Motivation, preference, socioeconomic, and building features: New paradigm of analyzing electricity consumption in residential buildings

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ABSTRACT

In strategic energy planning, human-oriented factors are uncertain and lead to unpredictable challenges. Thus, decision-makers must contextualize the target society to address these uncertainties. More precisely, uncertainties lead to performance gaps between assumed and actual sustainability target outcomes. This study proposed a new framework that considers vital elements, including occupant motivation, preference, socioeconomic characteristics, and building features (MPSEB). To utilize this model, a thorough face-to-face survey questionnaire was administered to measure these elements. This study explored how these elements affect the patterns of residential energy consumption in a region with numerous expat communities of various ethnic and cultural backgrounds. In particular, the study investigated the patterns of energy behaviors and human-building interactions among the residents of Qatar by collecting empirical evidence and conducting a subsequent survey analysis. Machine learning approaches were employed to explore the survey data and determine the interdependencies between features, as well as the significance of the fundamental factors influencing human-building interactions. The XGBoost method was used to conduct a feature importance analysis to determine factors contributing to residential energy consumption. The results revealed the primary behavioral and socioeconomic factors that affect residential energy consumption, and confirmed the influence of human factors in Qatar while considering its diverse population.

1. Introduction

The energy consumption of buildings, particularly in the residential sector, accounts for a substantial portion of global energy consumption [1]. Occupants and residents play a significant role in decreasing energy use in buildings [2–4]. Residential energy use has been the focus of social sciences, and the energy crisis in the 1970s attracted research interest in energy consumption behavior and related aspects such as culture, lifestyle, attitudes, and knowledge. Social science research was regarded as equally important in the analysis of energy issues, alongside more traditional engineering and economic approaches [5–9]. I, social and behavioral science began to be applied to energy research [9–11] with a cluster of behavior-based energy-efficiency studies. Behavior-based energy efficiency programs use intercessions to impact consumers' energy use behavior to achieve energy and/or peak demand savings [5].

In addition to energy efficiency and smart energy management in

buildings, human factors play a key role in energy use [12,13]. Efficient demand-side management strategies rely strongly on changes in human behavior. Moreover, considerable efforts have been undertaken to introduce advanced metering and communication infrastructure, smart management, and monitoring systems in buildings to enhance performance and energy efficiency. Nevertheless, human factors are still an essential component and may become the weakest link in the chain, requiring increased attention. Given the significant impacts of human behavior on building energy consumption, predicting behavior has become increasingly important.

Behavioral models have been used in various studies to investigate the parameters that affect human behavior [14,15]. For example, Michie et al. [15] developed a behavior change wheel (BCW) framework based on a review of existing behavior change interventions. The BCW framework aims to guide the design of interventions to strengthen the known weak elements of motivation, opportunity, and capability to improve the effectiveness of behavioral change interventions [2].

Wilson and Marselle [16] examined the comprehensiveness of the BCW framework in the field of energy behavior to design and implement energy conservation policies and strategies. They mapped the framework through four energy-behavior change guidance documents and found that energy-relevant behavioral determinants can be generalized into reflective motivation, physical and social opportunity, and psychological ability (MOA) groups. In psychology, motivation is defined as the processes of the brain that direct and energize human behavior toward goals [15,17]. Motivation measures the occupants' level of interest and involvement and their perceived personal relevance with a piece of information provided [18]. Li et al. [2] defined the factors influencing occupants' motivation in the energy sector as willingness, readiness, desire, and interest in utilizing information provided to adopt designated energy-saving behaviors. They developed motivation metrics and divided them into external and internal stimuli to demonstrate that energy intervention strategies should focus on improving these metrics. Therefore, the occupants' motivation level is related to their level of involvement and their involvement in the energy reduction strategies.

Researchers have applied various psychological frameworks and approaches to investigate human behavior and to promote pro-environmental behavior [19–22]. Vlek [19] applied the needs-opportunities-abilities (NOAs) framework to investigate the determinants of consumers' environmental behaviors. Abraham and Michie [22] developed a theory-linked taxonomy of generally applicable behavior-change techniques (BCTs) to identify techniques that contribute to effectiveness across interventions. Li et al. [2] and Ölander and ThØgersen [20] applied motivation, opportunity, and ability to explore consumer behavior and energy use behaviors in buildings, suggesting that motivation is facilitated by ability and opportunity. However, these frameworks and approaches, which were primarily developed in the field of psychology, did not consider key parameters such as building features and occupants' socioeconomic characteristics in the energy use domain or examine their impact on occupants' behavior.

To address this gap and examine the characteristics of occupants' energy behavior in residential buildings, this study proposed a new framework that considers vital elements, including occupants' motivation, preference, socioeconomic characteristics, and building features (MPSEB). The aim is to achieve:

(1) To understand the human characteristics and building features that highly contribute in residential buildings electricity consumption in the State of Qatar,
(2) To understand the discrepancies in electricity consumption attitude and behavior in the Qatari society based on their socioeconomic characteristics, motivation, and preferences.
(3) To determine the significant factor and the important features that affect the resident's motivation and preferences in electricity consumption

To utilize this framework, a thorough face-to-face survey questionnaire was administered to measure these elements of the framework. Human-driven factors in transitioning societies have not been empirically analyzed. In recent years, such societies have undergone demographic and economic transitions; therefore, in-depth investigations are needed. This study used applied theoretical social science research on energy to determine the primary drivers of human behavior related to residential energy consumption. Doha was selected as the study area as, at the national level, there are concerns related to its sustainable energy policies and its path toward the preferred transition, considering the fast-growing economy. Only Qatari citizen residents benefit from energy subsidies. This dualism contributes to the complexity of the social dimension that must be considered in energy policy strategies [23].

2. Literature review

Previous studies relied upon qualitative and quantitative methods to investigate the various behaviors and characteristics of occupants on building energy consumption [3,14,24–26]. Elements that describe the occupants' energy use behavior and characteristics in these studies include the intensity of energy use, attitudes, actions they perform or do not perform, and personal or social norms that may influence the level of energy consumption. Moon and Ahn [27] noted that technological investment alone does not guarantee compliance, net-zero energy or an improved sense of comfort in buildings. Although human factors are increasingly regarded as the prime factor in building energy sustainability, these factors are frequently neglected in the design and function of buildings. Furthermore, uncertainties regarding the relationships between the inhabitants, building systems, and occupant variables influence the precision of building energy use calculations. Human behaviors are hard to predict, but the theory suggests that interaction-based trends and habits for building occupant groups, derived from empirical studies, can provide insight into human-building interactions. Ozcelik et al. [28] simulated a single-occupancy workplace and analyzed human reactions to physical multimodal distress. In their study, human-building interactions were focused on visual decision-making and, therefore, on reacting actively to multimodal sensory changes in single-occupancy workplaces.

Previous studies have reported direct correlations between demographics and energy-building interactions. Considering the determined patterns, researchers have identified correlations between thermal comfort and gender [29]; between reactions to indoor environment change and thermal comfort preference and age and gender [30]; willingness association with demand response (DR) strategies and demographics [31]; home energy consumption patterns and new energy-related technologies [32]; relationships and disparities between racial/ethnic, spatial, and energy use intensity [33]; financial burden of home energy expenses and ethnicity [34]; home energy efficiency and ethnicity [35]; and willingness to accept an energy audit and demographic factors [36]. The correlations between socioeconomic processes and human factors that interact with the built environment have been examined in many studies. According to Drehobl and Ross [34], interdependencies exist between household income levels and energy expenses. Their results can support low-income homes becoming more energy-efficient than average homes. Furthermore, Franke and Nadler [37] demonstrated that compared with tenants, homeowners pay more attention to home energy efficiency and energy performance certificates. Strategic energy policy and planning can be enhanced by considering the reduction in energy expenses and energy pollutants in renter and low-income communities. Bednar et al. [35] investigated the relationship between utility bill payments and income levels. The results revealed that low-income families consume more energy per unit area, the likelihood of service shutdown is seven times higher in low-income households, and 40% of low-income families have missed bill payments compared to 14% of high-income families. Bradshaw et al. [38] investigated the relationship between household income level and home weatherization treatments and demonstrated that low-income families save energy through practices such as envelope air sealing, attic insulation, and the installation of programmable thermostats. Furthermore, Reanes [33] found that home energy efficiency was positively correlated with educational level and household income. Boucher [39] investigated 1670 zip codes to explore the interdependencies between temporal trends and sociospatial tendencies related to the per capita occurrence of home energy audits. According to the results, energy audits occur more frequently in highly educated households than in high-income ones.

The aforementioned factors have received considerable attention in the literature. Identifying the main behavioral drivers and human attitude factors in energy efficiency and human-building interactions could inform energy policies, such as population segment targeting to improve
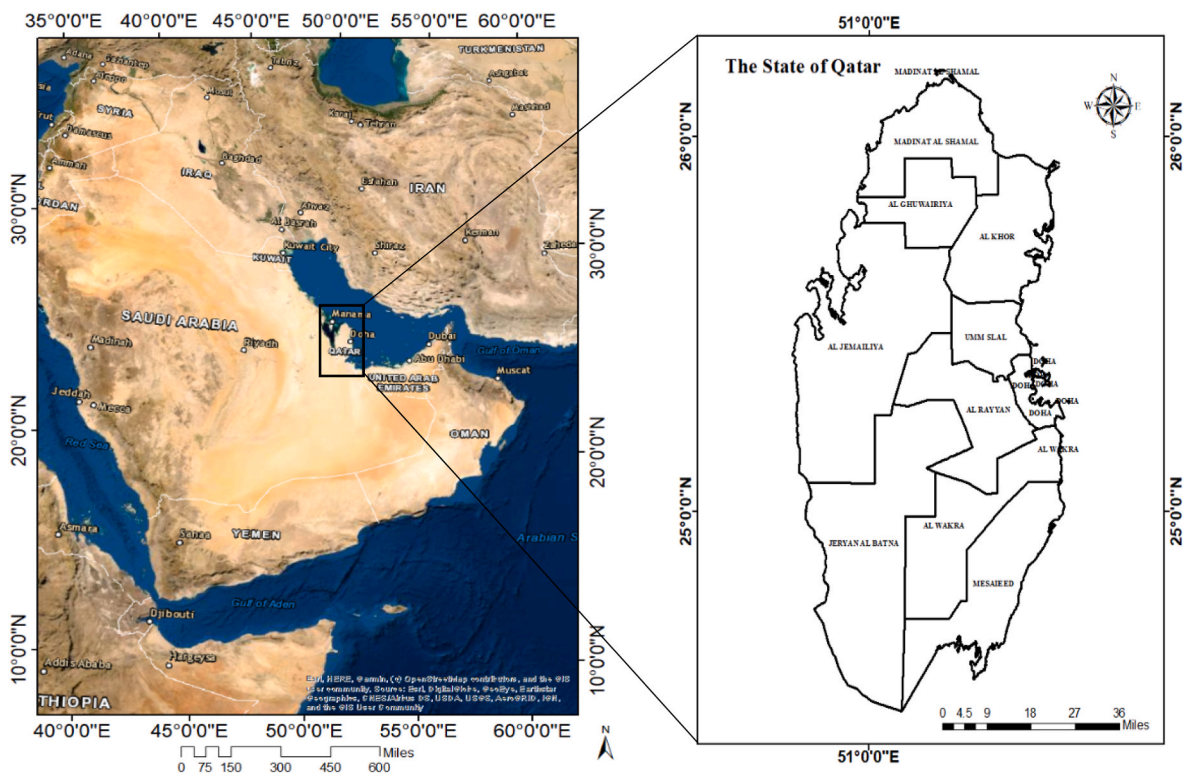
Fig. 1. Map showing the location of Qatar [54].

awareness, incentive modeling, and DR program planning. For example, emphasizing increased participation in a DR program does not always imply higher energy savings. Performance incentives and motivating strategies are more effective in increasing DR participation [40]. Biresselioglu et al. [41] evaluated the main human-oriented drivers of household energy use patterns, including perception and awareness, based on a national survey [41]. The subjects' knowledge of energy efficiency solutions, as well as other factors such as preference and security concerns, were the focus of the survey. The findings revealed that less than half of the participants interacted with or selected appliances based on their prior knowledge of energy-efficiency ratings. Less than 50% of participants were aware of air-conditioning technologies and less than 5% were aware of the use of renewable energy resources in water or space heating. Financial drivers and energy bills were the subjects' primary energy concerns. Al-Marri et al. [23] investigated the patterns of energy use in Qatar and the consumer awareness of renewable energy sources. Due to energy subsidies in Qatar, the study showed that energy efficiency concerns are unrelated to economic drivers and that approximately 70% of respondents are unaware of their energy and water consumption. In contrast, more than 80% of energy subsidy recipients believe that conserving energy is important, and more than half of those polled reported environmental issues as their primary concern. In addition, Al-Marri et al. found that education level influenced energy awareness. Guerra-Santin et al. [42] evaluated human attitude factors in building energy conservation using monitoring data. The findings showed that subjects were more likely to conserve energy when their actions were convenient. Furthermore, human attitudes are likely to be influenced by building conditions and user control opportunities, whereas respondents who are unconcerned with energy efficiency perceive thermal comfort as a key driver. Koupaei [43] evaluated user perceptions of the main drivers of smart thermostat use. Saving energy and money was the least important concern among users of smart thermostats, whereas comfort, ease of use, and installation were the most important factors. Hong [44] explored several issues related to building energy efficiency concepts, applications, and occupant

behavior. According to the findings, energy-aware user behavior can result in a 20% reduction in energy consumption in buildings, whereas non-monetary information-based interventions can result in significant savings. Franke et al. [37] demonstrated that financial incentives are the most critical factor in encouraging homeowners to adopt energy-saving practices and that energy awareness influences homebuyers' decision-making. Darby [45] examined the factors influencing people's willingness to participate in DR program. Users reported comfort and user experience as the important factors in contrast to financial incentives and technical considerations which are the dominant strategic perspectives in designing DR programs. The main behavioral factors that can encourage human participation in DR programs were assessed in a study on strategic DR planning to reduce winter peak demand [46]. Financial drivers and convenience factors, such as the day of the week of curtailment, were found to be most relevant. Furthermore, awareness, privacy, homeownership, and age were all positively correlated with users' willingness to participate in DR programs. Financial incentives have also been demonstrated to be more effective than environmental incentives in improving demand flexibility [31].

