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The effect of changing heat use patterns on residential energy efficiency in a Japanese smart community

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In light of the prospective development of smart communities and the significant effect of residential energy consumption on global CO_2 emissions, addressing sustainable household energy efficiency solutions is extremely critical. Given the lack of properly designated energy models for residential energy reduction, the primary objective of this study is to implement integrated energy prediction models and occupant-related parameters in proposing human-centered energy-saving and low-carbon building solutions. Specifically, on-site electricity monitoring and behavioral questionnaires were conducted before inputting the real-time data into physics-based modeling for building energy forecasts. Calculated energy-saving ratios are used to assess the influence levels of heating usage patterns and discuss the potential of energy efficiency scenarios. The findings highlight that household attributes and energy management systems substantially enhance the dwelling's energy efficiency. Prominent impact factors are family income, property ownership, and energy consumption patterns, which may also pertain to occupant habits. Consequently, a rigorous focus must be placed on these elements, including controlling setpoints and schedules for primary residential end-use systems such as Heating Setpoints and Schedule Modes, which significantly reduces up to 38% of energy consumption in heating systems and 14% in total household energy end-uses. The paper uncovers the significance of integrating multi-directional approaches, including physical and social elements in modeling, predicting, and implementing a holistic human-centered smart system. This system correlates occupant activities with household energy consumption patterns to optimize energy savings while maintaining occupant comfort and fostering a sustainable indoor environment in smart communities.

Keywords Housing energy efficiency, Smart community, Heating energy usage, Occupant behaviors

Abbreviations

AI	Artificial intelligence
BEM	Building energy modeling
E	Total energy consumption
E_{ac}	Heating energy consumption
EE	Energy efficiency
EEI	Energy efficiency index
EEM	Energy efficiency modeling
EEU	Energy end-use
EMS	Energy management system
ESR	Energy saving ratio
ESR_{ac}	Energy saving ratio of the air conditioning for heating
EPS	Energyplus
JPY	Japanese Yen
HEMS	Home energy management system
HEL	Hourly electricity load

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HVAC	Heating, ventilation and air conditioning
HSSM	Heating setpoints and schedules modes
IEA	International energy agency
ICT	Information and communication technology
OCC	Occupancy
OS	Openstudio
OCR	Occupancy rate
P_{ac}	Proportion of Heating energy consumption to total energy consumption
S	South
SE	South East
SSE	South South-East
SW	South West
SU	Sketchup

Energy consumption in residential areas has become a matter of concern because of its significant effect on global CO_2 levels, as the building sector accounted for almost 40% of total global energy consumption in 2016[1], while residential subsectors comprise about 40% of the total building energy consumption[2]. There has been a growing interest in sustainable energy consumption in smart communities, providing comparative insights into the factors that compose the drivers of energy use. Among them, one of the prioritized energy-efficient solutions is to explore buildings in terms of unique architecture, diverse layout, occupancy status, and individual behaviors[3]. A paper published in this area[4] claimed that heating systems, including air conditioning, contributed to the main consumption in households due to the intensive demand for heating in the winter. Furthermore, optimizing building envelope characteristics to enhance energy efficiency while maintaining thermal comfort is essential due to the significant energy consumption[5].

In most cases, occupancy patterns and their associated behaviors are the primary drivers of building occupants, influencing the efficiency of HVAC systems[6]. Although occupancy displays patterns, these factors are random and variable, leading to unpredictable fluctuations, particularly the probability that different locations are occupied at various times[7]. Connecting to human behaviors in this context, Smart and sustainable frameworks are thoroughly associated with the future trends of energy management[8]. Sustainable energy consumption has emerged as a prominent research focus in the Asia-Pacific regions, where potential cutting-edge technologies were explored, such as green technological innovation in a Chinese smart city[9], and AI technologies in solar photovoltaic systems in Japan[10]. In a smart city, sensors collect data on transportation and the environment, which is transmitted to a central database for assessment or utilized by AI to derive insights[11]. Several studies have identified smart community requirements as environmental and social considerations in Japan, where the application of ICT should be promoted to visualize energy usage and control the Home Energy Management Systems (HEMS)[12]. Japan situates its smart communities inside a comprehensive framework that intentionally incorporates energy and sustainability policies, alongside other policy domains[13]. For energy performance in the original study[4], reciprocal relationships of underlying variables and usage outputs uncover unanticipated patterns, which effectively examine the complex fluctuations of energy end-use across household categories and behaviors. Conversely, the suggested path analysis demonstrated outstanding statistical results regarding the connections among variables and the impact levels of these drivers on home energy usage[14].

In Japan, the government first launched Japan Smart Communities in 2010 and Jan Smart Community Alliance in 2015[15,16], which aimed to create a sustainable environment and conserve energy resources. According to The Energy Conservation Center[17], energy consumption in Japanese detached houses was significantly greater than in apartments (Fig. 1), mainly driven by Heating, Ventilation, and Air Conditioning (HVAC) systems. The end-use of heating is substantially larger than that of the cooling system, being nine times higher in apartments

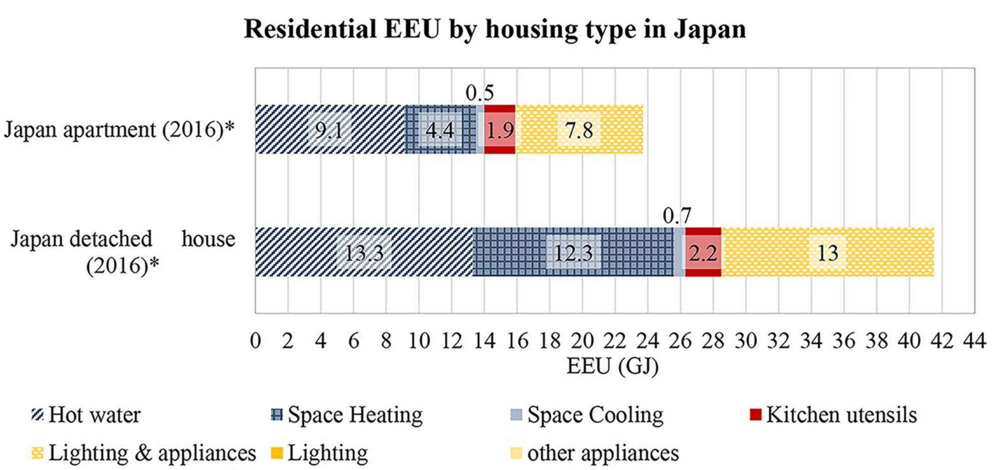


Fig. 1. Energy use in households categorized by dwelling type in Japan * The Energy Conservation Center, Japan[17,19].

and eighteen times higher in detached buildings. From 2010 to 2014, 26 projects were implemented, including the Higashida Smart Community, which claims to cut off 50% of CO_2 emissions compared to comparative areas in Kitakyushu[18]. Estimating energy savings from efficiency by the IEA[13] elucidated a notable decrease in energy consumption and increased energy savings from 2010 to 2021 (Fig. 2). This number emphasizes the initial successful results of the Smart Community, which also affected the national gross energy consumption.

Research gaps and purposes

Energy consumption in the household sector is remarkably influenced by occupant behavior[20,21]. However, the inherent studies concerning the impacts of human behaviors on building energy consumption mostly focused on a single direction toward only technological or social aspects, lacking practical solutions for behavioral changes. According to a state-of-the-art study, the flexibility of user demand can be interpreted to minimize energy consumption by employing various typical routines with the practice of personal energy consumption monitoring[22]. Total energy consumption data is readily accessible in many national reports and scientific research. However, segmented HVAC energy consumption data is often unavailable due to the high costs of sub-metering and the complexity of mechanical and electrical configurations[23]. Recognizing this research gap, in mild and cold climate zones where the residents mostly depend on heating systems, it is essential to conduct a thorough study on the end-use of heaters or the heating function of air conditioners in smart HEMS. Additionally, upon investigating behavioral studies, regarding the theory from intentions to actions, intentions govern actions, but some are discarded completely, while others are adjusted to comply with changing situations[24]. Therefore, a practical application for tackling various parameters on saving heating energy consumption is emerging and crucial in this research field. For these reasons, there is a potential gap in developing unique dynamic models that utilize the relationship between heating energy usage and human behaviors to predict household energy consumption and energy-saving prospects. This study will then examine the users' energy use behaviors and offer adjustable solutions for the energy-saving strategy, considering heating demand in a case study of the Japanese Smart Community.

