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Energy consumption prediction for households in a society with an ageing population

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ABSTRACT

Social aging significantly impacts household energy consumption patterns and demand, particularly in megacities like Shanghai. This study addresses the gap in understanding high-frequency impacts of aging on energy use by employing advanced machine learning techniques. Using Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM), we analyze high-frequency hourly energy consumption data from 14,000 households in Shanghai (2016–2023) to identify distinct consumption patterns and their relationship with household characteristics. The study also simulates future scenarios incorporating demographic aging and income growth. The results reveal that an aging society not only increases overall energy demand but also significantly alters hourly consumption patterns, amplifying disparities between peak and non-peak hours. These shifts, compounded by income growth, highlight the need for tailored energy policies addressing demographic transitions. This research contributes to sustainable energy planning by providing actionable insights into the intersection of aging demographics, economic development, and urban energy consumption. The findings align with the United Nations Sustainable Development Goals (SDGs) by promoting efficient and inclusive energy strategies.

1. Introduction

The rapid aging of societies worldwide, particularly in urban megacities such as Shanghai, presents a pressing challenge for energy consumption management. By 2050, the United Nations predicts that 22 % of the global population will be aged 60 or older, with urban centers witnessing even higher proportions due to concentrated economic activity and better healthcare facilities. In Shanghai alone, projections indicate that by 2050, over 44.5 % of the population will fall into this demographic group, creating a profound shift in energy demand patterns. Aging populations are characterized by distinct consumption behaviors, such as increased energy use during daytime hours and heightened sensitivity to extreme weather conditions. Despite these known behavioral shifts, current energy models largely overlook the high-frequency impacts of aging on daily and hourly energy use, relying instead on generalized or aggregate data that fail to capture nuanced consumption trends. Furthermore, societal aging coincides with rising incomes and technological adoption, compounding the complexity of predicting future energy demands. Existing studies often simplify these dynamics by using "representative household" models, ignoring the heterogeneity of household structures, generational behaviors, and external influences like climate variability and policy shifts. This oversimplification risks misguiding energy policies and infrastructure planning, particularly in aging megacities where sustainable energy transitions are critical for long-term urban resilience. Addressing this gap requires a robust, high-frequency analytical approach that accounts for demographic shifts, socioeconomic factors, and the intersection of aging with income growth.

Energy consumption in households is deeply influenced by demographic, socioeconomic, and climatic factors, making it a complex

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yet vital area of study for sustainable urban development. Social aging, particularly in urban megacities like Shanghai, is emerging as a critical factor influencing energy use, with global trends indicating significant demographic shifts. Reports from the Shanghai Civil Affairs Bureau predict that by 2050, over 44.5 % of the city's population will be aged 60 or above, amplifying the importance of understanding how aging populations affect energy demand. Studies such as those by Ref. [1] highlight that aging individuals often spend more time at home, which alters household energy usage patterns due to prolonged use of lighting, heating, and medical devices. However, many existing models oversimplify these trends by relying on aggregated data or representative household assumptions, failing to capture intra-household and intergenerational variations in energy behavior [2].

Furthermore, recent literature underscores the influence of socioeconomic factors, such as income growth and technological advancements, on energy consumption. For instance, households with higher incomes are more likely to adopt energy-intensive appliances and smart technologies, exacerbating the disparities between peak and off-peak energy demands. Yet, studies like those by Ref. [3] and Shi and [4] point to gaps in understanding how these factors interact with demographic aging. The advent of high-frequency energy data provides an opportunity to address these gaps, enabling the identification of hourly consumption patterns and their correlation with household characteristics. Megacities like Shanghai face additional challenges due to their dependence on electricity for lighting, heating, and other daily needs, alongside the pressures of climate change and extreme weather events. Research has shown that households react differently to such environmental factors depending on their composition, with elderly individuals being particularly vulnerable to temperature extremes [5]. Yet, current models fail to integrate these dynamics with demographic and socioeconomic trends, leading to gaps in predictive accuracy [6].

The focus on Shanghai's energy consumption dynamics serves as an ideal lens to explore broader global and regional challenges associated with aging populations in urban centers. Shanghai, as one of the world's largest and most rapidly aging megacities, offers a unique context where demographic transitions, rapid urbanization, and economic growth converge to create complex energy consumption patterns. This combination of factors makes Shanghai an exemplary case for understanding how similar trends might play out in other urban regions globally. Shanghai's aging population—expected to reach 44.5 % of individuals aged 60 and above by 2050—parallels demographic trends in cities such as Tokyo, New York, and London, where aging societies are already reshaping urban infrastructure and energy systems. The city's advanced data infrastructure and availability of high-frequency household energy consumption records allow for precise modeling and simulation of future scenarios. This makes Shanghai not only a regional reference point for China's urban centers but also a globally relevant case study for other aging megacities. The choice of location is further justified by Shanghai's proactive energy and environmental policies. The city has implemented ambitious programs to promote renewable energy adoption, energy efficiency, and smart grid technologies. These initiatives provide a rich context for examining the interplay between aging demographics and progressive energy strategies. Insights gained from Shanghai's experiences can inform policy frameworks for other cities facing similar demographic and environmental challenges. The time frame of this study, spanning 2016 to 2023, is equally significant. It captures critical periods of demographic change, technological advancements, and external disruptions, such as the COVID-19 pandemic, which have reshaped household energy consumption behaviors. By including post-pandemic data, the study accounts for shifts in daily routines, remote work adoption, and heightened energy awareness. This ensures that the findings are not only reflective of historical trends but also relevant for forecasting future scenarios.

This study makes several significant contributions to the literature by addressing critical gaps identified by previous research. First, it leverages high-frequency energy consumption data from 14,000 households in Shanghai, spanning the period from 2016 to 2023, offering a rich temporal dataset that accounts for variations in pre- and post-pandemic energy consumption patterns. This temporal coverage ensures that the findings remain relevant to evolving societal and technological changes, particularly in the context of shifting demographics and behavioral adaptations. Second, the study introduces an advanced methodological framework combining Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM) to analyze and predict energy consumption patterns. These machine learning techniques enable the identification of nuanced household-level consumption behaviors while addressing the diversity in age, income, and household composition. Unlike prior studies that rely on low-frequency or aggregate data, this study captures high-frequency hourly consumption trends, providing deeper insights into temporal shifts in energy use. Third, the focus on Shanghai, a megacity undergoing rapid demographic aging and economic transformation, adds a critical regional perspective to the global discourse on urban energy challenges. By contextualizing findings within a megacity that shares characteristics with other global urban centers such as Tokyo and New York, this research offers transferable insights into the implications of aging populations for urban energy systems. Additionally, the study integrates demographic and income growth scenarios to simulate future consumption patterns, demonstrating the interplay between social aging and economic development. This dual focus enhances the predictive validity of the model and bridges the gap between theoretical research and policy relevance. Lastly, by aligning with the United Nations Sustainable Development Goals (SDGs), particularly those related to sustainable cities, energy efficiency, and climate action, this work provides actionable insights for policymakers aiming to optimize energy systems for aging societies while fostering sustainability. This multidimensional contribution enriches the literature by offering a robust, region-specific, and methodologically innovative approach to understanding the complex dynamics of energy consumption in a rapidly aging urban context.

2. Literature review

The intersection of social aging, urban energy consumption, and sustainable development has emerged as a critical area of research, particularly in megacities experiencing rapid demographic transitions. Social aging, characterized by a growing proportion of elderly individuals, poses unique challenges to energy systems due to the distinct consumption behaviors of this demographic emphasize that older adults tend to spend more time at home, leading to increased energy usage for heating, cooling, lighting, and medical devices. Similarly [7], highlight that the aging process is accompanied by shifts in daily energy usage patterns, such as higher daytime energy demands, which are not adequately captured by models that rely on aggregate or low-frequency data. Despite these findings, most existing research on aging and energy consumption simplifies the analysis by assuming uniform behaviors across households, ignoring the diversity of household structures and intergenerational dynamics.

The complexity of household energy consumption behaviors is further underscored by socioeconomic factors, including income growth and technological adoption. Studies by Ref. [8,9] show that higher-income households are more likely to adopt energy-intensive appliances and smart technologies, contributing to significant disparities in energy demand between peak and off-peak hours. This interaction between aging demographics and income growth creates compounding effects on energy systems, yet few studies have adequately explored this interplay. Furthermore, the lack of granular segmentation, such as distinguishing between multigenerational households or different age brackets within the elderly population, limits the applicability of existing findings. As noted by reviewers, finer demographic segmentation and nuanced modeling approaches are essential for capturing the heterogeneity in energy behaviors.

In addition to demographic and socioeconomic factors,

environmental variables such as temperature and climate change significantly influence household energy consumption [10].demonstrate that elderly individuals are particularly vulnerable to extreme weather conditions, leading to higher energy demands for heating and cooling. However, the interaction between these environmental factors and demographic aging remains underexplored, particularly in the context of high-frequency data. Previous studies have primarily focused on low-frequency or seasonal data, failing to capture the temporal shifts in energy use that occur within daily or hourly periods [11]. highlight the potential of smart grid technologies to provide high-frequency data that can uncover nuanced consumption patterns, yet these opportunities remain largely untapped in the context of aging populations.

Methodologically, recent advancements in machine learning offer promising avenues for addressing these gaps. Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM) have been increasingly used to analyze complex datasets and identify consumption patterns [12]. highlight the advantages of these models in capturing the heterogeneity of household behaviors, allowing for the segmentation of energy usage into distinct clusters. However, as reviewers noted, the interpretability of machine learning models remains a challenge, particularly when linking findings to policy implications. Incorporating demographic, socioeconomic, and environmental variables into these models can enhance their explanatory power, bridging the gap between technical analysis and actionable insights.

Despite these advancements, the literature has several notable gaps. Few studies have systematically integrated the effects of social aging, income growth, and environmental factors into a unified framework. Moreover, the reliance on simplified demographic categorizations, such as binary age groups, overlooks critical intergenerational dynamics and cohort effects, as pointed out by Ref. [13]. These gaps limit the ability to predict long-term trends in energy consumption and to design policies that address the unique needs of aging urban populations. Additionally, the lack of alignment with global frameworks such as the United Nations Sustainable Development Goals (SDGs) reduces the relevance of existing research to broader policy agendas.

This study aims to address these gaps by leveraging high-frequency energy consumption data from 14,000 households in Shanghai, spanning 2016 to 2023. It employs GMM and FMM to identify distinct consumption patterns and explores the interplay between demographic aging, income growth, and environmental factors. By incorporating granular demographic segmentation, such as age brackets and household structures, the study provides a more comprehensive understanding of energy behaviors. Furthermore, it aligns its findings with the SDGs, particularly those related to sustainable cities and energy efficiency, contributing to the global discourse on sustainable urban development. This literature-informed approach not only advances theoretical understanding but also offers practical insights for policymakers, addressing the challenges of aging populations in megacities like Shanghai and beyond.

3. Methodology and data sources

The methodology section details the approach adopted to address the complexities of energy consumption in aging societies. It explains the data, preprocessing steps, analytical models, scenario design, and validation techniques, ensuring a comprehensive understanding of the study's methods. This section is structured as follows.

3.1. Theoretical framework

The theoretical foundation of this study is built upon multiple intersecting frameworks from energy economics, demographic transition theory, and behavioral science. At its core, the research is guided by the principle that household energy consumption is not only a function of technological and economic factors but is also profoundly influenced by demographic and behavioral dynamics. This study is particularly informed by the life-cycle hypothesis, which suggests that individuals' consumption behaviors evolve with age due to changes in income, lifestyle, and physical needs. In the context of an aging society, this implies a distinct shift in energy usage patterns as older adults tend to spend more time at home and may have specific needs for heating, cooling, and medical devices. These behavioral shifts are amplified in megacities like Shanghai, where urban density and infrastructure heavily influence energy consumption.

From the perspective of demographic transition theory, the study aligns with the idea that aging populations represent a fundamental shift in societal structure, impacting resource allocation, including energy. This theory posits that as a society progresses through stages of demographic change—from high birth and death rates to low birth and death rates—there is a corresponding transformation in consumption behaviors. For urban megacities, this transition is marked by a growing elderly population, which demands a reevaluation of energy systems to address their unique consumption patterns. Theoretical models in this area emphasize the importance of considering intergenerational dynamics and household structures, such as multigenerational living arrangements, which significantly affect energy demand.