3. Study area

Qatar is located in the Middle East at 25° 30′ N and 51° 15′ E (Fig. 1) and is bordered by the Arabian Gulf and Saudi Arabia. Qatar covers approximately 11,437 km^2, with a population of 2.8 million in 2019 [47, 48]. Since its establishment in 1971, Qatar has witnessed rapid population growth and economic development attributed to the discovery of hydrocarbon energy sources [49,50]. Population growth and economic development have accelerated in the last decade since Qatar was awarded the hosting of the FIFA World Cup 2022 [51–53]. These factors have put more pressure on the electricity demand and supply processes. The annual electricity generation and consumption rate have increased in the last few decades in Qatar for many reasons, including population growth and economic development in the country as well as intensive demand for cooling during hot summers, highly subsidized electricity

Fig. 2. Survey components.

Table 1
Components of the questionnaire survey.

Socioeconomic characteristics	Gender, age, monthly income and expenses, number of persons in a household, job category, level of education, and occupants' nationality.
Residential buildings characteristics	Floor area of the building, number of bedrooms, home type, construction year, appliance type, and how often is the building is occupied.
Residents' preference characteristics	Preferred indoor temperature during the summer ((1) Cold (below 21 °C), (2) Moderate (21 °C–23 °C), (3) Hot (above 23 °C)), preferred lighting (i.e., light, dark, or moderate), to what extent they use their electricity appliances (i.e., rarely, moderate, very often), and to what extent they are willing to pay for renovation/upgrade at home to lower their energy consumption (i.e., not interested, highly interested, not sure).
Human attitude characteristics	Consider climate change, societal, economic, environmental concerns in energy consumption, as well as the amounts on energy bills (electricity prices), and different human factors (i.e., religion, culture, and income)

tariffs, and ambitions for a higher standard of living [54]. The electricity market in the country is considered a demand-oriented market, meeting the needs of the various socioeconomic sectors. Between 1985 and 2017, electricity generation increased by 1000% [54]. Furthermore, the average annual growth in the electricity generation rate was 9.9% between 2006 and 2016 and increased by 27.4% in 2020 compared to 2016. In addition, the annual installed capacity (MW) in the country has increased since 2005; the average growth rate of electricity consumption was 16.9% between 2008 and 2016. During the past few years, energy consumption per capita in the country is among the highest in the world and has grown rapidly at a rate of 2.6% compared to a 1% growth in income per capita [54]. Therefore, there is a gap between the electricity demand and supply. In response, the government has invested in multi-billion-dollar projects aimed at capacity expansion for new generation, transmission, and distribution network assets [55].

4. Data collection

Primary data were collected by developing and administrating a revealed preference (RP) paper-based self-administered questionnaire survey designed to investigate residential consumption behavior in Doha, Qatar. This type of survey is suitable for collecting data to investigate the electricity consumption behavior among residents. Moreover, it allows researchers to collect data from a large sample over a short period [56–58]. Furthermore, using the RP questionnaire survey

enables researchers to obtain reliable information about the actual behavior of residents and ensures higher external validity [59]. The survey was designed to be completely anonymous and to capture the main components of the proposed framework. Hence, it was divided into four sections, as shown in Fig. 2 and Table 1. A total of 3155 surveys were randomly distributed; however, only 1960 surveys were completed fully. Incomplete surveys were omitted from the analysis.

The purpose of conducting the survey is to collect data to analyze the electricity consumption behavior and human-building interaction in Qatar. The purpose of the survey was introduced to respondents prior to questioning. The design, sampling, and distribution method used for this study reflect the survey's purpose and target population. The survey was designed to satisfy the requirements to assess the human-building interaction in terms of electricity consumption as well to find electricity saving opportunities. Furthermore, the survey was designed to gather information that enable us to understand the variances and interdependencies of building and human factors in residential buildings and to develop new policies based on human electricity consumption habits. The targeted sample aim to reflect the country's socioeconomic, demographic and building features to better assess human energy behavior in the country. To maintain the useful information in the whole sample, an imputation methods and data preprocessing were used to fill the missing values with zeros to maintain the filled information in the sample. The survey was randomly distributed in many areas in Qatar and among different home types to ensure the greater likelihood of a comprehensive response and to avoid bias findings by eliminating the probability of concentrating the survey distribution on specific community or areas. The survey focuses on capturing the four elements of the model: consumer motivation, consumer preferences, consumer socioeconomic characteristics, and building features. The questions in each group designed to cover many factors in each group aiming to understand each component in a comprehensive way and reflects the normative goals (environmental/social motivations), gain goals (economic motivation), human electricity consumption habits and patterns, human-building interactions behavioral factors.

In this study, respondents were asked about their home construction year, total floor area, building type, hours of occupation on weekdays and weekends, and the number of bedrooms. These factors directly influence human well-being, comfort, and consumption patterns. For example, in older housing, consumers set the heating temperature at higher set points, use the heating system for a longer period, and experience greater discomfort. This indicates that there may be discrepancies in expected strategic outcomes for upgrade incentives when decision-makers neglect human behavior and building conditions in their analysis [60].
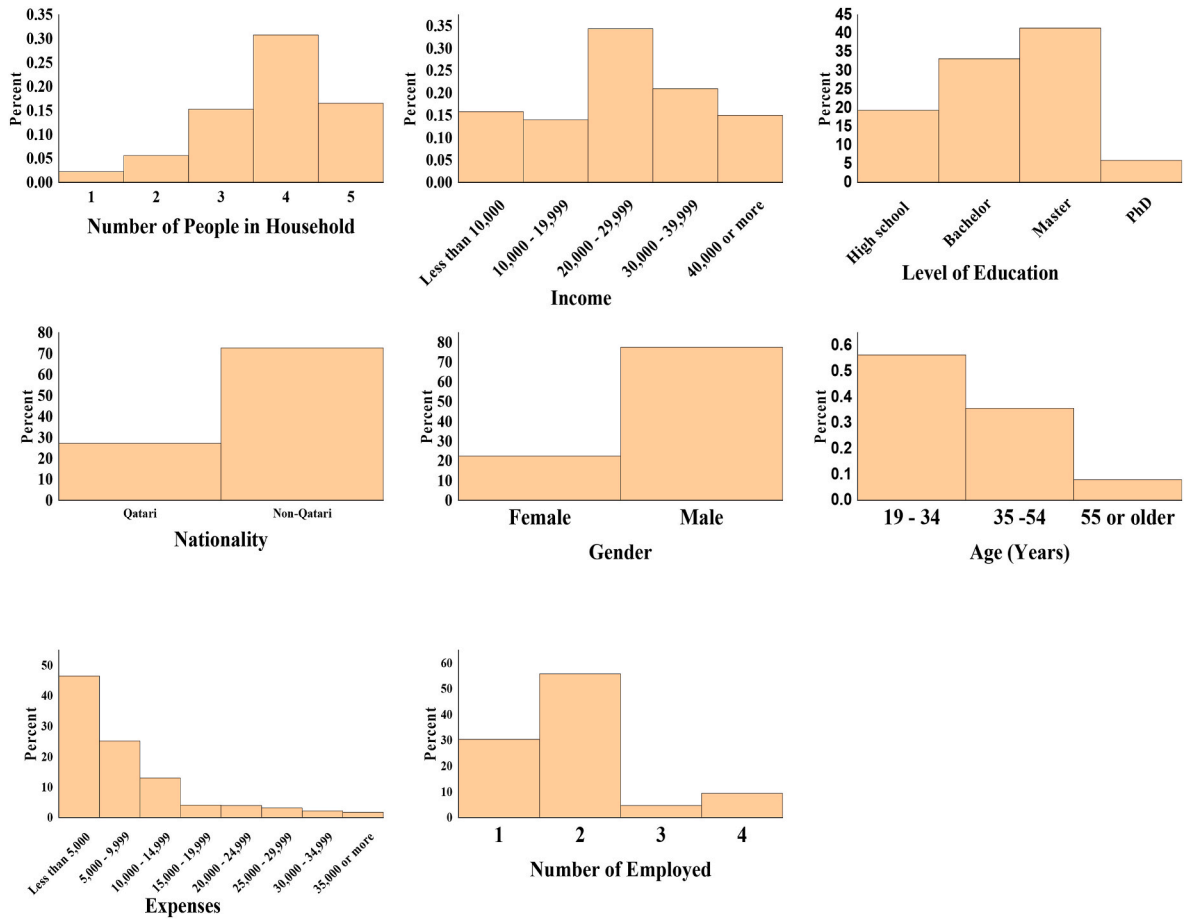
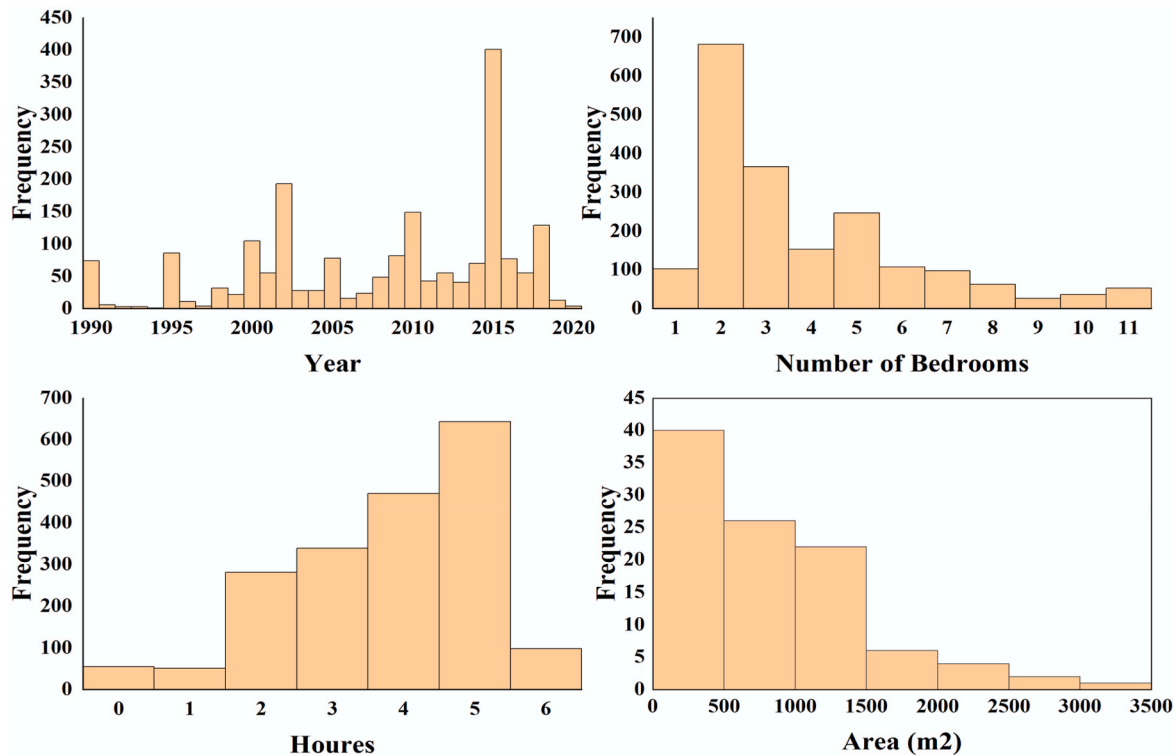**Fig. 3.** Socioeconomic characteristics of the sample.

