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Occupants' behavioural diversity regarding the indoor environment in social housing. Case study in Northern Spain

Silvia Perez-Bezos [a,*], Olivia Guerra-Santin [b], Olatz Grijalba [a], Rufino Javier Hernandez-Minguillon [a]

[a] CAVIAR Research Group, Department of Architecture, University of the Basque Country (UPV/EHU), Donostia - San Sebastian, Spain
[b] Department of the Built Environment, Eindhoven University of Technology, Eindhoven, the Netherlands

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ABSTRACT

Previous research has shown that differences in preferences, habits, and uses can exist in buildings with similar characteristics, which can influence building performance, energy efficiency, and the well-being of occupants. Among this diversity, those residing in social housing have specific socio-economic and cultural characteristics. This study aims to provide evidence of the diversity of thermal preferences and heating-related behaviours in public social rental housing. It also seeks to develop a methodology for identifying behavioural and occupancy patterns that can be applied in building simulation programs and building stock management. To identify occupancy and heating patterns, quantitative and qualitative data analysis methods were applied. The data was collected from a variety of sources, including sensors and surveys. Advanced statistical methods were used to analyse the data and identify patterns and trends. The study was conducted in 58 dwellings of a public social rental housing building in northern Spain. The results showed a lack of association between perceived and monitored thermal comfort. Additionally, variability in the use of the dwelling has been found among similar socioeconomic profiles. The analysis of behavioural diversity revealed six clusters based on energy consumption behaviour, including occupancy patterns and heating usage. The patterns obtained can be integrated into building performance simulation programs, resulting in a more nuanced and accurate representation of energy consumption patterns. Moreover, these patterns can provide valuable insight into the diversity of energy consumption behaviours. This can be leveraged to unlock new opportunities for energy savings, efficiency gains, and enhancing the well-being of occupants across a variety of use cases.

1. Introduction

In recent years, there have been efforts to improve the energy efficiency of residential buildings and reduce their environmental impact over their lifespan. These efforts also aim to improve the quality of life for occupants. However, there is an understanding of building performance as something primarily homogeneous, based on standards, regulations and comfort models, where usage profiles and generic comfort ranges are defined for a specific climate or population. Previous research has shown that buildings with similar characteristics can have diverse uses, habits, and preferences among their occupants. This suggests that diversity can exist within a group of people with specific social characteristics and that it can influence building performance and energy efficiency, ultimately, affecting the well-being of the people who reside there. Occupants play a significant role in building performance [1] and, therefore,

* Corresponding author. Department of Architecture, School of Architecture, Oñati Plaza, 2, 20018, Donostia - San Sebastian, Spain.
E-mail address: silvia.perezb@ehu.eus (S. Perez-Bezos).

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using homogeneous models without considering the possibility of variability in preferences and uses may result in a gap between predicted and actual building performance [2].

Although the academic debates focus on the energy aspects of the building, more focus is beginning to be given to the subjective experiences of the occupants in terms of comfort and well-being [3]. Previous studies have identified three performance gaps: prediction (the difference between simulated and measured data), expectation (the difference between occupants' expectations pre- and post-occupancy), and outcome gap (the difference between comfort related survey results and monitored data) [4]. Regarding the outcome gap, traditionally, thermal comfort has been measured using stationary methods that rely on environmental and physiological variables. Recent studies have introduced new variables such as gender, age, and culture to establish more specific comfort standards [5], but there is often a gap between these standards and user perception due to the lack of consideration for individuality [6,7]. While recent research has explored new variables linked to individual characteristics, there are currently no consolidated methods in this aspect [8].

Guerra-Santin and Tweed [9] identified two ways in which people influence building performance: differences in behaviour between households, which are closely associated to the pre-bound effect, and user-building interaction, which is close related to the rebound effect. The rebound effect is the decrease on energy savings after the introduction of refurbishment solutions or building efficiency improvement systems because of changes on occupants' behaviour compensating for the energy saved. Although the rebound effect can be seen in any household group, it can particularly affect vulnerable groups, such as families living in social housing, where occupants may face economic difficulties in meeting the costs associated with interventions or maintenance of facilities in new buildings. Moreover, low energy consumption compared to calculated standards may be due to households' economic vulnerability and energy-saving preferences over comfort [10,11]. On the other hand, the pre-bound effect refers to lower energy savings resulting from and overestimation of energy consumption before refurbishment, cause, to some extent, by the use of standard occupancy profiles. In this case, the influencing factors are the diversity of households, their preferences, and needs [12]. When estimating a building's energy consumption, making assumptions about the building's operation, occupancy, and operating hours can result in significant discrepancies between actual and calculated energy consumption. This is because, in many cases, these assumptions are based on generalizations or homogeneous standards for different types of occupants. Furthermore, this variability in behaviour can exist within the same building. Indoor environmental quality and energy consumption can be significantly impacted by occupants' behaviour, regardless of a building's characteristics and quality. There are various factors that can influence this behaviour, such as economic status and the ability to use alternative resources for controlling the indoor environment [13].

These effects and building performance gaps influence the environmental impact of the building, its energy efficiency, and the economic, technological, and environmental viability of interventions. For example, Cozza et al. [14] found an overestimation of 37% of expected savings using theoretical consumption data, while the estimate of savings using real consumption data prior to refurbishment was 3.6%. Therefore, including occupants' preferences, needs, and particularities in the process design of new and refurbished buildings could help to meet their real needs and improve their quality of life and overall satisfaction.

In this sense, designs that do not respond to the occupants' needs and lifestyles move away from the objectives of improving their well-being and health, beyond energy efficiency or the environmental and economic payback it may represent. In the pursuit of improving the comfort and well-being of residents, thermal comfort is closely related to energy consumption and building performance. Furthermore, it is one of the comfort parameters that can have the most significant impact on the energy performance of the building and the well-being of the occupants [15]. Therefore, understanding occupants' behaviour and thermal preferences could help to reduce the gap between the expected and actual building performance.

On the other hand, individuals have unique behaviours, preferences, and needs. Among this diversity, those residing in social housing have specific socio-economic and cultural characteristics. Furthermore, households that access social housing may have specific characteristics that can lead to situations of economic, energy, or socio-cultural vulnerability. This suggests that prioritizing the needs and preferences of social housing residents in policy and decision-making processes could mitigate building performance gap and improve user's wellbeing.

Based on this context, the present study aims to provide evidence of the diversity of thermal preferences and heating and domestic hot water (DHW) related behaviours in public social rental housing and to develop a methodology to identify behavioural and occupancy patterns applicable in building simulation programs and building stock management. By addressing the outcome gap related to thermal comfort and identifying possible occupant behaviour profiles, it is possible to gain a deeper understanding of the complex dynamics that influence energy efficiency and well-being in these residential buildings. The analysis was conducted in 58 dwellings of a building in northern Spain, which is representative of the public social rental housing stock in the area.

The patterns obtained using the proposed methodology can be integrated into building simulation programs and building stock management, allowing for a more nuanced and accurate representation of energy consumption patterns. This behavioural variability can be incorporated into the analysis either by using independent data from each profile or by establishing a range that covers the different profiles of the building. This makes it applicable to specific actions that will be the same for the entire building or adaptable for each housing unit. Additionally, these patterns can provide valuable insight into the diversity of energy consumption behaviours, which could be leveraged to optimize control systems for peak shaving and load shifting. By taking a more holistic approach to energy consumption analysis, we can unlock new opportunities for energy savings, efficiency gains, and enhancing the well-being of occupants across a variety of use cases.

The study seeks to uncover new insights that can be leveraged to improve the quality of life for residents in social rental housing, and ultimately create more sustainable and livable communities. This can lead to more effective management of social housing stock and better outcomes for vulnerable households. Additionally, including this diversity in simulation processes for refurbishment can lead to more inclusive and sustainable housing options for all individuals.

The structure of the paper is as follows. In Section 2, this paper presents the most relevant aspects of previous literature on indoor hygrothermal comfort analysis and occupant behaviour for simulation. In Section 3, the methodology used in the process is described, and the results are presented in three parts. First, the analysis of the relationship between indoor thermal parameters and comfort. Second, the analysis of behavioural diversity related to indoor temperature, energy consumption, heating, and DHW related practices. Third, the analysis of occupancy profiles. Finally, in Section 4, the most relevant conclusions are presented.

2. Literature review

Occupant behaviour refers to their presence, movement, and interaction with the dwelling and its equipment. According to Polinder et al. [16], occupant behaviour that affects energy consumption can be defined as "observable actions or reactions of a person in response to external or internal stimuli, or respectively actions or reactions of a person to adapt to ambient environmental conditions (such as temperature, indoor air quality, and sunlight), household, and other activities."

Occupant behaviour can be adaptive when changes are made to adapt the environment to their needs, such as opening or closing windows, controlling blinds, adjusting the thermostat, or turning lights on and off. Alternatively, residents can adapt themselves to the environment by adjusting their clothing, consuming hot or cold food and drinks, or moving around the house. Non-adaptive behaviour, on the other hand, refers to actions that do not improve comfort but still have an impact on the building's energy consumption, such as presence in the house or use of appliances or electronics [17]. Stazi et al. [18] and Peng et al. [19] identified the driving factors that affect people's behaviour, including environmental, time-related, contextual, physiological, psychological, social, and random factors.

While the role of occupants in building performance is widely recognized by various authors [20,21], a more detailed study of users' behaviour, needs, preferences, and perceptions is necessary [22]. Incorporating this understanding into building design, interventions, and housing management is also critical. Occupant behaviour is generally studied by monitoring and collecting occupancy data, developing behavioural models, and implementing them in simulation tools [23]. However, these approaches often focus on technical aspects rather than socio-economic ones.

Although there has been an increase in the study of defining behavioural and occupancy profiles for energy savings and reducing environmental impact, these profiles and preferences regarding the indoor environment and thermal comfort may vary throughout the lifecycle of a building according to different factors [24], especially in social rental housing. The high turnover rate of the building stock, combined with the diversity of preferences, perceptions, and behaviours, makes it challenging to include households in the study of building energy performance. In this sense, understanding occupants' thermal comfort situation and behavioural diversity for buildings simulation can provide solutions that respond to the reality of households. To analyse the diversity of comfort and behaviours, it is necessary to consider the context of the current research, as well as the requirements that are taken into account in the design and study of building performance.

2.1. Indoor hygrothermal comfort diversity

As Stazi et al. [18] pointed out, environmental factors influence occupants' behaviour, and consequently, the building performance. Environmental factors refer to physical aspects related to the characteristics of the dwelling and its surroundings, such as orientation, envelope, or climatic zone, as well as indoor environment-related parameters [25]. One of the most critical environmental parameters is thermal aspects, which affect the energy vulnerability of households and the health of people. These parameters, including temperature, relative humidity, and air velocity, among others, are indicators of thermal comfort [26]. ASHRAE defined thermal comfort as "the condition of the mind in which satisfaction is expressed with the thermal environment" [27].

Although comfort can be objectively measured through models, satisfaction and well-being are determined by individuals' subjectivity. Therefore, each person may have specific preferences, leading to a diversity of responses in similar socio-economic and architectural contexts. However, while data on the lived experience is typically obtained through occupant surveys or interviews, the measured data is often compared to standards or accepted models that are used to determine if the measurements indicate a satisfactory environment. In many cases, subjective responses collected through surveys may not coincide with the comfort ranges established in regulations and recommendations for comfort models. Coleman et al. [4] refers to this discrepancy as the "outcome gap," which is the difference between measured performance and people's perception. According to Coleman, several studies analyse this gap in office buildings [28,29], but this type of analysis is less common in residential buildings [30].

Comfort is a subjective experience, but it has traditionally been measured using comfort models that take into account both indoor and outdoor environmental data, as well as factors associated with people. The two most commonly used models of thermal comfort are the heat-balance model and the adaptive model. The heat-balance model is based on studies conducted by Fanger in laboratories and controlled climate chambers. The adaptive model, on the other hand, is based on a series of field studies aimed at analysing the acceptability of the thermal environment. This model takes into account the context and external environment, as well as people's behaviour and requirements [31].

Three of the most commonly used standards based on these models are ISO 7730:2005 [32], ASHRAE Standard 55–2017 [27], and EN 16798–1:2020 [33]. ISO 7730:2005 is based on heat-balance models, while ASHRAE Standard 55–2017 and EN 16798–1:2020 follow the adaptive approach. All of these standards use the PMV-PPD index and heat-balance model as a basis for defining the standard for temperature control or thermal comfort.

Both PMV and PPD are used to evaluate and compare thermal environments, but they do not predict people's responses or perceptions. These models are mainly applied in environments where clothing type and activity level are known [34]. However, in residential buildings, obtaining clothing and activity data can be challenging, especially in vulnerable environments or when analysing a large number of homes.

One advantage of the adaptive model over PMV is that the former takes into account the relationship between factors associated with people, clothing, and activity, as well as considering the outdoor environment in the calculation. Previous research has shown that occupants' behaviour influences thermal comfort. Therefore, people tend to seek thermal comfort by adapting their clothing or activity type [35].

