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Clustering-based agent system (CAS) to simulate the energy-related behaviours of office occupants

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ABSTRACT

Rapid urbanization and building sector growth emphasize the critical role of energy conservation in addressing global energy consumption and greenhouse emissions. Despite advancements in energy-efficient technologies, an 'energy performance gap' exists between predicted and actual energy use, significantly influenced by occupant behaviour. This study explores energy-related behaviour in office buildings by integrating existing behavioural theories including the Theory of Planned Behaviour and the Self-determination Theory, and construct of habit and comfort. Data from an online survey were analyzed using principal component analysis, two-step cluster analysis, and descriptive statistics, identifying three behavioral clusters: 'Cautious Saver', 'Compelling Dissatisfied', and 'Coherent Potent'. These clusters represent distinct energy-related behaviours. A Clustering-based Agent System (CAS) was then proposed to simulate the energy-related behaviours of these clusters, offering a dynamic and adaptive modelling framework. The study advocates for a comprehensive approach, integrating behavioural theories to provide insights for developing accurate occupant behaviour models.

Abbreviations: BD: Biodiesel; BR: Blending Ratio; BSFC: Brake Specific Fuel Consumption; BTE: Brake Thermal Efficiency; CI: Compression Ignition; CM: Coating Material; CO: Carbon Monoxide; CT DEE: Coating Thickness Diethyl Ether; D-Gun: Detonation Gun; DOA: Degree of Adiabacity; EGT: Exhaust Gas Temperature; HC: Hydrocarbon; HVOF: High-velocity oxy-fuel; IC: Internal Combustion; LHR: Low Heat Rejection; NO_x: Oxides of Nitrogen; PVD: Physical Vapour Deposition; SEM: Scanning Electron Microscopy; SI: Spark Ignition; TBC: Thermal Barrier Coating; TMF: Thermal Mechanical Fatigue; WCO: Waste Cooking Oil; XRD: X-ray Diffraction; YSZ: Yttria-Stabilised Zirconia

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Occupant behaviour; two-step cluster analysis; energy efficiency; behavioural theories; behavioral modelling; agent-based modelling; office buildings

1. Introduction

Rapid urbanization and the growth of the building sector have drawn attention to environmental issues (Chuai et al. 2021). Buildings account for one-third of primary energy consumption, 40% of global energy consumption, and 30% of energy-related greenhouse emissions (Li et al. 2021). Energy-efficient buildings featuring intelligent control systems, building automation systems (BAS), and building management systems (BMS) are often proposed to optimize energy use (Wong, Li, and Wang 2005). However, despite these advancements, actual energy savings frequently fall short of design expectations, resulting in what is known as the 'energy performance gap' (De Wilde 2014).

The 'energy performance gap' emerges as a significant research area focusing on discrepancies between predicted and actual building energy consumption (Ali et al. 2020). This difference arises from various factors, such as insufficient feedback between building administrators and designers, design faults or inaccurate assumptions, shortcomings in modelling tools, construction quality, excessive use of installed equipment, fluctuations in environmental conditions, inadequate facility management, and occupant behaviour. These factors collectively hinder the effective implementation of smart building initiatives and energy efficiency strategies (Ullah, Sepasgozar, and Wang 2018).

Occupant behaviours are influenced by a combination of stochastic processes and various physical, psychological, and physiological factors (Abdelwahab, Kent, and Mayhoub 2023). While much research has focused on predicting behaviours driven by physical factors like lighting, heating, and ventilation, the impact of non-physical factors remains less explored (Tuniki, Jurelionis, and Fokaides 2021). Non-physical elements, such as age, gender, preferences, perceptions, motivations, habits, and cultural or ethnic characteristics, play a crucial role in how occupants interact with their environments (Abdelwahab, Kent, and Mayhoub 2023; O'Brien et al. 2020). These factors shape individual preferences and interactions within buildings yet are often underrepresented in existing literature (O'Brien et al. 2020).

These stochastic mechanisms make occupant behaviour a major source of uncertainty in building energy modelling, contributing significantly to the energy performance gap

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(Gaetani, Hoes, and Hensen 2018). The building research community has increasingly focused on occupant behaviour modelling. In 2013, the International Energy Agency (IEA) launched the Energy in Buildings and Communities (EBC) Annex 66 (International Energy Agency 2018), which aimed to study the importance of occupant behaviour in buildings, improve modelling techniques, and formalize simulation approaches. Following this, in 2017, the IEA approved EBC Annex 79, 'Occupant-centric building design and operation', to address practical implementation issues related to occupant modelling. Within the context of IEA-EBC Annex 79, the focus is on four main areas: (1) multi-domain environmental exposure, building interfaces, and human behaviour; (2) data-driven occupant modelling strategies and digital tools; (3) occupant-centric building design; and (4) occupant-centric building operation (O'Brien et al. 2020).

1.1. Research gap

While much research has focused on the physical factors influencing occupant behaviour, such as lighting, heating, and ventilation (D'Oca, Corgnati, and Hong 2015; Hong et al. 2015; Khosrowpour, Gulbinas, and Taylor 2016; Rafsanjani, Ahn, and Eskridge 2018; Schweiker and Wagner 2016), there remains a significant gap in exploring the non-physical factors that impact energy-related behaviours in buildings. Understanding social, economic, cultural, and comfort-related concerns is essential for comprehensively understanding how occupants use buildings (Deng et al. 2021; Gunay and O'brien 2018). This inherent uncertainty, driven by individual differences, underscores the need for further efforts to develop behavioural models and psycho-social constructs that can effectively explain and predict energy-related behaviours (Deng et al., 2018).

This study contributes to this gap by providing a deeper understanding of energy-related behaviours in office buildings from a psycho-social perspective by identifying behavioural clusters. A two-step clustering approach was chosen to identify clusters because it handles both categorical and continuous data, automatically determines the optimal number of clusters, and requires minimal data preparation (Ortiz and Bluyssen 2019). Similar to the approach of this study, several studies have employed two-step cluster analysis to profile individuals across various contexts and purposes. Zhang, Ortiz, and Bluyssen (2019) utilized correlation analysis, principal component analysis, and two-step cluster analysis to uncover profiles among school children based on their preferences and needs for indoor environmental quality in classrooms. Similarly, Eijkelenboom and Bluyssen (2020) employed a survey and two-step cluster analysis to categorize outpatient staff into different groups based on their comfort and building-related preferences. Ortiz and Bluyssen (2019) investigated home occupant profiles using a mixed-method approach involving questionnaires, interviews, indoor environmental monitoring, and energy consumption measurements. Initially, they used a two-step cluster analysis to profile home occupants regarding emotions, comfort preferences, and locus of control, which mirrors the methodology in our study. In a subsequent study, Ortiz and Bluyssen (2022) focused on office workers, employing two separate two-step cluster analyses. The first analysis addressed indoor environmental quality preferences, while the second explored psycho-social comfort preferences through a questionnaire survey.

1.2. Objectives of the study

This study proposes a hybrid model that combines behavioural theories with a **Clustering-based Agent System (CAS)** framework to accurately reflect energy-related behaviour in office buildings. By integrating the Theory of Planned Behaviour and Self-Determination Theory, supplemented by constructs of habit and comfort, the model aims to capture the complexity of occupant behaviour. The CAS framework is intended for practical application, enabling accurate representation and predicting energy-related behaviours in office environments. Accordingly, the study has three main objectives:

(1) **Integrating behavioural theories to understand energy-related behaviour comprehensively:** The study addresses a research gap (Harputlugil and de Wilde 2021) by integrating intentional, motivational, habitual, and comfort drivers from existing behavioural theories, comprehensively examining energy-related behaviours. This holistic approach enhances understanding of complex dynamics and informs strategies for promoting energy-efficient practices.
(2) **Profiling different groups of office occupants:** The study uses a clustering-based method using psycho-social data to categorize and analyze district energy-related behaviour of office occupants. This approach seeks to identify different groups of office occupants regarding their psycho-social characteristics
(3) **Proposing a clustering-based agent system (CAS):** The study suggests a clustering-based agent system (CAS) that integrates the identified occupant clusters into building simulation tools, utilizing a decision-making flowchart to guide and simulate occupant behaviours more accurately.