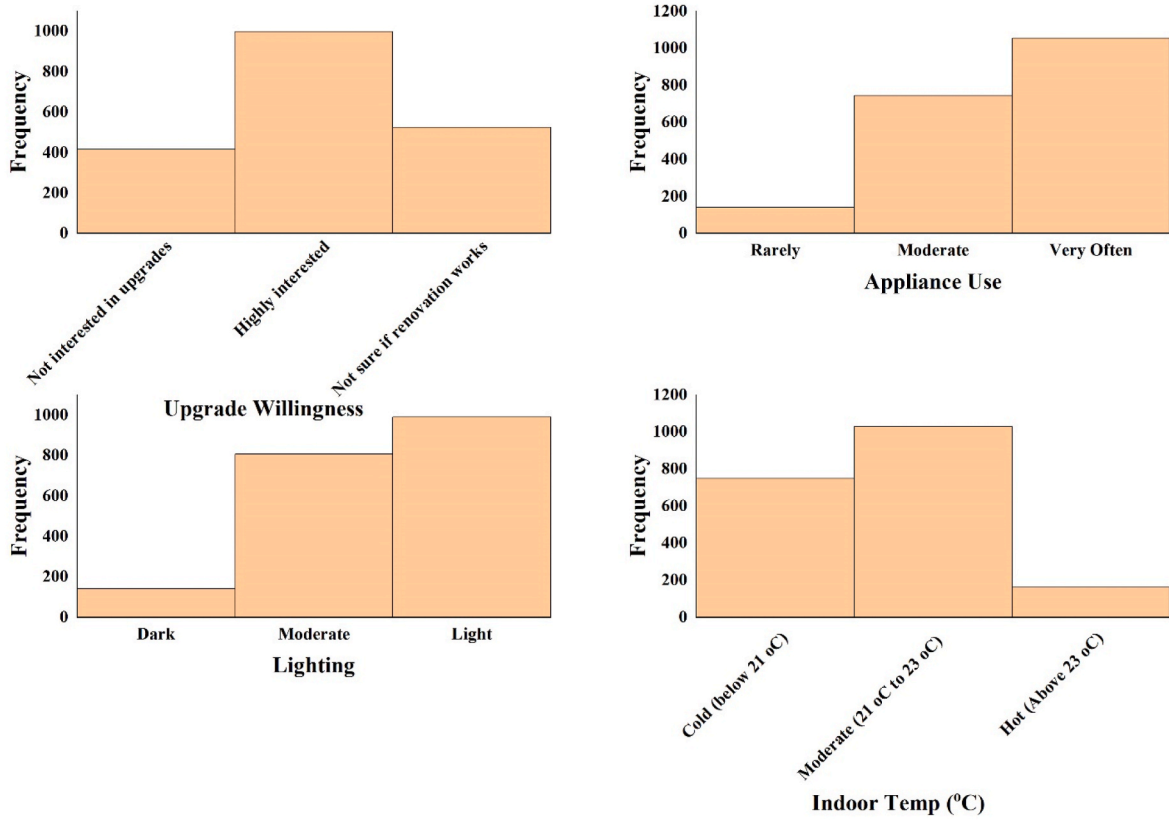**Fig. 4.** Frequencies of residential buildings characteristics component.

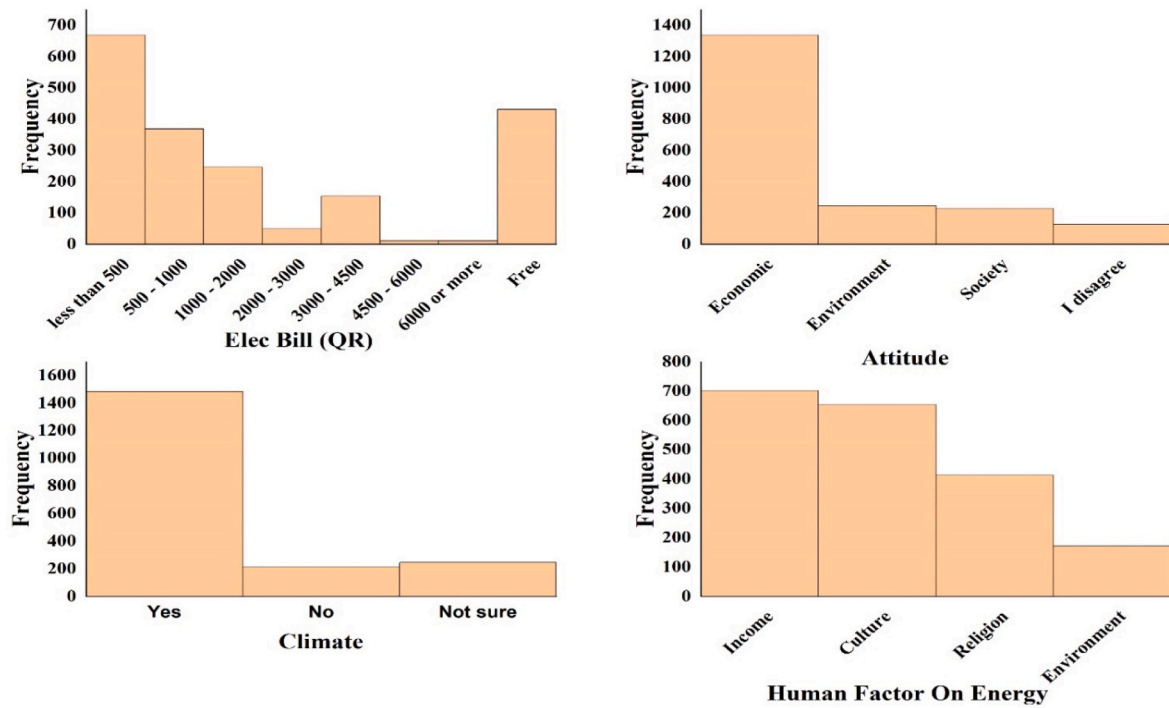**Fig. 5.** Frequencies of occupant preferences.

Fig. 6. Frequencies of occupant motivation component.

Prior studies found that motivation is directly associated with human behavior. Motivation is a measure of the level of interest and involvement of occupants [61,62]. Therefore, human attitude characteristics are a primary component in understanding occupants' consumption

behavior. However, motivating the population to reduce electricity consumption in Qatar is challenging because of the high gross domestic product (GDP) per capita, hot climate, fast-growing energy demand, subsidized electricity for expats and free electricity for citizens, and
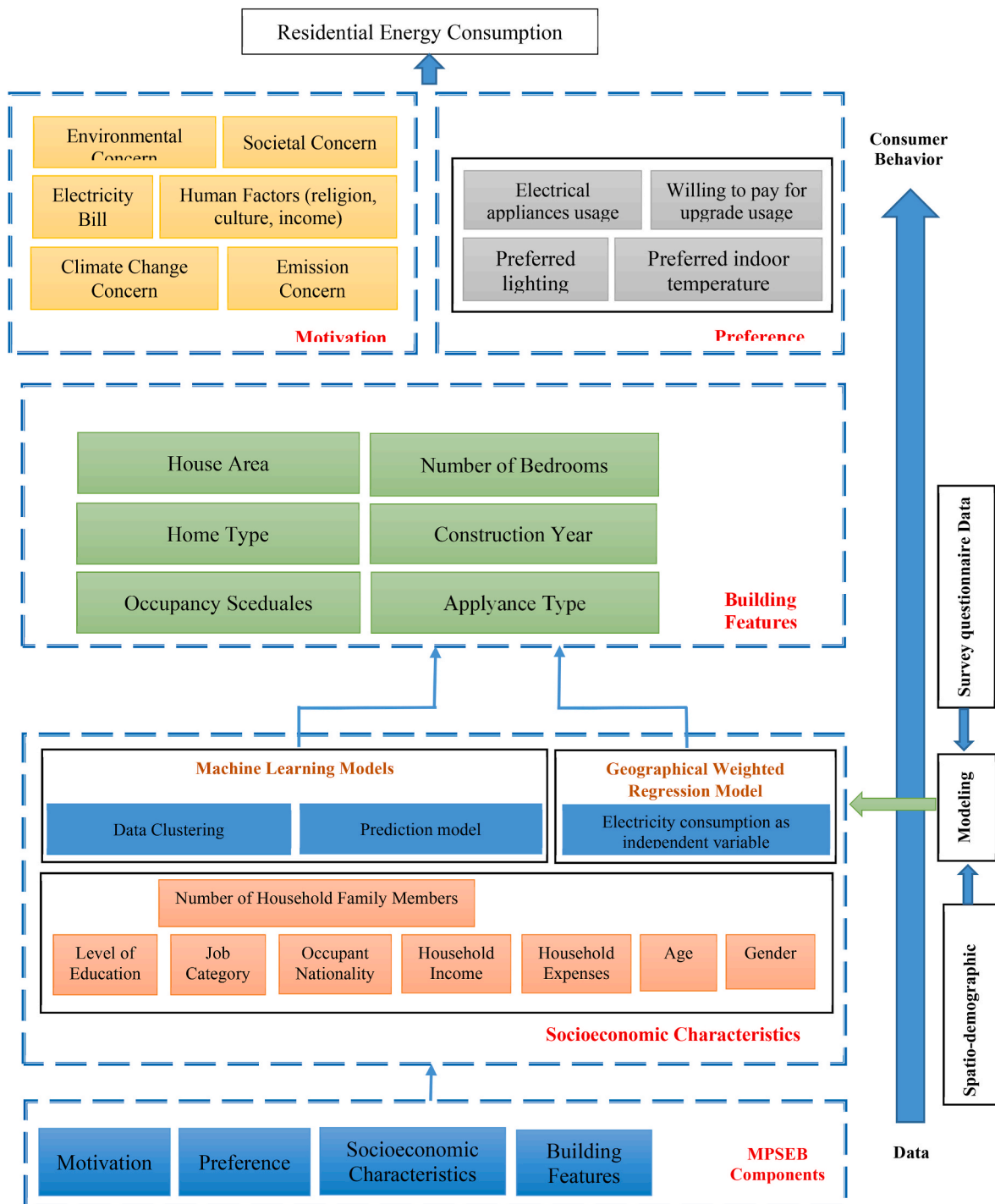
Fig. 7. Flow chart for research methodology.

demographic characteristics. Furthermore, an understanding of motivation is critical in elucidating pre-action behavioral factors. Therefore, residents were asked to state their motivation to reduce electricity consumption and their economic, social, and environmental concerns. Furthermore, respondents were asked if they were willing to upgrade their building retrofits for cost and energy savings. These elements were considered a gauge to understand the external motivation factors that may benefit society and decrease individual expenses. Another motivating factor considered in this study was the electricity bill, which can motivate residents to increase/decrease electricity consumption and is regarded as a primary target variable.

