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Identification of factors influencing electricity consumption in Yaoundé City, Cameroon

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This study explores the factors influencing household electricity consumption in Yaoundé, Cameroon, where energy poverty, frequent power cuts and high tariffs pose major challenges to ensuring reliable, affordable and permanent access to electricity for populations, given the energy potential the country enjoys. Using a multinomial logistic regression model, the analysis reveals that the number of occupants, rooms, size of dwelling and number of electrical appliances have a significant impact on consumption, particularly in the low and medium consumption segments. The model explains 62% of the variation in consumption, leaving 38% unexplained, suggesting the need to explore other factors such as energy behaviour. The study recommends various measures to improve energy efficiency, including banning the import of second-hand appliances, encouraging the purchase of new appliances through tax adjustments, and awareness-raising campaigns targeted by consumption segment. For low-consumption households, the focus could be on adopting energy-efficient appliances, while for high-consumption segments, demand reduction at peak times could be encouraged. These strategies aim to improve energy efficiency and electricity conservation. Although focused on Yaoundé, this study could be applied to other cities in Cameroon and sub-Saharan Africa facing similar challenges, thus promoting an integrated approach to strengthening regional energy sustainability.

Keywords: household electricity consumption, electricity conservation, regression model, Yaoundé power outages

Introduction

Increased household electricity consumption in sub-Saharan Africa is attracting growing attention not only because of its impact on the economic and social development of the countries in that region, but also because of the effects it can have on the environment, due to the consequent climate change. In many African countries, access to reliable, electricity of high quality is a vital component of a good quality of life and a sustainable future.

The International Energy Agency (IEA 2019) reports that in sub-Saharan Africa, the residential sector accounted for 65% of final energy consumption, compared with 22% worldwide and less than 20% in advanced economies. This makes it the largest electricity-using sector in this part of Africa. This trend underlines the importance of access to electricity for development.

However, this contrasts with the observations of Ebhota and Inambao (2016) and Blimpo and Cosgrove-Davies (2019), who report that over 600 million people in sub-Saharan Africa still lack access to electricity. Zigah and Creti's (2023) comparative analysis highlights significant disparities between countries. While South Africa boasts an electrification rate of 86%, the DRC achieves just 15.5%. The study also highlights the disparities between urban and rural areas, with urban electrification rates often two to three times higher than rural rates in many countries.

In many large cities in sub-Saharan Africa, where demand for electricity is rising sharply due to rapid population growth, increased urbanization and improved living conditions, households face major challenges in terms of access to electricity (Lyakurwa and Mkuna 2019). Frequent power cuts limit domestic activities, economic opportunities and household comfort. In addition, electricity tariffs can be unaffordable for many low-income households, restricting their access to reliable electricity.

Yaoundé, the capital city of Cameroon, presents a noteworthy case study that sheds light on these dynamics. According to the World population review (United Nations 2023), Yaoundé's population will rise from around 1.8 million in 2005 to around 4.337 million in 2022.

Despite these observations, understanding of the specific factors behind this increase remains limited due to the small number of studies on this issue in the Yaoundé context. However, work has been carried out on a national scale, although not on the same aspects or with the same objectives as our study (Dieudonné et al. 2022; Guefano et al. 2021a, 2021b; Jacques Fotso, Mvogo, and Bidiasse 2023; Nsangou et al. 2020, 2022).

Previous research, such as those carried out by Agbandji et al. (2020) and Tchagnao and Bayale (2021) has identified critical determinants of electricity consumption, including socio-economic factors, housing characteristics and appliance use. Agbandji et al. (2020) point out that elements such as household income, household size and appliance equipment directly influence electricity consumption. Similarly, Ali et al. (2021) highlight that in fast-growing cities, electricity consumption is strongly correlated with urbanization and increased household purchasing power.

By examining the specific case of the city of Yaoundé, the present study aims to provide elements for a good understanding of the factors behind the increase in household electricity consumption. To this end, household surveys will be conducted to gather empirical data. The analysis will cover variables such as gender, marital status, age, household size, type of dwelling, number of appliances, to name but a few. An analysis will determine

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the relative impact of each factor on electricity consumption. Also, the study draws on the theoretical framework developed by Jones, Fuertes, and Lomas (2015), which highlights the importance of these factors in understanding urban energy demand in developing countries. This theoretical framework includes:

- **Socio-economic factors:** such as household income, number of occupants, age and level of education, which influence energy consumption patterns.
- **Housing characteristics:** including size, type, age and thermal insulation, which can explain variations in energy consumption.
- **Appliance usage:** appliance ownership and frequency of use directly influence electricity consumption.

Similar approaches have been used successfully in other contexts. For example, Ali et al. (2021) applied this framework to the study of electricity consumption in Seremban, Malaysia, revealing the significant influence of household income and the criticality of the number of rooms in the household as a factor in household electricity consumption.

We recognize the limitations of this study. It does not include all the factors likely to have an impact on electricity consumption. Among other things, it focuses on the socio-economic profile of households (where household income, level of education and employment are not taken into account), housing characteristics and the number of electrical appliances.

Although focused on Yaoundé, the results of this study may have wider implications for other cities in Cameroon and sub-Saharan Africa facing similar challenges.

The rest of the paper is organized as follows: first, a section dedicated to the literature review, then a methodology section outlines the systematic approach employed to conduct this study, followed by section presenting the findings, which are subsequently examined and discussed, and finally a conclusion.

Literature review

The continuous increase in household electricity consumption has garnered interest among both researchers and policymakers. To contextualize the present study within the current landscape, this section provides a literature review highlighting relevant previous studies addressing this theme, presenting the main factors influencing electricity consumption. This approach aims to better guide our work.

In this pursuit, the findings of several earlier research studies revealed that factors significantly impacting household electricity demand can be grouped into various categories: demographic, socio-economic, technological, building and appliance characteristics, consumption behaviours, and even climatic variations.

Socio-economic factors

The impact of socioeconomic factors on household electricity consumption has been the subject of numerous studies in the literature. The substantial correlation between household socio-economic characteristics and their level of electricity consumption has been extensively documented (Ali et al. 2021; Ye, Koch, and Zhang 2018). For instance, Jones and Lomas (2015) the determinants of high electricity demand within British households, emphasizing their socio-economic characteristics. Their study, based on a sample of 315 households, revealed that household income level is an important factor in electricity consumption. Higher-income households are likely to consume more electrical energy due to their ability to acquire a greater number of electrical and electronic appliances.