The ISO 7730:2005 [32] is based on Fanger and others' work. Thermal comfort is calculated under a controlled environment using predicted mean votes (PMV) based on a scale from -3 to 3 (cold to hot), regarding six different parameters: air temperature, mean radiant temperature, relative humidity, air movement, clothing insulation, and metabolic rate. ASHRAE 55–2017 [27] establishes different hygrothermal comfort ranges based on the outdoor environment and the conditions in the dwelling. ASHRAE replaces the previous PMV with the adaptive graph for naturally conditioned spaces only, also the same parameters as ISO 7730 influence the perception of thermal comfort. Standard EN 16798 applies PMV to buildings with mechanical cooling and an adaptive model, or adaptive model to buildings with natural ventilation and no mechanical cooling.

The main difference between ASHRAE and EN 16798 is the location and size of the databases used to define comfort equations. ASHRAE is based on 21,000 measurements from different countries, while EN 16798 relies on data from European countries such as France, Portugal, Greece, UK, and Sweden. Additionally, the ASHRAE standard is specifically applied to offices or spaces with sedentary activities and determined clothing insulation. In contrast, EN 16798 allows the adaptive model to be applied to spaces without specific clothing conditions and where thermal conditions are determined by people's behaviour.

On the other hand, it can be argued that adaptive models incorporate the influence of occupants' behaviour more extensively in the calculation of comfort ranges. However, discrepancies may still arise when non-adaptive occupant behaviours play a significant role in the indoor environment.

The literature suggests the need for further research into the diversity of thermal preferences and requirements, as well as the study of the outcome gap in specific contexts, such as residential buildings and vulnerable groups. As Coleman states, "The critical question we must ask ourselves is which data type, Environmental System or Human System, is indicative of 'real' performance? In other words, we can measure indoor conditions and compare them to a standard, but if the occupants are not satisfied, does it really matter that the quantitative measurements meet the standard?" [4].

2.2. *Occupant behaviour for simulation*

To ensure efficient building performance and reduce environmental impact, the role of occupants is becoming increasingly important. However, including occupant-related aspects in the design and management of building is complex due to the variability and diversity of users.

The diversity of behaviours and the relationship between social and physical factors in housing have been previously studied. Braulio-Gonzalo et al. [36] addressed socio-demographic factors that explain variability in energy behaviour in residential buildings. They developed a methodology to identify variables with the greatest impact on energy consumption and detect possible prediction models that include these types of variables. The results demonstrated that household profiles have a greater impact on energy consumption than other analysed variables. A previous study by van den Brom [37] quantified the proportion of variance in heating energy consumption attributed to behaviour and building characteristics. Results indicated that about 50% of the variance in energy consumption between households is due to differences associated with people, while the other 50% is related to building characteristics. Van der Brom et al. conducted this analysis with a database of social housing in the Netherlands.

Previous studies have analysed this diversity of needs and behaviours and defined household profiles and occupant behaviour (OB) models [11,38]. OB models have been classified in the literature in various ways. Stazi et al. [18] differentiated them by the object of study, such as occupancy [39–41] and interaction with building devices [42,43]. Carlucci et al. [44] classified the models as static schedules (data-driven models), stochastic models, and rule-based models. The first one includes time-dependent users' profiles, such as those defined in regulations. The second considers behaviours as stochastic, which can evolve over time and are the result of complex relationships between factors.

Gaetani et al. [45] classified models according to their complexity and classify them as non-probabilistic models (schedules and data-driven models), probabilistic models (stochastic models), and agent-based models. Non-probabilistic models refer to those representing simplified scenarios based on regulations (schedules) and those based on real data with data-driven models (data-driven models). Agent-based models predict the influence of people by modelling each individual, the interactions between people and with the building. Previous research used non-probabilistic [46–48], stochastic [49–51], and agent-based models [52]. Causone et al. [53] developed a data-driven procedure to create occupancy and electricity consumption profiles for application in building energy models with real data. The procedure used machine learning algorithms to obtain model inputs from smart meter electricity records. Jeong et al. [54] developed a model of occupant A/C usage behaviour that reproduces the diversity of heating and air conditioning consumption based on real data. Such models could be incorporated into energy simulation tools to predict real energy usage for a given residential building, which would benefit various stakeholders such as residents themselves, managers, policymakers or designers.

Real behavioural data and OB models can serve to building performance simulation (BPS) [55–57] and prediction [41,58]. Therefore, it is possible to improve the accuracy of simulation results. This would result in more precise outcomes for life cycle analyses and economic feasibility. Additionally, it can be incorporated into the development of customized building and equipment designs, refurbishment, and control strategies.

Previous literature has examined OB models for their application in BPS. Cuerda et al. [59] explored methods to reduce the gap between expected and actual building energy performance using simulation tools. The study quantified the relative effect of different building parameters on energy consumption and developed an approach to monitoring residential buildings. The study also tested and calibrated methodologies for simulation software in two case studies: pre- and post-refurbishment. Results showed a four-fold difference in potential energy savings between models adjusted with standard and actual parameters, while also highlighting the impact of actual weather data and user behaviour on simulation models.

Serrano Jimenez et al. [48] conducted a parametric analysis on a residential building in Spain, using real data on various scenarios of energy consumption by residents and based on the standards defined in energy certification procedures. Their aim was to analyse profitability and real energy and economic savings with different scenarios. The results showed that economic profitability and energy savings resulting from a reduction in energy consumption depend substantially on real consumption patterns. Ren et al. [60] used data mining methods, cluster analysis, and decision trees to define behaviour patterns associated with thermostat control and heating use in US households. They used the decision tree to determine the relationship between thermostat settings, housing and heating system characteristics, and heating use.

Although current standards generally represent simplified occupant behaviour, Zambrano et al. [61] collects previous research that has demonstrated the added value of integrating OB models into BPS. The objectives of the simulations in these studies cover different aspects, from optimizing facade design [62], identifying the most influential aspects of energy needs [63], and evaluating thermal comfort [64]. The study [61] also identifies gaps observed in previous literature that need to be addressed for the integration of OB models into building simulation processes. These gaps include the need for detailed research on OB in different contexts related to climatic zones, building typologies, countries, and people's aspects. It also proposes the need for validation and testing of the developed models.

Since occupant behaviour is highly context-dependent, understanding the behavioural variability and defining profiles based on specific buildings can lead to better models. To achieve this, monitoring data is required. Guerra-Santin and Tweed classified techniques for investigating building operation into two main groups: physical monitoring and occupant investigation. The first one measures the actual conditions of the building such as temperature, relative humidity, heating and DHW consumption, opening and closing of windows, noise, presence of people and use of appliances. The second one is based on asking people about the activity they carry out in the building and the reasons for the mode of use, for which surveys, interviews, journals, observation or accompaniment through the building are applied. Previous research has employed both physical monitoring [42,53,65] and occupant investigation [40,66], as well as mixed methods that combine data from occupants with building monitoring [16].

Other studies, such as those by Silva et al. [67], included surveys and subjective perception data in relation to monitoring data [30,68,69]. Silva et al. [67] compared qualitative and quantitative results (surveys and monitoring) of residential buildings in Luxembourg, with a focus on indoor air quality using centralized and partially decentralized ventilation. The study highlighted the importance of knowing the habits and opinions of residents in order to reduce the consumption of raw materials and improve their quality of life. The surveys included socio-demographic data, such as sex, age, time spent in the dwelling, and number of people living in the dwelling, as well as behavioural data.

Building monitoring allows for the observation of not only occupants' behaviour, but also their needs and attitudes towards the dwelling. This, in combination with analyses from the field of social sciences [70], can help provide solutions that are tailored to real needs. Simplified methods for measuring occupants' behaviour can increase the gap between simulation and reality [17]. Therefore, it is important to understand occupants' behaviour by combining qualitative and quantitative approaches. As argued by Martincigh et al. [71], monitoring data or simulations should be combined with the opinions of users. By studying the behaviour and perceptions of households, stakeholders can identify solutions that meet the needs of residents, thereby reducing the gap between expected and actual housing performance. This approach can lead to significant optimization of building performance and improvement of perceived comfort. According to Harputlugil et al. [72], the definition of comfort conditions and the analysis of residents' lifestyles are understudied. In this sense, households' perception of the Indoor Environment Quality (IEQ) of the dwelling can provide significant information about the real needs of the households. The results of Bakaloglou et al. [10] showed that income, energy costs, the number of people in the dwelling, the age of the residents, the number of electrical equipment, and comfort preferences are influential factors in the building performance gap in the French residential environment. Given the diversity of habits and lifestyles across cultures, regions, and socio-economic and demographic characteristics, it is essential to pay attention to the particularities of households in order to provide solutions that meet real needs.

There is an opportunity to further study the social and construction factors that influence people's behaviour in the context of social housing. Additionally, defining OB models in contexts such as social housing in temperate climates requires detailed research.

3. Methodology

3.1. Research approach

The study approach follows the methodology defined by Guerra-Santin et al. [12] for analysing the behaviour and needs of people in social rental housing. Guerra-Santin used the Mixed Approach for Sustainability Labs [73] based on Mixed Method Research [74], which combines qualitative and quantitative data in response to research questions and hypotheses. In this research, qualitative and quantitative data are merged to relate the results of both data types. In the study [12], Guerra-Santin analysed two dwellings using a strategy that includes the use of the heating system, occupants' attitudes and heating-related practices, and occupancy profiles. In this case, the aim is to integrate these aspects into the analysis of occupants' behavioural diversity in social housing. Therefore, the methodology needs to be adapted for its application to a larger number of dwellings.

As stated in Ref. [12], this study includes objective and subjective data to analyse how people's perceptions and preferences influence households' behaviour. The objective data consists of measured data associated with the indoor and outdoor environment of dwellings, as well as energy consumption. Social and dwelling characteristics are also included in this category. Subjective data consists of information provided by households associated with their use of the dwelling and their perception of the indoor environment. Data can be classified as either quantitative (e.g., indoor environment parameters and energy consumption) or qualitative (e.g., household characteristics, dwelling characteristics, comfort, and daily practices). Quantitative analysis has been applied to the analysis of occupants' behaviour and occupancy, including indoor environment parameters, energy consumption, and the presence of residents. Qualitative analysis allows for a qualitative description of households and dwellings, including their hygrothermal preference of the indoor environment. This second case includes variables related to the comfort and characteristics of the households and dwellings.

The combination of both types of data (quantitative and qualitative) makes it possible to analyse the diversity of households in relation to hygrothermal comfort and occupants' behaviour. Furthermore, crossing the two types of data is used to detect patterns and define behavioural and occupancy profiles. Fig. 1 shows the research approach of this study.

3.2. Case studies and data collection

The methodology described in this document has been applied to a social housing building located in the Basque Country, a region in the north of Spain. The sample consisted of 58 dwellings that participated in the a project for energy management of social housing in the region [75]. The building, constructed in 2010, has a total of 8 floors and 126 dwellings, which are divided into three different typologies: corner dwellings, front-to-back oriented, and mono-oriented. The building has a centralized natural gas heat generation system with individual control in each dwelling. The ventilation system is hybrid, with mechanical extraction in kitchens and natural ventilation. Considering the climatic classification of the Spanish TBC the building is located in climate D. As for the classification according to Köppen [76] the region is classified as Cfb: warm temperate, fully humid and warm summer. Table 1 summarises the main characteristics of the building.

To identify occupancy and heating patterns, both quantitative and qualitative data analysis methods were used. Data was collected from a variety of sources, including sensors and surveys. The survey data was collected in the first half of 2021 as part of a Basque Government's project. The survey analysis focused on the winter period and included socio-economic characteristics, perception of the indoor environment, and behavioural variables. The household perception and opinion questions were answered using a Likert scale. The questions pertaining to the capacity to maintain a comfortable temperature inside the dwelling gave respondents a choice of three responses on an ordinal scale: "no" (1), "sometimes" (2), and "yes" (3). The question about the respondent's perception of indoor thermal comfort ranked the answers on a three-point ordinal scale determined by the variable. Additional information regarding the surveys can be found in a previous research [77].

The monitoring campaign included long-term monitoring of energy consumption for heating and DHW, indoor temperature, and relative humidity in the building, as well as the energy self-management AuGe system carried out by STECHome within the AuGe project [78]. This energy self-management system provides real-time information on dwelling performance, temperature, and relative humidity to control and measure occupants' interaction with the building. Hourly data was selected for the winter period (December 2020 and January, February, and March 2021).

The technical equipment used included temperature and humidity sensors, actuators on shut-off valves, and consumption data control units for heating and DHW, with occupants accessing the system via tablets or mobile apps. Temperature and humidity sensors from Bmeters were used, which have an accuracy of ± 0.4°C and ± 3%, respectively. Heating and DHW consumption were measured using the Sontex Superstatic 789, which measures flow rate in individual tubes with an accuracy of ± 0.0005 m^3/h. The Wireless M-Bus communication protocol was established using a gateway C300 and R300 repeaters from Usanca manufacturer, allowing

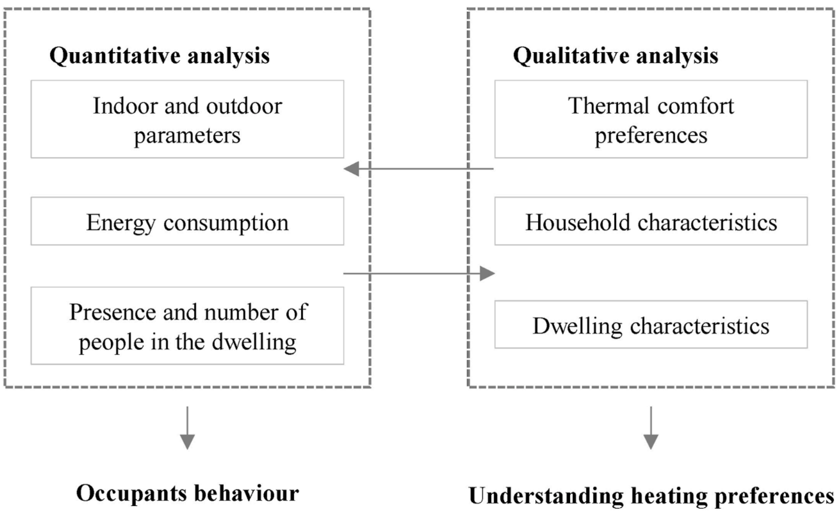

Fig. 1. Research approach.

