sustainability

MDPI

Article

Building Occupant Energy Labels (OEL): Capturing the Human Factors in Buildings for Energy Efficiency

Timuçin Harputlugil [1] and Pieter de Wilde [2,*]

[1] Faculty of Architecture, Department of Architecture, Çankaya University, Ankara 06815, Türkiye; tharputlugil@cankaya.edu.tr
[2] Division of Energy and Building Design, Lunds Tekniska Högskola (LTH), Lund University, SE-22100 Lund, Sweden
* Correspondence: pieter.de_wilde@ebd.lth.se

Abstract: Occupancy is one of the primary contributors to the energy performance gap, defined as the difference between actual and predicted energy usage, in buildings. This paper limits its scope to residential buildings, where occupant-centric consumption often goes unaccounted for in standard energy metrics. This paper starts from the hypothesis that a simple occupant energy efficiency label is needed to capture the essence of occupant behaviour. Such a label would help researchers and practitioners study a wide range of behavioural patterns and may better frame occupant interventions, potentially contributing more than expected to the field. Focusing on the residential sector, this research recognises that the complexity of occupant behaviour and its links to different scientific calculations requires that researchers deal with several intricate factors in their building performance assessments. Moreover, complexity arising from changing attitudes and behaviours—based on building typology, social environment, seasonal effects, and personal comfort levels—further complicates the challenge. Starting with these problems, this paper proposes a framework for an occupant energy labelling (OEL) model to overcome these issues. The contribution of the paper is twofold. Firstly, the literature is reviewed in depth to reveal current research related to occupant behaviour for labelling of humans based on their energy consumption. Secondly, a case study with energy simulations is implemented in the UK, using the CREST tool, to demonstrate the feasibility and potential of OEL. The results show that labelling occupants may help societies reduce building energy consumption by combining insights from energy statistics, surveys, and bills gathered with less effort, and can assist decision-makers in determining the best match between buildings and occupants. While the focus of this study is on residential buildings, future research is recommended to explore the applicability of OEL in office environments, where occupant behaviour and energy dynamics may differ significantly.

Keywords: occupant behaviour; occupant labelling; energy efficiency

Academic Editor: Vincenzo Costanzo

Received: 7 November 2024
Revised: 10 January 2025
Accepted: 30 January 2025
Published: 3 February 2025

Citation: Harputlugil, T.; de Wilde, P. Building Occupant Energy Labels (OEL): Capturing the Human Factors in Buildings for Energy Efficiency. *Sustainability* **2025**, *17*, 1216. https://doi.org/10.3390/su17031216

1. Introduction

Humanity, spending most of its time indoors, is the primary source of energy consumption and greenhouse gas emissions worldwide. As a result of human activities, particularly the release of greenhouse gases, the global surface temperature has risen to 1.1 °C above the 1850–1900 level [1]. Additionally, in 2022, there was a significant increase in the level of greenhouse gases [2]. Moreover, August 2024 tied with August 2023 as the warmest August on record globally, with an average ERA5 surface air temperature of 16.82 °C, which is 0.71 °C higher than the August average for the period 1991–2020 [3]. Within this, human activity buildings are responsible for approximately 40% of total energy use. Occupants, being at the centre of building operation and management, are key drivers for this energy consumption [4]. Development, sustainability and consequently energy efficiency are still leading topics in academic research. The growing importance of these topics forces more research efforts, development of further policies, and deeper interventions. In recent years, big steps have been taken forward in order to achieve international targets for controlling energy consumption, decreasing green gas emissions whilst minimising waste for a sustainable world.

Numerous studies in the building science literature cover a broad spectrum of topics related to occupant behaviour (OB). Some of the most frequently areas of research with the most cited articles include energy efficiency, carbon emissions, thermal comfort, indoor environmental quality, health and well-being, technology interaction, social and psychological factors, policy and regulations, sustainability and environmental impacts, remote work, mobility and space utilisation as well as data-driven modelling and simulation [5–8]. Much of the work on OB is highly complex and falls within the domains of social and behavioural sciences [9], building science [10], sensing and control technologies [11], and data science [12]. Within the social dimension, the study of occupant behaviour encompasses various sub-fields, such as user behaviour, attitudes, and individual or household consumption patterns. Basic energy-related occupant behaviour includes actions such as adjusting thermostat settings, opening/closing windows, controlling lighting, manipulating blinds, control of HVAC systems, and moving between spaces. In addition, behavioural adaptations such as clothing choices, beverage consumption, and metabolic rate changes can impact personal comfort levels, which in turn affect building energy consumption. Finally, the direct and indirect drivers of occupant behaviour, whether at the individual, local, whole-space, or zonal level, can have varying impacts on building energy consumption. Understanding these factors is important for effective building energy management and carbon emissions reduction strategies [12]. To investigate the complexities in these various fields, a range of specialised methods for data gathering and analysis are employed, such as surveys, interviews, sensor data collection, simulations, and more. Each of these approaches requires distinct expertise due to the complexity of analysis and the harmonisation of methods across different domains.

Much of the work on OB is highly complex and intrinsically interdisciplinary [13]. However, understanding the basics of OB is essential for building science professionals to comprehend the physical load that occupants create for buildings, such as thermal load, ventilation load, and CO_2 production. These factors directly impact control measures such as thermostat settings, window position etc., which in turn affect the energy use and overall carbon emissions of the building. Furthermore, understanding the expectations of occupants regarding thermal building performance and required comfort conditions is crucial to developing effective energy efficiency and carbon emissions reduction strategies. According to Delgado and Shealy [14], although energy policy and products typically receive the most attention, the bulk of a building's life cycle costs are incurred during the operations and maintenance phase. Supporting this perspective, household behavioural factors significantly influence residential energy consumption [15]. Given the substantial energy consumption during the operational phase and the critical role of occupants, there could be a shift in residential energy policy from a focus on technological solutions to one emphasising behavioural change [15].

On average, more than 70% of the building stock in the European Union (EU) consists of residential buildings [16]. This makes residences one of the key types of buildings when researching occupant behaviour, although privacy is always seen as a big concern. From this point of view, any attempt to decrease energy consumption in residences will have a wider effect compared to any other building type. Occupants have different reasons for using different spaces. For instance, a residence is the most relaxing space compared to other social spaces. Activities, clothing conditions and privacy are all organised by the specific occupants of a residence. Moreover, occupants feel free to activate, control and change thermal conditions as well as lighting, visual and acoustics. This provides a certain control of indoor environmental quality conditions. Weber and Perrels [17] and Kim et al. [18] pointed out the importance and effect of lifestyle over energy consumptions related to occupant behaviour. Rather than technical issues which may be quantified and could be reported regularly, socio cultural factors may not be addressed as easily. Household socio-economic characteristics, such as the number of residents, their ages, income, employment, place of residence of occupants are found to have a significant effect on energy consumption [19,20]. Moreover, dwelling attributes such as size, energy class, location, etc., also have a significant positive effect on energy consumption [15,21].

Despite the breadth of existing occupant behaviour studies, there remains a clear gap in delivering a systematic approach that links occupant-specific consumption metrics with broader energy efficiency strategies. To provide a direct statement on how the proposed occupant energy labelling (OEL) framework fills specific gaps in existing methodologies, OEL introduces quantifiable thresholds for occupant-driven consumption, thus bridging the disconnect between purely technological solutions and the nuanced behavioural dimension. Unlike existing methodologies, OEL not only highlights variability in occupant behaviour but also operationalises these insights into a labelling system, making it more feasible to incorporate behavioural factors into building policies, performance assessments, and targeted interventions. Moreover, it can be adapted to dwellings with differing numbers of occupants—ranging from individuals to larger family groups—thereby recognising that collective household dynamics can diverge significantly from patterns observed in single-occupant households. In doing so, OEL provides a comprehensive tool to identify, compare, and potentially influence occupant-driven energy consumption—a contribution that stands apart from the more fragmented approaches prevalent in current research.

A critical aspect of understanding OB lies in recognising the influence of socio-economic conditions and personal habits on building energy use. While maintaining comfort is the primary motive behind energy consumption in buildings, comfort itself is shaped by a wide range of occupant-centric parameters, such as metabolic rate, clothing choices, health status, cultural attitudes, and everyday routines [4,10]. At the same time, factors like income, vulnerability, and life stage further complicate how individuals or households interact with indoor environments. In some cases, energy use patterns may adapt to the most sensitive or at-risk member in a group—adjusting thermal settings for a baby's needs, for example—while in others, financial constraints might limit an occupant's ability to maintain ideal comfort conditions. These realities underscore that occupant populations are far from homogeneous, making it both challenging and controversial to categorise people solely by region or building type [5]. Consequently, efforts to reduce energy use must consider the nuanced interplay of occupant demographics, personal habits, and socio-economic contexts to ensure equitable and effective outcomes.

Considering the complexity of OB and its links and dependencies to different scientific calculations requires that researchers deal with several intricate factors in their building performance assessments. Moreover, the complexity of changing attitudes and behaviours based on building typology, social environment, seasonal effects and due to personal comfort levels make the problem harder. Starting with these problems, this paper proposes a framework for an OEL model to overcome these problems.

1.1. Motivation

Despite the complex and often unpredictable behaviour of people, several methods are used to predict energy consumption of humans in buildings. These range from very static ‘block schemes’ to stochastic and highly dynamic models. However, only a limited number of metrics has been introduced to quantify the energy consumption in buildings as directly related to humans. For this reason, building simulations plays a major role [22]. Simulations mostly contribute to bottom-up approaches which are based on deep analysis of several parameters related to humans and buildings in different ways as explained in the earlier section.

Human behaviour is complex, and human actions are governed by several factors. Investigating each factor separately and trying to correlate drivers and corresponding actions is an important limitation for researchers. On the other hand, if the researchers had a simple occupant energy efficiency label developed from the statistics including different building types, with a variety of users in different strata, then this would allow them to more easily quantify the energy consumption through simulations for any given building.

In the realm of energy efficiency, traditional methodologies often focus on a bottom-up approach, meticulously detailing each occupant’s activity and its specific energy impacts [23]. However, this method can be cumbersome and imprecise due to the complex variability in human behaviour across different settings. To address these challenges, this paper introduces a novel approach called occupant energy labelling (OEL), which leverages a top-down strategy. This method significantly simplifies the process by gathering broad usage statistics of how occupants interact within indoor environments, rather than dissecting each interaction individually. OEL offers a substantial advantage in its ability to apply a unified framework across various contexts and scenarios without the need for setting up individual simulations for each undefined occupant pattern. This approach not only streamlines research and application but also enhances the feasibility of implementing energy efficiency measures at a larger scale. Moreover, the energy usage of occupants is subject to change throughout their lifetimes, influenced by key factors such as age, social roles, and interactions with other occupants. These interactions vary significantly depending on the type of building whether it is a residential home or a professional workplace. For example, an individual might exhibit different energy consumption behaviours at home compared to their workplace due to differing environmental and social influences. The variability and complexity of these factors make it challenging to accurately categorise people into static groups or predict their energy use with traditional methods. Thus, OEL represents a transformative shift towards a more adaptable and scalable model for assessing and enhancing energy efficiency in various occupant-driven environments. This introduction of OEL in this paper marks a critical step forward in energy efficiency research, offering a more practical and less labour-intensive alternative to the traditional, detail-oriented bottom-up approach.

1.2. Aim and Objectives

This paper aims to define the main framework for OEL and to understand the extent to which OEL represents occupant behaviour-dependent energy consumption in residential buildings.

Occupants are typically individuals belonging to social groups. Their specific interactions and personal traits and social behaviours may change over time. Moving from this point, the paper seeks to explore how a number of occupants, each of them with different habits and backgrounds, impacts building energy consumption within certain time intervals.

The study investigates the feasibility of labelling occupants based on their energy consumption, which is influenced by their behaviours. This involves developing a quantitative approach that considers energy consumption for specific end uses, such as thermal energy for space heating, domestic hot water, lighting, appliances, total energy consumption and gas demand. These metrics will include peak and minimum values, and their variations based on the dwelling characteristics.

