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Decoding urban energy use variability: A bottom-up approach in Ecuador

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ABSTRACT

Energy consumption is crucial for economic development and individual well-being, particularly in densely populated urban areas. This study examines energy consumption patterns in Ecuadorian urban households using a bottom-up approach and clustering techniques to identify trends, socioeconomic disparities, and potential opportunities for demand management. Primary data from Quito (620 observations) and Guayaquil (474 observations) were used. A structured three-phase selection process successfully narrowed 48 initial variables to seven, significantly improving segmentation accuracy. The optimal 2-cluster solution revealed significant disparities in income, housing characteristics, and resource access. Income emerged as a key determinant of technology adoption and energy usage, highlighting socioeconomic gaps. The findings provide valuable insights for policymakers by emphasizing energy services' importance for economic and personal advancement. The reliance on fossil fuels and the pressing need for decarbonization necessitate transitioning to more sustainable energy systems. By identifying distinct consumption profiles and the influence of income on technology and energy usage, this study can inform demand management strategies, promote energy-saving initiatives, and facilitate the adoption of cleaner technologies. It is essential to raise awareness of the social impact of energy subsidies and to encourage a shift in consumer behavior through education and incentives for responsible energy consumption in Ecuador.

1. Introduction

Reliable energy services are essential for societies to function effectively. They meet fundamental human needs and support the production of goods and services, enhancing overall societal well-being and prosperity [1]. Consequently, energy emerges as a crucial factor in driving economic development [2,3] and individual progress [4]. Nevertheless, energy requirements depend on the development and progression within their socioeconomic frameworks. These dynamics are shaped by many factors, including geographical location, technological advancements, and user characteristics [1,6,7]. The bottom-up (BU) approach enables a comprehensive analysis of the energy landscape at the sectoral level [8], providing valuable insights into consumer behavior and energy consumption patterns that emerge from diverse activities. Consequently, the analysis of disaggregated data is instrumental in informing the assessment of public policies designed to foster the efficient management of energy demand [5].

The increasing energy demand, coupled with rapid technological advancements and population growth, has increased reliance on fossil fuels, such as gasoline and diesel. These energy sources are significant contributors to carbon dioxide (CO_2) emissions, a major greenhouse gas linked to climate change [9]. While the proportion of renewable energy in the global energy mix is growing, it is still insufficient to reduce increasing CO_2 emissions [10]. Tackling this issue demands enhanced efforts toward decarbonizing the energy sector, emphasizing the need to transform energy generation methods and adjust consumption patterns to boost efficiency and sustainability.

This study employs the BU approach to analyze the behavior of energy consumers within the urban residential sector of Ecuador. It utilizes primary data and clustering techniques based on the profiling of energy consumers in urban residential areas. The clustering findings are constructed, compared, and discussed at two levels to explore the distinctions among different consumers. The first level involves three clusters, which is the recommended number for grouping according to the analysis. The second level consists of two clusters, a relevant segmentation that incorporates essential aspects providing insight into the data that explains the behavior of urban consumer residents. The model initially included 48 endogenous and exogenous variables to categorize

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urban households. A structured three-phase variable selection approach was applied: first, related variables were grouped to enhance interpretability and reduce dimensionality; second, using Multiple Correspondence Analysis (MCA), redundant variables were eliminated based on their statistical contributions; and third, consumer perception and preference variables were excluded to minimize subjectivity and noise. This process led to the selection of 16 variables. However, further refined to 7 key variables that define the country's energy consumption patterns. These homogenizing variables were crucial for distinguishing household profiles, reducing unnecessary variability, and improving the clarity and accuracy of the clustering results.

Through this process, we gained a deeper understanding of the energy consumption behaviors in Ecuador, ensuring that the profiles accurately reflect the underlying patterns in both urban centers. These were applied to household typologies using the K-means clustering algorithm, displaying the resulting profiles in 4 categories: i) Spatial and sociodemographic characteristics (SSC), ii) Family and housing structure (FHS), iii) Infrastructure and energy consumption patterns (ICP), and iv) Eco-innovation process (EIP).

The Eco-innovation process (EIP) within the urban residential sector was assessed across four stages based on environmental awareness: i) Notion and reflection, ii) Cognitive stage, iii) Experimentation and action, and iv) Attitude and lifestyle. A 4-point Likert scale was utilized to gauge responses, with categories ranging from Total disagreement (1 = Not acceptable) to Total agreement (4 = Outstanding).

The findings elucidate differences among profiles, highlighting that a milestone related to monthly income determines whether a household can acquire goods. Consequently, high-income households can decide which technology to use for cooking and water heating. In contrast, low-income households are constrained in using electric showers and LPG stoves. Similarly, the former have overcome the gap that allows them to acquire their own vehicle, turning them into direct consumers of liquid fuels.

Based on the above, the study aims to address two research questions: i) What similarities and disparities exist among household profiles regarding energy consumption and its related aspects? and ii) What strategies could promote the adoption of more responsible energy consumption households?

Therefore, distinguishing between energy-consuming household profiles facilitates the development of strategies to manage energy demand in the country. For instance, high-income households, which often have more opportunities to adopt energy-saving measures, should prioritize raising awareness. On the other hand, policy strategies that encourage a gradual transition away from outdated and polluting technologies are expected for low-income households. Overall, Ecuadorian society and much of the world must enhance their knowledge and awareness of energy consumption, particularly regarding the true energy cost and the inequities associated with current subsidies.

Consequently, this research fills a significant gap in the literature by providing a comprehensive understanding of energy consumption dynamics and demand management across various scales. Utilizing Ecuador as a case study, it uniquely employs a bottom-up (BU) approach and incorporates eco-innovation as a practical management tool. A notable innovation of this study is the application of exploratory clustering techniques to identify and refine household profiles through an iterative process, uncovering country-specific characteristics and distinguishing factors. This methodology enriches our understanding of energy consumption patterns and offers a replicable framework for sustainable energy planning in developing regions.

The article is structured as follows: Section 2 explains the drivers of household energy consumption and the theoretical model of energy consumption behavior developed by Araujo et al. [11] using the BU approach and the eco-innovation concept. Section 3 details our methods, which include a variable selection procedure, determining the number of clusters, and cluster modeling. Section 4 presents the results of constructing, comparing, evaluating, and discussing clustering findings at two levels (3 and 2 clusters). Section 5 provides a deeper understanding of the profiles through homogenization analysis, validation, and cluster refinement, improving the accuracy of household segmentation. Furthermore, strategies to promote more responsible energy consumption are outlined. Finally, Section 6 summarizes the conclusions drawn from the study.

2. Theoretical background

2.1. Drivers of urban residential energy consumption behavior

Energy consumption is deeply embedded in the cultural, political, and economic systems of countries [12]. Although it has been suggested that developing countries may show greater awareness in terms of energy [13], changing consumption patterns presents a significant challenge for all regions [14,15].

Understanding the drivers that explain the behavior of energy end-users is crucial in this context. Given that households constitute the core of society and ensure the continuity of socially accepted paradigms, the study of residential consumers becomes essential [16]. For households, energy commodities are fundamental inputs representing a significant family budget component [1,17].

Therefore, analyzing the structuring, composition, dynamics, perceptions, and knowledge of energy consumption is essential to understanding household energy consumption behavior. This approach will contribute to formulating strategies that promote transformations in consumption patterns [18]. Among the variables and relationships identified in the literature review that have a direct connection with the increase in energy consumption in the urban residential sector are:

i) Urbanization dynamics typically promote economic growth, which is reflected in household incomes. In turn, higher-income households enhance their purchasing power; therefore, they have more appliances, electronic devices, vehicles, and larger homes (square meters of construction) [19,20]. These control variables resulting from higher incomes imply higher energy consumption.
ii) One significant factor impacting energy consumption is energy prices, which are often influenced by energy subsidies. Consequently, low energy prices relative to incomes do not incentivize fundamental behavior changes [13].
iii) Family size is a factor that will drive higher energy consumption, as more people need to meet their basic needs, comfort, and lifestyle requirements [19,21].
iv) The education level of the household head is positively related to an increase in household income and is also an indirect driver of higher energy consumption [13,22,23].

Now, among the determinants that seem to have an inverse relationship with decreasing energy consumption, the following were identified:

v) Comprehensive and stringent environmental regulations [20,24], energy knowledge likely to materialize into concrete actions [15,25], and technological changes that demonstrate incremental improvements, focusing on replacing obsolete technologies and acquiring more efficient products at the household level [15,24,26,27]. These efforts fall within the concept of eco-innovation or sustainability-oriented innovation, which includes changes in production patterns and the acceptance and consumption of technologies, products, processes, services, market approaches, and organizational structures that reduce the environmental impact of the economy and daily activities [11,28].

Eco-innovation stands out as a key management tool, with consensus on its primary objective of reducing environmental impacts [29–32].

These innovations should aim to meet needs and improve the quality of life [33], emphasizing that eco-innovation is more than just a healing technology; it constitutes a broad and multifaceted process [34].

In this context, both internal and external factors play a crucial role in driving eco-innovation [31,35], which, in the case of the study, aims to promote responsible energy consumption. Consequently, it is necessary to consider consumers' multidimensional nature, practices, and dynamics to identify eco-innovation drivers that break down barriers and enable fundamental changes [16,36]. An important aspect is that internal drivers may have a more significant impact than external ones, as systems have limited control over external factors [31]. As a result, increasing knowledge exchange and collaboration are crucial aspects of these processes [37].

Consequently, eco-innovation involves changes in the approaches to the production, marketing, and consumption of technologies, processes, and services. It also encompasses measures to reduce the environmental impact of economic and daily activities, promoting the efficient and responsible use of resources. Thus, eco-innovation emerges as a novel management strategy among many that can contribute to generating real changes.