Similarly, in rapidly growing cities such as Seremban in Malaysia, Ali et al. (2021) also observed a correlation between income level and the growth of household electricity consumption. Other studies, such as those conducted by Bedir, Hasselaar, and Itard (2013), Cayla, Maizi, and Marchand (2011), Özcan, Gülay, and Üçdoğruk (2013), and Zhou and Teng 2013), have also confirmed the significant impact of household income level on electricity consumption. Furthermore, household size has been identified as another key factor contributing to increased electricity consumption, with larger households tending to consume more due to the larger number of residents using electrical appliances, heating, and air conditioning, as highlighted by Hara et al. (2015), Ningi, Taruvinga, and Zhou (2020), and Wahlström and Hårsman (2015). Likewise, Bridge's conclusions based on a study conducted in Nicaragua in 2017, regarding the measurement of living standards, emphasized a correlation between larger households and high consumption of energy resources (Bridge 2017).

On the other hand, the study by C. Chen, Xu, and Day (2017) on 642 households in winter and 838 households in summer in China confirmed the significant impact of factors such as household size, income level, and occupants' age on electricity consumption. Other studies, such as those presented by Jones, Fuertes, and Lomas (2015b), Sakah et al. (2019), and Wallis, Nachreiner, and Matthies (2016), have highlighted the propensity of households with children and adolescents for increased electricity consumption due to the number of electrical appliances used, often without awareness of the financial implications related to electricity bills. Similar results were observed in studies conducted in Japan by Hara et al. (2015) and in Benin by Agbandji et al. (2020), where factors such as the gender of the household head, household size, and income, as well as ownership of electrical appliances, were identified as influencing household electricity demand. In summary, previous research confirms that socio-economic factors such as household size (Agbandji et al. 2020; Jones, Fuertes, and Lomas 2015; Tchagnao and Bayale 2021), income level (Cayla, Maizi, and Marchand 2011; Hara et al. 2015; Jones and Lomas 2016), occupants' age (Jones, Fuertes, and Lomas 2015; Wallis, Nachreiner, and Matthies 2016), as well as education level (Salari and Javid 2017; Wijaya and Tezuka 2013), play a significant role in household electricity consumption.

Technological factors

The impact of technological factors on domestic electricity consumption has been examined in various previous studies, highlighting the significant evolution of household daily life under the influence of technological advancements. The implementation of measures and technologies aimed at increasing energy efficiency in households is a recurring theme in the literature, consistently showing a correlation with reduced electricity consumption (Di Foggia 2018; Liu and Ren 2018; Pais-Magalhães, Moutinho, and Robaina 2020). According to Reyna and Chester (2017), technological advancements have led to a diversification of household appliances, thereby contributing to mitigating energy inefficiency. However, the comfort provided by these devices is sometimes offset by substantial electricity consumption, thus highlighting a trade-off between comfort and electricity consumption (Ali et al. 2021; Firth et al. 2008; Wijaya and Tezuka 2013), as demonstrated by Firth et al. (2008) in the UK. Their research identified appliances such as electric kettles, washing machines, electric showers, televisions, and lighting contributing to approximately a 10% increase in electricity consumption. Agbandji et al. (2020) emphasized the significant influence of household appliances such as fans, blenders, refrigerators, and radios on domestic energy demand. Similar studies conducted by Esa, Abdullah, and Hassan (2016) highlighted the importance of the diversity of electrical load usage in households as a key factor in assessing determinants of electricity consumption. More specific analyses, such as that conducted by Sakah et al. (2019) in Tema, Ghana, indicated that ownership of appliances such as air conditioning, freezer, fan, refrigerator, and television explained part of the 57% variation in total household electricity consumption. Nsangou et al. (2022) in Cameroon employed various machine learning models (quantile regression, decision trees, and artificial neural networks) to demonstrate that several factors, including electrical appliances, exert a significant influence on electricity consumption. Bedir and Kara (2017) in a study in the Netherlands confirmed the significant impact of appliances such as entertainment, cooking, and cleaning appliances on electricity consumption. In temperate regions facing often extreme weather conditions, the presence of certain appliances such as dryers and heating systems (Huebner et al. 2016; Salari and Javid 2017), and air conditioners (Ashouri et al. 2018) is a significant factor in electricity consumption.

In light of these observed facts, previous research converges on the understanding that technological advancements, while bringing improvements in energy efficiency, are also associated with a diversification and increase in electricity consumption. This reality, analyzed across different regions and climatic contexts, underscores the importance of technology management to mitigate negative effects on domestic electricity consumption.

Factors related to services and comfort

The pursuit of comfort conditions significantly influences household electricity consumption. This dynamic, examined through consumption studies in Kuwait (Jaafar et al. 2018), Malaysia (Kubota et al. 2010), and other regions, reveals that consumer choices are strongly oriented towards advanced technological solutions. For example, Aqilah Hisham et al. (2019), through a survey conducted in Malaysia comprising 19 households, including low-cost apartments and terrace houses, showed that occupants' comfort levels were achieved when air conditioner temperatures ranged between 16 and 28°C. This orientation leads to the use of a high number of appliances such as air conditioners, electric heaters, sophisticated entertainment devices, and others, thereby resulting in increased electricity demand.

In parallel, the emergence of connected devices, grouped under the term Internet of Things (IoT), brings a new perspective on how households interact with their electrical equipment. Despite the considerable benefits they offer in terms of comfort and remote management, their use also leads to a significant increase in electricity demand. These devices, such as smart thermostats, connected lighting, and smart home security systems, require constant electrical power, highlighting the importance of effective energy consumption management.

The pursuit of comfort in households, facilitated by the adoption of advanced technologies and connected devices, requires special attention to balance the benefits of comfort with responsible electricity consumption management.

Factors related to household consumption patterns

Electricity consumption habits have a major influence on household electricity consumption. One of the main causes of increased electricity consumption in households is the growing and prolonged use of electronic devices such as smartphones, tablets, computers, televisions, etc., reflecting a shift in electricity consumption-related behaviours (J. Arham et al. 2018; Chen, Wang, and Steemers 2013; Jaafar et al. 2018). With rapid technological evolution, new electronic devices are constantly introduced to the market, and their adoption by consumers is swift. This trend leads to increased electricity demand as these devices require electrical power to operate. Ashouri et al. (2018) confirmed that the behaviour of Japanese household occupants had a significant impact on their electricity consumption. Results obtained in the UK by Jones and Lomas (2016) underscored the importance of consumption patterns related to the duration of use of specific appliances such as computers, phones, and household appliances. Similarly, Huebner et al. (2016), through a study involving 845 households in the UK, concluded that the duration of use of household appliances significantly influences these households' overall electricity consumption. In France, studies by Pal et al. (2019) confirmed that occupants' behaviour in using electrical appliances influenced electricity consumption in offices. In the USA, Steemers and Yun (2009) revealed after a study that occupants tended to consider outdoor temperatures when using heating and cooling appliances, greatly influencing increased electricity consumption in these households.