4.1. Survey components

4.1.1. Socioeconomic characteristics

The descriptive analysis aim to provide a better understanding of the distribution and representative of the data in each category. Qatar has a very young population,–85% of the population is aged 15–64, comprised of primarily expatriate communities. According to the 2015 national census data, approximately 39.8% of the inhabitants resided in the municipality of Doha with more men (78%) than women (22%) in the Doha population. Fig. 3 shows the primary demographic characteristics of the sample with a right-skewed distribution in age groups (57% are in the 25–34 age group).
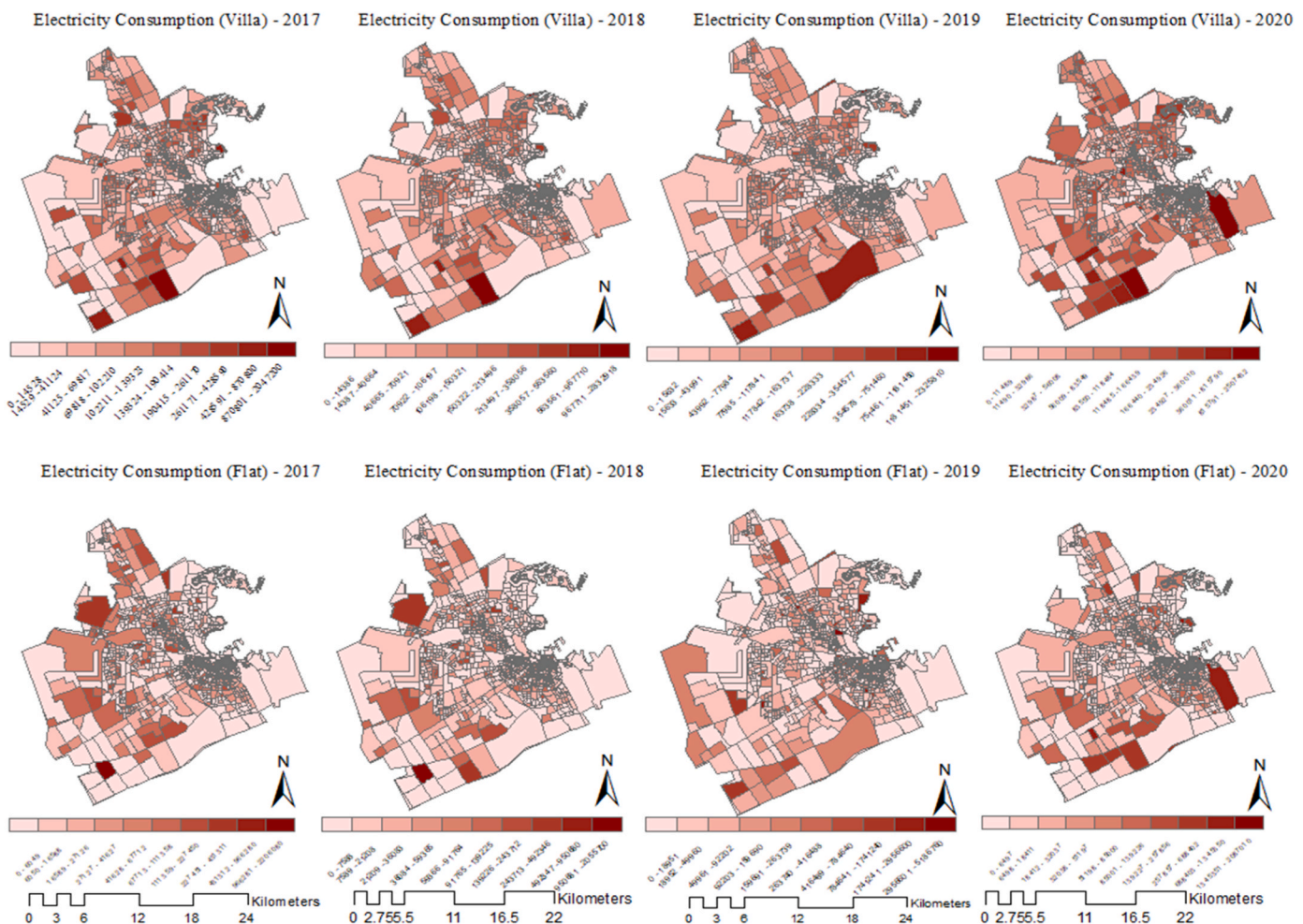
Fig. 8. Spatial distribution of electricity consumption across Doha.

4.1.2. Residential building characteristics

Fig. 4 shows the frequencies of residential building characteristics. Both the year of construction and the number of bedrooms are very diverse. However, what is notable is that most of the buildings were constructed in 2015, and the majority of the respondents has 2 bedrooms, followed by 3 and 5 bedrooms. A significant number of respondents reported having between 6 and 11 bedrooms, implying exceptionally high energy consumption. Furthermore, most of the respondents reported spending 5 h a day at the house, followed by four, three, and 2 h. These houses are also large in Qatar, which has important implications for energy policies. The majority of respondents have a residential unit of 500 m^2, followed by 1000 m^2, and 2000 m^2.

4.1.3. Residents' preference characteristics

Fig. 5 depicts the frequency of various preferences, such as the extent of use of electrical appliances and preferred temperature and lighting options at home. Approximately 1000 respondents were willing to pay for home renovations/upgrades to lower their energy consumption. However, 400 were not interested in upgrading. Importantly, approximately 500 respondents were unsure whether renovation was effective. This finding implies that a substantial number of respondents are not sufficiently informed about the benefits of upgrading and potential energy savings. This implies that decision-makers can target awareness-raising at this segment of the population and encourage participation in energy-saving projects. Furthermore, a small number of respondents (approximately 200) rarely used electrical appliances. The remaining respondents reported moderate to very frequent use, demonstrating the importance of energy-saving programs and upgrades. Fig. 5 shows that

the vast majority of respondents preferred light and moderate lighting, compared with less than 200 respondents who reported preferring dark conditions. Finally, approximately 700 respondents reported preferences for a cooler indoor environment (below 21 °C), which requires the substantial use of electricity. However, the majority of respondents preferred warmer temperatures (above 21 °C), whereas the lowest number opted for moderate temperatures (21–23 °C).

4.1.4. Human motivation characteristics

Fig. 6 indicates that the majority of the respondents pay less than 500 Qatari Riyal for their electricity bill, followed by those who have free electricity and those who pay between 500 and 1000 Qatari Riyal. The survey was designed to investigate the motivation for using smart energy solutions, such as central automation and smart thermostats. The vast majority of the respondents supported smart solutions if these translated into cost savings. Economic concerns were much more prominent in the answers than environmental and social concerns. Remarkably, the vast majority were concerned with emissions and climate change (more than 1400 respondents). The majority of respondents stated that income influenced energy use (approximately 700 respondents), followed by culture (slightly less than 700) and religion (approximately 400 respondents). The lowest number of respondents selected environmental concerns as a factor in energy use (approximately 200).

5. Research methodology

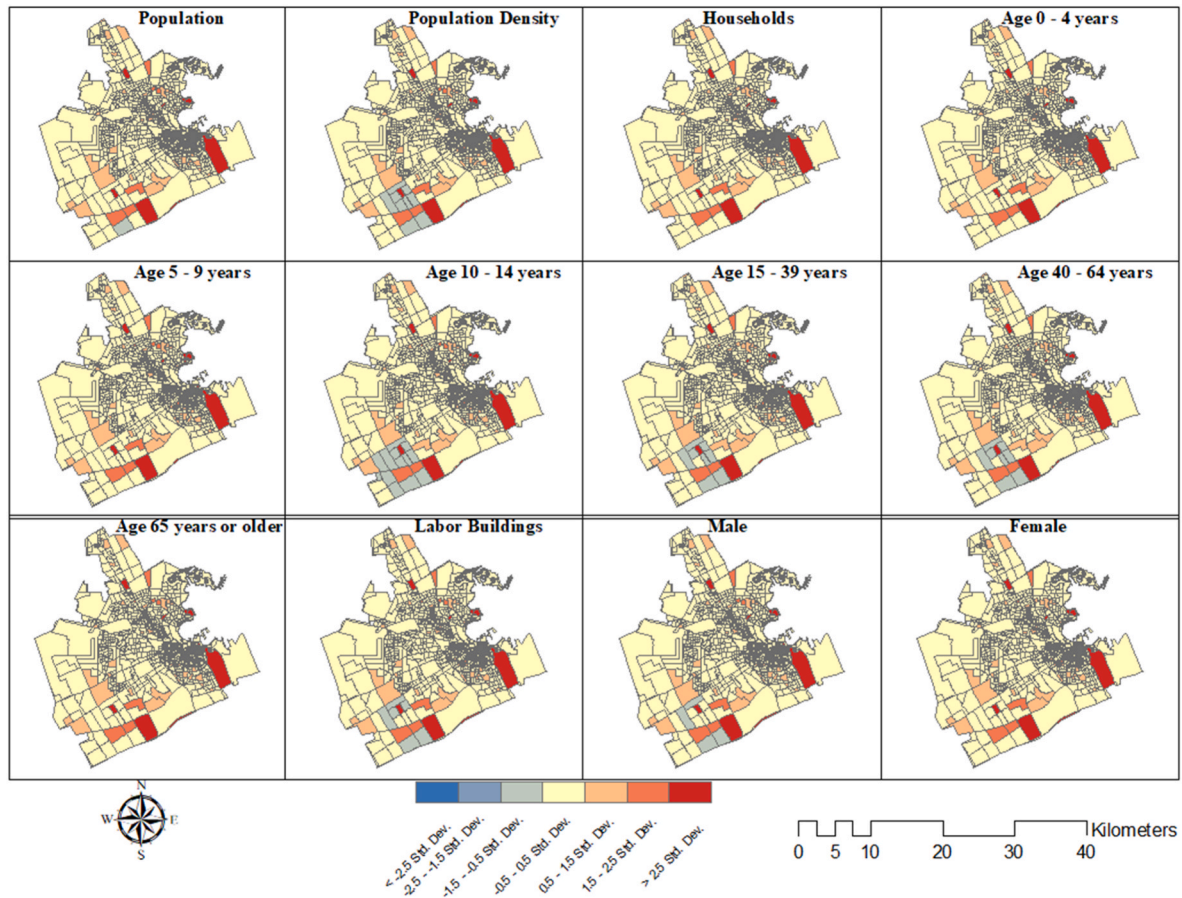This study uses different methods and processes for data analysis to

Fig. 9. Spatial correlation between various social factors and electricity consumption.

assess the residential electricity consumption behavior. Fig. 7 shows the association between specific analysis steps and analytical methods. Spatial analysis is first performed to determine the areas with high electricity consumption and the influence of different socioeconomic factors on electricity consumption. A geographically weighted regression (GWR) model was used to investigate the significance of the spatial distribution of socioeconomic factors in Doha to determine if these factors play a significant role in increasing electricity consumption in the city. This model is widely used to examine the relationship between dependent and independent variables. In this study, the model was used to examine the relationship between electricity consumption and different socioeconomic explanatory variables on a block scale. The GWR model is a linear regression model for spatially varying relationships [47]. Furthermore, this model assumes dynamic relationships and is proven to perform better than other linear spatial regression models. GWR estimates a local parameter for each zone separately and incorporates it into the geographical context [29–31]. The GWR can be expressed mathematically as [63,64].

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_{ij} X_{ij} + \varepsilon_i, i = 1, 2, \ldots, n$$

Where:

     y_i is the value of the electricity consumption rate,
     β_{i0} is the intercept,
     β_{ij} is the j_{th} regression parameter,
     X_{ij} is the value of the j_{th} explanatory parameter,
     i: is the zone, and
     ε_i is a random error term

Second, different machine-learning methods were used to examine the variables considered in this study. Spearman's rank-order correlation was applied to investigate the strength and direction of the monotonic relationships between the electricity bill and other features. In machine learning, feature correlation [65], also known as feature selection, is the process of selecting a subset of relevant features (variables and predictors) for use in the model. The Pearson correlation coefficient measures the degree of linear dependence between the two variables. This linear relationship is logical, even when the mathematical dependence between the two variables follows a nonlinear function. A perfect Spearman correlation of $+1$ or -1 occurs when one of the features is a perfect monotone function of the electricity bill feature. The mathematical formulation of the ratio of the covariance of the two variables and their standard deviations is:

$$\rho xy = \frac{\sum xy}{\sigma(X)\sigma(Y)} = \frac{E[(X - \mu x)(Y - \mu y)]}{\sigma(X)\sigma(Y)} = \frac{E[XY] - E[X]E[Y]}{\sqrt{E[X^2] - E[X]^2}\sqrt{E[XY^2] - E[Y]^2}}$$