2.2. Conceptual model of energy consumption for the urban residential sector

The conceptual model integrates endogenous and exogenous variables distributed across four categories according to Araujo et al. [11], Vasseur et al. [38], and Ofetotse et al. [39], namely: i) Spatial and sociodemographic characteristics (SSC), ii) Family and housing structure (FHS), iii) Infrastructure and energy consumption patterns (ICP), and iv) Eco-innovation process (EIP), as shown in Table 1.[1]

The endogenous variables are divided into: i) Urban/rural area disaggregation (Na), ii) Geographic disaggregation (Ng), iii) Housing location (Nl), iv) Monthly energy income and expenses (Ns), v) Family structure and head of household characteristics (Nf), vi) Description and type of housing (Nh), vii) Infrastructure and patterns of use of appliances and devices (Nd), viii) Infrastructure and patterns of use of private vehicles (Nv), and ix) Eco-innovation covering the stages of Notion and reflection, Cognitive, Experimentation and action, and Attitude (Nei) related to energy consumption. On the other hand, exogenous variables in the system, cutting across the four categories, play a significant role in household energy consumption patterns. The Price of energy by fuel type (PE) is the predominant economic aspect. Non-economic aspects include Technological and market trends (TMT), Ecological cultural atmosphere (ECA), and Current energy laws and regulations (ELR).

3. Methodology and data

This study utilized primary data collected through simple random sampling in Ecuador's two largest cities. In Quito, 620 observations were gathered in October 2021, while in Guayaquil, 474 observations were obtained in August 2022, totaling 1094 observations. Together, these cities represent approximately 5.5 million residents and 1.46 million households, accounting for over 32 % of all households in the country [40]. The sample size surpasses the minimum requirement of 385 households per city, calculated based on a 95 % confidence level with a 5 % margin of error. This ensures that the sample is statistically representative and significantly reduces bias in the results. The research adopts a disaggregated analysis within the BU approach, utilizing 48 endogenous and exogenous variables to classify urban households. The considerable number of variables affecting the energy consumption of urban households and their interrelationships necessitates diverse techniques to comprehend these behaviors.

After a comprehensive review of the primary dataset, the data underwent systematic processing and preparation for in-depth analytical exploration. Critical steps included identifying relevant variables, transforming numerical data into categorical formats, and aggregating related variables. As noted by Ofetotse et al. [39], feature selection significantly enhances quality and helps minimize unnecessary noise. The inclusion of all variables can compromise analytical effectiveness, as overly broad variable subsets often fail to capture the dataset's complexity, leading to poor clustering outcomes [39]. Consequently, a total of 16 variables were carefully selected for analysis, facilitating the extraction of household typologies through the K-means clustering method. The data cleaning, processing, and analysis were performed using the R programming language.

The normalization process standardized the data by centering and scaling. Centering involved subtracting each column's mean to achieve a mean of zero, while scaling divided the centered values by their standard deviation, resulting in all variables having a standard deviation of one. This ensured comparability across variables and improved the reliability of the analysis [39,41].

Following normalization, the K-means clustering technique was employed to reveal patterns and group the data into coherent clusters. This iterative process confirmed cluster consistency and relevance by assessing their alignment with the dataset. The data was rescaled to its original units to ensure interpretability and practical applicability in real-world scenarios. K-eans is a widely utilized unsupervised learning algorithm that partitions data into clusters by assigning each data point to the nearest centroid while minimizing the sum of squared distances within clusters. The algorithm iteratively reduces intra-cluster inertia [42,43], defined by Eq. (1):

$$\mathrm{minimise}(\mathrm{W_k}) = \sum_{r=1}^{k} \frac{1}{\mathrm{n_r}} \mathrm{D_r} \tag{1}$$

where W_k represents the average intra-cluster sum of squares, k is the number of clusters, n_r is the total number of points in the cluster r, and D_r

Table 1
Conceptual model of urban residential energy consumption (Araujo et al. [11].

Categories	Spatial and sociodemographic characteristics (SSC)		Family and housing structure (FHS)		Infrastructure and energy consumption patterns (ICP)		Eco-innovation process (EIP)	
Endogenous Variables	Na	Disaggregation into urban and rural areas	Nf	Family structure and characteristics of the head of household	Nd	Infrastructure and patterns of use of artifacts and devices	Nei	Notion and reflection
	Ng	Geographical disaggregation	Nh	Description and type of dwelling	Nv	Infrastructure and patterns of use of own vehicles		Cognitive
	Nl	Location of housing in parishes						Experimentation and action
	Ns	Income and monthly energy expenses						Attitude and lifestyle
Exogenous Variables	**PE** – Price of energy by type of fuel **TMT** – Technological and market trends **ECA** – Ecological cultural atmosphere **ELR** – Current energy laws and regulations							

is the sum of distances between points within the cluster.

K-means clustering is particularly effective for analyzing energy consumption. It categorizes households with similar usage behaviors, providing policymakers with actionable insights to develop targeted strategies [39,44]. By clustering consumers based on their behaviors, K-means aids in formulating tailored, data-driven policies that address the specific needs of distinct groups and promote efficient energy utilization. Implementing computations in R, utilizing the K-means() function from the statistics package, provides a streamlined approach to clustering analysis. This function allows users to specify the desired number of clusters and generates essential statistical outputs, such as the within-cluster sum of squares, facilitating detailed and comprehensive analysis [45]."

Moreover, the NbClust package enhances the clustering process by providing 30 different indices to identify the optimal number of clusters, strengthening the validity and reliability of the results [44]. This study refined an initial three-cluster solution to two, revealing distinct consumer profiles based on factors such as appliance ownership, electronic device usage, vehicle ownership, and energy expenditures.

This methodology uncovered key homogenizing variables, including the number of Household Members (Variable 4, FHS1), with the majority of households consisting of four members; the Gender of the Household Head (Variable 5, FHS2), which is predominantly male; Age (Variable 6, FHS3), typically ranging from 35 to 44 years; and Weekly Vehicle Use (Variable 9, ICP4), which averages 3.5 h and shows slight variation across profiles. Additionally, the Eco-Innovation Process (EIP) category was re-evaluated, resulting in the exclusion of four variables (EIP1 to EIP4, Variables 13–16). This finding underscores a limited culture of eco-innovation and responsible energy consumption within the population.

Ultimately, geographical disaggregation (Variable 1, SSC1) was excluded after an analysis of variance (ANOVA), which indicated no statistically significant differences among city profiles. This finding shows minimal influence on cluster differentiation, justifying the decision to refine the dataset by focusing on variables that offer meaningful contributions to the cluster analysis.

As a result, a new K-means clustering analysis was conducted utilizing a refined set of 7 variables, resulting in an enhanced evaluation of cluster outcomes and a clearer understanding of household profiles. The refinement significantly improved the accuracy of the analysis, leading to a more profound understanding of household behavior. Fig. 1 displays the methodology employed to identify household clusters based on their energy consumption patterns and behaviors.

3.1. Variable selection procedure

The theoretical model comprises 48 variables designed to categorize urban household consumers [11]. As Ofetotse et al. [39] demonstrate, feature selection plays a crucial role in enhancing clustering quality and minimizing noise. However, including all variables can reduce effectiveness, as excessively broad subsets often do not capture the dataset's complexity, leading to suboptimal clustering results [39].

To address this issue, a systematic variable selection methodology was implemented in three distinct phases. Initially, related variables were grouped to enhance interpretability and effectively reduce dimensionality. Next, redundant variables were removed based on their statistical significance and contributions. Finally, variables related to consumer perception and preference were excluded to minimize subjectivity and extraneous noise. This comprehensive and structured approach, illustrated in Fig. 2, ensured that only the most relevant variables remained for analysis.

Initially, the related variables were systematically categorized based on their functional roles, as they represent similar underlying dynamics. This methodological choice improves interpretability and reduces dimensionality, aligning with the findings of Ofetotse et al. [39]. By merging comparable variables, the information is effectively condensed into a more manageable set of dimensions, facilitating a streamlined analytical process and allowing for a focused assessment of the results. This approach not only clarifies the dataset but also helps to reveal more significant patterns that might otherwise remain hidden due to excessive dimensionality.

For instance, (Variable 3, SSC3), from the Spatial and Sociodemographic Characteristics (SSC) category, titled Monthly Energy Expenses, aggregates five components related to household expenditures on electricity, LPG, low-octane gasoline, premium gasoline, and diesel. (Variable 9, ICP1), designated Total Appliances encompasses information on eight different household appliances. Meanwhile, (Variable 10, ICP2), labeled Total Electronic Devices, joins data from five distinct types of electronic devices. In addition, variables on the Eco-Innovation process have been organized into stages: (Variable 13, EIP1) represents Notion and Reflection, (Variable 14, EIP2) corresponds to the Cognitive Stage, (Variable 15, EIP3) reflects Experimentation and Action, and (Variable 16, EIP4) signifies Attitude and Lifestyle. This iterative grouping process reduced the dataset of 48 variables to 25.