Conversely, according to Kubota et al. (2010), Malaysian terrace houses revealed that occupants did not consider outdoor temperatures before using air conditioning. The reasons cited indicated that the country usually experiences hot and humid seasons, with outdoor temperatures remaining almost constant throughout the year. In the same country, the works of Kubota et al. (2010) and Zaki et al. (2017) respectively showed that air conditioning appliances had an average operating time of 6 h/day, which contributed significantly to increasing electricity consumption in households.

To address these energy challenges, it is imperative to implement tailored energy efficiency strategies. Encouraging the adoption of energy-efficient appliances, raising awareness among occupants about the impacts of their behaviours on consumption, and implementing financial incentives for reducing electricity demand are avenues worth exploring.

Methodology

Description of the study area

Yaoundé was chosen as the study site because of its status as Cameroon's political capital, its urban diversity, and its central role in the country's energy challenges. Located 200 km from the Atlantic coast, Yaoundé lies at a latitude of 4° North and a longitude of 11° 35' East. The city is surrounded by seven hills, which influence its characteristic equatorial climate. Yaoundé is one of Cameroon's two largest cities, alongside Douala, the economic capital. It is located in the Centre region and is the capital of the Mfoundi division, which has the status of an urban community. Its surface area is estimated at 304 km², of which 183.2 km² is urbanized, i.e., 59.10% of the total. Seven subdivisions make up the city, with each having a dedicated mayor. The location of Yaoundé and its seven subdivisions are shown in Figure 1.

The city boasts a diversity of facilities and is characterized by three distinct types of urban fabric:

- The modern fabric, which accounts for 20% of the city's surface area and is home to around 25% of its population. This fabric is characterized by buildings made up of durable materials and a good level of infrastructure.
- The dense popular fabric, made up of spontaneous neighbourhoods that are homes to almost 70% of the population and cover 60% of the urban area. These areas have underdeveloped road infrastructures, poor sanitation and low levels of connection to electricity and drinking water networks.
- The rural fabric, located on the outskirts of the city, is marked by a lower population density, retaining a bucolic charm and peaceful atmosphere.

This urban and demographic diversity makes Yaoundé particularly interesting for our study.

Survey questionnaire development and data collection

Previous studies have shown that various socio-economic and housing-related factors can influence household electricity consumption (Agbandji et al. 2020; Jones and Lomas 2015, 2016; Tchagnao and Bayale 2021). The aim of this study is to identify the factors contributing to increased electricity consumption at household level. A questionnaire was designed to survey occupants on relevant factors that would provide insights into the questions asked. The questionnaire consists of three main parts: the socio-economic profile of the household, a description of the dwelling including certain relevant characteristics, and electricity consumption habits. Figure 2 shows the main aspects taken into account when designing up the questionnaire for the households to be surveyed.

In detail, the questionnaire covers several variables grouped into different sections. Table 1 illustrates some of the variables included in the questionnaire.

Sample size calculation

To determine the size of the representative sample of households in the study area, we used data on the estimated population of Yaoundé at the time the survey took place (September 2022), i.e. 4.1 million inhabitants, with an average of 4.6 people per household (INS 2022). These data enabled us to estimate the number of households in the city at 891,304. The required sample size was calculated using the following formula:

$$n = \frac{X^2 NP(1-P)}{d^2(N-1) + X^2 P(1-P)} \tag{1}$$

where:
n is the required sample size, X the value of the desired confidence level (1.96), N the population size (891,304), P the population proportion (0.50 to obtain maximum sample size), d the degree of precision expressed as a proportion (0.037).

Household selection method

Households within each subdivision were selected using the itinerary method (Survey-Magazine 2024). This technique is particularly suited to the urban context of Yaoundé for several reasons:

> It ensures systematic geographical coverage of the city, enabling representation of the different types of neighborhoods and habitats.
> It minimizes selection bias by following a predefined route, rather than letting interviewers choose households freely.
> It is effective in a context where addressing is often incomplete and imprecise. It enables interviewers to adapt to the realities of the field, such as housing density or accessibility of areas, which is particularly useful in complex urban environments such as Yaoundé.

In each subdivision, routes were defined starting from a reference point (subdivision town hall or main markets) and following predetermined directions. Interviewers were given specific instructions to select households along these routes, with a regular interval between each selected household.

Data collection

Data collection was carried out using a structured questionnaire, designed to gather information on: (i) the household's socio-economic profile; (ii) housing characteristics; (iii) electricity consumption habits.

Although the initial sample was set at 700 households, the application of the itinerary method in the field led to a slight increase in the sample size, bringing the final