Drawing on the insights mentioned above, this research will examine the effects of changing occupant numbers in a single residence on energy consumption and aims to identify specific intervals. In doing so, it will establish correlations between occupant numbers and energy demands across different end uses, providing a comprehensive understanding of behavioural impacts.

The findings of this study are expected to lay the groundwork for a concept, framework, and metric related to OEL. In particular, the metrics will facilitate actionable insights by quantifying the influence of occupant behaviour on specific energy uses and their implications for conservation strategies.

The research not only explores the OEL framework but also aims to define a new metric. It is believed that the outcomes of this research will benefit societies and communities dealing with topics such as fuel poverty, optimised energy consumption, and building energy efficiency.

The paper presents the general layout of the research, covering the early steps of occupant labelling. Labelling will provide opportunities to capitalise on profiles, patterns, and interactions based on the numbers and habits of occupants, which, when classified, can better align with building energy conservation goals. By incorporating measurable values for each energy use type, the labelling system aims to deliver targeted interventions to improve building performance.

The work will help researchers, through the use of data from labelled occupants, with building performance simulation. The paper also explores why occupant labelling should extend beyond occupant profiling. Different from occupant profiling, occupant labelling for energy aims not only to define the underlying factors but also to quantify the outcomes of these factors affecting energy consumption. By focusing on measurable outputs such as energy consumption per end use, averages, peak/minimum values, and the effects of dwelling characteristics, the study moves beyond theoretical profiling to enable practical applications in energy management.

Considering all, the paper has the following main objectives: (i) to develop a framework for OEL in residential buildings; (ii) to quantify the influence of occupant behaviour on energy consumption through measurable outputs; (iii) to examine the effects of changing occupant numbers within residence/s and establish correlations between occupant levels and energy demands; (iv) to move beyond occupant profiling by introducing a new metric that focuses on measurable energy outcomes rather than theoretical classifications; (v) to define further steps for development of OEL.

1.3. Research Methodology

The research presented in this paper consists of a theoretical part which develops the OEL framework, and an applied part with demonstrates the feasibility of that framework. A literature review was conducted to connect to earlier research about the topic, structuring driving factors of occupants for energy consumption in residential buildings. This analyses the underlying factors and considers the performance metrics used for calculation and also investigates the effects of occupant behaviour on building energy consumption as reported in previous academic work. The outcomes are used to develop the OEL framework and defines the theoretical approach.

Secondly, a case study is implemented. For this purpose, the CREST Demand Tool, v 2.3 [24] developed by Loughborough University, is used. Different archetypes of residences (with their thermal performance statistically provided for the UK context) are simulated with different numbers of occupants for the month of January. For this purpose, more than 9000 simulations were conducted. The outcomes of the simulations were analysed statistically using Multivariate Analysis of Variance (MANOVA), correspondence, and decision tree approaches.

1.4. The Need for Occupant Energy Labelling (OEL)

A primary goal of building performance metrics and test methods is to reduce Green House Gas (GHG) emissions and increase energy efficiency by quantifying the impact and thus supporting the appropriate deployment of emerging technologies and the effective application of products and systems [25]. Developing tailored metrics across various fields is crucial for ensuring comprehensive energy conservation in a well-adapted and efficient manner.

Several factors influence when, how, and to what degree an occupant engages with their building [26]. To represent the users in building performance simulation, occupancy profiles and patterns are typically used to simulate different types of user behaviours. However, occupancy profiles in building simulations aim to improve energy predictions by modelling occupant behaviour, but they often rely on assumptions or static schedules rather than real data, even though occupant behaviour is unpredictable and changes over time [11,27]. However, most profiles or patterns are not correlated with buildings or their energy classes. On the other hand, energy consumption is always correlated to the occupants of buildings.

OEL is a necessary attribute to be developed because building performance is directly influenced by occupant behaviour. To accurately determine final energy consumption and efficiency, buildings and occupants must be evaluated together. While building performance can be estimated prior to occupancy using simulation-based assumptions, real-life performance gaps often arise due to various factors. Bottom-up approaches require significant data collection and analysis, while top-down methods can utilise existing data sources, such as Time User Surveys (TUS) and real-time consumption metrics like bill analysis. However, bottom-up approaches may struggle to account for variations across different cultures, geographies, and societies. By focusing on the total energy consumption of communities rather than individual buildings, energy use can be more effectively assessed through building energy labels. Extending this approach to include occupant labelling and integrating both building and occupant data has the potential to reduce overall energy consumption at a societal level.

Changing occupant behaviour to reduce energy consumption can be achieved through awareness campaigns, financial incentives, and technological tools like energy monitors and smart thermostats. Educational efforts and nudging techniques, such as default energy-efficient settings and reminders, can subtly encourage sustainable habits. By defining OEL, awareness of energy use can be enhanced, helping occupants better understand their consumption patterns and their role in reducing demand. Furthermore, different dwelling types may require distinct profiles for energy efficiency, as building characteristics and usage patterns influence how occupants interact with energy systems. These strategies, combined with tailored profiles, can promote immediate reductions in energy use while fostering long-term behavioural changes aligned with energy efficiency goals.

1.5. Development of Occupant Energy Labelling (OEL)

This concept of OEL was developed around six main building performance aspects that are of high importance in residential buildings, namely lighting demand, appliance demand, total electricity demand of the dwelling, hot water demand, thermal energy for space heating, and gas demand. To study the impact of occupancy on each of these, simulations were conducted with varying numbers of occupants (from one to five) across four different house types in the UK, each with different overall floor areas and thermal envelope characteristics. The effects of occupancy on total energy consumption were examined through multiple simulations.

The simulations explore the impact of varying occupants in different types of residences, identifying which areas of the residence are influenced and how these effects correlate with human behaviour. The findings then inform the development of OEL parameters, where building energy labels and occupant energy labelling are combined to guide reduced energy consumption. This approach is expected to contribute to the works to facilitate the pairing of appropriate building types with the corresponding number and type of occupants, ultimately minimising energy use at a societal level. The outcomes are anticipated to establish a framework for developing OEL. The framework does not aim to define exact parameters but provides a foundation for detailing the parameters that can be used for OEL. Currently, this approach is limited by the capabilities of the simulation tools, the number of simulations and case study. As the model evolves, additional parameters can be included to further refine occupant energy labelling. Moreover, this labelling system considers not only individual impacts but also the combined effects of multiple occupants. This means that the energy consumption patterns of occupants living together, such as families, are evaluated based on their collective schedules to create a comprehensive OEL.

2. Literature Review

"Buildings don't use energy: people do" [28].

The concept of 'occupancy' extends beyond a mere designation, encapsulating the nuanced interplay between individuals and the built environment [29]. This interaction becomes particularly pertinent as buildings evolve in complexity and connectivity, prompting a shift in design and operational strategies to accommodate more than just the decisions of traditional individual stakeholders. Concurrently, the nuances of occupant behaviour—shaped by variables such as age, income, and health—have a direct correlation with building energy consumption and the pursuit of thermal comfort. The user-friendliness of controls, the nature of the space occupied, and the influence of external expenses like energy costs, further steer occupants' approaches to regulating their indoor climate [30]. Understanding the impact of occupant behaviour on building energy use requires a combined analysis with indoor climate studies [31]. Energy consumption is higher in homes continuously occupied during the day, including weekends, compared to those left unoccupied or with varying occupancy patterns [32].

Occupant behaviour is influenced by several factors and several research projects have attempted to reveal these underlying factors. IEA Annex 66 [33] suggested that building performance which is affected by climate, building envelope and building equipment is considered to be driven by technical and physical factors, whilst energy which is used based on operation, maintenance and occupant behaviour related to indoor environmental conditions as well as social factors are considered to be influenced by factors. It means that building energy use is affected by humans when it comes to humans directly responding to thermal performance [33]. The Annex 66 report details that occupant behaviour is triggered by on external factors, namely comfort, culture and economy which cause movements and actions for energy consumption. Impacts of human behaviour are observed by energy usage which is a basis of a building performance. The report defines behaviour based on physiology, psychology and economy.

Based on research by Fabi et al. [34] factors that influence occupant behaviour can broadly be termed as "drivers" and encompass both external and individual elements. These drivers cover physical environmental factors, contextual factors, psychological factors, physiological factors and social factors, which are the catalysts that provoke a response from building occupants, prompting them to take action [34]. They suggest that occupants react to Indoor Environmental Quality (IEQ) conditions to balance their comforts.

Steemers and Yun have provided valuable insights into the factors influencing energy demand through a series of studies. In their initial paper [35], they argue that while climate and building characteristics are commonly considered primary determinants of energy demand, the influence of occupant behaviour alongside socio-economic factors plays a crucial and often underappreciated role. Building upon this foundation, their subsequent research [36] delves deeper into how occupant behaviour, in conjunction with socio-economic and physical factors, significantly impacts domestic cooling energy demand.

D'Oca and Hong [37] categorised the driving factors into five categories: physical (indoor and outdoor environment), psychological (preferences, attitudes), physiological (age, sex), contextual (type of environment where the occupants are located), and social (income, lifestyle).

Humphreys [38] believes environmental comfort is flexible, subject to cultural and historical variation, and not completely constrained by human physiology. Hong et al. [39] summarised the effects of energy-related occupant behaviour in buildings based on main drivers shaped around time (day, week, month), environment (climate, indoor, outdoor, weather), system (properties, state), occupant (attributes, attitudes, location, state) and buildings (component, properties, location).

Wei et al. [40] provide a comprehensive overview of the literature on factors influencing of occupant space-heating behaviour, identifying two main categories and nine sub-categories that encompass a total of 27 drivers. These drivers include the following: outdoor climate, indoor relative humidity, dwelling type, dwelling age, dwelling size, room type, house insulation, type of heating system, type of temperature control, type of heating fuel, occupant age, occupant gender, occupant culture/race, occupant education level, social grade, household size, family income, previous dwelling type, house ownership, thermal sensation, perceived indoor air quality (IAQ) and noise, health, time of day, time of week, occupancy, heating price, energy use awareness. Based on their findings, Wei et al. [40] attempted to establish a link between these influencing factors and building performance simulation inputs.

Research spanning multiple domains that thoroughly analyse the interactions between occupants and buildings, incorporating insights from various disciplines, was extensively discussed by O'Brien et al. [41] and Schweiker et al. [42]. All these studies indicate that the drivers of energy consumption by occupants are complex, dependent on multiple factors, and require expertise from diverse disciplines. Employing bottom-up approaches to define each detail over an extended period remains a challenging and difficult task.

Occupant Energy Labelling (OEL)

Representing the current behaviours of occupants within a specific context does not inherently guarantee energy efficiency, nor does it provide a comprehensive forecast of their future behaviours if the context changes [43]. For this reason, the authors believe that there is a need for occupant energy labelling, which generally involves setting minimum and maximum figures, rather than pinpointing precise figures for energy consumption. For this purpose, this section will delve into the literature for a better understanding of the content. A limited amount of work on OEL is available in the English-language literature from indexed papers. Although the titles may not explicitly reference OEL, they often explore related concepts, such as occupant building interaction [5,12], occupant modelling [44] statistical analysis [45], data mining [46,47], machine learning [48], developing KPIs

[49] and clustering [50]. A more closely related approach can be described as cluster analysis, which has been employed in several studies.

A detailed review by Xu et al. [51] identifies the interaction between occupant behaviours (effects of multi-occupant behavioural interactions) as one of the research gaps. Understanding the variability in occupant energy consumption behaviours over their lifetimes is crucial for developing effective energy efficiency strategies. This variability is influenced by a myriad of factors, including metabolic changes due to ageing, family dynamics, the developmental stages of children, and financial constraints, which together can significantly affect an individual's energy use. Moreover, relocating to different geographical areas and experiencing climate variations also plays a role in shaping overall energy consumption patterns. These factors not only influence occupant behaviour but also challenge the initial classifications used in energy consumption studies.

The existing literature, including the work by Schweiker et al. [42], identifies several key factors affecting energy consumption: geographic location, building and system design, the occupants themselves, and temporal changes. With a specific focus on the occupants, this research aims to delve deeper into how their indoor energy consumption correlates with their economic status, educational background, perceptions of indoor environment quality (IEQ), physiological factors, life stages, and the number of occupants sharing a space. These elements are intertwined, suggesting that understanding and influencing occupant behaviour could lead to more effective energy efficiency interventions.