1.3. The theoretical background

1.3.1. The theory of planned behaviour

The theory of planned behaviour (TPB) proposed by Ajzen (1991) is widely used to study occupant behaviour, particularly in environmental behaviour research (Gao et al. 2017). According to the TPB, behaviour intention is influenced by attitude, subjective norms, and perceived behaviour control (Ajzen 1991). Attitude refers to an individual's positive or negative evaluation of behaviour. Subjective norms reflect social expectations and opinions of significant individuals, and perceived behaviour control relates to an individual's perception of their ability to control or perform the behaviour (Ajzen 1991; Gao et al. 2017). The TPB has been extensively used to explore environmental behaviours, including pro-environmental behaviour, green purchasing, low-carbon travel, walking, and recycling (Cheung, Chan, and Wong 1999; Correia et al. 2021; Hu, Wu, and Chen 2021; Seles and Afacan 2019). It has been applied to predict the residents' intentions to engage in energy-saving behaviours, accounting for up to 81% of the variance. TPB has also been used to understand energy-related behaviours among office occupants, explaining a variance of 46% to 61% in pro-environmental behaviours (Greaves, Zibarras, and Stride 2013).

1.3.2. The self-determination theory

The self-determination theory (SDT), formulated by Ryan and Deci (Ryan and Deci 2000), offers a comprehensive framework for understanding human motivation and occupant behaviour. Motivations can be categorized along the internal-external continuum based on perceived autonomy (Budzanowska-Drzewiecka and Tutko 2021). The continuum begins with amotivation, indicating a lack of intention to act (Baxter and Pelletier 2020). Introjected regulation, the next level, is driven by the need to avoid negative feelings (Baxter and Pelletier 2020). Identified regulation represents recognizing the importance of behaviours (Ryan and Deci 2000), while integrated regulation reflects behaviours that are fully internalized and aligned with one's identity (Baxter and Pelletier 2020). Intrinsic regulation represents the most self-determined motivation, driven by inherent satisfaction and enjoyment (Baxter and Pelletier 2020). SDT has primarily been studied in pro-environmental behaviour, showing that individuals with higher self-determined motivation exhibit more remarkable pro-environmental behaviour (Budzanowska-Drzewiecka and Tutko 2021; Pelletier and Aitken 2014). It has been applied to various forms of pro-environmental behaviour (Baxter and Pelletier 2020), including household energy-saving (Dave et al. 2013), purchasing (Gao et al. 2018), recycling (Huffman et al. 2014), and green employee behaviours (Zhang, Zhang, and Jia 2021). However, there is a lack of integrated studies applying SDT to investigate pro-environmental behaviour, specifically in building energy efficiency.

1.3.3. Habit and comfort

Habit, automatic responses performed without conscious effort, are essential to understanding energy-saving behaviours. Habits can act as barriers to change, preventing individuals from adopting environmentally friendly actions (Sopha and Klöckner 2011; Wood and Rünger 2016). Despite their significance, habits are often overlooked in favour of factors like values, norms, attitudes, intentions, and motivation (Verplanken and Sui 2019). Many interventions focus on intrinsic motivation to foster sustainable change, but breaking well-established habits requires more than rational processes (Verplanken and Sui 2019). Besides, previous research showed that these models have only been able to explain approximately 20-30% of the variations in human behaviour.

Moreover, since individuals spend most of their time indoors, indoor environmental quality (IEQ) significantly affects their health, comfort, productivity, and energy usage (Rubinstein 1984). In office environments, IEQ encompasses various aspects such as thermal conditions, indoor air quality, lighting, and acoustic environments. Studies have specifically examined how indoor conditions in office environments impact occupants' comfort, health, and productivity (Lenoir, Baird, and Garde 2012; Rasheed and Byrd 2018). These studies have highlighted the importance of creating supportive and healthier office spaces that enable occupants to maintain focus and conserve energy in their work environment. Therefore, this study takes into account the comfort perceptions of office occupants to gain a better understanding of their energy-related behaviours.

2. Research methods

2.1. Study participants and data collection

Participants for this study were purposefully selected from the general population of full-time employees in private sector office settings in three major cities in Türkiye: Ankara, İstanbul, and Muğla. According to Köppen–Geiger climate classification, Ankara falls under the Csb Climate zone (interior Mediterranean) with significant temperature fluctuations between hot, dry summers and cold, snowy winters (Kottek et al. 2006). İstanbul has a transitional climate, encompassing temperate, subtropical climate (Cfa), Mediterranean climate (Csa), and oceanic climate (Cfb). It experiences hot and humid summers, with cold, rainy, and occasionally snowy winters (Kottek et al. 2006). Lastly, Muğla belongs to the Csa Climate Zone (hot-summer Mediterranean climate), with hot and dry summers and warm and rainy winters (Kottek et al. 2006).

The survey size was determined based on previous behavioural studies that utilized clustering-based approaches in areas such as home occupants' energy behaviour ($n = 316$) (Ortiz and Bluyssen 2018), coffee consumption ($n = 210$) (Carvalho et al. 2015), academic and behavioural risk profiles ($n = 146$) (Hagaman et al. 2010), academic performance and lifestyle behaviours ($n = 248$) (Dumuid et al. 2017), and sport participation ($n = 303$) (Chian and Wang 2008). These studies served as the baseline for defining the starting sample size of this research. The authors initially collected 350 responses. However, the final sample consisted of 276 participants due to missing answers and inconsistent replies. Office buildings were included in the sample based on three main criteria:

(1) **Having at least 20 occupants:** This criterion was chosen to ensure a diverse set of psycho-social characteristics among the occupants. Studying buildings with more occupants allows us to analyze energy-related behaviours influenced by their varied backgrounds, attitudes, and preferences. This diversity is crucial for understanding how different psycho-social clusters approach energy usage and conservation.
(2) **Operating under mixed-mode heating and cooling systems (with both natural and mechanical ventilation):** This criterion was selected to investigate the preferences and behaviours of occupants regarding their adjustment strategies. In buildings with mixed-mode systems, occupants can choose either natural ventilation (like opening windows) or mechanical ventilation (like air conditioning). This criterion allows for analyzing which adjustment strategies occupants prefer based on their psycho-social clusters.
(3) **Being no more than 25 years old:** This criterion ensures that the study focuses on structures with relatively modern infrastructure and HVAC systems since newer buildings are more likely to comply with current building standards and incorporate recent technological advancements.

The study seeks to gather detailed and relevant data on occupants' energy-related behaviours and preferences by selecting office buildings based on these criteria. This contributes to a better understanding of how modern office environments can be designed and managed to optimize energy efficiency while accommodating diverse psycho-social characteristics.

Table 1. The distribution of participants is based on the affiliation of office buildings and their respective private sectors.

	Sectors	n(%)
Ankara Chamber of Industry		
	Machine	40 (14.5)
	Business and Management	62 (22.5)
	Food	11 (4.0)
	Other	5 (1.8)
Ankara Chamber of Commerce		
	Finance	37 (13.4)
	Communication	15 (5.4)
	Transportation and Logistics	14 (5.0)
	Food	13 (4.7)
	Hotel Management	25 (9.1)
	Other	5 (1.8)
İstanbul Chamber of Industry		
	Electrical and Electronics	9 (3.3)
	Chemistry	13 (4.7)
İstanbul Chamber of Commerce		
	Finance	2 (0.7)
	Automotive	8 (2.9)
Muğla Chamber of Commerce		
	Transportation and Logistics	17 (6.2)
Total		276 (100)

Organizations affiliated with the chambers of industry and commerce in Ankara and İstanbul were invited to participate in an online email survey outlining the inclusion criteria for the study. Additionally, one invited organization extended its participation by including its sub-company in Muğla, affiliated with the Muğla Chamber of Commerce. Ultimately, office buildings that agreed to participate and met the inclusion criteria were recruited for the study. The participating organizations represented various private sectors such as machines, business and management, food, finance, communication, transportation and logistics, hotel management, electrical and electronics, chemistry, automotive, and transportation and logistics. The goal was to gather a diverse sample that reflected sector variations, participant demographics (age and gender), office layout and size, and climate. Table 1 illustrates the distribution of participants based on the affiliation of office buildings and their respective private sectors.