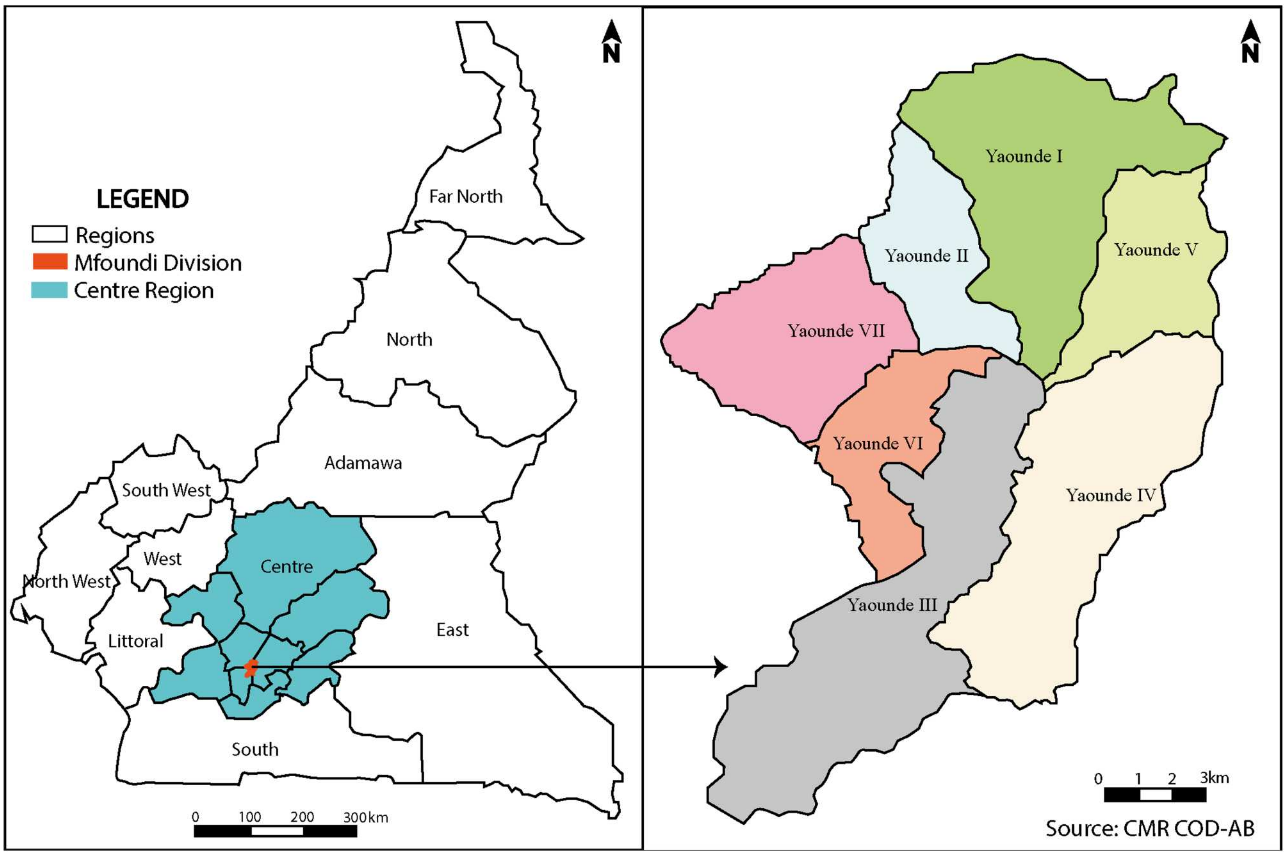

Figure 1: Location of the study area. Left: map of Cameroon with its ten administrative regions. The region in blue represents the Centre region and its divisions, and in red the Mfoundi division, whose capital is Yaoundé. On the right, the city of Yaoundé and its seven arrondissements.

number to 749 households. This increase is the result of several factors linked to the itinerary method:

> To ensure adequate representativeness of each area within the boroughs, some itineraries had to be extended or adjusted, resulting in the inclusion of additional households. The diversity of habitat types and the varying density of households in certain neighborhoods sometimes necessitated the addition of survey points to maintain the representativeness of the sample.
> The availability and willingness to participate of the households we met enabled us to collect data from slightly more households than initially planned. In addition, to compensate for any non-responses or incomplete data, the interviewers were allowed to include a few extra households, thereby increasing the sample size.

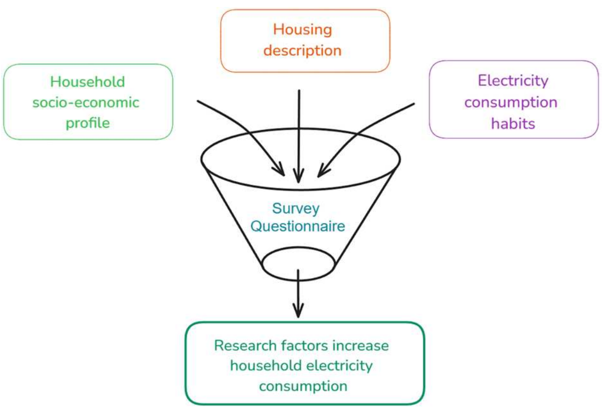

Figure 2: Design of the survey questionnaire.

Analysis of collected data

To analyze the collected data, we begin with an initial pre-processing and encoding of the variables. For relevant categorical variables, we use the so-called ‘one-hot’ or ‘dummy’ encoding method. One-hot encoding transforms each unique value of a categorical variable into a new binary column. Each column represents a distinct category and indicates the presence (1) or absence (0) of that category for each observation. The aim is to convert these categorical variables into numerical values without introducing erroneous ordinal or numerical relationships between categories.

In this specific context, the independent variables include parameters such as socio-economic profile (age, gender, household size), housing characteristics (living area, number of rooms) and consumption habits (type of appliances). The dependent variable is electricity consumption in kWh per month, segmented into different categories.

To better understand the impact of the independent variables on the dependent variable, we use an analytical tool: the multinomial logistic regression model. This model enables us to disentangle the complex relationships between variables. In so doing, it offers a better understanding of the factors influencing electricity consumption. Multinomial logistic regression is particularly suitable when modelling a dependent variable with more than two nominal categories. This is particularly the case in this study, with electricity consumption segments.

Table 1: Components of the questionnaire survey.

Part of questionnaire	Variables
Socio-economic profile	Gender, age, marital status, number of occupants, ownership
Housing characteristics	Type of dwelling, living area, number of rooms, construction material
Electricity consumption habits	Type of appliance, range of electricity consumption, condition of appliance at purchase, motivations for choice of purchase, energy-saving habits, percentage of electricity in expenditure, bills in relation to monthly income

Model formulation

The multinomial logistic regression model (Wang et al. 2018) is expressed through the following equation:

$$log\left(\frac{P(Y=j)}{P(Y=reference)}\right) = \beta_{0j} + \beta_{1j}X_1 + \ldots + \beta_{kj}X_k + \epsilon_j \tag{2}$$

where:

- Y represents the dependent variable, which is the electricity consumption category in kWh per month (less than 110 kWh, 111–400 kWh, 401–800 kWh, 801–2000 kWh).
- $P(Y=j)$is the probability that the observation belongs to category j (for example, consumption segment j).
- $P(Y=reference)$ is the probability of belonging to the reference category (the category against which other segments are compared, usually the one with the most data or the lowest consumption). In our case, it is the category with the lowest consumption and practically no data, which is the 801–2000 kWh category.
- β_{0j} is the intercept for category j.
- β_{1j}, ……, β_{kj} are the coefficients associated with each independent variable for category j. These coefficients measure the impact of independent variables (such as housing size, number of appliances) on the log-odds of belonging to category j compared to the reference category.
- X_1, …., X_k are the independent variables (socioeconomic profile, housing characteristics, consumption habits).
- ϵ_j represents the error term specific to category j, capturing variations unexplained by the model.

Variance-covariance Matrix and coefficient estimation

In this model, the coefficients β_{ij} are estimated by maximizing the likelihood (MLE, Maximum Likelihood Estimation). MLE finds the values of β_{ij} that maximize the probability of observing the collected data, given the model.