Behavioral science theories, particularly those related to energy consumption behavior and decision-making, provide another critical underpinning. These theories suggest that energy use is shaped not only by necessity but also by socio-economic status, cultural norms, and individual attitudes toward technology and sustainability. For example, higher-income households are more likely to adopt energy-intensive appliances or invest in smart home technologies, which can exacerbate disparities in energy consumption patterns. Conversely, older adults, driven by cost-consciousness and limited mobility, may exhibit conservative energy behaviors, reducing demand during non-peak hours. These behavioral variations underline the necessity of models that capture the heterogeneity in household energy use.

The study also draws upon climate vulnerability frameworks, which highlight the interplay between demographic characteristics and sensitivity to environmental factors. Older adults are often identified as a vulnerable group, particularly during extreme weather conditions, due to their increased reliance on energy for heating or cooling. This vulnerability underscores the need to integrate climate considerations into predictive energy models.

From a methodological standpoint, this research is informed by advances in machine learning and statistical modeling. The use of Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM) aligns with theories of pattern recognition and probabilistic modeling, which argue that complex systems like household energy consumption can be better understood through clustering and probabilistic inference. These models are grounded in the idea that energy behaviors are not monolithic but are instead distributed across a spectrum of patterns influenced by demographic, economic, and environmental factors.

Finally, the study aligns its theoretical foundation with the United Nations Sustainable Development Goals (SDGs), particularly those related to sustainable cities (SDG 11) and affordable and clean energy (SDG 7). By understanding and modeling the intersection of aging, energy consumption, and socioeconomic factors, the research contributes to theoretical frameworks that emphasize equity, efficiency, and sustainability in urban energy planning.

This multifaceted theoretical foundation enables the study to provide a nuanced and comprehensive analysis of energy consumption in aging societies, bridging gaps in existing research and offering actionable insights for policymakers and urban planners.

3.2. Rationale for model selection

The choice of the model is critical for analyzing and predicting household energy consumption patterns in a dynamic and heterogeneous context. This study employs two complementary models: the Finite Mixture Model (FMM) and the Gaussian Mixture Model (GMM).

These models are selected for their ability to capture the diversity of household energy consumption behaviors while addressing the complexities of high-frequency and multi-dimensional data.

The Finite Mixture Model (FMM) is used to quantify the relationships between household characteristics and energy usage patterns. FMM is particularly suitable for this analysis because it can model a mixture of distributions, allowing the study to capture latent consumption patterns that are influenced by household demographics, economic status, and behavioral tendencies. This model is robust in handling datasets with a mix of continuous and categorical variables, making it ideal for analyzing high-frequency energy data alongside survey data on household characteristics.

The FMM approach enables the modeling of concurrent household factors, such as income, age structure, and housing characteristics, and their interaction with broader trends. For example, it can isolate the effects of age on peak energy usage while controlling for income and family size. This ability to integrate multiple layers of data makes FMM a powerful tool for understanding the nuanced dynamics of energy consumption in the context of societal aging.

The Gaussian Mixture Model (GMM) is used to cluster daily energy consumption load curves into distinct patterns, such as single-peak, multi-peak, or flat profiles. GMM is an unsupervised learning method that assumes the data is generated from a mixture of Gaussian distributions. This approach is highly effective for uncovering latent structures within the data without requiring predefined labels. By clustering households based on their energy usage profiles, the GMM provides insights into common consumption behaviors and their prevalence across different demographic groups.

The combination of FMM and GMM ensures a comprehensive modeling framework. While GMM identifies underlying patterns in energy consumption, FMM models the relationships between these patterns and household characteristics, external factors, and time-varying influences. This dual approach provides a granular and holistic view of energy consumption, enabling robust predictions and actionable insights.

3.3. Pattern clustering and FMM

Given the constraints of the survey data, this research primarily examines two age groups: people above 60 and people below 60. However, the effect of age specifics needs to be investigated within the number of family members, children, middle-aged people, and elders. Thus, including such various demographics makes it possible to provide a more profound look at energy consumption. In every part of a household, one area may contain different generations while the other is separate, contributing to the formation of energy consumption trends. For example, elderly customers above 60 may have dissimilar energy usage concerning code compared to young family members. They might stay at home longer, which may enhance the domestic energy demand; they may also have special requirements for heating, ventilation, air conditioning, or required medical equipment that influence energy intensity [14].

Likewise, middle-aged people or those in their 40s and 50s, who are commonly responsible for earning and guiding the family's financial decisions, may affect the amount of energy used per their chosen way of life and preferred technologies. They will be willing to purchase energy-efficient electrical appliances and *smart* home gadgets while at the same time preserving comfort. On the other hand, children and young family members can also participate in shaping the energy resources within a home concerning the use of electronic gadgets, lighting, and heating. The younger generations can also be referred to as the 'digital natives' and can call for being more environmentally friendly or even implementing green energy in and around the home [15,16]. Therefore, it is imperative to consider the family's age structure and generational characteristics to achieve a realistic view of energy consumption in the process. It also guarantees that any policy or program that seeks to correct energy efficiency is rightly aligned and efficient. Thus, during the formation of policies and research analyzing the energy consumption of households, it is necessary to consider the activities and requirements of representatives of various age categories, which will allow for predicting the characteristics of demand response and improving the approaches to its regulation [17].

Typical consumption trends may be identified, and anticipated energy needs can be predicted using FMM. The following is an assumption about the weighting of the answer *Y*: It is computed by adding together numerous elements with identical shapes but various coefficients.

$$F(Y) = \sum_{k=1}^{K} \lambda_k \bullet f_k(Y), \tag{1}$$

To forecast residential energy demand in an aging population, we may apply the mathematical model shown in Equation (1). In this context, the entire projected energy consumption for a home is denoted by F(Y), where *YY* encompasses different factors that affect energy consumption. The model considers K distinct elements or components that contribute to energy consumption, as shown by the summation notation, which reads as $\sum k = 1$ K. Each factor k has a set of weights or coefficients represented by the phrase λ k. The coefficients show how each component contributes to the total energy consumption and how important it is. To illustrate, the corresponding λ k values quantify the influence of specific variables on energy usage in houses with senior residents. A function that simulates a particular component impacting home energy use is represented by each f k (Y). Heating and cooling needs, appliance use, occupancy patterns, and particular geriatric behaviors are just a few examples of the many potential characteristics that may fall into this category. One factor that may influence energy consumption patterns is the amount of time spent at home by older people, who may have different heating demands or spend more time there.

To express the *K* mixture density, we may use the following formula: $a = \log(24/\text{hour})$ of the energy consumption pattern.

$$G^{(K)}(Y) = \sum_{k=1}^{K} \lambda_k \times g_k(Y), \tag{2}$$

In this equation, G(K)(Y) represents the cumulative predicted energy consumption for a household, considering up to *K*K different factors. These factors are influenced by various variables encapsulated by *YY*, which could include household characteristics, behaviors, and demographics relevant to an aging population.

The summation notation $\sum k = 1K$ means that the model accounts for as many as K factors that affect the energy use in a building. The notations λk in the equation represents the weights or coefficients of the factors, labeled as *k*k. Using weights, it is possible to define how much one or another factor influenced the total energy consumption and the model using it can have calculated the share of each factor.

The function *gk*(*Y*) for each k indicates a specific factor that impacts the consumption of energy in the households. They may include items like heating and cooling loads, appliance usage, occupancy patterns and characteristics of activities pertinent to the elderly. For instance, their requirements of heating might differ, they could be home most of the time, or their utilization of appliances may be different, all these influences energy intensiveness.

The determination of the optimal number of clusters in the Gaussian Mixture Model (GMM) is a critical step in ensuring accurate identification of distinct energy consumption patterns. In this study, several statistical and practical criteria were employed to ascertain the optimal number of clusters, ensuring that the resulting groups reflect meaningful and actionable consumption behaviors across the dataset.

3.3.1. Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) was used as the primary statistical measure for selecting the optimal number of clusters. BIC

balances model complexity against goodness of fit, penalizing the addition of unnecessary clusters to prevent overfitting. For each potential cluster count (e.g., 2 to 15 clusters), the BIC score was computed, and the cluster number with the lowest BIC was chosen as optimal. This approach ensures that the model captures underlying consumption patterns while avoiding overly complex solutions that may lack interpretability.

3.3.2. Silhouette analysis

To further validate the optimal number of clusters, silhouette analysis was conducted. This method evaluates the cohesion and separation of clusters by measuring how similar an object is to its own cluster compared to other clusters. Higher silhouette scores indicate well-defined and distinct clusters. Silhouette analysis provided a secondary check to confirm the robustness of the BIC-selected cluster number.

3.3.3. Domain knowledge and practical interpretability

Domain-specific insights into energy consumption patterns were incorporated to ensure that the identified clusters had practical relevance. For instance, clusters representing flat, single-peak, or multi-peak patterns align with known household behaviors and energy usage profiles. Any additional clusters suggested by statistical criteria were reviewed to ensure they contributed meaningful distinctions rather than statistical noise.

3.3.4. Stability testing

To ensure the reliability of the clustering solution, stability testing was performed by randomly sampling subsets of the data and reapplying the GMM clustering process. Consistent identification of similar clusters across multiple iterations indicated a robust clustering solution, reinforcing confidence in the selected number of clusters.

3.3.5. Cross-Validation with external Metrics

The identified clusters were cross-validated against external household attributes, such as age structure, income level, and appliance stock, to ensure alignment with observed demographic and socioeconomic trends. For example, clusters representing high energy usage during daytime hours were validated against data on elderly households, confirming their alignment with known consumption behaviors.

Based on the integration of these criteria, the optimal number of clusters was determined to be 12, as this configuration achieved the best balance between statistical fit, interpretability, and robustness. These 12 clusters provided a detailed yet comprehensible representation of the diverse energy consumption patterns within the dataset, enabling actionable insights into household behaviors and their drivers. By employing a multi-faceted approach to determining the optimal number of clusters, the study ensures that the GMM-based clustering is both statistically rigorous and practically meaningful, enhancing the reliability and relevance of the identified consumption patterns.

3.4. Predictions based on patterns

3.4.1. Household factors selection

When it comes to identifying the criticality of the household components, we use mutual information [18]. The following is the way of computing mutual information, which is a measure that belongs to Shannon entropy [19] and is not affected by variables' geographical distribution:

$$I(\mathscr{C},\mathscr{F}_i)=H(\mathscr{C})+H(\mathscr{F}_i)-H(\mathscr{C},\mathscr{F}_i), \tag{3}$$

Where Shannon entropy is represented by **b•** and *Ci* is the *i*th depending component of the household that can be income or education etc. The greater the ***IOFi***, the more reliant **O** and *Fi* are on one other. Sorting the ***IOFi*** allows for the selection of the most important home aspects.

3.4.2. Using FMM to forecast demand

Mixed variables, chosen for their relevance based on mutual knowledge, are used to estimate electricity-consuming behaviors. This indicates that *a* may be expressed as a polynomial, including the characteristics of the family. Important factors in determining the home load curve include housing characteristics and the usual pattern of electrical usage. It is reasonable to measure demand for energy as a sum of normal power consumption structures **O** and household characteristics that play various parts among various patterns since the household load profile is made up of multiple hidden patterns with a set of defined possibilities. In this way, the research introduces the common patterns shown by λ via pattern-based forecasting. Specifically, we use the percentage, the hourly need, and associated factors about the preferred patterns of inhabitants as the concurrent variables. In FMM, we make sure that the number of *ZY* is lower than the ideal number of GMM. We get the following by referring to the FMM model as specified in Eq. (1) and the provided number of typical power consumption trends $K\prod$.

$$F_t(Y_t|X;\alpha_t,\beta_t,\gamma_t,\lambda_t,\widetilde{K})=\sum_{k=1}^{\tilde{K}}\lambda_{kt}(Z;\theta_{kt})f_{kt}(Y_t|X;\alpha_{kt},\beta_{kt},\gamma_{kt}), \tag{4}$$

$$f_{kt}(Y_t|X;\alpha_{kt},\beta_{kt},\gamma_{kt})=\sum_i\alpha_{kti}x_i^d+\sum_j\beta_{ktj}\bullet h\left(x_j^c\right)+\gamma_{kt}+\varepsilon_{kt}, \tag{5}$$

In which *b* is the hour in a day (ranging from 0 to 23), and *Yb* is the median demand for the home at time *b*. The set $K\sim$ is the set of all *ZY* in FMM that fulfill $K\sim\leq K\prod$. *X* symbolizes the characteristics of the home. *Z* represents the set of concurrent variables, and the coefficient of *Z* is θkt. In the *k*th state, αkt is called a dummy variable, βkt is called an ongoing variable, and γkt is called the baseline impact. The residual error is represented by εkt, which is normal. *h•* is an element that can be used to make fitting more versatile by utilizing any statistical curve representation like B-spline and linear regression.