At this point, Multiple Correspondence Analysis (MCA) was performed to identify redundant variables, following the methodology outlined by Hisschemöller et al. [46]. This analytical method was chosen because it effectively clarifies complex relationships among multiple categorical variables and reveals hidden patterns and associations

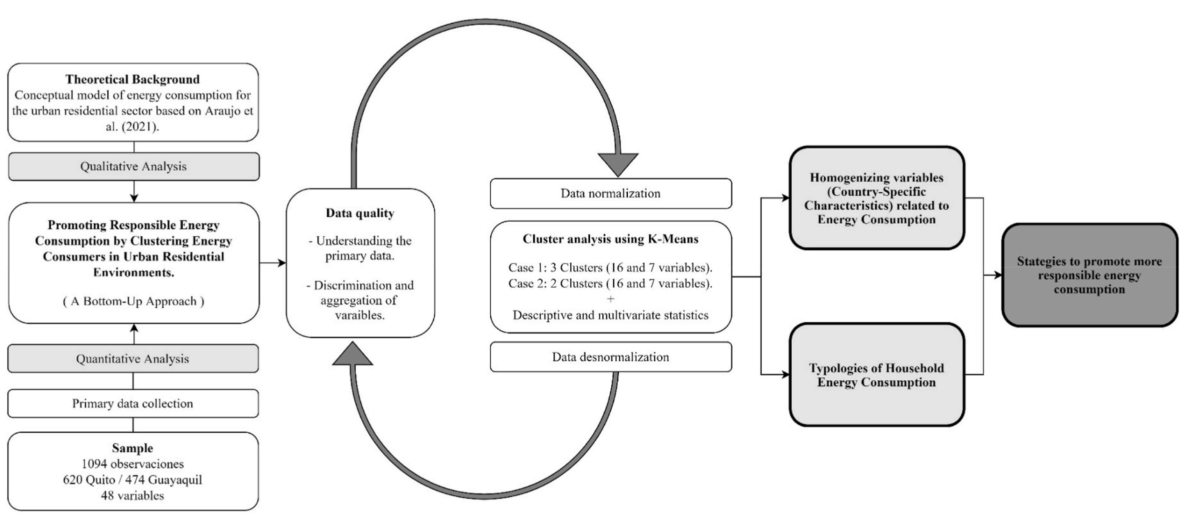


Fig. 1. Research methodology.

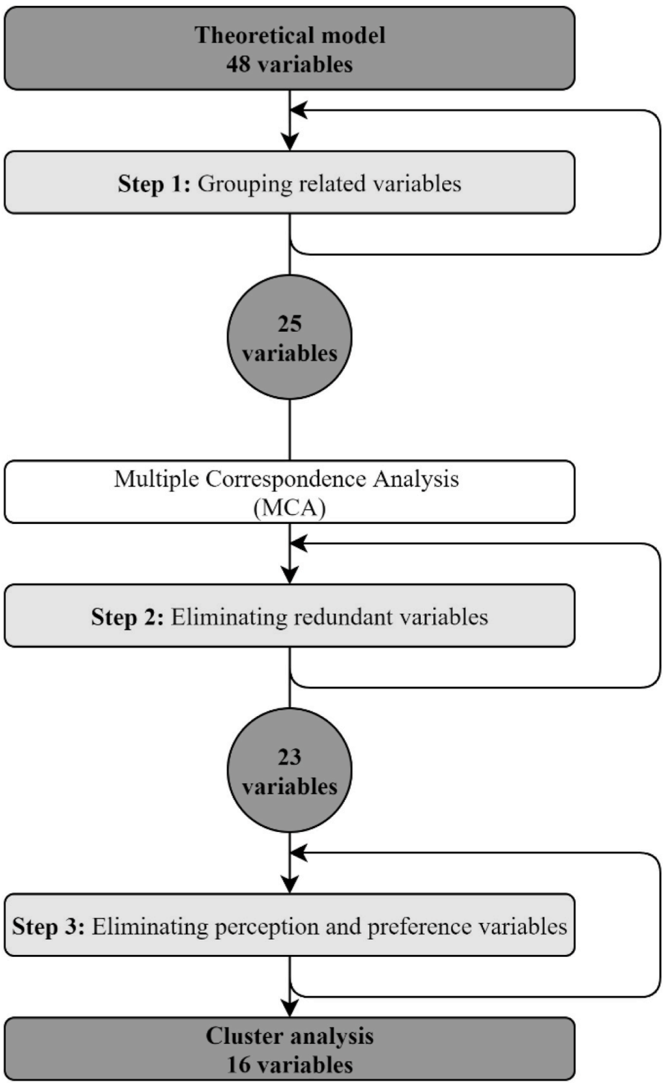


Fig. 2. Structured variable selection process for clustering analysis.

within the dataset.

In the second step, redundancies among variables were systematically addressed and eliminated. For instance, the City and District Zone pair includes only two categorical levels—Quito and Guayaquil—while the latter features a more nuanced categorization with 27 levels. The contribution of the City variable to the main dimensions (Dim 1 and Dim 2) of the Multiple Correspondence Analysis (MCA) is relatively balanced between Quito and Guayaquil, suggesting that this variable effectively captures the structural variability inherent in the dataset. In contrast, the District Zone shows a significant disparity in contribution values across its various categories, which may negatively affect the robustness of the analysis by introducing extraneous variance. Consequently, the District Zone variable was removed to facilitate the retention of Geographical Disaggregation (Variable 1, SSC1). Similarly, for the Housing Construction Area and Type of Construction variables, the former was retained and corresponds to Variable 8, FHS5. At this point, the dataset was reduced to 23 variables.

In the third step, variables related to consumer perception and preferences were systematically excluded after a thorough examination of the data and the study's contextual framework using the methodology outlined in Ref. [39]. These variables, which are inherently subjective and open-ended, do not produce precise or consistent patterns suitable for clustering analysis. Instead, they tend to introduce variability that does not align with stable groupings. However, this exclusion does not diminish the potential significance of these variables. Rather, they provide valuable contextual insights that enhance the understanding of the data and facilitate a more nuanced interpretation of consumer behavior within the specific context of the study. The excluded variables were: i) Preference for cooking technologies, ii) Preference for heating technology, iii) Main purpose of using electronic devices at home, and responses to the following questions: iv) What is the first image or word that comes to mind when you think about the energy sector? v) What is the main problem that Ecuador's energy sector should solve? vi) What motivates you to take action toward efficient energy consumption? vii) What additional measures would encourage you to engage more effectively in optimal energy use?

In this way, a structured selection of variables was implemented to ensure a comprehensive evaluation of the data. As shown in Fig. 3, 16 key variables were selected to analyze and extract household typologies using the K-means clustering technique. This process resulted in a more focused and interpretable subset of variables, effectively reducing uncertainty within the model and enhancing its relevance. By refining the selection, we emphasized the most impactful factors, leading to more precise insights and a robust analysis.

3.2. Determining the number of clusters

A combination of methods was utilized to determine the optimal number of clusters, ensuring robustness and reliability. The Silhouette Graphical Method was applied as recommended by García et al. [43], Ofetotse et al. [39], and Santoso and Magdalena [47]. Additionally, the NbClust package in R, which evaluates 30 indices to identify the optimal cluster count, was employed in accordance with Amitha et al. [48] and Malatesta and Breadsell [44].

The Silhouette Graphical Method indicated that three clusters provided the best separation and cohesion, as shown in Fig. 4 (a). The NbClust results revealed that nine methods recommended a three-cluster solution, six suggested two clusters, three proposed ten clusters, and two supported either zero or four clusters, as depicted in Fig. 4 (b). Given the strong agreement between the results of the Silhouette Graphical Method and most NbClust indices, the three-cluster solution was prioritized for further analysis. However, the second-best option, the two-cluster solution, was also explored to enable a comprehensive comparison.

3.3. Models of clusters

The analysis concluded that three and two profiles are suitable for characterizing energy consumers in the urban residential sector of the case study. At this point, descriptive and multivariate statistical techniques were utilized to establish the properties and differences of the resulting profiles. The analysis of the 16 variables facilitates the identification of common factors among energy consumers in Ecuador. These variables do not undermine the model, as they provide a more accurate depiction of the population, which, in turn, becomes a defining characteristic of the country. This refinement allowed for a new K-means clustering analysis using a reduced set of seven variables, improving the assessment of cluster outcomes and delivering a clearer understanding of household profiles. This analysis reinforces the findings and is detailed in Section 5.2: Cluster Refinement: Homogenization Analysis and Cluster Validation.

Consequently, the research establishes a baseline that explains the behavioral patterns of energy consumers in the urban residential sector under a BU approach, supported by eco-innovation as a novel management tool. This contributes to understanding domestic energy consumption dynamics in developing countries' urban areas. The characteristics of the constructed clusters will be detailed, and the discussion will expand on the analysis of similarities and differences between clusters. Relevant relationships and identified barriers are presented. Thus, the work delves into understanding the variables and