Once the coefficients are estimated, the precision of these estimates is assessed using the variance-covariance matrix of the estimates. This matrix allows us to calculate the standard errors of $\hat{\beta}_{ij}$ (the estimated coefficients) and to conduct statistical tests to determine the significance of the coefficients. If a coefficient is statistically significant, it means that the associated variable has a substantial impact on the probability of belonging to a given consumption category.

Results and discussion

Sociodemographic profile of respondents

Analysis of the results reveals a complex and evolving demographic composition of the households studied. Although men remain in the majority as heads of household (58%), the significant proportion of women (42%) in this role suggests a progression towards greater gender equality in family management. This trend, while in line with traditional social structures observed in many developing countries (Alkon, Harish, and Urpelainen 2016), indicates a gradual social transition.

The predominance of married households (61.42%) and the high representation of the 25–34 age bracket (41%) depict a young, family-oriented population. This demographic composition can significantly influence electricity consumption patterns, as pointed out by Jones, Fuertes, and Lomas (2015) in their study on the determinants of household energy consumption.

Housing characteristics provide additional information: 42.72% of households live in apartments, with an average of 4.95 rooms per dwelling and an average household size of 4.34 people. These data, in line with studies on urban lifestyles and population density (Firth et al. 2008), suggest medium to large household sizes, which can have a considerable impact on electricity consumption (Brounen, Kok, and Quigley 2012).

With regard to economic aspects, 66.62% of households allocate less than 5% of their income to electricity bills. This relatively low percentage can be explained either by efficient energy management, relatively high incomes enabling these costs to be easily absorbed, or modest incomes requiring careful management of energy expenditure (Ye, Koch, and Zhang 2018). Analysis of electricity consumption reveals a high concentration of households in the first two segments: 58.34% consume less than 110 kWh per month, while 40% are in the 111–400 kWh bracket. This distribution highlights the predominance of low-to-moderate consumption. The higher segments are far less represented, with only 1.47% of households consuming between 401 and 800 kWh, and a marginal 0.13% exceeding 800 kWh up to 2000 kWh.

These results offer a detailed insight into the sociodemographic characteristics and electricity consumption habits of the households studied, providing a solid basis for further analyses of the factors influencing energy consumption. Table 2 shows the descriptive statistics for the variables studied.

Figure 3 shows a graphical distribution of the data in Table 2. Analysis of the different variables in this table reveals the following.

Table 2: Descriptive statistics.

Variables				Total number (N)	Percentage (%)
Sex					
Male				434	57.94
Female				315	42.06
Marital status					
Single				251.00	33.51
Married				460.00	61.42
Widowed				2.00	3.34
Divorced				13.00	1.74
Age range (years)					
Less than 25				62.00	8.28
[25–34]				307.00	40.99
[35–44]				243.00	32.44
[45–54]				120.00	16.02
55 and above				17.00	2.27
Type of housing					
Room				123.00	16.42
Studio				183.00	24.43
Apartment				320.00	42.72
Villa				117.00	15.62
Manor				6.00	0.0
Living area (m²)					
Less than 20				121,00	16.15
[20–50]				193.00	25.77
[51–90]				232.00	30.97
[91–120]				104.00	13.89
[121–140]				49.00	6.54
More than 140				50.00	6.68
Electricity consumption					
Segment 1 (Less than 110 kWh)				437.00	58.34
Segment 2 (110–400 kWh)				300.00	40.05
Segment 3 (401–800 kWh)				11.00	1.47
Segment 4 (801–2000 kWh)				1.00	0.13
Percentage of income allocated to electricity bills (%)					
Less than 5%				499.00	66.62
5–10%				208.00	27.77
11–15%				32.00	4.27
More than 15%				10.00	1.4
Variables	*N*	Min	Max	Mean	Std. Dev
Number of occupants	749	1.00	17.00	4.341	1.9874
Number of rooms	749	1.00	18.00	4.953	2.6324
Number of appliances	749	2.00	17.00	6.688	2.6296

Distribution of electricity consumption by gender

Analysis of electricity consumption by gender (Figure 3 graph a) reveals an almost similar trend between men and women, with a notable concentration in the 'less than 110 kWh' and '111–400 kWh' consumption bands. Men are in the majority in all consumption bands, although this difference is more marked in the 'less than 110 kWh' band. On the other hand, the gap narrows considerably in the '111–400 kWh' segment. It is important to note the under-representation of both genders in the '401–800 kWh' and '801–2000 kWh' consumption bands. This distribution suggests that gender has a moderate impact on electricity consumption, with male-headed households tending to consume slightly more. This could be attributed to differences in household size, income or consumption habits.

Distribution by age category

Electricity consumption also varies by age group (Figure 3 graph b). Households headed by individuals aged 25–34 dominate the first consumption segment, while those headed by individuals aged 35–44 dominate the second. While the first consumption segment dominates in the first three age categories (under 25, 25–34 and 35–44), this is less the case beyond. In fact, electricity consumption tends to fall more into the '111–400 kWh' segment, particularly for households headed by individuals aged 45–54 and over 55. This distribution indicates that electricity consumption increases with age, probably due to the accumulation of assets, the size of the dwelling or generational differences in living habits.

Distribution by marital status

Married people dominate the first three electricity consumption bands (Figure 3 graph c), followed by singles, who are more represented in the 'less than 110 kWh' band. This latter point can be explained by the fact that a person living alone generally consumes less electricity, due to a smaller dwelling and fewer rooms requiring lighting or equipment. Widowers (or widows) and divorcees show higher electricity consumption in the '111–