Table 1
Case study building summary.

Outdoor climate condition	
Köppen-Geiger climate zone	Cfb
Local climatic zone	D
Building properties	
Year of construction	2010
Number of stories	Ground + 8
Heating/DHW energy system	Centralized
Heating/DHW energy class	Natural Gas
Ventilation	Hybrid
Dwelling typology	Corner dwelling (15.5%)
	Front-to-back oriented (55.2%)
	Mono-oriented (29.3%)
Floor area	89.53 m^2
Social profile[a]	
1a>75	0%
1a<75	13.8%
2a	13.8%
2a_1c	10.3%
2a_2c	13.8%
2a_3c	12.1%
1a_c	10.3%
3a	10.3%
3a_c	15.5%
Occupant-based climate control	
Control system	Self-management system

[a] 1a<75: one adult under 75; 2a: two adults; 2a_1c: two adults and one child under 16; 2a_2c: two adults and two children under 16; 2a_3c: two adults and three or more children under 16; 1a_c: one adult with one or more children under 16; 3c: three or more adults; 3a_c: three or more adults with one or more children under 16.

remote control and self-management of the heating system and the ability for users and the public administration to check total energy consumption.

The building was part of an initiative carried out by the management entity to address energy poverty. As part of the project, the entity ensured that heating was provided to maintain a temperature of 18°C. This was achieved by measuring the energy consumption used to reach that temperature. As a result, households only had to pay for the consumption aimed at achieving higher temperatures. Consequently, it has been considered that heating behaviours and usage may vary compared to a previous period before the project.

The data from the survey conducted in the spring of 2021, which asked about comfort during the winter, was compared with data monitored during the same period (December 2020–March 2021).

3.3. Data analysis: analysis of household diversity

Data analysis involves several steps including selection, cleaning, processing, transformation, data mining, and interpretation. Whether the data comes from a single source or multiple sources (e.g., for the comparison of social housing managed by different administrations), it is necessary to work with uniform data. Four main steps have been applied in this case:

- Anonymization: The data has been anonymized, and no personal information has been processed. All personal values and any possible identification of the dwelling have been excluded.
- Unification of readings and rounding to hourly readings: When working with data collected separately, some of the variables had different monitoring data collection intervals. Therefore, it was necessary to unify the databases to a common interval. In this case, hourly data was chosen as it provided the necessary information for the analysis.
- Unification of the format of variables and observations: The format of the data can vary between databases. It is important to format variables and readings in a common format so that all data are comparable regardless of the building or data source (e.g., variable name, reading name, data type, etc.).
- Unification of different readings in a single database: To analyse different databases simultaneously, it is proposed to unify the different readings and sources in a single database to facilitate data processing. Additionally, missing data and their causes have been reviewed.

Qualitative and quantitative methods were used to identify occupancy and heating patterns. These methods provide a deeper understanding of the factors that influence occupancy and heating patterns, as well as the challenges and opportunities associated with these patterns. Details of these methods are presented in the following sections.

3.3.1. Analysing the diversity of comfort requirements: Indoor hygrothermal comfort

To assess the diversity of thermal requirements and the outcome gap in social housing resident-reported thermal comfort and calculated thermal comfort levels were compared. To define comfort levels in dwellings, a format applicable to different regulations, periods of analysis, and parameters of the indoor environment was used. Hygrothermal comfort was analysed as the percentage of hours in a comfortable situation during the winter period from December 2020 to March 2021. The UNE-EN 16798 standard [33] was used to establish the comfort ranges, where the temperature was dependent on the external temperature, and a relative humidity range of 25–60% was recommended. This regulation was selected to define the comfort models because it is based on field studies conducted in various European countries with similar climate conditions. Furthermore, the adaptive model was applied, which is recommended for residential buildings without air conditioning or mechanical ventilation. Although other regulations may suggest different comfort ranges than EN 16798, the aim was not to contrast perception data with different comfort models, but rather to observe how occupants' behaviour and particularities could influence determining the comfort situation.

Using the monitoring data, the number of hours in comfort was calculated for each environmental factor analysed, temperature and relative humidity. This calculation produced a percentage value of comfort per dwelling and per parameter. This indicator provides significant information that can be compared with different environmental factors, allowing for the determination of which dwelling is more or less comfortable. It also enables the comparison with other dwellings or buildings for the same environmental factor and the identification of possible causes of differences in comfort between dwellings.

The outcome gap was also analysed by comparing objective data obtained via monitoring with subjective data obtained via surveys. To conduct this comparison, association tests were applied: Kruskal-Wallis test for quantitative and qualitative variables, and Pearson's correlation test for quantitative variables. The quantitative variables included the percentage of time spent in comfortable temperatures and the percentage of time spent in comfortable relative humidity. The qualitative variables were those that could explain perceived hygrothermal comfort and occupants' satisfaction: comfort temperature, capacity to maintain a comfortable temperature in the dwelling and winter thermal comfort.

The association test was complemented with descriptive analyses to help explain possible associations. The analysis involved comparing the measured data with the perceived data, based on the occupancy of the dwelling. Three occupancy times were established based on the TBC [79]: morning from 7 to 15h, afternoon from 15 to 23h, and night from 23 to 7h.

3.3.2. Analysis of behavioural diversity: temperature and energy consumption

To analyse the variability of behaviour in relation to indoor temperature, heating, and DHW energy consumption, each dwelling was studied individually. This individual analysis allowed for the observation of variability and the detection of patterns or diverse behaviours.

The analysis of diversity was approached using two types of analysis: descriptive and inferential. First, a visual observation was made of the households' situation in relation to indoor temperature and energy consumption. The hourly average of the 24-h period was taken into account for the analysis. Figures were created for each household for the variables of temperature, heating consumption, and DHW consumption.

Then, a statistical analysis was performed by applying the Kruskal-Wallis association test. This tested the monitored data on temperature, relative humidity, and heating consumption with the socio-economic characteristics of the households and the characteristics of the dwellings. Additionally, the correlation between indoor temperature and heating consumption was analysed using Pearson's correlation test.

3.3.3. Heating and DHW related practices and occupancy profiles

The hypothesis was based on the existence of behavioural diversity that was unrelated to the characteristics of the households or dwellings. Therefore, the definition of profiles was proposed based on real data: heating and DHW consumption. Two types of clustering were proposed: time-series clustering and stratification into equal groups.

Time-series clustering was applied to heating consumption. This is an unsupervised learning method that involves taking dynamic data that changes over a period of time and grouping it into clusters based on shared features, without any prior knowledge of the data. This type of clustering was applied to understand the variation when consumption occurs, beyond the amount of energy used. This is likely to reflect habits and preferences when compared to the occupancy of the dwelling.

The clustering method used in this study is agglomerative hierarchical clustering. However, it is a challenging task to cluster different time series into similar groups due to the ordered sequence of each data point. The default distance metric used in clustering algorithms is Euclidean distance, but it is not suitable for time series data because it is invariant to time shifts and ignores the time dimension of the data. This can result in two highly correlated time series being measured as further apart if one is shifted by even one time step. To overcome this limitation, Dynamic Time Warping (DTW) distance was used instead. DTW is a technique used to measure similarity between two temporal sequences that do not align exactly in time, speed, or length. Unlike Euclidean distance, DTW is shape-based and takes into account out-of-phase events. When selecting the number of clusters, it was crucial to ensure that the groups are distinct. The number of clusters to be used was determined using the Elbow method and Silhouette method.

The calculation of the heating activation temperature and operating temperature, also known as setback and setpoint temperatures respectively, was based on the daily minimum and maximum temperature. The method was intended to be applicable to different time periods. The available data on heating and domestic hot water (DHW) consumption were stratified into three equal groups, following the stratification system previously applied by Karatasou et al. [80], Jones et al. [81], and Summerfield et al. [82]. The dwellings were thus classified into "low", "mid", and "high" energy groups. In this case, it was intended to detect the hours of highest consumption for each group.

4. Results

In this section, the results are presented and classified in three sub-sections: indoor hygrothermal comfort analysis and its relation to indoor parameters, occupants' behavioural diversity analysis, and pattern detection and profile definition.

4.1. Analysing the diversity of comfort requirement: exploring the relationship between indoor parameters and comfort

The hygrothermal comfort of households was studied both from the perspective of residents and through objective data obtained by monitoring indoor temperature and relative humidity. The survey results showed that 63.8% (n = 37) of households reported feeling comfortable, while 34.5% (n = 20) felt cold and only 1.7% (n = 1) felt hot. When asked about their capacity to maintain the desired temperature, 51.7% (n = 30) responded "yes", 39.7% (n = 23) responded "sometimes", and only 8.6% (n = 5) responded "no".

The percentage of hours spent in thermal comfort was calculated using the UNE-EN 16798 standard. The results indicated that 55.6% (SD = 30.45) of the analysed hours were spent in thermal comfort. The average relative humidity during these hours was 73.2% (SD = 27). A preliminary analysis of the comfort situation revealed significant variation between households: 56.9% of households experienced more than 50% of the hours in comfort for temperature, whereas 82.8% of households experienced more than 50% of the hours in comfort based on relative humidity data. These calculations took into account day and night hours as well as weekends. In general, relative humidity data showed more comfort than temperature data. Fig. 2 shows a larger dispersion for temperature than for relative humidity, indicating that the comfort situation varies significantly between the different households.

To determine the outcome gap, the percentage of hours spent in comfort and survey results were analysed. The analysis showed that, according to the applied regulation, households spent 55.8% of their time in comfort, while 63.8% of the households claimed to be in a comfortable situation according to the survey. This slight discrepancy in the results may be due to occupants' temperature preferences. Although a dwelling may be outside the comfort range according to regulations, residents may still consider the temperature comfortable. To check for statistical associations in the sample, the Kruskal-Wallis test was applied for qualitative variables and Pearson's correlation test for quantitative variables.

Table 2 displays the results of the association tests. No association was observed between the parameters of perceived comfort and the monitored data. The Kruskal-Wallis test showed that there was statistically non-significant difference in comfort responses regarding the variations in measured temperature. This implies that although the standard indicates that the conditions were comfortable, occupants' perception may differ. This highlights the significance of considering people's perception when discussing their well-being and thermal satisfaction.

To analyse variations in comfort results, Fig. 3 compares monitored temperature and relative humidity (objective data) with household perception. The figure compared the following data: average monitored temperature and relative humidity during morn-

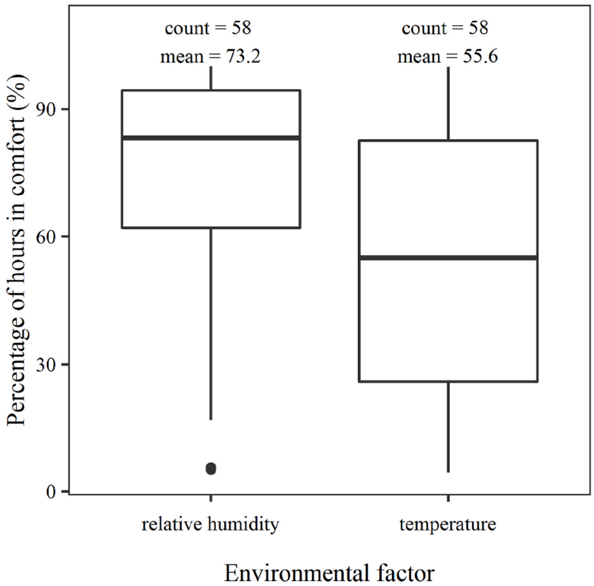

Fig. 2. Results of the monitored data based on UNE-EN 16798 standard.

Table 2
Kruskal-Wallis results for the calculated and reported data.

Variable	% hours in comfort (T)		% hours in comfort (RH)	
	chi-squared	p-value	chi-squared	p-value
Comfort temperature	3.53	.317 ^{ns}	3.16	.367 ^{ns}
Capacity to maintain a comfortable temperature in the dwelling	3.05	.218 ^{ns}	1.07	.586 ^{ns}
Winter thermal comfort	2.9	.235 ^{ns}	0.45	.799 ^{ns}

^{ns}Non-significant.

