What was the air conditioner set to before the adjustment? (If you made multiple adjustments, please select the temperature before the first adjustment.)	20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, have not adjusted the air conditioner settings.
Until 1:00 PM today (or before responding to this survey), if you adjusted the air conditioner's temperature setting, what was the temperature setting after the adjustment? (If you made multiple adjustments, please select the final temperature setting after the last adjustment.)	20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, have not adjusted the air conditioner settings.

4.2.2. Validation Experiment Results

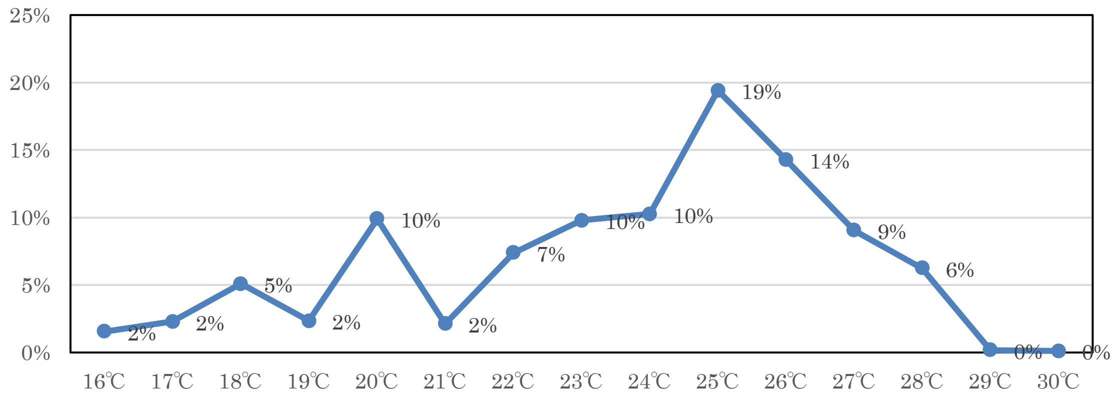
The validation experiment was conducted in an office environment at Kyushu University's campus in Fukuoka, Japan. The experiment ran from July to August 2024, lasting 30 days, with 10 participants. The experiment took place in a research office, and participants were incentivized with cash rewards. During this period, a total of 224 valid questionnaires were collected.

The participants' task was to record their air conditioner usage behavior, thermal comfort, and satisfaction in the office environment during their daily work, providing real experimental data for the study. The experiment aimed to validate the theoretical results obtained from the simulation by observing participants' behaviors, focusing on how people adjust air conditioner temperature settings in an actual office environment. Before the experiment began, participants completed a preliminary questionnaire, which was consistent with the online questionnaire on air conditioner behavior discussed earlier (Table 4.1), focusing on their environmental awareness and air conditioner usage habits.

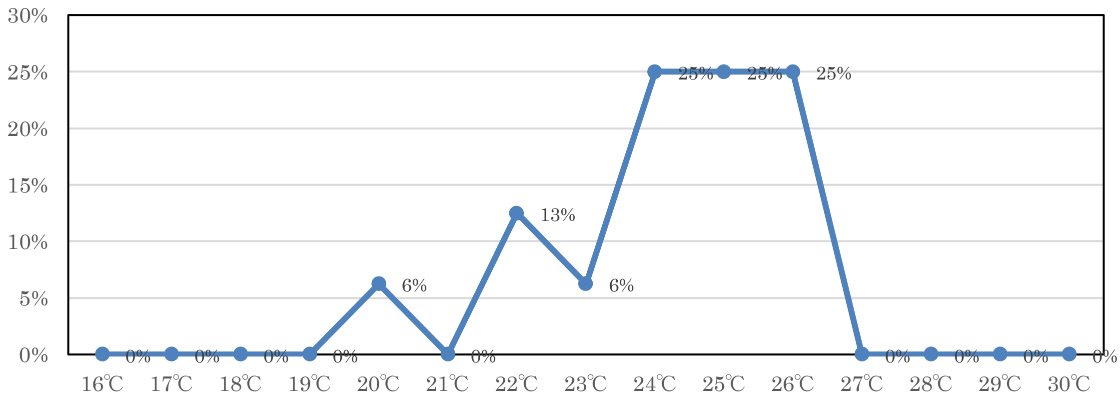
To determine whether there are significant differences between the simulation results and actual behavior, this study not only compares the experimental and simulation results but also uses statistical analysis to evaluate the degree of difference between the two. If significant differences are found, the study will further investigate potential causes, including model assumptions, the complexity of behavioral factors, and external environmental influences. Through this detailed comparative analysis, the study aims to ensure that the simulation results accurately reflect actual behavior, thereby enhancing the model's accuracy and practical applicability.

(1) Comparison of Temperature Preferences from Questionnaires

As shown in Figure 4.10, this is the result of the online questionnaire on air conditioner temperature preferences from Table 4.1 in Section 4.4.1. Figures 4.11 and 4.12 display the questionnaire results for summer and winter air conditioner temperature preferences, respectively, from the validation experiment in the office environment. It can be seen from the figures that the temperature preference trends from the validation experiment are similar to those from the online questionnaire. In summer, the highest proportion of people prefer temperatures of 25°C and 26°C. However, in winter, there is no clear pattern in temperature preferences. As mentioned in the previous correlation analysis, winter air conditioner temperature preferences do not show a strong correlation with factors such as environmental psychology. Therefore, the winter scenario will not be considered in the validation experiment.

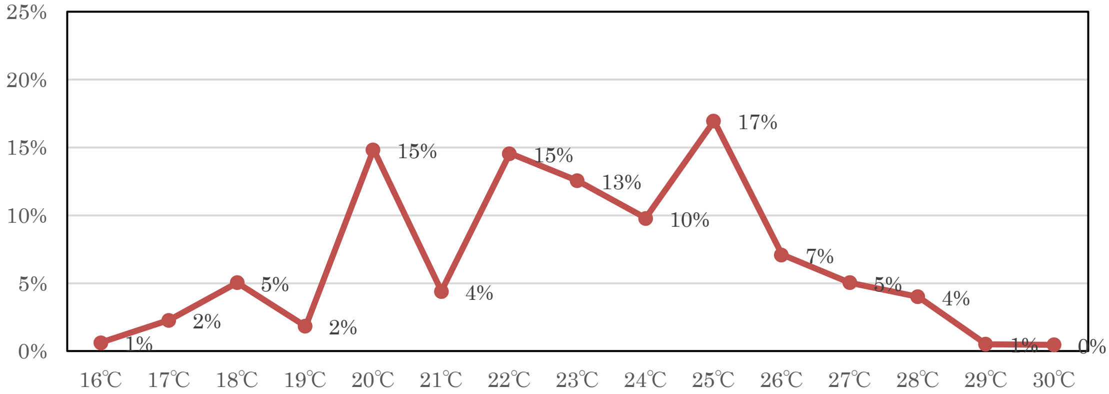


a) Results of online questionnaires

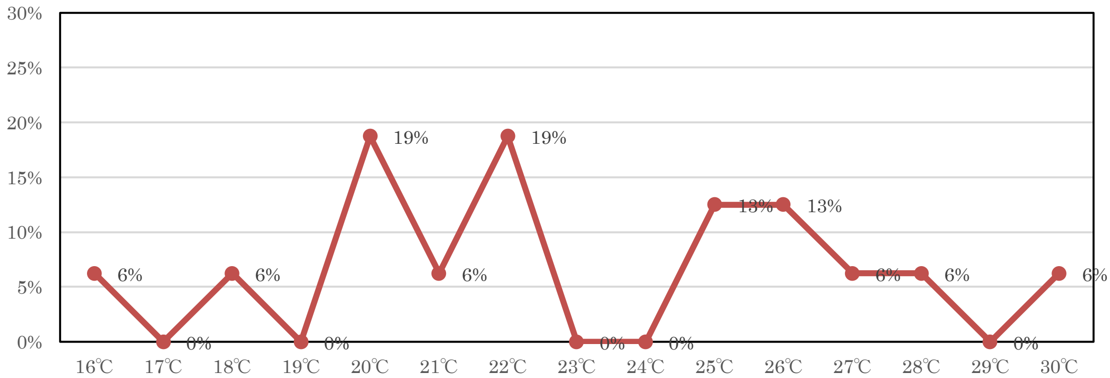


b) Results of experimental questionnaires

Figure 4.10 Comparison of Air Conditioner Temperature Preference Results from Online and Experimental Questionnaires (Summer)



a) Results of online questionnaires



b) Results of experimental questionnaires

Figure 4.11 Comparison of Air Conditioner Temperature Preference Results from Online and Experimental Questionnaires (Winter)

(2) Comparison of adjusted temperature simulation results and questionnaire results

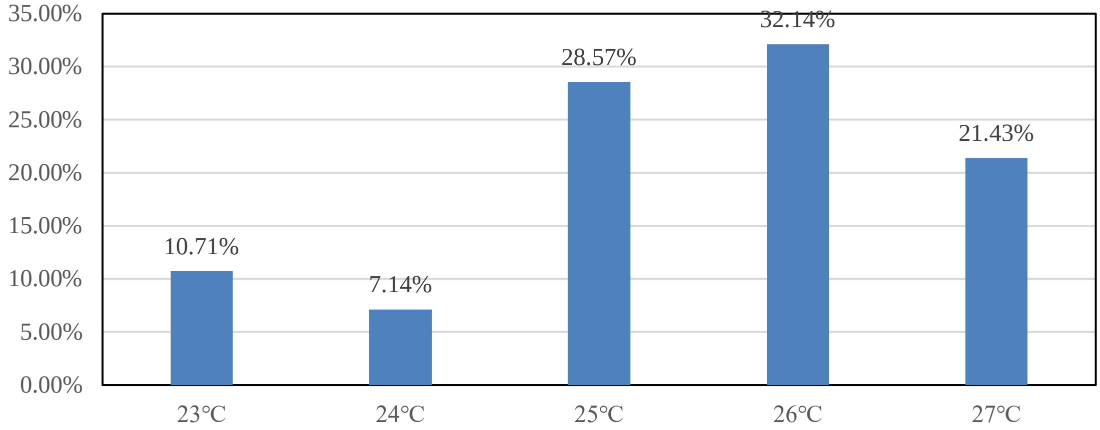
To further validate the findings, this study conducted a simulation using the actual data and average awareness levels of ten participants. The average awareness data are shown in Table 4.7. Besides awareness, the input data included: daily working hours from 9:00 to 18:00; age categorized as young; and an initial temperature of 25°C. The initial temperature of 25°C was chosen because the actual behavior results indicated that 25°C was the most frequently adjusted temperature.

In the validation experiment questionnaire (Table 4.6), participants were asked about the air conditioner temperatures before and after adjustments throughout the day. Similarly, the simulation included post-adjustment air conditioner temperatures, with the average values presented earlier. The figure below shows the percentage distribution of post-adjustment temperatures from the experimental questionnaire results and simulation results.

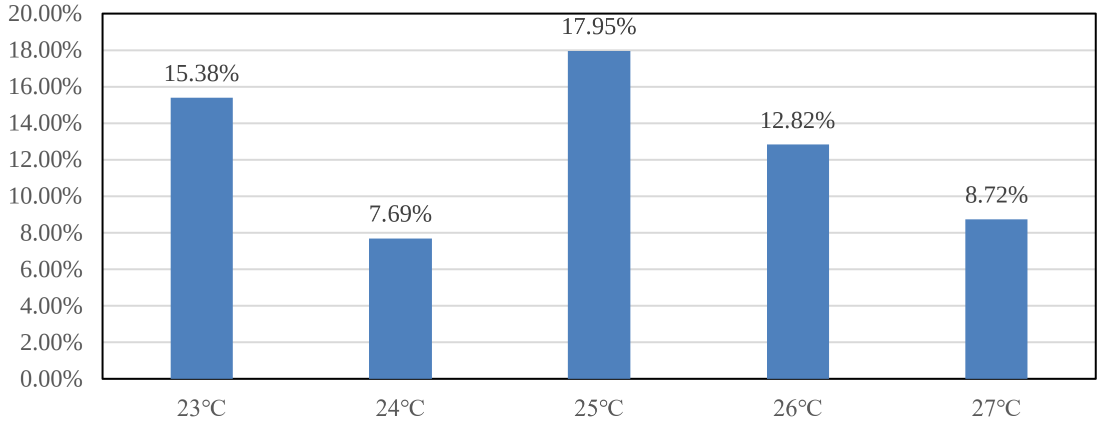
As shown in Figure 4.12, panel (a) represents the validation experiment results, and panel (b) represents the simulation results. To clearly compare the experimental and simulation results, temperatures outside the range of 23°C to 27°C were excluded from panel (b). It can be observed that the highest percentage temperatures in the experiment and simulation results were 26°C and 25°C, respectively, but the overall trend is largely similar.

Table 4.7 The average consciousness of the subjects

ATT	SN	PBC	PMN	DN	EPK	INT
4.28	3.72	3.91	3.09	3.91	4.03	3.81



a) Adjusted temperature experimental questionnaire results



b) Adjusted temperature simulation results

Figure 4.12 Adjusted temperature results

(3) Comparison of Simulation Results and Questionnaire Results

According to the questionnaire results shown in Table 4.8, in the summer office environment, people rarely regulate their body temperature by wiping sweat or blowing on their hands, but more frequently choose to drink iced beverages. Since drinking water is a necessary physiological activity, its purpose is not limited to regulating body temperature, and therefore, these behaviors cannot be considered direct factors influencing air conditioner temperature adjustments. Consequently, this study focuses on air conditioner temperature adjustment behavior. The data show that during the experiment, the average number of air conditioner adjustments per person per day was 0.17.

To further validate the accuracy of the simulation results, the study compared actual data with the simulation results. The simulation results in Figure 4.5 indicate that at an initial temperature of 28°C, individuals in the young age group with low, medium, and high awareness levels adjusted the air conditioner 0.15, 0.16, and 0.20 times per day, respectively. At an initial temperature of 25°C, the adjustment frequencies were 0.05, 0.09, and 0.09 times, respectively. Since the initial air conditioner temperature in the experiment typically remained at the last set temperature from the previous day, ranging from 23°C to 27°C, it can be inferred that the actual temperature adjustment range falls within these simulation results.

When the data from the validation experiment participants were input into the simulation model, the resulting number of air conditioner adjustments was 0.14 times, close to the 0.17 times recorded in the questionnaire. This indicates that the error between the simulation results and actual behavior is minimal, confirming that the simulation model in this study has high accuracy and reliability. By comparing the simulation results with actual results, it can be concluded that the simulation tool effectively reflects the actual behavior of people adjusting air conditioner temperatures in an office environment.

Table 4.8 Survey Results on the Frequency of Adaptive Behaviors

	Wiping sweat/fanning yourself with your hand or paper	Rubbing your hands/blowing warm air on your hands	Taking off clothes (such as a jacket)	Putting on clothes (such as a jacket)	Using electrical devices such as a fan;	Drinking cold beverages	Increasing the air conditioner temperature	Lowering the air conditioner temperature
frequency (per person per day)	0.15	0.00	0.12	0.04	0.01	2.39	0.00	0.17

4.3. Simulation of Lighting Behavior and Energy Consumption

In Section 4.2, the simulation of air conditioner behavior was largely validated through the experimental results. Following this, the study will apply the framework used for air conditioner simulation to model lighting energy-saving behaviors and energy consumption.

The lighting-related behaviors primarily include the two actions listed in Table 3.10 of Chapter 3: B1 "Turn off the lights when you are the last to leave the room" and B2 "In the office, lights are only turned on in areas where people are present." In the simulation system, the mathematical model established from the questionnaire results in Chapter 3 will be used to calculate the probabilities of these behaviors.