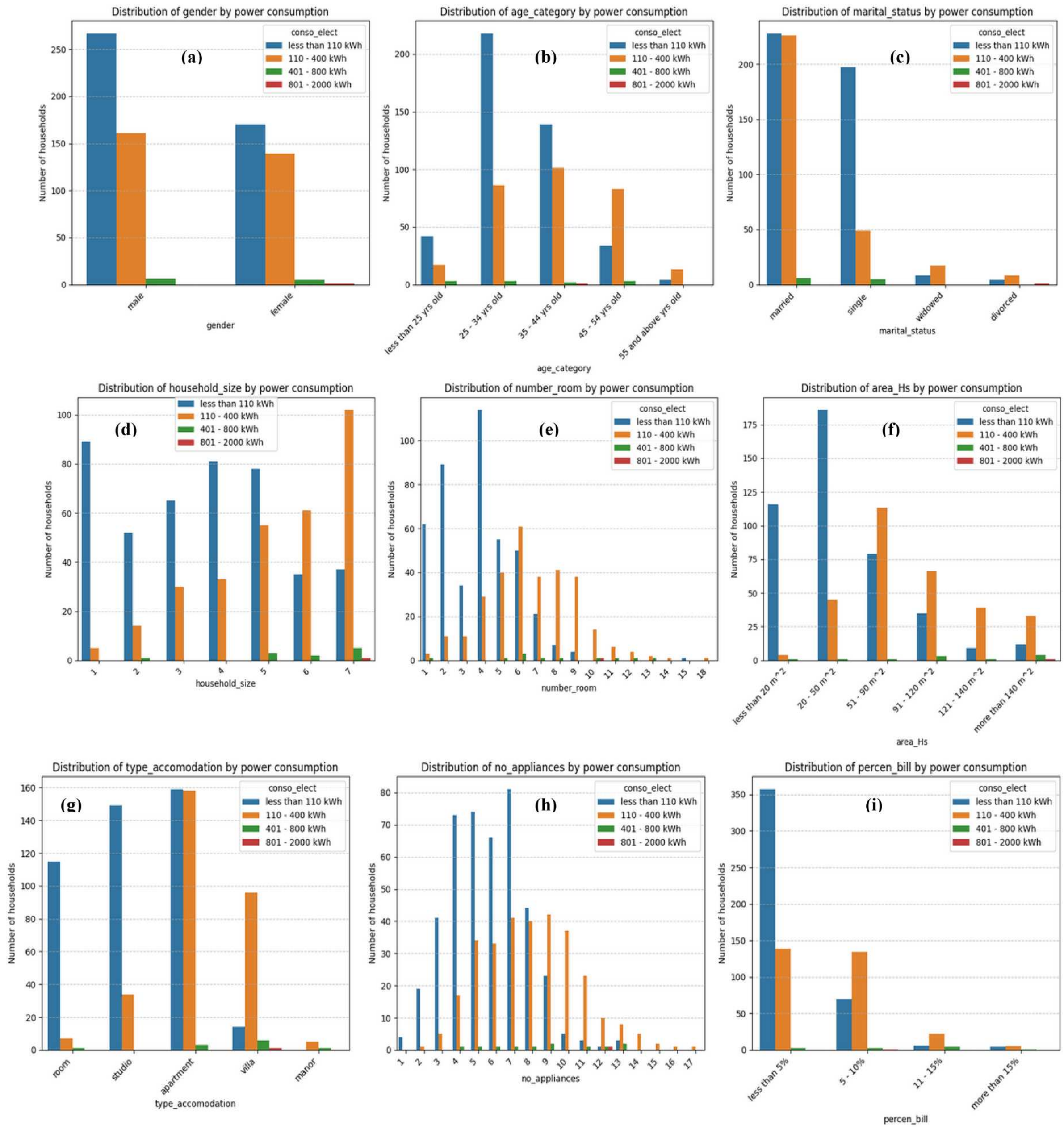

Figure 3. Distribution of variables considered in the multinomial logistic regression model as a function of electricity consumption segments.

400 kWh' bracket, possibly due to changes in lifestyle or personal circumstances. These trends may be linked to socio-economic factors or individual choices specific to each marital status.

Distribution by household size

A clear trend shows that consumption increases with household size (Figure 3 graph d). In the range (less than 110 kWh), there is a relative balance between households of 1–5 people. However, in the range (111–400 kWh), an increasing trend in household size is observed. The presence of one- to three-person households consuming more than 110 kWh of electricity per month could be linked to lifestyle. In general, it is logical that electricity consumption increases with household size, due to the increased use of household appliances and the desire to maintain a certain level of living comfort.

Distribution by number of rooms

The number of rooms in a dwelling is also an important indicator of trends in electricity consumption (Figure 3 graph e). An increase in the number of rooms is generally associated with higher electricity consumption. Households occupying dwellings with fewer rooms, often in the 'less than 110 kWh' segment, tend to be more energy-efficient. This may be due to lower incomes, a desire to save money or the use of more energy-efficient appliances. On the other hand, homes with more rooms, which are in the higher consumption segments, have higher energy requirements due to their size and equipment.

Distribution by living area

A similar trend to that observed for the number of rooms is also present when it comes to living area (Figure 3 graph f). Smaller areas (under 50 m²) are concentrated in the 'under 110 kWh' segment, while areas over 51 m² dominate the '111–400 kWh' segment. These findings reveal that the living space in a home is an indicator of the evolution of electricity consumption, certainly due to the increased need for lighting, air-conditioning and equipment for well-being satisfaction.

Distribution by housing type

Apartments lead the way in the 'less than 110 kWh' and '111–400 kWh' segments (Figure 3 graph g). In the first segment, households living in apartments appear to be more energy-conscious, which explains their moderate electricity consumption. However, in the '111–400 kWh' segment, these households consume slightly more, probably due to their lifestyle or household size. Smaller dwellings, such as bedrooms and studios, are mainly located in the 'less than 110 kWh' segment, which is consistent with the fact that these occupants are fewer in number and have a relatively modest standard of living. Villas and manor houses, on the other hand, have higher electricity consumption, often located in the '111–400 kWh' and '401–800 kWh' segments, due to their size and the equipment they house. These observations show that the type of dwelling can have a direct impact on a household's electricity consumption.

Distribution by number of appliances

Figure 3 graph (h) shows a strong link between the number of appliances in a household and the amount of energy consumed. A predominance of the number of appliances between 1 and 8 is observed in the first segment, compared to the second segment. This trend could imply that households with appliances and electricity consumption below 110 kWh consume slightly less electricity than those in the 111–400 kWh segment. This is probably due to new appliances, infrequent use or low-consumption appliances. There is no clear positive correlation between the number of appliances and consumption. The trend reverses when the number of appliances exceeds 8. This distribution shows that the number of appliances can be considered an indicator of electricity consumption, reflecting both the standard of living and the consumption habits of households.

Distribution by percentage of electricity bill in relation to income

Analysis of Figure 3 graph (i) on the proportion of income spent on electricity reveals that:

For the consumption segment below 110 kWh, the majority of households spend less than 5% of their monthly income on electricity, a smaller proportion allocate between 5% and 10% of their income, and very few households in this segment spend more than 10% of their income on electricity.

In the 111–400 kWh consumption segment, there is a more balanced distribution between expenditure categories, with a significant number of households spending between 5% and 10% of their income on electricity. This segment also includes most households spending more than 10% of their income on electricity.