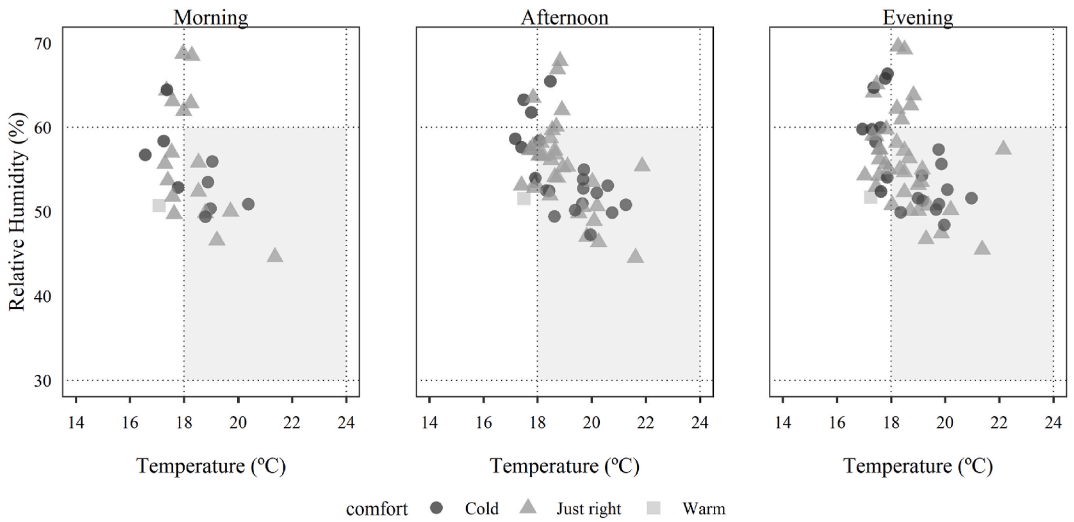

Fig. 3. Relation of reported thermal comfort and monitored data.

ing, afternoon, and evening hours; perceived thermal comfort. In each period of the day only responses from households with occupants present during that time range were included. In the figure, the comfort area for temperature and relative humidity is shown as a shaded area based on the ranges established in the UNE-EN 16798 standard.

There is not a significant variation in temperature and relative humidity between mornings, afternoon, and evening periods. However, some dwellings that fall within the normative comfort ranges reported discomfort based on both objective and subjective data, while others outside the comfort ranges reported comfort. Therefore, there was a general divergence between perceived and monitored comfort, which may indicate the important influence of individual opinions on the perception of comfort.

4.2. Behavioural diversity: temperature and energy consumption

After comparing the variability between the measured, objective data and the perceived, subjective data, we analysed whether there was a correlation between household and dwelling characteristics and indoor environmental factors and household energy consumption. To conduct the analysis, the Kruskal-Wallis test was applied to the categorical variables and the Pearson correlation test to the numerical variables.

The results in Table 3 shows that indoor environmental parameters, temperature and relative humidity, were associated with various dwelling characteristics, such as the type of dwelling, the number of facades with openings, and the number of rooms in the dwelling. Heating consumption was associated with most of the dwelling characteristics, including perceived thermal comfort in winter. However, there was no statistically significant differences in heating consumption medians between other social parameters' categories, such as the number of people or income. This suggests that there may be other socioeconomic or daily life factors that influence heating use.

A detailed analysis of the variables associated with environmental factors and heating consumption was performed. In Fig. 4, the influence of dwelling typology and the number of façades with windows on indoor temperature was analysed. The results showed that south-facing mono-oriented dwellings had a higher average temperature compared to north-south facing front-to-back oriented

Table 3
Kruskal-Wallis and Pearson test results for the monitored and reported data.

Variable		Temperature (°C)	Relative humidity (%)	Heating consumption (kWh)
Spatial factors	Relative position in the building	.284	.095	.007[a]
	Dwelling typology	.047[a]	.056	.001
	Living room orientation	.813	.273	.025[a]
	Number of facades for ventilation	.024[a]	.019[a]	.001
	Floor area (quantitative)	.069	.054	.002
	Number of rooms	.098	.008[a]	.120
Human factors	Number of people living in the dwelling (quantitative)	.575	.086	.286
	Social profile	.271	.110	.097
	Household income	.915	.201	.094
	Children under 5 years old living in the dwelling	.318	.591	.147
	Use of heating system	.848	.886	.511
	Occupancy	.822	.879	.977
	Winter thermal comfort	.270	.516	.048[a]

[a] Association with 95% confidence level.

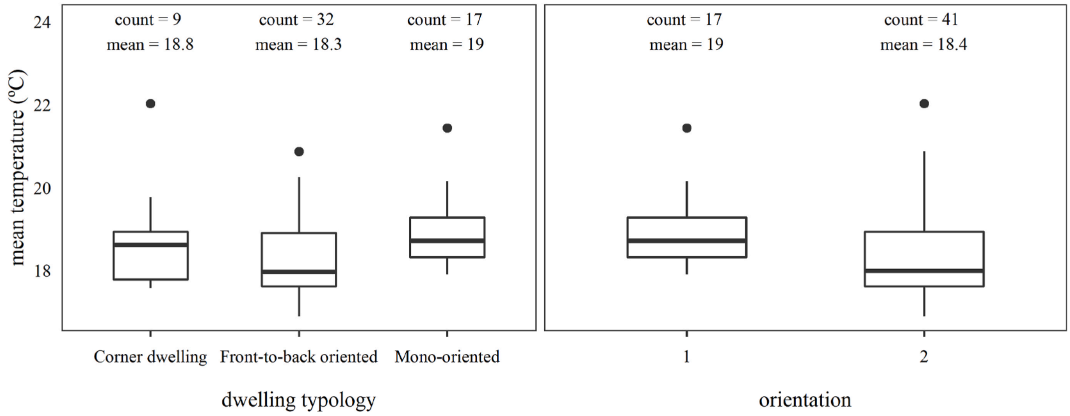

Fig. 4. Temperature results by dwelling type and number of façades with openings.

dwellings, which had a slightly lower temperature of 18.3°C. Although front-to-back oriented dwellings were more common than other typologies, mono-oriented dwellings were less dispersed than corner and front-to-back typologies. Similarly, dwellings with a single orientation had a higher average temperature and lower dispersion than those with two orientations (i.e. corner and front-to-back oriented dwellings).

Regarding heating consumption, as shown in Fig. 5, dwellings located on the first floors of the building presented higher consumption, while the average for the middle and upper floors was similar. This difference in consumption may be due to higher heat loss through the lower floors compared to the upper floors. The typology of the dwelling also affected heating consumption, as shown in Table 3. Fig. 5 indicates that corner and front-to-back oriented dwellings had higher consumption than mono-oriented dwellings. A larger outdoor surface area, north, east, or west orientation, and other factors may influenced the need for higher heating consumption to reach comfortable temperatures.

In order to achieve certain temperatures in a dwelling, heating consumption must be proportional. However, this relationship may be affected by various factors, such as the characteristics of the dwelling and the habits of the people living there. Pearson's correlation test was used to analyse the average winter temperature of dwellings and their total heating consumption. In the sample, both variables were found to be weakly correlated, $r(56) = .24$, $p = .067$. Similarly, when these parameters were compared to average income per person and housing typology, a slight upward trend was observed, but no clear correlation was found. Other variables, such as ventilation habits and use of other heating appliances, may also influenced the weak correlation of temperature and heating consumption.

Since most of the variables were found to be independent, particularly those associated with the household, the variability and diversity of behaviour related to indoor temperature and energy consumption (heating and DHW) were analysed. Fig. 6 includes daily averages of temperature. An analysis of the weekly variation of heating consumption in winter has been also developed, as shown in Fig. 7.

No clear pattern of average temperatures was observed either among the number of people or by orientation, so the variation may be related to other social or housing variables. Three distinct groups were found: dwellings where temperatures were below 18°C throughout the day ($n = 14$), dwellings where temperatures fluctuated between below 18°C and above it ($n = 26$), and dwellings

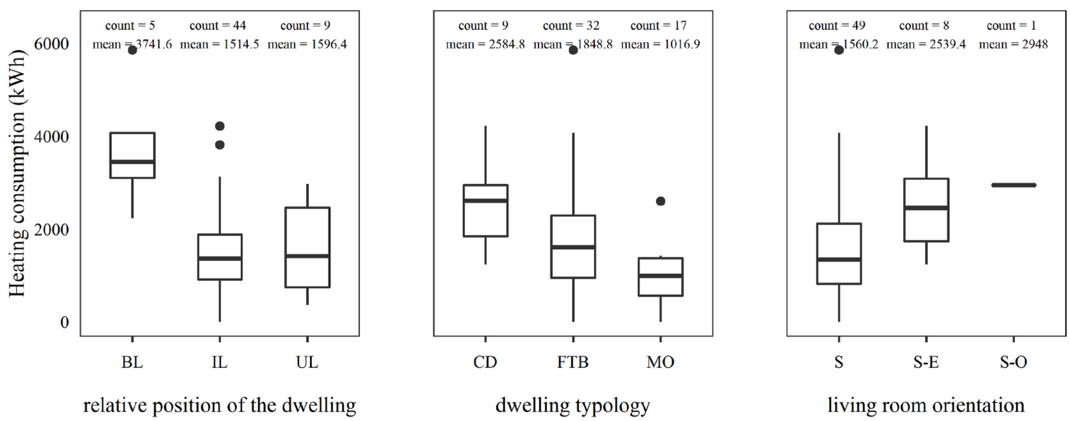

Fig. 5. Heating consumption by relative position, dwelling typology and living room orientation.
*BL: bottom-level; IL: intermediate level; UP: upper level; CD: corner dwelling; FTB: front-to-back oriented; MO: mono-oriented dwelling; S: south; S-E: south-east; S-O: south-west.

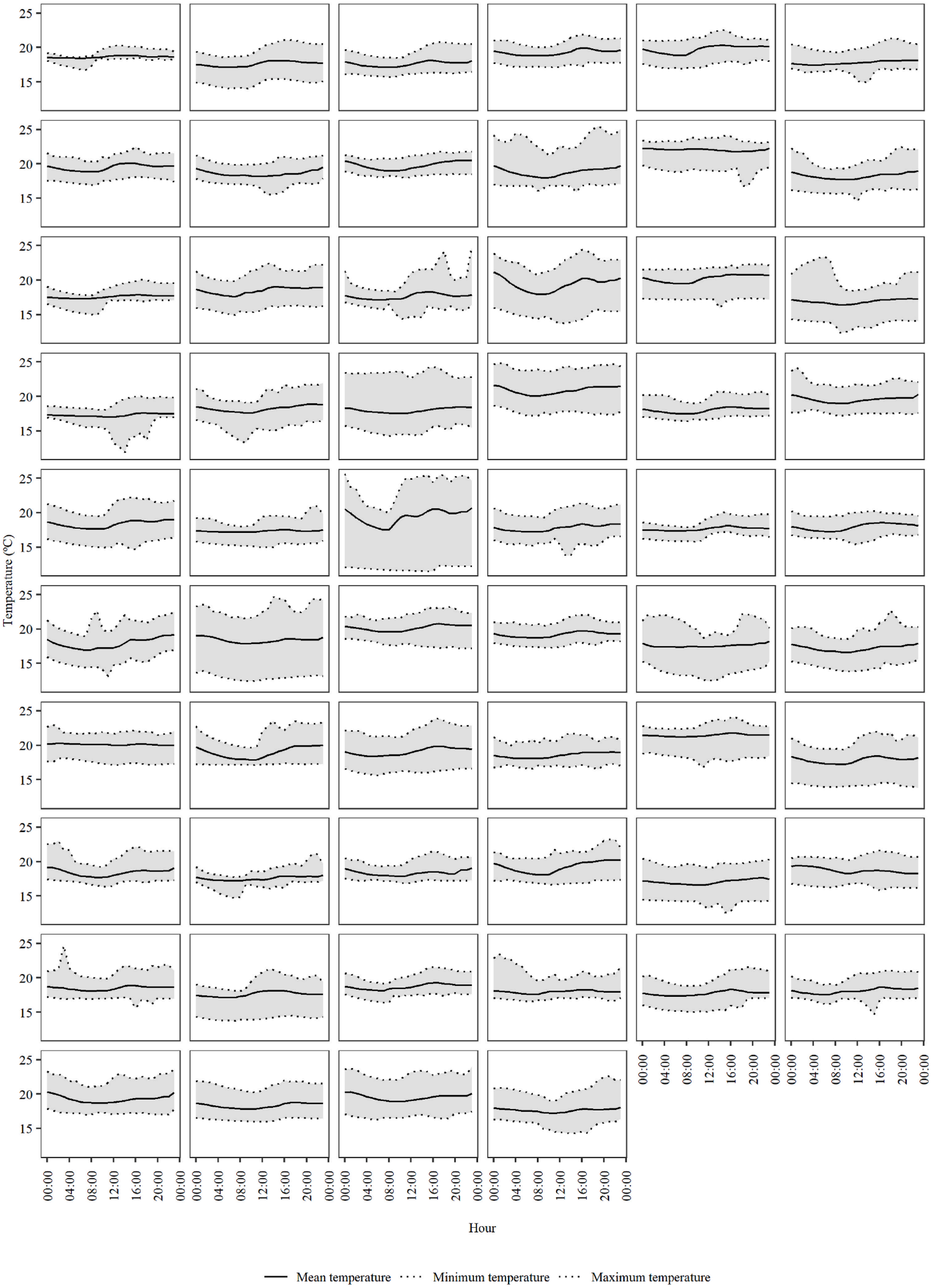

Fig. 6. Hourly average temperature per household.