4.3.1. Agent and Decision-Making Framework

As mentioned earlier, this study uses data to build a regression model, which is then integrated into the simulation system to determine behavior probabilities. However, unlike air conditioning behavior, lighting behavior is less influenced by thermal environments and other factors, so this study focuses solely on the impact of awareness on behavior. The relevant equations are shown below:

$$Y_{\mathrm{INT}} = \beta_1 + aX_{\mathrm{ATT}} + bX_{\mathrm{SN}} + cX_{\mathrm{PBC}} + dX_{\mathrm{PMN}} + eX_{\mathrm{DN}} + fX_{\mathrm{EPK}} \tag{1}$$

$$P_{B1} = \beta_2 + gY_{\mathrm{INT}} \tag{2}$$

$$P_{B2} = \beta_3 + gY_{\mathrm{INT}} \tag{3}$$

In this study, we use three regression equations to analyze the decision-making processes for two lighting behaviors under different levels of environmental awareness. Equation (1) primarily describes how behavioral intention (Y_{INT}) is influenced by various environmental psychological factors. By incorporating variables such as attitude (X_{ATT}), subjective norm (X_{SN}), perceived behavioral control (X_{PBC}), personal moral norm (X_{PMN}), descriptive norm (X_{DN}), and environmental knowledge (X_{EPK}), we can quantify their impact on energy-saving behavioral intentions. β_1 is a constant term used to adjust the baseline value of the model, ensuring the accuracy of the regression equation. In Equations (2) and (3), PB1 represents the probability of turning off the lights after work, while PB2 represents the probability of using lighting based on the number of people and the area of the room.

The simulation flowchart for office lighting usage is shown in Figure 4.13. The simulation method for B1 involves randomly selecting an agent as the last person to leave the office and calculating the probability of turning off the lights upon departure. For B2, the simulation randomly selects an hour to simulate an area where personnel have left (such as for meetings), and similarly selects an agent as the last person to leave, calculating the probability of turning off the lights. The simulation period spans 24 hours from the start of the workday, as lighting energy consumption continues until the next workday begins if the lights are not turned off.

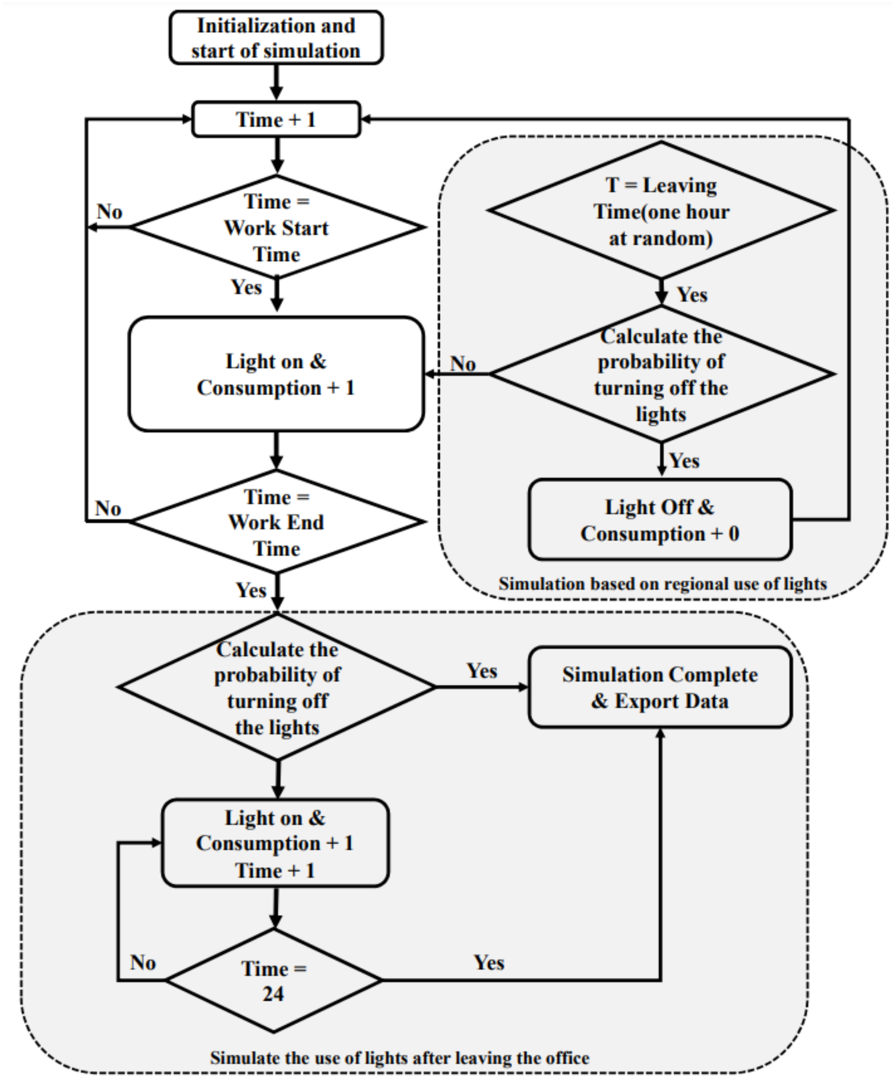


Figure 4.13 Process of simulating people's lighting decision behavior

4.3.2. Introduction of NetLogo System Setting

Based on the statistical analysis of the questionnaire results, this study established a simulation system in NetLogo that simultaneously considers physical and psychological factors. The simulation system interface is shown in Figure 4.14, with the components described as follows:

1. View: The "View" section of the interface is used to observe the movement of agents.
2. Number of People Setting Sliders: This slider allows the adjustment of the number of people in the simulation to observe the impact on the simulation results.
3. Setting Slider for Frequency of Leaving the Office During Working Hours: This slider is used to adjust the frequency of groups leaving the office during working hours (e.g., for meetings).
4. Power of Lighting: This slider allows adjustment of the lighting power in the simulation to suit different simulation scenarios.
5. Number of People with Different Levels of Consciousness: This slider allows changing the number of people with different levels of awareness in the same room.
6. Different Awareness Setting Sliders: The sliders from ATT to INT represent awareness-related input data, as detailed in Equations (1), (2), and Table 1. The input values range from 1 to 5, corresponding to the questionnaire options.
7. Simulation Setup and Start Button: Click "setup" to update the configuration, and click "go" to start the simulation.
8. Plot: The plot on the interface visualizes changes in lighting energy consumption during the simulation.

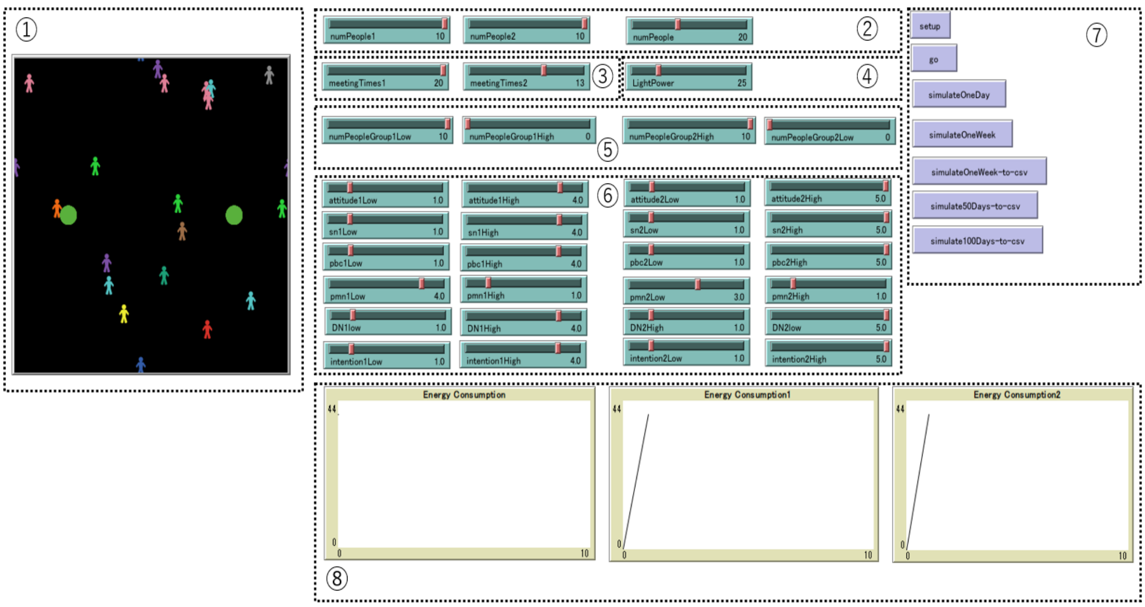


Figure 4.14 The view of lighting decision behavior simulation system using NetLogo

4.3.3. Simulation Setting

This study aims to develop a widely applicable tool to simulate the impact of environmental awareness on energy consumption. As shown in Figure 4, various sliders can be used to modify input data based on different scenarios, such as human awareness, lighting power, weekly meeting frequency (i.e., frequency of leaving the room), and the number of people in the room. The simulation results will be recorded in a CSV file. To examine the impact of awareness on two lighting behaviors (PB1 and PB2) and energy consumption, the study simulates a typical office scenario.

According to the Ministry of Health, Labour and Welfare's Labor Standards Policy [6], employers are generally prohibited from requiring employees to work more than 8 hours per day or 40 hours per week. If the working hours exceed 6 hours, employers must provide at least a 45-minute break; if working hours exceed 8 hours, at least a 1-hour break is required. Therefore, the simulation in this study sets the working hours from 9:00 to 18:00, with a lunch break from 12:00 to 13:00.

For the simulation of B1, one person is randomly selected at 18:00 as the last to leave, and the probability of turning off the lights is calculated. To simulate the impact of awareness on B2, the room is divided into two groups, each using one light. One hour is randomly selected during working hours each day to determine if each group will temporarily leave (simulating scenarios such as meetings). If one group stays while the other leaves, one person is randomly selected as the last to leave, and their likelihood of using lighting is assessed.

According to the Japanese Industrial Standards (JIS) lighting regulations, the standard illuminance for Japanese offices is 750 lux. Considering that the typical efficiency of LED lighting is 100 lumens per watt, the power density for office lighting should be approximately 7.5 watts per square meter. Based on the Xymax Real Estate Research Institute's 2022 Office Space per Person Survey [7], the average office space per person in Japan in 2022 was about 3.66 tsubo (approximately 12 square meters). Therefore, the required lighting power per person per group in this study is 90 watts. With 10 people per group, the lighting power per group is 900 watts.

According to research by Elie Azar et al., users in commercial and public buildings can be categorized into high energy consumers (HEC), medium energy consumers (MEC), and low energy consumers (LEC) to observe differences in energy consumption levels [8]. Similarly, this study categorizes individuals into three groups based on their awareness levels: high awareness, medium awareness, and low awareness. The specific settings are shown in Table 4.9. In addition to these data, all other data and information, including the regression models mentioned earlier, are integrated into the NetLogo code interface.

Table 4.9 Setting of simulation

Input	Setting
Environmental awareness	High awareness: 5; Medium awareness: 3; Low awareness:1
Working time	9:00~18:00
Number of groups	3 groups (high awareness, medium awareness, and low awareness) Maximum 10 persons per group
Length and frequency of temporary absence (meetings)	1 hour at a time, once a day

4.3.4. Simulation results

This study focused on simulating the occurrence probability of two energy-saving lighting behaviors and the corresponding energy consumption under three levels of environmental awareness. Since all data were derived from questionnaires, the simulation results only consider the impact of awareness on lighting behavior and energy consumption, excluding factors such as overtime, necessity of lighting, or forgetting to turn off the lights. Due to the randomness of the simulation and potential variation in individual results, each scenario was simulated 1,000 times, with the average taken.

To further explore the specific impact of awareness on two behaviors—B1 (turning off lights when leaving the office) and B2 (switching lights on and off according to the number of people in the office area)—the study conducted independent simulations for each behavior. In the B1 simulation, it was assumed that individuals would not choose lighting areas based on the number of people in the room. In the B2 simulation, only the behavior of selecting lighting areas based on the number of people was considered, meaning that all lights would be turned off when everyone left the room.

First, the B1 simulation results focus on whether the last person leaving after 18:00 turns off the lights. Table 4.10 shows the daily average results after 1,000 simulations. The table indicates that, excluding other factors, awareness level significantly impacts the behavior of turning off lights and energy consumption. The daily lighting energy consumption for the low-awareness group was 14.90 kWh, while for the high-awareness group, it was only 10.33 kWh. The probability of the low-awareness group failing to turn off the lights when leaving the room was 0.50 times per day, compared to 0.23 times per day for the high-awareness group.

Next are the B2 simulation results. To simulate the behavior of turning off lights based on the number of people and the area, one group was randomly selected to leave the room for one hour between 9:00-12:00 and 13:00-18:00 each day, while the other group stayed in the room. The simulation assessed whether the leaving group would turn off the lights and the resulting energy consumption in this scenario. Table 4.11 compares the daily average results after 1,000 simulations.

The table shows that the behavior of using lighting based on the number of people and area is slightly less influenced by awareness than the behavior of turning off lights when leaving the room. Ensuring the lights are turned off upon leaving, the daily lighting energy consumption for the low-awareness group was 7.05 kWh, 7.00 kWh for the medium-awareness group, and 6.92 kWh for the high-awareness group. However, this only reflects the energy consumption for a scenario where one group leaves for one hour per day. The number of times the low-awareness group failed to turn off the lights was 0.85 times per day, 0.78 times per day for the medium-awareness group, and 0.68 times per day for the high-awareness group.

Table 4.10 The simulation results of B1

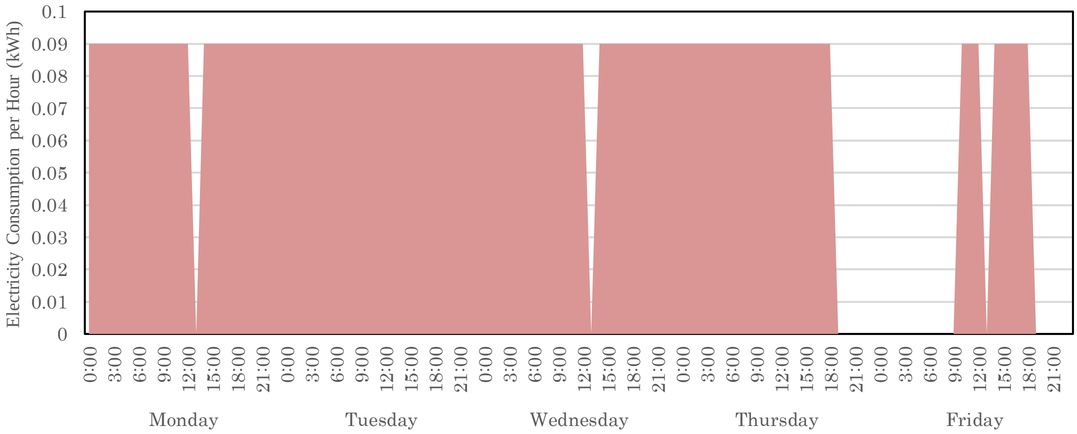
	Average daily electricity consumption on a working day (kWh)	The average number of times the lights are left on when leaving on a working day
Low awareness group	13.90	0.50
Medium awareness group	12.38	0.38
High awareness group	10.33	0.23

Table 4.11 The simulation results of B2

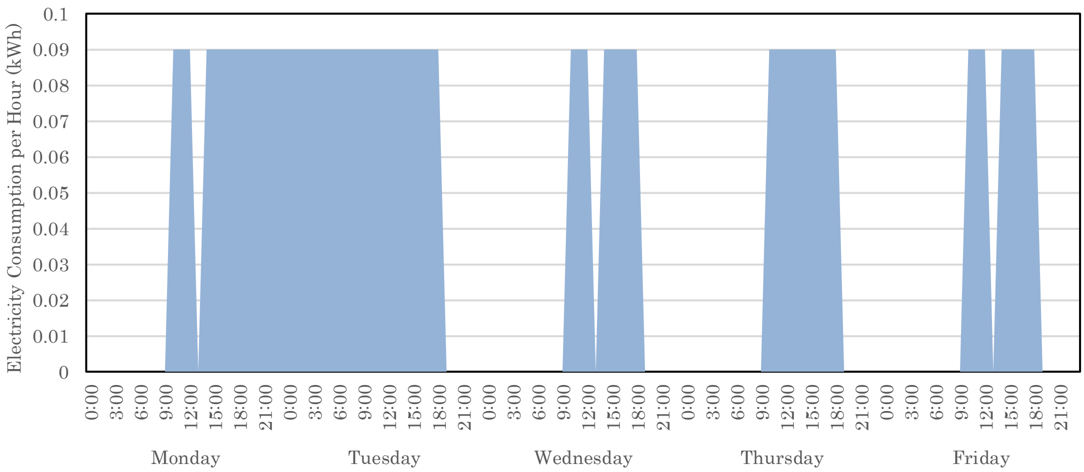
	Average daily electricity consumption on a working day (kWh)	The average number of times the lights are left on when leaving on a working day
Low awareness group	7.05	0.85
Medium awareness group	7.00	0.78
High awareness group	6.92	0.68

To provide an intuitive understanding of the electricity consumption behavior and resulting energy consumption of individuals with low, medium, and high awareness levels, this study created a sample weekly lighting energy consumption simulation diagram, as shown in Figure 4.15. This figure compares the lighting usage of the low, medium, and high awareness groups during workdays over a week. From the figure, it is evident that the low-awareness group consistently consumes more electricity, with lights remaining on for longer periods. The medium-awareness group shows greater variation, occasionally turning off the lights. The high-awareness group demonstrates the highest energy efficiency, frequently turning off the lights and consuming the least electricity. This result indicates that the higher the awareness level, the more significant the energy-saving behavior.