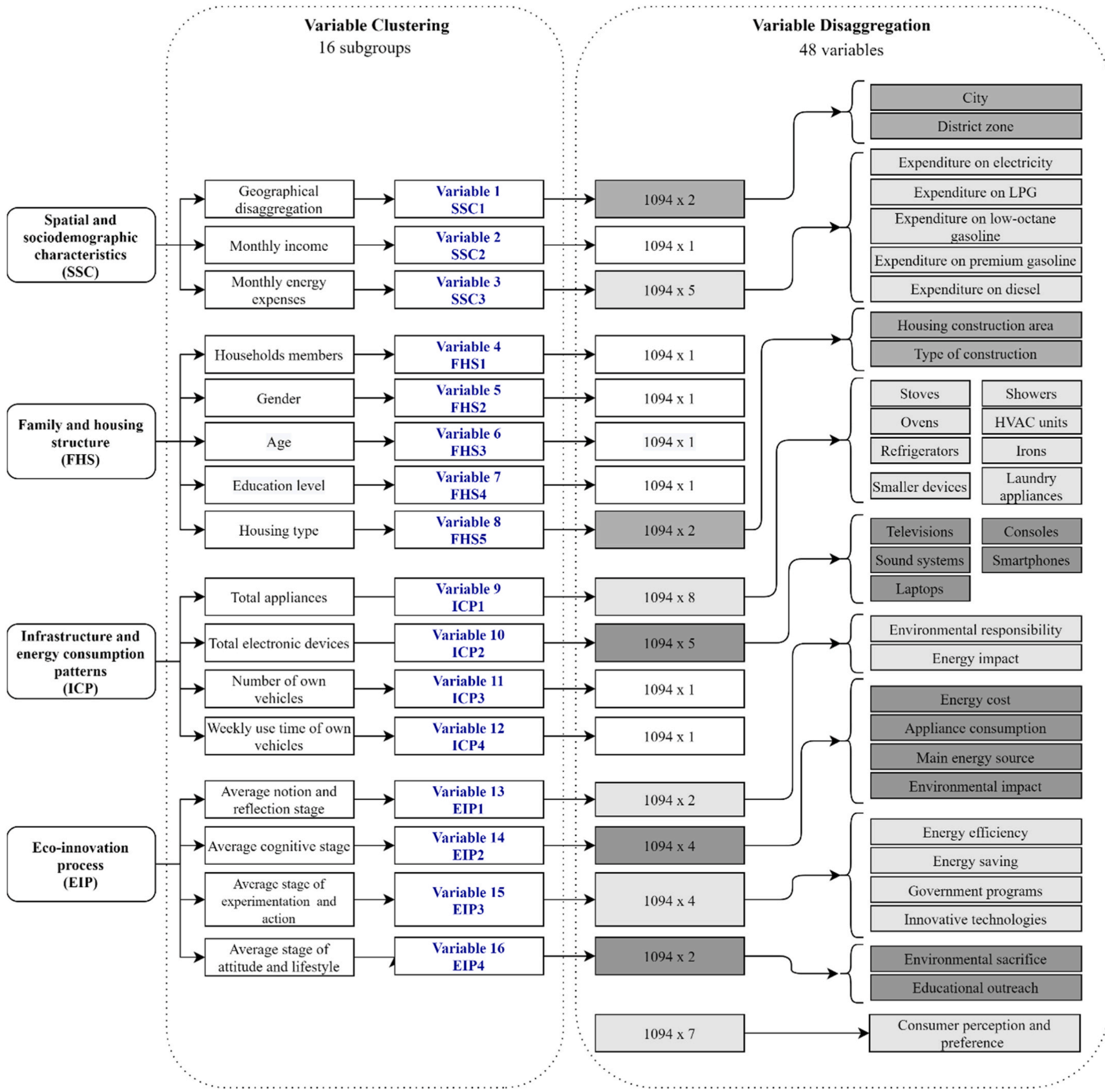


Fig. 3. Data attributes and vector sizes for clustering analysis.

their relationships that explain energy consumer behavior, followed by proposing various tactics aimed at promoting responsible energy consumption in similar contexts.

4. Results

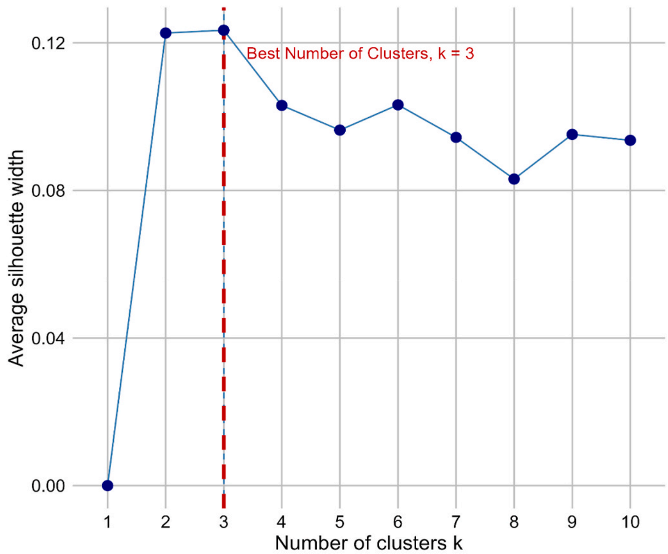
4.1. Characteristics of the clusters

The cluster analysis categorizes households based on energy consumption and income levels. CASE 1 identifies three clusters with varying energy expenses and appliance usage, while CASE 2 simplifies the segmentation into two clusters, highlighting differences in energy consumption and vehicle ownership. Below are the key characteristics of each cluster.

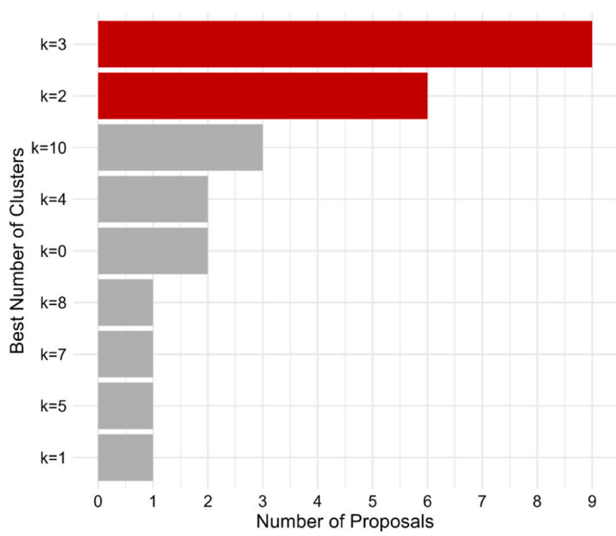
CASE 1 [3 clusters – 16 variables]

- Cluster 1.1 – HT1.1 (31.7 %, 347 observations): High-income households are characterized by the highest energy expenses and consistent vehicle ownership.
- Cluster 1.2 – HT1.2 (48.3 %, 528 observations): Mid-income households with moderate energy expenses, no vehicle ownership, and slightly higher appliance usage than HT1.3.
- Cluster 1.3 – HT1.3 (20.0 %, 219 observations): Low-income households with the lowest energy expenses, minimal appliance usage, and no vehicle ownership.

CASE 2 [2 clusters – 16 variables]



(a) Silhouette Graphical Method



(b) NbClust results

Fig. 4. Determination of the optimal number of clusters.

- Cluster 2.1 – HT2.1 (45.7 %, 500 observations): High-income households with the highest energy expenses and consistent vehicle ownership.
- Cluster 2.2 – HT2.2 (54.3 %, 594 observations): Low- and mid-income households with lower energy expenses and no vehicle ownership. The profiles derived from the cluster analysis are detailed in Table 2.

4.1.1. Spatial and sociodemographic characteristics (SSC)

In CASE 1 [3 clusters – 16 variables], Cluster 1.1 (HT1.1) comprises households with monthly incomes ranging from \$523.00 to \$1291.00. These households allocate between \$60.01 and \$80.00 to monthly energy expenses, with an average expenditure of \$70.00. Approximately 50 % of this amount is spent on gasoline, 40 % on electricity, and 10 % on liquefied petroleum gas (LPG). An examination of petroleum prices reveals the impact of liquid fuel subsidies in Ecuador; for instance, in 2016, the price of a liter of gasoline was \$0.61, compared to \$0.68 in Colombia and \$0.99 in Peru [49]. In response to these prices, Executive Decree 619 (2018) resulted in the liberalization of premium gasoline prices [50], and Executive Decree 1054 (2020) established a pricing system with monthly adjustments and fluctuation bands for low-octane gasoline and diesel prices [51].

Regarding electricity, the government introduced the "Dignity Rate" in 2007, which set residential tariffs at \$0.04 per kWh for low-consumption households. However, by 2022 [52], electricity prices had risen to \$0.0929 per kWh, while actual costs were estimated to be between \$0.14 and \$0.16 per kWh [53].

In terms of LPG, Ecuador has implemented substantial subsidies, making this fuel widely preferred for cooking in approximately 85 % of urban homes. The government has maintained a fixed price of \$1.60 for 15 kg LPG cylinders since 2000 [54], despite the estimated actual cost per cylinder being about \$15.00 [55].

Clusters 1.2 (HT1.2) and 1.3 (HT1.3) consist of households with incomes below \$522.00, who allocate between \$20.01 and \$40.00 for energy expenses, averaging around \$30.00. For these clusters, 80 % of their energy expenditure is devoted to electricity, while the remaining 20 % is spent on LPG. Notably, neither cluster reports owning vehicles, indicating that LPG and electricity are essential energy sources for households across all income levels.

In CASE 2 [2 clusters – 16 variables], the distinction between groups is more evident. Cluster 2.1 (HT2.1) includes households with monthly incomes ranging from \$523.00 to \$1291.00, averaging \$70.00 in energy expenses, which is similar to Cluster 1.1. Conversely, Cluster 2.2 (HT2.2) consists of households with incomes below \$522.00, incurring monthly energy expenses of about \$30.00, with 80 % of that allocated to electricity and 20 % to LPG.

4.1.2. Family and housing structure (FHS)

In all groups, households predominantly consist of four individuals. The household heads, who are predominantly male, have an average age of 35–54. Additionally, these households can be located in either Quito or Guayaquil.

For CASE 1 [3 clusters – 16 variables], the highest level of education completed by the household head for HT1.1 is third-level education, while for HT1.2 and HT1.3, it is secondary education. HT1.1 and HT1.2 live in homes with 2–3 bedrooms, 2 bathrooms, a kitchen, a living room, and a dining room, with construction areas ranging from 100 to 150 m^2. In contrast, HT1.3 households live in homes with 1–2 bedrooms, a bathroom, a kitchen, and a social area, with construction areas under 100 m^2.

For CASE 2 [2 clusters – 16 variables], household heads in HT2.1 have completed third-level education, while those in HT2.2 have secondary education. The former group resides in homes with construction areas between 100 and 150 m^2, while the latter lives in homes with construction areas less than 100 m^2.

4.1.3. Infrastructure and household energy consumption patterns (ICP)

For the cluster analysis, variables including the total number of appliances and electronic devices in the home were used. In both cases, it was found that the number of appliances and electronic devices increases with income level. It is noteworthy that HT1.1 and HT2.1 households have their own vehicles and therefore record direct use of gasoline.