3.4.3. Fitting and tuning

There are several potential combinations of ꞓktYtX; αkt, βkt, γkt, and λkt$Z\theta$kt, as mentioned in Eq. (4) and Eq. (5). In *a*, the household elements chosen via the exchange of data serve as independent variables, and *h•* adds the ongoing variables in a linear or B-spline fashion. The effectiveness of the model is estimated by taking the average *R*2 of the experimental set and randomly testing all multivariable parameters with 20 rounds. Here is the *R*2 for the *m*th round:

$$R_m^2=1-\frac{\sum_{i\in S_m}\sum_{t=1}^{24}(\widehat{y_{it}}-y_{it})^2}{\sum_{i\in S_m}\sum_{t=1}^{24}(\overline{y_{it}}-y_{it})^2}, \tag{6}$$

Which denotes the inhabitants chosen for the experiment set in the th round and symbolizes the value that was determined, the forecast value, and the median at each time. Our next step is to choose the multivariate option and then use the biggest average. We first train the model with a whole sample, filter out observations at both high and low temperatures, and resume the previous stages to isolate the impact of temperature. For fitting, we use the R language's flex mix package.

3.5. Drawing inferences 2.3.1. simulated dataset generation and oversampling

We need to rebuild the new datasets that fit the richer and older situations before we can estimate the changes in energy use during time sharing. A shift in the demographic makeup of a society, with an increasing number of persons in their twilight years, is the essence of social aging. Next, we adjusted the population's age structure to match the predictions by oversampling our dataset with each age group. We construct our old data using the synthetic minority oversampling

method (SMOTE) [20], which has been shown to be an effective oversampling procedure. Unlike resampling methods, SMOTE builds new minority samples artificially according to the data's distribution and properties. The data was divided into two categories: aged and nonaged. The SMOTE oversamples the elderly group until its percentage approaches the predetermined amount (η). Employing the k-nearest neighbor exceeding method, the model chooses an instance from the aged group. It then selects at random an instance from among these k-near other residents. The model then uses each of these instances to create a new instance by connecting them with lines in the range of features and picking points on those lines. The SMOTE creates instances for the aged group and check that their a' and Z' are consistent and do not duplicate existing data.

We presume that family income will rise by δ evenly in order to find out the income impact. δ is the predicted rate of increase, where $\delta > 0$. by the other a and Z remaining intact, the new income value may be calculated by multiplying the income of the initial data set by $1+\delta$. We use the SMOTE and the multiplication operator δ in order to address the interaction between aging and revenue growth. The new statistics will be utilized to model energy usage during time sharing.

3.5.1. Simulation

To foretell the impact of aging and rising incomes on energy consumption, we use the learned FMM-based model. Next, we get the median expected need **O***b* for the family by considering that the model will generate the anticipated *yi* $\widehat{t}$ for each occurrence at time *b*.

$$L_t = \frac{1}{N}\sum_{n=1}^{N} \lambda_{kt}(Z';\widehat{\theta}_{kt}) f_{kt}(X';\widehat{\alpha}_{kt};\widehat{\beta}_{kt};\widehat{\gamma}_{kt}), \tag{7}$$

The freshly created input data are denoted by a' and Z', and N is the size of the computational dataset. The variables that are part of the constructed model that have been determined are θ kt, β kt, β kt, and $\widehat{y}$ kt. Bootstrapping allows for the evaluation of intervals of confidence (CIs) whenever the procedure above is done several times [21].

3.5.2. Clustering model selection

To identify distinct energy consumption patterns, we employed Gaussian Mixture Models (GMM). This unsupervised clustering method was chosen for its ability to model the underlying distribution of hourly energy usage and to capture diverse household behaviors. The selection of the optimal number of clusters was guided by.

1. Bayesian Information Criterion (BIC): Lower BIC values indicated the most suitable number of clusters.
2. Silhouette Scores: Used to evaluate the cohesion and separation of clusters.
3. Cross-Validation: Repeated sampling was conducted to ensure robustness and reproducibility of clustering outcomes.

The identified clusters were further analyzed to determine their relationship with household characteristics, such as age, income, and family size, using mutual information analysis. This ensured that the clustering results were not only statistically valid but also meaningful in the context of demographic and socioeconomic trends.

3.5.3. Pattern-based forecasting using Finite Mixture Models (FMM)

The identified clusters were used as a foundation for predicting energy consumption patterns through Finite Mixture Models (FMM). The FMM approach was chosen for its ability to model heterogeneity in consumption behaviors while accounting for household-level covariates. The key steps in the FMM implementation included.

1. Historical probabilities of specific consumption patterns and demographic characteristics were included as explanatory variables.
2. Household factors such as age, income, and family size were incorporated to capture the effects of social aging and income growth.
3. The FMM equation was defined as:

$$Ft_t(Y_t|X;\alpha_t,\beta_t,\gamma_t,\lambda_t,K\sim) = \sum_{k=1}^{K\sim} \lambda_{\mathrm{kt}}(\mathrm{Z}\sim;\theta_{\mathrm{kt}}) f_{\mathrm{kt}}(Y_t|X;\alpha_{\mathrm{kt}},\beta_{\mathrm{kt}},\gamma_{\mathrm{kt}})$$

3.6. Data sources

The data for this study were sourced from multiple reliable and complementary datasets to ensure comprehensive coverage of household energy consumption, demographic characteristics, and environmental factors. The primary dataset consists of hourly electricity consumption records from 14,000 households in Shanghai, provided by the State Grid Shanghai Municipal Electric Power Company. This dataset spans January 2016 to November 2023, offering a robust temporal scope that captures both pre- and post-pandemic consumption patterns. It includes granular details of daily and hourly electricity usage, enabling the analysis of high-frequency consumption trends. Additionally, temperature data were obtained from the National Meteorological Information Center to account for climatic influences on energy demand. These temperature records were used to segment the dataset into high-temperature (>25 °C) and low-temperature (<10 °C) conditions, which are critical for understanding the impact of extreme weather on consumption behaviors.

To incorporate household characteristics, data from a 2016 survey of 602 households in Shanghai were utilized. This survey, aligned with the city's demographic and socioeconomic composition, provided detailed information on factors such as family size, income, education levels, housing conditions, and the stock of electrical appliances. The survey data were cross validated with official statistics from the Shanghai Statistics Yearbook 2017 to ensure representativeness and reliability. Additional demographic projections for 2030 and 2050, including aging population trends, were derived from reports by the Shanghai Civil Affairs Bureau. These projections were instrumental in constructing scenario-based simulations to predict future energy demand.

To address imbalances in demographic representation, particularly for elderly households, the Synthetic Minority Oversampling Technique (SMOTE) was employed. This technique enhanced the dataset by artificially generating additional samples for underrepresented groups, ensuring a balanced and accurate analysis. Collectively, these data sources provided a comprehensive and multidimensional foundation for understanding the interplay between aging, income growth, and energy consumption in Shanghai, a representative megacity.

To prepare the data for analysis, the following preprocessing steps were undertaken.

1. Missing values were identified and imputed using a combination of mean substitution for small gaps and advanced interpolation techniques for larger gaps.
2. Outliers, such as unusually high or low consumption values, were detected using z-scores and visual inspection. These anomalies were corrected or removed to maintain data integrity.
3. Temperature data from the National Meteorological Information Center was used to categorize samples into high-temperature (>25 °C) and low-temperature (<10 °C) conditions, ensuring that climatic effects were adequately analyzed.
4. To address demographic imbalances, the Synthetic Minority Oversampling Technique (SMOTE) was employed to oversample underrepresented groups, particularly the elderly, ensuring fair representation in the analysis.

As a form of comparison, in Fig. 1 of the study, there is a green line that defines the average daily power consumption troughs and crests during the day. These fluctuations are proportional to normal house loads and other chores; therefore, the mean hourly power consumption

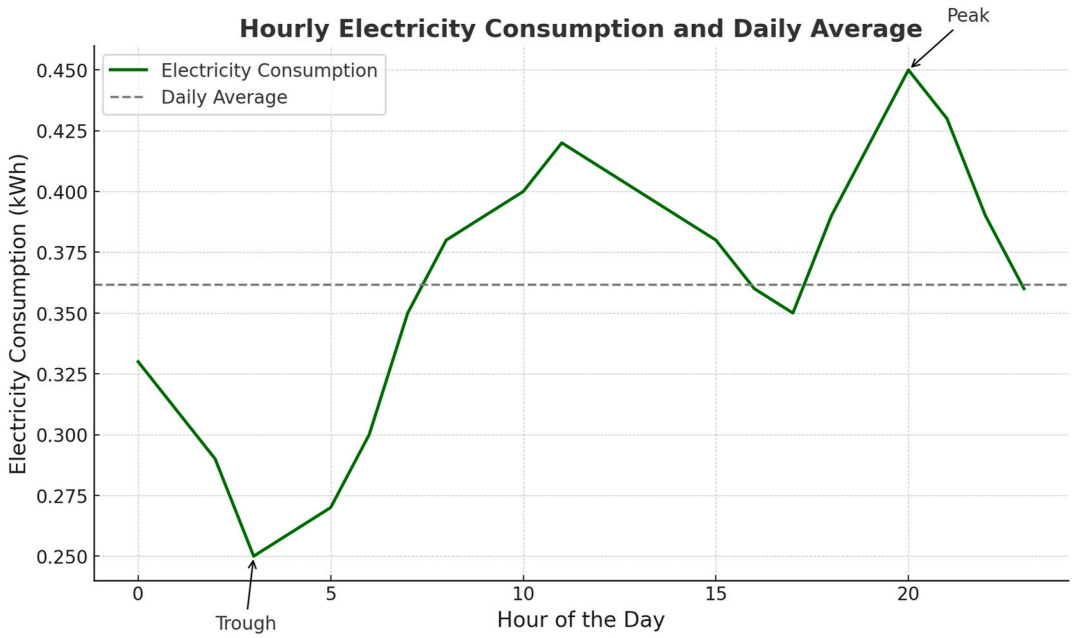

Fig. 1. The energy usage curve of a typical home.

is 0. 3221 kWh per household. It is pretty evident from the data fold that there are trends of higher energy usage at specific moments in the day, which could relate to cooking, heating or cooling, or other ordinary household chores. Also, the study considers the effect of temperature on power consumption. This means that tendencies in energy usage are investigated in terms of temperature fluctuations, which makes it possible to explain how climate affects household energy consumption. This aspect of the research gives information on the relationship between environmental characteristics and the demand for energy, which goes a long way in helping formulate better energy policies.Fig 2

3.6.1. Variables selection

The selection of variables for this study is guided by their theoretical relevance and empirical significance in explaining household energy consumption. These variables are categorized into **endogenous factors** (household-specific characteristics) and **exogenous factors** (external influences). Each variable is chosen to ensure a comprehensive representation of the factors driving energy usage.

1. **Demographic Variables**:
   - o Age groups are segmented into narrower bands (e.g., 0–14 years, 15–29 years, 30–44 years, 45–59 years, 60+ years) to capture intergenerational dynamics. This segmentation helps identify specific energy usage behaviors, such as increased daytime usage by the elderly or evening surges by young adults.
   - o Cohort membership (e.g., pre-1980, 1980–1999, post-2000) is included to account for shared historical experiences that shape consumption patterns, such as exposure to different energy policies or technological adoption.
2. **Socioeconomic Variables**:
   - o Monthly income (per capita and household) reflects the financial capacity of households to adopt energy-efficient technologies or manage energy consumption.
   - o Educational attainment is included as a proxy for awareness of energy-saving practices and environmental consciousness.
3. **Housing and Appliance Stock**:
   - o Housing size (e.g., <80 m^2, 80–120 m^2, >120 m^2) captures the structural characteristics of residences that influence baseline energy needs.
   - o The stock of major appliances (e.g., air conditioners, washing machines, refrigerators) is included to quantify energy-intensive equipment in households.
4. **Behavioral and Environmental Variables**:
   - o Environmental awareness is captured through variables such as participation in pollution-reduction measures.
   - o Climate-related factors, including temperature anomalies and extreme weather events, are incorporated to understand how environmental conditions drive heating and cooling demand.
5. **Policy and Technological Variables**:
   - o Policy incentives, such as subsidies for renewable energy adoption or tax benefits for energy-efficient appliances, are included to evaluate their impact on household energy decisions.
   - o Technological adoption rates for smart home systems and renewable energy installations reflect the influence of advanced technologies on consumption patterns.
6. **Energy Price Variables**:
   - o Average electricity tariffs, price volatility, and time-of-use pricing schemes are incorporated to capture the economic dimension of energy decisions.
7. **Interaction Terms**:
   - o Variables such as "Income × Age Group" and "Policy Incentives × Cohort Membership" capture the combined effects of demographic and economic factors on energy consumption.