A multi-directional approach considering technological and behavioral perspectives is necessary for integrating their advantages and disadvantages into a practical energy-saving solution for households. The gaps identified are related to the following research questions: (1) What is the connection between occupant behavior and corresponding energy use patterns? (2) What are the recommended techniques to better predict overconsumption behaviors in households?

To address these questions, smart communities have approached ICT in various regions worldwide to utilize information technologies in building energy management systems. However, it is still an emerging topic in the Asia-Pacific region, and Japan is one of the leading countries establishing Smart Communities and has obtained significant research and practice achievements. According to Pan et al.[25], residential buildings are relatively more straightforward in applying networking technologies to control or change energy use. In this project, we conducted real-time energy monitoring that can observe detailed data of the end-use electricity, including the water heater and air conditioners in the heating system of a Smart Community located in a residential area of Japan. The study's principal objective is to combine correlated components in summarizing the investigation derived from the real-time database of a Smart Community, which reveals insights into energy usage patterns from its influence on residential heating energy consumption. The relationship between electricity usage and occupant, as explored in previous studies on household characteristics[4] and sensitivity analysis conducted in Japan, Higashida Smart Community[26], forms the foundation for further comparison and discussion. The

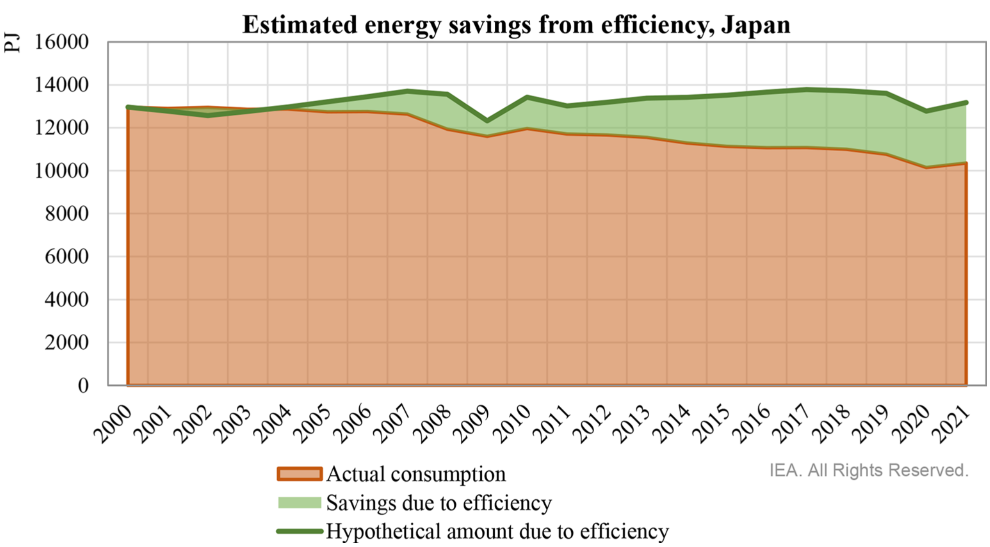


Fig. 2. Estimated energy savings in Japan 2021, IEA, Energy End-uses and Efficiency Indicators, IEA, Paris https://www.iea.org/data-and-statistics/data-product/energy-efficiency-indicators, Licence: Terms of Use for Non-CC Material[19].

introduced method in this study will examine the interactive linkages among energy, housing features, and human behavior. Based on this understanding, we put the aim of our research through the case study to emphasize the research outline in the next section.

This study concentrates on Higashida Smart Community's apartments for its advanced energy management system (EMS) in terms of detailed data analysis and occupancy information to determine the lifestyle of mid- and high-income families. The residential consumer demonstrates substantial possibilities for energy reduction in response to rising electricity prices, and the impacts are contingent upon the desires of residential consumers to alter their power consumption patterns[27]. With the potential development of smart communities and smart buildings and the indisputable impact of residential energy consumption on global CO_2 emissions, this study carries out various aspects of demand response correlated with the residential lifestyle by exploring the influence of heating usage patterns on energy efficiency strategies toward sustainability in building sectors and the indoor environment.

Case study and framework

Investigation in the case study of Higashida smart community

This study examines the on-site measured hourly electricity load (HEL) of twelve apartment units in the Higashida Smart Community. It collected household characteristics and occupancy (OCC) status using questionnaires and subsequently analyzed their energy-related lifestyles based on the observed real-time data. The authors received approval from the manager of the residence in Higashida Smart Community and household heads for the questionnaire and measurement investigation in each household. All methods were carried out with the relevant guidelines and regulations. Experimental protocols were approved by Gao's Laboratory of the University of Kitakyushu. Informed consent was obtained from all relevant investigating subjects and/or their legal guardians. Personal information collected during the survey was strictly protected under an agreement on information security. The building block photo is shown in Fig. 3 – Higashida apartment block (left), and the configuration of Panasonic monitoring in a household is shown on the right of Fig. 3.

The method studies the interactive links among three aspects: electricity usage, household characteristics and occupant behavior, while assessing the correlations among various groupings of household parameters. The correlation between electricity reports and the occupancy rate (OCR) enables us to understand the activities of household occupants on weekdays and weekends. The measurement period was from January 13, 2018, to February 28, 2018. The analysis of the annual power consumption transition in Japan found that the variance in monthly energy use increased over recent decades (from 1995 to 2017) due to heightened demand for heating and cooling systems in July and January (the hottest and coldest periods in Japan)[28,29].

Higashida apartments are one of the pivotal elements adopted in the project "Reducing 20% of the whole city's CO2 emissions" by Japan's Ministry of the Environment. With the concept of eco-friendly dwelling, they introduced electricity from natural gas cogeneration that generates less CO_2 than standard thermal power generation, high heat insulation, and energy-saving technology. The apartment's design surpassed Japan's next-generation energy efficiency criteria[29], including high-performance double glazing with thermal insulation properties and vinyl-insulated wooden walls to minimize heating and cooling demands. All residences possess identical construction and materials, retrofitted with a high-efficiency water heating system (Eco-cute) utilizing CO_2 refrigerant heat pumps, which diminish CO_2 emissions relative to traditional water heaters. These systems contribute to advancing energy efficiency within Japan's environmental conservation plan, established in 2018[30].

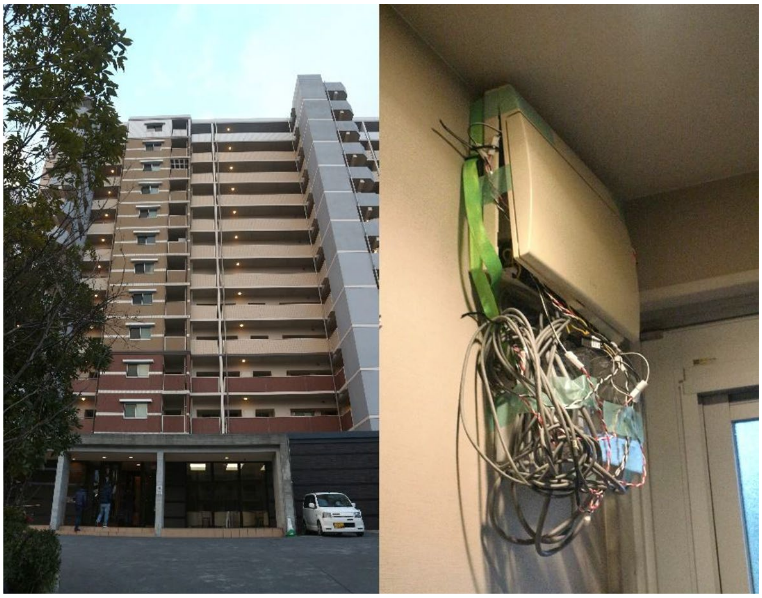


Fig. 3. Higashida apartment block (left), and Panasonic monitor setting in a household (right).