For households in the first segment (less than 110 kWh), the low proportion of income devoted to electricity may indicate: (a) Modest incomes, where even low consumption represents a significant proportion of the budget. (b) Efficient energy management, characterized by limited use of electrical appliances and potentially a small dwelling with few occupants.

For households in the second segment (111–400 kWh), those devoting less than 5% of their income to electricity may have comfortable incomes, easily absorbing these expenses despite higher consumption. Households spending more than 5% of their income on electricity could have the following characteristics: (a) More spacious homes. (b) More electrical appliances. (c) larger families.

Following a graphical analysis of the various variables involved in the search for factors likely to contribute to changes in household electricity consumption, the next section focuses on the interpretation of Tables 3 and 4, which present the results of the multinomial logistic regression applied to the 'less than 110 kWh' and '111–400 kWh' consumption segments. These segments were selected because together they represent 98.39% of the data collected. On the other hand, the multinomial logistic regression model applied to the consumption segments '401–800 kWh' and '801–2000 kWh' did not provide convergent and exploitable results. This analysis will highlight relevant variables and examine strong correlations or potential links between these variables and observed electricity consumption levels.

Factors influencing domestic electricity consumption

Application of the logistic regression model to the various electricity consumption segments identified by households produced the results shown in Tables 3 and 4, corresponding respectively to the 'less than 110 kWh' and '111–400 kWh' consumption segments. On the other hand, the segments '401–800 kWh' and '801–2000 kWh' did not produce conclusive results due to the lack of model convergence, attributable to the small amount of data available.

Examination of Tables 3 and 4 reveals that analysis of the factors influencing electricity consumption shows nuanced results.

Constant

The constant (const) for both segments is positive and significant ($p < 0.05$), indicating a positive basic probability of belonging to the segments studied. The coefficient of the constant is higher in the segment below 110 kWh (2.3117) than in the 111–400 kWh segment (1.9381). This implies a higher propensity to consume in the former segment than in the latter, and could indicate that, even in the absence of the other explanatory variables, households have an intrinsically higher probability

Table 3: Estimates from multiple regression analysis for the first consumption segment (less than 110 kWh).

	Coefficient	Std. Error	*t*-ratio	*p*-value	Odds Ratio	
Const	2.3117	0.789	2.930	0.003	10.092	**
Gender_male	0.2174	0.198	1.098	0.271	1.243	
Age	0.0053	0.241	0.022	0.982	1.005	
Marital status	−0.5683	0.252	−2.255	0.024	0.566	**
Household size	0.0213	0.075	0.284	0.031	1.022	**
No of rooms	0.1781	0.089	2.001	0.047	1.195	**
Area of Hs (m²)	1.4147	0.496	2.852	0.004	4.115	**
Type of accommodation	0.8371	0.408	2.052	0.028	2.310	**
Number of appliances	0.1990	0.049	4.061	0.000	1.220	***
Perc_revenue [Less than 5%]	3.3273	0.614	5.416	0.000	27.864	***
Perc_revenue [5–10%]	1.3264	0.612	2.168	0.030	3.767	**
Second segment	−3.5802	3.018	−1.186	0.236	0.028	
Third segment	−3.7667	17.357	−0.217	0.828	0.023	
Fourth segment	−4.0214	18.253	−0.220	0.916	0.018	

Model summary: Pseudo-$R^2 = 0.619332$; Log-likelihood = 562.91; p-value = 0.00000.
Signification: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of belonging to the low-consumption segment, probably due to behaviours or economic conditions favouring lower consumption.

No significant link for gender and age of household head

Unlike to some previous studies (Mutua and Kimuyu 2015; Wijaya and Tezuka 2013), that emphasized the importance of the gender of the household head in predicting electricity consumption, our research found no significant relationship between the gender of the household head and electricity consumption along the different electricity consumption segments, as evidenced by the high p-values ($p > 0.1$). The coefficients of the 'Gender_male' variable for the consumption bands (Less than 110 kWh) and (111–400 kWh) are 0.2174 and 0.1823 respectively, with p-values of 0.271 and 0.438. This information indicates that this variable has no significant effect on electricity consumption at the 0.05 threshold. Similarly, the age of the head of household showed no significant relationship with electricity consumption (p-value = 0.982 for the first segment and 0.945 for the second segment). These differences may be explained by distinct geographical and socio-economic contexts, implying that in some contexts, gender and age may play a more or less important role.

Direct relationships with consumption in the first segment

In contrast, the direct relationship observed between household size, number of rooms, living area, type of dwelling and number of electrical appliances shows a direct relationship with electricity consumption in the first two segments (less than 110 kWh and 111–400 kWh). For example:

– *Household size:* This turns out to be a significant factor in both segments, with positive coefficients (0.0213 in the <110 kWh segment and 0.4764 in the 111–400 kWh segment) and p-values of 0.031 and 0.002 respectively. The odd-ratio is also greater than 1, indicating that increasing household size increases the probability of belonging to these segments. This result is logical, as a larger number of people in a household generally leads to higher energy consumption, as observed by Firth et al. (2008), who showed that electricity consumption increases with household size. However, the effect is more marked in the 111–400 kWh segment, where the coefficient is higher,

Table 4: Estimates from multiple regression analysis for the first consumption segment (111–400 kWh).

	Coefficient	Std. Error	*t*-ratio	*p*-value	Odds Ratio	
Const	1.9381	0.912	2.125	0.034	6.945	**
Gender_male	0.1823	0.235	0.776	0.438	1.200	
Age	0.0087	0.127	0.069	0.945	1.008	
Marital status	0.1985	0.139	−1.428	0.153	0.820	
Household size	0.4764	0.153	3.114	0.002	1.610	***
No of rooms	0.1066	0.058	1.838	0.066	1.112	*
Area of Hs (m²)	0.1173	0.053	2.213	0.027	1.124	**
Type of accommodation	0.3415	0.147	2.322	0.020	1.407	**
Number of appliances	0.1937	0.046	4.211	0.000	1.213	***
Perc_revenue [Less than 5%]	1.1865	0.283	4.192	0.000	3.275	***
Perc_revenue [5–10%]	0.9322	0.381	2.447	0.014	2.540	**
First segment	−0.2156	0.326	−0.661	0.509	0.806	
Third segment	−0.9654	0.425	−2.272	0.023	0.380	
Fourth segment	−3.5892	0.650	−5.522	0.000	0.027	

Model summary: Pseudo-$R^2 = 0.619332$; Log-likelihood = 562.91; p-value = 0.00000.
Signification: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

indicating that household size plays a more important role as consumption increases, due to the diverse uses that people in these households make of electricity on a daily basis.