However, addressing these elements individually, as in a bottom-up approach, presents significant challenges. This method requires an exhaustive detailing of every possible scenario, entangling the study in the complexities of disparate fields and potentially overlooking the holistic view of energy consumption patterns. In contrast, this research posits that a top-down approach, predicated on labelling occupants for energy efficiency using statistical data, offers a more viable solution. By establishing a framework for minimum and maximum energy consumption based on broad interactions and behaviours, this method seeks to normalise consumption patterns, thereby simplifying the process of estimating energy consumption with minimal adjustments.

The hypothesis underpinning this research suggests that labelling occupants from a top-down perspective, as opposed to unravelling the myriad complexities inherent in a bottom-up approach, is not only more efficient but also more beneficial in crafting overarching energy efficiency strategies. To test this hypothesis, the study employs a case study methodology, aiming to demonstrate the advantages of the proposed top-down approach. The findings from this case study are anticipated to provide compelling evidence supporting the adoption of OEL as a standardised method for improving energy efficiency, thus advocating for a strategic shift in how energy consumption patterns are analysed and addressed.

To contextualise the need for OEL and its advantages over existing approaches, it is essential to examine the methodologies currently used to analyse energy consumption. Building energy labelling provides a holistic view of energy efficiency and facilitates benchmarking across buildings. However, it often overlooks occupant-specific behaviours and does not account for behavioural variations over time. Similarly, appliance energy labelling offers granular insights at the device level, helping users select energy-efficient products, yet it neglects overall energy use and how occupants interact with devices. More behaviour-focused methods, such as occupant profiling and cluster analysis, link energy consumption to behavioural patterns or group trends, offering valuable insights into how individuals or groups use energy. Nonetheless, these methods frequently lack numerical thresholds, broader applicability, or the ability to drive actionable interventions.

OEL aims to address these limitations by introducing a behaviour-centric and metric-driven framework that combines the strengths of existing methods while overcoming their shortcomings. OEL integrates behavioural variability with measurable metrics, such as minimum and maximum energy consumption values, across specific end uses like heating, lighting, and appliances. This quantitative focus distinguishes OEL from occupant profiling and clustering, which often remain descriptive. Furthermore, OEL does not only aim to identify patterns but also seeks to provide actionable outcomes, such as tailored conservation strategies and benchmarks for improving energy efficiency.

What makes OEL unique is its dual approach: it considers both individual and group dynamics while accounting for variations in dwelling types, occupant numbers, and temporal behaviours. Unlike traditional methods that focus on static building or appliance characteristics, OEL actively incorporates the behavioural dimension, bridging the gap between physical systems and occupant interactions. This makes OEL particularly suitable for addressing the energy performance gap, as it captures the real-world impact of occupant behaviour on energy use.

To enhance the clarity of this section, Table 1 summarises the focus, strengths, and weaknesses of existing labelling approaches. It underscores the limitations of these methods and highlights the need for a structured, comprehensive framework like OEL. By combining occupant behaviour analysis with quantifiable metrics, OEL provides a foundation for more effective energy efficiency strategies, paving the way for applications in both residential and, potentially, commercial contexts.

Table 1. Different labelling approaches.

Approach	Focus	Strengths	Weaknesses
Building Energy Labels	Overall building performance	Provides a holistic view of building energy efficiency; enables benchmarking across buildings.	Ignores occupant-specific behaviours; does not account for behavioural variations over time.
Appliance Energy Labels	Device-specific consumption	Focuses on granular details; helps users choose energy-efficient appliances.	Does not capture overall energy use; neglects how occupants interact with devices.
Occupant Energy Profiling	Behavioural energy use patterns	Links behavioural habits with energy consumption; enables targeted feedback for occupants.	Often lacks numerical thresholds for energy use; limited to profiling without actionable metrics.
Cluster Analysis	Grouping based on energy use	Identifies consumption trends within groups; highlights shared characteristics.	Overlooks individual behaviours and contextual factors; may oversimplify complex patterns.

3. Methodology

Occupants are the main reason of the building's energy use. Referring to the metaphor of Plato's Cave, the effect of occupancy on energy consumption in buildings can be observed as consumption in numerical values although underlying factors with drivers cannot be easily defined or tracked. As demonstrated in the earlier literature review section, this energy usage dependency can be classified in different ways and parameters. Although a wide range of literature can be found in the domain, a holistic approach is missing.

For this purpose, a hypothetic case study is structured based on simulations. For this study 4 different types of houses from across the UK are selected with their different archetypes, square metre floor area and thermal performances. Different numbers of occupants are simulated for a month in January in Loughborough, the default location used in the simulation tool. The weather data for 2015 are used. All simulations are performed with CREST demand tool V. 2.3 [24] developed by Loughborough University. The CREST model is an integrated thermal–electrical demand model based on a bottom-up activity-based structure, using stochastic programming techniques to represent dwelling diversity, producing calibrated and validated output at high-resolution, based on reduced-order thermal–electrical networks to represent thermal dynamics, and developed as free open-source software to promote transparency and further research.

The CREST Tool was chosen for this study due to its specific strengths in addressing the research objectives and its alignment with the study's scope and constraints. Its ease of setup and demonstrated reliability in prior research make it a practical choice for conducting simulations efficiently. One of the primary reasons for selecting CREST is its extensive use of UK-specific data derived from national statistics, ensuring that the simulations reflect realistic occupant behaviour patterns within the context of the UK housing sector. Moreover, CREST's ability to perform rapid simulations allows researchers to conduct numerous runs within a reasonable timeframe, which is crucial for exploring multiple scenarios and refining energy consumption models. The software's built-in library of building types and occupancy profiles—based on comprehensive UK surveys—provides a robust foundation for capturing the variability in occupant behaviour across different dwelling types. These features significantly reduce the need for manual input, streamlining the setup process while maintaining data accuracy. From a methodological perspective, the open-source calculation methodology of CREST enhances transparency and allows for reproducibility of results, which are critical for academic rigor. Additionally, the tool's preloaded database of dwelling parameters, tailored to UK conditions, ensures that building characteristics are accurately reflected in the simulations.

The decision to use CREST also stems from its comparative advantages over other simulation tools. Many alternative tools lack the specific focus on UK housing and the integration of occupant behaviour patterns, making them less suitable for this study's objectives. CREST's strengths in data relevance, simulation speed, and alignment with national statistics made it the most appropriate choice for developing the occupant energy labelling (OEL) framework. Lastly, initial test runs using CREST yielded consistent and satisfactory results, further reinforcing its suitability for this research. By leveraging CREST's capabilities, the study ensures a methodologically sound approach to exploring occupant behaviour-driven energy consumption, providing actionable insights for the OEL framework.

Three primary methods MANOVA, correspondence analysis, and decision trees were employed to capture the multifaceted relationships between occupant numbers, residential typologies, and various energy consumption categories (e.g., heating, lighting, appliances, domestic hot water), as well as gas and water usage, in order to assess how different factors coalesce into occupant-cantered energy patterns. MANOVA (Multivariate Analysis of Variance) was used first to simultaneously evaluate differences across multiple dependent variables, offering insights into whether occupant composition and dwelling type significantly influence overall consumption. In this step, typical statistical indices—including mean squares, F-factors, and partial eta squared values—were calculated, and reliability relationships of correlations were plotted to gauge the robustness of observed patterns. Correspondence analysis was then performed to uncover patterns and associations within categorical data, thereby helping to visualise and interpret how particular occupant or residence categories align with specific energy consumption traits. Finally, decision trees provided a classification-based approach that pinpoints which variables (e.g., occupant count, building attributes) exert the greatest predictive power over energy usage, thereby identifying the most dominant correlations among different consumption behaviours. Taken together, these complementary methods establish a robust analytical framework for determining whether occupants can be effectively labelled based on distinct consumption behaviours, laying the groundwork for an occupant-centric energy labelling system.

Research is based on residential buildings for several reasons. Research on residential energy consumption is particularly challenging due to diverse theoretical frameworks, inconsistent terminology, and limited knowledge about occupant behaviour [52]. However, focusing on residential buildings is crucial. Firstly, residences account for approximately 70–80% of all buildings, making them a prime area for energy research. Secondly, since residents typically pay their own energy bills, their behaviours reflect real-world decision-making and financial incentives. Finally, studies on occupant behaviour in residential buildings reveal significant opportunities for energy savings. These buildings exhibit more diverse patterns of occupancy hours and activities compared to office buildings, underlining the importance of understanding how individuals interact with their homes to optimise energy use [11].

Case Study

The developed model facilitates simulations of occupants, randomly selected from diverse profiles, across four distinct building typologies prevalent in the UK: detached, improved detached, semi-detached, and terraced houses. The thermal characteristics applied to each house typology in the simulations are detailed in Table 2.

Table 2. Thermal values of the houses used for simulation.

Residence Type	Dwelling (DW)	Transfer Coefficient Between (W/K)	Building Thermal Capacitance (J/K)	Coefficient Representing Ventilation Heat Loss (W/K)	Ventilation Rate (Air Changes per Hour) (h^{-1})	Global Irradiance Multiplier (m^2)	Floor Area Living Space) (m^2)	Volume (Living Space) (m^3)
Detached	Dwelling 1	437.5	22,638,446.4	73.6	1	4.2	136	571.20
Improved Detached	Dwelling 2	128.7	24,646,439.6	74.4	0.4	4.5	136	571.2
Semi Detached	Dwelling 3	247.6	12,876,155.4	46.7	1	4.3	87	365.4
Terraced	Dwelling 4	197.3	11,863,842.6	10,40	1	2.7	58	243.6

Weather data files from 2015 were utilised for a comprehensive series of simulations conducted using the CREST tool. Given that in the UK, heating loads are emphasised while cooling loads are often disregarded, these simulations specifically focused on a one-month period during winter, in January. This particular month was subjected to thorough analysis. The simulations examined the energy dynamics of the four distinct categories of houses, considering variations in occupancy levelsranging from one to five occupants. This assessment spanned the entire 31 days of January 2015. Furthermore, to enrich the dataset and provide a more nuanced understanding of energy use, each case simulation was expanded to include 10 different scenarios of occupant behaviour patterns. In this manner, more than 6000 measurement values have been obtained for each energy consumption. This approach increased the volume of data tenfold, offering a deeper insight into the variability of energy consumption across different living situations.

The simulations are categorised based on the type of housing (DW):

- Detached House (represented as DW1)
- Improved Detached House (represented as DW2)
- Semi-Detached House (represented as DW3)

- Terraced House (represented as DW4)

Occupancy levels (OC) range from one to five, with the following classifications:

- 1 occupant (represented as OC1)
- 2 occupants (represented as OC2)
- 3 occupants (represented as OC3)
- 4 occupants (represented as OC4)
- 5 occupants (represented as OC5)

4. Research Results

These classifications are depicted in the graphics. For each simulation run, ten random occupant behaviour patterns (based on activity) are simulated to gather a more comprehensive dataset for accurate analysis. The simulations measure factors effecting energy consumption in residences namely: lighting demand, appliance demand, total electricity demand of the dwelling, domestic hot water demand, thermal energy used for space heating and gas demand. Averages can be found in the tables (Tables 3–8) The total electricity demand of the dwelling is the sum of lighting demand and appliance demand, while the gas demand includes energy used for domestic hot water and thermal energy. Besides kWh based energy consumptions with different number of occupants in four different type of houses are represented in Figure 1. Supplementary materials related to the some parts of the research is provided and linked in supplementary material title at the end of the manuscript.