4.1.4. Eco-innovation process based on the notion of environmental awareness (EIP)

Since the Eco-innovation process aims to understand how households engage with responsible energy thinking and behavior, four progressive stages were evaluated: the Notion and Reflection stage, the Cognitive stage, the Experimentation and Action stage, and finally, the Attitude and Lifestyle stage, all related to responsible energy consumption.

In CASE 1 [3 clusters – 16 variables], HT1.1 (higher-income) had the

Table 2
Characterization of typologies CASE 1 [3 clusters] and CASE 2 [2 clusters] with 16 variables.

Variable	CASE 1 [3 clusters]			CASE 2 [2 clusters]	
	Cluster 1.1 HT1.1	Cluster 1.2 HT1.2	Cluster 1.3 HT1.3	Cluster 2.1 HT2.1	Cluster 2.2 HT2.2
Number of observations	347	528	219	500	594
City	Quito	Quito	Guayaquil	Quito	Guayaquil
Gender	M	M	M	M	M/F
Age [years]	45 to 54	35 to 44	35 to 44	35 to 44	35 to 44
Education	Completed third level education	Completed secondary school	Completed secondary school	Completed third level education	Completed secondary school
Number of members	4	4	3	4	4
Construction area and type of home	2/3 bedrooms, 2 bathrooms, kitchen, living room, and dining room = 100–150 m^2	2/3 bedrooms, 2 bathrooms, kitchen, living room, and dining room = 100–150 m^2	1/2 bedrooms, one bathroom, kitchen, and social area = less than 100 m^2	2/3 bedrooms, 2 bathrooms, kitchen, living room, and dining room = 100–150 m^2	1/2 bedrooms, one bathroom, kitchen, and social area = less than 100 m^2
Monthly income	Between $523.00 and $1291.00	Less than $522.00	Less than $522.00	Between $523.00 and $1291.00	Less than $522.00
Monthly energy expenditure	Between $60.01 and $80.00	Between $20.01 and $40.00	Between $20.01 and $40.00	Between $60.01 and $80.00	Between $20.01 and $40.00
Total number of appliances	9	7	6	9	6
Total number of electronic devices	9	6	5	9	5
Number of owned vehicles	1	0	0	1	0
Average stage of awareness and reflection	3.362	3.559	2.941	3.423	2.961
Average cognitive stage	3.249	3.429	2.245	3.320	2.979
Average action stage	2.630	3.045	2.022	2.797	2.634
Average attitude and lifestyle stage	2.566	3.135	2.187	2.758	2.771

highest scores at all stages: 3.362 in the notion stage, 3.249 in the cognition stage, 2.630 in the action stage, and 2.566 in the attitude stage. HT1.2 had slightly lower scores, while HT1.3 had the lowest scores, with 1.941 in the notion stage and 2.187 in the attitude stage. The lower-income group showed lower scores across all stages.

In CASE 2 [2 clusters – 16 variables], HT2.1 outperformed HT2.2, achieving scores of 3.423 compared to 2.961 in the notion stage and 3.320 versus 2.979 in the cognitive stage, among others.

The analysis reveals a disparity in energy consumption behaviors among income groups, with higher-income households showing more involvement in energy-related actions. However, the differences are not substantial enough to be deemed significant, indicating that the variations in energy consumption behaviors are not as pronounced as anticipated. Both cases illustrate a decline in scores as energy consumption behaviors grow more complex, emphasizing that efforts to enhance energy literacy and eco-friendly practices should aim to close this gap and promote more sustainable consumption patterns across all income levels.

4.2. Cluster evaluation

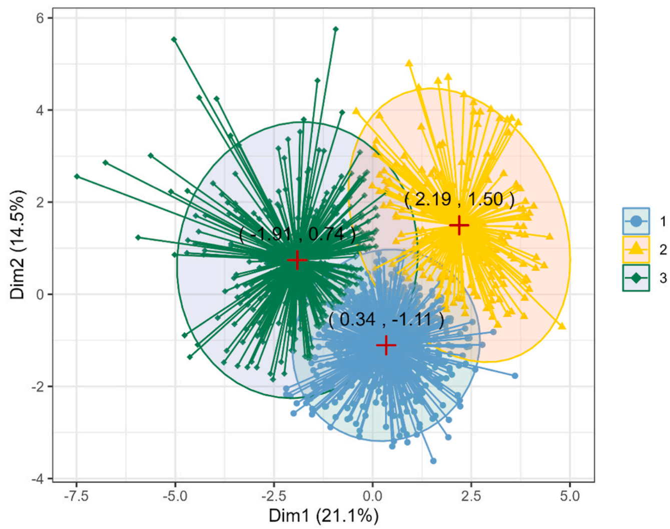
Since the study utilizes a cross-sectional dataset, internal (unsupervised) assessments were performed to measure the quality of the constructed clusters without requiring external information. Fig. 5 shows the graphical representation of the clusters created for the two analyses. Similar to the studies conducted by García et al. [43] and Ofetotse et al. [39], the evaluation was carried out using the Davies-Bouldin Index and the Silhouette Coefficient.

i) Davies-Bouldin Index: This measure provides insights into the cohesion and separation of clusters. Cohesion indicates how close two points within a cluster are, while separation measures the distance between two clusters and their centroids. This index can take values ranging from 0 to infinity, with 0 representing the optimal clustering value [39,43,47].
ii) Silhouette Coefficient: This metric ranges from −1 to 1 and evaluates an individual point's average distance from the centroid to the other points within the cluster. For two clusters, it reflects the average distance to the points in the opposite cluster. A value closer to 1 indicates better clustering [39,43,47].

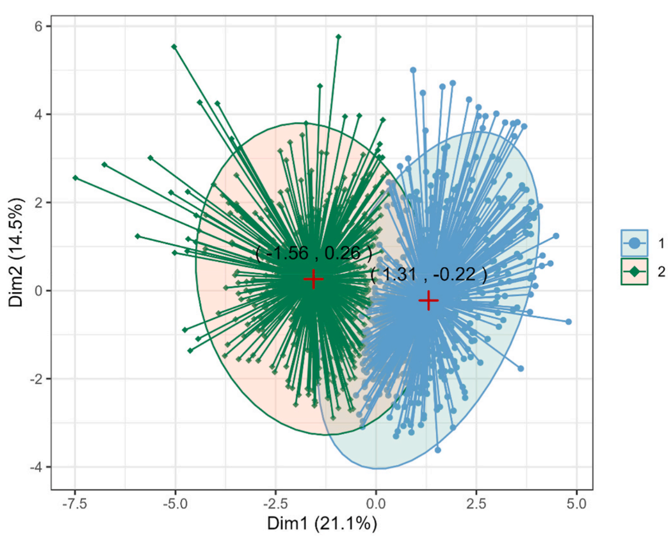
The results are similar in both cases. For CASE 1 [3 clusters – 16 variables], the Davies-Bouldin Index is 0.65195, and the Silhouette Coefficient is 0.09. For CASE 2 [2 clusters – 16 variables], the values obtained are 0.66198 and 0.16, respectively.

The Davies-Bouldin Index shows a slightly higher value for CASE 2 (0.66198) compared to CASE 1 (0.65195), indicating that the 2-cluster solution exhibits marginally less compactness and separation than the 3-cluster solution. However, this difference is minimal, suggesting that the two clustering solutions are relatively similar in their overall separation and compactness. The Silhouette Coefficient for both cases remain low, with CASE 1 showing a notably lower value of 0.09 compared to CASE 2 at 0.16. A low Silhouette value shows that the elements within each cluster are not distinctly separated from those in other clusters, implying that the clustering may require further refinement. While the 2-cluster solution demonstrates slightly better cohesion and separation than the 3-cluster solution, both approaches reveal low Silhouette values.

Notably, the CASE 2 solution provides a more balanced segmentation with superior overall separation. While the differences are modest, the clustering results offer valuable insights into energy consumption patterns within the urban residential sector of Ecuador. These findings suggest that the identified clusters are significant and serve as a basis for further analysis and categorization of households based on their energy consumption behaviors. Consequently, in the discussion, we will redefine these clusters by addressing the homogenizing variables identified in this preliminary analysis to strengthen both the robustness and



(a) CASE 1 [3 clusters]



(b) CASE 2 [2 clusters]

Fig. 5. Graphical representation of clusters CASE 1 [3 clusters], CASE 2 [2 clusters] with 16 variables.

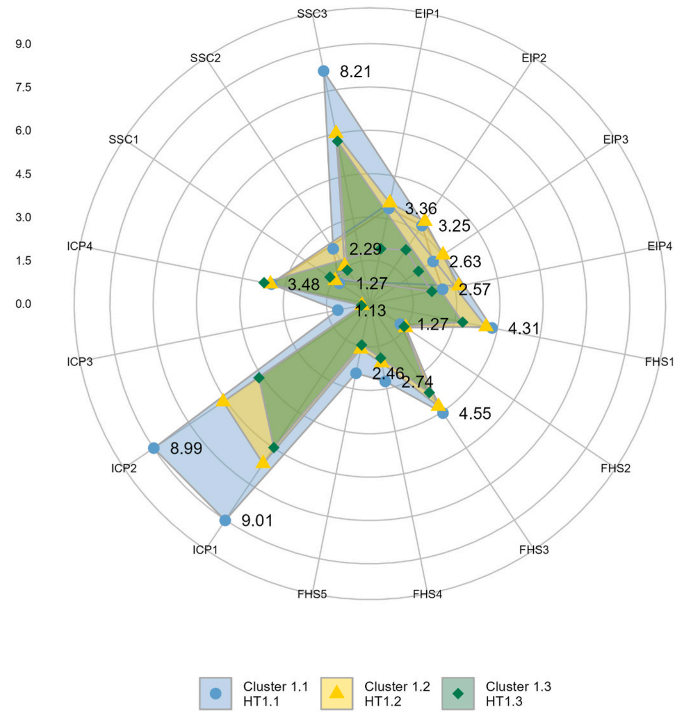
applicability of the results.