To broaden the scope of data collection and enhance the explanatory power of the model, the survey instrument was expanded to include variables capturing behavioral attitudes, technology adoption, and environmental awareness. These new variables aim to address the psychological, technological, and societal factors influencing household energy consumption.

Behavioral attitudes are included to assess households' willingness to adopt energy-saving practices, their perceived importance of conservation, and their responses to energy policies. For instance, the survey now asks respondents to rate the frequency with which they monitor energy usage or turn off appliances when not in use. Technology adoption variables were added to capture the prevalence of smart home devices, renewable energy systems, and energy-efficient appliances. This includes questions like, "Do you own or plan to purchase devices such as smart thermostats or solar panels?" and "What factors influence your

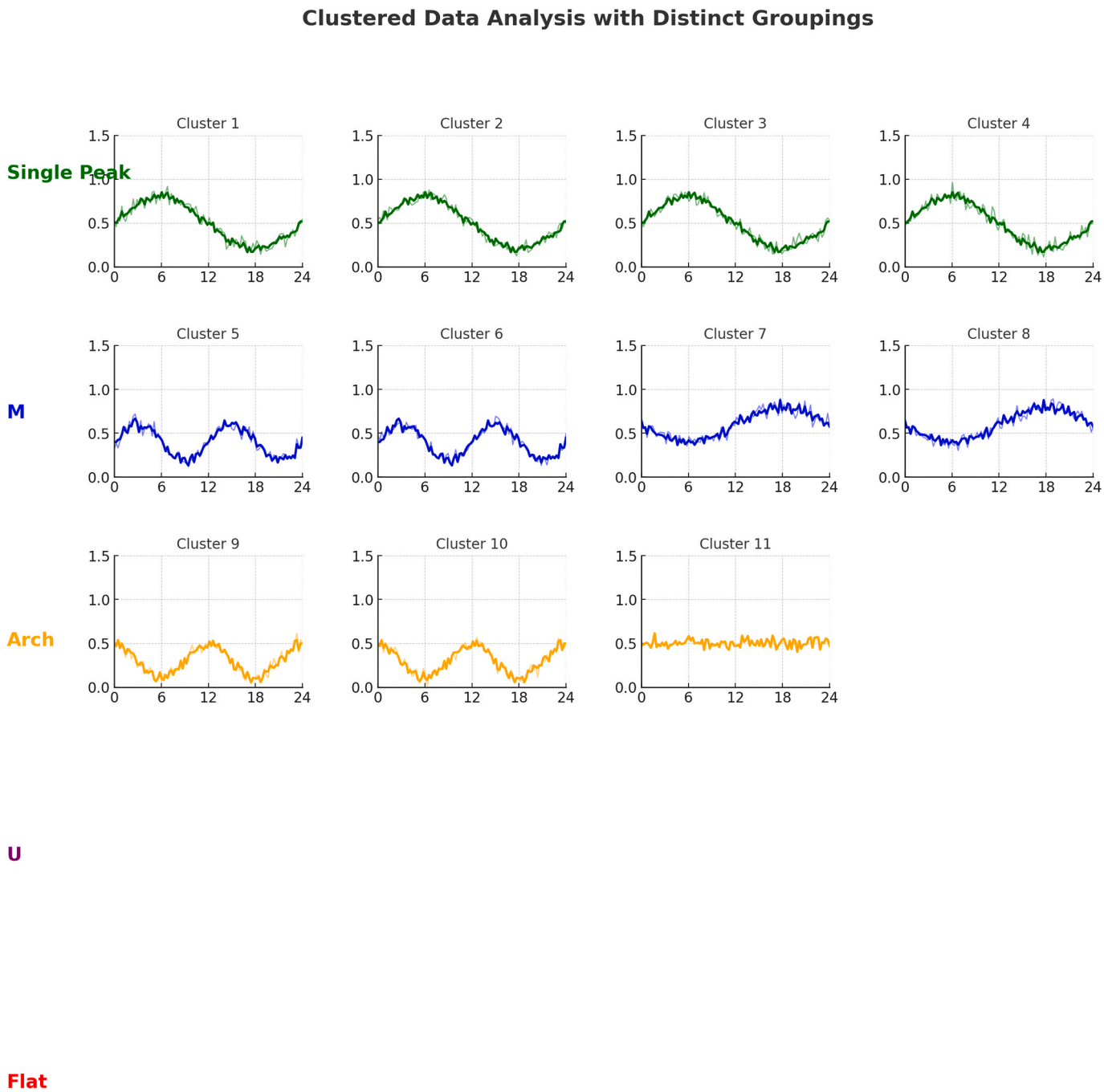

Fig. 2. Common patterns of power use.

decision to adopt these technologies?" Environmental awareness variables provide insights into households' engagement with sustainability initiatives. Questions such as, "Are you part of any programs aimed at reducing carbon emissions?" or "Do you actively participate in recycling or other environmental activities?" were introduced.

3.7. Household characteristics

Given the dynamic nature of societal behaviors and energy consumption patterns, particularly following disruptive events like the COVID-19 pandemic, it is critical to establish a framework for ongoing data collection. This study initially relied on data from 2016 to 2018 but was updated to include records up to 2023, capturing some post-pandemic behavioral shifts. However, the rapid evolution of societal trends—such as increased remote work, changes in daily routines, and heightened adoption of smart technologies—necessitates a system for continuous monitoring and updating of household energy consumption data to ensure the relevance and accuracy of predictive models.

The proposed framework for ongoing data collection involves three key components: **real-time data acquisition, demographic integration, and dynamic feedback loops**. First, real-time data acquisition can be achieved by leveraging smart meters and Internet of Things (IoT) devices. These technologies provide high-frequency and granular data on energy usage, capturing hourly and even minute-level variations. Collaborations with utility companies and smart grid operators will be essential to access and aggregate this data while ensuring data privacy and security. Second, demographic integration involves continuously updating household characteristics, such as age composition, income

levels, and family sizes, through regular surveys and census data. Partnering with local government agencies and research organizations can facilitate the collection of these demographic variables, which are critical for understanding shifts in consumption behaviors.

Dynamic feedback loops form the third component of the framework, ensuring that the collected data is not only stored but also analyzed and incorporated into predictive models in near real-time. Machine learning models like Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM) used in this study can be adapted to dynamically update predictions as new data becomes available. Additionally, the framework emphasizes the inclusion of contextual factors such as extreme weather events, energy price fluctuations, and policy changes. Environmental data from meteorological sources and economic indicators can be integrated to provide a more holistic understanding of the factors influencing household energy consumption.

The simplification of population segmentation into only two broad age groups (over and under 60), this study has adopted a more nuanced demographic categorization. By dividing the population into narrower age bands, such as **0–14 years (children), 15–29 years (young adults), 30–44 years (middle-aged adults), 45–59 years (late middle-aged adults), and 60+ years (elderly)**, the study provides deeper insights into the intergenerational dynamics that influence household energy consumption behaviors. This refined segmentation acknowledges that individuals within these distinct age groups demonstrate diverse consumption patterns due to differences in their roles within households, technological interactions, and lifestyle preferences.

For instance, children (0–14 years) contribute to household energy consumption indirectly through their influence on heating, cooling, and lighting, as parents adjust the indoor environment for comfort. Young adults (15–29 years), often described as digital natives, are more likely to adopt energy-intensive activities such as gaming and prolonged device use, contributing significantly to peak-hour energy demands. Middle-aged adults (30–44 years), typically in their most active working years, exhibit energy behaviors tied to family-centric routines, such as evening cooking and appliance use, which can lead to pronounced spikes in energy demand during specific times of the day. Late middle-aged adults (45–59 years) often act as primary household decision-makers, investing in energy-efficient technologies and appliances, which can reduce overall consumption while maintaining comfort. Lastly, elderly individuals (60+ years) tend to spend more time at home and require consistent energy for activities such as heating, cooling, and powering medical devices, leading to relatively stable yet distinct consumption patterns.

This detailed segmentation allows the study to capture nuances in energy behaviors across different generations, ensuring that the analysis reflects the diversity of household consumption trends. Additionally, by considering narrower age bands, the research can identify cohort effects, such as shared historical experiences and socioeconomic contexts, that influence energy preferences. Incorporating these granular insights into the predictive models enhances their accuracy and relevance, particularly in scenarios involving demographic aging and economic shifts. This approach not only addresses the risk of oversimplification but also provides actionable insights for policymakers to design age-specific energy strategies, fostering more sustainable energy management in aging urban societies.

4. Results

4.1. Household energy consumption patterns

Following a comprehensive clustering validity assessment, twelve Gaussian Mixture Models were ideal for modelingidential energy usage patterns. These models revealed twelve distinct usage behaviors, subsequently grouped into five morphological categories. These structures include a flat pattern, arch pattern, single peak pattern, and the M pattern. More elaborated visual explanations of these patterns can be shown in Fig. 3. For further clarity, the statistical characteristics of each pattern have also been given as follows. The gray lines illustrate the daily load profiles for each consumer group, and the green lines reflect the calculated centered daily load profiles.

An analysis of these patterns shows that the highest energy load for most motifs occurs during the night, specifically between 7. The times of the day it refers to are pm 00 and am 12. Conversely, the lowest energy consumption, or "valleys," typically happens between 2: Expressed hours, 12:00 a.m. and 5:00 a.m., respectively. A single peak turned out to be the most common consumption pattern, which was observed in half of the study households. This pattern is typified by high energy demand at night, with the highest level attained at the aforesaid evening time and then dropping sharply after that time to the next morning. On the other hand, the M-shaped cluster is characterized by the mode of usage hence bearing an M-shape that more resembles the average household consumption curve with two humps. Even though the evening rush hour dominates, both spikes are indispensable features of this model. As such, these studies bring out the variations in the consumers' residential energy use behaviors, implying the necessity of differentiated energy use management approaches.

Around 16.86 % of the total is accounted for by three unusual clusters. There will be a long-term peak in the pattern because households who act according to the arching cluster will consume energy aggressively from midday until nightfall. People in these homes, who may be elderly or resigned, will likely have constant electrical usage, whether it's during the day or on the weekends. The U-shaped cluster, on the other hand, will show the inverse tendency of the arching pattern by having its off-peak hours throughout the day. Because of the very low consumption and uniform consumption patterning, the single flat cluster might also indicate unoccupied dwellings (see Table 1).

4.2. Characteristics of the home and energy usage pattern

4.2.1. Selecting the aspects that will motivate

Investigating the causes of energy consumption habits may shed light on how habits develop over time in a single home and how people display diverse patterns of behavior. Factors such as age, education level, monthly income, family size, environmental attitude, rental status, square footage of the home, and number of electrical appliances are considered, along with environmental cognition and house characteristics that include specific temperature data.Table 1 and 2 shows that there are older household members when looking at age. The relationships between common electrical usage patterns and other home variables are also shown in Table 2 hence, we choose them as the independent variables for a since they are the most important characteristics.