Table 3. Lighting demand (average in kWh/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	1.680	2.986	3.524	3.884	4.478	3.310
DW2	1.682	2.990	3.644	4.124	4.537	3.395
DW3	1.822	2.978	3.632	4.189	4.672	3.459
DW4	1.662	3.149	3.460	4.455	4.632	3.472
Total	1.711	3.026	3.565	4.163	4.580	3.409

Table 4. Appliance demand (average in kWh/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	7.081	8.877	10.311	11.009	12.380	9.932
DW2	7.035	9.247	9.707	11.000	12.145	9.827
DW3	7.059	9.073	10.289	11.401	12.006	9.965
DW4	7.081	9.137	10.704	10.982	12.654	10.112
Total	7.064	9.083	10.253	11.098	12.296	9.959

Table 5. Total electricity demand of the dwelling (average in kWh/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	8.761	11.863	13.835	14.893	16.858	13.242
DW2	8.717	12.237	13.351	15.124	16.681	13.222
DW3	8.881	12.051	13.921	15.589	16.678	13.424
DW4	8.744	12.286	14.164	15.437	17.286	13.583
Total	8.776	12.109	13.818	15.261	16.876	13.368

Table 6. Domestic hot water demand (average in litres/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	65.944	117.860	158.239	208.311	227.263	155.523
DW2	65.674	120.347	158.044	200.941	231.516	155.304
DW3	66.515	124.112	156.628	209.184	244.493	160.186
DW4	69.341	126.317	166.268	203.717	234.641	160.057
Total	66.868	122.159	159.795	205.538	234.478	157.768

Table 7. Thermal energy used for space heating (average in kWh/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	55.637	56.303	53.168	51.707	50.774	53.518
DW2	30.791	28.087	27.378	26.099	24.328	27.337
DW3	37.510	35.289	33.219	31.777	29.591	33.477
DW4	20.996	18.737	17.803	15.234	14.574	17.469
Total	36.233	34.604	32.892	31.204	29.817	32.950

Table 8. Gas demand (average in m^3/day).

	OC1	OC2	OC3	OC4	OC5	Average
DW1	7.202	7.574	7.434	7.534	7.512	7.451
DW2	4.214	4.215	4.320	4.423	4.383	4.311
DW3	5.031	5.077	5.042	5.160	5.109	5.084
DW4	3.061	3.100	3.231	3.115	3.212	3.144
Total	4.877	4.992	5.007	5.058	5.054	4.997

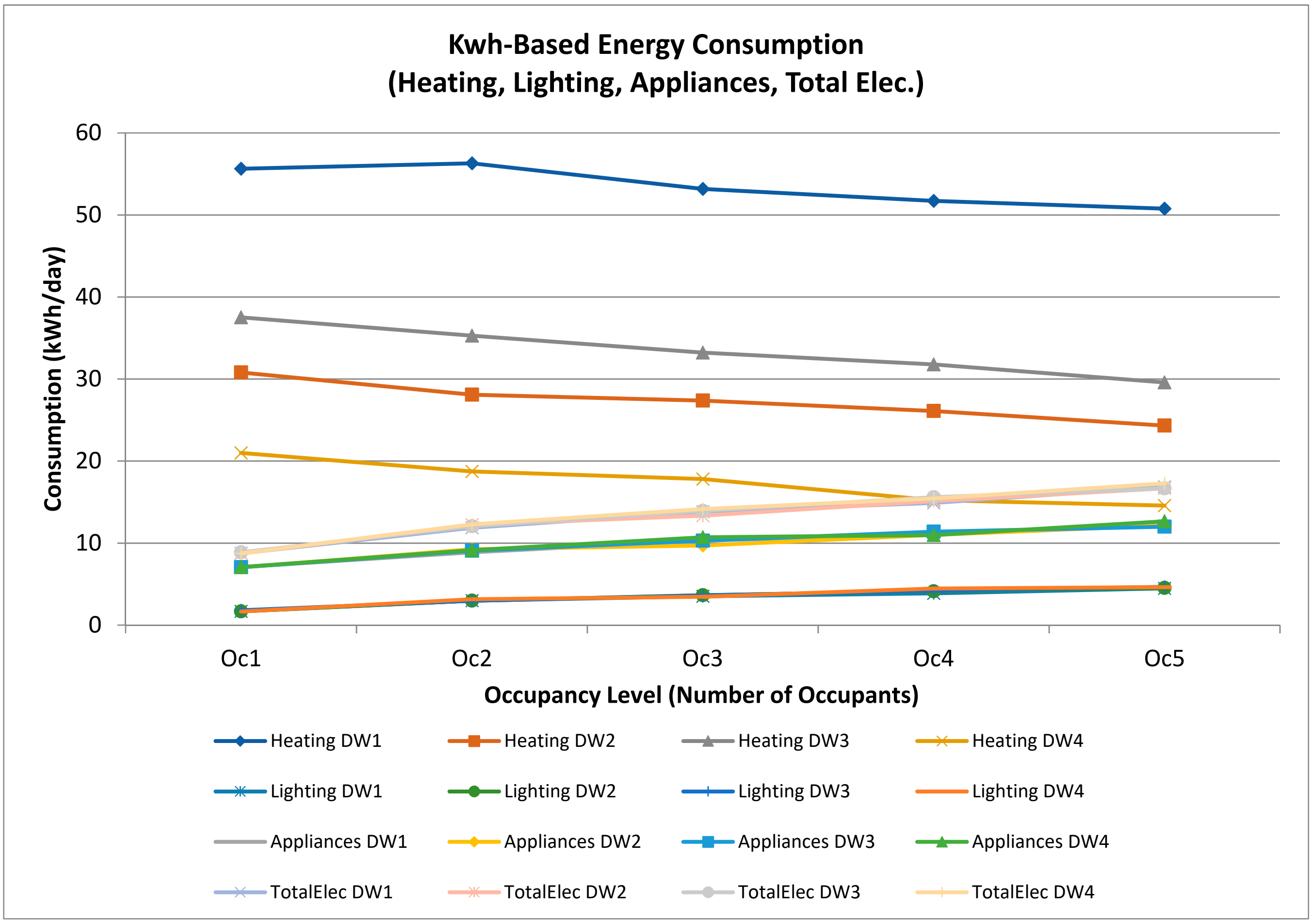

Figure 1. kWh-based energy consumption (thermal energy used for space heating, lighting, appliances, total electricity demand).

4.1. Analysis of Simulation Results

This section covers the statistical analyses of the data obtained from the simulations. The statistical methods applied are multivariate variance analysis, correspondence analysis and decision tree.

4.1.1. Multivariate Variance Analysis (MANOVA)

According to the results of multiple comparisons, both dwelling type (DW) and the number of occupants (OC) have a significant effect on the dependent variables (consumption) ($p < 0.05$). However, the interaction between dwelling type (DW) and the number of occupants (OC) does not seem to have an effect on the dependent variables ($p = 0.099$). When the partial eta squared values are examined, it is seen that dwelling type has a slightly greater effect on the dependent variables compared to the number of occupants (Table 9).

Table 9. Multivariate test results (the effect of factors on consumption).

Multivariate Tests [a]						
Effect (Pillai's Trace)	**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**	**Partial Eta Squared**
Intercept	0.952	30,581.502	4.000	6177.000	0.000	0.952
DW	0.567	360.373	12.000	18,537.000	0.000	0.189
OC	0.427	184.751	16.000	24,720.000	0.000	0.107
DW * OC	0.010	1.270	48.000	24,720.000	0.099	0.002

[a] Design: Intercept + DW + OC + DW * OC.

4.1.2. Variance Analysis

Upon examining the variance analysis table, it can be stated that housing type has a significant effect on lighting energy consumption ($F(3, 6180) = 3.000$, $p = 0.029$, $\eta p^2 = 0.001$) and heating energy consumption ($F(3, 6180) = 2617.120$, $p = 0.0001$, $\eta p^2 = 0.560$). Notably, heating energy consumption shows a substantial effect based on housing type ($\eta p^2 = 0.560$). The number of occupants significantly affects all dependent variables (consumption) ($p < 0.05$). When examining the partial eta squared (ηp^2) values, the energy types most affected by different levels of occupant count (OC) are, in order: hot water usage ($\eta p^2 = 0.349$), lighting ($\eta p^2 = 0.263$), electrical appliances ($\eta p^2 = 0.122$), and heating energy consumption ($\eta p^2 = 0.037$) (Table 10).

It is understood that the energy type that best explains the total variation in the model, in terms of the types of energy considered, is the energy used for heating the space ($\eta p^2 = 0.567$; $Radj^2 = 0.566$). This is followed by the amount of hot water used ($\eta p^2 = 0.350$; $Radj^2 = 0.348$), lighting energy ($\eta p^2 = 0.266$; $Radj^2 = 0.263$), and energy used by electrical appliances ($\eta p^2 = 0.123$; $Radj^2 = 0.121$).

Table 10. Analysis of variance table (the effect of different levels of factors on consumption).

Tests of Between-Subjects Effects							
Source	**Dependent Variable**	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Corrected Model	Lighting demand	6267.290 [a]	19	329.857	117.712	0.000	0.266
	Appliance demand	20,121.400 [b]	19	1059.021	45.792	0.000	0.123
	Hot water demand (litres)	22,047,374.802 [c]	19	1,160,388.147	175.510	0.000	0.350

	Thermal energy for space heating	1,110,998.200 [d]	19	58,473.589	426.485	0.000	0.567
Intercept	Lighting demand	72,052.646	1	72,052.646	25,712.497	0.000	0.806
	Appliance demand	614,911.613	1	614,911.613	26,589.010	0.000	0.811
	Hot water demand (litres)	154,321,987.170	1	154,321,987.170	23,341.348	0.000	0.791
	Thermal energy for space heating	6,731,451.777	1	6,731,451.777	49,096.789	0.000	0.888
DW	Lighting demand	25.216	3	8.405	3.000	0.029	0.001
	Appliance demand	64.470	3	21.490	0.929	0.426	0.000
	Hot water demand (litres)	34,402.188	3	11,467.396	1.734	0.158	0.001
	Thermal energy for space heating	1,076,466.354	3	358,822.118	2617.120	0.000	0.560
OC	Lighting demand	6190.280	4	1547.570	552.261	0.000	0.263
	Appliance demand	19,828.727	4	4957.182	214.350	0.000	0.122
	Hot water demand (litres)	21,949,601.328	4	5,487,400.332	829.975	0.000	0.349
	Thermal energy for space heating	32,715.471	4	8178.868	59.654	0.000	0.037
DW * OC	Lighting demand	51.794	12	4.316	1.540	0.102	0.003
	Appliance demand	228.203	12	19.017	0.822	0.628	0.002
	Hot water demand (litres)	63,371.286	12	5280.941	0.799	0.652	0.002
	Thermal energy for space heating	1816.375	12	151.365	1.104	0.352	0.002
Error	Lighting demand	17,317.857	6180	2.802			
	Appliance demand	142,921.971	6180	23.127			
	Hot water demand (litres)	40,859,245.205	6180	6611.528			
	Thermal energy for space heating	847,313.492	6180	137.106			
Total	Lighting demand	95,637.793	6200				
	Appliance demand	777,954.985	6200				
	Hot water demand (litres)	217,228,607.177	6200				
	Thermal energy for space heating	8,689,763.469	6200				
Corrected Total	Lighting demand	23,585.147	6199				
	Appliance demand	163,043.372	6199				
	Hot water demand (litres)	62,906,620.008	6199				
	Thermal energy for space heating	1,958,311.692	6199				

[a] R Squared = 0.266 (Adjusted R Squared = 0.263). [b] R Squared = 0.123 (Adjusted R Squared = 0.121). [c] R Squared = 0.350 (Adjusted R Squared = 0.348). [d] R Squared = 0.567 (Adjusted R Squared = 0.566).

4.1.3. Energy Consumption by Housing Type (DW)

It was found that the dwelling type had a significant effect on two of the dependent variables: lighting energy and the energy used for space heating. In terms of lighting energy consumption, the energy used in DW4-type dwellings was significantly higher than that in DW1-type dwellings ($p = 0.044$). For space heating energy, significant differences were observed between all pairwise combinations of dwelling types ($p < 0.05$). The dwelling type with the highest space heating energy consumption was DW1, while DW4 had the lowest consumption. The smallest difference in average consumption was between DW3 and DW2, while the largest difference occurred between DW1 and DW4.