Where, for a dataset with N records and means μ:

$$\sum xy = \frac{1}{N} \sum_{i=1}^{N} x_i - \mu y \left(y_i - \mu y \right)$$

Then the extreme gradient boosting (XGBoost) model [58] was applied to perform machine learning to measure the relative significance of motivation, preference, building features, and socioeconomic factors. XGBoost is a new framework for gradient-boosted machine decision trees designed for speed and performance, particularly K Classification and Regression Trees. It is one of the implementations of gradient boosting machines (gbm) and is one of the best performing algorithms utilized for supervised learning [66]. The model's algorithm is based on
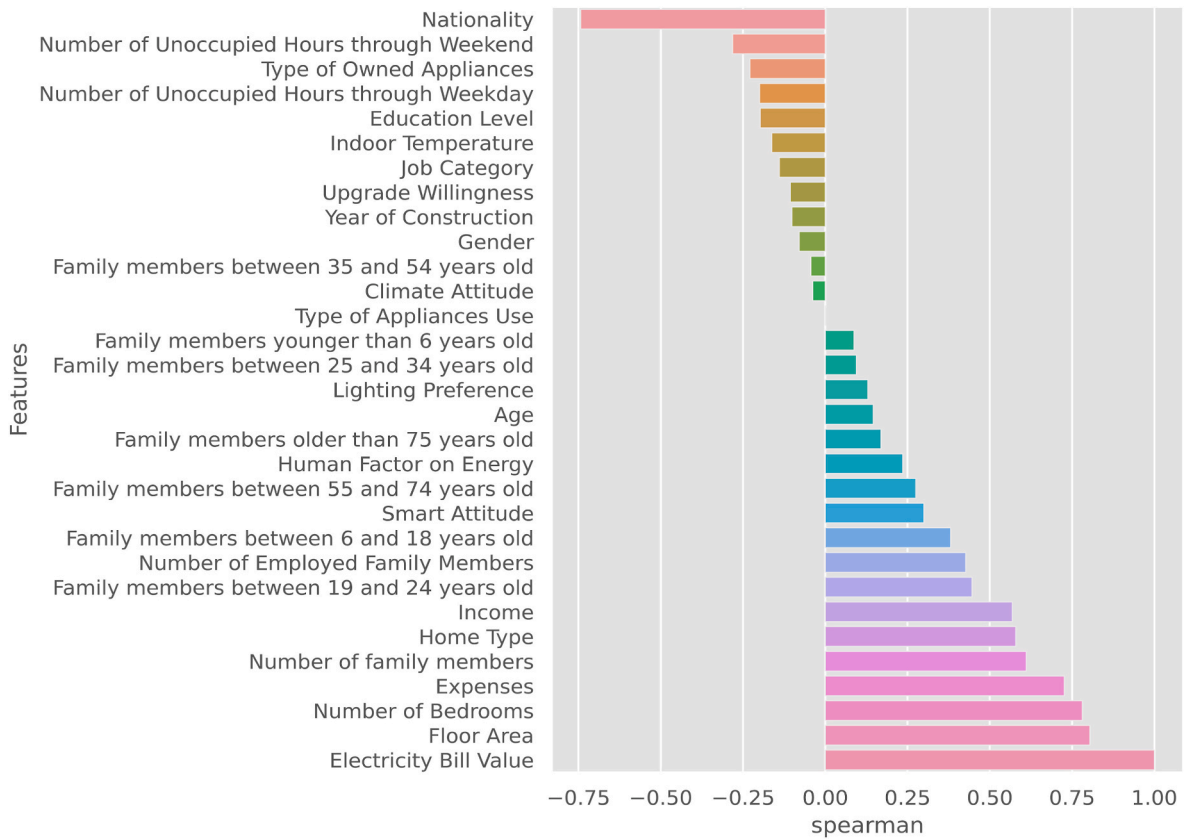
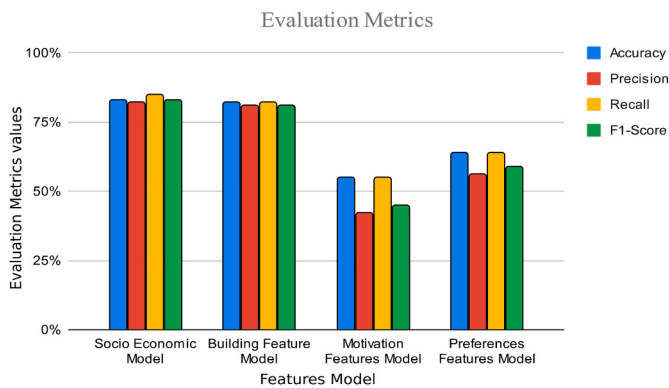**Fig. 10.** Correlations between survey features and the Electricity Bill.

Fig. 11. Training the model on the features included in the four clusters.

Fig. 12. Incremental improvement of generalized model over aggregated features sets.

Table 2
Evaluation metrics values of the model.

	Motivation Features	Motivation And Preferences Features	Motivation, Preferences and Building Features	Overall Features
Accuracy	55%	72%	82%	85%
Precision	42%	69%	81%	82%
Recall	55%	72%	82%	85%
F1-Score	45%	70%	81%	83%

the concept of "boosting". This concept works by developing strong learners through additive training strategies by combining all the predictions of a set of weak learners [67]. The general unregularized XGBoost algorithm for the prediction at step t is as follows:
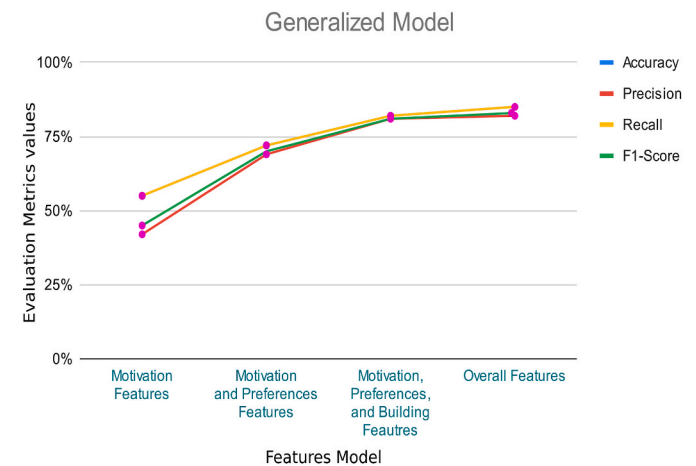
$$f_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = f_i^{(t-1)} + f_t(x_i)$$

Where $f_t(x_i)$ is the learner at step t,

$f_i^{(t)}$ and $f_i^{(t-1)}$ are the predictions at steps t and t-1,
x_i is the input variable

To evaluate the goodness and to prevent over-fitting of the model from the original function, the XGBoost derives the following analytic expression:
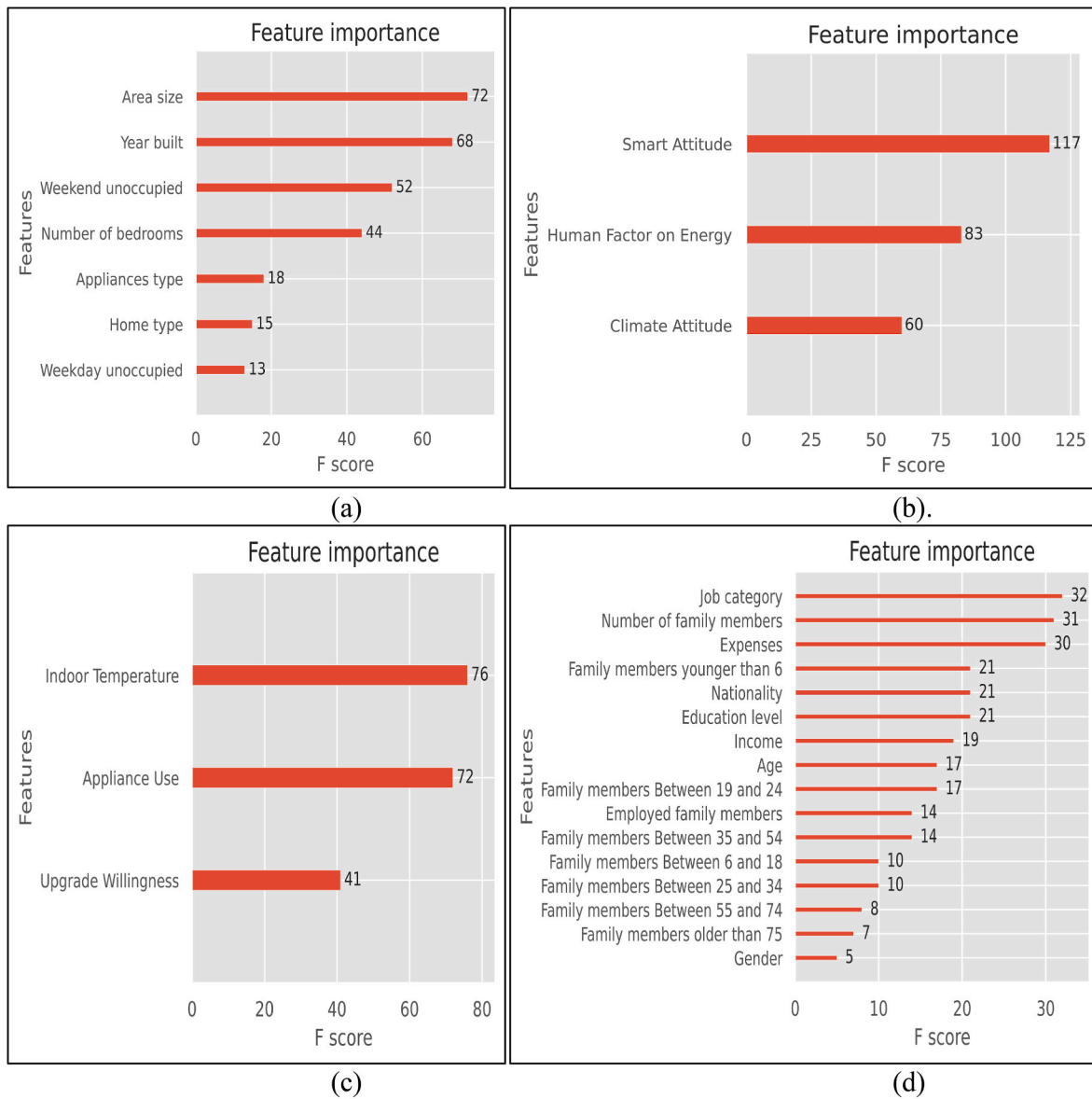
Fig. 13. F-score of the features in the four clusters (a) building features, (b) motivation, (c) preference, and (d) socioeconomic characteristics.

$$Obj^{(t)} = \sum_{k=1}^{n} I(n_i y_i) + \sum_{k=1}^{t} \Omega(f_i)$$

Where i is the loss function,

n is the number of observations used and

Ω is the regularization term defined as: $\Omega(f) = yT + \frac{1}{2}\lambda\|w\|^2$ Where w is the vector of scores in the leaves,

λ is the regularization parameter,

γ is the minimum loss needed to further partition the leaf node

The SHapley Additive exPlanations (SHAP) method was used for in-depth analysis of the primary factors that influence household energy consumption patterns. SHAP [68,69] is a game theoretic method for explaining the output of any machine learning model. It establishes a link between optimal credit allocation and local explanations through the use of game theory's traditional Shapley values and their related extensions. SHAP is defined as follows:

$$g(z)' = \emptyset_0 + \sum_{j=1}^{M} \emptyset_j z_j'$$

Where: g is the explanation model, $z' \in \{0, 1\}^M$ is the coalition vector or simplified features, M is the maximum coalition size and $\emptyset_j \in R$ is the feature attribution for a feature j, the Shapley values.

Afterwards, we conducted various experiments to investigate the possibility of categorizing the target population into similar energy-oriented patterns. Four machine-learning algorithms (K-means clustering, spectral clustering, DBSCAN Algorithm, and Gaussian Mixture Models (GMMs)) were tested to select the best algorithm based on the Silhouette Score. This step of analysis is important to determine the best policy practices to reduce electricity consumption in residential buildings focusing on human building interaction mechanism.
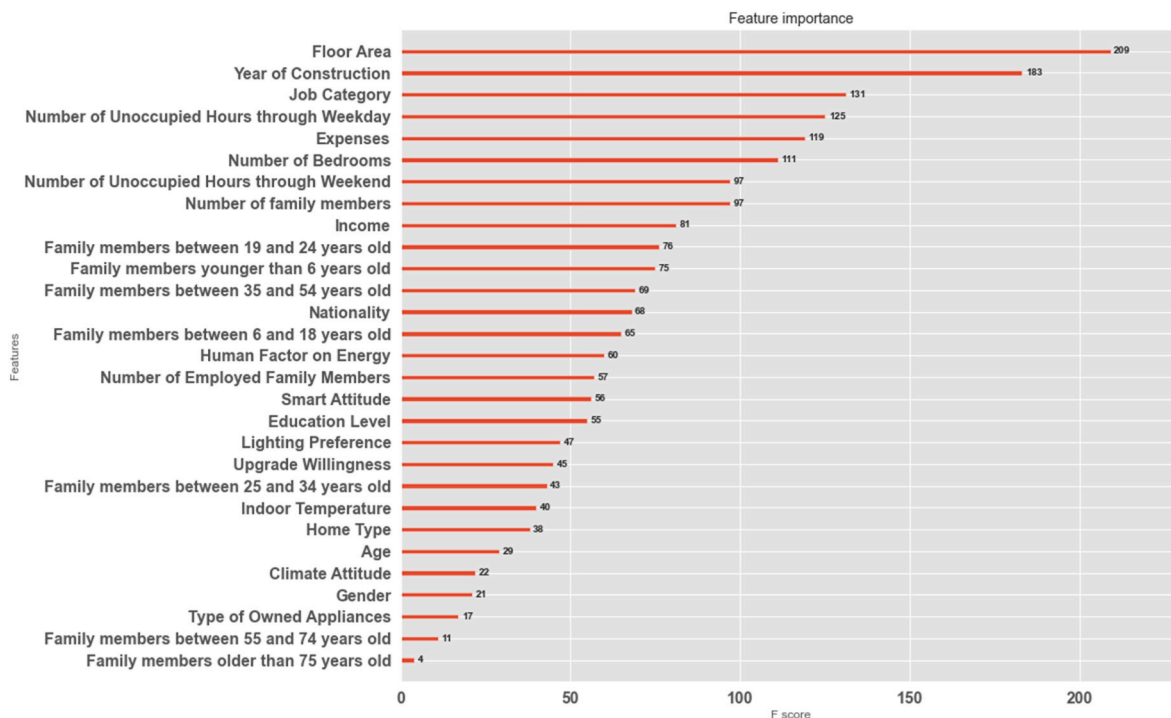
Fig. 14. Feature importance analysis of the energy consumer categories based on demographic and socioeconomic factors.