5. Discussion and tactics to encourage a more responsible energy consumption

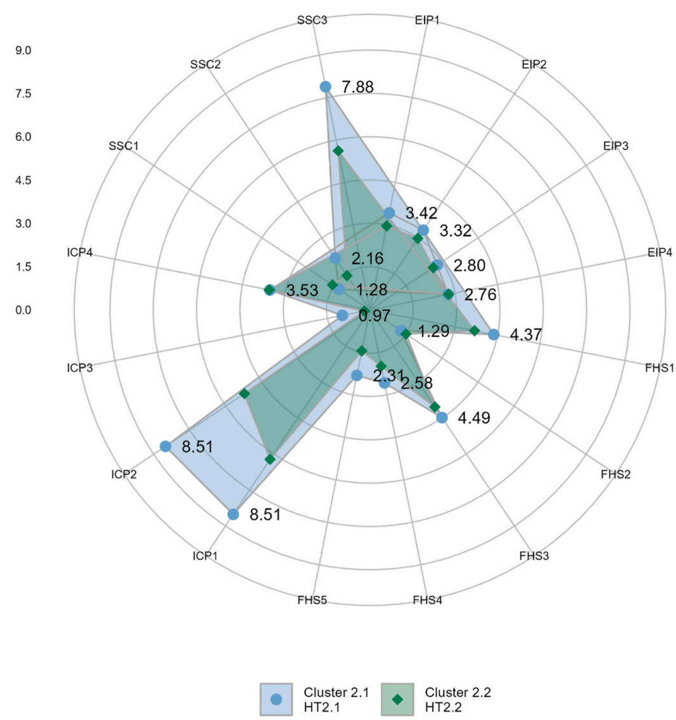
Fig. 6 presents the assessment of the typologies resulting from the cluster analysis in CASE 1 [3 clusters – 16 variables] and CASE 2 [2 clusters – 16 variables], allowing for the visualization of similarities and differences between the clusters and the identification of relevant relationships and barriers.

5.1. Similarities and differences between the clusters

For CASE 1 [3 clusters – 16 variables], HT1.2 and HT1.3 households are similar in Spatial and Sociodemographic Characteristics (SSC), Family and Housing Structure (FHS), and Home Energy Consumption Infrastructure and Patterns (ICP). Both have incomes below $522.00 and allocate an average of $30.00 to energy expenses for LPG and electricity. HT1.1 households with higher incomes show higher values in the Eco-innovation Process (EIP) and are the highest energy consumers.



(a) CASE 1 [3 clusters 16 variables].



(b) CASE 2 [2 clusters – 16 variables]

Fig. 6. Comparison of the characterization of the resulting typologies from the cluster analysis.

For CASE 2 [2 clusters – 16 variables], HT2.1 households with higher incomes show higher values in the SSC, FHS, and ICP categories. HT2.2 households have lower incomes and show subtle differences in the Eco-innovation Process (EIP), indicating favorable but not profound environmental awareness.

The comparison of both analyses shows that HT1.1 households from

CASE 1 are the same as HT2.1 from CASE 2. HT1.3 households from CASE 1 resemble HT2.2 from CASE 2, with HT2.2 showing higher EIP ratings. HT2.2 households are an average of HT1.2 and HT1.3 households. In conclusion, intra-cluster analysis highlights modest disparities in energy consumption behaviors, with higher-income households showing slightly greater engagement in energy-related behaviors.

However, these differences are not statistically significant, underscoring the importance of enhancing energy literacy and eco-friendly practices across all income groups to foster sustainable consumption patterns. Additionally, the comparison between CASE 1 and CASE 2 reveals similar outcomes. The 2-cluster solution shows better cohesion and separation, as indicated by a higher Silhouette Coefficient (0.16 versus 0.09), suggesting it may be more effective for identifying distinct energy consumption patterns. These findings provide a structured basis for further analysis.

5.2. Cluster refinement: Homogenization Analysis and Cluster Validation

5.2.1. Homogenization and exclusion of non-significant variables

The identification of homogenizing variables—shared characteristics that enable the grouping or classification of individuals within the dataset—was a key step in this study. Nine variables were identified that homogenize the population, including Household Members (Variable 4, FHS1), where most households consist of four members; Gender (Variable 5, FHS2), which is predominantly male; and Age (Variable 6, FHS3), which typically falls between 35 and 44 years. Additionally, the variable Weekly Use Time of Own Vehicles (Variable 12, ICP4) averaged 3.5 h.

The entire Eco-Innovation Process (EIP) category was re-evaluated, leading to the exclusion of four variables (EIP1 to EIP4, Variables 13 to 16) due to insignificant differences across the four developmental stages. This reflects that, despite technological advancements or public policies, individuals have not adopted sustainable practices nor developed sufficient environmental awareness, demonstrating a limited culture of eco-innovation and responsible energy consumption.

Ultimately, Geographical Disaggregation (Variable 1, SSC1) was excluded after assessing its significance in differentiating clusters. An Analysis of Variance (ANOVA) was performed to validate this decision and to compare variances among city profiles. The results indicated no statistically significant differences, confirming that geographical disaggregation had no meaningful impact. This finding further supported the refinement of the dataset, allowing for the prioritization of variables that substantially contribute to cluster differentiation. A one-factor ANOVA was conducted to compare energy consumption between Quito and Guayaquil, yielding $F(1) = 0.1698$, $p > 0.05$, which suggests no significant differences between the two cities. Essentially, Ecuador enjoys a mild climate all year round, and no notable differences were observed between the cities, with other factors, such as income, proving to be more critical for differentiating the profiles.

In summary, the analysis and exclusion of nine non-significant variables facilitated the identification of common patterns based on shared characteristics. This refinement illuminated the key factors influencing energy consumption behaviors, enhanced the clustering process, and provided a more precise understanding of the energy consumer profile [39].

5.2.2. Refined cluster characteristics and evaluation

This refinement enabled a new K-means clustering analysis using 7 variables, enhancing the clarity and efficiency of the process. The silhouette method suggested 2 clusters, while the NbClust package identified 3 clusters as the optimal solution, supported by 10 methods, with 7 favoring 2 clusters. Below are the key characteristics of CASE 1 (3 clusters) and CASE 2 (2 clusters).

CASE 1 [3 clusters - 7 variables]

- Cluster 1.1 – HT1.1 (19.7 %, 215 observations): High-income households ($1292–$2460) living in larger homes with 3–4 bedrooms, 3 bathrooms, and areas between 150 and 200 m^2. These households reported the highest energy expenses ($60–$80 per month), owned an average of 10 appliances, and consistently reported vehicle ownership.
- Cluster 1.2 – HT1.2 (50.5 %, 552 observations): Mid-income households ($523–$1291) living in homes with 2–3 bedrooms, 2 bathrooms, and areas between 100 and 150 m^2. These households reported moderate energy expenses ($20–$40 per month), owned an average of 7 appliances, and lacked vehicle ownership.
- Cluster 1.3 – HT1.3 (29.8 %, 327 observations): Low-income households (less than $522) residing in smaller homes with less than 100 m^2, 1–2 bedrooms, and 1 bathroom. These households reported the lowest energy expenses ($10–$20 per month), owned an average of 5–6 appliances, and had no vehicle ownership.

CASE 2 [2 clusters - 7 variables]

- Cluster 2.1 – HT2.1 (39.6 %, 433 observations): High-income households (averaging $1292–$2460) with the highest energy expenses (around $70 per month), living in homes with 3–4 bedrooms, 3 bathrooms, and areas between 150 and 200 m^2. These households owned up to 10 appliances and consistently reported vehicle ownership.
- Cluster 2.2 – HT2.2 (60.4 %, 661 observations): Low- and mid-income households (less than $1292) with lower energy expenses (around $30 per month), living in homes with less than 3 bedrooms, 1–2 bathrooms, and areas under 150 m^2. These households owned an average of 5–6 appliances and had no vehicle ownership.

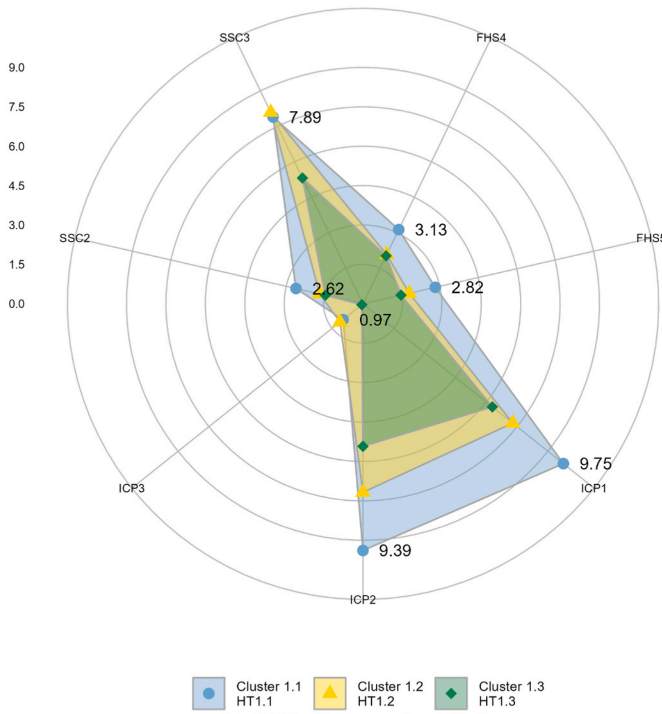
The evaluation of clustering using seven variables showed significant improvement after removing homogenizing variables. Specifically, when assessing the three-cluster solution (CASE 1), the Davies-Bouldin Index (DBI) was 0.6253, and the Silhouette Coefficient was 0.2057. In comparison, the two-cluster solution (CASE 2) produced a lower DBI of 0.5095 and a higher Silhouette Coefficient of 0.2639. These results indicate better separation, internal homogeneity, and greater cohesion within the clusters.