4.1.4. Energy Consumption by Number of Occupants (OC)

The analyses based on energy consumption patterns among different user types, labelled OC1 through OC5 reveals that OC5 is generally the highest consumer of energy across various categories (lighting, electrical devices, hot water, and space heating), while OC1 is typically the lowest. The energy consumption differences between (pairwise comparisons of) OC5-OC4, OC3-OC2, and OC4-OC3 are relatively small, but the gap widens significantly between (pairwise comparisons of) OC5-OC1. It is evident that the number of individuals in a group has a noticeable impact on energy consumption. While adding or removing a single person has a minimal effect, increasing or decreasing the number by two or more people leads to a substantial change in average energy usage, particularly for electrical devices, hot water, and space heating.

4.1.5. Cross-Validation of Occupants (OC) Across Different Housing Types (DW)

The differences in average lighting energy consumption, based on binary combinations of different levels of housing types, were examined according to occupant types. It was found that there were no significant differences in lighting energy consumption across different housing types for occupants classified as OC1, OC2, and OC3 ($p > 0.05$). However, a significant difference was identified in the average lighting energy consumption for OC4 occupants between the DW4 and DW1 housing types ($p = 0.0001$). On the other hand, no significant differences were observed in lighting energy consumption for OC4 occupants when comparing other housing types ($p > 0.05$). In terms of energy consumption from electrical devices and hot water, no significant differences were found when comparing different levels of housing types based on occupant types ($p > 0.05$). Conversely, for energy consumption related to space heating, significant differences were found across all binary combinations of different housing types based on occupant types ($p < 0.05$).

4.1.6. Cross-Validation of Housing Types (DW) Across Different Occupants (OC)

The differences in average lighting energy consumption were examined based on binary combinations of different occupant types for each housing type. Comparisons of average energy consumption across different occupant types were made according to housing types. In terms of lighting energy consumption, significant differences in average consumption were found for the binary combinations of all occupant types, except for OC3-OC4 in the DW1 housing type ($p > 0.05$), with other combinations showing significant differences ($p < 0.05$). In the DW2 housing type, the differences in average consumption between all combinations of occupant types were significant ($p < 0.05$). Similarly, in the DW3 housing type, the average consumption differences between all occupant type combinations were also significant ($p < 0.05$). In the DW4 housing type, significant differences were found for all occupant type combinations except for OC2-OC3 and OC4-OC5 ($p > 0.05$), with the remaining combinations showing significant differences ($p < 0.05$).

Regarding the energy consumed by electrical appliances, significant differences were found in average consumption for all occupant type combinations in the DW1 housing type, except for OC3-OC4 ($p > 0.05$), with other combinations showing significant differences ($p < 0.05$). In the DW2 housing type, significant differences were observed for all occupant type combinations except for OC3-OC2 ($p > 0.05$). In the DW3 housing type, significant differences were found for all combinations except for OC4-OC5 ($p > 0.05$). In the DW4 housing type, all occupant type combinations showed significant differences except for OC3-OC4 ($p > 0.05$).

In terms of domestic hot water consumption, significant differences were observed between all combinations of occupant types in the DW1 housing type ($p < 0.05$).

Regarding energy consumption for space heating, significant differences were found in average consumption between all combinations of occupant types in the DW1 housing type, except for OC1-OC2 and OC1-OC3 ($p > 0.05$), while the remaining combinations showed significant differences ($p < 0.05$). In the DW2 housing type, significant differences were found between all combinations except for OC2-OC3 and OC2-OC4 ($p > 0.05$). Similarly, in the DW3 housing type, significant differences were found between all combinations except for OC1-OC2 and OC2-OC3 ($p > 0.05$). In the DW4 housing type, significant differences were observed for all combinations except for OC1-OC2, OC3-OC2, OC3-OC4, and OC4-OC5 ($p > 0.05$).

The highest average differences in lighting energy consumption for each housing type were found in the combinations of OC5-OC1, OC4-OC1, and OC3-OC1 occupant types, respectively. The lowest average difference was observed between OC4-OC3 in the DW1 housing type, and between OC5-OC4 in the DW2, DW3, and DW4 housing types.

4.2. Correspondence Analysis

In this research, correspondence analysis was conducted using two different approaches. In the first approach, energy consumption sources, housing types (DW), and occupants (OC) were evaluated independently (Figure 2). In the second approach, energy consumption sources, housing types (DW), and occupants (OC) were examined in relation to each other (Figure 3). The consumption averages obtained from a dataset with a uniform distribution (exact balance across all categories) were used as weights. For both graphics the blue colours represent the columns (energy types), while the red colours indicate the variables in the rows (occupant types—OC and housing types—DW).

4.2.1. Evaluation of Energy Consumption Types for DW and OC Categories Independently

The first dimension explains 98.4% of the variation, while the second factor accounts for 1.5%. Thus, there is only a 0.05% loss in the total variation explained (Table 11).

Table 11. Reliability table (1).

	eValue	%	Cum %
1	0.028698	98.42317	98.42317
2	0.000446	1.528009	99.95118
3	0.000014	0.04882	100
	0.029158		

When examining the line graph, it appears that in the first dimension (x-axis), the variables OC4, OC5, DW2, and DW4 are separating from the variables OC2, OC1, and DW1. In the second dimension (y-axis), it seems that the variables OC4, OC5, and DW1 are differentiating from the variables DW2, DW4, OC2, and OC1 (Figure 3).

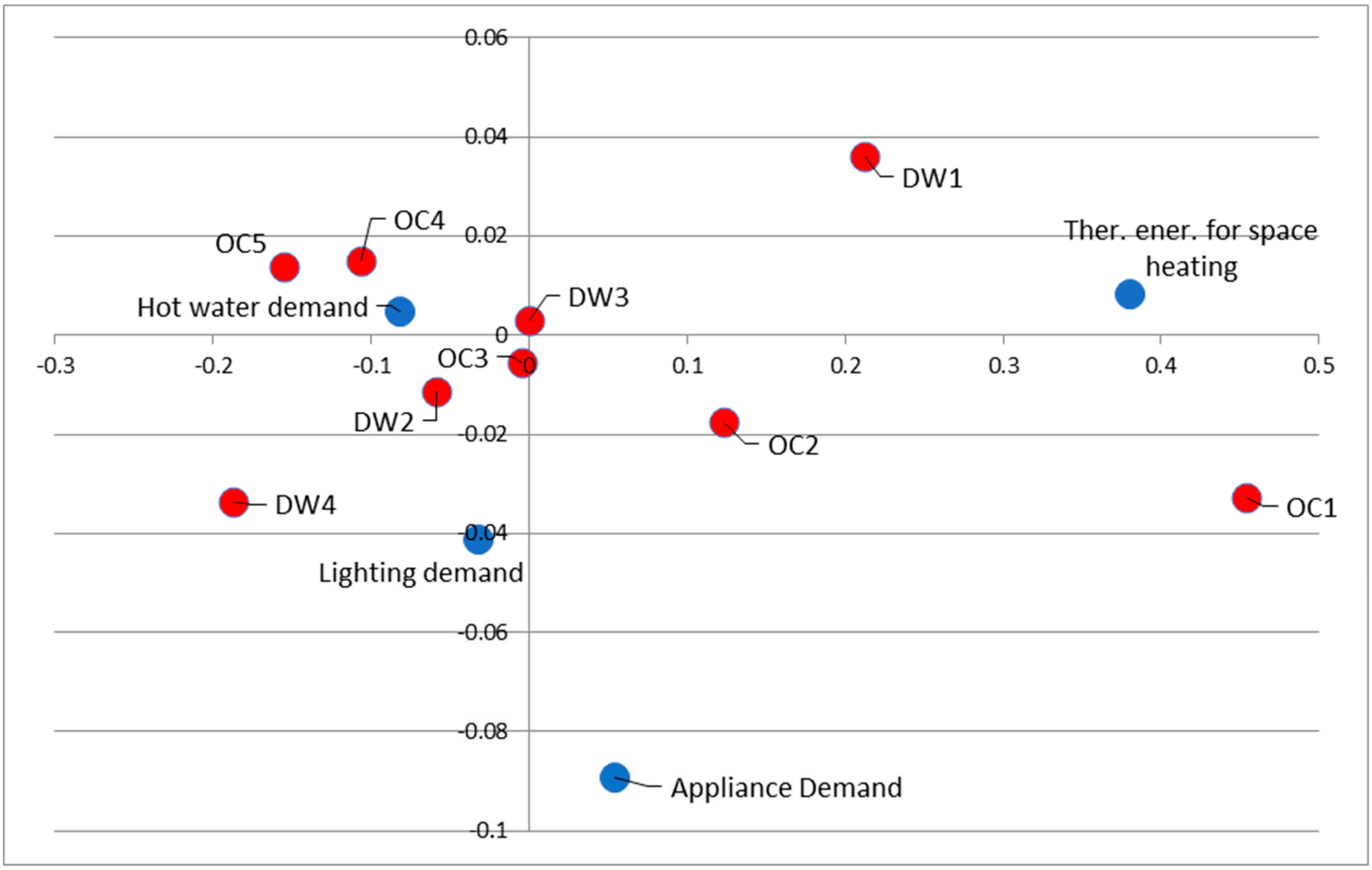

Figure 2. Combined graph (1) (X axis represents Dimension1, and Y axis represents Dimension2).

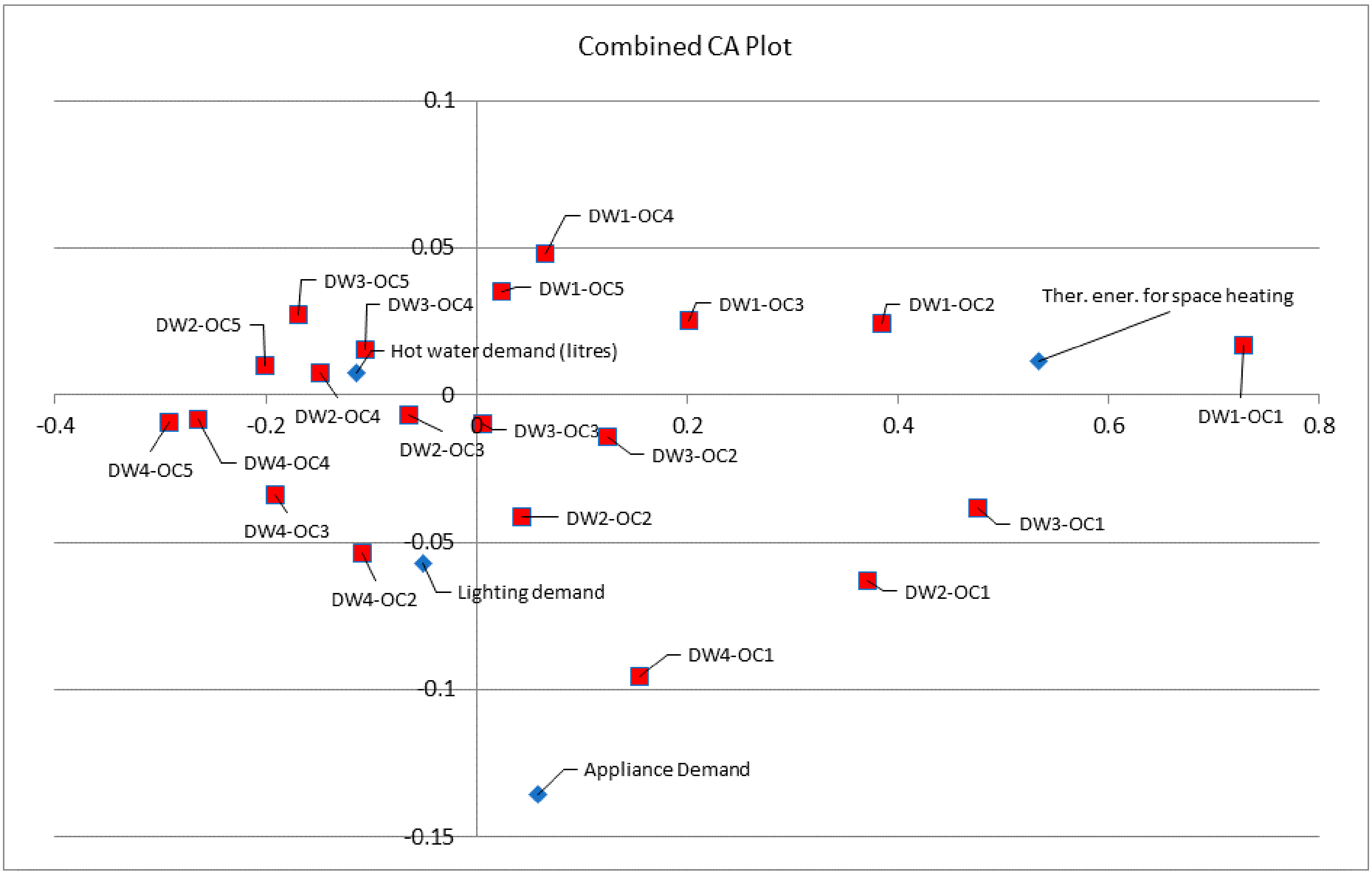

Figure 3. Combined graph (2) (X axis represents Dimension1, and Y axis represents Dimension2).