Regarding architectural design, Higashida apartments consist of two blocks, predominantly south-facing. The first block, built in 2008, comprises 86 units on five floors. The second block, built in 2009 with 139 units, is located on 13 floors, which level down from the West to the East to extend southern-facing facades (Fig. 4). Both blocks feature expansive balconies with access to courtyards, facilitating natural light and ventilation. Regarding building type and layout design, Japanese apartments are categorized as low-rise apartments with limited stories and mid-rise/high-rise apartments featuring many levels and elevators[31]. These selected apartments are the second ones designed with a *Genkan* (a small area as an entryway inside Japanese houses before the entrance to a house), living room, kitchen, *tatami room* (Japanese traditional-styled rooms, featuring a type of mat flooring based on a module about 0.9 m by 1.8 m), two or three bedrooms, a bathroom, and a toilet.

Framework

The present study delineates four phases in the inquiry, as seen in Fig. 4. The Panasonic Energy Monitor recorded energy data, whereas a questionnaire survey gathered information on dwelling design and household occupancy. During the second phase, data were gathered and examined to identify correlations between energy use and influencing factors, such as temperature, household features, occupancy, and lifestyle. In the third phase, we will conduct the Building Energy Model on OpenStudio (OS) and SketchUp (SU) and complete our findings and recommendations regarding the energy use lifestyle in the fourth and fifth phases.

Methodology

Building energy simulation

Building Energy Simulation has indicated successful energy consumption prediction in building energy analysis and provided highly applicable energy conservation strategies in many studies via OS SU[32–34]. Simulating Energy Performance can explain detailed usage patterns and predict future consumption using occupancy-focused management in intelligent buildings[35], thermal comfort indicators[5] and environmental and climatic conditions[36]. By adjusting the air conditioning's working modes in the simulation input stage, compared to the baseline HVAC energy usage, EnergyPlus (EPS) forecasted precisely 72–76% and provided options to reduce up to 20–60%[26]. In this paper, we processed accumulated household data into the BEM graphical Interface named OS and SU to simulate the energy use of a housing sample. In this step, a three-dimensional model was built based on the housing floor plan and elevation on SU. The SU design software is linked with the OS to apply energy measurement simulation developed from EPS for architectural simulation. These two tools are independent but flexible in modifying and cooperating with architectural features in the energy management system. In other words, the combination of SU and OS is a visualization version of applying the Home Energy Management System (HEMS) to residential houses.

Based on the investigation, housing characteristics such as floor plans, building construction, HVAC equipment, and occupancy status serve as the input, and the output is the end use of energy consumption. The graphical user interface of OS is user-friendly, and it is widely used by researchers and engineers to conduct diverse analyses regarding energy consumption, site and source Energy, EEU, lifestyles (occupancy and schedules), housing measurements (building size and material), ownership, and equipment (Fig. 5 a). For the HVAC simulation setting, we design thermal zones – a zoning architectural space which is occupied for HVAC systems operation – according to the architectural spaces in SU (Fig. 5 b). The software calculates HVAC energy consumption based on the heat change balance algorithms that were acquired in the associated EPS Program running behind the OS.

Energy-saving ratio

One of the most popular evaluation methods for comparing building energy consumption performance is the Energy Efficiency Index (EEI). The proposal of a uniform index for building energy efficiency technologies has garnered significant attention due to its potential benefits[37]. By incorporating the EEI model (EEM) into an energy management program, it is possible to dramatically reduce the energy consumption of a building[38]. Energy Input can be widely understood as Energy Performance, including Site and Source Energy or Energy End-Use (EEU). thermal; for example, regarding housing and household characteristics, they can include floor area (m2), number of family members, occupant profiles, occupancy rate (%), and HVAC setpoint (degree

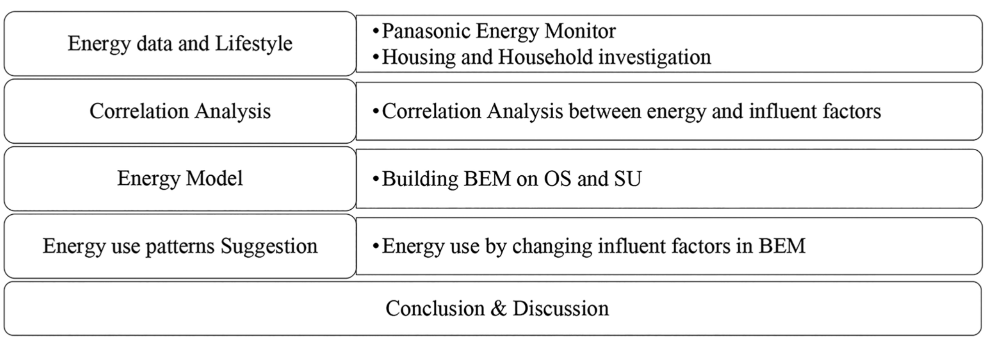


Fig. 4. Research outline.

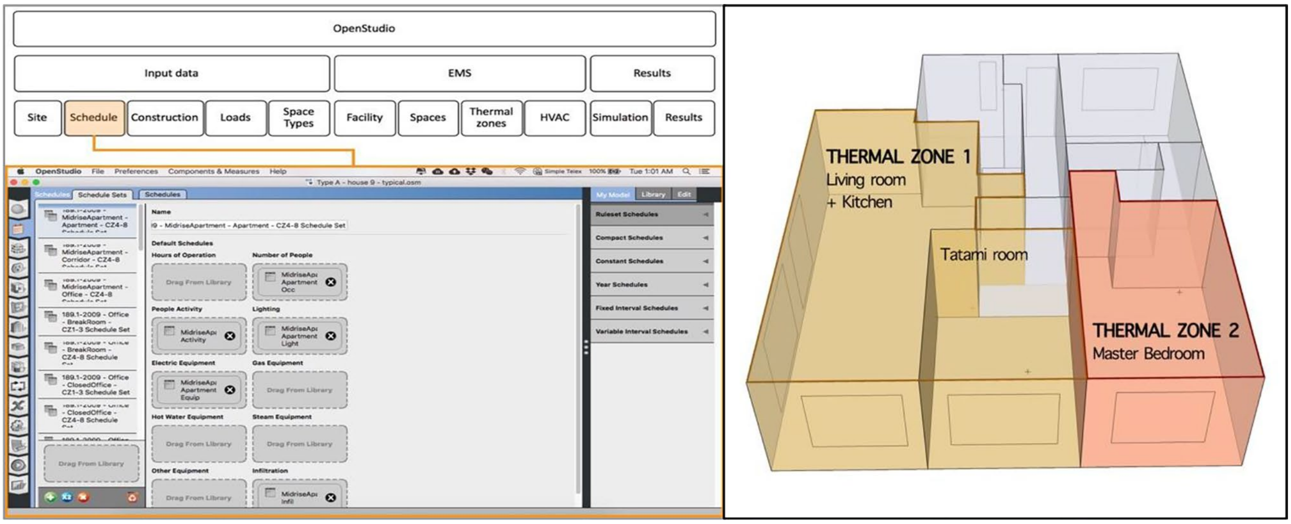


Fig. 5. (a) OS interface and in-output concept (b) Spatial design of thermal zone in SU.

Celsius). This paper focuses on the EEI of EEU under the concept of HVAC Setpoints and Schedule Modes (HSSM), explicitly referring to HVAC systems that provide a variety of HVAC setting modes to save energy use according to occupant behavior and human comfort. We evaluate energy efficiency (EE) by using the energy-saving ratio (ESR) and observing both energy input (HVAC load) and energy drivers (occupancy rate) to anticipate the activity of the HSSM. The percentage of HVAC electricity savings from changing HSSM can be counted in function (1):

$$\boldsymbol{ESR_{ac}} = \frac{|\boldsymbol{E_{acs}} - \boldsymbol{E_{ac}}|}{\boldsymbol{E_{ac}}} \times 100\%. \tag{1}$$

Where $\boldsymbol{E_{acs}}$ presents HVAC energy consumption after setting up the EEM, $\boldsymbol{E_{ac}}$ is the observed HVAC energy consumption and $\boldsymbol{ESR_{ac}}$ reflects the energy-saving ratio of the HVAC system after EEM.