Data collection took place online using the SurveyMonkey platform, with participation from organizations that agreed to participate in the study. Ethical approval for the study was obtained from the Bilkent University Ethics Committee, ensuring the protection of participants' rights and privacy. Before beginning the survey, participants were provided with detailed information about the research and asked to sign a voluntary participation consent form in adherence to ethical guidelines. The research process is summarized in Figure 1.

2.2. Measures

An online survey was used to collect psycho-social behavioural data. The survey was developed as a questionnaire based on the constructs of the two theories: TPB (Ajzen 1991; Gao et al. 2017) and SDT (Budzanowska-Drzewiecka and Tutko 2021; Ryan and Deci 2000). The questionnaire was also expanded by adding two variables: habit (Verplanken and Sui 2019) and comfort (Agyekum, Hammond, and Salgin 2021; Lee, 2019). The survey aimed to assess constructs relevant to energy-saving behaviour and is expected to provide critical psycho-social insights for building energy efficiency solutions and simulation modeling. A more extensive and diverse sample of participants can be reached using an online questionnaire format. The survey was composed of five parts. The first part was the background section, which included questions about demographic information, office layout, office size, office location, and organization name. The second part used the TPB constructs: attitude (ATT)- 3 items; subjective norm (SN)- 3 items; perceived behavioural control (PBC)- 3 items (Ajzen 1991; Gao et al. 2017). The third part included the original SDT constructs: integrated regulation (INTEG)- 4 items; identified regulation (IDEN)- 3 items; introjected regulation (INTRO)- 4 items and external regulation (ER)- 4 items (Budzanowska-Drzewiecka and Tutko 2021; Ryan and Deci 2000). The fourth part included habit construct (H)- 6 items. The habit was measured using a self-report habit index developed by Verplanken and Sui (2019). The fifth part was comfort (C)- 6 items. To assess comfort, participants were asked to rate their general perception of various indoor environmental quality parameters in their offices, including indoor temperature, indoor air quality, natural lighting, and artificial lighting (Agyekum, Hammond, and Salgin 2021; Lee, 2019). The study did not include the acoustic environment in the questionnaire's comfort section because it focuses on factors directly influencing building energy consumption. While acoustic comfort is important for occupant satisfaction, especially in office settings (Wen et al. 2024), its impact on energy-related behaviour is more indirect. For instance, occupants might move to quieter areas in noisy environments like open-plan offices, leading to changes in energy use patterns. The 'Discussion and Conclusion' section further discusses the acoustic environment's significance in indoor environmental quality.

All the constructs were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). It is worth noting that the constructs were translated from English to Turkish. The questionnaire underwent a translation process, including translation into Turkish, back-translation into English to ensure accuracy, and evaluation by three content experts specializing in social psychology and human behaviour. Based on their feedback, some measurement items were modified in the Turkish version of the questionnaire to enhance its validity. A detailed explanation of the operational definition and measurement items for each construct was given in the Appendix.

2.3. Data analysis

The data analysis was conducted using IBM SPSS Statistics 29. From a total of 350 responses, incomplete or missing data were excluded, and responses with a standard deviation below 0.25 were removed. This resulted in 276 valid responses for further analysis.

First, descriptive statistics were analyzed to provide an overview of the study participants. Next, Principal Component Analysis (PCA) was performed on the psycho-social, motivational, habitual, and comfort variables, following the approach used in similar studies (Eijkelenboom and Bluyssen 2020; Ortiz and Bluyssen 2022; Zhang, Ortiz, and Bluyssen 2019). PCA is an exploratory data analysis method that captures dataset variations by reducing them to a smaller set of linearly uncorrelated variables known as principal components (PC) (Margaritis et al.

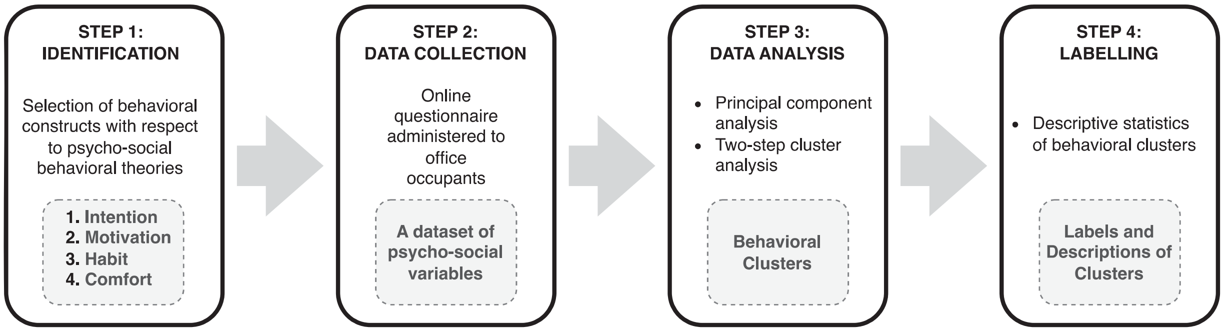

Figure 1. Process diagram of the study (drawn by the author, 2023).

2020). In this study, the goal of the PCA was to reduce the original number of psycho-social factors by replacing them with PCs while retaining the essential information with minimal loss.

The feasibility of PCA was assessed using the Kayser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity (BTS), where a p-value below 0.001 indicated appropriate data suitability. The number of PCs was determined based on eigenvalues greater than 1, KMO values exceeding 0.7, Varimax orthogonal rotation, and significant factor loadings of 0.4 or higher. PCA is often used as an initial step to reduce dimensionality before applying other multivariate techniques like cluster or discriminant analysis (Jolliffe 2002).

Subsequently, a Two-step cluster analysis was conducted using the PCs from the PCA to categorize the office workers based on their self-reported answers (Vajčnerová et al. 2016). Two-step cluster analysis was chosen for its ability to handle categorical and continuous data simultaneously, automatically identify the optimal number of clusters, and require minimal data preparation (Eijkelenboom and Bluyssen 2020). This method was suitable for analyzing demographic, intentional, motivational, habitual, and comfort data relevant to the present study's Akaike's Information Criterion, and log-likelihood distance measures were used for the analysis. The validation of the final model involved four steps: checking the silhouette measure coefficient (recommended value > 0.0 and preferably > 0.2), examining cluster differences (p-value < 0.05), controlling the predictor importance of variables (recommended > 0.02), and comparing the outcome of the model on two randomly split datasets. Finally, descriptive statistics for each cluster were analyzed to identify and label the obtained behavioural clusters. Figure 2 illustrates the process of the two-step cluster analysis.

3. Results

3.1. Descriptive analysis

In the descriptive analysis, Cronbach alpha values ranged from 0.732 to 0.956, indicating good reliability. The gender distribution was balanced, with 135 (48.9%) females and 141 (51.1%) males. The average age of the participants was 36.43 years (SD = 8.524). 65.9% of participants had a college degree ($n = 182$, 65.9%), while 15.9% ($n = 44$) completed senior high school or below, and 17.4% ($n = 48$) held a master's degree or higher. The office layout was equally divided between shared enclosed spaces and open-plan offices ($n = 111$, 40.2% each), with 19.6% ($n = 54$) occupying individual offices. The majority worked in small office rooms accommodating 1–4 occupants ($n = 122$, 44.2%), followed by large office rooms accommodating ten or more occupants ($n = 95$, 34.4%), and middle-sized office rooms accommodating 5–10 occupants ($n = 59$, 21.4%).