The combined graph (1) (Figure 2) indicates that the DW3 and OC3 variables, positioned near the graph's centre, reflect average energy consumption levels. In the upper-right section, the DW1 housing type stands out for its significantly higher energy usage for space heating, highlighting a notable relationship between this housing type and space heating demand. Additionally, the OC5 variable shows a stronger association with OC4 regarding hot water consumption. The graph also suggests that hot water usage varies more prominently across different occupant types.

The energy used for lighting is closely associated with DW2 and DW4 housing types, though the relationship is stronger for DW4. For energy consumption related to electrical devices, OC1 and OC2 occupant types show a notable correlation, with OC2 exhibiting a stronger association than OC1.

In the first dimension of the column graph (x-axis), space heating energy is distinguished from hot water and lighting energy. In the second dimension (y-axis), space heating and hot water consumption are separated from lighting and electrical device usage. The distribution of these energy types across different corners of the graph suggests they exhibit distinct consumption patterns.

4.2.2. Evaluation of Energy Consumption Types Through Pairwise Combinations of DW and OC Categories

The first dimension explains 98.1% of the variation, while the second factor accounts for 1.8%. Thus, there is only a 0.8% loss in explaining the total variation (Table 12).

Table 12. Reliability table (2).

	eValue	%	Cum %
1	0.056113	98.13821	98.13821
2	0.001017	1.777902	99.91612
3	0.000048	0.083884	100
	0.057177		

In the first dimension of the bar chart (x-axis), space heating and electrical appliance energy use are distinguished from hot water and lighting energy. Similarly, the second dimension (y-axis) differentiates space heating and hot water consumption from lighting and electrical appliance usage. The distribution of these energy types across different corners of the chart confirms that they exhibit distinct consumption patterns. The DW3-OC3 combination, located near the centre of the chart, can be described as having average values across the energy types consumed. See Figure 3.

- In the upper-left corner, the hot water consumption is highest for the DW3-OC5 and DW2-OC5 combinations.
- In the upper-right section, the energy used for space heating shows the strongest relationship with the DW2-OC5 and DW3-OC5 combinations.
- In the lower-left corner, lighting energy consumption is closely associated with DW4-OC4 and DW4-OC5, with DW2-OC5 also playing a significant role.
- In the lower-right section, the energy consumed by electrical appliances is most closely related to the DW-OC1 combination, as indicated by its proximity to the origin and narrower angles, suggesting a stronger relationship than with other combinations.

4.3. Decision Tree

The decision tree method creates a tree-based classification model to group cases or predict the values of a dependent (target) variable based on the values of independent (predictor) variables. In this study, the decision tree method was used to determine which factors significantly affect the target variable and at which levels these effects are concentrated.

Comprehensive Inclusion of Independent Variables in the Model

In the model conducted using the Chi-Square Automatic Interaction Detection (CHAID) method, housing type (DW) and various types of energy consumption were used as independent variables. The results indicate that the most influential variables in predicting the consumer type are hot water consumption, lighting energy, and energy used by electrical appliances. The model resulted in a structure with a depth of three, comprising a total of 54 nodes and 37 terminal nodes. The number of nodes represents each point where a split occurs, while terminal nodes are those where no further splits are possible, and final predictions are made. Terminal nodes represent homogeneous groups at the model's endpoints, with each terminal node corresponding to a distinct group or final classification. The presence of 54 nodes and 37 terminal nodes demonstrates that the model performs highly detailed groupings and involves numerous splits before reaching the final outcome.

In the model's risk table (Table 13), the estimated risk is 0.580 without applying cross-validation, and 0.597 with cross-validation. These values can be considered high. However, the fact that the two risk estimates are equal or very close, despite the high risk, indicates that the model is internally consistent.

Table 13. Risk Table.

Risk		
Method	**Estimate**	**Std. Error**
Resubstitution	0.580	0.006
Cross-Validation	0.597	0.006

Growing method: CHAID. Dependent variable: occupant type (OC).

The comparison of actual and predicted user types reveals that the model, while correctly identifying OC1 as a medium level, underestimates the other types, especially OC4. This suggests that the model struggles to distinguish between different user types, particularly OC4. With an overall accuracy of only 42.0%, the model's reliability is low (Table 14).

Table 14. Accuracy differences across user categories.

Classification						
Observed	**Predicted**					
	OC1	**OC2**	**OC3**	**OC4**	**OC5**	**Percent Correct**
OC1	895	224	100	20	1	72.2%
OC2	332	382	265	142	119	30.8%
OC3	161	261	376	199	243	30.3%
OC4	48	163	271	295	463	23.8%
OC5	47	72	214	252	655	52.8%
Overall Percentage	23.9%	17.8%	19.8%	14.6%	23.9%	42.0%

Growing method: CHAID. Dependent variable: occupant type (OC).

Based on these outcomes created decision tree model can be found below (Figure 4). A classification tree was used to divide users into 10 distinct groups based on their daily hot water consumption. Each group represents approximately 10% of the total users. The consumption ranges for these groups are as follows: Group 1: ≤41 L/day, Group 2: 41–66 L/day, Group 3: 66–92 L/day, Group 4: 92–117 L/day, Group 5: 117–141 L/day, Group 6: 141–168 L/day, Group 7: 168–201 L/day, Group 8: 201–239 L/day, Group 9: 239–294 L/day, Group 10: >294 L/day.

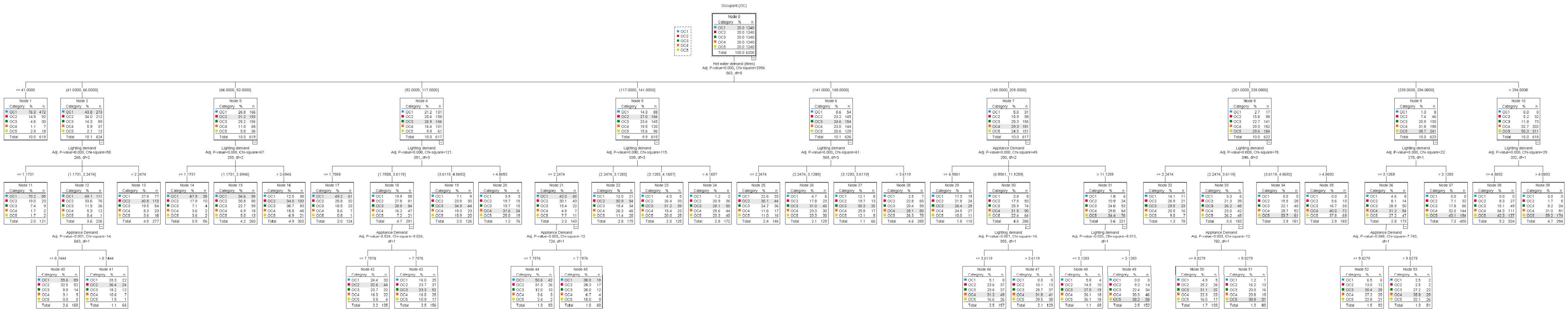

Figure 4. The decision tree model.

For the first group, users with hot water consumption of 41 Litres/day or less constitute 10% of all users, with a 76.3% probability of belonging to the OC1 user type. Following this, 19.0% of the group is composed of OC2 users, while the proportions of OC3 (7.4%), OC4 (1.7%), and OC5 (1.7%) are considerably lower. Since this group is sufficiently homogeneous, it is designated as a terminal node, meaning no further splitting was required.

The second group's differentiation is primarily based on lighting energy consumption. This consumption is categorised into three levels: (i) 1.1731 kWh or less, (ii) 1.1731–2.2474 kWh, and (iii) more than 2.2474 kWh. Within the second group, the first subgroup comprises 2.0% of the population and has a 55.6% probability of belonging to the OC1 user type. Due to its homogeneity, this subgroup is considered a terminal node and requires no further division.

The second subgroup within the second group is further divided into two homogeneous groups based on electrical appliance energy consumption. This consumption is categorised into two levels: (i) 8.744 kWh or less, and (ii) more than 8.744 kWh. In the first of these subgroups, there is a 55.6% probability of belonging to the OC2 user type, slightly surpassing the 32.5% probability of being OC1. In the second subgroup, the probability of being OC2 is 36.4%, marginally exceeding the 33.3% probability of being OC1 (Node 40 and Node 41). Due to their homogeneity, both subgroups were deemed terminal nodes and required no further division.

Within the tenth group, characterised by the highest hot water consumption, there is a 50.3% probability of belonging to the OC5 user type, compared to a 32.7% probability of being OC4. At the second level of this group, lighting energy consumption emerges as the primary differentiating factor. For those with lighting energy consumption of 4.8692 kWh or less, the probability of being OC5 is 42.3%, and OC4 users have a 34.3% probability. Conversely, when lighting energy consumption exceeds 4.8692 kWh, the probability of being OC5 increases to 59.2%, while the probability of being OC4 decreases to 31.0%.

For this research, mandatory inclusion of housing type (DW) as an independent variable was also applied, along with regression tree methods. Due to the extensive nature of the research and the constraints of graphical layout, a detailed outcome cannot be provided here. Since this study was conducted within the context of OEL, its primary focus was on establishing the underlying infrastructure necessary for this labelling, rather than presenting numerical results. As seen in the initial decision tree example, it was observed that when classifying energy consumption, it is possible to establish relationships between the consumption levels of individuals within a group and those in other groups, or in other words, to correlate different consumption patterns. With more detailed and real-world datasets, it would be possible to classify users into different energy consumption classes based on their consumption levels and corresponding groupings, and to compare these classes across various housing types.

5. Discussion

Based on the preliminary outcomes of the simulations, which are limited within operational constraints, the basic findings can be summarised as follows:

Analysis methods: Multivariate Variance Analysis (MANOVA), correspondence analysis, and decision tree methods can assist building energy researchers in developing occupant labelling from various perspectives. The first two methods can help researchers define correlations and assess their effects on consumption, either individually or in conjunction with building type and occupant type. In contrast, decision tree analysis can facilitate the clustering and classification of occupants based on their energy consumption across different factors. Additionally, decision trees can enable researchers to make predictions about occupant consumption based on historical statistical data. Large datasets, such as TUS, can be utilised for this type of analysis.

Complexity of occupant behaviour: Individual actions and building energy consumption patterns interact in detail, complicating reliable forecasting. While bottom-up methodologies offer valuable insights, they require extensive data that are often challenging to collect. On the other hand, top-down approaches tend to yield more consistent results and facilitate easier data acquisition, making them more practical for large-scale applications. However, applying bottom-up research across diverse contexts introduces additional challenges. Variations in cultural, geographical, and climatic factors can limit the transferability of findings between regions, complicating efforts to develop universally applicable models. Furthermore, occupant behaviour is not static; it evolves throughout an individual's life cycle and in response to shifting social norms, leading to noticeable changes over time, particularly in longitudinal studies. In addition to these temporal and contextual factors, the type and condition of a building also shape occupant behaviour. For example, individuals often exhibit greater energy consciousness when they are directly responsible for paying their utility bills, yet this behaviour may diminish in environments like offices where they do not bear the cost. Similarly, social norms and cultural backgrounds influence how individuals behave in shared spaces, prompting them to adjust their actions to align with communal expectations.