6. Results and discussion

6.1. Descriptive analysis

6.1.1. Spatial distribution of electricity consumption

Mapping the annual residential electricity consumption at the block level revealed changes in the consumption rates across space, time, and sector (villa or flat) between 2017 and 2020, as shown in Fig. 8. The blocks with high annual electricity consumption changed and gradually increased in many blocks in the residential sector of Doha. These blocks are scattered across different areas of the city due to the spatial distribution of each sector within the city. Electricity consumption increased in the central and northern parts of the city in the residential villa sector, and in the south in the flat sector. Electricity consumption in both residential villas and flats was affected by the COVID-19 pandemic due to imposed lockdown policies when the number of infections increased in the country.

6.1.2. Effects of socioeconomic factors on spatial electricity consumption

Mapping the correlation between social factors and electricity consumption at the block level enabled us to understand the effect of social determinants on electricity consumption and provided indications of consumption behavior. In this study, six social determinants were considered, namely population, population density, number of household members, age, gender, and labor housing. The GWR was used to determine the effect of each of these social factors on electricity consumption in the residential flat sector in 2020. Fig. 9 shows the clustering of high positive correlations across the six features in the southern parts of the city and blocks in the northern parts. The southern area of the city is the location of many industrial and commercial activities with higher population and population density, which is related to other social factors.

6.2. Feature correlation

Spearman's rank-order correlation was applied to investigate the strength and direction of the monotonic relationships between the electricity bill and other features. A perfect Spearman correlation of +1 or −1 occurs when one of the features is a perfect monotone function of the electricity bill feature. The results in Fig. 10 show that nationality has a strong negative association with the electricity bill value. Qatari individuals usually consume more electricity than other nationalities. Many building features have a positive correlation with electricity consumption (electricity bill) values such as floor area, number of bedrooms, and home type. Furthermore, many socioeconomic features have a positive correlation with electricity consumption, such as household monthly income and expenses, and the number of people in the household.

The classification model was trained separately on each set of features, as shown in Fig. 11. The results show that including socioeconomic and building features outperformed the motivation and preference models in terms of accuracy, precision, recall, and F1-score. This demonstrates the importance and impact of socioeconomic and building characteristics on electricity consumption.

We conducted a second experiment to construct a generalized model containing overall features. To approach this model, we documented the evaluation metric values of the model with respect to incorporating each set of features one at a time, as shown in Table 2. The entries in the table show that using only the motivation features led to weak performance (i. e., the accuracy was approximately 55%). By adding motivation features, the model's performance improved (i.e., the accuracy increased by nearly 16%). The highest accuracies were achieved by incorporating the building and socioeconomic features, as shown in Table 2.

Fig. 12 shows the incremental improvement in the generalized model over the aggregated feature sets. As can be seen from the line chart, the model's performance followed an upward trend in terms of the different evaluation metrics (i.e., accuracy and precision). We expect this performance to be enhanced by adding further features.

The previous figures show the feature importance of different sets. The importance of each feature was measured using an F-score. This score is a metric that determines how many times each feature is split. As our XGBoost model consists of the number of boosted trees that represent the estimators, in our model we have 100 estimators. Each feature is represented by a node in the tree, and the number of nodes split to make
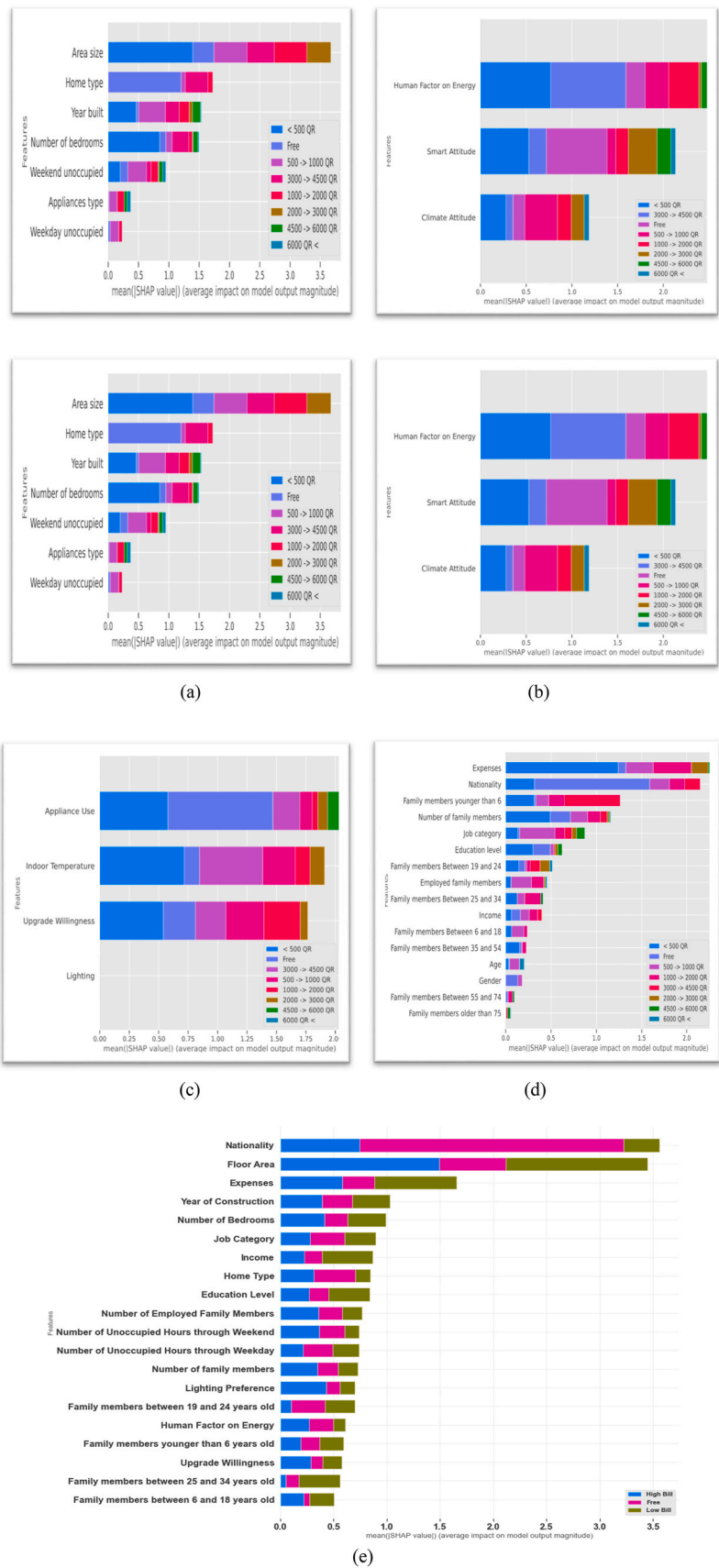
Fig. 15. Feature importance analysis of the energy consumer categories based on demographic and socioeconomic factors using SHAP, (a) building features, (b) motivation, (c) preference, (d) socioeconomic, (e) all features.
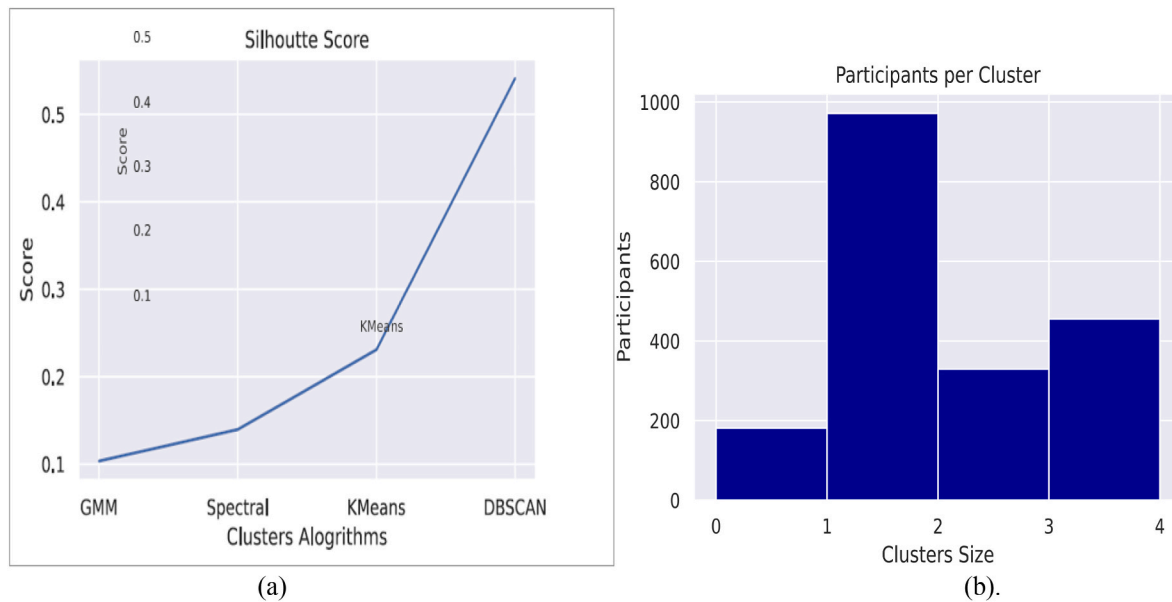
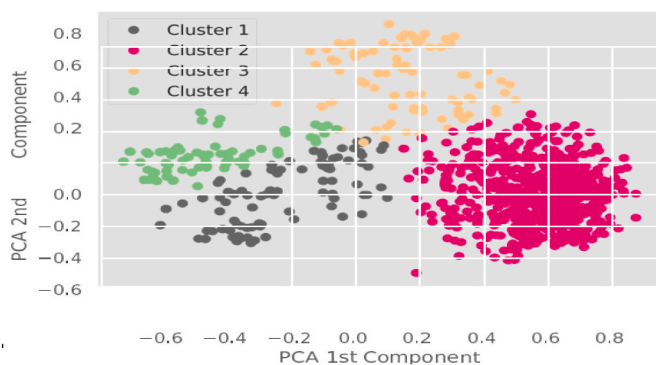Fig. 16. (a) Cluster algorithms, (b) cluster size.

Fig. 17. Principal component analysis Cluster Algorithms.

the final decision represents the F-score. Indoor temperature was the most influential feature in the performance of the preference model [Fig. 13(a)], while job category, smart attitude, and area size were the most influential features in the socioeconomic, motivation, and building feature models, respectively [Fig. 13b, c, d]. Our results seem reasonable as the building size, temperature preference, job category, and the number of individuals residing in a home are considered significant factors in determining electricity consumption.

We developed an XGBoost model to measure the relative significance of building features and socioeconomic factors, which outperformed motivation and preference. The model was based on 16 attributes. Furthermore, the independent variables were used to classify electricity consumption (electricity bill) into three categories:

- Category 1 (Low Bill): Residents with a low electricity bill,
- Category 2 (Free Bill): Residents that do not pay electricity because Qatari citizens receive free electricity from the state, through subsidized rent fee packages,
- Category 3 (height bill): Residents with a high electricity bill.

A ten-fold cross-validation analysis was conducted, which allowed the XGBoost estimators to classify the three categories. The average accuracy was 93.5%, F1 score 92.67%, precision score 92.97%, and recall score 92.61%.

A feature importance analysis based on XGBoost classification was conducted to identify the main factors influencing human energy consumption patterns. The results are shown in Fig. 14, indicating that floor area, year of construction, and job category were the most influential features in the socioeconomic, motivational, and building feature models. Furthermore, awareness of the consequences for individuals is not always related to energy consumption. Moreover, our results indicate that monthly household expenses are a more critical factor affecting the household's energy consumption patterns than income level. Importantly, the household monthly expenses include data on appliance use, appliance types, and building characteristics. Moreover, the gender of the users does not influence the household's aggregate behavior, in contrast to ethnic group and age. Considering behavioral factors, Fig. 14 shows that a family member's consequence awareness does not positively or negatively affect household energy patterns.