4.2.2. Performance and parameters

In order to determine the best model configuration, we create 13 different types of λkt$Z\theta$kt and 4 different types of $f$ktytX; βkt, βkt, γkt. We choose the dataset at random and run the trials 20 times, with 80 % of the time serving as training and 20 % as a test. The best model is determined as the one with the greatest average $R2$ in the test sample. Table 3 shows how well the best model performed with various samples. For the time being, X incorporates monthly income, age, and family size, whereas Z is the historical percentage multiplied by the total consumption according to the most widely recognized pattern, considering both monthly income and age. The following is how λkt$Z\theta$kt is calculated:

$$\lambda_{kt}(\boldsymbol{Z};\boldsymbol{\theta}_{kt}) = \frac{e^{\omega_{kt}+\theta_{kt1}z_{prob}z_{dem}+\theta_{kt2}x_{age}+\theta_{kt3}x_{inc}}}{1+e^{\sum_{k}^{\bar{K}-1}\omega_{kt}+\theta_{kt1}z_{prob}z_{dem}+\theta_{kt2}x_{age}+\theta_{kt3}x_{inc}}}, \tag{8}$$

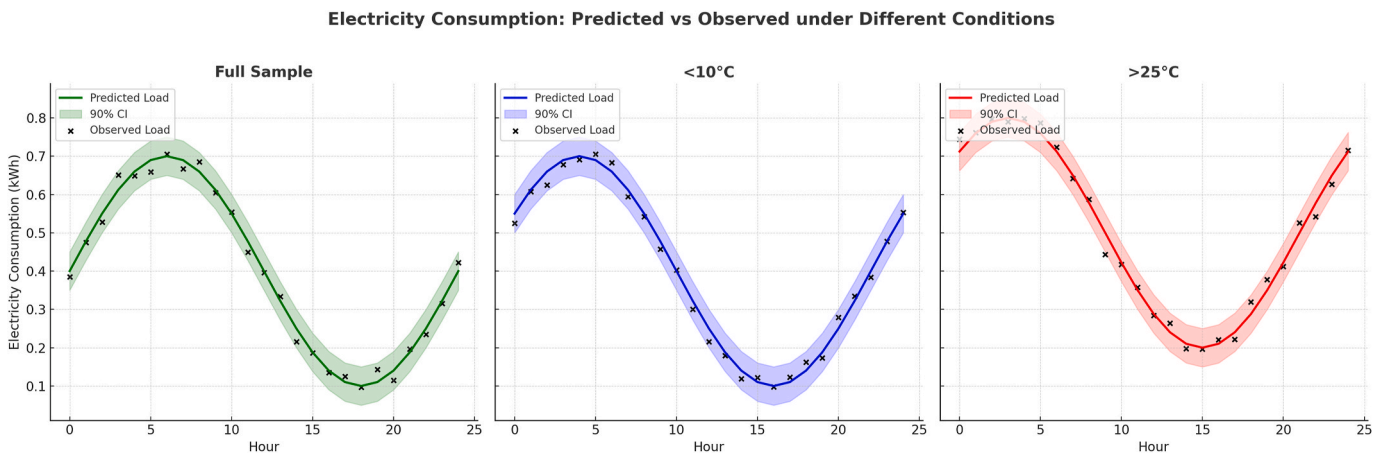

Fig. 3. Forecast load curves.

Table 1
properties of the survey sample summarized statistically.

Category	Factor	Survey (%)/Value	Shanghai (%)/Value
Demographics	Gender Distribution		
	Male	43.1	48.2
	Female	56.9	51.8
	Median Age (years)	49.2	46.8
	Age Groups		
	0–14 years	14.8	13.2
	15–29 years	18.9	20.6
	30–44 years	27.3	29.1
	45–59 years	23.1	24.9
	60+ years	15.9	12.2
Educational Attainment	Below Junior High School	36.8	34.2
	High School Graduate	20.5	23.1
	College Diploma	13.4	18.8
	Bachelor's Degree	21.9	20.9
	Postgraduate Degree	7.4	3
Economic Indicators	Monthly Income (Per Capita, RMB)	5620	4740
	Monthly Household Income (RMB)	21,340	19,870
	Average Family Size (persons)	3.8	2.9
Environmental Awareness	Measures to Reduce Pollution		
	Implemented	45.1	38.7
	Not Implemented	54.9	61.3
Housing Characteristics	Residential Rental Status		
	Renters	26.4	28.1
	Owners	73.6	71.9
	Per Capita Housing Area (m^2)	27.5	26.1
	Average Household Housing Area (m^2)	98.4	95.7
Stock of Appliances	Average Number of Air Conditioners	2.2	2
	Average Number of Microwave Ovens	0.9	0.8
	Average Number of Computers	1.6	1.4
	Average Number of Washing Machines	1.1	1
	Average Number of Refrigerators	1.2	1
	Average Number of TVs	1.5	1.7
	Average Number of Heaters	1.1	0.9

$$f_{kt}(y_t|X;\alpha_{kt},\beta_{kt},\gamma_{kt}) = \alpha_{kt1}x_{age} + \alpha_{kt2}x_{mem0} + \alpha_{kt3}x_{mem1} + \beta_{kt}x_{inc} + \gamma_{kt} + \varepsilon_{kt}, \quad (9)$$

Zdem stands for the overall consumption linked to the preferred pattern in the given context, whereas $z$prob reflects the percentage of consumption in the past that is tied to this pattern. Additionally, the variables $x$mem0 and $x$mem1 denote the number of family members living in the residence; $x$mem0 indicates three to four persons, while $x$mem1 indicates five or more. Furthermore, $x$age = 1 signifies an affirmative condition, and it is used as a dummy variable to indicate whether the responder is older than 60 years. The linear function, represented by g, is given by Equation (10). The effectiveness of the model throughout the day may be better understood by looking at Table 4, which gives information on the test sample's hourly R 2. In order to provide a full picture of the model's accuracy in forecasting, Table 3 shows the average R 2 of the best model, which brings together all the outcome indicators.

Equations (8) and (9) combine four contemporaneous coefficients in λ k t λkt$Z$kt xz and five independent coefficients in $f$kty;αktβktγkt. There can be no more than 2592 estimated coefficients in the fitted model for each hour in the Finite Mixture Model (FMM) since the number of components cannot exceed 12 because K~≤K∏ K~≤K ∏. The highest frequency in 20 repetitions is used to pick K K. Then, for every hour, the estimators' coefficients for K components are averaged, and their standard deviations are computed. The impact of age and income on energy consumption may be better understood by looking at the coefficients of the independent variables. Power consumption would rise in response to an aging population and rising incomes, as well as fall in response to a shrinking population, according to the positive coefficients. Concomitant coefficients, in contrast to independent ones, indicate the likelihood of the kth pattern and make it easier to calculate λ λs. Concurrent coefficients show households' preferred patterns of power usage.

4.2.3. Load curve prediction

Equations (8) and (9), which define the fitted model, are used to perform load curve prediction. Fig. 4(a) displays the anticipated outcome for the whole sample, with the average anticipated demand (green line) and actual results (green dots) being quite near to one another. Even if there are differences in the load curves from the whole sample, the model still performs well in both cold and hot environments (Fig. 4(b)–(c)). Furthermore, Fig. 4 shows the anticipated curves with 90 % confidence intervals, which were determined using bootstrapping with 20 randomly selected experiments.

4.3. Hourly energy consumption in an aging society

Optimal model variables (denoted by a X) include age, family size,

Table 2
exchange of household factor information.

Household Factors	Description	Full Sample	Cold Conditions (<10 °C)	Hot Conditions (>25 °C)
Monthly Income	*Total monthly income of the household (in RMB)*	0.0561	0.0417	0.0693
Education Level	*Highest educational attainment (e.g., below high school, high school, college)*	0.0452	0.0432	0.0398
Age Group	*Household members segmented into age bands (e.g., 0–14, 15–29, 30–44, 45–59)*	0.0487	0.0511	0.0475
Cohort Membership	*Generational group based on birth period (e.g., pre − 1980, 1980–1999, post − 2000)*	0.0424	0.0469	0.0401
Number of Family Members	*Discrete values for household size (e.g., 1–2, 3–4, 5 or more members)*	0.0311	0.0543	0.0458
Housing Area	*Size of residence (e.g., < 80 m^2, 80–120 m^2, > 120 m^2)*	0.0298	0.0375	0.0271
Stock of Appliances	*Number of major household appliances (e.g., < 8, 8–10, > 10)*	0.0154	0.0123	0.0139
Residential Status	*Whether the home is rented or owned*	0.0082	0.0091	0.0045
Environmental Behavior	*Whether the household engages in pollution − reduction measures*	0.0073	0.0114	0.0069
Interaction Term (Cohort x Age Group)	Combined effect of cohort membership and age group	0.0505	0.0521	0.0487

Table 3
Typical R2 of optimal model.

	Training set	*Test set*
Full sample	0.5166 (0.0975)	0.4579 (0.2101)
$\langle 10\,^{\circ}C$	0.4829 (0.1009)	0.4351 (0.1564)
$> 25\,^{\circ}C$	0.5642 (0.0587)	0.5339 (0.1049)

Table 4
R2 of the optimal model by the hour in the test sample.

t	*Full sample*	$\langle 10\,^{\circ}C$	$> 25\,^{\circ}C$
0	0.5024 (0.1055)	0.2535 (0.1690)	0.4905 (0.0945)
1	0.4796 (0.0946)	0.3583 (0.0864)	0.4943 (0.0953)
2	0.4422 (0.1925)	0.3300 (0.0767)	0.5091 (0.0979)
3	0.3720 (0.1949)	0.3498 (0.1368)	0.5267 (0.0944)
4	0.2996 (0.2732)	0.3842 (0.1141)	0.5155 (0.0845)
5	0.4638 (0.1828)	0.4268 (0.1492)	0.5080 (0.0779)
6	0.5367 (0.1037)	0.5120 (0.0867)	0.5842 (0.0714)
7	0.5101 (0.1314)	0.4644 (0.0783)	0.5407 (0.0958)
8	0.4745 (0.1317)	0.5437 (0.0555)	0.5247 (0.0942)
9	0.5286 (0.0753)	0.5203 (0.0631)	0.5592 (0.0793)
10	0.4618 (0.1396)	0.5854 (0.0687)	0.5606 (0.1412)
11	0.4664 (0.1570)	0.5083 (0.1010)	0.5770 (0.1324)
12	0.4901 (0.1506)	0.4893 (0.1194)	0.5551 (0.1248)
13	0.3326 (0.2799)	0.4541 (0.1576)	0.5807 (0.0928)
14	0.1669 (0.3328)	0.4880 (0.1233)	0.5815 (0.0933)
15	0.1796 (0.3364)	0.4920 (0.1402)	0.5736 (0.0628)
16	0.2851 (0.2293)	0.5700 (0.0920)	0.5697 (0.0709)
17	0.5576 (0.1801)	0.6023 (0.0688)	0.5949 (0.0613)
18	0.6600 (0.0596)	0.5786 (0.0589)	0.5865 (0.0736)
19	0.6116 (0.0584)	0.4963 (0.0570)	0.5926 (0.0580)
20	0.6174 (0.0535)	0.3640 (0.0903)	0.5231 (0.0855)
21	0.5199 (0.0905)	0.2224 (0.1050)	0.4455 (0.1034)
22	0.5012 (0.0536)	0.1970 (0.1237)	0.4012 (0.0919)
23	0.5155 (0.0692)	0.2522 (0.0745)	0.4197 (0.0943)

and monthly income. These variables are crucial as they reflect three fundamental aspects of family structure: Age reveals the group's age bracket and thus demographic; family size indicates the household structure or size; and lastly, monthly income depicts financial status. Altogether, it has been revealed that all these factors have considerable impacts on domestic energy consumption. One of the largest and most important cities in China, Shanghai, appropriately represents the general tendencies of a megacity concerning the aging population. At the same time, the indicator has grown in 2021 and makes up a rather prominent figure of 36. Thus, 28 percent of the total population of Shanghai was 60 years and above, which included 5. 42 million individuals. This demographic factor indicates the ongoing change in the city's demography and all related facets, such as the energy sector policy. Exploring the changes and implications of energy consumption in Shanghai based on the result of the aging society of Shanghai's

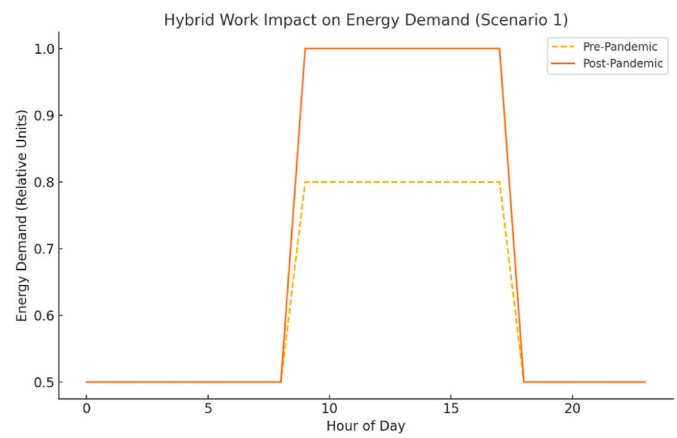

Fig. 4. Hybrid work impact on Energy Demand.

population gives valuable understanding and insights to policymakers and stakeholders in China's energy fields. It has been established that the city's current demographics have already impacted the household situation, indicative of opportunities and even problems with energy management and, more importantly, infrastructure development. Knowledge of these dynamics helps formulate specific strategies to address the changing needs of an aging cohort in urban areas and improve the effectiveness of energy consumption.