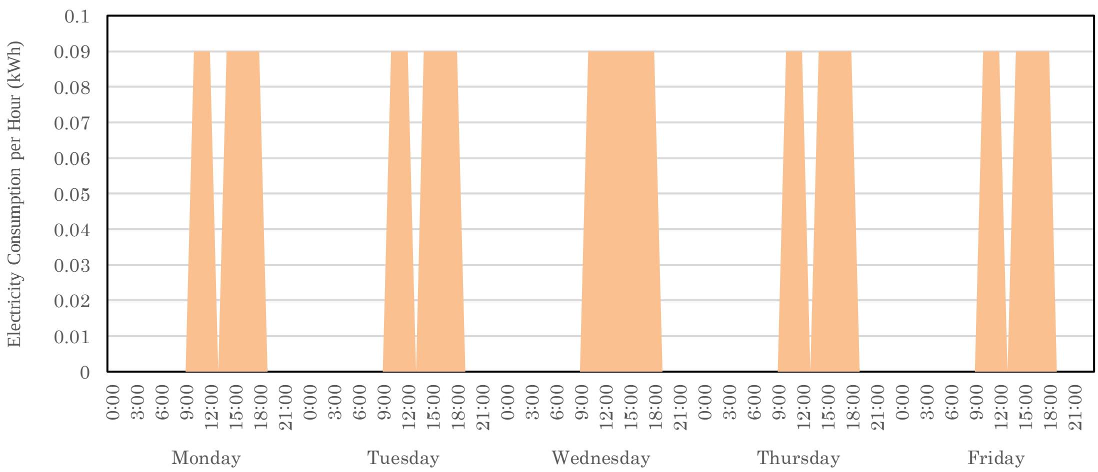
In conclusion, the figure clearly illustrates the significant impact of awareness levels on energy usage behavior. Higher awareness levels lead to more conscious and frequent energy-saving behaviors, not only reducing unnecessary energy waste but also effectively improving lighting energy efficiency.



a) Low-Awareness Room



b) Medium-Awareness Room



c) High-Awareness Room

Figure 4.15 Schematic of lighting use in a random week

4.4. Summer Office Cooling Load Simulation

This study validated the consistency between the air conditioning behavior simulation results and actual conditions, demonstrating that the model effectively reflects real-world air conditioning usage patterns. Additionally, we simulated the impact of lighting behavior on building energy consumption, further enhancing our understanding of various energy consumption behaviors within buildings. Based on this, the next step will be to combine the simulation results of air conditioning and lighting behaviors to thoroughly analyze the specific impact of air conditioning behavior on building cooling load energy consumption.

4.4.1. Simulation Settings

This chapter leverages EnergyPlus as the primary tool for simulating office cooling load, aiming to comprehensively analyze how air conditioning and lighting behaviors impact energy consumption during summer months. EnergyPlus, renowned for its capability to model detailed energy flows within buildings, allows for a nuanced examination of cooling demands. In this simulation, hourly air conditioning usage data and lighting behavior outputs generated by NetLogo in earlier sections serve as key inputs, shaping the custom schedules used in the model. These inputs capture the dynamic interactions between occupant behaviors and building systems.

The air conditioning behavior simulation focuses on summer usage, with validation experiments conducted from July to August. Therefore, the office cooling load simulation uses July as the representative month to reflect typical usage patterns during this period. Additionally, since the validation experiment was conducted at Kyushu University in Fukuoka Prefecture, Japan, this study used weather data from Fukuoka to ensure the model reflects the actual geographic and climatic conditions.

The simulation also adheres to spatial parameters consistent with those discussed in Section 4.3. Specifically, the office area setup is based on the findings from the "2022 Office Space per Person Survey" conducted by the Xymax Real Estate Research Institute [7]. This survey indicates that, on average, each person in Japan occupies approximately 3.66 tsubo, which translates to about 12 square meters. Accordingly, the total office area in the simulation is calculated by multiplying the number of occupants by 12 ㎡ per person. This approach ensures that the spatial dynamics within the simulation are realistic and consistent with typical office environments in Japan.

Aside from the specific inputs related to location, schedules, office area, lighting, and occupant activities, all other parameters in the model use the default settings of EnergyPlus. This consistency in model setup simplifies the simulation process while maintaining accuracy, allowing the focus to remain on the behavioral aspects influencing cooling loads. Table 4.12 provides a comprehensive overview of the input parameter settings utilized in the simulation, offering detailed information on the model configuration that underpins subsequent analysis.

Table 4.12 Simulation Settings

Item	**Parameter**	**Specifications**
Simulation tools	Software version	EnergyPlus V9.6
	Weather location	Fukuoka Prefecture (Japan)
	Office size	12 ㎡/person
Internal gains	Number of people	2 people/10 people/20 people
	Watts of Lights per person	90W/person
	Electric equipment	7.64 W/ ㎡*1)
Control parameters	Simulation periods	July 1~July 30
	Indoor air temperature	The results of the time-based air conditioning temperature simulation in Chapter 4.2.
	Lights operating schedule	The results of the time-based lighting simulation in Chapter 4.3.
	COP（Coefficient of Performance）	3*1)
*note: 1) EnergyPlus Default setting		

The detailed process for calculating office cooling loads is illustrated in Figure 4.16. This process integrates multiple data sources and simulation tools to achieve a comprehensive and accurate cooling load analysis. Specifically, the schedules for air conditioning and lighting—key factors influencing cooling loads—were generated through a behavioral simulation program developed in NetLogo, as previously discussed. This simulation program models various occupant behaviors and environmental awareness levels, which influence air conditioning and lighting usage patterns.

Once generated, these behavior-driven schedules are inputted into EnergyPlus, a widely used building energy simulation software, to conduct the final cooling load calculations. EnergyPlus takes into account the behavioral data from NetLogo along with other physical parameters, such as building specifications, internal gains, and external weather data, to calculate the cooling loads more realistically. This integrated workflow, leveraging NetLogo for behavioral simulation and EnergyPlus for energy calculations, enables a detailed examination of how varying occupant behaviors impact overall energy demand in office environments.

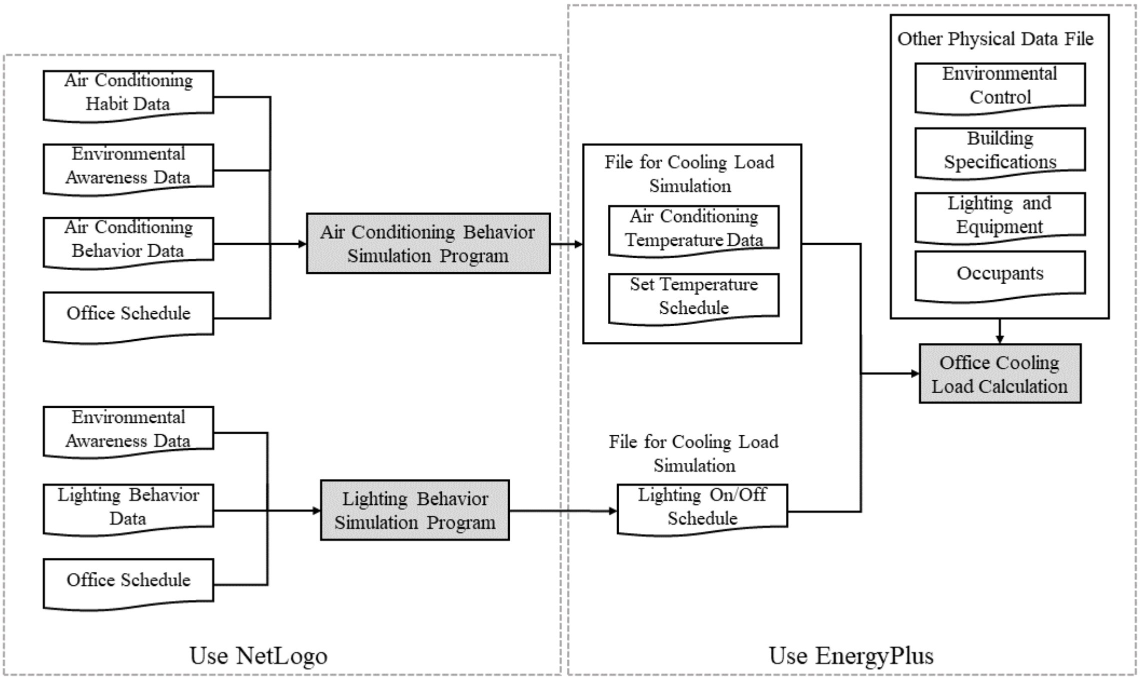
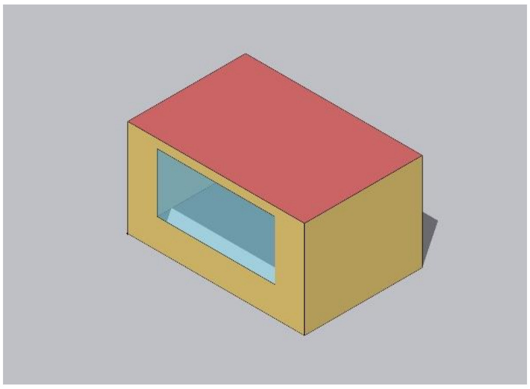
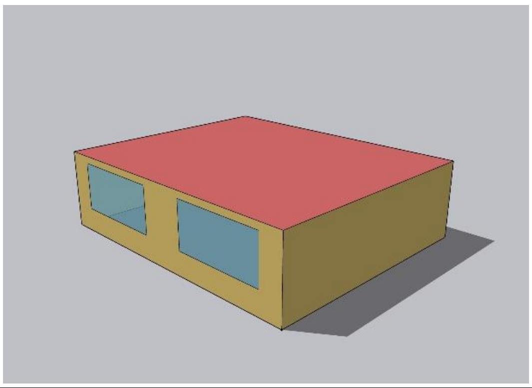


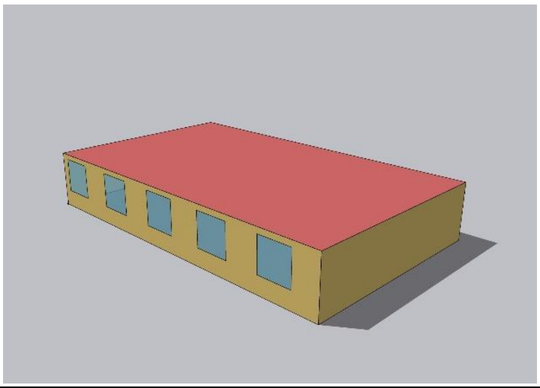
Figure 4.16 Process for calculating office cooling loads

Similar to the air conditioning behavior simulation, the office cooling load simulation categorizes offices into three different sizes: 2-person, 10-person, and 20-person offices. Additionally, the simulation classifies personnel's environmental awareness into three levels: low, medium, and high. Consequently, the simulation includes a total of nine different scenario combinations.

The specific settings for each scenario combination are detailed in Table 4.13. Different office sizes represent typical configurations ranging from small to medium and large office spaces, as illustrated in the table, while the varying levels of awareness reflect differences in energy-saving behavior among individuals. This multi-dimensional simulation design aims to comprehensively assess the impact of office size and occupant behavior on cooling loads, providing robust support for optimizing energy management in office spaces. Table 4.13 outlines the parameter settings for each scenario combination in detail.

Table 4.13 Simulation conditions for the 9 cases

Office types	Cases	Conditions
2-person office 	Case1	Environmental awareness level: Low
		Room size: 24 ㎡
	Case2	Environmental awareness level: Medium
		Room size: 24 ㎡
	Case3	Environmental awareness level: High
		Room size: 24 ㎡
10-person office 	Case4	Environmental awareness level: Low
		Room size: 120 ㎡
	Case5	Environmental awareness level: Medium
		Room size: 120 ㎡
	Case6	Environmental awareness level: High
		Room size: 120 ㎡

20-person office 	Case7	Environmental awareness level: Low
		Room size: 240 ㎡
	Case8	Environmental awareness level: Medium
		Room size: 240 ㎡
	Case9	Environmental awareness level: High
		Room size: 240 ㎡

4.4.2. Simulation Results

The study simulated the nine scenarios (cases) and produced the average daily air conditioning cooling load energy consumption for July, as detailed in Table 4.14. According to the data, in the 2-person office scenario, the low-awareness group (case1) had an average daily energy consumption of approximately 6.4 kWh, which is about 12% higher than the medium-awareness group (case2) and about 58% higher than the high-awareness group (case3). In the 10-person office scenario, the low-awareness group (case4) consumed approximately 14.68 kWh daily, which is about 19% more than the medium-awareness group (case5) and about 86% more than the high-awareness group (case6). In the 20-person office scenario, the low-awareness group (case7) had an average daily consumption of about 22.82 kWh, which is approximately 5% higher than the medium-awareness group (case8) and about 44% higher than the high-awareness group (case9).

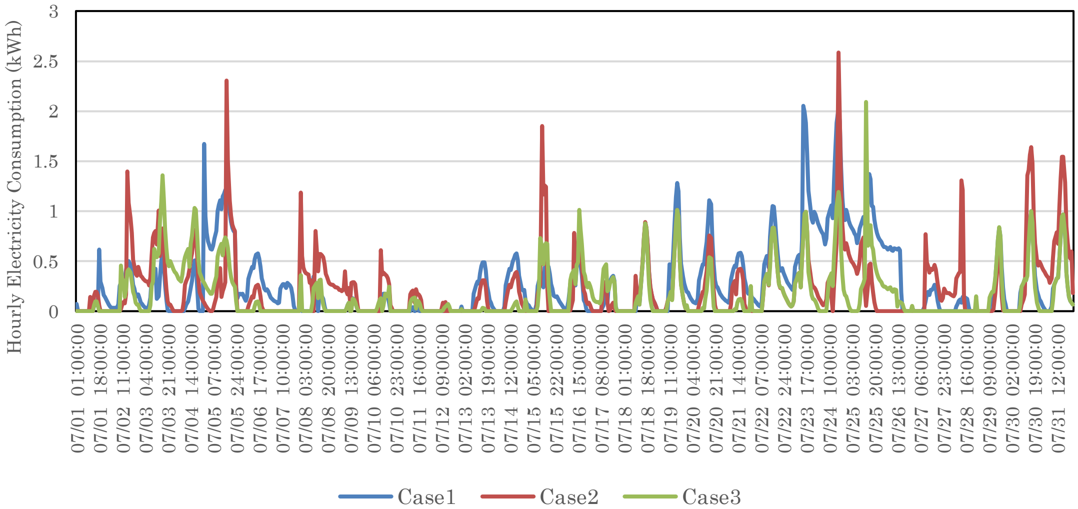
The data clearly show that the level of environmental awareness significantly impacts office air conditioning energy consumption. While total energy consumption increases with the number of office occupants, the differences in consumption between different awareness levels remain evident. This disparity is particularly pronounced between the medium-awareness and high-awareness groups.