3.2. Principal component analysis

An initial PCA was performed with all 41 variables by 276 subjects. Based on the analysis, the KMO measure (KMO = 0.902, $p < 0.001$) and the BTS support the feasibility of conducting PCA. The analysis yielded seven components, explaining a cumulative variance of 72.004%. As illustrated in Table 2, the rotated component matrix revealed the following components:

- Component 1 (INHER): Represents inherent motivation, with an eigenvalue of 12.925, explaining 34.014% of the variance. It includes eleven items related to perceived behavioural control, intrinsic motivation, and regulation, with a high reliability (Cronbach's alpha = 0.940). Key variables like IM1, IM2, and PBC3 strongly contribute to this component.
- Component 2 (H): Associated with habitual energy-saving behaviour, this component has an eigenvalue of 4.718, explaining 12.417% of the variance. It includes five items, with significant loadings for H2, H3, and H4, reflecting the automatic nature of these behaviours (Cronbach's alpha = 0.892).
- Component 3 (C): Labelled 'comfort' relates to satisfaction with environmental factors like temperature and lighting. This component explains 7.794% of the variance with an eigenvalue of 2.962, and key loadings are found in variables C1, C2, and C3 (Cronbach's alpha = 0.871).
- Component 4 (INTRO): Represents 'introjected regulation', focusing on emotions like guilt and shame tied to not engaging in energy-saving behaviours. It has an eigenvalue of 2.093, accounting for 5.509% of the variance, with significant loadings on INTRO1-INTRO4 (Cronbach's alpha = 0.915).
- Component 5 (ER): Named 'external regulation', this component includes four items related to external motives, such as avoiding criticism and seeking approval. It explains 4.506% of the variance, with an eigenvalue of 1.712 (Cronbach's alpha = 0.912).
- Component 6 (ATT): Focuses on attitudes toward energy-saving behaviour, with three items assessing evaluations of such practices. It has an eigenvalue of 1.600, accounting for 4.210% of the variance, with high loadings on ATT1-ATT3 (Cronbach's alpha = 0.928).

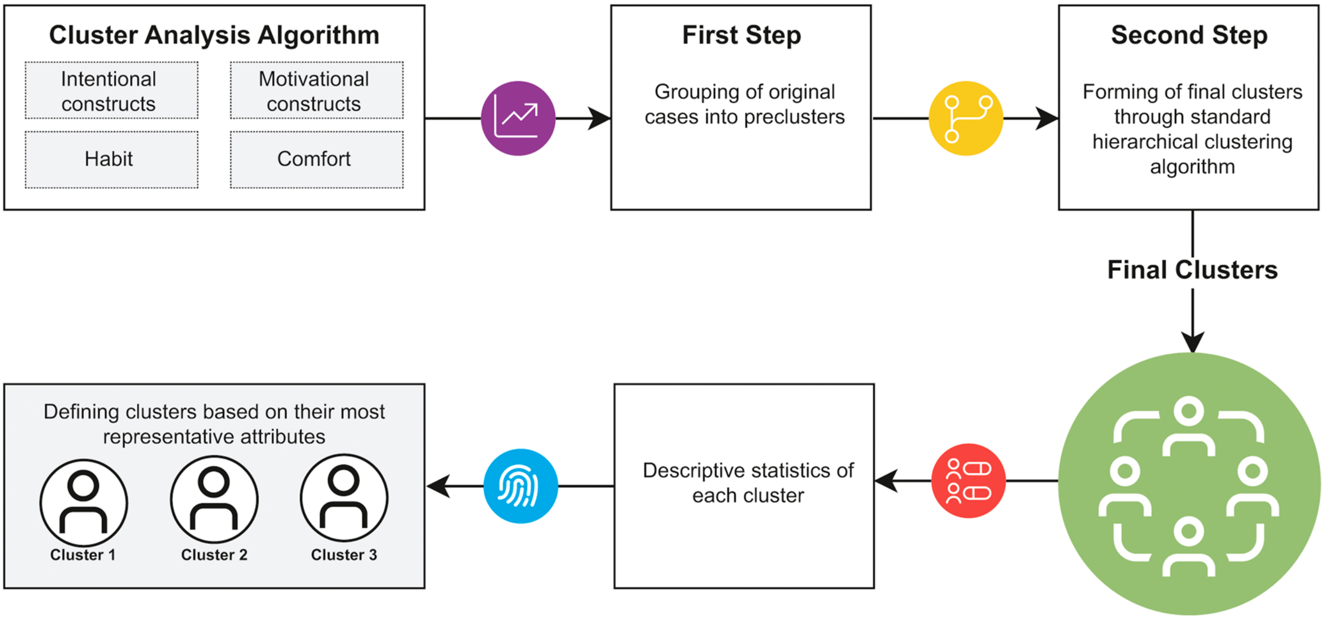

Figure 2. Two-step clustering process of the study (drawn by the author, 2023).

- Component 7 (SN): Related to 'subjective norm', this component includes three items reflecting societal expectations about energy-saving behaviour. It has an eigenvalue of 1.353, explaining 3.560% of the variance, with key loadings on SN1-SN3 (Cronbach's alpha = 0.828).

Consequently, the seven obtained components were considered new constructs for further analysis. The constructs are inherent motivation (INHER)- 11 items, habit (H)- 5 items, comfort (C)- 6 items, introjected regulation (INTRO)- 4 items, external regulation (ER)- 4 items, attitude (ATT)- 3 items, and subjective norm (SN)- 3 items.

3.3. Two-step cluster analysis

A two-step cluster analysis was conducted using the new variables derived from the seven components obtained from PCA to classify office occupants based on their intentional, motivational, habitual, and comfort expressions. Initially, there were 39 variables, but after PCA, it was found that three variables, PBC1, INTEG1, and H1 (see Table 2), did not belong to any of the seven components. Consequently, these three variables were excluded from further analysis, and the two-step cluster analysis proceeded with 36 variables. Demographic factors, office type, and office size were not considered in the clustering process to ensure the clusters were primarily based on relevant intentional, motivational, habitual, and comfort factors. The analysis yielded three clusters, namely Cluster 1 with 130 members (47.1%), Cluster 2 with 65 members (23.6%), and Cluster 3 with 81 members (29.3%). The final model's silhouette measure of cohesion and separation was 0.2, indicating a reasonable distinction between the clusters (Tkaczynski 2016).

The variable with the lowest predictor importance score was ER3, with a rating of 0.08, surpassing the recommended threshold of 0.02. On the other hand, IDEN2 had the highest predictor importance score of 1.00. The ANOVA results indicated that all 36 variables in the final analysis were statistically significant ($p < 0.001$), demonstrating substantial variations among the three identified clusters. The database was split into two to validate the cluster solution, and the results of the final solution were compared, revealing minor discrepancies, as seen in Table A2 in the Appendix. These findings supported the validity of the generated cluster solution (Norušis 2011).

3.4. Description of clusters

In this study, the identified clusters represented distinct groups of office occupants characterized by their prominent intentional, motivational, habitual, and comfort-related responses to office buildings and energy-saving behaviour. Following the principles of traditional clustering studies, it was suggested that individuals within each cluster share similar subconscious cognitive processes (Ortiz and Bluyssen 2018). This implies that members of a particular segment, such as office occupants, exhibit similar behavioural responses to specific environmental stimuli. Based on these descriptive findings, the clusters were labeled referring to their energy-saving behaviours as Cluster 1: '**Cautious Saver**', Cluster 2: '**Compelling Dissatisfied**', and Cluster 3: '**Coherent Potent**'. Table 3 provides a descriptive overview of each cluster, including background information, intentional and motivational characteristics, habitual tendencies, and comfort perceptions of the office occupants. Figure 3 illustrates the characteristics of clusters based on their psycho-social characteristics.