The SHapley Additive exPlanations (SHAP) method was used for in-depth analysis of the primary factors that influence household energy consumption patterns. Drawing on coalitional game theory, we used the SHAP method to calculate the Shapley values. The feature values of data instances are assumed to behave as players in a coalition. Accordingly, the Shapley values demonstrate a fair distribution of payouts among the features. Furthermore, a group of feature values represents a player. This is the case for pixels that are grouped into superpixels to explain an image. Therefore, the prediction is distributed among the superpixels. Importantly, in SHAP, the Shapley values are used as an additive feature attribution method. The feature importance analysis using SHAP depicted in Fig. 15 confirmed the results of the feature importance analysis based on the XGBoost classification, the floor area, year of construction, and job category were the most influential features in the socioeconomic, motivation, and building feature models. We also found that an individual's awareness of consequences does not necessarily impact the energy consumption category. Furthermore, we determined that ethnicity can influence the household's energy behavior, especially in Category 2 "Free." These results seem reasonable because, in Qatar, free electricity is provided for Qatari citizens through subsidized rent fee packages. Moreover, we determined that the respondent's floor area and expenses group could influence household energy behavior, particularly regarding "Low Bill" and "High Bill" survey participants.

6.3. Clustering of participants

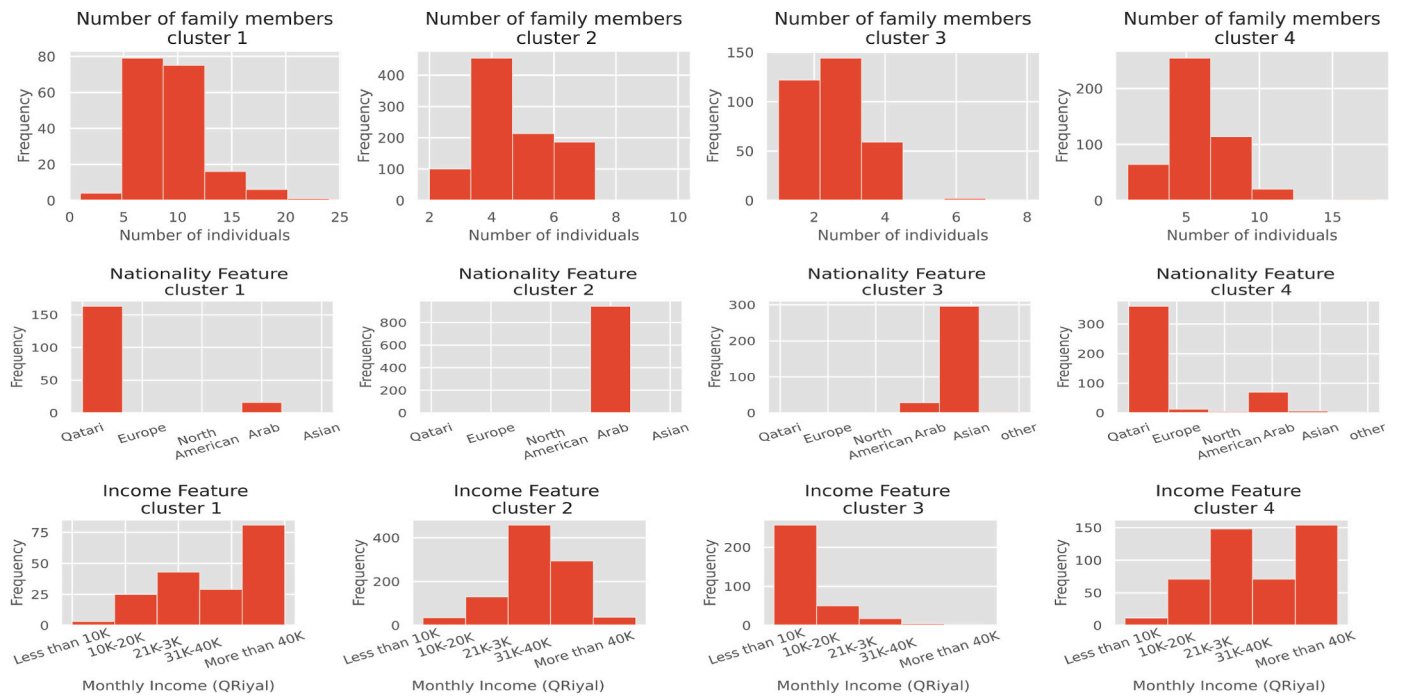We conducted various experiments to investigate the possibility of

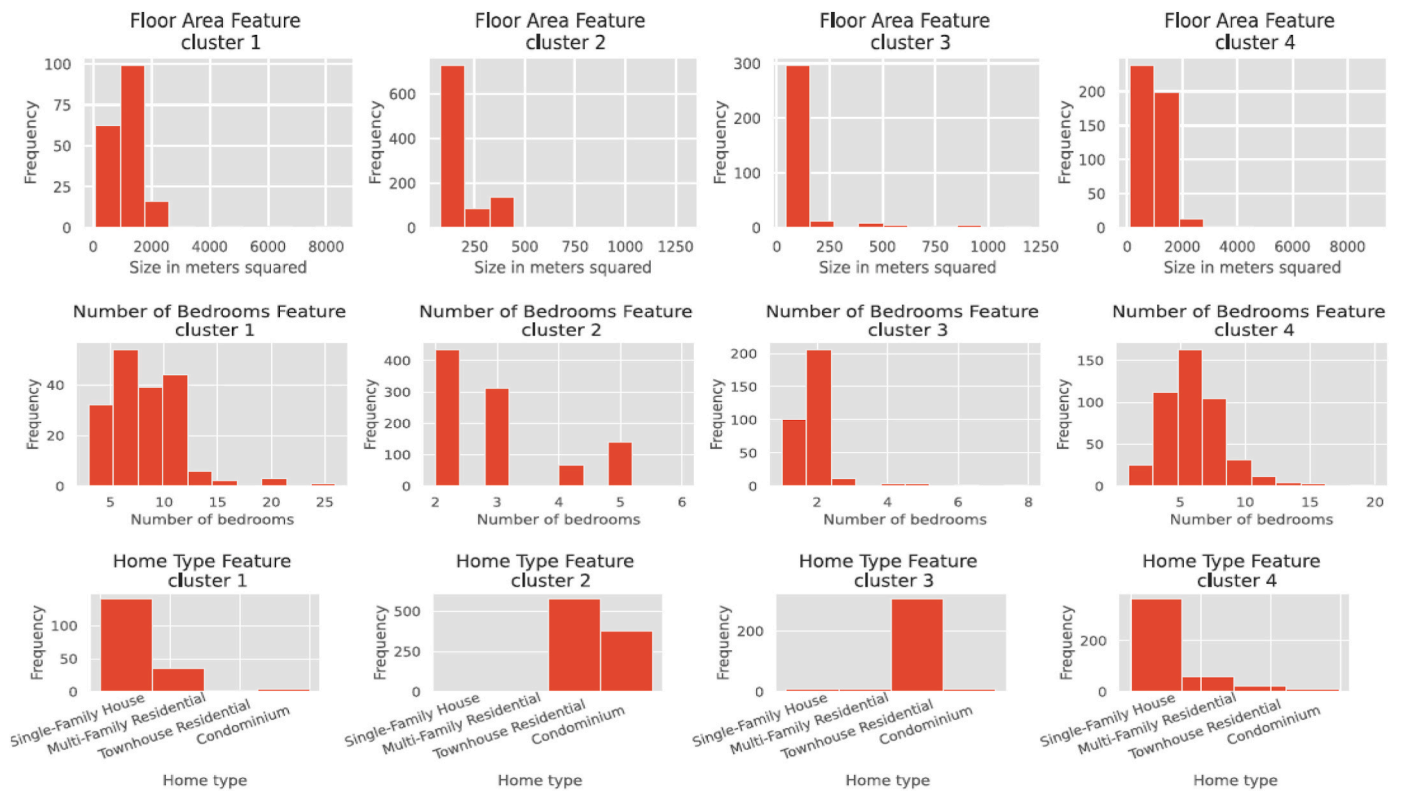**Fig. 18.** Clusters of socio-economic features.

Fig. 19. Clusters of building features.

categorizing the target population into similar energy-oriented patterns. Four machine learning algorithms were tested to select the best algorithm based on the Silhouette Score. Although DBSCAN outperformed the other algorithms, as shown in Fig. 16(a), we chose K-means to build our clustering model, as the distribution of the samples among the different clusters was more reasonable than DBSCAN. Fig. 16(b) shows

the sizes of the four clusters. We set the hyperparameter K in K-mean to four clusters.

Principal component analysis (PCA) (Fig. 17) is commonly used for dimensionality reduction by projecting each data point onto only the first few principal components to obtain lower-dimensional data while preserving the variation in the data.
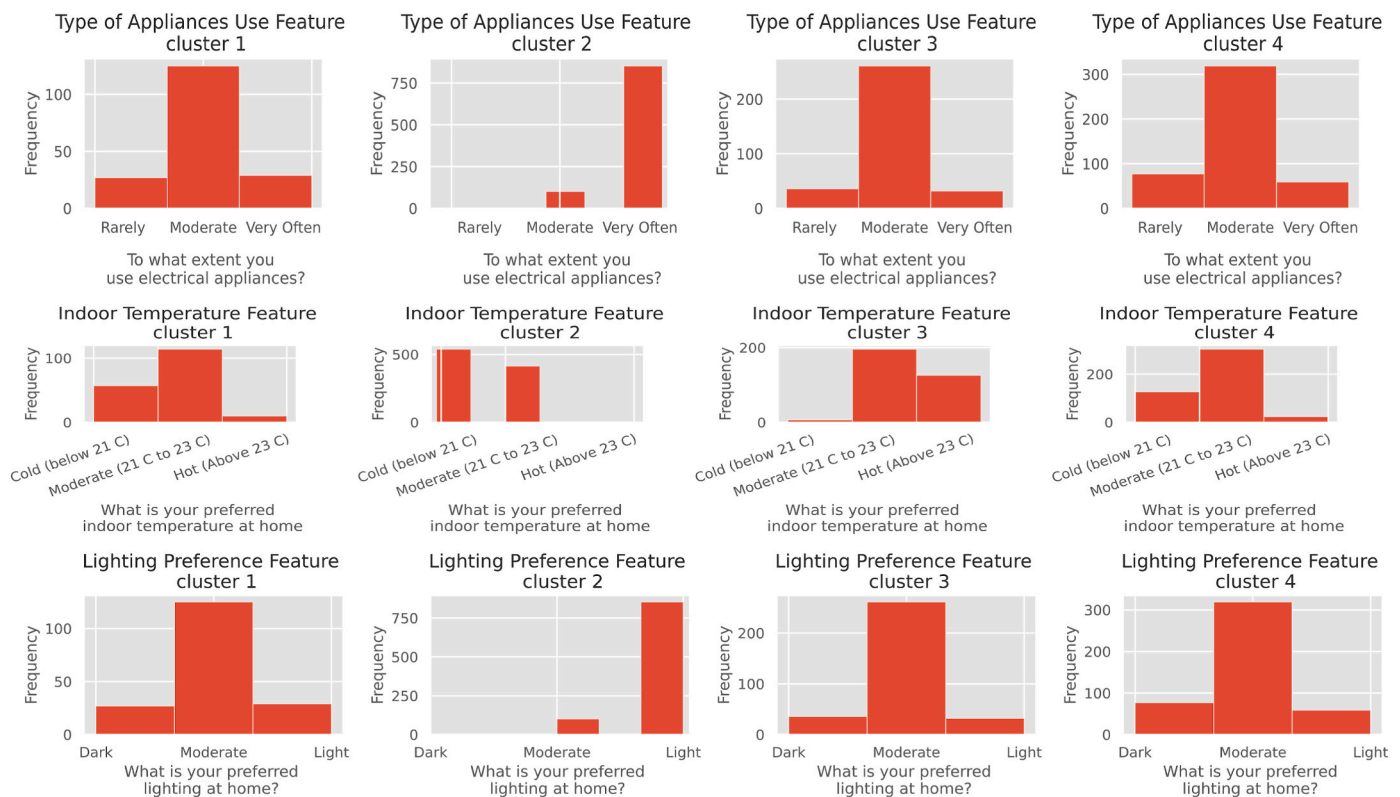
Fig. 20. Clusters of motivation features.