Table 4.14 Simulation Results of each cases

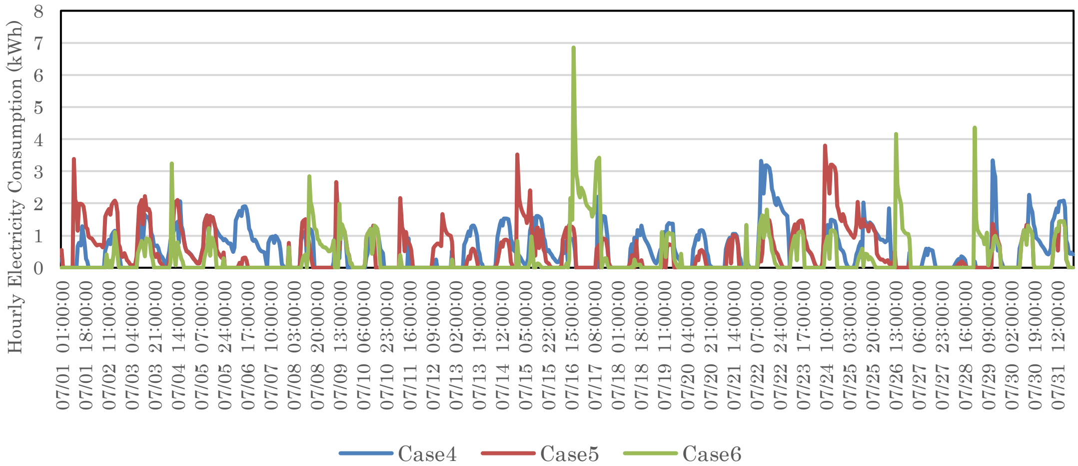
2-person office		10-person office		20-person office	
Case	Average daily energy consumption(kWh)	Case	Average daily energy consumption(kWh)	Case	Average daily energy consumption(kWh)
Case1	6.4	Case4	14.68	Case7	22.82
Case2	5.71	Case5	12.31	Case8	21.56
Case3	4.06	Case6	7.87	Case9	15.81

As shown in Figure 4.17, the simulation results for case1 to case9 throughout July are presented. The figure indicates that the highest energy consumption peaks do not always occur in rooms with the lowest environmental awareness. For instance, in panel (a), the highest energy consumption peaks often appear in the medium-awareness room (case2). However, while the low-awareness rooms may have lower peak consumption, their overall energy consumption levels are higher, and this high-consumption state persists for a longer duration. Similarly, in the 10-person office, the highest consumption peak occurs in the high-awareness room (case6), and in the 20-person office, the peak can also appear in the high-awareness room (case9). Nevertheless, the low-awareness rooms (case4 and case7) consistently show sustained high levels of energy consumption, indicating that their total energy consumption is higher, even if their consumption peaks are not the highest.

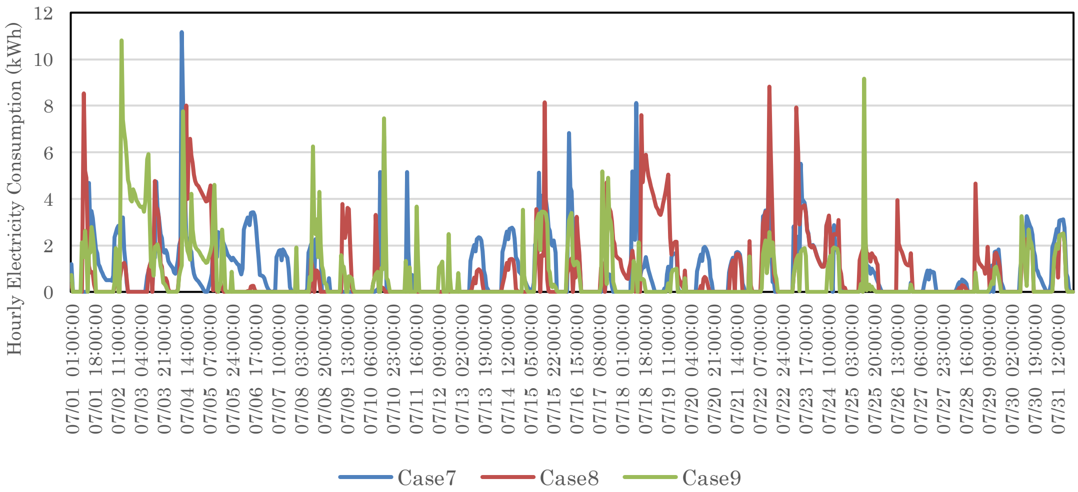
This phenomenon indicates that while high-awareness rooms may occasionally exhibit higher energy consumption peaks, the long-term high energy consumption state in low-awareness rooms significantly increases overall energy usage. As shown in the previous analysis (Table 4.3), there is a significant positive correlation between awareness and temperature preferences in summer, meaning that the higher the awareness, the higher the preferred air conditioning temperature in summer. Therefore, it can be inferred that the occurrence of higher energy consumption peaks in high- and medium-awareness rooms compared to low-awareness rooms might be an incidental result of the simulation. In contrast, low-awareness rooms are more likely to set the air conditioning to a lower temperature during summer, leading to a sustained high energy consumption state, ultimately resulting in the highest total energy consumption for low-awareness rooms.



a) 2-person office (case1~3)



b) 10-person office (case4~5)



c) 20-person office (case7~9)

Figure 4.17 Office Cooling Load Simulation for July

4.5. Discussion and Conclusion

4.5.1. Air Conditioning Usage Behavior

According to the survey results, there is a positive correlation between energy-saving intentions and summer air conditioning temperature preferences. However, this correlation is not reflected in the simulation results shown in Figures 4.6 and Figures 4.8. This discrepancy may be due to the simulation inputs including not only environmental awareness but also other influencing factors such as age, the number of people in the room, and temperature preferences. The combined effects of these factors could influence the level of awareness and summer air conditioning temperature preferences in the simulated environment.

In the correlation analysis, no significant relationship was observed between awareness and temperature preferences during winter. There are several possible reasons for this phenomenon, such as the influence of clothing adjustments and heat generated by other equipment indoors during winter. Additionally, regional and temporal differences might have contributed to the lack of correlation. For instance, the significant climate differences between Hokkaido and Okinawa in winter in Japan could have resulted in notable variations in air conditioning usage behavior.

The survey results also indicate a significant positive correlation between age and summer air conditioning temperature settings ($P<0.01$). In the simulation results shown in Figures 4.6 and Figures 4.8, for scenarios with the same number of people and awareness levels, the average temperature setting for the older group is slightly higher than for the other two groups, which aligns with the survey findings. The ASHRAE Handbook also states that individuals aged 40 and above should choose an effective temperature that is 1°C higher than that for people under 40 [9]. Therefore, in offices with an older average age, setting higher air conditioning temperatures can improve energy efficiency while meeting more occupants' comfort needs.

However, regarding the impact of clothing on temperature change probability and preferences, no significant differences were found between different types of clothing. This contrasts with the findings of Sloot et al. [10], who identified a significant correlation between clothing and summer temperature preferences in German office buildings. This study suggests that cultural differences in office attire and behavior between Germany and Japan may be the cause of these differences.

In the simulation results, individuals with higher environmental awareness adjusted the air conditioning temperature less frequently in office environments across different age groups. This indicates that implementing measures to raise environmental awareness in office buildings, such as energy-saving lectures and environmental awareness campaigns, can effectively enhance the energy efficiency of building air conditioning systems. The simulation results also show that in scenarios with more occupants, the per capita number of temperature adjustments is lower, suggesting that the number of people in the office significantly impacts air conditioning usage. Therefore, designing office spaces to include more shared open office areas could help reduce air conditioning energy consumption.

In scenarios with different initial temperature settings, air conditioning adjustments were significantly more frequent at 28°C compared to 25°C, although the average set temperature was almost the same. Since frequent air conditioning on-off cycles can lead to increased energy waste, the initial office temperature setting should consider behavioral changes due to comfort level variations, rather than focusing solely on energy efficiency.

4.5.2. Office Summer Cooling Load

According to the office summer cooling load simulation results, individuals with different levels of environmental awareness have a significant impact on office energy consumption. The simulation results from the three types of rooms show that while the energy consumption gap between low and medium awareness groups is not very noticeable, the gap between medium and high awareness groups is substantial. This indicates that individuals with high environmental awareness demonstrate greater energy-saving advantages.

The survey results in Chapter 3 also reveal that most people have a medium level of environmental awareness. Therefore, enhancing the environmental awareness of the medium-awareness group could significantly reduce overall energy consumption. Since this group constitutes a large proportion of the office environment, targeting them with environmental education and energy-saving awareness programs could unlock substantial energy-saving potential.

The monthly simulation data also show that while energy consumption peaks do not always occur in low-awareness rooms, the frequent and intense use of air conditioning and lighting by low-awareness individuals results in significantly higher overall energy consumption in these rooms compared to others. This suggests that long-term adherence to energy-saving behaviors is more critical for reducing energy consumption than short-term actions. For instance, during the hottest periods, temporarily lowering the air conditioning temperature to enhance comfort, followed by consistently setting the temperature at an energy-saving level, can more effectively reduce energy consumption. This long-term strategy not only maintains indoor comfort but also significantly reduces energy waste. Therefore, fostering sustained energy-saving behaviors, such as maintaining optimal air conditioning temperature settings, can lead to more sustainable energy management, reduce office operating costs, and promote the long-term development of green office environments.

4.5.3. Lighting Behavior and Energy Consumption

According to the survey results, there is a significant positive correlation between environmental awareness and energy-saving lighting behavior, indicating that the higher the level of environmental awareness, the more likely individuals are to adopt energy-saving lighting practices. This relationship is also validated in subsequent simulation results, showing that stronger environmental awareness leads to a higher frequency of the two energy-saving lighting behaviors.

In the B1 simulation ("I turn off the lights when I leave the room"), the impact of awareness on lighting energy consumption is particularly pronounced. Over an eight-hour workday, considering only the effect of awareness, the low-awareness group's electricity consumption is 34% higher than that of the high-awareness group, and the frequency of leaving lights on is 117% higher. This significant difference highlights that improving employees' energy-saving awareness can substantially reduce energy waste. Implementing educational programs, reminders, and reward systems in office buildings can effectively lower lighting energy consumption, achieving greater energy efficiency.

In the B2 simulation ("I choose lighting areas based on the number of people in the room"), the impact of awareness is similarly notable. In the simulation, one group leaves the room for one hour each day. Due to the short duration of room vacancy, the difference in daily average lighting consumption is not significant. However, in terms of the frequency of leaving lights on, the low-awareness group is 25% higher than the high-awareness group. This suggests that while short-term behavioral differences may be minimal, the more frequent energy-inefficient behaviors of the low-awareness group can lead to significant energy waste over time.

These results underscore the critical role of environmental awareness in promoting energy-saving behavior. Systematic awareness-raising strategies, such as energy-saving training, behavioral incentives, and regular reminders, can effectively reduce long-term energy consumption and enhance overall office energy management efficiency. Continuous cultivation of energy-saving behavior not only conserves energy but also helps companies create a sustainable, green office environment.

4.5.4. Conclusion

This chapter simulated air conditioning behavior, lighting behavior, energy consumption, and office cooling loads. The results not only demonstrate the significant impact of environmental awareness on energy consumption but also reveal that environmental psychology, age, and the number of occupants in a room significantly influence individual air conditioning behavior. In the simulation of lighting patterns, the findings indicate that an individual’s environmental psychology significantly affects lighting usage behavior. For example, during an eight-hour workday, the lighting energy consumption caused by the low-awareness group leaving the office without turning off the lights was twice that of the high-awareness group, and the frequency of not turning off the lights was six times higher. The combined effects of lighting and air conditioning behaviors also showed that the office cooling load simulation results were significantly influenced by low, medium, and high awareness levels.

This study uniquely combines awareness with behavioral modeling, offering originality and innovation, and holds significant implications for energy management in various office buildings. Depending on the awareness and characteristics of building occupants, managers can enhance energy management through various forms of environmental psychological interventions and environmental design.

However, the study has certain limitations. Real-world office buildings are more complex than the system established in this study. Lighting is also influenced by the nature of the work and lighting requirements. Factors such as interpersonal interactions and the types of job roles in different office buildings can affect air conditioning usage in varying ways. Future research will explore more factors influencing human behavior. Additionally, the study plans to expand future simulations beyond lighting and air conditioning to include multiple behavioral models, aiming to find more effective methods to reduce building energy consumption and enhance occupant comfort.

Additionally, this study has some limitations in the questionnaire analysis and design. For instance, the analysis did not account for the impact of regional differences on air conditioning usage during winter, and the questionnaire design did not fully consider the behavioral differences caused by regional and seasonal variations. Future research should conduct a more in-depth analysis of regional differences to ensure that the findings of this study can be applied more accurately to different regions.

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Chapter-5
Summary

5.1. Summary of the Study
5.2. Research Limitations and Future Directions

Chapter 5. Summary

5.1. Summary of the Study

The purpose of this study was to build a simulation system to quantify and analyze the impact of varying levels of environmental awareness on building energy consumption. To achieve this, an integrated conceptual model was first developed based on existing research, combining awareness levels with internal and external building factors to provide a theoretical framework. Next, data on energy consumption behaviors and environmental awareness were collected through a large-scale survey, and a mathematical model was developed to represent the relationship between the two. This model was then embedded into the simulation system to enable simulations of air conditioning and lighting usage behaviors and their associated energy consumption. Below is a summary and overview of each chapter of this study.

Chapter 1 introduces the importance of awareness and behavior in managing energy consumption within buildings, discussing how human behavior influences energy use. Through a brief review of related studies, the research objective is established: to use simulation analysis to investigate the impact of awareness and behavior on building energy consumption.

Chapter 2 provides a literature review that explains the application and significance of the extended Theory of Planned Behavior (TPB) model and DNAs framework in understanding energy-related human behavior in buildings. It summarizes how factors such as personal moral norms, descriptive norms, and environmental knowledge influence behavior in the extended TPB model, and explores how the DNAs framework provides a new perspective for multidimensional behavioral analysis. By integrating these two theoretical frameworks, a more comprehensive model was constructed to examine the complex relationship between behavior and building energy consumption.

Chapter 3 analyzes the relationship between energy-saving behavioral intentions and influencing factors in office buildings from the perspectives of environmental psychology and environmental behavior. Based on the literature review, this study extended the TPB model and conducted research by distributing surveys in actual office buildings in Japan, followed by validation experiments to establish the relationship between behavioral intentions and actual behaviors. Using an online survey platform, data were collected and analyzed statistically to verify the model hypotheses. The results confirm the effectiveness of the extended TPB model in predicting individual energy-saving intentions and behaviors within office buildings. The findings of Chapter 3 hold significant implications for energy management in office buildings, indicating that, given the TPB model’s applicability in predicting energy-saving intentions, managers can enhance employees' attitudes toward energy-saving behaviors through multi-layered environmental psychology interventions, thereby influencing their actual energy-saving behaviors.

Chapter 4, building on the findings of Chapter 3, simulates air conditioning behavior, lighting behavior, energy consumption, and office cooling loads. The results show that awareness has a significant impact on energy consumption, and that factors such as environmental psychology, age, and the number of occupants in a room also significantly affect individual air conditioning behaviors. For lighting behavior, the simulation results further indicate that an individual's environmental psychology significantly affects lighting usage behavior in office buildings. For example, over an eight-hour workday, the energy consumption from leaving lights on by the low-awareness group was twice that of the high-awareness group, and the frequency of leaving lights on was six times higher. Under the combined effects of lighting and air conditioning behaviors, the simulation results for office cooling loads show significant differences in cooling loads between low, medium, and high awareness levels.

This study's integration of awareness with behavioral modeling is both innovative and original, holding significant implications for energy management in office buildings. Depending on the awareness and characteristics of occupants in different office buildings, managers can enhance the effectiveness of energy management through various forms of environmental psychological interventions and environmental design.

5.2. Research Limitations and Future Directions

This study has several limitations. First, in Chapter 3, the extended TPB model shows limited explanatory power for certain behaviors, suggesting the need for larger-scale surveys and more in-depth statistical analyses in future research to better identify influencing factors. Additionally, real office buildings are more complex than the system modeled in this study. For instance, lighting behavior is influenced by the nature of the work and lighting requirements, and air conditioning usage can vary based on interpersonal interactions and job types within the building. Air conditioning cooling loads are also impacted not only by user behavior but by the heat emissions of other equipment within the room, adding further complexity to the simulation.

Given these limitations, this study offers the following potential avenues for further development: Future research could refine survey design to include a broader range of behaviors, establishing a more rigorous mathematical model that describes the relationship between environmental awareness and various behaviors. Furthermore, as shown in Figure 5.1, in terms of energy consumption simulation, it is possible to improve accuracy and predictive capability by not only focusing on air conditioning and lighting behaviors but also incorporating the relationships between various other awareness factors and multiple behaviors into the model.