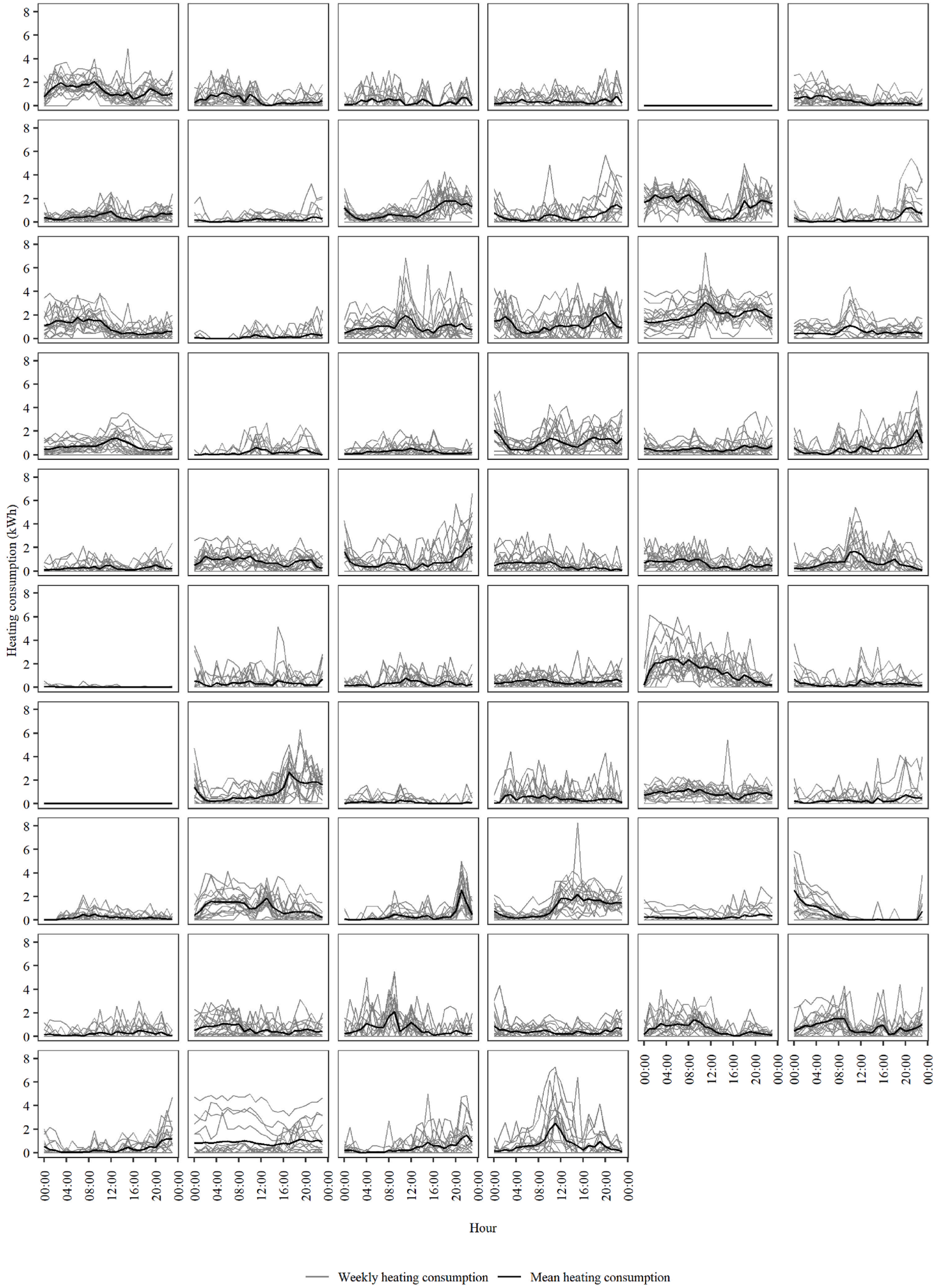

Fig. 7. Weekly heating consumption by household.

where temperatures were above 18°C throughout the day (n = 18). These groups may indicate different patterns in heating use and ventilation habits. In the second group, where temperatures fluctuate, the pattern was generally repeated in different dwellings, with temperatures below 18°C at night and/or in the early morning hours.

There were dwellings with daily maximum and minimum temperature range higher than the average, which may indicate a greater use of heating. If the range was smaller but the temperature was within the comfort range, it may indicate that the heating was set at a constant temperature. When the minimum temperature drops very low at a certain point, it may be due to the dwelling being empty at that time or to occasional ventilation. The number of people in the dwelling may also influence the range to be higher during that time period (e.g. the more people in the room, the higher the heating gains).

Patterns of heating consumption can be observed among dwellings in terms of both the period of consumption (morning, afternoon, or evening) and the amount of energy consumed. However, some of the dwellings in the sample had zero or almost zero consumption, which may indicate the use of other appliances to heat the dwelling or a lower indoor temperature. Weekly consumption variation of each dwelling was analysed to detect patterns or habits, or on the contrary, independence in heating habits. Fig. 7 shows the weekly consumptions of each dwelling and the average winter consumption of the dwelling itself. In general, a certain pattern of consumption is observed: heating use is constant comparing to the winter average and heating use tends to be in the same time slots. However, there are several dwellings where there is an increase in consumption in certain weeks, as well as variation in peak hours. This second case occurs mainly in dwellings with low consumption.

The behaviour of DHW consumption was also analysed. It was observed that although the peak consumption hours were similar across the households, there was some variation in the amount of DHW consumed.

The analysis of household behaviour revealed significant diversity associated with social characteristics. While there was some association between energy consumption and dwelling characteristics, differences in behaviour and social characteristics may lead to a profiling approach with variables not linked to social factors.

4.3. Heating and DHW related practices and occupancy profiles: Pattern detection and profile definition

In environments where variability is observed, it may be necessary to group and detect behavioural patterns. These profiles provide insight into the actual use of the building, allowing for more targeted management and adaptation of interventions to the actual behaviour of households. In the following sections, behavioural and occupancy profiles have been defined for heating and DHW consumption.

4.3.1. Heating consumption

After examining the data, we found a weak correlation between consumption and temperature, and no association between temperature, heating consumption and the socio-economic characteristics of the households. As a result, we decided to group the households based on the type of consumption, that is, based on when the heating is activated in the dwelling. Although there was an association between dwelling typology and temperature, heating, and DHW consumption, it was decided not to use these variables as profiling factors. The decision was based on limitation in comparing with other case studies and in applying the methodology to dwellings with different typologies.

Time-series clustering was used to analyse heating consumption, and employed Dynamic Time Warping distance metric to measure the similarity between the time series data. The number of clusters was selected after applying both the elbow method and the silhouette method, which indicated that the optimal number of clusters was six. These analysis measured the proximity of the observations within each cluster and the proximity of the observations in each cluster to the contiguous cluster. During the calculation process corrections were made. Additionally, four dwellings were excluded from the grouping since they were presented as outliers and generated a distortion in the results. Fig. 8 shows the six clusters, the consumption trend of each dwelling and the average of the cluster. Fig. 9 shows the average daily consumption of the excluded outliers.

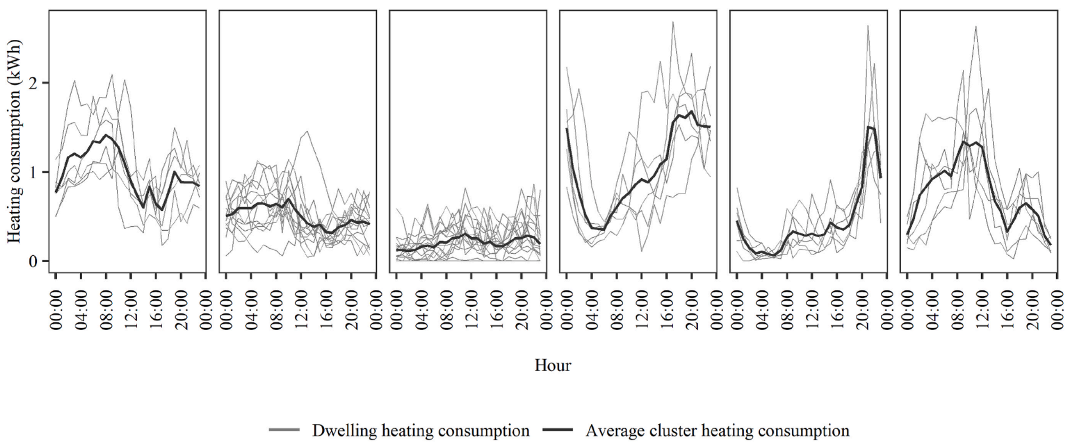

Fig. 8. Obtained clusters' heating consumption.

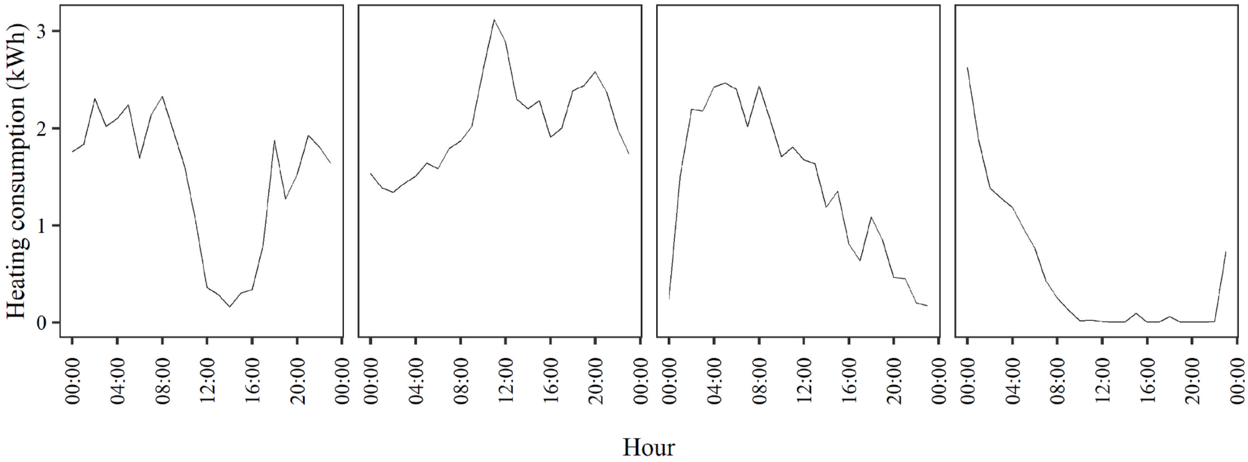

Fig. 9. Outliers' heating consumption.

To describe the differences between the clusters, the winter consumption of each group was analysed, as well as the time of day when this consumption occurs. Consumption was divided into 3 equal parts based on the maximum consumption of the clusters (morning: 7-15h, afternoon: 15-23h, evening: 23-7h). They can be classified as follows:

– All-day consumers (cluster 1): Tend to consume energy at a constant rate throughout the day and night.
– Steady energy consumers (cluster 2): Tend to consume energy at a constant rate throughout the day.
– Low-energy consumers (cluster 3). Tend to consume energy at a relatively low rate throughout the day.
– Warm nighters (cluster 4): Tend to consume more energy at night and less energy in the mornings.
– End-of-Day consumers (cluster 5): Tend to consume more energy in the late afternoon.
– Early risers (cluster 6): tend to consume more energy in the mornings and less energy at night.

All-day consumers and warm nighters have high heating consumption, but the timing of this consumption varies. Based on the period of consumption, it can be observed that all-day consumers have higher consumption at night, reaching maximum consumption in the morning, but they drop at the end of the morning and rises slightly in the afternoon. This cluster continuously remains within the mid to high consumption thresholds. In contrast, warm nighters show the opposite consumption trend: the cluster reaches minimum consumption in the evening and rises progressively until it reaches maximum consumption in the afternoon.

Steady energy consumers and end-of-day consumers present a higher percentage of dwellings in the mid group, but with different trends in terms of consumption hours. Steady energy consumers have higher consumption at night and in the early hours of the morning, reaching the medium consumption range. However, the cluster drops in the early afternoon and does not rise again until the early hours of the evening. End-of-day consumers, on the other hand, have very low consumption at night and slightly higher consumption in the morning. In this case, consumption rises in the late afternoon, reaching its peak from 21:00 to 22:00.

Low-energy consumers have a relatively low heating consumption. This cluster has constant, but low consumption. 50% of the dwellings in early risers cluster have mid consumption, and the other 50% have high consumption. The hours of consumption are similar to all-day consumers. In this case, the consumption at night and in the evening is lower than the previous one. For the outliers, three of them have high consumption, and the remaining one has medium consumption.

Regarding annual and daily consumption, Low-energy consumers have the lowest consumption both for the entire winter period and for the average daily consumption. Likewise, warm nighters have the highest consumption in both cases. Table 4 shows the heating consumption of each cluster, as well as the average daily temperature.

Examining the socio-economic characteristics presented in Table 5, it is evident that the two lowest income groups (clusters 5 and 3) use the least amount of heating. However, this is not true for cluster 4, which is the third group in terms of income, but has the

Table 4
Numerical description of clusters.

	Cluster 1 All-day consumers		Cluster 2 Steady energy consumers		Cluster 3 Low-energy consumers		Cluster 4 Warm nighters		Cluster 5 End-of-Day consumers		Cluster 6 Early risers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Average daily heating consumption (kWh/d)	23.81	4.36	12.09	2.76	4.93	2.89	24.28	3.57	10.26	2.40	18.38	4.24
Total winter consumption (kWh)	2857.67	523.01	1450.69	331.77	591.35	346.21	2913.34	428.49	1231.50	287.51	2205.17	508.70
Average daily temperature (°C)	18.62	0.43	17.92	0.41	18.57	0.56	19.61	0.49	18.96	0.49	17.82	0.37

*SD: Standard Deviation.