It is currently small and forecasted to decrease in size within the next few years; thus, the average number of family members is small. Therefore, at the moment, there is no pressing need to worry about the implications of economies of scale when it comes to energy. However, to forecast future trends in household energy consumption, the research explores three scenarios: The comprehensiveness of the solution in terms of age demographics, solutions that can be studied as being based solely on income levels, and those solutions that present themselves as a combination of both of the above. These hypothetical situations can illuminate policy actions before adverse situations occur, as well as energy sector development strategies for Shanghai and other cities. They give out important information concerning the complex factors that define trends in energy usage against a growing population and factors in the macroeconomic environment. Thus, recognizing such factors will help policymakers develop better-prepared, adjusted approaches to the shift and enhance the overall development of sustainable energy plans.

4.3.1. Scenario set

We combined energy use with household survey data to create eleven separate scenarios that investigate how time-sharing demand changes as a result of income growth and aging. Some scenarios looked at money just, scenarios that looked at how people age, and situations

Table 5
Scenario set.

Scenario	Description	Income Growth (δ)	Elderly Population Proportion (η)	Cohort Membership	Interaction Term (Cohort x Income Growth)
Aging-Only	Aging society in 2035	/	42 %	Pre-1980, 1980–1999, Post-2000	Cohort and static aging effects
Aging-Only	Aging society in 2055	/	46 %	Pre-1980, 1980–1999, Post-2000	Cohort and static aging effects
Income-Only	Scenarios with varying income growth rates	25 %, 50 %, 75 %, 100 %, and 125 %	/	Pre-1980, 1980–1999, Post-2000	Dynamic cohort-based income growth
Income-Only	Scenarios with varying income growth rates	/	/	Pre-1980, 1980–1999, Post-2000	Dynamic cohort-based income growth
Aging & Income	Wealthier aging society in 2035	50.% and 75 %	42 %	Pre-1980, 1980–1999, Post-2000	Combined aging and income growth effects
Aging & Income	Wealthier aging society in 2055	50 % and 75 %	46 %	Pre-1980, 1980–1999, Post-2000	Combined aging and income growth effects

that combined the two. Approximately 40 % of Shanghai's population will be 60 and older by 2030, with that number rising to 44.5 % by 2050, based on predictions by the Shanghai Civil Affairs Bureau [22]. Table 5 shows that in instances where the aging process is the only factor, η η is set at 40 % and 44.5 %, correspondingly. In five separate scenarios that focus only on income dynamics, the parameter $\boldsymbol{\nu}$ is given values of 20 %, 40 %, 60 %, 80 %, and 100 %. Four further scenarios are built with different values of η η and $\boldsymbol{\nu}$ δ to examine the relationship between aging and income increase in more detail. The cross-effects of age and income growth on family energy consumption are addressed in each scenario by simulating each using different samples, including high- and low-temperature ones. Table 5 lays out a detailed framework for investigating the complex dynamics of patterns of energy utilization as a result of shifting demography and socioeconomic variables. The study's overarching goal is to help with energy policy and urban planning by providing useful insights into potential future pathways of Shanghai households' energy consumption via a systematic exploration of several scenarios.

To understand the interplay between post-pandemic recovery trajectories and household energy consumption, this study evaluates four distinct scenarios. Each scenario reflects a plausible combination of behavioral, economic, and technological trends influenced by the COVID-19 pandemic. The analysis captures variations in energy demand across demographic groups, time periods, and climatic conditions, enabling comprehensive insights into future energy consumption patterns.

4.3.1.1. Scenario 1: Permanent hybrid work adoption. The pandemic has normalized remote and hybrid work arrangements, significantly altering residential energy demand. In this scenario, energy usage during traditional working hours (9:00 a.m. to 5:00 p.m.) experiences a sustained increase due to a greater number of people working from home part-time. Fig. 5 illustrates the shift in daytime energy demand, highlighting the differences between pre-pandemic and post-pandemic recovery periods. As shown, peak daytime energy consumption increases by approximately 15 % in households with working-age members (30–44 years). However, the overall daily demand remains consistent, as evening consumption decreases due to reduced commuting and evening appliance usage. This scenario emphasizes the need for load balancing policies, such as incentivizing off-peak energy usage or adopting dynamic pricing models.

4.3.1.2. Scenario 2: accelerated green transition. In this scenario, pandemic recovery is coupled with robust government initiatives to promote renewable energy adoption and energy efficiency. Households increasingly invest in technologies such as solar panels, energy-efficient appliances, and smart home systems. Fig. 6 demonstrates the projected impact of widespread renewable energy adoption on household energy demand.

Energy demand shifts from centralized electricity grids to distributed generation systems, with solar power contributing up to 25 % of household energy needs in urban areas by 2030. Notably, households with higher income levels are more likely to adopt these technologies, leading to disparities in energy self-sufficiency. Policymakers must address this inequality by subsidizing renewable energy systems for low-income households.

4.3.1.3. Scenario 3: economic Rebound with high energy prices. As economic activity accelerates post-pandemic, global energy prices are expected to rise due to increased demand. In this scenario, households respond to high energy costs by adopting energy-saving behaviors and technologies. Fig. 7 showcases the relationship between rising energy prices and household energy consumption patterns. The analysis reveals

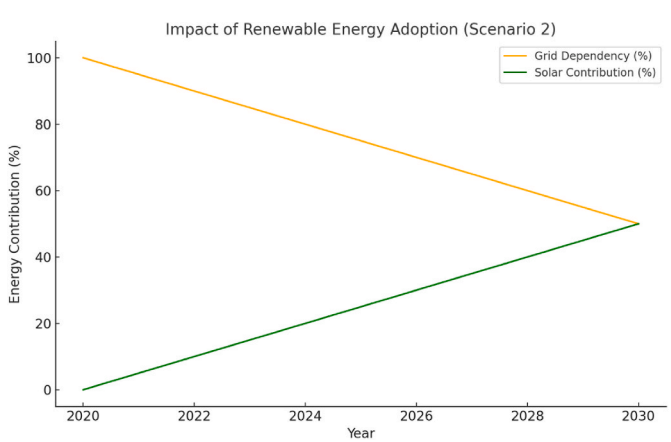

Fig. 5. Impact of renewable energy adoption.

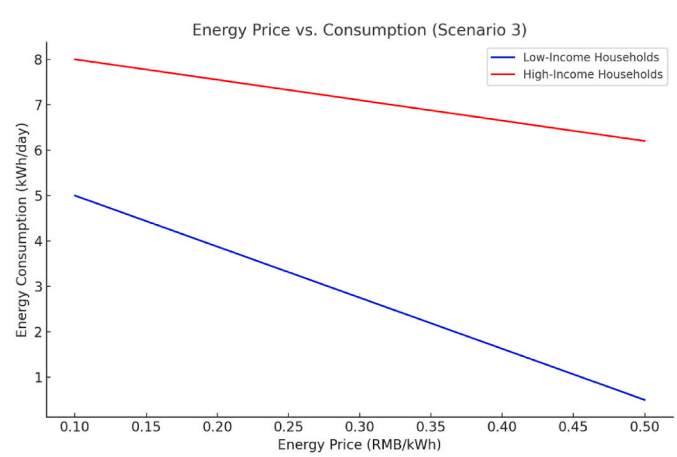

Fig. 6. Energy price vs consumption.

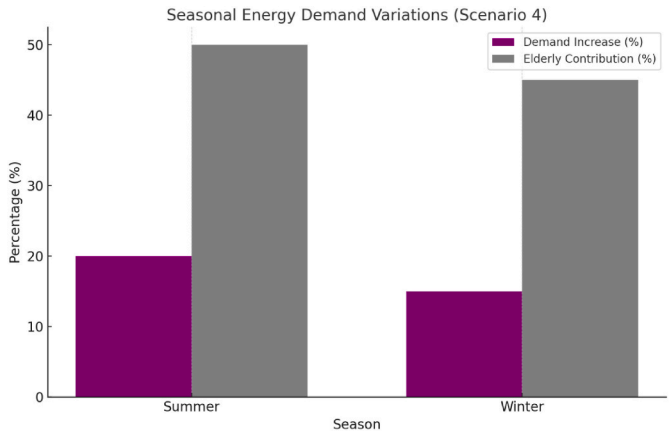

Fig. 7. Seasonal energy demand variations.

a 10 % reduction in overall energy consumption, driven primarily by middle- and low-income households reducing non-essential energy usage. Conversely, high-income households maintain or even increase their consumption, facilitated by investments in energy-efficient technologies. This scenario underscores the importance of targeted policies, such as tiered pricing and incentives for energy-efficient retrofits, to mitigate the impact on vulnerable populations.

4.3.1.4. Scenario 4: climate-driven adaptation. The intensification of climate change exacerbates extreme weather events, leading to increased demand for heating and cooling. In this scenario, energy consumption patterns show significant seasonal variations. Fig. 8 illustrates the projected change in energy demand during summer and winter months under extreme climatic conditions.

Cooling demand in summer increases by 20 % in regions experiencing heatwaves, while heating demand in winter rises by 15 % in areas with prolonged cold spells. Elderly households, who are more susceptible to extreme temperatures, contribute disproportionately to this increase. The results highlight the need for climate-resilient energy policies, such as expanding energy subsidies during extreme weather events and improving insulation in residential buildings.

4.3.2. Aging society

Under the aging population, household electrical energy consumption is usually increasing. The energy consumption trend is shown in Fig. 5(a), where there is a forecasted decline of energy consumption by 0. Fifty percent reduction of existing KWH consumptions per day to 0050 by 2030. Thus, this decline is expected to go deeper by 2050, with a further decline of 0. 0011 kWh/day. This trend has been observed before in countries in the East Asian region, including Japan, the Republic of Korea, and China, where life expectancy has been found to decline with total energy use.

The results of the conducted analysis correlate with the existing trend of a decrease in energy consumption in cases when the critical

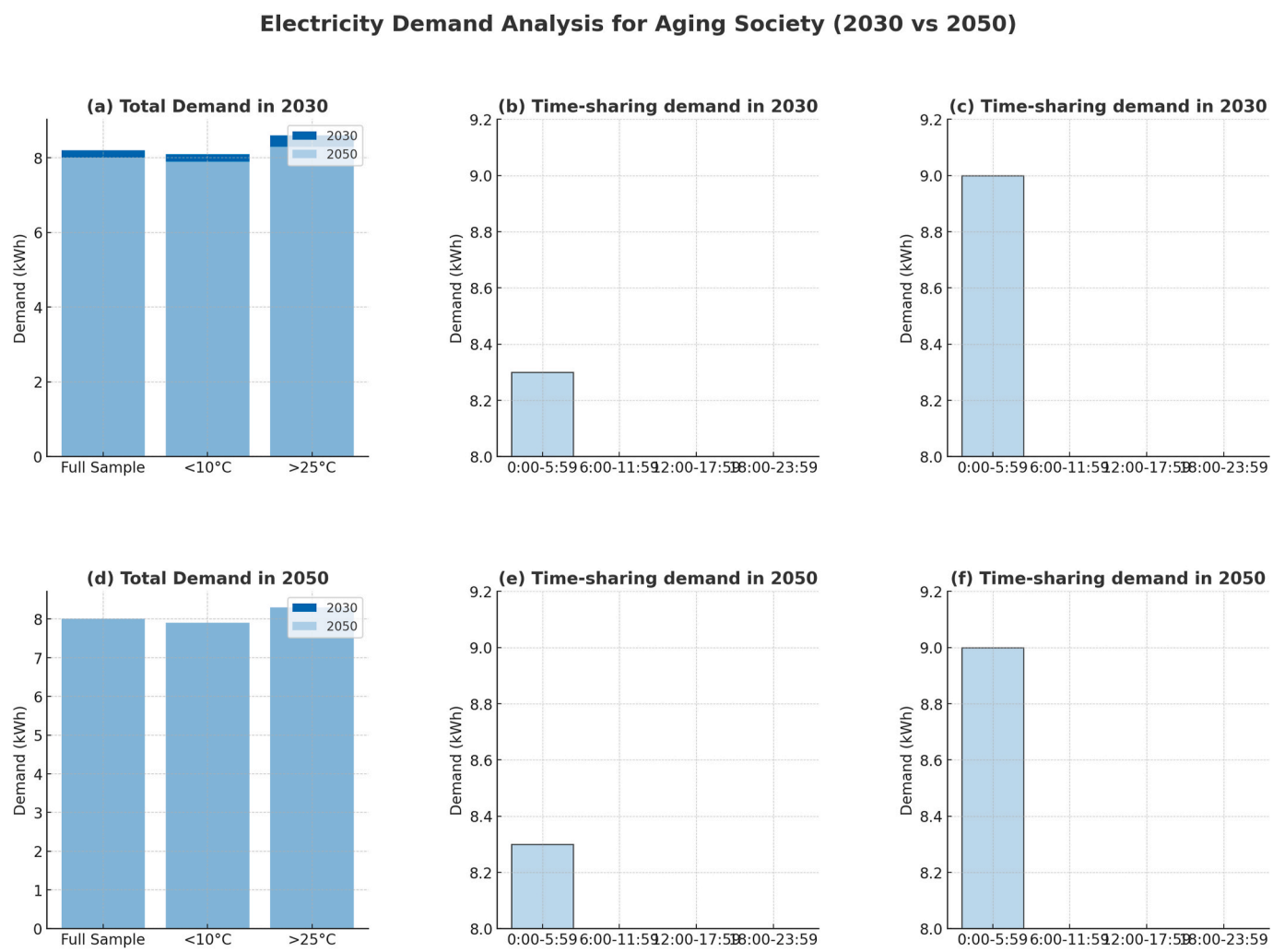

Fig. 8. Modifications to energy use should be made in circumstances when aging is considered.