Future research could also explore additional variables, such as office space layout, types of

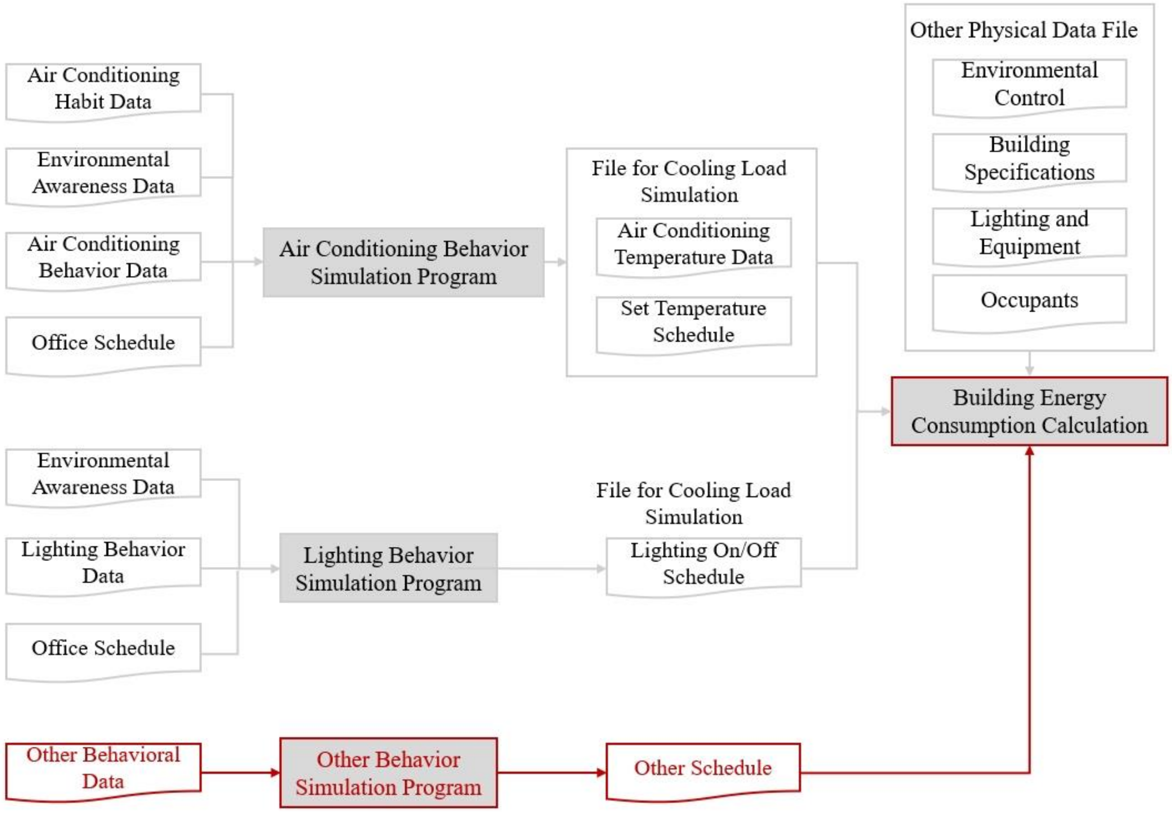


Figure 5.1 Building Energy Consumption Simulation Flowchart

equipment, and usage intensity, to simulate energy consumption patterns that more closely reflect real-world office environments. Ultimately, this would aid in providing more effective decision support for energy management in office buildings and offer new insights and practical approaches for the comprehensive optimization of building energy savings and management.

Through these improvements, the model could become a more versatile tool for understanding and predicting energy consumption behaviors in a variety of office settings, contributing to more sustainable office designs and operational strategies. By expanding and refining the current framework, future studies could better capture the nuanced interactions between user awareness, behavior, and building energy performance, supporting the development of green building practices and policies that align with evolving environmental goals.

Appendix

1. **Other Analysis of air-conditioning-related questionnaires**
2. **Other figures and tables**
3. **Questionnaire Japanese Version**

Appendix

1. Other Analysis of air-conditioning-related questionnaires

In this study, there are several items in the questionnaire related to air conditioning usage behavior that have not been simulated. However, these items are statistically significant in relation to air conditioning usage behavior in the statistical analysis. Therefore, these analysis results are included in this appendix.

1.1. Correlation Analysis

Table A.1 presents the correlation analysis between environmental awareness and thermally adaptive behaviors. Each behavior item (P1 ~ P6) represents different energy-saving adaptive behaviors (as shown in Table 4.1 in the previous section). Specifically, P1 represents "Endure," P2 represents "Adjust clothing," P3 represents "Drink water," P4 represents "Use an electric fan or fan in summer / Use equipment such as underfoot heaters and chair carpets in winter," P5 represents "Open the window in summer / Use thermal items such as blankets and hand warmers in winter," and P6 represents "Change the air conditioner temperature setting."

The table shows that environmental awareness variables (e.g., ATT, SN, PBC) have a significant positive correlation with energy-saving behaviors P1 through P5, with a particularly strong influence of attitude (ATT) on endurance (P1) and clothing adjustment (P2). This suggests that employees with higher environmental awareness are more likely to adapt to temperature by enduring or adjusting clothing rather than relying on changes to air conditioning temperature settings. Additionally, the correlation between environmental awareness and P6 (adjusting the air conditioner temperature) is negative, with ATT and SN showing significance at the 0.01 level for this behavior. This indicates that higher environmental awareness may reduce dependence on adjusting the air conditioning settings, reflecting a tendency among environmentally aware individuals to adopt other means of adapting to the ambient temperature, thus reducing the need for air conditioner temperature adjustments.

In addition to environmental awareness variables, factors such as age and job position also have a significant impact on adaptive behaviors. The data show a higher correlation between age and endurance (P1) as well as air conditioner temperature adjustment (P6), with older employees particularly inclined to endure temperature changes rather than frequently adjusting air conditioning settings. Job position shows a positive correlation with adjusting air conditioner settings in summer, indicating that higher-ranking employees are more likely to adjust air conditioning settings, potentially due to greater autonomy in controlling their office environment.

The influence of the number of people in the room shows a positive correlation with endurance (P1) and a negative correlation with air conditioner temperature adjustment (P6), suggesting that in a more crowded environment, individuals are more likely to tolerate temperature changes rather than frequently adjusting air conditioning settings. This reflects the inhibiting effect of collective environments, where individuals in shared spaces tend to adapt to ambient temperatures through endurance rather than directly changing air conditioning settings.

The significant correlations between temperature preferences (T1, T2) and environmental awareness variables are also noteworthy. The data indicate that ATT has a significant positive correlation with summer air conditioner temperature preference (T1), suggesting that individuals with stronger environmental awareness tend to set air conditioning at higher temperatures in summer to conserve energy. However, the correlation between winter temperature preference (T2) and environmental awareness is not significant, possibly due to varying personal heating needs, leading to a more dispersed preference. Overall, these data suggest that individuals with high environmental awareness tend to cope with temperature changes through endurance or other means, reducing the frequency of air conditioning adjustments, especially in summer. The results imply that fostering environmental awareness among employees can effectively promote energy-saving behaviors in office environments.

Table A.1. Correlation analysis of environmental awareness and thermal adaptation-related behavior

				Summer						Winter					
		T1	T2	P1	P2	P3	P4	P5	P6	P1	P2	P3	P4	P5	P6
ATT	Corr. Coef.	.206**	.073*	.270**	.282**	.247**	.087**	.033	-.161**	.248**	.337**	.235**	.046	-.069*	-.128**
SN	Corr. Coef.	.200**	.064	.233**	.255**	.248**	.130**	.076*	-.173**	.215**	.314**	.225**	.080*	-.025	-.137**
PBC	Corr. Coef.	.165**	.050	.177**	.203**	.198**	.096**	.071*	-.166**	.147**	.240**	.199**	.102**	.027	-.138**
PMN	Corr. Coef.	.158**	.039	.184**	.210**	.208**	.116**	.071*	-.120**	.158**	.252**	.212**	.056	.000	-.093**
DN	Corr. Coef.	.204**	.024	.142**	.173**	.174**	.149**	.103**	-.140**	.093**	.191**	.189**	.069*	.042	-.104**
EPK	Corr. Coef.	.166**	.021	.159**	.214**	.177**	.124**	.078*	-.146**	.150**	.245**	.198**	.062	-.009	-.118**
INT	Corr. Coef.	.225**	.012	.211**	.249**	.213**	.127**	.077*	-.150**	.171**	.299**	.228**	.056	-.037	-.108**
Age	Corr. Coef.	.231**	.049	.146**	.084*	.060	.061	.021	.150**	.141**	.131**	.089**	-.081*	-.045	.151**
Position	Corr. Coef.	.025	-.050	-.001	.048	-.017	.097**	.073*	.128**	.022	.022	.070*	-.011	.068*	.151**
Number of people	Corr. Coef.	-.001	.020	.055	.036	.025	-.041	-.046	-.118**	.046	.021	.000	-.047	-.076*	-.142**

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

1.2. Gender T-Test

The t-test is a statistical method commonly used to examine the differences between two groups, helping us determine whether there is a statistically significant difference between the data from these groups. In this study, the t-test was applied to analyze gender differences to explore the variations in energy-saving adaptive behaviors between men and women. The specific analysis results are shown in Table A.2.

Under winter conditions, the t-test results indicate significant gender differences in four specific behavioral items. These behaviors include adjusting clothing (P2), drinking hot water (P3), using equipment such as underfoot heaters and chair carpets (P4), and using thermal items such as blankets and hand warmers (P5). Among these, adjusting clothing and using blankets show particularly significant gender differences (with a significance level of **P<0.01), while drinking hot water and using heating equipment show slightly weaker but still statistically significant differences (with a significance level of *P<0.05).

These results suggest that there are notable differences between men and women in how they respond to cold environments in winter. Women may be more inclined to increase warmth by adding clothing, using hand warmers, or blankets, while men exhibit a relatively lower frequency or tendency for these behaviors. These findings on gender differences help us better understand the impact of gender on energy-saving behaviors and comfort regulation, providing empirical evidence for developing more inclusive energy-saving policies and behavior interventions.

Table A.2 t-test of gender and thermal adaptation-related behavior

		T1	T2	Summer						Winter					
				P1	P2	P3	P4	P5	P6	P1	P2	P3	P4	P5	P6
Male	Mean	8.40	7.54	3.92	4.59	4.56	3.60	3.02	4.18	4.04	4.89	4.03	2.91	2.67	4.12
	SD	3.187	2.747	3.282	3.622	3.493	3.312	2.931	3.258	3.307	3.616	3.191	2.825	2.648	3.281
Famale	Mean	8.16	8.01	4.19	4.69	4.65	3.53	2.96	3.91	4.10	5.25	4.26	4.21	2.97	3.86
	SD	3.106	2.784	3.442	3.747	3.660	3.297	2.987	3.214	3.482	3.885	3.504	3.725	3.122	3.253
F		.050	.010	2.010	1.418	2.145	.234	.005	.778	1.861	8.447	9.121	65.596	6.659	.904
Sig.		.824	.919	.157	.234	.143	.629	.943	.378	.173	.004**	.003**	.000**	.010*	.342

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

1.3. ANOVA test

Analysis of Variance (ANOVA) is a statistical method used to examine whether there are significant differences between three or more independent samples or groups. In this study, ANOVA was applied to explore whether different reasons for temperature regulation influence individuals' decisions to engage in energy-saving behaviors in specific environments. Specifically, this study hypothesizes that individuals' energy-saving behavior patterns may vary according to their primary reasons for temperature regulation. Therefore, ANOVA was used to verify whether these behavioral differences are statistically significant.

As shown in Table A.3, different reasons for temperature regulation show significant differences across various behaviors, including summer temperature preference (T1), winter temperature preference (T2), "Endurance" (P1) and "Change air conditioner temperature setting" (P6) in summer adaptive behaviors, and "Endurance" (P1), "Adjust clothing" (P2), and "Change air conditioner temperature setting" (P6) in winter adaptive behaviors. These significant differences suggest that individuals' preferences for winter temperature settings, as well as the frequency of adjusting air conditioner settings and tendency towards energy-saving behaviors in specific seasons, vary according to their chosen reasons for temperature regulation.

Further analysis reveals significant differences in winter temperature preferences among individuals with different reasons for temperature regulation, potentially reflecting a balance between comfort and energy-saving behaviors. Additionally, the reasons for temperature regulation affect the frequency of air conditioner adjustments in both summer and winter. Overall, these results support the study's hypothesis that individuals' choices of reasons for temperature regulation are closely related to their energy-saving behavior patterns.

Table A.3 ANOVA analysis of main reasons to consider when changing temperature and thermal adaptation-related behavior

	T1	T2	Summer						Winter					
			P1	P2	P3	P4	P5	P6	P1	P2	P3	P4	P5	P6
F	2.711	4.581	4.586	1.682	1.319	.506	1.204	2.890	3.431	3.195	1.730	1.923	.624	3.169
Sig.	.013*	.000**	.000**	.122	.246	.804	.302	.009**	.002**	.004**	.111	.074	.711	.004**

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

1.4. Frequency Distribution Analysis

Due to the limitations of independent sample t-tests and ANOVA in providing detailed explanations of specific differences, this study created frequency distribution charts for the items that showed significant differences in these analyses. The aim is to observe where the specific differences are reflected.

1.4.1. Frequency Distribution Analysis of Gender-Adaptive Behaviors

Figures A.1(a) to A.1(d) display the frequency distribution of choices for various energy-saving behaviors among different genders when feeling cold in winter. These include adjusting clothing (Figure A.1(a)), drinking hot water (Figure A.1(b)), using heating equipment (such as underfoot heaters and chair cushions, Figure A.1(c)), and using thermal items (such as blankets and hand warmers, Figure A.1(d)). These frequency distribution charts reveal behavioral differences between men and women in response to low temperatures.

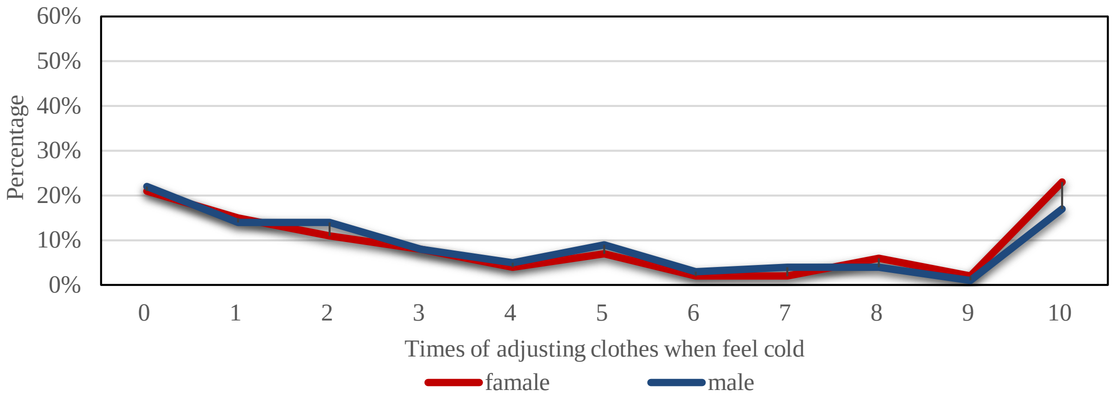
Figure A.1(a) shows that while both men and women adjust clothing, women are more inclined to frequently adjust layers to maintain comfort when feeling cold. Specifically, women are more likely to choose higher frequency options for adjusting clothing (e.g., selecting this option 8-10 times out of 10 cold instances), indicating a greater reliance on clothing adjustments to adapt to temperature changes.

Figure A.1(b) further illustrates the differences between men and women in drinking hot water. Women more frequently choose to drink hot water to raise body temperature when feeling cold, with a significantly higher proportion of women than men in high-frequency options. For example, among those who choose to drink hot water 2 or more times out of every 10 cold instances, women show a generally higher distribution than men, reflecting a tendency among women to regulate body temperature by drinking hot water.

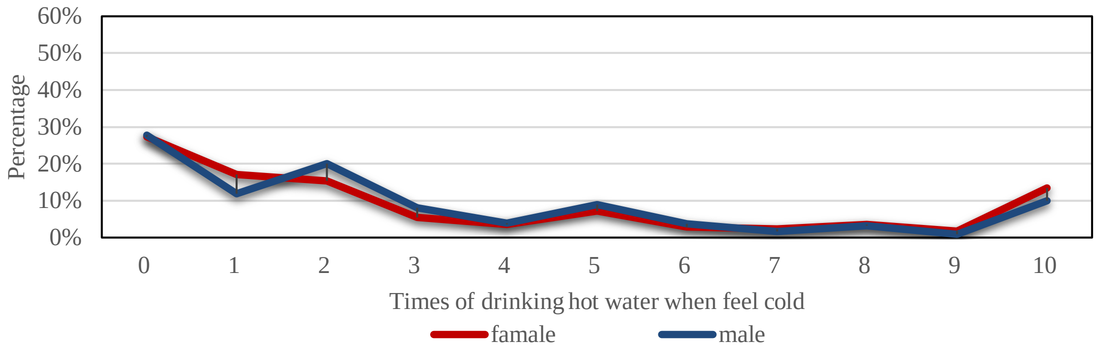
In Figure A.1(c), there is a clear difference in the frequency of using heating equipment (e.g., underfoot heaters and chair cushions) between genders. Women show a noticeably higher proportion in frequently using heating equipment, particularly in higher frequency options (e.g., using these items 7-10 times out of 10 cold instances). This suggests that women are more inclined than men to rely on external heating devices for comfort.