3.4.1. Cluster 1: cautious saver

- *Background information*: Cluster 1 ($n = 130$, 47.1%) is the largest and consists of participants with an average age of 35.30 years (SD = 8.354). In this cluster, 43.8% of participants ($n = 57$) were females, and 56.2% ($n = 73$) were males. 68.5% of participants ($n = 89$) had a college degree, while 18.5% ($n = 24$) had completed a master's degree or above, and 12.3% ($n = 16$) had completed senior high school or

Table 2. Component loadings, percentage of explained variance, and Eigenvalues of the seven components extracted from the PCA.

	Component						
	1	2	3	4	5	6	7
	Eigenvalue: 12.925 % of Variance: 34.014	Eigenvalue: 4.718 % of Variance: 12.417	Eigenvalue: 2.962 % of Variance: 7.794	Eigenvalue: 2.093 % of Variance: 5.509	Eigenvalue: 1.712 % of Variance: 4.506	Eigenvalue: 1.600 % of Variance: 4.210	Eigenvalue: 1.353 % of Variance: 3.560
ATT1						.844	
ATT2						.883	
ATT3						.820	
SN1							.781
SN2							.849
SN3							.808
PBC1**							
PBC2	.535						
PBC3	.856						
IM1	.873						
IM2	.889						
IM3	.878						
INTEG 1**							
INTEG2	.619						
INTEG3	.521						
INTEG4	.529						
IDEN1	.701						
IDEN2	.735						
IDEN3	.725						
INTRO1				.725			
INTRO2				.808			
INTRO3				.786			
INTRO4				.784			
ER1					.739		
ER2					.924		
ER3					.918		
ER4					.911		
C1			.733				
C2			.804				
C3			.867				
C4			.850				
C5			.585				
C6			.675				
H1**							
H2		.704					
H3		.776					
H4		.796					
H5		.787					
H6		.669					

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
*Rotation converged in 7 iterations.
**Removed variables for further analysis.
***ATT: Attitude, SB: Subjective norm, PBC: Perceived behavioural control, IM: Intrinsic motivation, INTEG: Integrated regulation, IDEN: Identified regulation, INTRO: Introjected regulation, ER: External regulation, C: Comfort, H: Habit.

below. In terms of office layout, 40.8% ($n = 53$) worked in open-plan offices, 39.2% ($n = 51$) in shared enclosed offices, and 20.0% ($n = 26$) in individual offices. Most participants (53,8%, n = 70) worked in small office rooms (1-4 occupants), followed by large office rooms (10+ occupants) at 29.2% ($n = 38$) and middle office rooms (5-10 occupants) at 16.9% ($n = 22$).

- *Intentional characteristics*: Cluster 1 had the highest mean scores for energy-saving ATT (4.6) and SN (3.9) compared to the other clusters.
- *Motivational characteristics:* Cluster 1 exhibited the highest mean score for overall INHER (4.7) and its components: PBC (4.7), intrinsic motivation (4.9), INTEG (4.5), and IDEN (4.9). They also had the highest mean score for INTRO (4.6). However, their mean score for ER (2.0) was not the highest among the clusters.
- *Habitual characteristics:* Cluster 1 demonstrated the highest energy-saving H (4.4) compared to other clusters.
- *Comfort:* Unlike other measurement items, the perceived comfort regarding IEQ in office buildings (3.5) was not the highest for Cluster 1.

3.4.2. *Cluster 2: compelling dissatisfied*

- *Background information:* Cluster 2 ($n = 65$, 23.6%) consisted of participants with an average age of 36.7 (SD = 7.960). In this cluster, 56.9% ($n = 37$) of participants were females, and 43.1% ($n = 28$) were males. Among the participants, 53.8% ($n = 35$) had a college degree, 16.9% ($n = 11$) had completed senior high school or below, and 29.2% ($n = 19$) had a master's degree or higher. In terms of office layout, 12.3% ($n = 8$) worked in individual offices, 41.5% ($n = 27$) in shared enclosed offices, and 46.2% ($n = 30$) in open-plan offices. The

Table 3. Characteristics of office occupants in different clusters.

	Cluster 1 130 (47.1)	Cluster 2 65 (23.6)	Cluster 3 81 (29.3)	Total 276 (100)
Background information				
Gender, *n* (%)				
• Female	57 (43.8)	37 (56.9)	41 (50.6)	135 (48.9)
• Male	73 (56.2)	28 (43.1)	40 (49.4)	141 (51.1)
Age, mean (SD)	35.30 (8.354)	36.7 (7.960)	38.05 (9.060)	36.43 (8.524)
Education, *n* (%)				
• Master's degree or above	24 (18.5)	19 (29.2)	5 (6.2)	48 (17.4)
• College or bachelor's degree	89 (68.5)	35 (53.8)	58 (71.6)	182 (65.9)
• Senior high school or below	16 (12.3)	11 (16.9)	17 (21.0)	44 (15.9)
Office layout, *n* (%)				
• Individual office	26 (20)	8 (12.3)	20 (24.7)	54 (19.6)
• Shared enclosed	51 (39.2)	27 (41.5)	33 (40.7)	111 (40.2)
• Open-plan	53 (40.8)	30 (46.2)	28 (34.6)	111 (40.2)
Office size, *n* (%)				
• Large office room (10 + occupants)	38 (29.2)	33 (50.8)	24 (29.6)	95 (34.4)
• Middle office room (5–10 occupants)	22 (16.9)	15 (23.1)	22 (27.2)	59 (21.4)
• Small office room (1–4 occupants)	70 (53.8)	17 (26.2)	35 (43.2)	122 (44.2)
Intentional characteristics, mean (SD)				
ATT	4.6 (0.7250)	3.4 (1.1796)	4.1 (0.5273)	4.2 (0.9316)
SN	3.9 (1.0614)	3.0 (0.9569)	3.7 (0.6433)	3.6 (0.9998)
Motivational characteristics, mean (SD)				
INHER	4.7 (0.2353)	3.9 (0.6011)	4.0 (0.1669)	4.3 (0.5242)
• PBC	4.7 (0.472)	3.9 (0.8075)	4.0 (0.4465)	4.3 (0.683)
• IM	4.9 (0.2843)	4.1 (0.7776)	4.1 (0.374)	4.4 (0.613)
• INTEG	4.5 (0.5953)	3.5 (0.836)	3.8 (0.4553)	4.0 (0.764)
• IDEN	4.9 (0.3156)	4.2 (0.6946)	4.0 (0.2516)	4.4 (0.5736)
INTRO	4.6 (0.4902)	3.5 (0.8770)	3.8 (0.4068)	4.1 (0.7450)
ER	2.0 (1.1911)	1.7 (0.5501)	2.5 (0.9744)	2.1 (1.0484)
Habitual characteristics, mean (SD)				
• H	4.4 (0.5848)	3.2 (0.7374)	3.9 (0.3729)	3.9 (0.7409)
Comfort, mean (SD)				
• C	3.5 (0.9159)	2.3 (0.7285)	3.8 (0.4228)	3.3 (0.9395)

[a]Cluster 1: Cautious Saver, Cluster 2: Compelling Dissatisfied, Cluster 3: Coherent Potent.
[b]ATT: Attitude, SB: Subjective norm, PBC: Perceived behavioural control, INHER: Inherent motivation, IM: Intrinsic motivation, INTEG: Integrated regulation, IDEN: Identified regulation, INTRO: Introjected regulation, ER: External regulation, C: Comfort, H: Habit.