If $\boldsymbol{E}$ represents total energy consumption, the proportion of HVAC energy consumption to total energy consumption $\boldsymbol{P_{ac}}$ is as follows (2):

$$\boldsymbol{P_{ac}} = \frac{\boldsymbol{E_{ac}}}{\boldsymbol{E}}. \tag{2}$$

According to the average EEU of the air conditioning system and total energy consumption, which was recorded in the real-time measurement process, we can determine the percentage of total energy savings from the activities of changing setting modes in HSSM using the following formula (3):

$$\boldsymbol{ESR} = \boldsymbol{ESR_{ac}} \times \boldsymbol{P_{ac}} = \frac{|\boldsymbol{E_{acs}} - \boldsymbol{E_{ac}}|}{\boldsymbol{E}} \times 100\%. \tag{3}$$

Correlation between energy use and its determinants

The measurement time was during the coldest period from January to February. According to the thermal environment, this period was considered the freezing point in Japan during the winter season. Temperatures ranged from − 1 °C to 14 degrees Celsius, relative humidity ranged from 35 to 100%, and wind speeds were intense (IBM[39]). Two critical electricity appliances supply the heating system: water heaters and air conditioners. Outdoor weather conditions (including temperature, humidity (dewpoint), and wind speed) in Fig. 6 and energy consumption trends in Fig. 7 show an insignificant connection between weather conditions and total energy consumption.

This research categorized the monthly income of households in Higashida into four distinct groups (Table 1): Group 1: Under 300,000 Japanese Yen (JPY); Group 2: From 300,000 JPY to under 500,000 JPY; Group 3: From 500,000 JPY to under 700,000 JPY; Group 4: From 700,000 JPY or above. The household income of these families exceeds the average recorded income in Kitakyushu, which was 397,445 JPY in 2018[40]. The age group of family members can be divided as follows: A1: adults aged between 35 and 40; A2: adults aged between 41 and 50; A3: adults aged over 60. C1: Children under six years old; C2: Children aged 6–11 years old; C3: Children aged 12–17 years old. Mothers are dominant occupants during the daytime, recorded 21 h/day, while fathers are present for only 10 h on weekdays. Older children tend to have lower occupancy than younger children. Occupancy rates (OCR) vary between 14 and 19.1 h a day per person (Table 1) and are mostly occupied by mothers. The average EEU and OCR in Fig. 8 indicate that each household's total energy consumption trends and OCR fluctuate independently. However, EEU and OCR mainly increase on weekends due to higher HVAC and lighting usage demand. According to the correlation plot chart between HEL and OCR in Fig. 10, HEL depends considerably

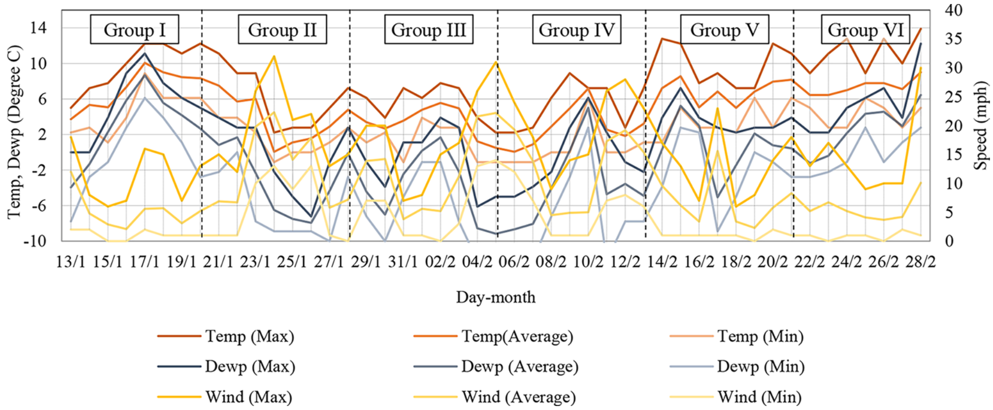


Fig. 6. Outdoor environment.

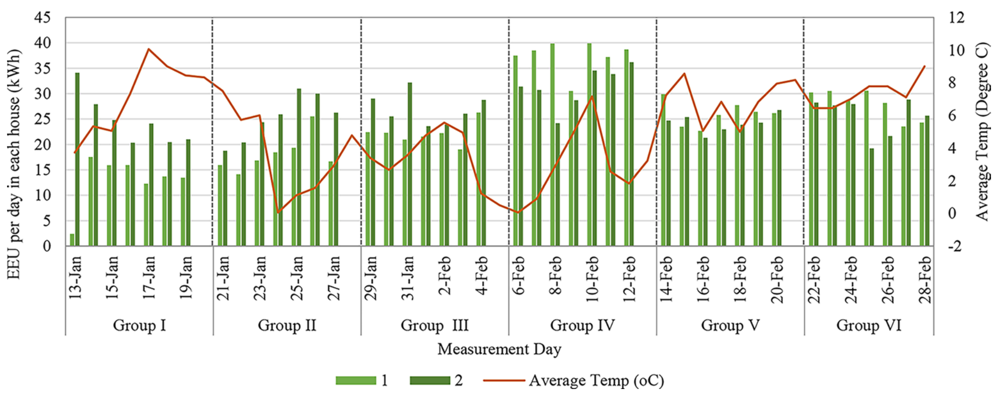


Fig. 7. Outdoor temperature and measured energy use.

Household		1	2	3	4	5	6	7	8	9	10	11	12
Size (people)		4	4	5	2	3	3	4	4	4	4	3	5
Age group (of head)	Father	A2	A2	A1	A3	A2	A2	A2	A1	A2	A2	A2	A2
	Mother	A2	A1	A1	A3	A2	A2	A2	A1	A1	A2	A2	A2
	Child 1	C2	C2	C3	N/A	C3	C2	C2	C2	C2	C2	C2	C3
	Child 2	C2	C2	C2	N/A	N/A	N/A	C2	C1	C2	C2	N/A	C3
	Child 3	N/A	N/A	C1	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	C3
	Child 4	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	C2
Income Group		2	2	3	4	3	3	4	2	3	3	3	3
Floor area (m^2)		86.7	88	104.5	83.5	83.1	86.7	104.8	75.3	99	99	99	80.5
Direction		SSE	SSE	SSE	S	SSE	SSE	SSE	S	SW	SW	SW	SSE
OCR(hours/day/capita)		17.3	14.1	16.8	19.1	17.9	15.7	17.5	17.1	16.1	16.4	16.3	14.0
EEU(kWh/week/capita)		29.1	43.0	32.5	88.3	77.4	75.9	78.9	58.5	48.7	51.3	73.3	36.8

Table 1. Household characteristics and EEU per capita in 7 days.

more on the presence of mothers and younger children (children group C1). In general, households number 4 and number 7 consumed the most substantial electricity, which also showed the highest income among the group. Conversely, household 1 consumed the least electricity and was recorded as the only unit that did not use air conditioning during the measured time.