factor is the aging population. This is opposite to previous findings that studied that older adults in some specified areas needed more energy, especially heating. There could be behavioral change, especially during the weather conditions; this could be one of the reasons that could explain the decrease observed. For instance, when people use a few appliances in summer or during the holiday season, the overall quantity of electricity used decreases. This phenomenon indicates the factors and trends affecting the demographic and climatic changes in energy usage in post-industrial societies.

Hypothetically, the overall power consumption in a typical household is expected to reduce, mainly due to the rising number of older adults. Senior citizens are among the most prudent energy users, often using the power only during extraordinary conditions, such as extremely hot or frigid days. This conservative behavior is apparent through their penchant for saving, and therefore, they would not spend many resources on indoor climate control like young people.

High-frequency data also reveal a sharp decline in the daytime electricity load during intense cold weather, as shown in Fig. 9 (b) and (c), 9(e), and 9(f). Notably, on warm evenings, elderly people may avoid turning off switches or controlling heating systems as often, and hence, the changes might be relatively harder to detect than when temperatures drastically vary. Considering our forecasts of the further development of the population aging in 2030 and 2050, probable trends in final energy consumption described above will only worsen. This highlights the part played by demographic changes in the determination of future energy demand. Solving these issues will entail measures to prevent the energy-related problems stemming from an aging society in future energy planning and policy-making measures.

Overall, the conclusions indicate that strategic approaches towards demographic developments are necessary to adequately reflect on how to control and utilize energy in the future four decades.

4.3.3. Income growth

Nighttime, namely between sunset and midnight, will see the largest spike in energy consumption due to rising incomes, as seen in Fig. 10(a) and (d). When the family's revenue doubles, the median daily power use will exceed 7.48 kWh. The disparity between daytime and nighttime needs will widen because of the substantial increase that occurs throughout the night. The peak demand period, which begins at 6:00 p.m. and ends at 11:59 p.m., will constitute 1.993 % of the total daily consumption needs.

It is important to note that occupants will use more power during hot or cold weather. Additionally, persons from more affluent homes may be more inclined to seek out a pleasant atmosphere, leading to higher demand during severe weather. Fig. 10(b) and (c) show that the median home energy consumption will rise by 0.52 kWh/day in the low-temperature configuration and by 0.31 kWh/day in the high-temperature set, representing a 5.94 % and 3.45 % increase, correspondingly. When it's chilly outside, people choose to forego using air conditioning in favor of low-power heating options like electric blankets and hot water bags, which results in a noticeable increase in energy usage. For the low-temperature sample, there might be an explanation for the higher electrical use in the home. The temporal allocation of home power usage differs, as shown in Fig. 6. Due to the hot weather,

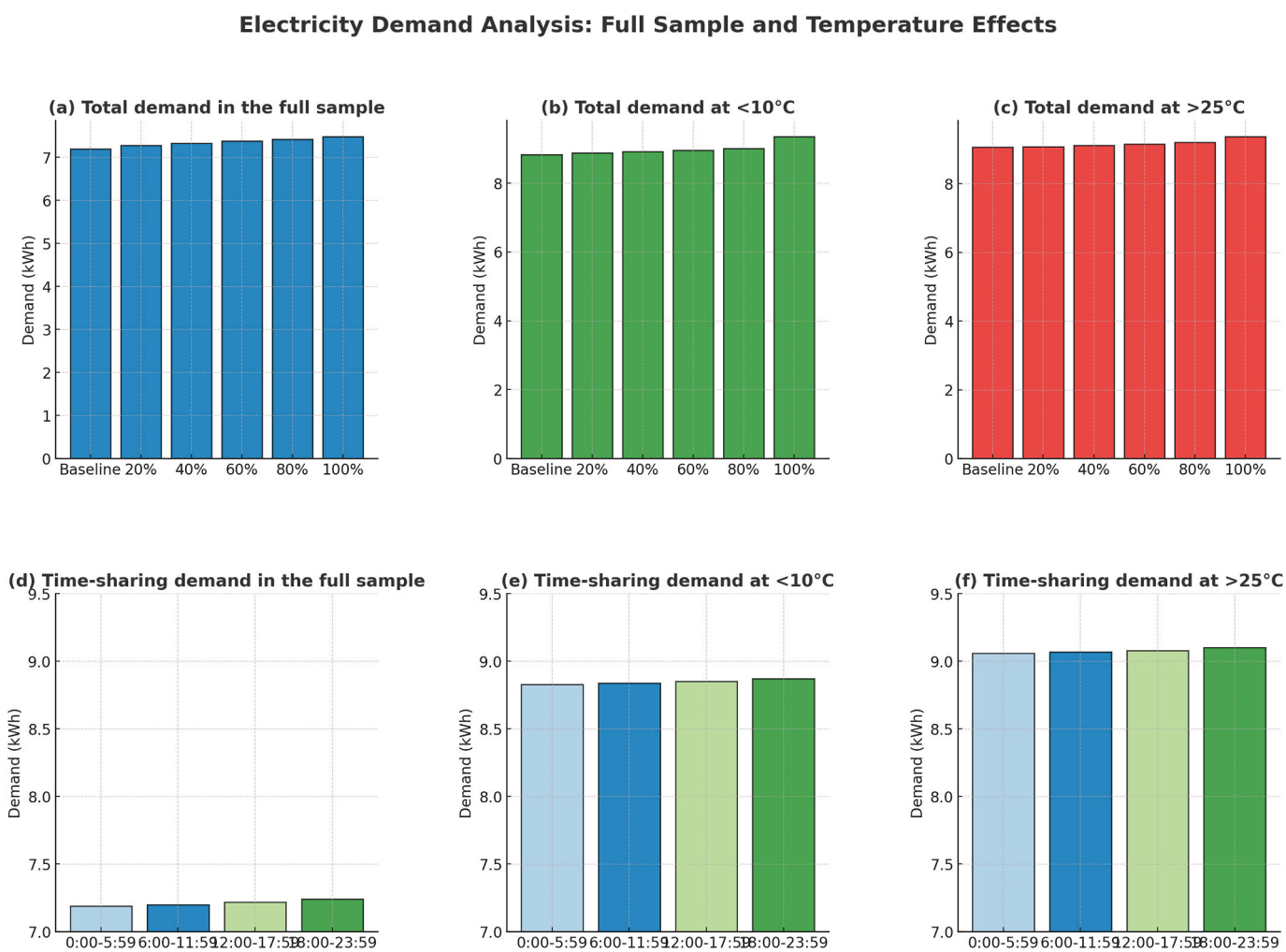

Fig. 9. Power use shifts in cases when income is the only variable.

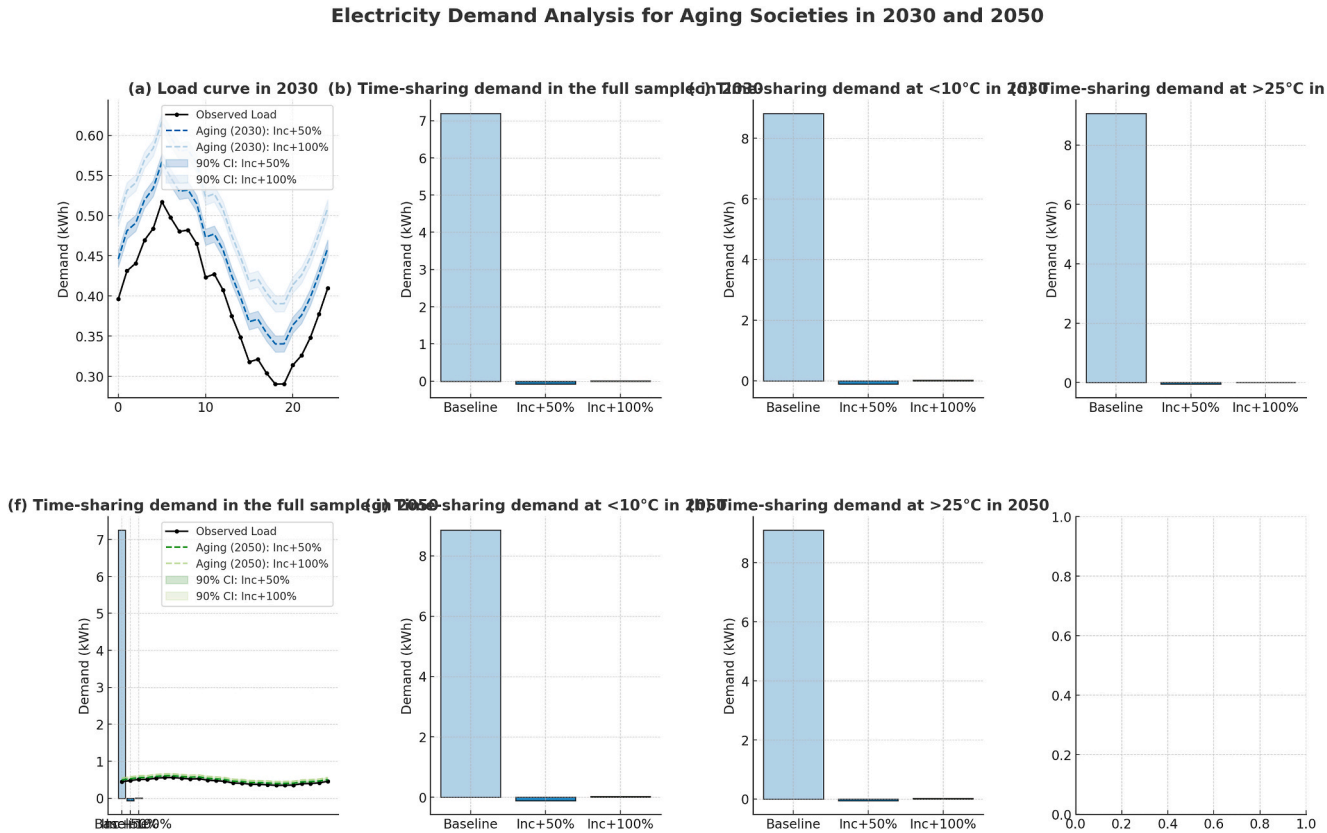

Fig. 10. There is little change in energy consumption trends across all scenarios, even when severe weather is included. Fig. 10 show that when temperatures are low, people tend to stay inside more, leading to an upward trend in energy consumption of 5.55 percent in 2030 and 5.41 percent in 2050, respectively. The majority of people like to do activities at home after work. Therefore, this spike in demand mostly happens in the evenings (6:00 p.m. to 11:59 p.m.). Consequently, a 0.36 kWh and 0.37 kWh increase in demand is anticipated during these specific hours. On the other hand, as seen in Fig. 7(d) and (h)—high temperatures tend to "smooth" out the distribution of demand increases. Social aging dynamics are expected to reduce total energy consumption during times of harsh weather, even while temperature mitigates the influence on demand patterns. Fig. 10(e) and (f) show that in comparison to scenarios where income growth is the only factor, demand increases due to lower temperatures are predicted to fall from 0.52 kWh in 2030 to 0.49 kWh in 2050 and 0.48 kWh in 2050 overall. In a similar vein, the growth in demand is anticipated to drop from 0.31 kWh to 0.24 kWh by 2030 and to 0.23 kWh by 2050 when temperatures above 25 °Prioritizing actions related to energy system planning is crucial, as shown by the discovered demand inequalities in the residential sector under various situations. When it comes to handling and controlling the changes in demand, strategies like peak shaving and valley filling are becoming more important, especially in light of changing demographic and environmental considerations.