Figure A.1(d) shows the distribution of using thermal items (such as blankets and hand warmers) between men and women. Similar to the previous behaviors, women have a higher frequency distribution for this behavior, especially in high-frequency options, where their proportion is significantly greater than that of men. Specifically, women are more inclined to use thermal items to maintain warmth when feeling cold. This difference indicates that women are more willing to use warming tools to cope with cold.

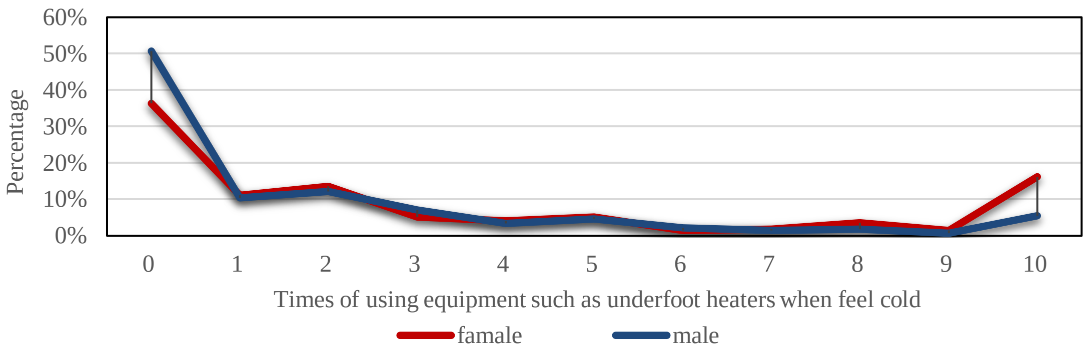
Overall, these frequency distribution charts clearly display the significant differences in gender-adaptive energy-saving behaviors when dealing with low temperatures. Women tend to respond to cold through multiple means, including adjusting clothing, drinking hot water, using heating equipment, and thermal items. These differences in behavioral choices suggest that women are more likely than men to engage in adaptive energy-saving measures in the office environment, with a notably higher frequency of behaviors for coping with the cold. This gender difference suggests that, in developing energy-saving strategies tailored to different genders, the proactive behavioral choices of women can be considered to enhance the overall effectiveness of energy-saving behaviors.



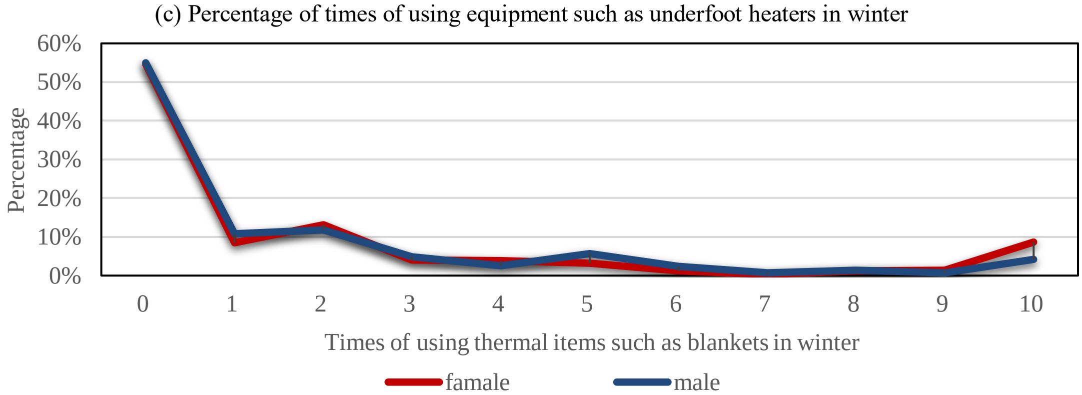
(a) Percentage of times of adjusting clothes in winter



(b) Percentage of times of drinking hot winter in winter



(c) Percentage of times of using equipment such as underfoot heaters in winter



(d) Percentage of times of using thermal items in winter

Figure A.1 Frequency distribution graphs about percentage of gender and different thermal adaptation-related behaviors –

1.4.2. Factors Influencing Air Conditioner Adjustment Behavior

Figure A.2 shows the proportional distribution of the main reasons people adjust air conditioning settings. As illustrated, "personal comfort" is the primary reason, accounting for 44%, meaning nearly half of the respondents reported adjusting the air conditioning temperature to meet their own comfort needs. The next most common reason is "others' comfort," at 21%, indicating that a significant number of people adjust the air conditioning for the comfort of colleagues or others in the office. Additionally, 11% of respondents adjust the air conditioning based on the number of people in the office, reflecting sensitivity to changes in the surrounding occupancy.

Other reasons are less prevalent, but some respondents are motivated by company policies and regulations (9%), energy costs (6%), and environmental awareness (8%) when adjusting the air conditioning. These data indicate that energy-saving or compliance with company regulations may also influence air conditioning use in specific circumstances. The proportion of respondents selecting "other" reasons is only 2%, suggesting that the majority of motivations for adjusting the air conditioning center around the aforementioned factors.

Overall, Figure A.2 highlights that comfort is the primary driver for air conditioning adjustments, though a notable proportion of people also consider environmental and policy-related factors.

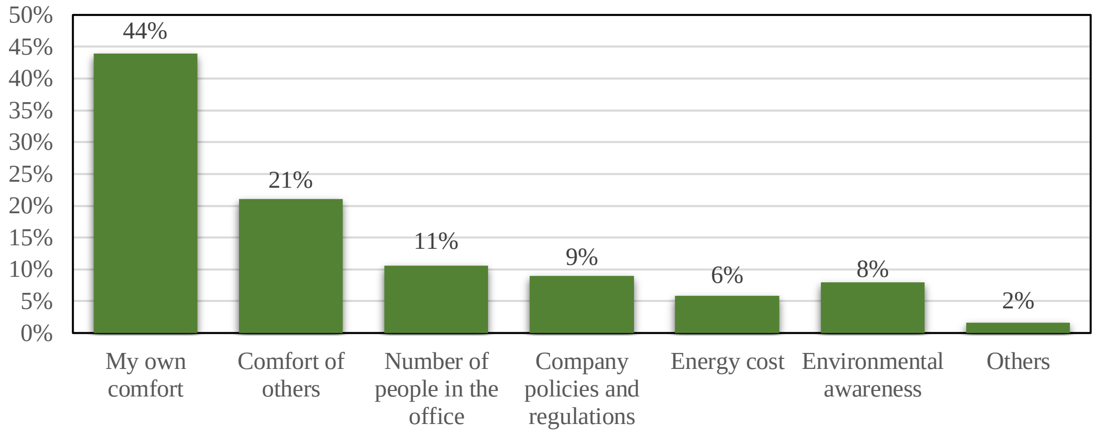


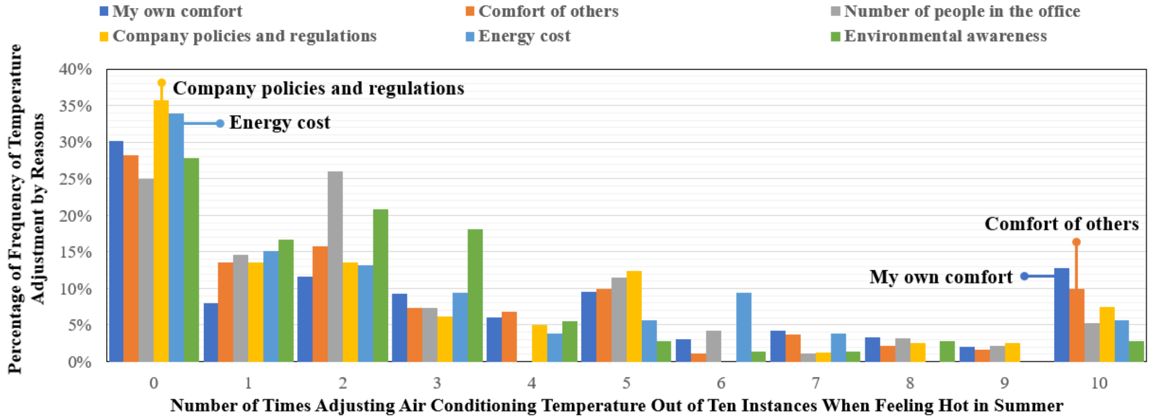
Figure A.2 Percentage of number of persons in each group for the main reasons to be considered when changing the temperature

Figure 3 illustrates the probability distribution of air conditioner temperature adjustment frequency in summer and winter environments, based on various reasons. The vertical axis represents the percentage of each reason group within the total population, while the horizontal axis shows the frequency distribution of temperature adjustments per 10 instances of feeling hot (in summer) or cold (in winter).

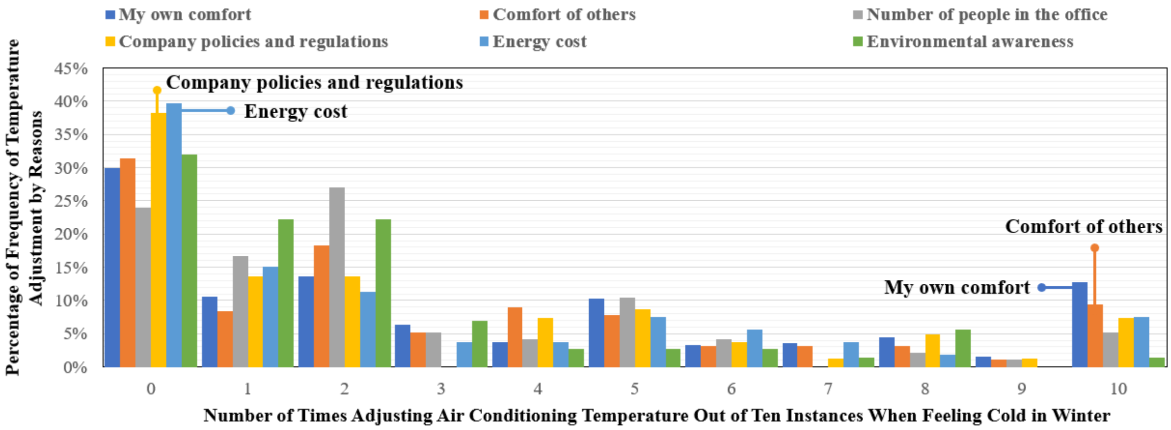
The figure reveals a significant relationship between the frequency of temperature adjustments and the underlying reasons for doing so. Those who "never adjust" (0 times) are primarily driven by "company policies and regulations" or "energy costs," suggesting that these individuals prioritize saving on energy expenses or complying with company policies and may be less inclined to frequently change air conditioning settings. At a low adjustment frequency (1-3 times), besides company policies and energy costs, the number of people in the office becomes a factor, especially in shared spaces where individuals may avoid frequent adjustments out of consideration for others or to minimize disruption.

As adjustment frequency increases to the 4-6 range, the distribution of reasons becomes more varied, including more personal factors like "personal comfort" and "others' comfort." This suggests that people in this range are seeking a balance between meeting their own comfort needs and considering others. At high adjustment frequencies (7-10 times), "personal comfort" and "others' comfort" emerge as dominant reasons. Those who adjust the temperature consistently (10 times) are mainly motivated by personal comfort, frequently modifying the air conditioning settings based on their own needs. Additionally, a segment of respondents frequently adjusts the temperature to ensure the comfort of colleagues or others in the office for "others' comfort."

In summary, Figure 3 highlights the distinct distribution differences in air conditioner temperature adjustment frequency based on different motivations: those prioritizing energy savings or company policies tend to adjust the temperature less or not at all, while those focused on personal or others' comfort adjust the temperature more frequently. This suggests that adjustment frequency is influenced not only by environmental factors but also by personal and collective comfort needs.



(a) Percentage of main reasons to be considered when changing the temperature and the number of times the air-conditioning temperature is changed in summer



(b) Percentage of main reasons to be considered when changing the temperature and the number of times the air-conditioning temperature is changed in winter

Figure A.3 Percentage of main reasons to be considered when changing the temperature and the number of times the air-conditioning temperature is changed

2. Other Analysis of air-conditioning-related questionnaires

Table A.4 presents the demographic statistics of the questionnaire shown in Table 3.2 of Chapter 3. These data were not included in the main text of Chapter 3, as they were not required there.

Table A.4 Demographic Statistics of the Questionnaire in Chapter 3

		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	535	50.0	50.0	50.0
	Female	534	50.0	50.0	100.0
Age	20 ~ 29	95	8.8	8.8	8.8
	30 ~ 39	237	21.9	21.9	30.7
	40 ~ 49	297	28.6	28.6	59.3
	50 ~ 59	268	24.8	24.8	84.1
	60 and above	172	15.9	15.9	100.0
Region	Hokkaido	54	5.0	5.0	5.0
	Tohoku Region	54	5.0	5.0	10.0
	Kanto Region	419	39.9	39.9	49.9
	Chubu Region	148	13.7	13.7	63.6
	Kinki Region	226	20.9	20.9	84.5
	Chugoku Region	60	5.6	5.6	90.0
	Shikoku Region	32	3.0	3.0	93.0
	Kyushu Region	76	7.0	7.0	100.0
Occupation	Public Servant	56	5.2	5.2	5.2
	Manager/Executive	31	2.9	2.9	8.0
	Office Worker (Administrative)	295	28.4	28.4	36.4
	Office Worker (Technical)	153	14.2	14.2	50.6
	Office Worker (Other)	216	20.0	20.0	70.6
	Self-employed	40	3.7	3.7	74.3
	Freelancer	14	1.3	1.3	75.6
	Homemaker	1	.1	.1	75.7
	Part-time/Temporary	218	20.2	20.2	95.8
	Other	45	4.2	4.2	100.0
Marital Status	Single	455	42.1	42.1	42.1
	Married	614	57.9	57.9	100.0
Children	With children	535	50.6	50.6	50.6
	Without children	534	49.4	49.4	100.0

Annual Income	Under 2 million yen	217	20.1	20.1	20.1
	2 million – under 4 million yen	313	30.1	30.1	50.1
	4 million – under 5 million yen	119	11.0	11.0	61.1
	5 million – under 6 million yen	99	9.2	9.2	70.3
	6 million – under 7 million yen	49	4.5	4.5	74.8
	7 million – under 8 million yen	47	4.3	4.3	79.2
	8 million – under 9 million yen	28	2.6	2.6	81.8
	9 million – under 10 million yen	20	1.9	1.9	83.6
	10 million yen and above	43	4.0	4.0	87.6
	Prefer not to answer	134	12.4	12.4	100.0
	Total	1069	100.0	100.0	

Table A.5 presents the demographic statistics of the questionnaire shown in Table 4.1 of Chapter 4. These data were not included in the main text of Chapter 4, as they were not required there.