Regarding housing space design, the building envelope comprises the roof, walls, doors, and windows. Depending on various layouts and building envelope design integration, a definition of green buildings is associated with these elements' impact on overall building energy conservation[21]. The presence of children's lifestyles, larger floor areas, larger family sizes, higher annual incomes, and an increase in the number of electrical

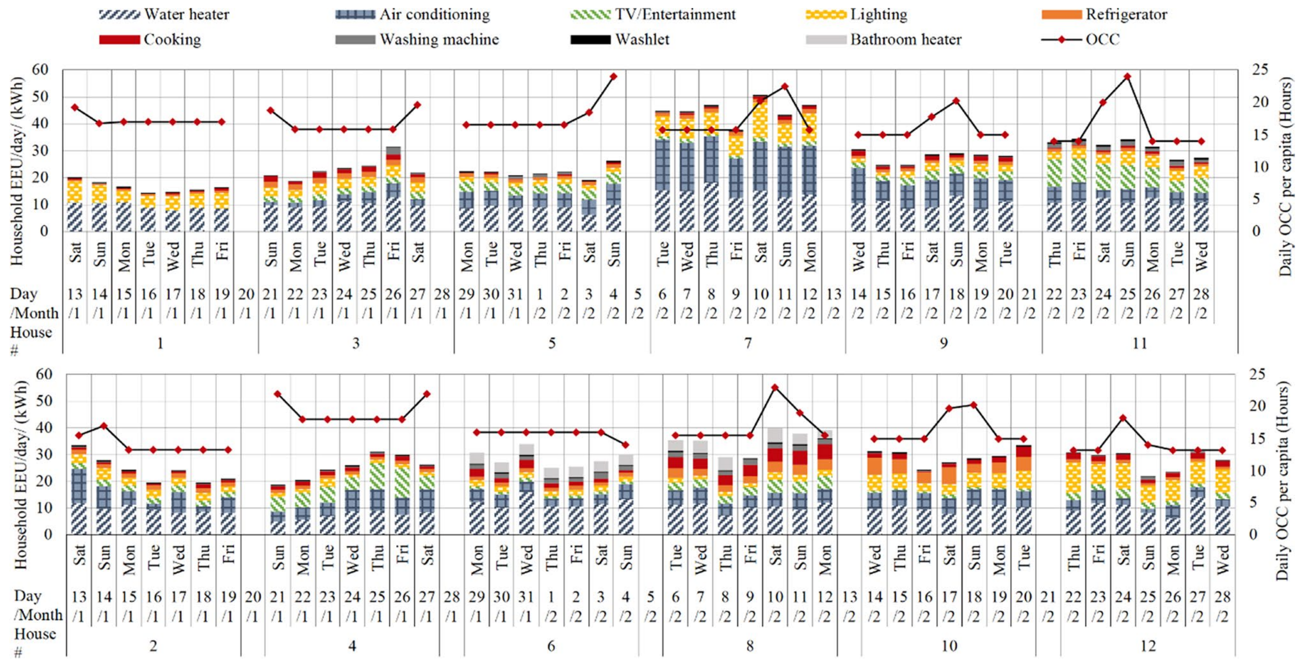


Fig. 8. Average EEU and OCR in 12 houses.

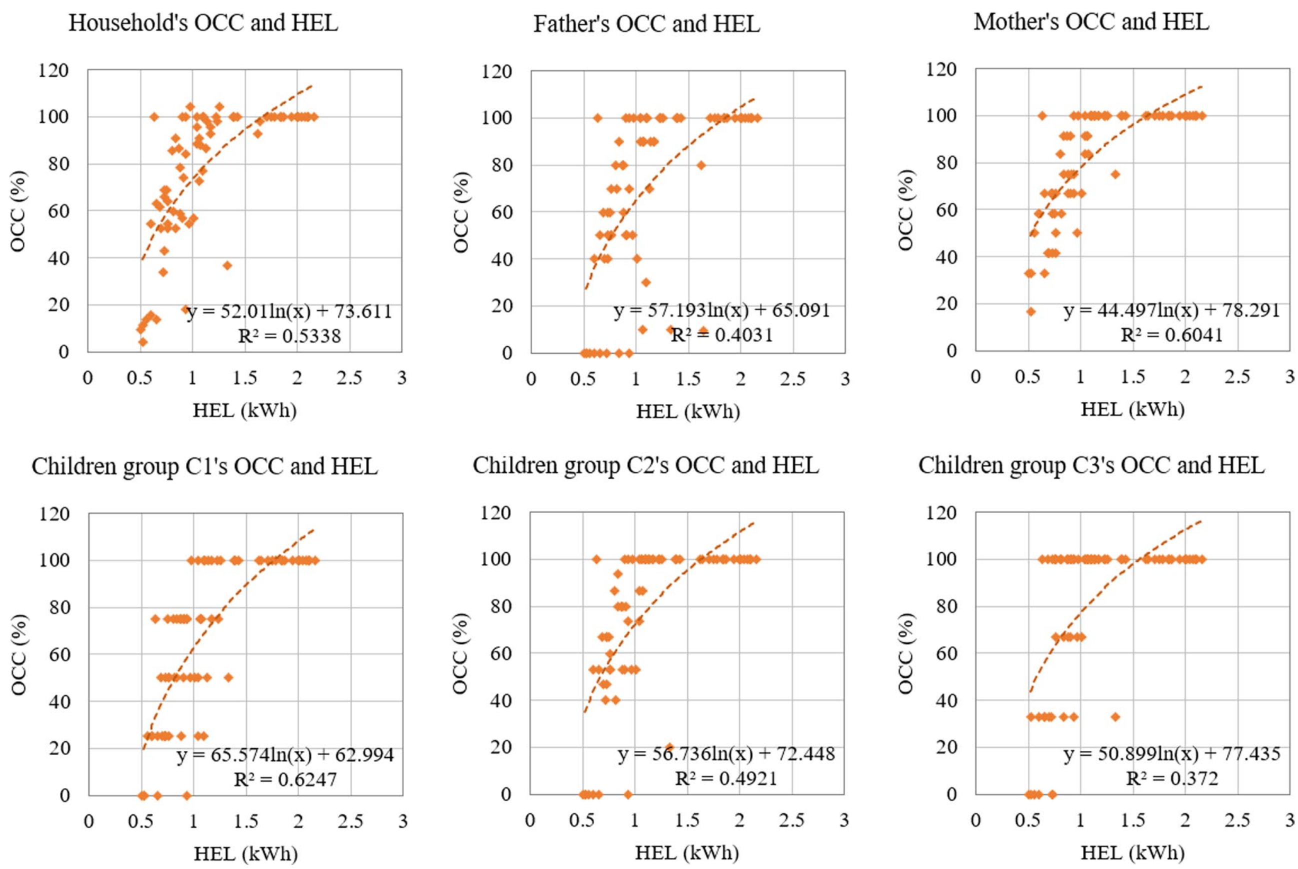


Fig. 9. Correlation between HEL and OCC.

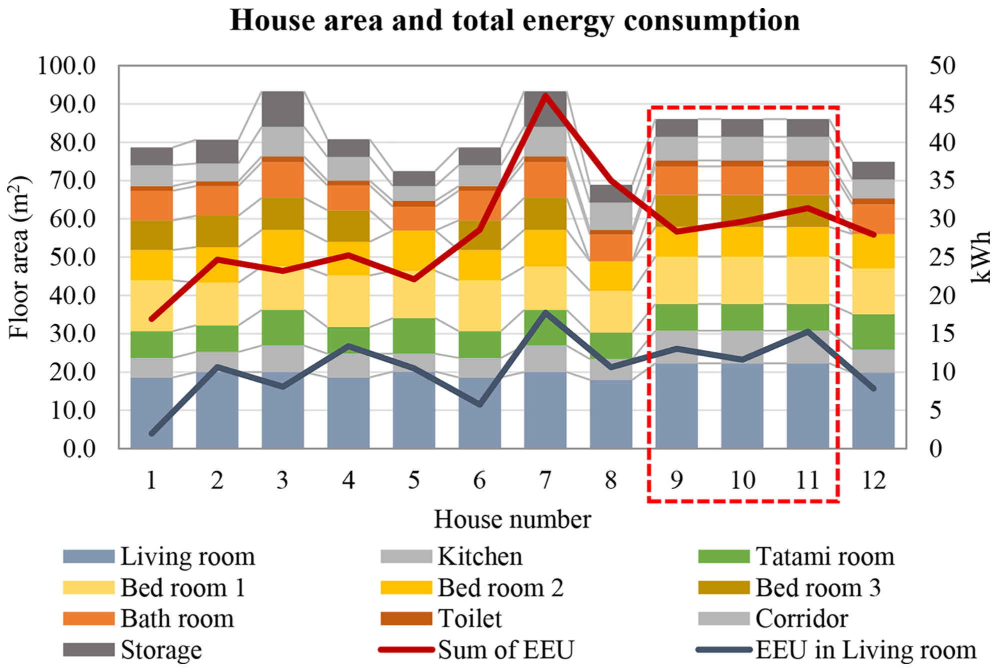


Fig. 10. House floor area by spaces and average daily energy consumption in 12 houses.