Segmenting human behaviors, which may influence energy consumption, can inform specific planning strategies and policies, such as improvements to human building interaction norms and past behaviors, as well as energy pricing regulations, promotional modeling, and energy awareness initiatives. Accordingly, our targeted population was categorized into four different clusters by applying the k-means algorithm (with K = 4). Figures [18–21] represent the distributions of the different clusters corresponding to socioeconomic, building, motivation, and preference features. As shown in Figs. 18–21, categories and patterns were determined. According to the distribution analysis, Cluster 1 consists of Qatari citizens, with household members ranging from 5 to 15. Their income is higher than 40,000 Qatari Riyal, and they typically reside in large, single-family houses with 5–10 bedrooms. This group is usually concerned about emissions and climate change. Moreover, they reported that culture and concerns about environmental issues are the main factors contributing to energy use.

Cluster 2 consisted primarily of Arab nationals. Their families, income, and houses were smaller than those of the Qatari citizens in Cluster 1. Their households consist of 2–6 individuals; their income ranges from 10,000 to 40,000 Qatari Riyal, and the number of bedrooms ranges from 2 to 4. They typically reside in townhouses, residential areas, and condominium complexes. They are also concerned with emissions and climate change. However, in contrast to the members of Cluster 1, Arab nationals reported income, culture, and religion as the main factors contributing to energy use.

Cluster 3 primarily consisted of Asian nationals. Their households typically have only two to four members. The lowest income was reported in cluster 3 (less than 10,000 Qatari Riyal). Cluster 3 residents live in the smallest housing areas (less than 100) in townhouses and residential complexes. Cluster 3 residents are not concerned with climate change. Income was singled out as the only factor contributing to energy use.

Finally, Cluster 4 comprised Qataris with small families. Their households have between five and ten members and tend to reside in

large, single-family homes with between five and ten bedrooms. Their income is higher than 10,000 Qatari Riyal. They are also concerned with emissions and climate change. In this Cluster, culture and income are the main factors contributing to energy-saving.

As previously discussed, Qatar's strategic power and energy policy is affected by high levels of uncertainty in demand projections and a set of sustainability and economic growth objectives. Policymakers must develop an optimal set of infrastructure development plans to determine the optimal location and timing of investment in sophisticated technologies through grid-expansion planning frameworks. A comprehensive assessment of energy consumption behavior will inform targets in energy policy in Qatar and the region, such as fostering energy consequence awareness and setting novel social and personal norms using socioeconomic and demographic factors to purposefully target society. Target in energy policy should be informed by the main factors motivating consumers to participate in energy efficiency programs and strategies (e.g., DR programs). Furthermore, authorities can investigate the relationship between indoor comfort zones and perceptions of human quality of life to propose tangible recommendations and guidelines for designing and controlling built environments.

Therefore, drawing upon the aforementioned studies, this study categorizes residents into four distinct clusters to help decision-makers specifically target population segments. The findings indicate the need for further climate change awareness-raising amongst Asian nationals. Moreover, lack of climate change awareness is likely to be correlated with low-income levels. Accordingly, financial incentives should be targeted at this Cluster. In contrast, other clusters were better informed about climate change. As Cluster 4 selected income as the critical factor contributing to energy use, financial incentives can also be used to target this segment. Arab nationals in Cluster 3 cited income, culture, and religion as affecting energy use. Accordingly, further studies should focus on the cultural and religious aspects related to climate change that can be employed to raise awareness and promote energy-saving practices. The Qatari nationals in Cluster 4 reported culture as the only
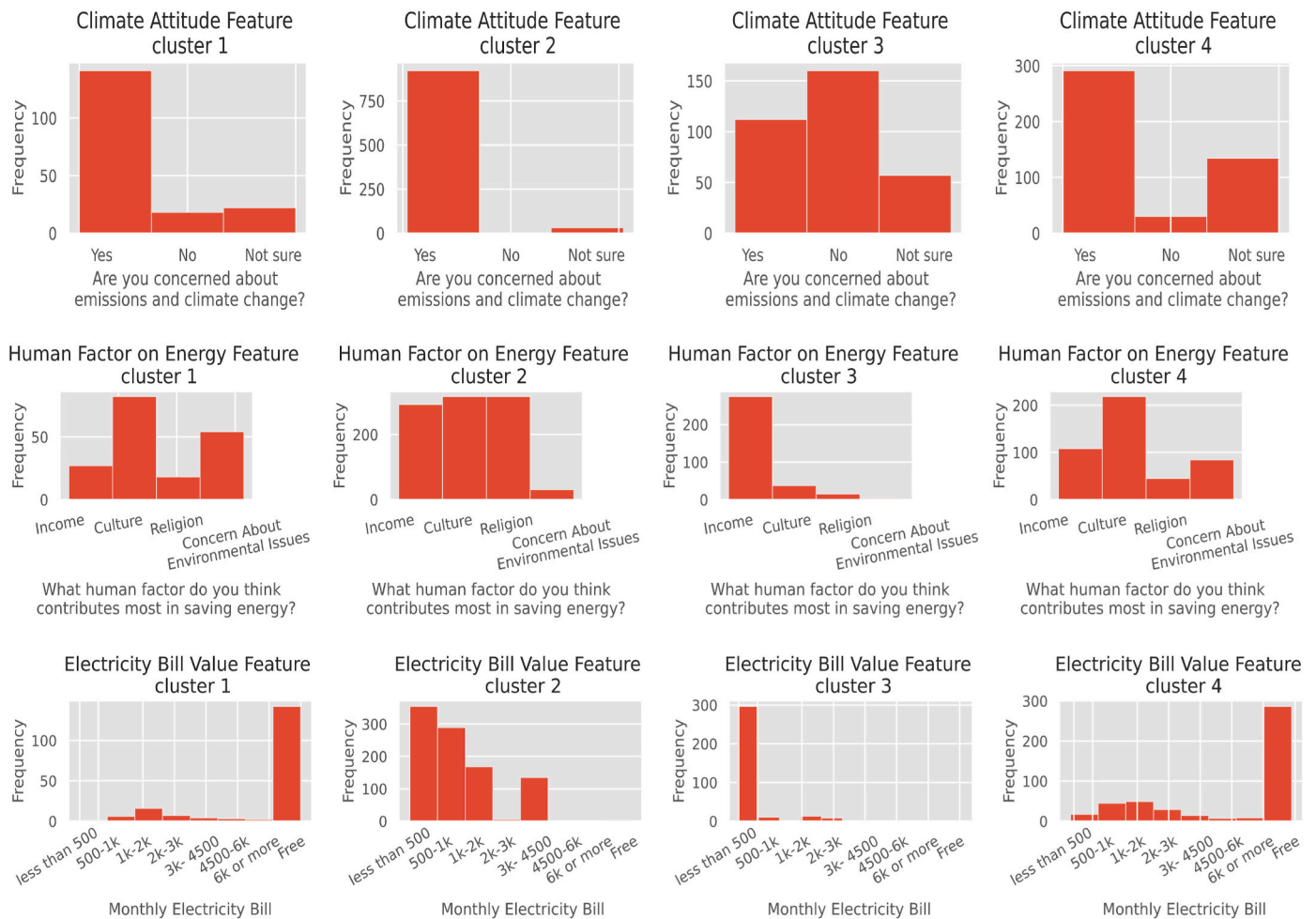
Fig. 21. Clusters of preference features.

significant human factor, which should be examined in detail. In particular, culture is related to so-called convenience factors, such as the user experience and perceptions of comfort, which have been identified in previous studies [46]. Our findings are in line with other studies that indicate the effectiveness of financial incentives. DR programs with monetary incentives can target all clusters that select income as a critical human factor. Establishing new social/personal norms and values and increasing a sense of responsibility are paramount for targeting Clusters 3 and 4.

7. Limitation of this study

This study generates important findings in the field of electricity consumption behavior in residential buildings in the State of Qatar through investigating the impact of motivation, preference, socioeconomic characteristics, and building features. The limitations of this study are as follows:

1 Although using RP data reflects the perceived knowledge and choices of resident's attitudes toward energy consumption and saving behavior in real time settings; however, one of the limitations of such data is the issue of collinearity among choice attributes, which may be difficult to decipher [70]. Furthermore, the validation of the findings based on self-reported responses highly depend on the self-perception of respondents, which might create a hypothetical bias.

2 The study focused on specific factors that may affect electricity consumption behavior of consumers. We are aware that there are

other factors that may affect electricity consumption behavior, such as the weather and construction material among others. Qatar is classified as Tropical and Subtropical Desert Climate (BWh) [52] with a very hot and humid summer, which increase electricity consumption due to the extensive use of air conditioning. This feature may not apply on other countries with moderate to cold climate.

3 There are discrepancies in the socioeconomic characteristics in the Qatari society, mainly between Qatar citizens and the expats living in the country, which affect electricity consumption. The electricity is subsidized for the expats and free for Qataris. Furthermore, the houses of most Qataris are larger due to family size and the possibility to benefit from getting a land and interest-free loan from the government to build a detached house. To overcome this limitation, future studies can build on the survey results of this study as detailed input to investigate the differences between Qataris and expats in electricity consumption behavior and pattern.

8. Conclusion and policy implications

In this study, we investigated a sample of 1960 participants from Doha, Qatar. This study aimed to explore the influence of behavioral, socioeconomic, and demographic factors on human-building interactions. The overall objective of this study was to identify critical human factors that influence energy use to propose specific and efficient guidelines for energy policy. Most importantly, the objective was to include human and social factors in strategic energy planning to mitigate the uncertainties related to human dimensions. We analyzed various interdependencies and specific characteristics of the target

society to inform energy policy. We categorized participants' bills into three categories (low, medium, and high) using the XGBoost method. Subsequently, we performed a feature relevance analysis, which revealed that ethnicity, age, and household costs can determine household energy consumption patterns. In addition, behavioral traits and human attitudes, which are not related to socioeconomic and demographic factors, offer sufficient variation to distinguish between the two consumption patterns. This finding can contribute to devising particular awareness-raising strategies for different target groups or propose specific interventions aimed at reducing energy consumption. For example, increased granularity in spatiotemporal energy pricing can be used to reduce electricity use, whereas community-based media campaigns can be developed to increase energy awareness. The analysis of building, socioeconomic, and demographic factors revealed that there are distinctive trends regarding human-building interactions, that the indoor environment plays a key role in the well-being of users and reported interior comfort levels. These findings can direct the use of tailored financial incentives based on community characteristics. Accordingly, well-being in built settings can be enhanced, whereas negative human-building interactions caused by human discomfort can be minimized. In addition, our study revealed that socioeconomic and demographic characteristics can influence attitudes toward home energy efficiency drivers, the self-responsibility components of energy usage, and climate change awareness. Moreover, the study found that human characteristics such as income level, ethnicity, and gender were associated with users' willingness to participate in DR programs including monetary incentives for reducing residential energy consumption. Overall, owners of older buildings and apartment dwellers were more likely to participate in DR initiatives than new homeowners, who had greater resistance. Recently, various initiatives aimed at limiting energy consumption were proposed in Qatar [71,72] such as i) establishing institutions through the collaboration of national funds, local banks, and foreign companies to generate appropriate industrial infrastructure and cutting-edge solar projects; ii) establishing research and development infrastructure (e.g., Qatar Science and Technology Park) through national programs to reduce GHG emissions; and iii) starting a Tarsheed campaign. These initiatives led to a 10% decrease in per capita electricity consumption compared to 2012. Our study found that energy strategy plans need to consider the human dimensions of the highly diverse population of locals, expatriates, and immigrants. To support ambitious targets for economic diversification and technological penetration, policymakers must consider human-centered factors, such as increasing a sense of personal responsibility, establishing new social and personal norms and values, incentive modeling to promote building energy efficiency, community-based awareness and education, and targeted electricity pricing. In particular, regulators must overcome regulatory impediments to subsidization plans and energy pricing. The effect of enforcement and taxation in regional real estate markets and marketing efforts (e.g., utility bill deferment offers) on residential energy use should be evaluated [73]. Energy efficiency plans must incorporate financial incentives and refunds to encourage participation by the private sector. Adequate legislation and infrastructure are required to address primary concerns, such as security, dependability, and consumer privacy, and to improve the quality of DR programs. Multidisciplinary methods are needed to investigate and incorporate the technological, political, economic, and environmental dimensions. Further research is needed to determine electricity consumption trends during the COVID-19 pandemic. In particular, a more detailed decomposition analysis is required to determine the consumption trends of different end-users.

CRediT authorship contribution statement

Esmat Zaidan: Conceptualization, Formal analysis, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Ammar Abulibdeh:** Writing – review & editing,

Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ahmad Alban:** Data curation, Formal analysis, Methodology, Software. **Rateb Jabbar:** Data curation, Formal analysis, Methodology, Software, Validation.

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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