Table A.5 Demographic Statistics of the Questionnaire in Chapter 4

		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Male	557	66.3	66.3	66.3
	Female	283	33.7	33.7	100.0
Age	20 ~ 29	47	5.6	5.6	5.6
	30 ~ 39	171	20.4	20.4	26.0
	40 ~ 49	216	25.7	25.7	51.7
	50 ~ 59	236	28.1	28.1	79.8
	60 and above	170	20.2	20.2	100.0
Region	Hokkaido	42	5.0	5.0	5.0
	Tohoku Region	51	6.1	6.1	11.1
	Kanto Region	353	42.0	42.0	53.1
	Chubu Region	109	13.0	13.0	66.1
	Kinki Region	159	18.9	18.9	85.0
	Chugoku Region	32	3.8	3.8	88.8
	Shikoku Region	25	3.0	3.0	91.8
	Kyushu Region	69	8.2	8.2	100.0
Occupation	Public Servant	54	6.4	6.4	6.4
	Manager/Executive	23	2.7	2.7	9.2

	Office Worker (Administrative)	226	26.9	26.9	36.1
	Office Worker (Technical)	158	18.8	18.8	54.9
	Office Worker (Other)	152	18.1	18.1	73.0
	Self-employed	45	5.4	5.4	78.3
	Freelancer	6	.7	.7	79.0
	Homemaker	2	.2	.2	79.3
	Part-time/Temporary	137	16.3	16.3	95.6
	Other	37	4.4	4.4	100.0
Marital Status	Single	320	38.1	38.1	38.1
	Married	520	61.9	61.9	100.0
Children	With children	462	55.0	55.0	55.0
	Without children	378	45.0	45.0	100.0
Main Attire in the Office	Formal (including uniforms)	196	23.3	23.3	23.3
	Semi-formal	106	12.6	12.6	36.0
	Casual	230	27.4	27.4	63.3
	Workwear	216	25.7	25.7	89.0
	Attire varies significantly by individual	82	9.8	9.8	98.8
	Other	10	1.2	1.2	100.0
Position	President/CEO	43	5.1	5.1	5.1
	Equivalent to Department Head	69	8.2	8.2	13.3
	Equivalent to Section Head	89	10.6	10.6	23.9
	Equivalent to Assistant Manager/Manager	92	11.0	11.0	34.9
	No managerial position or no subordinates	369	43.9	43.9	78.8
	Part-time/Temporary	155	18.5	18.5	97.3
	Other	23	2.7	2.7	100.0

Table A.6 presents the mathematical regression model of all behaviors and awareness factors from Table 3.10 in Chapter 3.

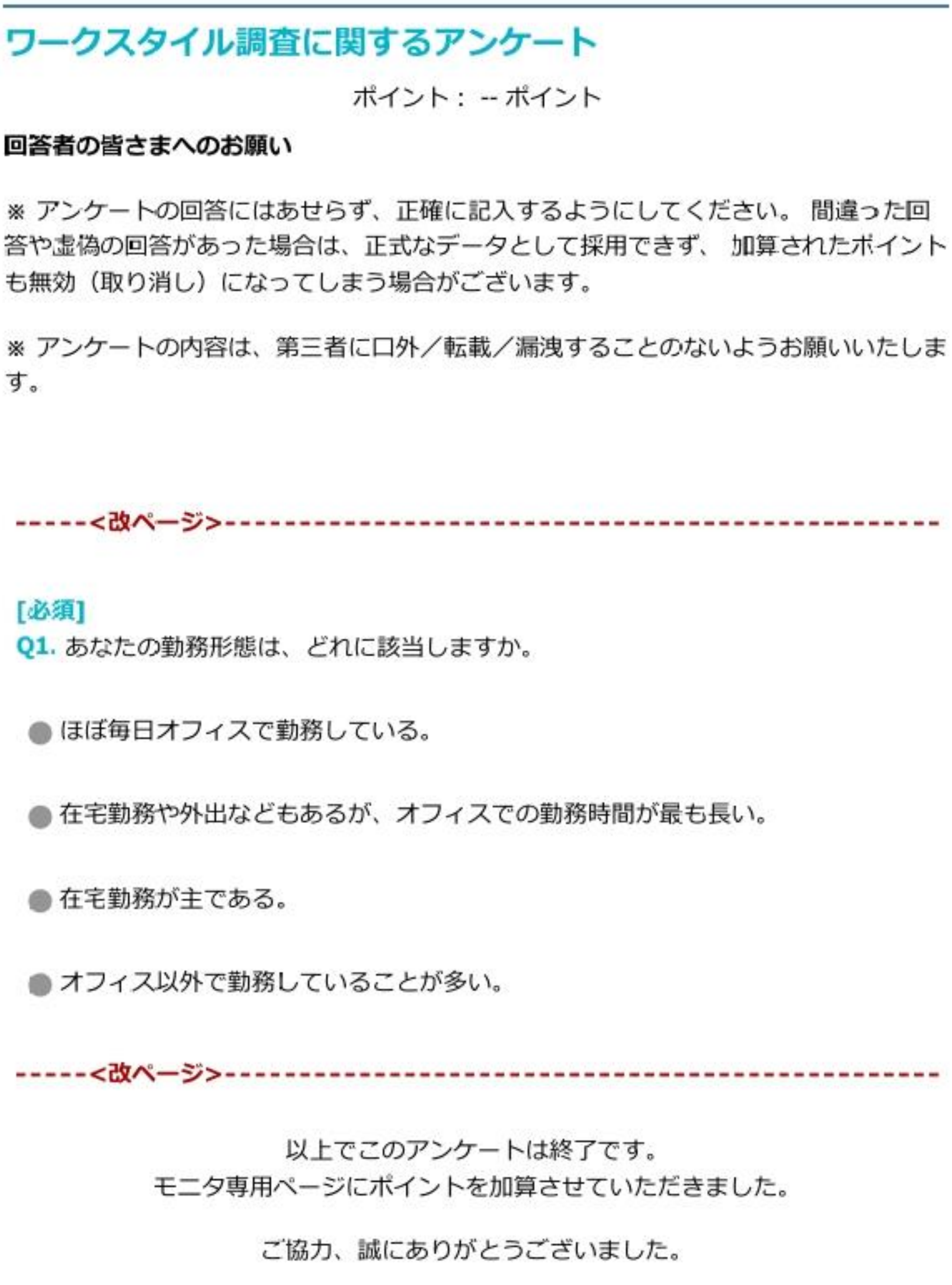
Table A.6 Regression model of all behaviors and awareness factors

Behaviors	Regression model
B1	$\boldsymbol{B1=0.277ATT+0.236SN+0.195PBC-0.2PMN+0.203INT+1.573}$
B2	$\boldsymbol{B2 = 0.458SN - 0.324PMN + 0.133DN + 0.186INT + 0.785}$
B3	$\boldsymbol{B3 = 0.277EPK + 0.903}$
B4	$\boldsymbol{B4 = 0.181ATT + 0.177SN + 0.265INT + 0.815}$
B5	$\boldsymbol{B5 = 0.229SN + 0.202DN + 0.263EPK + 0.863}$
B6	$\boldsymbol{B6 = 0.365SN + 0.304DN + 0.583}$
B7	$\mathbf{B7 = 0.231ATT + 0.314SN + -0.288PMN + 0.15DN + 0.212INT + 0.639}$
B8	$\mathbf{B8 = 0.2SN - 0.277PMN + 0.17DN + 0.234INT + 0.633}$

3. Questionnaire Japanese Version

3.1. Screening Questionnaire

Figure A.4 is the webpage interface of the screening questionnaire mentioned in Chapter 3



ワークスタイル調査に関するアンケート

ポイント： -- ポイント

回答者の皆さまへのお願い

※ アンケートの回答にはあせらず、正確に記入するようにしてください。 間違った回答や虚偽の回答があった場合は、正式なデータとして採用できず、 加算されたポイントも無効（取り消し）になってしまう場合がございます。

※ アンケートの内容は、第三者に口外／転載／漏洩することのないようお願いいたします。

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[必須]
Q1. あなたの勤務形態は、どれに該当しますか。

- ほぼ毎日オフィスで勤務している。
- 在宅勤務や外出などもあるが、オフィスでの勤務時間が最も長い。
- 在宅勤務が主である。
- オフィス以外で勤務していることが多い。

-----<改ページ>---

以上でこのアンケートは終了です。
モニタ専用ページにポイントを加算させていただきました。

ご協力、誠にありがとうございました。

Figure A.4 webpage interface of the screening questionnaire

3.2. Original Japanese Version of the Questionnaire in Chapter 3 and Webpage Interface

Tables A.7 and A.8 are the Japanese original versions of Table 3.2 in Chapter 3. Table A.7 relates to psychological factors, and Table A.8 relates to behavioral factors.

Table A.7 Original Japanese Version of the Questionnaire (Awareness)

環境意識	設問
行動への態度 Attitude (ATT)	ATT1 増え続けるエネルギー需要は、社会にとって深刻な問題である。
	ATT2 地球温暖化や化石燃料の枯渇に関して、私自身にも責任の一端がある。
	ATT3 日常生活での省エネは、環境保全のために有用であると思う。
主観的規範 Subjective norm (SN)	SN1 あなたの会社の管理者(役員等)は、使用してないときにオフィスの照明や空調の電源をオフにしてほしいと考えている。
	SN2 私にとって大切な人たちは、できるだけ節電したほうがいいと考えている。
	SN3 私は、省エネに関する決定をするときに、私にとって大切な人たちの意見を重視している。
知覚行動制御性 Perceived behavioral control(PBC)	PBC1 普段の生活の中で省エネを実施するための知識やノウハウを持っている。
	PBC2 省エネを進める上で、利便性が損なわれないことも私にとって重要な要素である。
	PBC3 省エネするかしないかは、完全に自分次第である。
個人的道徳規範 Personal moral norm (PMN)	PMN1 日常生活の中で省エネをすることには道徳的な責任がある。
	PMN2 私は日常的に電気、ガスや石油・石炭などのエネルギーを使っており、私の行動は気候変動に影響があると感じる。
	PMN3 日常生活における省エネは、私自身の道徳的な義務によって行うものである。
記述的規範 Descriptive norm (DN)	DN1 私の会社では、複数の社員が省エネ行動をしている。
	DN2 自分にとって大切な人たちは、省エネ行動に参加している。
	DN3 私のマネージャーや上位の管理職の社員が省エネ行動に参加している。
環境に関する知識 Environmental	EPK1 温室効果ガスは、地球からの熱放射を抑える働きをする。
	EPK2 過去 150 年間に大気中の温室効果ガスが増加した原因は、ほぼすべて人間の活動にある。

Protection Knowledge(EPK)	EPK3 日常生活における省エネのコツをよく知っている。
行動意図 Intention (INT)	INT1 今後はより一層気をつけて、省エネの知識やコツを蓄積していきたいと思う。
	INT2 私は今後、環境への影響を減らすために親環境的な行動をとろうと思う（例：パソコンの電源を切る、印刷を減らす、マイボトルを使うなど)。
	INT3 今後、省エネに取り組むつもりである。
5:そう思う; 4:ややそう思う; 3:どちらとも言えない; 2:あまりそう思わない; 1:まったくそう思わない	

Table A.8 Original Japanese Version of the Questionnaire (Behaviors)

行動	設問内容
B1	部屋を最後に出るときは照明を消す。
B2	オフィスでは、人がいる場所だけ、照明を点灯するようにしている。
B3	省エネのために、暖房時はエアコンの温度を上げ、冷房時は下げている。
B4	オフィスで暑さ、寒さを感じる時はエアコンの設定を変える前に、衣服を調整する。
B5	室内の在室者が多い場合でも空調の設定温度を積極的に操作する。
B6	OA 機器（PC、モニター、プリンターなど）を省エネモードに設定している。
B7	2 階上がったり、3 階下りたりする程度であれば、エレベーターを使わず、階段を使う。
B8	1 時間以上席を離れるときは PC の電源を切るかスリープモードにする。
5:毎回する; 4:よくする; 3:時々する; 2:たまにする; 1:ほとんどしない	

Figure A.5 is the webpage interface of the questionnaire of table 3.2 in chapter 3

環境意識・エネルギー使用習慣に関するアンケート

ポイント： -- ポイント

回答者の皆さまへのお願い

※ アンケートの回答にはあせらず、正確に記入するようにしてください。 間違った回答や虚偽の回答があった場合は、正式なデータとして採用できず、 加算されたポイントも無効（取り消し）になってしまう場合がございます。

※ アンケートの内容は、第三者に口外／転載／漏洩することのないようお願いいたします。

-----<改ページ>---

[必須]
Q1. あなたの性別を教えてください。

- 男性
- 女性

-----<改ページ>---

[必須]
Q2. あなたのご年齢をお選びください。

- ～20歳
- 20～29歳
- 30～39歳
- 40～49歳

● 50～59歳

● 60歳～

-----<改ページ>---

[必須]

Q3. 次の文章を読んで、選択肢に該当するものを一つ選び、回答して下さい。（選択肢：まったくそう思わない、あまりそう思わない、どちらとも言えない、ややそう思う、そう思う）

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
増え続けるエネルギー需要は、社会にとって深刻な問題である。 ›	●	●	●	●	●
地球温暖化や化石燃料の枯渇に関して、私自身にも責任の一端がある。 ›	●	●	●	●	●
日常生活での省エネは、環境保全のために有用であると思う。 ›	●	●	●	●	●
あなたの会社の管理者(役員等)は、使用してないときにオフィス ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
の照明や空調の電源をオフにしてほしいと考えている。					
私にとって大切な人たちは、できるだけ節電したほうがいいと考えている。 ›	●	●	●	●	●
私は、省エネに関する決定をするときに、私にとって大切な人たちの意見を重視している。 ›	●	●	●	●	●
普段の生活の中で省エネを実施するための知識やノウハウを持っている。 ›	●	●	●	●	●
省エネを進める上で、利便性が損なわれないことも私にとって重要な要素である。 ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
省エネするかしないかは、完全に自分次第である。 ›	●	●	●	●	●
日常生活の中で省エネすることには道徳的な責任がある。 ›	●	●	●	●	●
私は日常的に電気、ガスや石油・石炭などのエネルギーを使っており、私の行動は気候変動に影響があると感じる。 ›	●	●	●	●	●
日常生活における省エネは、私自身の道徳的な義務によって行うものである。 ›	●	●	●	●	●
私の会社では、複数の社員が省エネ行動をしている。 ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
自分にとって大切な人たちは、省エネ行動に参加している。	●	●	●	●	●
私のマネージャーや上位の管理職の社員が省エネ行動に参加している。	●	●	●	●	●
温室効果ガスは、地球からの熱放射を抑える働きをする。	●	●	●	●	●
過去150年間に大気中の温室効果ガスが増加した原因は、ほぼすべて人間の活動にある。	●	●	●	●	●
日常生活における省エネのコツをよく知っている。	●	●	●	●	●
温室効果ガスは、地球からの熱放射を抑える	●	●	●	●	●

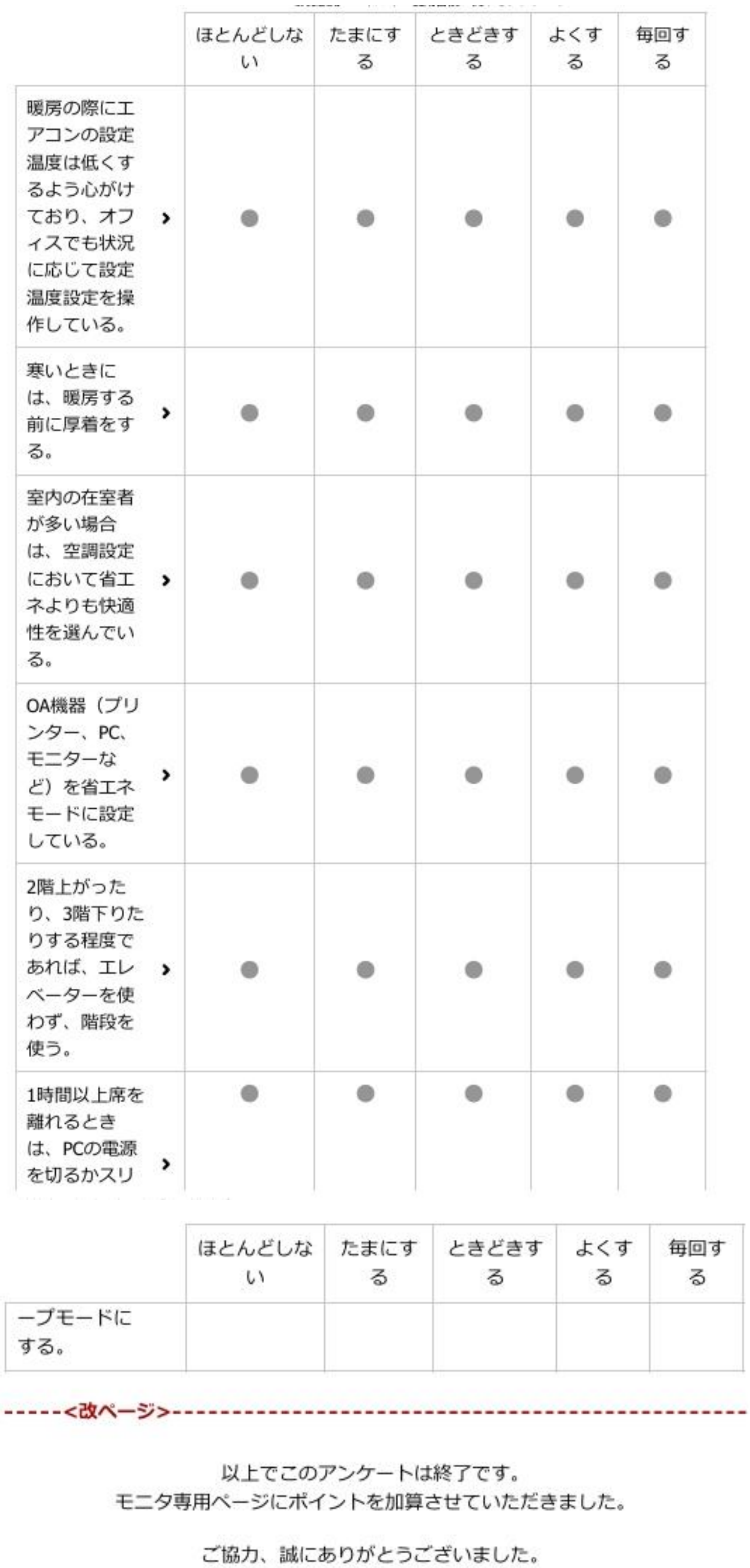
	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
働きをする。					
過去150年間に大気中の温室効果ガスが増加した原因は、ほぼすべて人間の活動にある。 ›	●	●	●	●	●
日常生活における省エネのコツをよく知っている。 ›	●	●	●	●	●