Effect of occupant numbers on energy consumption: Research shows that the number of occupants directly influences energy consumption. However, the extent of this impact is non-linear and varies depending on the type of building. This observation highlights that allocating space per person, measured in square metres, is not a practical criterion for predicting energy efficiency or consumption. Such an approach fails to capture the non-linear dynamics of occupant interaction and energy use, which can significantly affect overall consumption patterns.

Consequently, labelling individual occupants as a strategy to address energy consumption issues is not effective. Instead, Sections 4.1.5 and 4.1.6 present a detailed statistical analysis, suggesting that OEL is more suitable for understanding the collective consumption behaviours of a group, such as a family, rather than individual usage within that group. Therefore, labelling efforts should reflect the life cycle of the group, their shared activities, and how these behaviours evolve over time.

Furthermore, occupant labelling must account for the different types of energy consumption within a residence, as these vary with the number of occupants. For example, domestic hot water and electricity consumption typically increase with more occupants, while some forms of energy use, such as thermal energy, may plateau beyond a certain point. This complexity emphasises the need for nuanced approaches that go beyond simple schemes to accurately represent real consumption patterns.

Diverse energy consumption in buildings: Energy is consumed in various ways within a building, influenced both by its structural attributes and the behaviours of its occupants. The total energy consumption varies significantly across buildings with different thermal properties, indicating that both the number of occupants and dwelling characteristics are important. These factors together influence different types of energy demands, yet their effects are complex and show considerable variability.

Impact of statistical profiles on simulation outcomes: Although the simulations are based on statistically created profiles, combining different statistical profiles of occupant's results in variations that are not merely additive. The difference in energy consumption between individual and average per person demonstrates that the integration of various behaviours can significantly alter the overall energy dynamics, challenging the simplicity of subtracting personal consumption from the average.

Based on these research outcomes, it becomes apparent that the bottom-up approach, which involves an intricate detailing of a myriad of factors across various fields to estimate energy consumption, encounters significant challenges. This methodology requires precise control and understanding of a vast array of changing parameters to make accurate predictions. However, the research also indicates that these parameters need to be flexible to accommodate differences in building types, which vary in area, volume, thermal capacity, and other physical properties. Furthermore, even when the number of people and their activity patterns remain constant, the correlation between the number of occupants and energy consumption is not straightforward or directly proportional. This complexity is compounded by the fact that occupants' energy consumption behaviours can change significantly over different life stages. On the other hand, using statistical data to analyse different types of buildings and the number of occupants provides more robust insights for estimating energy consumption. This strategic shift leads to the development of OEL. This innovative approach aids policymakers by offering a more predictable and scalable tool for estimating future energy consumption needs. In contrast to the granular focus of the bottom-up approach, the top-down strategy used to estimate energy consumption simplifies the development of OEL patterns. These patterns can be effectively tailored based on age, gender, life period, perceptions of indoor environment quality (IEQ), and the number of occupants in the same indoor environments.

OEL represents a transformative advancement over traditional methods, providing a framework that allows for the standardisation of energy consumption estimates across diverse populations and building types. This model not only enhances the accuracy of predictions but also supports the implementation of energy policies that can dynamically adjust to changes in occupant behaviour and building characteristics.

Although the focus on residential buildings might appear to limit the model's broader applicability, this targeted scope underscores the unique challenges and advantages of OEL within a highly variable domestic environment. Unlike commercial or institutional settings—where occupant turnover, schedules, and responsibilities can vary significantly—the residential context highlights how personal habits, cultural factors, and household compositions critically influence energy use. At the same time, these conditions reveal the potential limitations of OEL, given that daily routines in homes are less standardised. Moreover, because residents generally pay their own utility bills, they tend to adopt more energy-conscious behaviours compared to occupants in other building types, such as offices where utility costs are typically covered by owners. Additionally, social norms in residential settings are usually less stringent, allowing occupants greater freedom in their actions. Furthermore, residential buildings outnumber other types, making them a prime focus for occupant-centred energy research. By concentrating on residences, the OEL approach captures a wide range of occupant-driven variables, offering deeper insights into how nuanced behaviours shape overall consumption patterns. Future investigations could therefore examine the extension of the OEL framework to other building types, while retaining its adaptability to the specific behaviours, schedules, and usage patterns inherent in each context.

From a policy perspective, the introduction of occupant energy labelling (OEL) provides an opportunity to integrate occupant-focused insights into frameworks such as building codes, incentive programs, and energy-saving campaigns. By capturing how individuals or household groups consume energy, OEL may support more refined strategies that motivate behavioural change and complement existing technology-centric measures. At the same time, these potential advantages must be weighed against privacy considerations, as labelling occupants based on their energy use may raise concerns regarding data collection and user consent. Ensuring that OEL implementations follow established global standards for data protection—through anonymisation practices, clear communication about data handling, and transparent consent procedures—would help maintain public trust. Striking an appropriate balance between leveraging occupant-specific information for policy gains and preserving individual privacy can position OEL as a responsible and effective tool in global energy efficiency efforts.

6. Limitations

This research is subject to several limitations. Accurately capturing the impact of occupants on energy consumption requires further studies supported by more granular data. Additionally, these datasets should be tested using various simulation tools across different geographic locations and climatic regions over extended periods. Such an approach would enable a more precise understanding of how individual behaviours influence energy consumption under varying conditions. A comprehensive understanding of energy consumption dynamics also necessitates detailed investigations into occupants' behavioural patterns and specific energy usage habits. Moreover, indoor environmental quality (IEQ) should be examined, as it plays a critical role in occupant comfort, which, in turn, influences energy-related decisions. These studies would provide deeper insights into the interaction between occupant behaviour and energy efficiency strategies, fostering more effective interventions.

It is important to note that this research does not focus on presenting numerical outcomes from simulations. Instead, it aims to explore whether OEL can be achieved through statistical analysis of existing data. As such, this study should be regarded as an initial step toward developing a structured framework for OEL, laying the groundwork for more advanced research in the future.

7. Future Work

As occupant behaviour is inherently dynamic and influenced by a range of cultural, climatic, and temporal factors, the occupant energy labelling (OEL) model must continuously evolve to remain robust and widely applicable. Accordingly, the following avenues of future work are outlined to address additional complexities, validate the model in diverse contexts, and ensure its practicality for policymakers and industry stakeholders.

Expanding datasets and climatic contexts: To enhance the universality of the occupant energy labelling (OEL) model, future studies must be conducted and should include data from multiple climatic zones and diverse cultural backgrounds. This broader dataset is expected to capture varying thermal preferences, cultural habits, and lifestyle factors, thereby improving the model's adaptability and robustness.

Long-term behaviour analysis: Although the current study provides valuable insights into occupant behaviour, long-term and historical data collection needs to be prioritised in future work. Extended datasets can help identify enduring trends, seasonal variations, and the impact of major life events on occupant energy consumption patterns.

Validation and predictive capabilities: While the proposed framework and simulations offer promising outcomes, further research is needed that involves validating the model with real-case scenarios to verify its predictive accuracy. Such real-world validation will enhance the OEL model's reliability and offer concrete evidence of its practicality in actual residential settings.

Integration of indoor environmental quality variables: Indoor environmental quality (IEQ) factors, including air quality, lighting, thermal comfort, and acoustics, significantly shape how occupants behave and use energy within a dwelling. Comfort conditions are highly subjective: even when common guidelines exist, each individual's perception of temperature, airflow, or lighting levels can vary widely. In households where multiple people share the same space, thermal settings and other comfort parameters often adapt to the most vulnerable member, for example, a family may heat a room more than usual to accommodate an infant's comfort needs, inadvertently increasing overall energy usage. Moreover, location-based considerations such as the dwelling's orientation, surrounding noise levels, and natural daylight availability can further influence occupant behaviour. Visual comfort and acoustic privacy, for instance, may lead occupants to modify window positions, blinds, or partitions, each affecting energy consumption patterns.

Recent global events, including a pandemic, have highlighted the importance of personal space and indoor air quality in safeguarding occupants' health and well-being. As individuals spend longer periods indoors, whether working, studying, or isolating, ventilation practices and occupant density both become critical factors in shaping energy consumption, comfort, and safety. Therefore, future iterations of the OEL model must integrate these multifaceted IEQ variables, not only to provide a more comprehensive understanding of behaviour-driven energy use but also to ensure that occupant-centric interventions prioritise health, comfort, and overall quality of life.

Policy and industry applications: Beyond academic discourse, ongoing research needs to explore diverse pathways for integrating the OEL model into policy frameworks and real-world building practices to drive occupant-centred energy efficiency initiatives. One potential avenue lies in developing standardised guidelines for occupant labelling that can be systematically adopted in building codes, incentive programs, and sustainability certifications. By establishing clear benchmarks and thresholds, the OEL model could guide policymakers in devising occupant-focused standards complementary to traditional building performance requirements while recognising occupant variability. Building practitioners could then leverage OEL metrics in designing or retrofitting residential spaces, tailoring energy systems and operational strategies to different occupant groups. Furthermore, incentive mechanisms such as tax rebates or reduced utility tariffs could be aligned with OEL-based ratings, rewarding households that achieve or maintain efficient occupant labels, while utilities or local governments might offer tiered benefits or targeted outreach programs to occupants identified as high energy users. Over time, widespread adoption of OEL metrics could also inform consumer choices in the real estate market, where potential buyers or renters would have access to occupant-centric efficiency data, thus fostering a competitive environment for occupant-friendly designs. Ultimately, expanding OEL into policy and industry realms aims not only to formalise occupant-focused labelling in regulations but also to create synergy among various stakeholders, policymakers, building owners, occupants, and utility companies, in adopting data-driven and behaviourally informed solutions for sustainable living.

Further real-case studies: Lastly, repeated and diversified real-case studies must be incorporated in upcoming research to validate the model's accuracy and practicality in various housing types and demographic profiles in different cultures. These case studies will help refine the OEL framework and potentially unveil context-specific best practices for reducing residential energy consumption. This will also help to understand long-term trends in occupant behaviour.

8. Conclusions

Energy consumption in buildings results from the dynamic interaction between occupants and the built environment, with both occupant behaviour and household characteristics playing critical roles. Given the diversity of occupant behaviour, labelling energy consumption solely at the individual level may not capture this complexity. Instead, collective labelling, such as for families or groups of cohabitants, or households, can provide more accurate assessments of energy consumption patterns.

The intensity and variability of energy consumption are significantly influenced by the number of occupants in a household. Furthermore, energy use varies not only with the number of occupants but also across different consumption activities. While this research does not directly address the influence of personal background, culture, geography, or life stages, these factors undeniably shape consumption patterns. Individuals' energy use evolves throughout their lives, suggesting that future research should account for these changes to refine occupant energy models.

This study represents an early attempt to explore whether OEL is feasible. Although it is based on limited data and statistical analysis, the findings suggest several outcomes for future development. A more advanced OEL framework should integrate behavioural insights, demographic statistics, and indoor environmental quality (IEQ) variables to reflect the diversity of occupant behaviour and its impact on energy use.

OEL has significant potential to correlate occupants with buildings, optimising energy management and promoting efficiency. This idea can also be extended by developing models applicable to urban settings, incorporating various occupant types and district-wide dynamics. Finally, the research suggests that OEL might serve as a valuable metric for estimating total energy consumption across large groups, with immense potential for further development. However, as this study only provides an initial framework, much work remains to be performed to fully realise the potential of OEL.

The final outcomes of the research are listed below:

- Energy consumption in buildings results from the interaction between humans and buildings, heavily influenced by occupants. Therefore, occupant behaviour varies based on the different characteristics of the house.
- Occupancy is not a singular concept. For this reason, groups of people living together, such as families, should be labelled collectively to accurately assess energy consumption.
- Energy intensity and consumption rates fluctuate with the number of occupants.
- The energy intensity associated with various consumption topics in residences may be affected by the number of occupants.
- Although not directly explored here, factors such as personal background, culture, and geography significantly influence energy consumption patterns.
- Although not directly explored here, a person's lifetime can impact energy consumption; the same individual may consume energy differently at various stages of life.
- Although not directly explored here, OEL should take into account indoor environmental quality IEQ variables for individual calculations.
- OEL should consider statistics regarding the demographics and behaviours of individuals.
- Decision tree analysis based on large datasets, such as TUS surveys, may help cluster occupants and enable decision makers to estimate the energy consumption breakdown of occupants according to their varying consumption patterns.
- OEL may have potential to correlate occupants with buildings optimising energy consumption.