5.2.3. Key changes and evaluation of clustering refinement

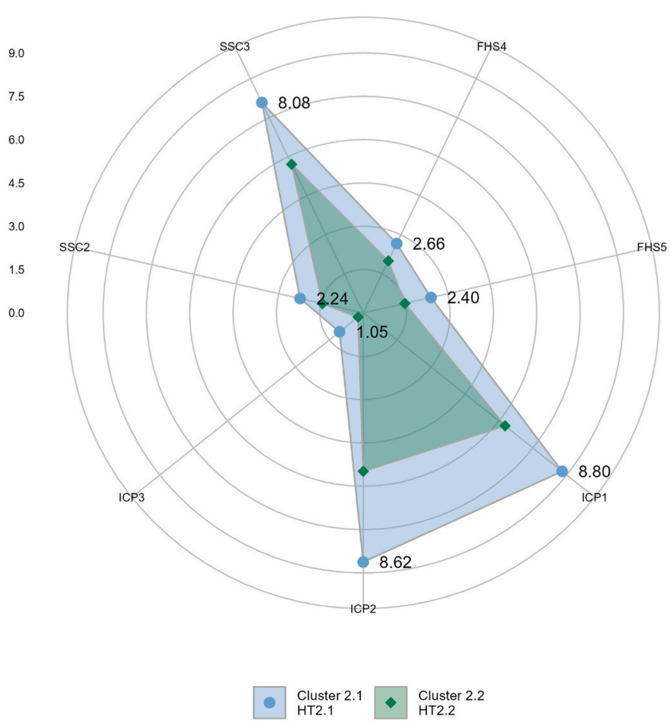
A comparison of the clustering results from analyses using 16 and 7 variables demonstrates a significant improvement in performance after the homogenizing variables were excluded. The analysis with seven variables achieved a lower Davies-Bouldin Index (DBI) of 0.5095 and a higher Silhouette Coefficient of 0.2639 for the two-cluster solution, illustrating that the clusters are more distinct and cohesive compared to the results with 16 variables.

The refinement to 7 variables significantly improved the clarity of the analysis, enabling sharper differentiation in income, housing characteristics, and resource access. While the 3-cluster solution offers a nuanced view of household profiles, the 2-cluster solution provides a more generalized yet precise classification, summarizing key differences between income groups. The results, illustrated in Fig. 7, underscore the value of this refinement in enhancing the understanding of household energy consumption patterns.

- Income and Housing Characteristics: In the 16-variable analysis, the highest income cluster (Cluster 1.1 – HT1.1) included households earning between $523.00 and $1291.00, living in homes with areas between 100 and 150 m^2. In the 7-variable analysis, this income range expanded to $1292.00–$2460.00, with larger homes having areas between 150 and 200 m^2. Lower-income clusters (Cluster 1.3 – HT1.3) consistently earned less than $522.00, with smaller homes of less than 100 m^2.



(a) CASE 1 [3 clusters 7 variables].



(b) CASE 1 [2 clusters 7 variables].

Fig. 7. Comparison of the characterization of the resulting typologies from the refined cluster analysis.

- Energy Expenditures: In the 16-variable analysis, lower-income households (Cluster 1.2 and 1.3) reported monthly energy expenditures between $20.01 and $40.00. In the 7-variable analysis, the lowest-income cluster (Cluster 1.3 – HT1.3) saw this range drop to $10.01–$20.00, highlighting tighter economic constraints. High-income households (Cluster 1.1 – HT1.1) consistently reported higher energy expenses of $60.01–$80.00.
- Appliances and Vehicle Ownership: In the 16-variable analysis, (Cluster 1.1 – HT1.1) owned an average of 9 appliances and at least one vehicle. Lower-income households (Clusters 1.2 and 1.3) owned 7 and 6 appliances, respectively, and no vehicles. The 7-variable analysis confirmed similar trends but highlighted sharper distinctions, with (Cluster 1.1 – HT1.1) owning up to 10 appliances and maintaining consistent vehicle ownership.

By removing homogenizing variables, the segmentation became more precise, providing a clearer reflection of energy consumption patterns in Ecuador's urban residential sector. This refinement improved the clustering quality, revealing significant consumption gaps that were less apparent in the initial analysis. The results show that the 2-cluster solution outperforms the 3-cluster solution, offering more distinct and cohesive segments. This enhanced differentiation between groups makes the 2-cluster solution more effective in understanding energy consumption disparities. The refinement to 7 variables also balanced the distribution of observations, increasing the analysis's reliability. Additionally, it enabled more defined distinctions in income, housing characteristics, and resource access, offering a clearer classification of households based on these factors.

5.3. Relevant relationships and barriers to energy consumption

The clustering analysis has allowed for the identification of relationships between the examined variables and categories, enabling the understanding of specific profiles through empirical evidence and literature-based insights. The most relevant findings are presented below:

i) Sociodemographic variables strongly influence energy consumption [56,57], a statement supported by identifying a direct relationship between income and monthly energy expenditure. Thus, household income shapes opportunities or limitations for energy consumption. In Ecuador, it is determined that LPG (liquefied petroleum gas) and electricity are essential in households regardless of income level. This is not the case for liquid fuels, whose direct consumption is only recorded in higher-income households (HT1.3 and HT2.2).

ii) Higher-income households tend to have members with higher educational levels. Academic achievements improve the household's income level, enabling them to own more appliances, electronic devices, and larger living spaces. Consequently, the level of education indirectly leads to higher energy consumption [13,22,23].

iii) The ownership of private vehicles directly relates to higher energy expenditure. Consequently, variables indicating ownership of assets, such as the number of appliances/electronics, electronic devices, living space, and private vehicles, are directly related to increased energy consumption.

iv) Scores related to the four stages of the eco-innovation process slightly decrease as the complexity of thoughts and behaviors about energy consumption increase. At the same time, households with lower energy expenses show slightly lower scores in the four stages. It is also identified that the stage of notion and reflection has a direct correspondence to the cognitive stage. The stage of experimentation and action is directly related to the stage of attitude and lifestyle. Finally, despite the favorable nature of the initial stages of the eco-innovation process, they are insufficient for households to adopt responsible energy consumption habits. It highlights that eco-innovation is a process that needs to be addressed from its initial stages to establish a solid foundation that enables significant steps towards more responsible consumption. Consequently, eco-innovation and environmental awareness are drivers of responsible energy consumption.

v) Other studies indicate that household size directly influences energy consumption [19,56]. However, in Ecuador, it acts as a homogenizing variable and thus shows no significant evidence. The same applies to the variables of gender and age of the head of household.

vi) A milestone related to monthly household income is found. This turning point determines whether a household can acquire certain goods. Thus, high-income households can decide which technology to use for cooking and water heating. In contrast, low-income households are constrained using electric showers and LPG stoves, presumably due to the initial acquisition investment. Similarly, the former have surpassed the income level milestone, allowing them to buy their own vehicle and making them direct consumers of liquid fuels and higher energy consumers.

It is challenging to identify elements within the system that would enable profound changes. Promoting more responsible energy consumption in urban residential settings requires coordinating holistic, participatory, and divergent strategies.

5.4. Challenges to encourage more responsible energy consumption

Households play a crucial role in driving progress toward sustainability, ensuring the continuity of socially accepted models [15]. The results reveal that energy consumption is primarily determined by variables in the following categories: SSC, FHS, and ICP. These create conditions of opportunity or limitation in households that significantly impact energy consumption behavior. Thus, most variables analyzed in the model developed by Araujo et al. [11] function as drivers of energy consumption.

Meanwhile, changes in energy consumption behavior appear to require some form of effort (cognitive) related to psychological variables [56], including awareness, discernment, understanding, reflection, perception, and thought, which in our model are associated with EIP.

Tactics aimed at positively influencing energy behavior are built under the discourse of energy efficiency. This is recognized as the ability to control nature, make calculated decisions based on "facts", and the idea that problems can be solved through technology improvements [15,58]. However, energy-efficient technologies alone are insufficient to address high levels of consumption [59].

Consequently, improvements can be made through changes in consumer habits and behaviors and more efficient technologies [15,60]. Other research findings reveal sustained reductions in electricity use and the ongoing adoption of efficient appliances among participants in energy efficiency programs in Switzerland, highlighting the role of environmental awareness and avoiding economic incentives [57]. In other words, to achieve energy efficiency, a combination of coordination mechanisms is needed to define priorities and solutions in each context that seek fundamental changes.

5.4.1. Use of more efficient technologies

Technological optimization is integral to strategies addressing climate change, tackling the current energy crisis, reducing energy consumption, and improving the quality of life with environmental benefits [15,24]. Technological advancements play a pivotal role in improving energy efficiency and reducing greenhouse gas emissions. Bogdanov discusses the significant impact of renewable technologies in reducing energy consumption and improving efficiency. This aligns with Ecuador's need to integrate renewable technologies like solar PV, which can provide sustainable solutions for reducing dependence on subsidized LPG and electricity while addressing climate change challenges [61].

Policies integrating renewable technologies and carbon-neutral strategies provide a roadmap for developing nations like Ecuador to transition towards more sustainable energy practices. By promoting incremental innovations and fostering market-based instruments such as subsidies for low-carbon technologies, Ecuador could address its reliance on subsidized LPG and electricity while gradually aligning with global net-zero targets [62].