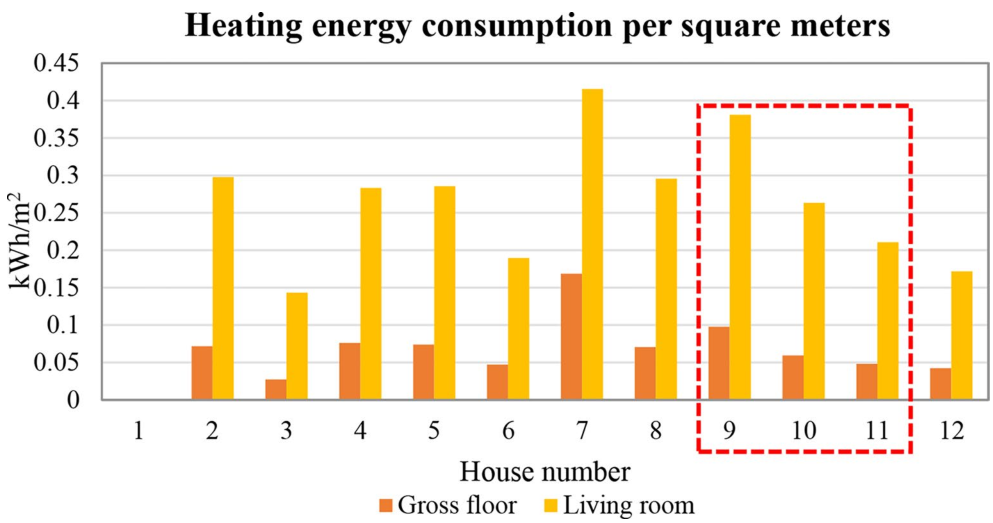


Fig. 11. Heating energy consumption per square meter by total area and living room in 12 houses.

appliances would all contribute to an increase in the amount of energy used in housing[41]. In general, participants spent less than 35 kWh/day except house 7, which consumed more than 45 kWh/day (Fig. 10). On average, 60% of the electricity that was used in living rooms and the tatami room only occupied about 40% of the total house spaces. Bedrooms, which accounted for 38% of the home's area, used only 13% of the total necessary electricity[4]. Figure 11 indicates that with the same floor area and spacing design (House 9, House 10, House 11), the energy consumption varied remarkably. The sum of floor area does not perform any linkage to the total use of energy consumption, and the demand response is contingent not on room size but on their function, while energy distribution varies according to the peculiarities of each residence. The floor plan designs of Houses 9–11 were chosen as the models for scenario simulation in the subsequent section to assess the effects of varying energy consumption patterns on heating end use.

Energy model design for HVAC energy usage patterns

According to the real occupancy status of each household, which was conducted by questionnaire investigation at Higashida Smart Community, we found several common lifestyles that could represent groups of inhabitants' HSSM (Figs. 12 and 13). Based on the occupants' daily schedule records and heating energy usage patterns in

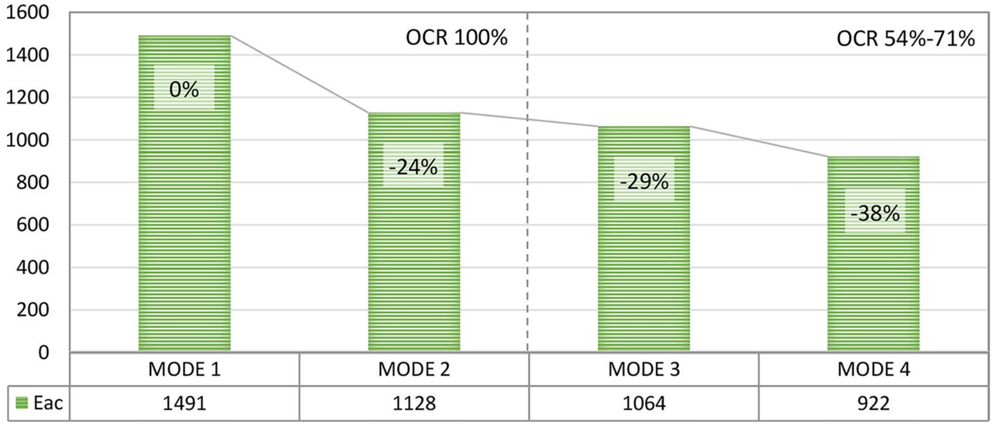


Fig. 12. Air conditioning predictive energy consumption by four scheduling modes in HSSM.

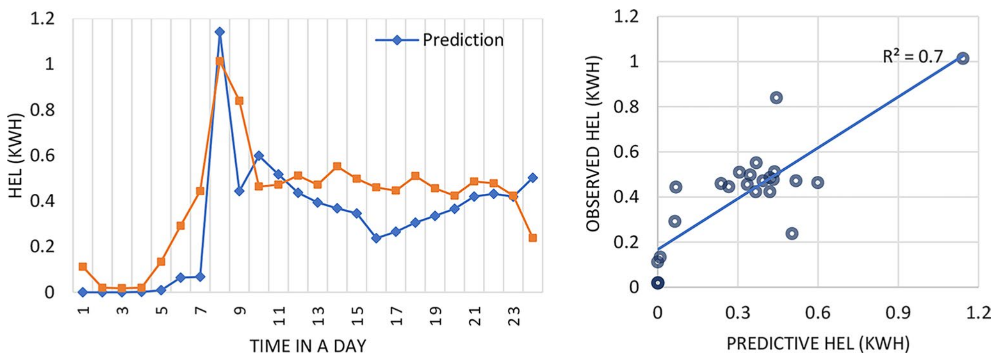


Fig. 13. Comparison between prediction and observation (model MODE 2 validation).

the survey, we designed four typical schedules and setpoints for simulating air conditioning usage (see Appendix – Figs. 14 and 15). The design of the air conditioning schedule, including four modes and energy-saving ratio after the simulation, is shown in Fig. 12; Table 2, which represent the concept of HSSM. The first mode functions as the full-time maximum usage for baseline: 24-hour air conditioning, indoor temperature setting: 24 °C. In the second mode, the primary schedule focuses on daytime activities for occupants who stay at home and use air conditioning constantly except during sleeping time, 7 AM – to 12 PM, indoor temperature: 24 º C. Mode 3 represents home activities 7 AM – 12 PM and 4 PM – 12 PM, switch off the air conditioning at noon time, temperature: 24 º C. For the final mode, we propose a flexible design related to home activities and outdoor temperature, based on the recommendations in previous studies, with an indoor temperature of 24 °C. The design of HSSM, including variable setpoints and daily schedules, is presented in Table 2, with the corresponding OCR and predictive savings of air conditioning energy and total energy savings. The results on ESR indicated that a saving mode used only for daytime activities could significantly reduce the HVAC energy consumption, which can be an energy-efficient plan for the household. In particular, mode 2, cutting down switch-on mode during sleeping time (from 0:00 AM to 7:00 AM), can gain 24% as of $\mathrm{ESR_{ac}}$ and 9% as of ESR. In the case of mode 3, we subtract three more hours at noon when the air temperature becomes warmer, $\mathrm{ESR_{ac}}$ can slightly increase to 29%, and ESR will get 10%. With the same schedule and OCR with Mode 3, if we set the air conditioning with dynamic switching for Mode 4 according to the example in Table 2, a remarkable reduction of EEU can be found, which reflects 38% of $\mathrm{ESR_{ac}}$ and 14% of ESR. The bar chart in Fig. 12 indicates that changing the HSSM can significantly improve the energy-saving ratio in a household while maintaining human thermal comfort based on the occupancy status. Although an energy-based lifestyle depends on individual choices, a positive lifestyle can save a significant amount of electricity used for air conditioning, equal to 9–14% of total consumption in winter.