Table 5
Socio-economic characteristics of the clusters.

%	Cluster 1 All-day consumers	Cluster 2 Steady energy consumers	Cluster 3 Low-energy consumers	Cluster 4 Warm nighters	Cluster 5 End-of-Day consumers	Cluster 6 Early risers
Number of people living in the dwelling						
1	16.7	23.1	5.9	16.7	0	33.3
2	33.3	38.5	17.6	33.3	0	33.3
3	33.3	7.7	29.4	0	33.3	0
4	0	15.4	23.5	16.7	50	33.3
>4	16.7	15.4	23.5	33.3	16.7	0
Household income						
< 800 €	33.3	23.1	29.4	33.3	50	33.3
800-1000 €	50	23.1	23.5	33.3	16.7	16.7
> 1000 €	16.7	53.8	47.1	33.3	33.3	50
Average income per person						
€/person	432.78	476.41	318.82	415	234.72	525
Social profile[a]						
1a<75	16.7	23.1	5.9	16.7	0	33.3
2a	16.7	15.4	17.6	16.7	0	0
2a_1c	16.7	0	17.6	0	16.7	16.7
2a_2c	0	7.7	23.5	0	16.7	33.3
2a_3c	0	7.7	23.5	16.7	0	0
1a_c	0	15.4	5.9	33.3	0	16.7
3a	33.3	15.4	0	16.7	0	0
3a_c	16.7	15.4	5.9	0	66.7	0
Dwelling typology						
Corner dwelling	50	15.4	0	33.3	0	16.7
Mono-oriented	33.3	23.1	52.9	0	33.3	0
Front-to-back oriented	16.7	61.5	47.1	66.7	66.7	83.3

[a] 1a<75: one adult under 75; 2a: two adults; 2a_1c: two adults and one child under 16; 2a_2c: two adults and two children under 16; 2a_3c: two adults and three or more children under 16; 1a_c: one adult with one or more children under 16; 3c: three or more adults; 3a_c: three or more adults with one or more children under 16.

highest consumption. This finding may be attributed to the fuel poverty project in which the case studies participated. Under this project, households paid the heating costs to achieve temperatures above 18°C. Households in the clusters obtained do not have a particular profile in terms of the number of people, income, or social profile. Table 5 shows the variability of behaviour that exists in the sample, where behaviour may be conditioned by other socioeconomic or lifestyle characteristics beyond income, age, or the number of residents.

Another parameter required for completing these profiles is the heating temperature. The set-back and set-point temperatures, which are the heating activation temperature and operating temperature respectively, are calculated based on the daily minimum and maximum temperatures. This method was intended to be applicable to different time periods, depending on the objectives. Therefore, the minimum and maximum temperatures of a single day were used as the minimum time period measured. If the analysed period was longer, the minimum and maximum temperatures of the daily average would be used instead.

In this study, the winter period was analysed by considering the minimum and maximum temperatures of the average daily temperature from December 2020 to March 2021. This temperature was defined based on the heating consumption clusters and the time of day at which it was reached. To ensure accuracy, the daily minimum and maximum temperatures for the entire period were also studied and averaged. Comparison of both results revealed similar and close values, leading to the conclusion that the proposed method is likely to be accurate.

Fig. 10 is a sample of Cluster 1 that contain information on set-back and set-point temperature, heating consumption, and occupancy of the dwelling. The profiles reveal that, despite having similar characteristics in terms of households' socioeconomic status (which is required to access public social rental housing) and building features, there are distinct variations in behaviour.

4.3.2. Domestic hot water consumption

To analyse DHW consumption, the total consumption in winter was stratified into three groups with an equal number of dwellings: low (n = 20), mid (n = 19), high (n = 19). The socioeconomic characteristics of the sample were previously analysed, but found that they did not provide relevant information. Although there was a rising percentage of people with the consumption of DHW, there was no statistical association. Table 6 shows the daily and total consumption in the winter period for each group.

Fig. 11 shows two or three peaks of DHW consumption that coincide with mealtimes and daily routines. In the first group with the lowest consumption, a peak is observed at 3:00 p.m., with a slight increase in the late afternoon between 9:00 p.m. and 10:00 p.m. In the medium and high consumption groups, three consumption peaks are observed: at 9:00 a.m., which coincides with the hours before work, at 3:00 p.m., and at 9:00 p.m., which coincide with lunch and dinner hours. Overall, the sample size is not sufficient to draw accurate conclusions regarding the relationship between socioeconomic characteristics and the consumption of sanitary hot water.

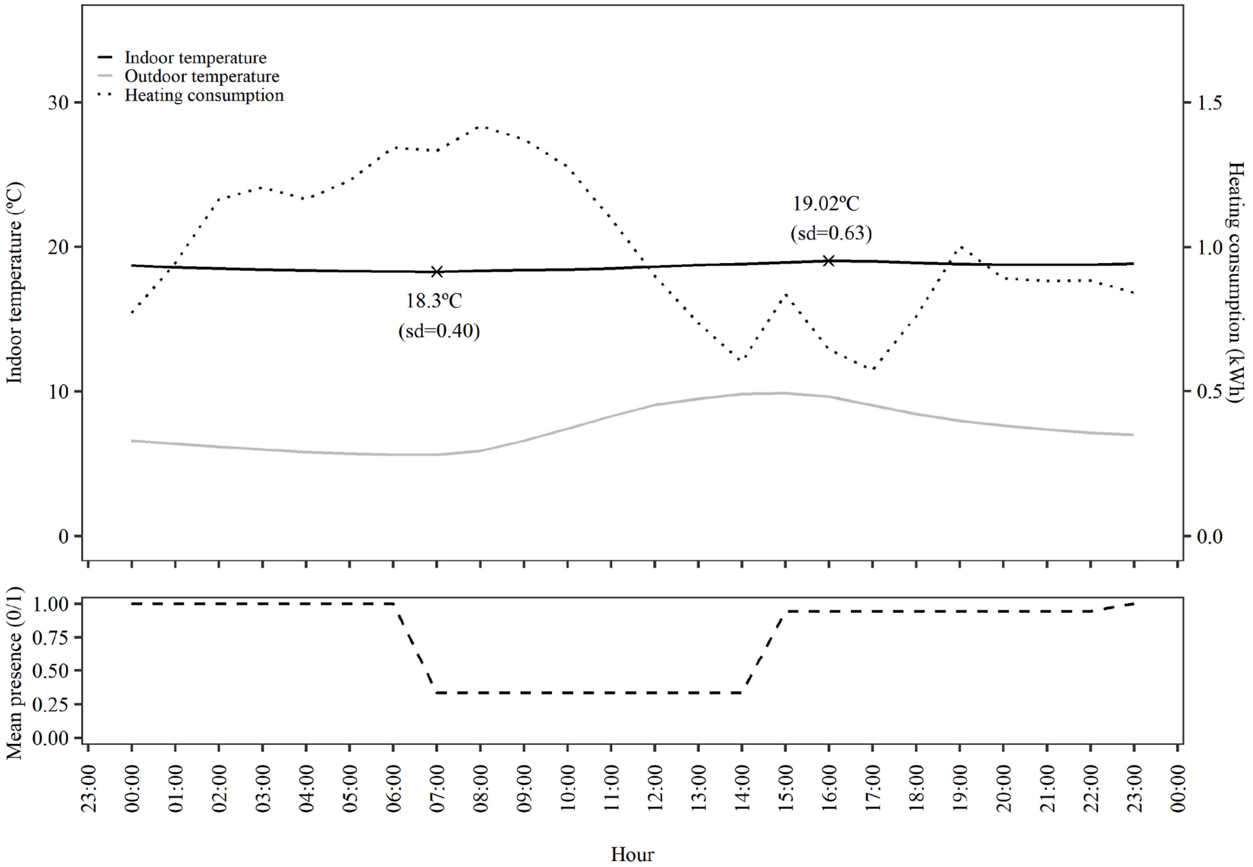

Fig. 10. All-day consumers (Cluster 1) mean weekly heating consumption, indoor temperature, outdoor temperature and presence.

Table 6
Domestic Hot Water consumption by group.

	Cluster 1		Cluster 2		Cluster 3	
	Mean	SD	Mean	SD	Mean	SD
Average daily DHW consumption (m^3/d)	0.05	0.03	0.11	0.02	0.2	0.04
Total winter consumption (m^3)	6.3	3.35	13.7	1.72	24.49	5.31

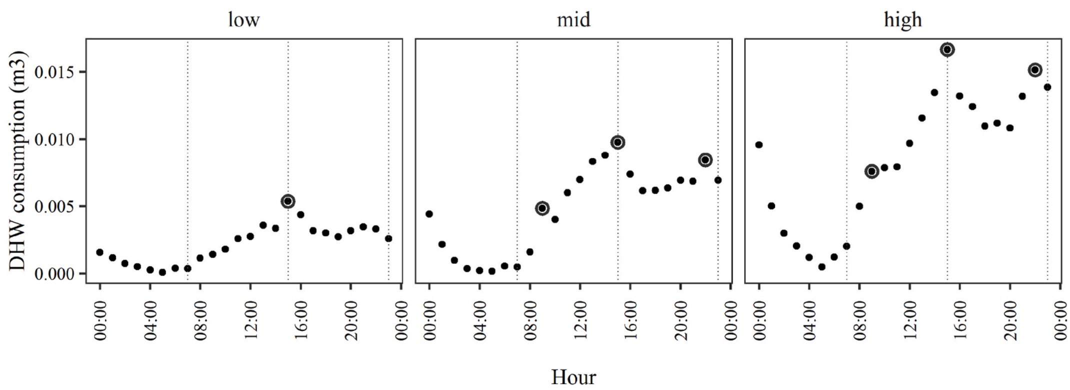

Fig. 11. Daily Domestic Hot Water consumption by group.

5. Discussion

There is a common perception that building performance can be defined as homogenous and based on non-specific standards and regulations, with occupancy profiles and generic comfort ranges tailored for a particular climate or population. However, previous research has uncovered a range of uses, habits, and preferences that can occur in buildings with similar characteristics, indicating that diversity can exist even within a group of people with similar social characteristics. This diversity can significantly affect building performance, energy efficiency, and occupants' well-being. This study aimed to provide evidence for the diversity of thermal preferences and heating-related behaviours in public social rental housing, by addressing the outcome gap and defining an approach to identify possible patterns of energy use and occupancy, applicable to BPS and social housing management improvement. The study was carried out in a building in Vitoria that is representative of the public social rental housing stock in the Basque Country, northern Spain.

The results reveal an outcome gap within the sample. The lack of correlation between resident-reported thermal comfort and calculated thermal comfort levels may be due to the subjective nature of personal satisfaction. These findings are consistent with previous studies that have also found a weak correlation between reported and calculated thermal comfort [30,83]. Touchie et al. [30] conducted a comparison between monitored data and interviews with residents under summer conditions. Based on a lack of consistent correlation between subjective and objective data, they suggested that indoor temperature alone may not be sufficient to determine thermal comfort due to the variability of survey responses. In the present study, as with the previous research, variability in perceptions of the thermal environment was observed regarding to the comfort model defined by regulations. This highlights the need to incorporate both types of data in the design of refurbishment proposals, as well as in the evaluation of a dwellings' thermal environment.

It has been observed variability in the behaviour of households with similar socioeconomic characteristics, particularly a lack of association between indoor temperature, relative humidity, heating consumption behaviour, and the studied socioeconomic characteristics. In contrast, an association between quantitative monitored data and housing characteristics has been observed. Since the case studies involve social rented housing, we assume for analysis purposes that there has not been any change in tenants during the analysed period. On the other hand, the results of Braulio-Gonzalo et al. [36] suggested that household profiles have a significant impact on energy consumption. They defined household profiles based on the number of people living in the dwelling. However, in our analysis to detect possible associations between social and spatial factors with indoor environment and energy consumption, as shown in Table 3, no association was observed with social profile or the number of people in the dwelling and heating consumption. This difference in results may be due to various circumstances, such as geographic and socioeconomic context, sample size, or defined OB models. Previous research [84], which included other socioeconomic variables, revealed that the presence of older people in the dwelling was a determining factor in the use of heating and ventilation. This suggests that it may be necessary to include other types of social variables in the analysis for the present study area.

By combining qualitative survey responses with quantitative parameter measurements, it is possible to define and detect behavioural and occupancy patterns that can be applied in simulation tools and building management improvement based on the actual use. After validating the variability of the occupant behaviour in groups with similar social characteristics, we proposed an approach to define behavioural and occupancy profiles based on real data. The results visually present the profiles and extract the numerical data for use in simulation tools. Moreover, it is possible to extract the necessary data for building management improvement based on the actual behaviour and occupancy of the dwellings. The obtained profiles can be compared to profiles defined for dwellings such as those of Guerra-Santin et al. [12] and Cuerda et al. [59]. Although the profiles obtained are comparable to those in other contexts, it is important to note that the results are specific to the architectural and social context of the sample. Nevertheless, the methodology proposed here can be replicated in other areas.

Since these profiles are defined based on heating energy consumption, it is possible that if the building or certain dwellings are energetically refurbished or specific actions are taken on passive and active systems, this could affect the obtained patterns. In other words, people's behaviours could vary. Therefore, the sample may differ from other patterns of buildings with similar social and architectural characteristics, since, as mentioned previously, the building is part of an initiative against energy poverty that facilitates access to heating up to 18°C.