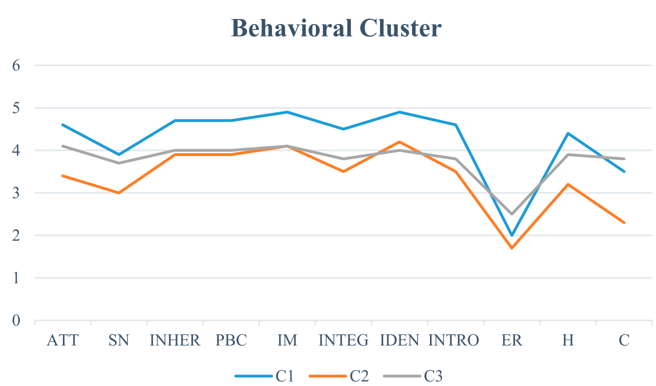

Figure 3. Psycho-social characteristics of behavioural clusters. [a] Cluster 1: Cautious Saver, Cluster 2: Compelling Dissatisfied, Cluster 3: Coherent Potent. [b] ATT: Attitude, SB: Subjective norm, PBC: Perceived behavioural control, INHER: Inherent motivation, IM: Intrinsic motivation, INTEG: Integrated regulation, IDEN: Identified regulation, INTRO: Introjected regulation, ER: External regulation, C: Comfort, H: Habit.

majority (50.8%, n = 33) worked in large office rooms (10+ occupants), followed by middle office rooms (5-10 occupants) at 23.1% (*n* = 15) and small office rooms (1-4 occupants) at 26.2% (*n* = 17).

- *Intentional characteristics:* Cluster 2 exhibited the lowest mean scores for ATT (3.4) and SN (3.0) towards energy-saving behaviour compared to the other clusters.
- *Motivational characteristics:* Cluster 2 had the lowest mean score (3.9) regarding overall INHER. Similarly, for PBC (3.9) and INTEG (3.5), Cluster 2 had the lowest mean scores. The mean score for IM (4.1) in Cluster 2 was the same as Cluster 3 but lower than Cluster 1. Only the mean score for IDEN (4.2) fell between the two clusters. The other motivational constructs in this cluster, including INTRO (3.5) and ER (1.7), showed the lowest mean scores compared to the other clusters.
- *Habitual characteristics:* Cluster 2 exhibited the lowest mean score (3.2) for energy-saving habits compared to the other clusters.
- *Comfort:* Cluster 2 had the lowest mean score (2.3) for C regarding IEQ in their work environments. Based on their low satisfaction rate towards their office environment and the lowest mean scores in psycho-social, overall motivational, and habitual constructs, this cluster was named the 'Compelling Dissatisfied Cluster'.

3.4.3. Cluster 3: coherent potent

- *Background information:* Cluster 3 (*n* = 81, 29.3%) consisted of participants with an average age of 38.05 (SD = 9.060).

50.6% ($n = 41$) were females (50.6%), and 49.4% ($n = 40$) were males in this cluster. Similar to the other clusters, the majority (71.6%, n = 58) of participants had a college degree, 21% ($n = 17$) had completed senior high school or below, and 6.2% ($n = 5$) had a master's degree or higher. In terms of office layout, 24.7% ($n = 20$) worked in individual offices, 40.7% ($n = 33$) in shared enclosed offices, and 34.6% ($n = 28$) in open-plan offices. The majority (43.2%, n = 35) worked in small office rooms (1-4 occupants), followed by large office rooms (10+ occupants) at 29.6% ($n = 24$) and middle office rooms (5-10 occupants) at 27.2% ($n = 22$).

- *Intentional characteristics:* The mean scores for ATT (4.1) and SN (3.7) in Cluster 3 fell between the mean scores of the other two clusters.
- *Motivational characteristics:* The overall INHER (4.0) in Cluster 3 fell between the two clusters. Motivational measurement items, including PBC (4.0), INTEG (3.8), IDEN (4.0), and INTRO (3.8), also fell between the mean scores of the other two clusters. The mean score for IM (4.1) was equal to Cluster 2 and lower than Cluster 1. ER (2.5) had the highest mean score among the clusters.
- *Habitual characteristics:* The mean score for energy-saving H (3.9) in Cluster 3 fell between the mean scores of the other two clusters.
- *Comfort:* Similar to other measurement items, the perceived C of occupants in Cluster 3 regarding the IEQ of their working environments fell between the mean scores of Cluster 1 and Cluster 2.

4. Clustering-based agent system (CAS)

To effectively incorporate the identified occupant clusters into building performance simulations, the study proposes the **Clustering-based Agent System (CAS)** utilizing an agent-based modeling (ABM) approach. ABM is an effective method for generating stochastic occupant behaviour models that closely replicate actual building occupants' behavioural patterns and interactions (Chapman, Siebers, and Robinson 2018). Reynaud et al. (2017) emphasized the ability of ABM to model reactive and adaptive individuals capable of collaborating to accomplish various tasks. Consequently, ABM is regarded as a more relevant approach that enhances the realism of simulated human activities compared to deterministic and stochastic models (Albouys-Perrois et al. 2022; Chapman, Siebers, and Robinson 2018; Simoiu et al. 2022).

ABM involves simulating the interactions of multiple autonomous agents within an environment. In building performance simulation, each agent represents an occupant or a group of occupants with distinct behaviour patterns and decision-making processes based on the identified clusters (Albouys-Perrois et al. 2022). Recent studies have demonstrated the effectiveness of ABM in capturing complex occupant behaviours within building environments. For instance, ABM has been utilized to model the impact of individual and collective occupant actions on building energy consumption, providing insights into potential energy savings through behaviour-driven interventions (Simoiu et al. 2022; Yue et al. 2020). The following section outlines the implementation of the proposed CAS using ABM and discusses its benefits and challenges.

4.1. CAS algorithm development

This study proposes the CAS, an ABM algorithm designed to simulate occupant behaviour in office buildings. The CAS integrates behavioural profiles of the identified clusters – 'Cautious Saver', 'Compelling Dissatisfied', and 'Coherent Potent' – into a building simulation environment to improve the accuracy of energy consumption predictions and occupant comfort analysis. This section provides a step-by-step guide to the algorithm's implementation, including the agents' decision-making process within the simulated environment. A flowchart of the decision-making process is provided in Figure 4, illustrating how agents navigate their environment, make adjustments, and interact with one another. The flowchart follows a structured approach from data availability to final simulation, incorporating steps to refine and rerun the simulation if necessary. This visual representation should help guide the implementation of the CAS algorithm in building performance simulation software.

4.2. Implementation

The first step in implementing the CAS algorithm involves initializing agents representing the different occupant clusters identified in the study: 'Cautious Saver', 'Compelling Dissatisfied', and 'Coherent Potent'. Each agent is assigned a unique profile derived from psycho-social data, encompassing parameters such as energy usage patterns, comfort preferences, and responsiveness to environmental changes. This initialization step is crucial as it defines each agent's baseline behaviours and decision-making processes within the simulation.

After initializing the agents, the next step is to define the simulated building environment. This environment includes spatial layouts, building systems (e.g. HVAC, lighting), and environmental variables (e.g. temperature, humidity). The building is divided into zones, such as individual offices, shared workspaces, and common areas, where agents will interact. The environment is set up to reflect real-world conditions as accurately as possible, ensuring that the interactions between agents and their surroundings can be realistically simulated.

The CAS algorithm's core lies in the agents' interaction and decision-making processes. Each agent follows a set of behavioural rules that dictate how it responds to environmental conditions and the actions of other agents. For example, an agent representing a 'Cautious Saver' might adjust the thermostat settings to conserve energy, while a 'Compelling Dissatisfied' agent might prioritize personal comfort over energy efficiency.

The decision-making process is dynamic, considering real-time environmental data (e.g. temperature, lighting levels) and predefined comfort thresholds. Agents evaluate their current environment against these thresholds and make decisions accordingly. This process is iterative, with agents continuously adjusting their behaviour based on feedback from the environment and interactions with other agents.