The introduction of new technologies requires transforming the market's supply and demand, functioning more efficiently when incremental improvements are identified [27]. At the household level, studies have often focused on selecting goods that maintain the same lifestyle while consuming less energy [15]. These advancements not only contribute to energy savings but also increase the competitiveness of businesses and generate monetary savings for consumers [15,24].

5.4.2. Changes in consumer habits and behaviors

Changes in energy consumption behavior seem to require cognitive and psychological effort [56]. Studies show that increasing energy knowledge would increase the likelihood of consumers turning possible actions into concrete actions, supporting energy-saving behavior [15,22,25]. Therefore, innovative ways of putting knowledge into the consumer's mind must be found, requiring the involvement of public and private actors at all scales. Some timely tactics for the context include:

i) To disseminate forms of energy efficiency through educational institutions so that their positive impacts remain within the institution and are transmitted to households and other organizations [63].

ii) To establish incentives through practical and achievable advice that addresses common daily challenges. This guidance should resonate with ideological, health, and material concerns [15], all centered on the premise that individuals, households, and organizations can gain from shifting their behaviors. Achieving these behavioral changes in energy consumption calls for systemic support, highlighting the importance of collaborative governance. Ecuador stands to gain from multi-stakeholder initiatives that engage public, private, and community sectors in educational and awareness programs. Such coordinated efforts could significantly raise the effectiveness of the proposed strategies, leading to a more profound impact on energy-saving behaviors across various socioeconomic groups. Dissemination can take place through advertisements, local exhibitions, newspaper articles, demonstrations, pamphlets, influencers, mobile platforms, websites, and other channels [15,62].

iii) To provide information to consumers about their current energy consumption. Studies suggest that this action can help promote energy savings [13,64,65].

iv) To create gamification applications that simulate habits and consumption patterns, allowing users to understand their behavior. Subsequently, to provide personalized energy-saving tips, demonstrating that such interactions enhance users' liveliness and self-sufficiency in their energy-related behaviors [66,67]. Additionally, studies have found evidence that general information campaigns aiming to promote energy savings may result in a rebound effect. Consequently, personalized information seems more effective in changing behavior [14,15].

v) To strengthen consumer awareness about electricity shortages and enhance household energy savings, Ecuador should leverage the nationwide power outages that began on October 27, 2023, to raise awareness about scarcity and responsible energy consumption.

vi) Encouraging feedback is crucial for both production and distribution companies and end consumers. In this way, companies will understand users' energy behaviors; on the other hand, consumers will increase their knowledge of how much energy they are using and in what ways [64,68]. This process aids in making informed decisions in both directions.

vii) Developing communication strategies to educate the population about the costs and inequity associated with subsidies [69]. These campaigns should be extensive and require concerted efforts from significant media, authorities, academics, business leaders, celebrities, etc. [15].

This is how policymakers should establish strong and comprehensive measures to guide the energy system toward sustainability by promoting cleaner and more efficient fuels, offering affordable cooking and heating technologies, and implementing broad strategies involving all users. In other words, energy policies should prioritize participation and regular reinforcement to improve long-term effectiveness. [57]. Policies should clarify that consumers play a vital role in the energy system, requiring relevant and targeted information to empower them to take concrete actions and make informed decisions.

Addressing energy management with a technocentric approach recognizes that solutions necessitate investments in efficiency through technical and technological innovations. However, it has become evident that including social, cultural, behavioral, and lifestyle factors is essential for shaping energy consumer profiles [70]. Therefore, this research takes a comprehensive perspective, integrating economic, non-economic, technological, and behavioral variables.

The energy system must be measurable and monitorable to transform energy behavior. This underscores the need to develop suitable data collection techniques, analytical methods, and behavior modeling. It also encompasses simulation applications that offer insights on energy savings and behavioral impact, as well as the formulation of relevant metrics and indicators [71].

This research addresses several challenges, with clustering analysis facilitating the development of initial strategies targeted at specific profiles. For high-income households with relatively more opportunities to adopt energy-saving measures, the focus is on promoting greater awareness. This allows them to make informed choices among the available technologies and concrete actions, primarily concentrating on enhancing internal aspects within the household. In contrast, low-income households are expected to face factors external to the system, needing the creation of policy strategies that encourage a gradual transition away from outdated and polluting technologies. Overall, Ecuadorian society must enhance its understanding of energy consumption. Importantly, recognizing the true cost of energy and the associated inequities linked to existing subsidies is essential.

Ultimately, our actions are shaped by the abilities, beliefs, habits, and knowledge we acquire throughout life. Households nationwide show a lack of awareness and understanding of sustainability, indicating that the proposed strategies stem from socialization experiences (family, schools, media, and others). In conclusion, achieving fundamental transformations requires holistic approaches that acknowledge the need for reductions and should not rely solely on technological change.

6. Conclusions

This study utilized clustering techniques to identify two distinct consumer profiles within Ecuador's urban residential sector, focusing on socio-demographic characteristics, housing structures, and technology usage. These profiles provide valuable insights into perceptions, knowledge, and behaviors related to responsible energy consumption. The data, collected randomly without concentrating on energy-related topics, reveal significant patterns, despite opportunities to enhance the cohesion and distinction between the clusters. Nine key homogenizing variables were identified, including household size (typically four members), the gender of the household head (predominantly male), and age range (35–44 years), among others. These findings underscore the potential for targeted energy efficiency strategies incorporating technological advancements and promoting behavioral change. However, the study also reveals a limited culture of eco-innovation, emphasizing the need for education and policies to promote sustainable practices. While this research provides a solid framework for understanding household energy consumption in Ecuador, its relevance to broader contexts requires careful examination. Nevertheless, the insights gained serve as an essential foundation for advancing energy policy and empowering stakeholders to bridge the gap between technology and behavior in achieving a more sustainable future.

Scores associated with the eco-innovation process decrease slightly as the complexity of thoughts and behaviors regarding energy consumption increases. Similarly, households with lower energy expenses tend to show lower scores across all four stages of this process. The results indicate that while the initial stages of the eco-innovation process appear promising, they do not lead to concrete actions or widespread adoption of responsible energy consumption behaviors. This finding highlights the urgent need for awareness campaigns, educational programs, and policies to bridge the gap between knowledge and actionable energy-saving habits. Policymakers can leverage these insights to design targeted demand-side management strategies focusing on the early stages of eco-innovation. Such initiatives may include subsidies or incentives for adopting energy-efficient technologies, community-based programs to promote behavioral change, and collaborative efforts between the public and private sectors to ensure accessibility and effectiveness. Addressing eco-innovation as a process is crucial for establishing a solid foundation for sustainable energy consumption. By integrating technological advancements with improved consumer education and well-structured incentives, we can empower households to make significant strides towards more responsible energy use, aligning individual actions with national and global sustainability goals.

Household income levels significantly impact energy consumption patterns and technology adoption. High-income households are more likely to invest in energy-efficient solutions such as solar panels and electric stoves. In contrast, low-income households often rely on electric showers and LPG stoves due to the high upfront costs. To ensure a rigorous and systematic analysis, a structured three-phase variable selection approach was implemented, refining the dataset from 16 to 7 key variables that define the country's energy consumption patterns. This method, based on statistical and analytical criteria rather than arbitrary selection, enhances the validity and robustness of the findings. By identifying consistent variables that differentiate household profiles, the approach strengthens the reliability of the clustering results. It offers a replicable framework for similar studies in other urban contexts with prolonged energy subsidies. This refined method clarifies household distinctions, revealing that high-income households consistently report monthly energy expenses ranging from $60 to $80 and own more appliances. In contrast, lower-income households typically spend between $10 and $20 per month and have access to fewer resources.

These findings highlight the urgent need for meticulously crafted policies to mitigate income-based disparities. Implementing subsidies or financial mechanisms for energy-efficient technologies, in conjunction with educational initiatives that promote ecological innovation, can empower economically disadvantaged households to transition towards more sustainable practices. By harnessing these insights, policymakers can formulate inclusive strategies that not only address disparities in energy access but also promote a sustained shift toward responsible and equitable energy consumption in the long term.

Nomenclature Section.

BU	Bottom-up approach	ICP	Infrastructure and energy consumption patterns
SSC	Spatial and sociodemographic characteristics	EIP	Eco-innovation process
FHS	Family and housing structure		
Variable 1, SSC1	Geographical disaggregation	Variable 9, ICP1	Total Appliances
Variable 2, SSC2	Monthly income	Variable 10, ICP2	Total Electronic Devices

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BU	Bottom-up approach	ICP	Infrastructure and energy consumption patterns
Variable 3, SSC3	Monthly energy expenses	Variable 11, ICP3	Number of Own Vehicles
Variable 4, FHS1	Household Members	Variable 12, ICP4	Weekly Use Time of Own Vehicles
Variable 5, FHS2	Gender of the Household Head	Variable 13, EIP1	Notion and Reflection Stage
Variable 6, FHS3	Age of the Household Head	Variable 14, EIP2	Cognitive Stage
Variable 7, FHS4	Education level of the Household Head	Variable 15, EIP3	Experimentation and Action Stage
Variable 8, FHS5	Housing type	Variable 16, EIP4	Attitude and Lifestyle Stage
Cluster 1.1, HT1.1	High-income households	Cluster 2.1, HT2.1	High-income households
Cluster 1.2, HT1.2	Mid-income households	Cluster 2.2, HT2.2	Low-income households
Cluster 1.3, HT1.3	Low-income households	DBI	Davies-Bouldin Index

CRediT authorship contribution statement

Gabriela Araujo-Vizuete: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrés Robalino-López:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ángel Mena-Nieto:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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