This study has proposed a methodology for obtaining energy consumption and occupancy patterns, which can be used to understand and detect problems in the management or behaviour of the building. As shown in Figs. 8 and 9, heating consumption trends can vary significantly, with some groups showing much higher consumption than others do. This suggests the use of other types of devices other than the building's heating system or the application of adaptive measures to the environment by the resident individuals.

One of the limitations of these results is that these patterns are specific to the building, location, social and cultural context of the households and the period analysed. Therefore, caution should be taken when applying these patterns to other buildings or time periods without further analysis and validation. Extrapolation of these results would only be valid for buildings with similar characteristics and equivalent socio-economic contexts. Additionally, the difference in frequency of data collection may affect the study of the outcome gap and produce difficulties when comparing the two types of data. Moreover, the study was limited by the socio-cultural context and the availability of data access, which resulted in a limited range of environmental and reported data parameters. Finally, it should be noted that the fuel poverty project in which the sample building participated might have influenced the behaviours and usage of the heating system, which could have affected the results of the study.

Nevertheless, these values, which relate to occupant behaviour and building performance, enable the establishment of a preliminary understanding of how occupants influence building performance and their well-being. The proposed method focuses on its application in residential buildings, where different types of households can be included, as well as in the management of buildings stocks, and in simulation tools. Furthermore, given the prevalence of energy support issues in the public sector, these findings confirm the advantages of using a self-management system to ensure energy support by the public administration to detect residents' needs and ensure their well-being. Additionally, long-term monitoring provided real data that could be compared with social data provided by the administration, enhancing our understanding of the relationship between occupants and building performance.

Further research should explore the association between resident-reported thermal comfort and calculated thermal comfort levels in residential buildings. This should involve a combination of specific parameters and data collection frequencies. Such research is especially important when the objective is not only to ensure adequate habitability of the dwelling but also to promote the well-being of residents. To define behavioural and occupancy profiles, a more detailed study is needed to determine how other factors related to household daily activities influence thermal comfort. These factors may include age, employment status, habits, among others. which would help to understand how such factors influence occupants' behaviour.

6. Conclusions

The main goal of this study was to provide evidence of the diversity of thermal preferences and heating and DHW related behaviours in public social rental housing in northern Spain. Additionally, the study aimed to develop an approach for identifying behavioural and occupancy patterns that can be applied in building performance simulation programs and building management. This approach would help to improve building performance, energy efficiency, and occupants' well-being.

The results have shown a lack of association between the monitored and perceived data, revealing an outcome gap in the monitored sample's results. This confirms the assumption made at the beginning of the study, which highlights the need to explore the diversity of thermal preferences and incorporate both quantitative and qualitative analyses in the study of thermal comfort in a residential community. The objective is not only to reduce the building's environmental impact, but also to enhance people's quality of life.

On the other hand, the analysis of environmental and energy behaviour related to heating and DHW consumption has identified a variability of trends among households in the sample. These results confirm that uniform models can result in building performance gaps. Consequently, energy efficiency and improvement of people's well-being objectives may not be reached.

Furthermore, the study's results showed a lack of association between human factors and environmental and consumption parameters. As a result, the study proposed a methodology for defining occupation and heating and DHW consumption profiles based on real data. As mentioned at the beginning of the research, each individual presents different behaviours, preferences, and requirements, even if they share similar social characteristics with others. This has been validated in the study, thus in order to identify patterns, it was proposed to begin with analysing real data on consumption and occupation, which can then be used to define their main social and architectural characteristics.

This study contribute to understanding the complex dynamics that influence energy efficiency in buildings and the well-being of users in residential contexts. This can lead to more effective management of social housing and better outcomes for vulnerable households. Additionally, including this diversity in simulation processes for refurbishment can lead to more inclusive and sustainable housing options for all individuals. By including specific cluster data or establishing ranges with maximum and minimum values, it is possible to define individualized solutions that adapt to each behavioural trend or general solutions for the building that cover different needs. However, greater efforts are needed to ensure that buildings and their facilities are adapted to the real needs and requirements of people, as well as ensuring energy improvement and reducing the environmental impact of the building stock.

Author statement

Silvia Perez-Bezos: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data Curation, Writing-Original Draft, Writing-Review & Editing, Visualization.
Olivia Guerra-Santin: Conceptualization, Methodology, Visualization, Supervision.
Olatz Grijalba: Supervision.
Rufino Javier Hernandez-Minguillon: Supervision.

Disclosure statement

No potential conflict of interest was reported by the authors.

Research ethics

Ethics approval from Ethics Committee for Research on Human Subjects, CEISH-UPV/EHU, BOPV 32, 17/2/2014, was obtained prior to conducting the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

[1] H. Yoshino, T. Hong, N. Nord, IEA EBC annex 53: total energy use in buildings—analysis and evaluation methods, Energy Build. 152 (Oct. 2017) 124–136, https://doi.org/10.1016/j.enbuild.2017.07.038.
[2] E. Delzendeh, S. Wu, A. Lee, Y. Zhou, The impact of occupants' behaviours on building energy analysis: a research review, Renew. Sustain. Energy Rev 80 (2017) 1061–1071 https://doi.org/10.1016/j.rser.2017.05.264, Elsevier Ltd.
[3] H. Patel, S.D. Green, Beyond the performance gap: reclaiming building appraisal through archival research, Build. Res. Inf. 48 (5) (2020) 469–484, https://doi.org/10.1080/09613218.2019.1672517.
[4] S. Coleman, M.F. Touchie, J.B. Robinson, T. Peters, Rethinking performance gaps: a regenerative sustainability approach to built environment performance assessment, Sustain. Times 10 (12) (Dec. 2018) 4829, https://doi.org/10.3390/su10124829.
[5] S. Yang, M. Shipworth, G. Huebner, His, hers or both's? The role of male and female's attitudes in explaining their home energy use behaviours, Energy Build. 96 (Jun. 2015) 140–148, https://doi.org/10.1016/j.enbuild.2015.03.009.
[6] Y. Geng, W. Ji, Z. Wang, B. Lin, Y. Zhu, A review of operating performance in green buildings: energy use, indoor environmental quality and occupant satisfaction, Energy Build 183 (Jan. 15, 2019) 500–514 https://doi.org/10.1016/j.enbuild.2018.11.017, Elsevier.
[7] T. Mamani, R.F. Herrera, F.M. La Rivera, E. Atencio, Variables that affect thermal comfort and its measuring instruments: a systematic review, Sustainability 14 (3) (Feb. 04, 2022) 1773 https://doi.org/10.3390/su14031773, Multidisciplinary Digital Publishing Institute.
[8] L. Arakawa Martins, V. Soebarto, T. Williamson, A systematic review of personal thermal comfort models, Build.Environ 207 (Jan. 01, 2022), 108502 https://doi.org/10.1016/j.buildenv.2021.108502, Pergamon.
[9] O. Guerra-Santin, C.A. Tweed, In-use monitoring of buildings: an overview of data collection methods, Energy Build. 93 (Apr. 2015) 189–207, https://doi.org/10.1016/j.enbuild.2015.02.042.
[10] S. Bakaloglou, D. Charlier, The role of individual preferences in explaining the energy performance gap, Energy Econ. 104 (Dec. 2021) 105611, https://doi.org/10.1016/J.ENECO.2021.105611.
[11] W. Poortinga, L. Steg, C. Vlek, G. Wiersma, Household preferences for energy-saving measures: a conjoint analysis, J. Econ. Psychol. 24 (1) (Feb. 2003) 49–64, https://doi.org/10.1016/S0167-4870(02)00154-X.
[12] O. Guerra-Santin, N. Romero Herrera, E. Cuerda, D. Keyson, Mixed methods approach to determine occupants' behaviour – analysis of two case studies, Energy Build. 130 (Oct. 2016) 546–566, https://doi.org/10.1016/j.enbuild.2016.08.084.
[13] J. Yu, G. Cao, W. Cui, Q. Ouyang, Y. Zhu, People who live in a cold climate: thermal adaptation differences based on availability of heating, Indoor Air 23 (4) (Aug. 2013) 303–310, https://doi.org/10.1111/ina.12025.
[14] S. Cozza, J. Chambers, C. Deb, J.L. Scartezzini, A. Schlüter, M.K. Patel, Do energy performance certificates allow reliable predictions of actual energy consumption and savings? Learning from the Swiss national database, Energy Build. 224 (Oct. 2020), https://doi.org/10.1016/j.enbuild.2020.110235.
[15] A. Zalejska-Jonsson, Perceived acoustic quality and effect on occupants' satisfaction in green and conventional residential buildings, Buildings 9 (1) (Jan. 2019) 24, https://doi.org/10.3390/buildings9010024.
[16] H. Polinder, et al., "Occupant behavior and modelling, in: Separate Document Volume II, Final Report Annex, 53, 2013.
[17] T. Hong, D. Yan, S. D'Oca, C. Chen, Ten questions concerning occupant behavior in buildings: the big picture, Build. Environ. 114 (Mar. 2017) 518–530, https://doi.org/10.1016/j.buildenv.2016.12.006.
[18] F. Stazi, F. Naspi, M. D'Orazio, A literature review on driving factors and contextual events influencing occupants' behaviours in buildings, Elsevier Ltd. Build.Environ. 118 (Jun. 01, 2017) 40–66, https://doi.org/10.1016/j.buildenv.2017.03.021.
[19] C. Peng, D. Yan, R. Wu, C. Wang, X. Zhou, Y. Jiang, Quantitative description and simulation of human behavior in residential buildings, Build. Simulat. 5 (2) (Jun. 2012) 85–94, https://doi.org/10.1007/S12273-011-0049-0/METRICS.
[20] S. Chen, G. Zhang, X. Xia, Y. Chen, S. Setunge, L. Shi, The impacts of occupant behavior on building energy consumption: a review, Sustain. Energy Technol. Assessments 45 (Jun. 2021) 101212, https://doi.org/10.1016/J.SETA.2021.101212.
[21] D. Charlier, Explaining the energy performance gap in buildings with a latent profile analysis, Energy Pol. 156 (Sep. 2021) 112480, https://doi.org/10.1016/J.ENPOL.2021.112480.
[22] M. Ortiz, L. Itard, P.M. Bluyssen, Indoor environmental quality related risk factors with energy-efficient retrofitting of housing: a literature review, Energy Build. 221 (Aug. 2020), https://doi.org/10.1016/j.enbuild.2020.110102.
[23] D. Yan, et al., Occupant behavior modeling for building performance simulation: current state and future challenges, Energy Build. 107 (Nov. 2015) 264–278, https://doi.org/10.1016/J.ENBUILD.2015.08.032.
[24] W. O'Brien, et al., Introducing IEA EBC annex 79: key challenges and opportunities in the field of occupant-centric building design and operation, Build. Environ. 178 (Jul. 2020) 106738, https://doi.org/10.1016/j.buildenv.2020.106738.
[25] H.P. Tuniki, A. Jurelionis, P. Fokaides, A review on the approaches in analysing energy-related occupant behaviour research, J. Build. Eng. 40 (Aug. 01, 2021), 102630 https://doi.org/10.1016/j.jobe.2021.102630, Elsevier.
[26] M.S. Andargie, M. Touchie, W. O'Brien, A review of factors affecting occupant comfort in multi-unit residential buildings, Build. Environ. 160 (Aug. 01, 2019), 106182 https://doi.org/10.1016/j.buildenv.2019.106182, Pergamon.
[27] R, A.-C. E. (ASHRAE), The American society of heating, in: ASHRAE Standard 55: Thermal Environmental Conditions for Human Occupancy, 7, 2017.
[28] J.H. Choi, V. Loftness, A. Aziz, Post-occupancy evaluation of 20 office buildings as basis for future IEQ standards and guidelines, Energy Build. 46 (Mar. 2012) 167–175, https://doi.org/10.1016/J.ENBUILD.2011.08.009.
[29] S. Leder, G.R. Newsham, J.A. Veitch, S. Mancini, K.E. Charles, Effects of office environment on employee satisfaction: a new analysis 44 (1) (Jan. 2015) 34–50, https://doi.org/10.1080/09613218.2014.1003176.
[30] M.F. Touchie, E.S. Tzekova, J.A. Siegel, B. Purcell, J. Morier, Evaluating summertime overheating in multi-unit residential buildings using surveys and in-suite monitoring, 2016-Decem, in: Thermal Performance of the Exterior Envelopes of Whole Buildings XIII International Conference, 2016, pp. 135–151 [Online]. Available: https://www.mendeley.com/catalogue/25aafae5-2f5b-3206-8ccd-253f40764ba7/. (Accessed 23 March 2020).
[31] N. Djongyang, R. Tchinda, D. Njomo, Thermal comfort: a review paper, Renew. Sustain. Energy Rev. 14 (9) (Dec. 2010) 2626–2640, https://doi.org/10.1016/J.RSER.2010.07.040.
[32] ISO, ISO 7730: Ergonomics of the Thermal Environment Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria, 3, 2005.
[33] UNE-EN, UNE-EN 16798-1 Energy Performance of Buildings Ventilation for Buildings, 2020.
[34] D. Khovalyg, et al., Critical review of standards for indoor thermal environment and air quality, Energy Build. 213 (Apr. 15, 2020), 109819 https://doi.org/10.1016/j.enbuild.2020.109819, Elsevier.
[35] M.O. Efeoma, O. Uduku, Assessing thermal comfort and energy efficiency in tropical African offices using the adaptive approach, Struct. Surv. 32 (5) (Nov. 2014) 396–412, https://doi.org/10.1108/SS-03-2014-0015.
[36] M. Braulio-Gonzalo, M.D. Bovea, A. Jorge-Ortiz, P. Juan, Contribution of households' occupant profile in predictions of energy consumption in residential buildings: a statistical approach from Mediterranean survey data, Energy Build. 241 (Jun. 2021) 110939, https://doi.org/10.1016/j.enbuild.2021.110939.