Once the agents and environment are defined, the simulation is executed over a specified period, such as a year. The simulation runs in real-time, with agents making decisions based on the changing conditions within the building. The goal of the simulation is to observe the emergent behaviours of the agents and

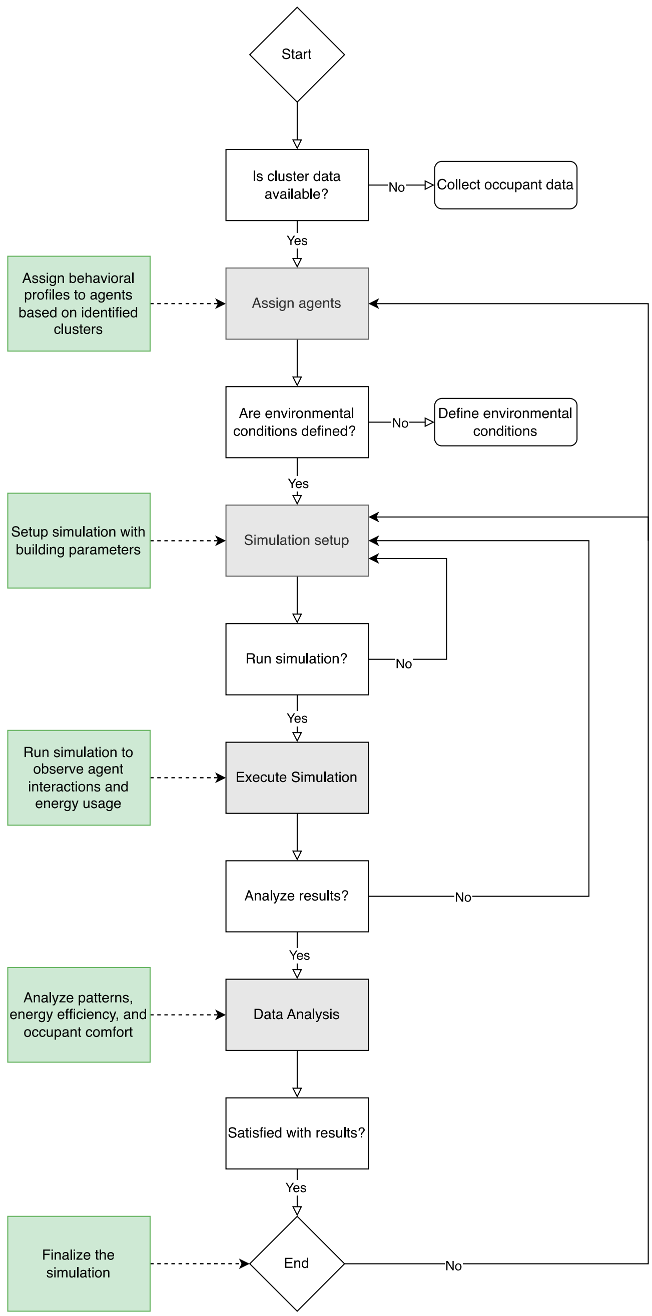

Figure 4. The proposed clustering-based agent system (CAS) approach framework.

their collective impact on the building's energy performance and occupant comfort levels.

Data on energy consumption, comfort levels, and agent behaviour are continuously collected during the simulation. This data is then analyzed to identify patterns and assess the effectiveness of different energy efficiency measures. The analysis also provides insights into how different occupant behaviours influence overall building performance, allowing for informed adjustments to building design and operation strategies.

The CAS approach offers several benefits. It provides a dynamic and adaptive simulation environment that captures real-time interactions and occupant adjustments to changing environmental conditions. This method enhances the accuracy of predictions regarding energy consumption and occupant comfort by modelling individual and group behaviours. Additionally, CAS is scalable, allowing it to be applied to buildings of various sizes and occupancy levels, making it versatile for different project requirements. Furthermore, CAS enables testing different energy-saving policies and control strategies by observing agent responses to various interventions.

5. Discussion and conclusion

This study aimed to enhance our understanding of energy-related behaviours in office buildings employing a psycho-social approach. This approach integrates theories of planned behaviour (TPB), self-determination theory (SDT), and considerations of habits and comfort perceptions. Demographic characteristics, including gender distribution, age, education level, office layout, and size, were crucial for understanding sample diversity. PCA identified seven components comprehensively explaining energy-related behaviour: INHER, H, C, INTRO, ER, ATT, and SN.

The two-step cluster classified office occupants into three distinct clusters: Cautious Saver, Compelling Dissatisfied, and Coherent Potent. Each cluster represents a unique group characterized by intentional, motivational, habitual, and comfort-related responses. The Cautious Saver cluster, demonstrating the highest mean scores for attitude (ATT $= 4.6$) and subjective norm (SN $= 3.9$), reflects a strong commitment to energy conservation and higher social influence. They also showed the highest levels of inherent motivation (4.7), intrinsic motivation (4.9), and perceived behavioural control (4.7), alongside strong energy-saving habits (H $= 4.4$). The Compelling Dissatisfied cluster, by contrast, had the lowest mean scores for ATT (3.4) and SN (3.0), along with the weakest motivational (e.g. INHER $= 3.2$) and habitual (H $= 3.2$) tendencies. Additionally, they reported the lowest comfort levels with a mean score of 2.3, aligning with their lower motivation and habitual scores. Lastly, the coherent cluster exhibited moderate scores across these factors, with ATT $= 4.1$, SN $= 3.7$, and H $= 3.9$, placing them between the other two clusters regarding energy-saving behaviours and comfort perceptions.

The findings of this study align with its objectives, providing a nuanced understanding of energy-related behaviours in office buildings through a psycho-social perspective. The clustering method successfully identified distinct behavioural patterns, revealing the complex interplay of intentional, motivational, habitual, and comfort factors influencing energy-saving behaviours. The study contributes to the existing body of knowledge by integrating multiple behavioural theories, addressing a research gap in understanding the holistic drivers of energy-saving behaviours in office settings. The insights gained can inform the development of targeted policies and interventions to promote energy efficiency in the workplace.

This study proposes using CAS to implement the identified behavioural clusters into building simulation tools. CAS allows for dynamic, adaptive simulations that capture office occupants' real-time interactions and behavioural adjustments. Integrating CAS into building performance simulations improves the accuracy of models for energy consumption and occupant comfort, contributing to occupant-centric design and operation strategies as emphasized in Annex 79 of the IEA.

5.1. Limitations

The number of clusters obtained in this study remained smaller than those of similar studies presented in the literature. For instance, Zhang, Ortiz, and Bluyssen (2019) identified six clusters of children based on their classroom preferences and needs. Similarly, Eijkelenboom and Bluyssen (2020) obtained six clusters of outpatient staff regarding their comfort and preference for indoor environmental quality. Ortiz and Bluyssen (2019) identified five clusters of home occupants considering their emotions and comfort. In a subsequent study, Ortiz and Bluyssen (2022) performed two cluster analyses for indoor environmental quality preferences and psycho-social comfort. They obtained four indoor environmental quality clusters and six psycho-social comfort clusters. Considering these results, the sample size of this study can be limited, where larger samples can be recruited in further studies to obtain more diversity.

Additionally, the sample in this study may not be fully representative. Reliance on self-report measures and a cross-sectional design introduces potential biases and limits causal interpretations. Excluding certain demographic factors and the questionnaire adaptation process may affect generalizability and measurement validity. Future research should address these limitations by incorporating more diverse samples.

This study primarily focused on factors directly influencing energy consumption in buildings, but it also acknowledges the importance of acoustic comfort in occupant satisfaction and behaviour. While not directly driving energy-related behaviours, acoustic comfort can indirectly affect energy use, particularly in office environments (Wen et al. 2024). For example, noise can lead to increased use of lighting or personal fans to maintain comfort or even cause occupants to work from home more often, shifting energy usage patterns. Although not included in this study's core analysis, acoustic comfort remains crucial to indoor environmental quality. Future research should explore its indirect impact on energy consumption to develop more comprehensive models.