-----<改ページ>---

[必須]

Q4. 次の文章を読んで、選択肢に該当するものを一つ選び、回答して下さい。（選択肢：ほとんどしない、たまにする、ときどきする、よくする、毎回する）

	ほとんどしない	たまにする	ときどきする	よくする	毎回する
部屋を最後に出るときは照明を消す。 ›	●	●	●	●	●
オフィスでは、人がいる場所に応じて、照明が点灯するエリアを変えている。 ›	●	●	●	●	●



	ほとんどしない	たまにする	ときどきする	よくする	毎回する
暖房の際にエアコンの設定温度は低くするよう心がけており、オフィスでも状況に応じて設定温度設定を操作している。 ›	●	●	●	●	●
寒いときには、暖房する前に厚着をする。 ›	●	●	●	●	●
室内の在室者が多い場合は、空調設定において省エネよりも快適性を選んでいる。 ›	●	●	●	●	●
OA機器（プリンター、PC、モニターなど）を省エネモードに設定している。 ›	●	●	●	●	●
2階上がったり、3階下りたりする程度であれば、エレベーターを使わず、階段を使う。 ›	●	●	●	●	●
1時間以上席を離れるときは、PCの電源を切るかスリープモードにする。 ›	●	●	●	●	●

-----<改ページ>---

以上でこのアンケートは終了です。
モニタ専用ページにポイントを加算させていただきました。

ご協力、誠にありがとうございました。

Figure A.5 webpage interface of the questionnaire of table 3.2 in chapter 3

3.3. Japanese Version and Webpage Interface of the Air Conditioning Questionnaire in Chapter 4

Table A.9 is the Japanese original version of Table 4.1 from Chapter 4.

Table A.9 Original Japanese Version of the Questionnaire in Chapter 4

カテゴリ	項目
心理的要因	**ATT1:** 増え続けるエネルギー需要は、社会にとって深刻な問題である。
	ATT2: 日常生活での省エネは、環境保全のために有用であると思う。
	ATT3: 地球温暖化や化石燃料の枯渇に関して、私自身にも責任の一端がある。
	SN1: あなたの会社の管理者(役員等)は、使用してないときにオフィスの照明や空調の電源をオフにしてほしいと考えている。
	SN2: 私にとって大切な人たちは、できるだけ節電したほうがいいと考えている。
	SN3: 私は、省エネに関する決定をするときに、私にとって大切な人たちの意見を重視している。
	PBC1: 普段の生活の中で省エネを実施するための知識やノウハウを持っている。
	PBC2: 省エネを進める上で、利便性が損なわれないことも私にとって重要な要素である。
	PBC3: 省エネするかしないかは、完全に自分次第である。
	PMN1: 日常生活の中で省エネをすることには道徳的な責任がある。
	PMN2: 私は日常的に電気、ガスや石油・石炭などのエネルギーを使っており、私の行動は気候変動に影響があると感じる。
	PMN3: 日常生活における省エネは、私自身の道徳的な義務によって行うものである。
	DN1: 私の会社では、複数の社員が省エネ行動をしている。
	DN2: 自分にとって大切な人たちは、省エネ行動に参加している。
	DN3: 私のマネージャーや上位の管理職の社員が省エネ行動に参加している。
	EPK1: 温室効果ガスは、地球からの熱放射を抑える働きをする。
	EPK2: 過去 150 年間に大気中の温室効果ガスが増加した原因は、ほぼすべて人間の活動にある。
	EPK3: 日常生活における省エネのコツをよく知っている。
	INT1 今後はより一層気をつけて、省エネの知識やコツを蓄積していきた

	いと思う。	
	INT2 私は今後、環境への影響を減らすために親環境的な行動をとろうと思う（例：パソコンの電源を切る、印刷を減らす、マイボトルを使うなど）。	
	INT3 今後、省エネに取り組むつもりである。	
	選択肢： 5:そう思う; 4:ややそう思う; 3:どちらとも言えない; 2:あまりそう思わない; 1:まったくそう思わない	
温度の好み	**T1(夏)/T2(冬):** 夏季と冬季において、オフィスにおける一番快適だと思う設定温度は何度ですか。	
暑さ（寒さ）を感じたときに熱適応行動をとる確率 **(夏/冬)**	**P1**（しばらく）がまんする **(夏/冬)**	勤務するオフィスで夏に暑い(冬に寒い)と感じることが 10 回あった場合、以下の行動を 10 回中何回とりますか。それぞれについておよその回数を記載してください。 **選択肢(回数):** 1，2，3，4，5，6，7，8，9，10
	P2 上着を脱ぐなどして、服装で調節する/上着を着るなどして、服装で調節する**(夏/冬)**	
	P3 飲み物を飲む (アイス/ホット) **(夏/冬)**	
	P4 夏: 扇風機やファンを使って涼む /**冬:** ブランケットやカイロ等の保温アイテムを使用する。	
	P5 夏: 窓を開ける /**冬:** 足下のヒーターやイス用カーペットなどの機器を使用する	
	P6 エアコンの設定温度を変更する**(夏/冬)**	
その他の基本情報	**年齢：**該当する年齢層を選択してください。選択肢: 20~29，30~39，40~49,50~59, 60 以上	
	職位: あなたの現在の職位に最も近いものを教えてください．選択肢: パート・アルバイト; 職位なし、または部下がいない職位; 係長・マネージャー相当; 課長相当; 部長相当; 社長	
	部屋人数: あなたが働いているオフィスにおいて、あなたがいる部屋には何人ぐらいの人がいますか。 **選択肢:** 自分のみ, 2 人,3~4 人,5~9 人,10~19 人,20~49 人, 50 人及び 50 人以上	
	あなたが、あなたのオフィスでエアコンの設定温度や風量を調整することを考えた場合、その行動に最も影響を与えている要因として該当するものをすべて選んでください: 室温など自分自身の快適さ, 他の人の快適さ，オフィス内の在室人数，会社の方針や規則，エネルギーコスト，環境への意識	

Figure A.6 is the webpage interface of the questionnaire of table 4.1 in chapter 4.

オフィスの空調習慣と意識に関するアンケート

ポイント： -- ポイント

回答者の皆さまへのお願い

※ アンケートの回答にはあせらず、正確に記入するようにしてください。 間違った回答や虚偽の回答があった場合は、正式なデータとして採用できず、 加算されたポイントも無効（取り消し）になってしまう場合がございます。

※ アンケートの内容は、第三者に口外／転載／漏洩することのないようお願いいたします。

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[必須]
Q1. あなたが働いているオフィスにおいて、あなたがいる部屋には何人ぐらいの人がいますか。

- 自分のみ
- 2人
- 3人~4人
- 5人~9人
- 10人~19人
- 20人~49人
- 50人及び50人以上

[必須]
Q2. あなたの現在の職位に最も近いものを教えてください？

- 社長
- 部長相当
- 課長相当
- 係長・マネージャー相当
- 職位なし、または部下がいない職位
- パート・アルバイト
- その他（詳細をご記入ください）

[必須]

Q3. あなたが、あなたのオフィスでエアコンの設定温度や風量を調整することを考えた場合、その行動に最も影響を与えている要因として該当するものをすべて選んでください。

- 室温など自分自身の快適さ
- 他の人の快適さ
- オフィス内の在室人数
- 会社の方針や規則
- エネルギーコスト
- 環境への意識
- その他（詳細を記入してください）

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[必須]

Q4. 夏季と冬季において、オフィスにおける一番快適だと思う設定温度は何度ですか。

	16℃ 以下	17℃	18℃	19℃	20℃	21℃	22℃	23℃
夏季 ›								
冬季 ›								

[必須]

Q5. 勤務するオフィスで夏に暑いと感じることが10回あった場合、以下の行動を10回中何回とりますか。それぞれについておよその回数を記載してください。

	0回	1回	2回	3回	4回	5回	6回	7回
（しばらく）がまんする ›								
上着を脱ぐなどして、服装で調節する ›								
飲み物を飲む ›								
扇風機やファンを使って涼む。 ›								
窓を開ける ›								
エアコンの設定温度 ›								

	0回	1回	2回	3回	4回	5回	6回	7回
を変更する。								

[必須]

Q6. 勤務するオフィスで冬に寒いと感じることが10回あった場合、以下の行動を10回中何回とりますか。それぞれについておよその回数を記載してください。

	0回	1回	2回	3回	4回	5回	6回	7回
（しばらく）がまんする ›	●	●	●	●	●	●	●	●
上着を着るなどして、服装で調節する ›	●	●	●	●	●	●	●	●
（温かい）飲み物を飲む ›	●	●	●	●	●	●	●	●
ブランケットやカイロ等の保温アイテムを使用する。 ›	●	●	●	●	●	●	●	●
足下のヒーターやイス用カーペットなど ›	●	●	●	●	●	●	●	●

	0回	1回	2回	3回	4回	5回	6回	7回
の機器を使用する。								
エアコンの設定温度を変更する。 ›	●	●	●	●	●	●	●	●

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[必須]

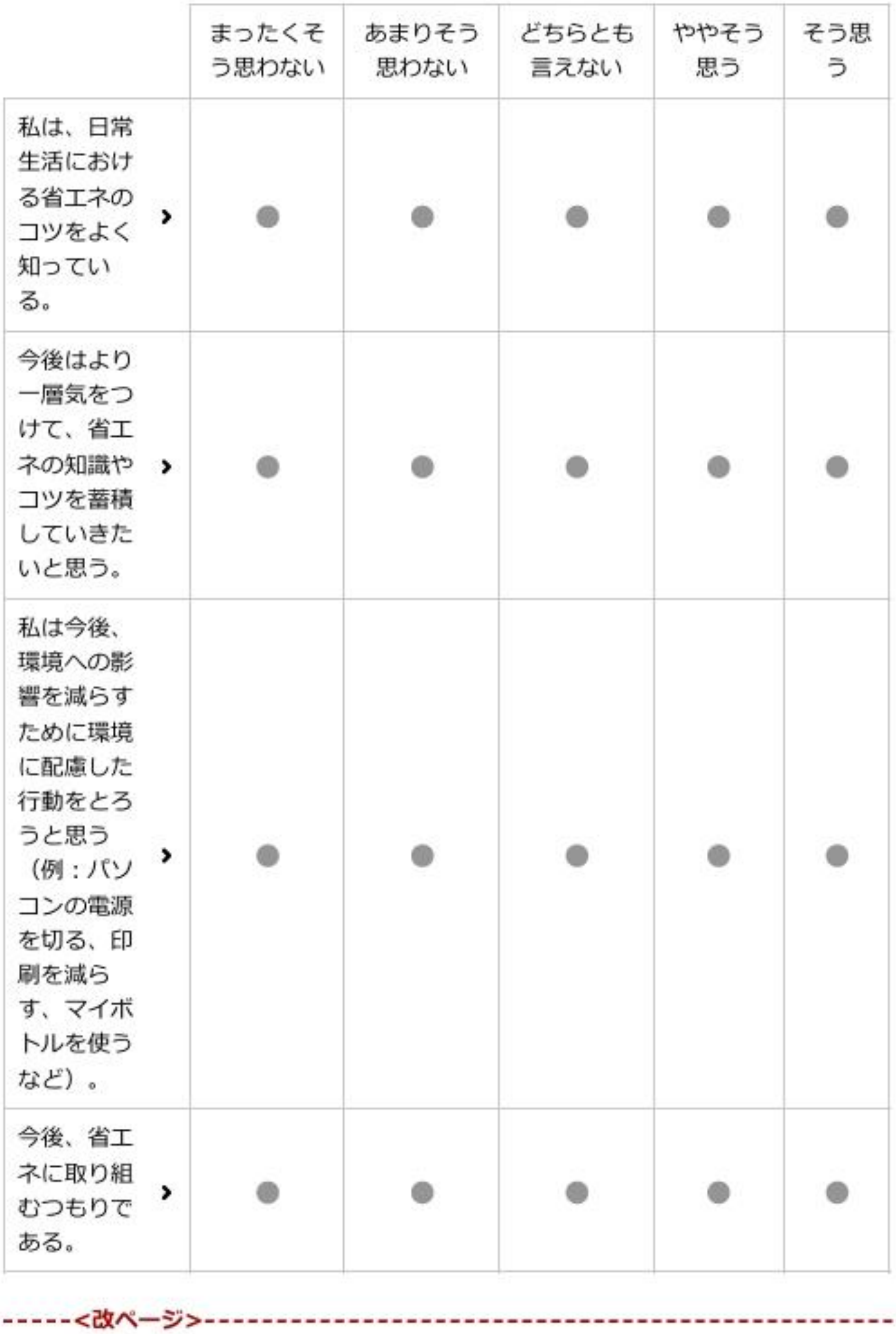
Q7. 次の文章を読んで、選択肢に該当するものを一つ選び、回答して下さい。（選択肢：まったくそう思わない、あまりそう思わない、どちらとも言えない、ややそう思う、そう思う）

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
増え続けるエネルギー需要は、社会にとって深刻な問題である。 ›	●	●	●	●	●
地球温暖化や化石燃料の枯渇に関して、私自身にも責任の一端がある。 ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
日常生活での省エネは、環境保全のために有用であると思う。 ›	●	●	●	●	●
あなたの会社の管理者(役員等)は、使用してないときにオフィスの照明や空調の電源をオフにしてほしいと考えている。 ›	●	●	●	●	●
私にとって大切な人たちは、できるだけ節電したほうがいいと考えている。 ›	●	●	●	●	●
私は、省エネに関する決定をするときに、私にとって大切な人たちの意見を重視している。 ›	●	●	●	●	●
普段の生活の中で省エネを実施するための知 ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
識やノウハウを持っている。					
省エネを進める上で、利便性が損なわれないことも私にとって重要な要素である。 ›	●	●	●	●	●
省エネするかしないかは、完全に自分次第である。 ›	●	●	●	●	●
日常生活の中で省エネすることには道徳的な責任がある。 ›	●	●	●	●	●
私は日常的に電気、ガスや石油・石炭などのエネルギーを使っており、私の行動は気候変動に影響があると感じる。 ›	●	●	●	●	●
日常生活における省エネは、私自身の道徳的 ›	●	●	●	●	●

	まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
な義務によって行うものである。					
私の会社では、複数の社員が省エネ行動をしている。					
自分にとって大切な人たちは、省エネ行動に参加している。					
私のマネージャーや上位の管理職の社員が省エネ行動に参加している。					
温室効果ガスは、地球からの熱放射を抑える働きをする。					
過去150年間に大気中の温室効果ガスが増加した原因は、ほぼすべて人間の活動にある。					



		まったくそう思わない	あまりそう思わない	どちらとも言えない	ややそう思う	そう思う
私は、日常生活における省エネのコツをよく知っている。	›	●	●	●	●	●
今後はより一層気をつけて、省エネの知識やコツを蓄積していきたいと思う。	›	●	●	●	●	●
私は今後、環境への影響を減らすために環境に配慮した行動をとろうと思う（例：パソコンの電源を切る、印刷を減らす、マイボトルを使うなど）。	›	●	●	●	●	●
今後、省エネに取り組むつもりである。	›	●	●	●	●	●

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Figure A.6 webpage interface of the questionnaire of table 4.1 in chapter 4