Supplementary Materials: The following supporting information can be downloaded at www.mdpi.com/xxx/s1.

Author Contributions: Conceptualisation, T.H. and P.d.W.; methodology, T.H. and P.d.W.; software, T.H.; investigation, T.H. and P.d.W.; resources, T.H. and P.d.W.; data curation, T.H.; writing—original draft preparation, T.H. and P.d.W.; writing—review and editing, T.H. and P.d.W.; supervision, P.d.W.; funding acquisition, T.H. All authors have read and agreed to the published version of the manuscript.

Funding: The research underlying this paper was funded by The Scientific and Technological Research Council of Turkey (TÜBİTAK) under grant number 1059B191800603.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets presented in this study are available on request to the corresponding author.

Acknowledgments: The financial support mentioned in the funding part is gratefully acknowledged.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. IPCC, 2023: Summary for Policymakers. In *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Core Writing Team, Lee, H., Romero, J., Eds.; IPCC: Geneva, Switzerland, 2023; pp. 1–34. https://doi.org/10.59327/IPCC/AR6-9789291691647.001.
2. National Oceanic and Atmospheric Administration Research, 2023. Available online: https://www.noaa.gov/news-release/greenhouse-gases-continued-to-increase-rapidly-in-2022 (accessed on1st of October 2024).
3. Copernicus Climate Change, Press Release, 2024. Available online: https://climate.copernicus.eu/copernicus-summer-2024-hottest-record-globally-and-europe (accessed on1st of October 2024).
4. Harputlugil, T.; de Wilde, P. The interaction between humans and buildings for energy efficiency: A critical review. *Energy Res. Soc. Sci.* **2021**, *71*, 101828.
5. Hong, T.; Yan, D.; D'Oca, S.; Chen, C.F. Ten questions concerning occupant behaviour in buildings: The big picture. *Build. Environ.* **2017**, *114*, 518–530.
6. Tuniki, H.P.; Jurelionis, A.; Fokaides, P. A review on the approaches in analysing energy-related occupant behaviour research. *J. Build. Eng.* **2021**, *40*, 102630.
7. Tam, V.W.; Almeida, L.; Le, K. Energy-related occupant behaviour and its implications in energy use: A chronological review. *Sustainability* **2018**, *10*, 2635.
8. Paone, A.; Bacher, J.P. The impact of building occupant behaviour on energy efficiency and methods to influence it: A review of the state of the art. *Energies* **2018**, *11*, 953.
9. Delzendeh, E.; Wu, S.; Lee, A.; Zhou, Y. The impact of occupants' behaviours on building energy analysis: A research review. *Renew. Sustain. Energy Rev.* **2017**, *80*, 1061–1071.
10. Yan, D.; Hong, T.; Dong, B.; Mahdavi, A.; D'Oca, S.; Gaetani, I.; Feng, X. IEA EBC Annex 66: Definition and simulation of occupant behaviour in buildings. *Energy Build.* **2017**, *156*, 258–270.
11. Balvedi, B.F.; Ghisi, E.; Lamberts, R. A review of occupant behaviour in residential buildings. *Energy Build.* **2018**, *174*, 495–505.
12. Hong, T.; Taylor-Lange, S.C.; D'Oca, S.; Yan, D.; Corgnati, S.P. Advances in research and applications of energy-related occupant behaviour in buildings. *Energy Build.* **2016**, *116*, 694–702.
13. Uddin, M.N.; Wei, H.H.; Chi, H.L.; Ni, M. Influence of occupant behaviour for building energy conservation: A systematic review study of diverse modeling and simulation approach. *Buildings* **2021**, *11*, 41.
14. Delgado, L.; Shealy, T. Opportunities for greater energy efficiency in government facilities by aligning decision structures with advances in behavioural science. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3952–3961.
15. Belaïd, F.; Roubaud, D.; Galariotis, E. Features of residential energy consumption: Evidence from France using an innovative multilevel modelling approach. *Energy Policy* **2019**, *125*, 277–285.
16. Building Stock Characteristics Report, EU. Available online: https://energy.ec.europa.eu/system/files/2016-11/characteristics_0.pdf (accessed on October 2024).
17. Weber, C.; Perrels, A. Modelling lifestyle effects on energy demand and related emissions. *Energy Policy* **2000**, *28*, 549–566.
18. Kim, J.H.; Suh, H.S.; Augenbroe, G.; Wang, Q. Domestic building energy prediction in design stage utilizing large-scale consumption data from realized projects. In *Building Simulation 2015: Proceedings of BS2015: 14th Conference of IBPSA, Hyderabad, India, 7–9 December 2015*; International Building Performance Association: Hyderabad, India, 2015.
19. Brounen, D.; Kok, N.; Quigley, J.M. Residential energy use and conservation: Economics and demographics. *Eur. Econ. Rev.* **2012**, *56*, 931–945.
20. Druckman, A.; Jackson, T. Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy* **2008**, *36*, 3177–3192.
21. Meier, H.; Rehdanz, K. Determinants of residential space heating expenditures in Great Britain. *Energy Econ.* **2010**, *32*, 949–959.
22. Touloupaki, E.; Theodosiou, T. Performance simulation integrated in parametric 3D modeling as a method for early stage design optimization—A review. *Energies* **2017**, *10*, 637.
23. Sanchez-Escobar, M.O.; Noguez, J.; Molina-Espinosa, J.M.; Lozano-Espinosa, R.; Vargas-Solar, G. The contribution of bottom-up energy models to support policy design of electricity end-use efficiency for residential buildings and the residential sector: A systematic review. *Energies* **2021**, *14*, 6466.

24. CREST Demand Tool. Available online: https://repository.lboro.ac.uk/articles/dataset/CREST_Demand_Model_v2_0/2001129 (accessed on October 2024).
25. Park, W.Y.; Shah, N.; Shiraishi, K.; Vine, E. Improving energy performance metrics to maximize the benefits of disruptive technologies. *Energy Res. Soc. Sci.* **2022**, *89*, 102678.
26. Ruiz, S.N.; Day, J.K.; Govertsen, K.; Kane, M. Communication breakdown: Energy efficiency recommendations to address the disconnect between building operators and occupants. *Energy Res. Soc. Sci.* **2022**, *91*, 102719.
27. Guerra-Santin, O.; Xu, L.; Boess, S. An interdisciplinary model for behaviour in residential buildings: Bridging social sciences and engineering approaches. *Energy Res. Soc. Sci.* **2024**, *118*, 103746.
28. Janda, K.B. Buildings don't use energy: People do. *Archit. Sci. Rev.* **2011**, *54*, 15–22.
29. Chen, Z.; Wen, J.; Li, Y.; Lo, L.J.; Grajewski, G.; Payne, W.V.; Bushby, S.T.; Pertzborn, A.; O'Neill, Z.; Yang, Z.; et al. Advanced co-simulation framework for assessing the interplay between occupant behaviours and demand flexibility in commercial buildings. *Sci. Technol. Built Environ.* **2024**, *30*, 1094–1113.
30. Hong, T.; Malik, J.; Krelling, A.; O'Brien, W.; Sun, K.; Lamberts, R.; Wei, M. Ten questions concerning thermal resilience of buildings and occupants for climate adaptation. *Build. Environ.* **2023**, *244*, 110806.
31. Yu, Z.; Fung, B.C.; Haghighat, F.; Yoshino, H.; Morofsky, E. A systematic procedure to study the influence of occupant behaviour on building energy consumption. *Energy Build.* **2011**, *43*, 1409–1417.
32. Santin, O.G.; Itard, L.; Visscher, H. The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy Build.* **2009**, *41*, 1223–1232.
33. IEA. Annex 66 Final Report. Available online: https://annex66.org/sites/default/files/2018FinalReport/Annex%2066%20Final%20Report%20-%20read.pdf (accessed on 1st of October 2024).
34. Fabi, V.; Andersen, R.V.; Corgnati, S.; Olesen, B.W. Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Build. Environ.* **2012**, *58*, 188–198.
35. Steemers, K.; Yun, G.Y. Household energy consumption: A study of the role of occupants. *Build. Res. Inf.* **2009**, *37*, 625–637.
36. Yun, G.Y.; Steemers, K. Behavioural, physical and socio-economic factors in household cooling energy consumption. *Appl. Energy* **2011**, *88*, 2191–2200.
37. D'Oca, S.; Hong, T. A data-mining approach to discover patterns of window opening and closing behaviour in offices. *Build. Environ.* **2014**, *82*, 726–739.
38. Humphreys, M.A. Quantifying occupant comfort: Are combined indices of the indoor environment practicable? *Build. Res. Inf.* **2005**, *33*, 317–325.
39. Hong, T.; D'Oca, S.; Turner, W.J.; Taylor-Lange, S.C. An ontology to represent energy-related occupant behaviour in buildings. Part I: Introduction to the DNAs framework. *Build. Environ.* **2015**, *92*, 764–777.
40. Wei, S.; Jones, R.; De Wilde, P. Driving factors for occupant-controlled space heating in residential buildings. *Energy Build.* **2014**, *70*, 36–44.
41. O'Brien, W.; Wagner, A.; Schweiker, M.; Mahdavi, A.; Day, J.; Kjærgaard, M.B.; Carlucci, S.; Dong, B.; Tahmasebi, F.; Yan, D.; et al. Introducing IEA EBC annex 79: Key challenges and opportunities in the field of occupant-centric building design and operation. *Build. Environ.* **2020**, *178*, 106738.
42. Schweiker, M.; Ampatzi, E.; Andargie, M.S.; Andersen, R.K.; Azar, E.; Barthelmes, V.M.; Berger, C.; Bourikas, L.; Carlucci, S.; Chinazzo, G.; et al. Review of multi-domain approaches to indoor environmental perception and behaviour. *Build. Environ.* **2020**, *176*, 106804.
43. Schweiker, M. Understanding occupants' behaviour for energy efficiency in buildings. *Curr. Sustain./Renew. Energy Rep.* **2017**, *4*, 8–14.
44. Osman, M.; Ouf, M. A comprehensive review of time use surveys in modelling occupant presence and behaviour: Data, methods, and applications. *Build. Environ.* **2021**, *196*, 107785.
45. Guerra-Santin, O.; Itard, L. Occupants' behaviour: Determinants and effects on residential heating consumption. *Build. Res. Inf.* **2010**, *38*, 318–338.
46. Amasyali, K.; El-Gohary, N.M. A review of data-driven building energy consumption prediction studies. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1192–1205.
47. Zhao, J.; Lasternas, B.; Lam, K.P.; Yun, R.; Loftness, V. Occupant behaviour and schedule modeling for building energy simulation through office appliance power consumption data mining. *Energy Build.* **2014**, *82*, 341–355.
48. Zhang, W.; Wu, Y.; Calautit, J.K. A review on occupancy prediction through machine learning for enhancing energy efficiency, air quality and thermal comfort in the built environment. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112704.
49. Andersen, K.H.; Johra, H.; Rohde, L.; Marszal-Pomianowska, A.; Heiselberg, P.K.; O'Brien, W. Increased Understanding of Building Operational Performance Through Occupant-Centric Key Performance Indicators. *Energy Build.* **2024**, *323*, 114756.
50. Mitra, D.; Chu, Y.; Cetin, K. Cluster analysis of occupancy schedules in residential buildings in the United States. *Energy Build.* **2021**, *236*, 110791.
51. Xu, X.; Yu, H.; Sun, Q.; Tam, V.W. A critical review of occupant energy consumption behaviour in buildings: How we got here, where we are, and where we are headed. *Renew. Sustain. Energy Rev.* **2023**, *182*, 113396.
52. Kumar, P.; Caggiano, H.; Cuite, C.; Andrews, C.J.; Felder, F.A.; Shwom, R.; Floress, K.; Ahamed, S.; Schelly, C. Behaving or not? Explaining energy conservation via identity, values, and awareness in US suburban homes. *Energy Res. Soc. Sci.* **2022**, *92*, 102805.