[37] P. van den Brom, A.R. Hansen, K. Gram-Hanssen, A. Meijer, H. Visscher, Variances in residential heating consumption – importance of building characteristics and occupants analysed by movers and stayers, Appl. Energy 250 (Sep. 2019) 713–728, https://doi.org/10.1016/j.apenergy.2019.05.078.
[38] K. Vringer, T. Aalbers, K. Blok, Household energy requirement and value patterns, Energy Pol. 35 (1) (Jan. 2007) 553–566, https://doi.org/10.1016/J.ENPOL.2005.12.025.
[39] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, F. Descamps, A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison, Build. Environ. 75 (May 2014) 67–78, https://doi.org/10.1016/j.buildenv.2014.01.021.
[40] L. Nikdel, A.E.S. Schay, D. Hou, S.E. Powers, Data-driven occupancy profiles for apartment-style student housing, Energy Build. 246 (Sep. 2021) 111070, https://doi.org/10.1016/j.enbuild.2021.111070.
[41] S. Hyun Kim, C. Soo Park, Predictability quantification of occupant presence in high-rise residential apartment buildings, Energy Build. 275 (Nov. 2022), https://doi.org/10.1016/J.ENBUILD.2022.112494.
[42] O. Guerra Santin, Behavioural Patterns and User Profiles related to energy consumption for heating, Energy Build. 43 (10) (Oct. 2011) 2662–2672, https://doi.org/10.1016/j.enbuild.2011.06.024.
[43] T. Hong, J. Kim, M. Lee, A multi-objective optimization model for determining the building design and occupant behaviors based on energy, economic, and environmental performance, Energy 174 (May 2019) 823–834, https://doi.org/10.1016/j.energy.2019.02.035.
[44] S. Carlucci, et al., Modeling occupant behavior in buildings, Build. Environ. 174 (May 2020) 106768, https://doi.org/10.1016/J.BUILDENV.2020.106768.
[45] I. Gaetani, P.J. Hoes, J.L.M. Hensen, Occupant behavior in building energy simulation: towards a fit-for-purpose modeling strategy, Energy Build. 121 (Jun. 2016) 188–204, https://doi.org/10.1016/J.ENBUILD.2016.03.038.
[46] O. Guerra-Santin, S. Boess, T. Konstantinou, N. Romero Herrera, T. Klein, S. Silvester, Designing for residents: building monitoring and co-creation in social housing renovation in The Netherlands, Energy Res. Social Sci. 32 (Oct. 2017) 164–179, https://doi.org/10.1016/j.erss.2017.03.009.
[47] E. Cuerda, O. Guerra-Santin, F.J. Neila González, Defining occupancy patterns through monitoring existing buildings, Inf. la Constr. 69 (548) (2017) 1–10, https://doi.org/10.3989/id.53526.
[48] A. Serrano-Jiménez, J. Lizana, M. Molina-Huelva, Á. Barrios-Padura, Decision-support method for profitable residential energy retrofitting based on energy-related occupant behaviour, J. Clean. Prod. 222 (Jun. 2019) 622–632, https://doi.org/10.1016/j.jclepro.2019.03.089.
[49] B. Jeong, J. Kim, R. de Dear, Creating household occupancy and energy behavioural profiles using national time use survey data, Energy Build. 252 (Dec. 2021), https://doi.org/10.1016/j.enbuild.2021.111440.
[50] H.C. Putra, C. Andrews, T. Hong, Generating synthetic occupants for use in building performance simulation, J. Build. Perform. Simul. 14 (6) (Nov. 2021) 712–729, https://doi.org/10.1080/19401493.2021.2000029.
[51] D. Wickrama Achchige, D. Chen, G. Kokogiannakis, M. Fiorentini, Probabilistic modelling of occupants' thermostat preferences for residential building energy simulation and rating, J. Build. Perform. Simul. (2022), https://doi.org/10.1080/19401493.2022.2147674.
[52] Z. Ding, T. Hu, M. Li, X. Xu, P.X.W. Zou, Agent-based model for simulating building energy management in student residences, Energy Build. 198 (Sep. 2019) 11–27, https://doi.org/10.1016/j.enbuild.2019.05.053.
[53] F. Causone, S. Carlucci, M. Ferrando, A. Marchenko, S. Erba, A data-driven procedure to model occupancy and occupant-related electric load profiles in residential buildings for energy simulation, Energy Build. 202 (Nov. 2019), https://doi.org/10.1016/j.enbuild.2019.109342.
[54] B. Jeong, J. Kim, D. Chen, R. de Dear, Development of a probabilistic behavioural model creating diverse A/C operation patterns of households, Energy 263 (Jan. 2023), https://doi.org/10.1016/J.ENERGY.2022.125680.
[55] O. Guerra-Santin, et al., Considering user profiles and occupants' behaviour on a zero energy renovation strategy for multi-family housing in The Netherlands, Energy Effic 11 (7) (Oct. 2018) 1847–1870, https://doi.org/10.1007/s12053-018-9626-8.
[56] E. Cuerda, O. Guerra-Santin, J.J. Sendra, F.J. Neila González, Comparing the impact of presence patterns on energy demand in residential buildings using measured data and simulation models, Build. Simulat. 12 (6) (Dec. 2019) 985–998, https://doi.org/10.1007/s12273-019-0539-z.
[57] G. Salvia, et al., Performance gap and occupant behavior in building retrofit: focus on dynamics of change and continuity in the practice of indoor heating, Sustain. Times 12 (14) (Jul. 2020), https://doi.org/10.3390/su12145820.
[58] X. Ren, C. Zhang, Y. Zhao, G. Boxem, W. Zeiler, T. Li, A data mining-based method for revealing occupant behavior patterns in using mechanical ventilation systems of Dutch dwellings, Energy Build. 193 (Jun. 2019) 99–110, https://doi.org/10.1016/J.ENBUILD.2019.03.047.
[59] E. Cuerda, O. Guerra-Santin, J.J. Sendra, F.J. Neila, Understanding the performance gap in energy retrofitting: measured input data for adjusting building simulation models, Energy Build. 209 (Feb. 2020) 109688, https://doi.org/10.1016/j.enbuild.2019.109688.
[60] X. Ren, D. Yan, T. Hong, Data mining of space heating system performance in affordable housing, Build. Environ. 89 (Jul. 2015) 1–13, https://doi.org/10.1016/j.buildenv.2015.02.009.
[61] J. Mahecha Zambrano, U. Filippi Oberegger, G. Salvalai, Towards integrating occupant behaviour modelling in simulation-aided building design: reasons, challenges and solutions, Energy Build. 253 (Dec. 2021) 111498, https://doi.org/10.1016/J.ENBUILD.2021.111498.
[62] M. Ouf, W. O'Brien, H.B. Gunay, Optimizing building performance using stochastic occupant models, ASHRAE Transactions 125 (2019) 96–105.
[63] Q. Darakdjian, S. Billé, C. Inard, Data mining of building performance simulations comprising occupant behaviour modelling, Adv. Build. Energy Res. 13 (2) (2019) 157–173, https://doi.org/10.1080/17512549.2017.1421099.
[64] M. Marschall, F. Tahmasebi, J. Burry, Including occupant behavior in building simulation: comparison of a deterministic vs. a stochastic approach, Simulation Series 51 (8) (Jan. 2019) 185–188 [Online]. Available: https://www.academia.edu/43878778/Including_Occupant_Behavior_in_Building_Simulation_Comparison_of_a_Deterministic_vs_a_Stochastic_Approach. (Accessed 1 June 2023).
[65] C. Carpino, E. Loukou, P. Heiselberg, N. Arcuri, Energy performance gap of a nearly Zero Energy Building (nZEB) in Denmark: the influence of occupancy modelling, Build. Res. Inf. 48 (8) (Nov. 2020) 899–921, https://doi.org/10.1080/09613218.2019.1707639.
[66] K. Primc, R. Slabe-Erker, B. Majcen, Constructing energy poverty profiles for an effective energy policy, Energy Pol. 128 (May 2019) 727–734, https://doi.org/10.1016/j.enpol.2019.01.059.
[67] M.F. Silva, S. Maas, H.A. de Souza, A.P. Gomes, Post-occupancy evaluation of residential buildings in Luxembourg with centralized and decentralized ventilation systems, focusing on indoor air quality (IAQ). Assessment by questionnaires and physical measurements, Energy Build. 148 (Aug. 2017) 119–127, https://doi.org/10.1016/j.enbuild.2017.04.049.
[68] P.X.W. Zou, D. Wagle, M. Alam, Strategies for minimizing building energy performance gaps between the design intend and the reality, Energy Build. 191 (May 2019) 31–41, https://doi.org/10.1016/J.ENBUILD.2019.03.013.
[69] P. van den Brom, A. Meijer, H. Visscher, Performance gaps in energy consumption: household groups and building characteristics, Build. Res. Inf. 46 (1) (Jan. 2017) 54–70, https://doi.org/10.1080/09613218.2017.1312897.
[70] M.V. Bavaresco, S. D'Oca, E. Ghisi, R. Lamberts, Methods used in social sciences that suit energy research: a literature review on qualitative methods to assess the human dimension of energy use in buildings, Energy Build. 209 (Feb. 15, 2020), 109702 https://doi.org/10.1016/j.enbuild.2019.109702, Elsevier Ltd.
[71] L. Martincigh, F. Bianchi, M. Di Guida, G. Perrucci, The occupants' perspective as catalyst for less energy intensive buildings, Energy Build. 115 (Mar. 2016) 94–101, https://doi.org/10.1016/j.enbuild.2015.04.018.
[72] T. Harputlugil, P. de Wilde, The interaction between humans and buildings for energy efficiency: a critical review, Energy Res. Social Sci. 71 (Jan. 2021) 101828, https://doi.org/10.1016/J.ERSS.2020.101828.
[73] N. Romero Herrera, Relationship between building technologies, in-situ and mixed-design interventions, in: D. Keyson, D. Lockton, O. Guerra-Santin (Eds.), Living Labs: Design and Assessment of Sustainable Living, Springer, 2016.
[74] John W. Creswell, Vicki L. Plano Clark, Designing and conducting mixed methods research, Aust. N. Z. J. Publ. Health 31 (4) (2007) https://doi.org/10.1111/j.1753-6405.2007.00096.x, 388–388.
[75] Stechome, Proyecto E-lagun, https://www.stechome.es/proyecto-e-lagun/. (Accessed 19 January 2023).
[76] H.E. Beck, N.E. Zimmermann, T.R. McVicar, N. Vergopolan, A. Berg, E.F. Wood, Present and future Köppen-Geiger climate classification maps at 1-km resolution, Sci. Data 2018 5 (1) (Oct. 2018) 1–12 https://doi.org/10.1038/sdata.2018.214, 51.
[77] S. Perez-Bezos, O. Grijalba, R.J. Hernandez-Minguillon, Multifactorial approach to indoor environmental quality perception of social housing residents in

Northern Spain, https://doi.org/10.1080/09613218.2022.2130739, 2022.
[78] STECHOME, AUGE project, https://www.stechome.es/autogestion-nuevo-proyecto-stechome-en-vivienda-social/, 2021. (Accessed 20 March 2023).
[79] Ministerio de Fomento, Código Técnico de la Edificación (CTE) Documento Básico Ahorro de Energia (DB-HE), https://www.codigotecnico.org/DocumentosCTE/AhorroEnergia.html, 2022. (Accessed 20 June 2022).
[80] S. Karatasou, M. Laskari, M. Santamouris, Determinants of high electricity use and high energy consumption for space and water heating in European social housing: socio-demographic and building characteristics, Energy Build. 170 (Jul. 2018) 107–114, https://doi.org/10.1016/j.enbuild.2018.04.019.
[81] R.V. Jones, K.J. Lomas, Determinants of high electrical energy demand in UK homes: socio-economic and dwelling characteristics, Energy Build. 101 (Aug. 2015) 24–34, https://doi.org/10.1016/J.ENBUILD.2015.04.052.
[82] A.J. Summerfield, R.J. Lowe, H.R. Bruhns, J.A. Caeiro, J.P. Steadman, T. Oreszczyn, Milton Keynes Energy Park revisited: changes in internal temperatures and energy usage, Energy Build. 39 (7) (Jul. 2007) 783–791, https://doi.org/10.1016/J.ENBUILD.2007.02.012.
[83] R. Becker, M. Paciuk, Thermal comfort in residential buildings – failure to predict by Standard model, Build. Environ. 44 (5) (May 2009) 948–960, https://doi.org/10.1016/j.buildenv.2008.06.011.
[84] O. Guerra-Santin, L. Itard, "Occupants' behaviour: determinants and effects on residential heating consumption, Build.Res.Inf 38 (3) (May 2010) 318–338, https://doi.org/10.1080/09613211003661074.