According to the result validation in Fig. 13, the HSSM can predict a similar trend of HEL compared with the observed HEL. The correlation coefficient R-squared with real observation is nearly 0.7, which is relatively acceptable for the prediction of dynamic modeling based on the OCC profile. To explain the high deviation at 6–7 AM and 4–5 PM in Fig. 13, the energy model on EPS is automatically set up due to the "switch on" time. Furthermore, HEL was computed using the heat balance platform, which combines the connections between the Zone Air Cooling or Heating System's building space and the air system[42]. But in reality, more influential factors impact the thermal balance from the indoor and outdoor environment. On an ongoing basis, the user's habits fluctuate, which means that these average values can alter. These scenarios also allow for the unexpected energy-

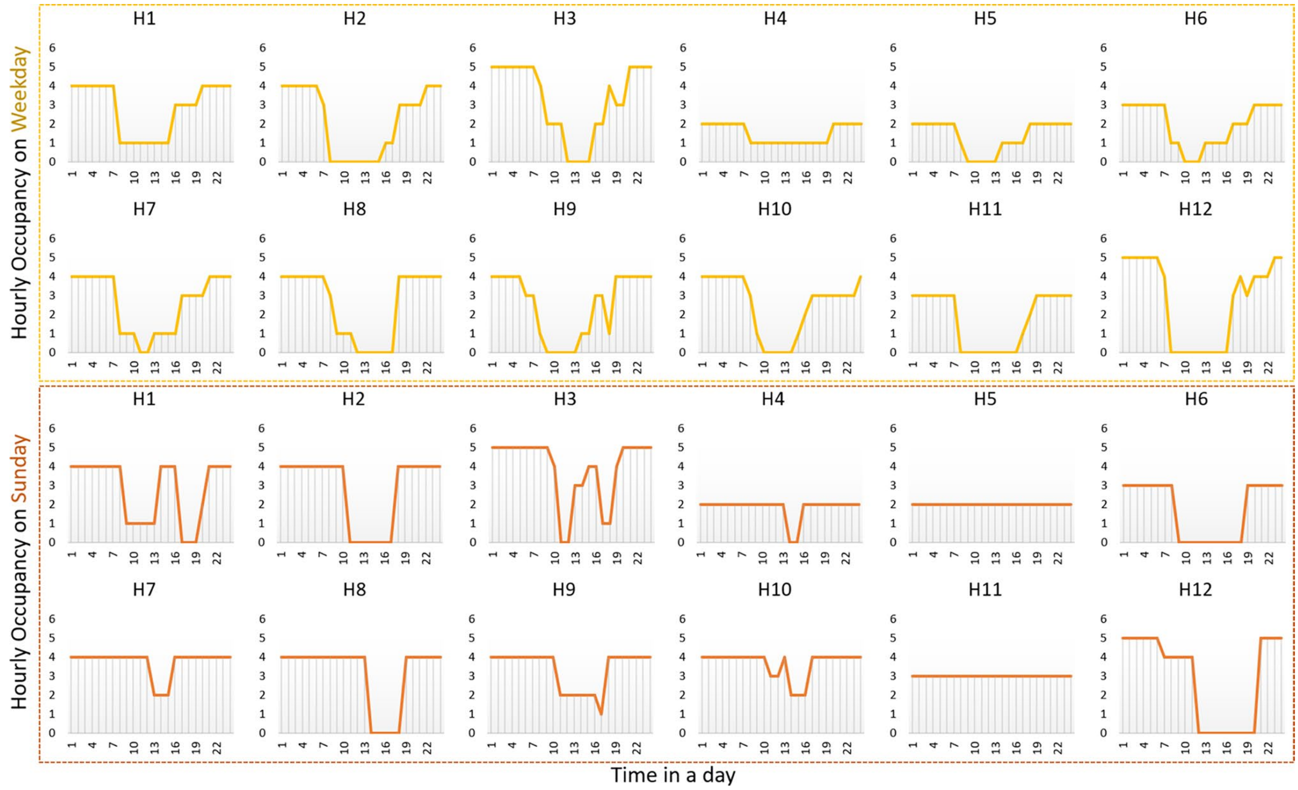


Fig. 14. Hourly occupancy of 12 households on weekdays and Sundays by on-site survey.

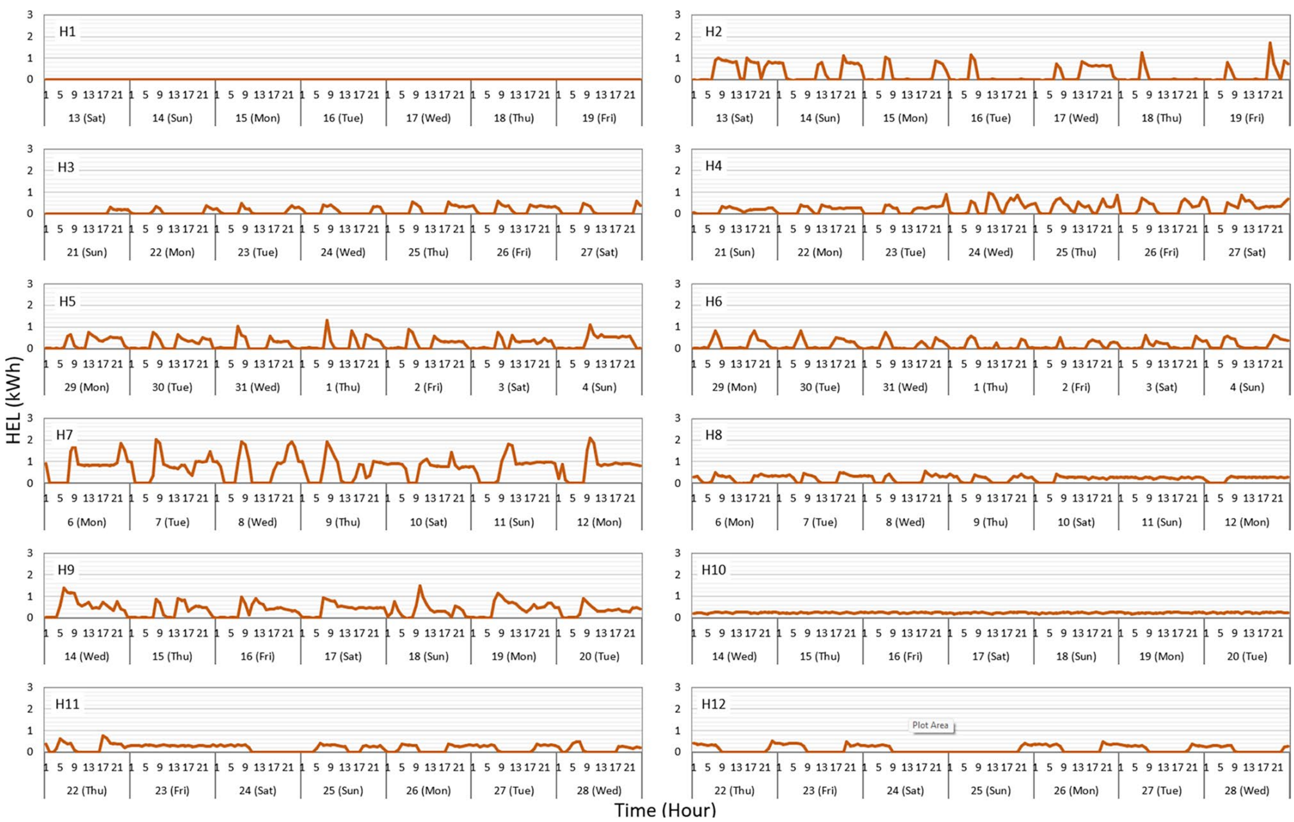


Fig. 15. Hourly electricity load of heating and air conditioning in one week.