Lastly, despite its advantages, the CAS approach presents several limitations. It can be computationally intensive, particularly in large buildings with many occupants, potentially leading to longer simulation times and the need for advanced computing resources. Accurate agent behaviour modelling requires detailed and high-quality data, which may be difficult to obtain or validate. Additionally, capturing the full spectrum of human behaviour and interactions is inherently complex, and simplifications may lead to less accurate representations. Ensuring that simulation outcomes accurately reflect real-world behaviours necessitates extensive validation, which can be resource-intensive.

5.2. Future research

Future research should focus on validating the CAS models in diverse built environments and exploring the potential of adaptive simulation tools that can dynamically respond to occupant behaviours and environmental changes. Additional field studies are recommended to measure the actions of these behavioural clusters in real-time, alongside simultaneous measurement of environmental parameters. Robust models can be developed by collecting data on how different behavioural clusters interact with varying indoor conditions. These models can then be implemented into simulation software as an extension, allowing for more precise simulations of occupant behaviour and its impact on energy consumption. Such an integrated approach can bridge the gap between predicted and actual energy usage, contributing to the design of energy-efficient buildings and effective energy management strategies.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability

Data will be made available on request.

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Appendix

Table A1. Constructs and measurement items in the study.

Construct	Operational definition	Items for measurement	Key references
Attitude (ATT)	An individual's overall assessment of regarding energy conservation in their workplace.	ATT1: I think that saving energy in my workplace is helpful for protecting the environment	(Ajzen 1991; Gao et al. 2017)
		ATT2: I think energy-saving behaviours in my workplace are a wise action	
		ATT3: I think energy-saving behaviours in my workplace are valuable for alleviating energy shortages.	
Subjective norm (SN)	An individual's perception of how significant individuals view their responsibility to engage in energy-saving behaviour within their workplace.	SN1: My colleagues think that I should save energy in my workplace.	(Ajzen 1991; Gao et al. 2017)
		SN2: My managers want me to save energy in my workplace.	
		SN3: People who are important to me want me to save energy in my workplace.	
Perceived behavioural control (PBC)	An individual's belief in their own resources and abilities to effectively engage in energy-saving behaviour within their workplace.	PBC1: I think that I am capable of saving energy in my company.	(Ajzen 1991; Gao et al. 2017)
		PBC2: I have the knowledge and skills to save energy in my company.	
		PBC3: Whether or not saving energy is entirely up to me.	
Intrinsic motivation (IM)	An individual's internal motivation and belief in their own ability to perform energy-saving behaviour in their workplace.	IM1: I derive pleasure from mastering new ways of helping.	(Budzanowska-Drzewiecka and Tutko 2021; Ryan and Deci 2000)
		IM2: I derive pleasure from improving the quality of the environment.	
		IM3: I derive pleasure from doing things for the environment.	
		IM4: I derive pleasure from contributing to the environment.	
	An individual's motivation influenced by external factors and external reasons to perform energy-saving behaviour in their workplace.	INTEG1: It is an integral part of my life	
		INTEG 2: It is inseparably linked with self-care	
		INTEG 3: It is my way of life	
		INTEG 4: It is a fundamental part of me	
		IDEN1: It is a sensible action	
		IDEN2: It is a way to contribute to the environment	
		IDEN3: It is an excellent idea to do something about the environment	
		INTRO1: I would regret it if I did nothing.	
		INTRO2: I would feel guilty if I did nothing.	
		INTRO3: I would feel bad if I did nothing.	
		INTRO4: I would be ashamed of my inactivity.	
		ER1: To avoid upsetting others	
		ER2: To gain approval	
		ER3: My friends insist	
		ER4: To avoid being criticized	
Habit (H)	An individual's spontaneous or automatic behavioural response to engage in energy-saving behaviour in their workplace.	H1: Saving energy in my workplace is something that gives me a strange feeling when I don't do it	(Verplanken and Sui 2019)
		H2: Saving energy in my workplace is something that I do automatically	
		H3: Saving energy in my workplace is something that I do without thinking about it	
		H4: Saving energy in my workplace is something that is part of my routine	
		H5: Saving energy in my workplace is something that is typical for me	
		H6: Saving energy in my workplace is something that does not require any active thought	
Comfort (C)	An individual's subjective satisfaction with the indoor environmental conditions in their workplace.	C1: I am satisfied with the temperature in my workplace	(Agyekum, Hammond, and Salgin 2021; Lee, 2019)
		C2: I am satisfied with the humidity in my workplace	
		C3: I am satisfied with the air quality in my workplace	
		C4: I am satisfied with the ventilation in my workplace	
		C5: I am satisfied with the amount of daylight in my workplace	
		C6: I am satisfied with the comfort of artificial lighting	

Table A2. Final solution variables and prediction importance.

Predictor Importance	Final Solution	First half solution	Second half solution
0.8–1.0	IDEN2 (1.00) IM3 (0.89) IDEN3 (0.87)	IDEN2 (1.00) IDEN3 (0.93) H3 (0.89)	IM3 (1.00) IM2 (0.98) IDEN2 (0.91) IM1 (0.87) IDEN3 (0.86) INTEG2 (0.82) IDEN1 (0.82)
0.6–0.79	IM2 (0.75) IDEN1 (0.72) INTEG2 (0.70) H3 (0.69) IM1 (0.69) INTRO2 (0.65) H2 (0.61)	IM3 (0.85) H2 (0.79) IM2 (0.78) H4 (0.74) INTRO2 (0.72) IM1 (0.71) INTEG2 (0.70) INTEG4 (0.63) C4 (0.63) INTRO1 (0.60) PBC3 (0.60)	PBC3 (0.63) INTRO2 (0.62)
0.4–0.59	C4 (0.59) INTRO3 (0.59) PBC3 (0.58) H4 (0.57) INTRO1(0.55) PBC2 (0.55) INTEG4 (0.54) C3 (0.51) INTEG3 (0.51) H5 (0.50) C1 (0.48)	INTEG3 (0.57) IDEN1 (0.54) INTRO3 (0.53) ATT2 (0.52) INTRO4 (0.51) ATT3 (0.50) ATT1 (0.50) C3 (0.50) PBC2 (0.49) C1 (0.49) H5 (0.47)	INTRO3 (0.57) H5 (0.52) INTRO1 (0.49) H2 (0.48) PBC2 (0.48)
0.2–0.39	INTRO4 (0.38) ATT2 (0.38) ATT3 (0.34) H6 (0.25) SN3 (0.24) C6 (0.20)	C2 (0.32) H6 (0.31) C5 (0.29) SN3 (0.24) C6 (0.21)	H3 (0.39) H4 (0.37) C3 (0.34) ATT2 (0.33) ATT1 (0.28) C5 (0.27) INTEG4 (0.26) ATT3 (0.26) INTEG3 (0.25) C4 (0.25) INTRO4 (0.25) C6 (0.22) H6 (0.20)
0.00–0.19	SN2 (0.16) C5 (0.15) ER4 (0.13) ER3 (0.13) SN1 (0.10) ER1 (0.09) ER2 (0.08)	SN2 (0.19) ER3 (0.19) SN1 (0.19) ER4 (0.18) ER2 (0.14) ER1 (0.09)	SN3 (0.18) SN2 (0.17) SN1 (0.11) C1 (0.11) ER3 (0.09) C2 (0.08) ER4 (0.07) ER2 (0.06) ER1 (0.02)

[a]ATT: Attitude, SB: Subjective norm, PBC: Perceived behavioural control, IM: Intrinsic motivation, INTEG: Integrated regulation, IDEN: Identified regulation, INTRO: Introjected regulation, ER: External regulation, C: Comfort, H: Habit.