– *Number of rooms and living area*: these two variables show positive and significant relationships with electricity consumption in both segments. In the 'Less than 110 kWh' segment, the coefficient for the number of rooms variable is 0.1781, with a p-value = 0.047, and for the living area variable, it is 1.4147 ($p = 0.004$). This information indicates a substantial impact of these variables on the probability of belonging to this segment. In the '111–400 kWh' segment, although these variables remain significant, their coefficients are lower (0.1066 for number of rooms and 0.1173 for surface area), indicating that their impact is more moderate in this intermediate consumption segment. These results confirm that the larger the dwelling and the more rooms it has, the higher the electricity consumption (Ali et al. 2021). We can deduce that these observations are the result of actions aimed at maintaining a certain level of comfort through air conditioning, lighting or even the fact that rooms are equipped with electrical appliances whose operation would contribute to increasing electricity consumption. This observation was made by Ningi, Taruvinga, and Zhou (2020) in their work. However, it should be noted that the high percentage of households belonging to the first consumption segment may be due to greater energy efficiency in larger dwellings, or to differences in the use of space.
– *Type of accommodation*: This is also a significant factor in both segments, with positive coefficients (0.8371 for <110 kWh and 0.3415 for 111–400 kWh) and p-values of 0.028 and 0.020 respectively. The odd ratio indicates that households living in certain types of dwelling, such as apartments, villas or other large dwellings, are more inclined to consume more electricity, probably due to structural characteristics such as the number of electrical appliances. Here again, the effect is most marked in the segment below 110 kWh, underlining the importance of housing type in the electricity consumption of low-consumption households.
– *Number of electrical appliances*: With almost similar coefficients in both consumption segments (0.1990 for <110 kWh and 0.1937 for 111–400 kWh), and highly significant p-values ($p = 0.000$), the number of electrical appliances is a predominant factor in the electricity consumption of the households in our study. The odd ratio (1.22) means that it is very likely that an additional appliance would contribute to an increase in household electricity consumption. Even so, this observation is consistent with the logic that a greater number of appliances leads to higher electricity consumption, irrespective of the consumption segment. This is also a conclusion from the analysis of the results of Firth et al. (2008) and Ali et al. (2021), who also found that the more appliances a household has, the higher its electricity consumption.
– *Percentage of income allocated to electricity*: the results show that households allocating a low percentage of their income to electricity (less than 5%) are more in the first consumption segment (coefficient = 3.3273, p-value = 0.000), as illustrated in Figure 3(i). This observation is in line with the study by Wang et al. (2018), which showed that households with a low income allocated to electricity generally adopt stricter energy-saving strategies. Indeed, these households, often constrained by tight budgets, tend to develop and prioritize energy efficiency actions to reduce their electricity bills. According to the opinions gathered, this involves reducing the use of certain appliances often deemed non-essential, and using household appliances more rationally, as well as opting for more energy-efficient equipment (lamps and electrical appliances). The majority of households surveyed said they prefer to buy new electrical appliances, as they are more energy-efficient than second-hand ones. For households that spend 5–10% of their income on electricity, the consumption segment to which they belong reflects a balanced management between the need for comfort and the need to control energy expenditure. Their behaviour could be influenced by a combination of economic factors, energy efficiency awareness and personal preferences, placing them in a lower or intermediate consumption category.

No significant relationships in other segments

The negative coefficients observed in Tables 3 and 4 are entirely logical and explainable. Indeed, one dependent variable (non-explanatory) cannot explain the behaviour of another variable of the same nature. Electricity consumption segments draw their explanations from the variables on which they depend to explain their behaviour.

Given the low level of data representation (1.6%) for the segments (401–800 kWh) and (801–2000 kWh), the multinomial logistic regression model applied to each segment produced no relevant results. In fact, a small amount of data made it difficult to estimate the parameters, leading to unusable results.

Explanatory power of the model

The relatively high explanatory power of our model (Pseudo-$R^2 = 0.619332$) indicates that the variables included in the model explain around 62% of the total variation in electricity consumption. However, 38% of the variation remains unexplained, highlighting the need to explore other potential factors, such as energy behaviours, or to take into account other variables not considered, to better understand household electricity consumption.

Practical and political implications

The results of this study offer several perspectives for energy demand management policies. For example, public authorities could encourage households to purchase new electrical appliances rather than second-hand or obsolete ones, by adapting taxation to make new appliances more affordable. This could lead to a reduction in electricity consumption costs, as new appliances are generally more energy-efficient, reducing overall electricity demand.

Awareness and education campaigns can be designed according to consumption segments to encourage specific behaviours. For example, a campaign for low-consumption households could focus on the benefits of adopting energy-saving appliances, while another for higher-consumption segments could encourage demand-reducing practices during peak hours.

Similarly, the study suggests that energy efficiency policies should specifically target households with large living spaces and many rooms, as these are the main consumers of electricity (Ali et al. 2021). Targeted energy efficiency programmes could be developed for these more energy-intensive households.

Conclusion

Yaoundé, as the capital of Cameroon, faces a number of challenges, including rapid urbanization and energy poverty marked by frequent power failures due to inadequate maintenance of the electrical infrastructure. Despite these difficulties, the city remains attractive, stimulating economic development and increasing demand for electricity.

The aim of this study was to understand the factors influencing household electricity consumption in Yaoundé. Using a multinomial logistic regression model, it was established that variables such as household size, number of rooms, living area and number of electrical appliances play a decisive role, particularly in the first consumption segments. These results, in line with the literature, underline the existence of a direct and significant link between these variables and electricity consumption. However, the study did not take into account other potentially influential factors, such as income, level of education or occupation.

The analysis shows that the influence of these factors varies according to consumption segment, which supports the need for energy policies tailored to different household types. However, for the higher consumption segments (401–800 kWh and 801–2000 kWh), the model did not show a clear link with the variables studied, due to insufficient data and a lack of model convergence.

To deepen this research, it would be pertinent to integrate additional variables, such as income, education and professional status, to better understand electricity consumption patterns. Studying households' energy behaviours, including their awareness of conservation practices and attitudes towards electricity use, could also offer avenues for targeted energy efficiency campaigns. Finally, extending this analysis to other regions of Cameroon or to other countries in sub-Saharan Africa would highlight specific regional factors influencing energy consumption.

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Contributions of authors

Léonce Wehnelt Tokam: Constructed the idea and wrote the paper. Data collection and data analysis.

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