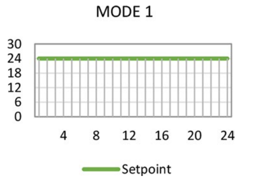
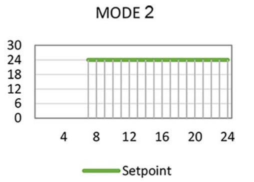
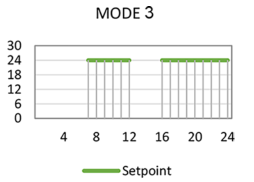
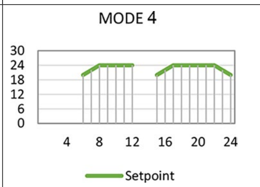
Setting mode (HSSM)	Air conditioning schedule and temperature setpoints in HSSM	Occupancy rate (OCR)	Air conditioning saving (ESR_{ac})	Total energy saving (ESR
MODE 1 (Baseline)		100%	0%	0%
MODE 2		100%	↓ 24%	↓ 9%
MODE 3		54–71%	↓ 29%	↓ 10%
MODE 4		54–71%	↓ 38%	↓ 14%

Table 2. Air conditioning setting mode and energy-saving ratio.

related behaviors that occupancy data and steady-state models cannot fully replicate. Combining the linear regression model with EPS[26], or integrating a dynamic physics-based model with other data-driven techniques can improve the energy model with good matching between measurements and predictions.

Discussion

Multiple variables influence household energy consumption, such as outdoor weather conditions, household characteristics, housing features, ownership, and energy management systems. However, household characteristics and HEMS contribute significantly to housing energy efficiency and energy-saving strategies. Accordingly, the primary drivers are family income, ownership, and energy usage patterns, which can also refer to occupant behaviors. This corresponds with the previous findings in Japan, which indicate that the energy demand for purposes other than heating is significantly elevated and influenced by residents' composition and behavior. Therefore, it is essential to enhance energy sharing and management initiatives through optimizing ICT utilization[12]. Consequently, a stringent emphasis must be directed towards these aspects, encompassing the regulation of setpoints and schedules for major residential end-use systems such as HVAC. This paper proposed the HSSM concept of changing energy usage patterns by adjusting HVAC setpoints and schedules according to the flexibility of occupancy status, such as OCC and OCR, under acceptable thermal comfort levels. Recommendations regarding household energy conservation in smart communities can be discussed as follows:

1) Energy usage patterns based on modifying HSSM are highly recommended for HVAC energy consumption management. An intelligent system that understands occupancy status and occupant usage patterns should be established to optimize HVAC systems under the housing energy efficiency control and inhabitant thermal comfort balance. This notion reaffirms the vital position of reducing air conditioning operation time and adjusting temperature setpoints to ease the intensity of use in the previous paper[14]. Energy-saving mode and occupancy sensors can detect unconscious energy waste and be programmed to process energy-saving actions according to human presence and unexpected abnormal incidents at home. Given the latest limits and policies affecting public life, advanced technology and ICT solutions are essential to maintain mobility, transit and safety by avoiding inappropriate behaviors and enhancing interaction among users and stakeholders[43]. Some research stated that the household sector's energy demand can decrease by 27% in household electricity consumption by using dynamic prices[44] or up to 57% by persuasive communication[45]. In the context of citizen-centered smart cities, the building energy model can delineate interconnected components of design research, such as a pragmatic sight focusing on conceptualizing specific requirements or possibilities, adopting technology and promoting cooperation among urban participants for collaborative innovation[46].

2) Behavioral–directional approaches toward building energy savings can be adopted by the reciprocal relationship between energy usage patterns represented by HSSM and the building monitoring and controlling systems represented by EMS. In this sense, our understanding of real energy-related activities strongly adheres to the actual usage recorded by energy monitoring and smart HEMS, thus resulting in an extensive intentional orientation in building EE strategies. This recognition strengthens the concept of the Theory of Planned Behavior[24,47], which postulates that intention and action in actuality can be influenced by deliberate control of human activities. Also, the application of a multidisciplinary approach in this study consolidates the existing theory called the Energy Cultures Framework[48], where the interplay among cognitive norms (such as environmental concern and comfort expectations), material culture (e.g., heating equipment and architectural features), and energy practices (such as the number of rooms heated and heating schedules) is key to understanding user energy behavior. To facilitate this proposal strategies into realistic practices, we need to promote extensive empirical studies that can experiment with the application and adaptation of this method in various cases of residential housing and climatic conditions.
3) HSSM should be set up based on the number of people in the family and the historical demand response data. Also, EMS synchronization for all household devices is recommended to enable correct correlations between energy and lifestyle. Recent technological advancements allow municipal authorities to gather data in real time and employ AI to enhance the administration of public services[11]. Enhancing AI functionality from the user's viewpoint is crucial for achieving a human-centered design. Users prefer to be understood by AI rather than learn how AI devices operate in their homes[49]. Therefore, the AI algorithms for smart devices under the control of HEMS should replace humans to consider setting up air conditioning based on the occupancy schedule and flexibly switching it earlier to gradually warm or cool the air instead of suddenly changing the temperature.
4) The Energy Model and Monitor facilitate predicting energy use in every household and remind residents of their energy behaviors by providing an energy performance report to compare with their neighbors or applying prepaid meters to limit over-consuming behaviors. Simulation-based methodologies should be integrated into architectural educational programs as a more dependable means for the early phase of conceptualizing architectural design[22]. A multi-directional approach for hybrid modeling is exceptionally crucial for tackling reciprocal relationships between social factors such as human behaviors and energy usage patterns toward sustainable Energy-saving programs that take humans as the center.
5) Besides advanced technical elements, linking spatial housing design to occupant behaviors in the early construction phase should be highlighted. One of the suggested architectural designs is the Passive House. This energy efficiency standard utilizes natural conditions to improve the indoor environment by optimizing energy use and reducing carbon emissions without interfering with active design techniques. Passive houses emphasize a minimal footprint, optimal orientation and dimensions of openings, sound insulation, airtightness, ventilation, and sunlight to attain low heating and cooling requirements[50]. Based on an investigation into passive dwellings, more attention needs to be paid to the leakage of buildings' partitions, which must be incorporated into the airtightness design[51]. Passive buildings are energy efficient because of their different materials and methods that can achieve these properties in building envelopes[52]. The design or retrofit of housing spaces can refer to historical data collected from a Smart Community database to maximize HVAC usage patterns occurring in particular spaces, such as minimizing living room height and glazing area, providing flexible partitions between frequent-used spaces and non-frequent-used spaces, flexibly adapting the passive design and active design to utilize the benefits of both techniques and maximizing energy-saving spaces.

Conclusion
The proposed approach and accumulated household energy-saving behavioral insights in this study can be further developed in various seasonal and climatic conditions, depending on specific research regions worldwide. The replication of this method will contribute to an in-depth evaluation from diverse behavioral perspectives of different case studies. To fill the gap in the limited size of data and short monitoring period, future studies can develop this method in other case studies across climate zones, different seasons, and other end-use types, such as cooling usage in hot-climate regions. This study carried out a novel perspective on recognizing the energy-saving potential of changing sophisticated usage patterns, particularly in the case of heating demands. Technological advancements are necessary for an adequate monitoring database in smart Home Energy Management Systems (HEMS), which guarantees comprehensive energy data while maintaining permitted privacy and security. By taking into account the user's perspective through several demand and comfort levels, the results call for constant expansion of sustainable building energy-related behaviors globally and in both established and developing Asian nations. Therefore, this enables policy-makers to carry out initiatives aimed at energy savings efficiently. Future works can potentially extend their investigation on a wider scale of databases in other end-use services, such as cooling and lighting systems, with more selections on input parameters due to the improvement of increasing smart meter technologies and ICT in Industry 5.0. The integrated method in this study takes the initiative step in prospective building energy conservation strategies in the region while ensuring occupant comfort and advocating a sustainable indoor environment in smart communities.

Data availability
The data supporting this study are available when reasonably requested from the corresponding author.

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Author contributions
Dr. Le Na Tran contributed to formulating the study question, proposing the research concept, conducting the literature evaluation, constructing the survey instrument, handling data collection, implementing the modeling and simulation process, and interpreting the results. She undertook the primary responsibility for composing the original and revised manuscript, as well as funding acquisition. Dr. Huong Thanh Hoang participated in project administration, management, and reviewing the revised manuscript. Dr. Qian Wu supported research resources and facilities; she contributed partly to the revision of the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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