Shanghai households will start to divide up their power use more equitably. The colder months are more tolerable, as the peak demand occurs mostly throughout the night. Electricity consumption drops in the early morning, and the demand rises from 6 p.m. to 11:59 p.m., accounting for around 3.9 % of the total, assuming a 100 % increase in income.

4.3.4. *All-inclusive case study*

We go further into the all-encompassing scenario that considers the impact of age and income on energy use. A richer aging society will experience demand growth and transfer, according to the simple aggregate of the two impacts (Fig. 10(a) and (e)). The time-sharing demand of an aging society in 2030 and 2050 under double income is shown in Fig. 10(b) and (f) to illustrate the dual impact. An unexpectedly greater rise of 4.44 % and 4.68 % in daily electricity usage is projected, surpassing the prior aging-only and income-only projections. Elderly citizens, who tend to be frugal, would feel more liberated to raise their energy usage as a result of a rise in family income. It is worth mentioning that the income-only growth scenario (Fig. 10(d)) predicts that over half of the extra new energy consumption would happen between 6:00 p.m. and 11:59 p.m. There will be a larger disparity in power consumption between peak and nonpeak hours of the day as a result of the interplay between income and age. In addition to a dramatic shift in overall demand, a richer aging society will also cause consumption patterns to be reallocated, as shown by a comparison of 2030 and 2050 scenarios, which shows that an older population will heighten choices about power usage.

4.4. *Refining energy consumption patterns*

The identified consumption patterns—flat, arch, single peak, and M-shaped—provide a robust foundation for understanding household energy behaviors. However, the complexity and diversity of household types and scenarios suggest that additional trends may exist that have been overlooked or misrepresented. The Gaussian Mixture Model (GMM) used for clustering effectively captures dominant patterns, but it may underrepresent niche or less prevalent behaviors, particularly in specific demographic or socioeconomic contexts. This limitation could result in an incomplete understanding of the variability in energy consumption across different households and scenarios.

For instance, some households, such as those with irregular schedules due to shift work or unique family dynamics, may exhibit multi-peak patterns with varying intensity and timing that do not align neatly with the current clusters. Similarly, working households often display distinct weekend energy usage, characterized by higher daytime consumption for leisure activities, cooking, and cleaning, which may not be fully captured in weekday-focused clustering. Seasonal variations also play a significant role in shaping energy use. In regions with

extreme temperatures, households may show markedly different patterns during summer and winter, such as continuous high cooling demand or prolonged heating periods, which could be diluted when averaged with data from milder seasons.

Another overlooked trend may involve low-occupancy or vacant homes, such as secondary residences or those frequently unoccupied due to travel. These homes may exhibit consistently low and sporadic energy use, which might not be adequately captured by the flat pattern category. Additionally, households adopting advanced energy technologies, such as solar panels or smart home systems, likely have unique consumption patterns. For example, homes with renewable energy installations may show high daytime energy generation with reduced grid dependency, deviating from traditional consumption trends. Such technology-driven behaviors are essential to capture in an increasingly digitized and sustainable energy landscape.

To address these potential gaps, the study could refine its pattern identification approach by increasing the granularity of clustering. Allowing for more clusters or introducing subcategories within existing patterns could highlight nuances in multi-peak or flat usage profiles. Temporal segmentation could further improve the analysis, with separate evaluations for weekday and weekend patterns to differentiate working and leisure-day behaviors. Similarly, analyzing seasonal patterns separately would provide insights into the impact of weather-related energy demands. Incorporating household-specific contextual variables, such as occupancy rates, adoption of smart technologies, or environmental awareness, into the clustering process could also reveal patterns driven by unique household characteristics.

Furthermore, household energy behaviors are dynamic and may evolve over time due to demographic shifts, income changes, or increased adoption of technology. Implementing a longitudinal analysis that tracks transitions in energy patterns over time can help identify emerging trends and adaptations. Validation of the identified patterns against external datasets or case studies from other urban centers or demographic contexts would strengthen the findings' robustness and ensure broader applicability. Addressing these nuances would enhance the study's utility for policymakers and energy planners. By identifying overlooked patterns, targeted interventions could be designed to cater to specific household types. For instance, irregular-use homes might benefit from incentives for energy efficiency, while multi-peak households could be encouraged to adopt peak-shaving technologies. Weekend-focused policies or solutions for seasonal energy management might further optimize energy use in specific scenarios.

5. Discussion

When planning future energy structures, social aging is an important factor to consider [23]. An analysis of Shanghai's energy consumption habits sheds light on the ways in which megacities and emerging nations will adapt to the effects of societal aging. Instead of concentrating on the low-frequency demand shift caused by societal aging, which has been the subject of earlier research, we find possible daily consumption reallocation using high-frequency hourly energy consumption data. Machine learning and unsupervised clustering provide accurate predictions about the impact of socioeconomic characteristics on energy consumption patterns in homes. Our research indicates that the demand for energy will not rise due to societal aging alone, and in fact, it will fall in hot and cold weather. A wider disparity between peak and nonpeak hours and an increase of 0.34 kWh in daily energy consumption are consequences of the demographic shift toward an older, high-income society. Results from our study corroborate those of earlier research that have shown that rising family incomes would cause a shift in energy consumption patterns associated with an older population. The reallocation of hourly distribution is happening at the same time as the growth in overall demand. These findings have important implications for the long-term planning of China's electrical grid and for the country's efforts to promote sustainable energy.

Given the constraints of the survey data, this research primarily examines two age groups: people above 60 and people below 60. However, the effect of age specifics needs to be investigated within the number of family members, children, middle-aged people, and elders. Thus, including such various demographics makes it possible to provide a more profound look at energy consumption. In every part of a household, one area may contain different generations while the other is separate, contributing to the formation of energy consumption trends. For example, elderly customers above 60 may have dissimilar energy usage concerning code compared to young family members. They might stay at home longer, which may enhance the domestic energy demand; they may also have special requirements for heating, ventilation, air conditioning, or required medical equipment that influence energy intensity. Similarly, people of mid-age or the 40s and 50s who are mostly the breadwinners and decide on the family's expenditure, lifestyle and preferred energy efficient technology, can influence the energetic flow per their chosen pathetic norm. They will be able to buy efficient electrical appliances in terms of energy consumption and smart home gadgets in the similar course enhancing comfort.

Conversely, children and young individuals of any family can also contribute to the determination of energy services in a household in aspects pertaining to the use of technology, artificial light, and warmth. The younger generation shall also be referred to as the 'digital natives' and can demand for more conservation or even installation of green energy within or around the home.

Therefore, it is imperative to consider the family's age structure and generational characteristics to achieve a realistic view of energy consumption in the process. It also guarantees that any policy or program that seeks to correct energy efficiency is rightly aligned and efficient. Thus, during the formation of policies and research analyzing the energy consumption of households, it is necessary to consider the activities and requirements of representatives of various age categories, which will allow for predicting the characteristics of demand response and improving the approaches to its regulation.

6. Conclusion and recommendations

6.1. Conclusion

This study offers valuable insights into the changing dynamics of household energy consumption in the context of demographic aging, focusing on Shanghai, China, from 2016 to 2023. Using advanced machine learning techniques such as Gaussian Mixture Models (GMM) and Finite Mixture Models (FMM), the research identifies distinct hourly consumption patterns across various household types and socioeconomic groups. The findings demonstrate that an aging population significantly impacts energy use, not only by increasing overall demand but also by reshaping hourly consumption behaviors. The prolonged presence of older individuals at home leads to heightened daytime energy use, while income growth further amplifies energy demand, particularly for energy-intensive appliances and leisure activities during peak evening hours. These shifts widen the disparity between peak and non-peak consumption periods, posing challenges for energy grid stability and sustainability.

The study's scenario-based simulations underscore the critical interplay between demographic transitions and economic development. As the elderly population in Shanghai is projected to grow substantially by 2050, the research highlights the urgent need for adaptive energy policies. These policies should address the rising energy needs of aging households, promote the adoption of energy-efficient appliances, and incentivize renewable energy systems. Additionally, the research emphasizes the importance of incorporating behavioral, technological, and environmental factors into energy modeling, ensuring a comprehensive understanding of the drivers behind consumption patterns.

6.2. Managerial implications

The findings of this study underline the critical need for tailored energy policies to address the unique challenges posed by demographic aging and economic transitions in urban centers like Shanghai. These insights hold relevance not only for Shanghai but also for other global megacities experiencing similar demographic shifts. Below are specific policy recommendations based on the study's findings.

- o Introduce subsidies or tax incentives for energy-efficient appliances and smart home systems tailored to aging households, as these groups are more likely to spend extended periods at home and require optimized energy use.
- o Implement policies to support retrofitting older buildings with energy-efficient technologies, such as improved insulation, efficient HVAC systems, and advanced lighting solutions, which can benefit both elderly populations and other residents.
- o Provide financial incentives for the installation of solar panels, battery storage systems, and other renewable technologies to reduce dependence on grid energy, particularly during peak hours.
- o Develop community-based renewable energy programs, such as shared solar projects, to ensure equitable access to sustainable energy for households with limited financial resources.
  oInvest in grid modernization to manage the disparity between peak and non-peak energy demands caused by aging populations and rising income levels.
- o Promote demand-side management programs, including dynamic pricing schemes and time-of-use tariffs, to encourage households to shift energy usage to off-peak hours.
- o Create targeted support programs for elderly and low-income households to ensure affordable energy access during extreme weather conditions.
- o Provide financial assistance or discounted tariffs for households requiring medical equipment or enhanced climate control systems, which are common needs among aging populations.
- o Encourage the adoption of smart grid technologies to enable real-time monitoring and management of household energy consumption.
- o Promote the development of data-driven energy management tools, such as mobile apps, that allow households to track and optimize their energy usage.
- o Launch public awareness campaigns emphasizing energy conservation and the benefits of adopting green technologies.
- o Tailor educational programs to different demographic groups, highlighting specific actions individuals can take to reduce energy consumption, such as adjusting thermostat settings or scheduling high-energy activities during off-peak hours.
- o Use scenario-based planning to anticipate future energy demands, considering both demographic aging and income growth.
- o Develop flexible and adaptive energy policies that can be updated as new trends emerge, ensuring their continued relevance and effectiveness.
- o Establish frameworks for ongoing collection of high-frequency energy consumption data, with a focus on understanding the needs of diverse household types and age groups.
- o Invest in research to explore the intersection of aging, technology, and energy consumption, ensuring that policies are informed by the latest evidence.

By implementing these policies, cities facing similar demographic transitions can create sustainable and inclusive energy systems. These strategies not only address the immediate challenges of demographic aging but also align with broader global goals, such as those outlined in the United Nations Sustainable Development Goals (SDGs), by promoting equitable, efficient, and environmentally friendly energy practices.

6.3. Limitation and future recommendations

This study, while providing valuable insights into the dynamics of household energy consumption in an aging society, has several limitations that present opportunities for future research. One significant limitation is the reliance on data primarily from Shanghai, which, although representative of a megacity undergoing demographic and economic transitions, may not fully capture regional variations or the diversity of urban and rural energy behaviors in other parts of China or globally. Expanding the geographic scope to include multiple cities or countries with varying socio-economic and demographic contexts could improve the generalizability of the findings. Additionally, the categorization of households into broad age groups (<60 and ≥ 60) limits the granularity of analysis. Future research could incorporate finer segmentation, such as dividing households into narrower age bands (e.g., 15–29, 30–44, etc.), to better understand intergenerational energy consumption dynamics and their implications.

Another limitation lies in the exclusion of certain external factors, such as the impact of specific climate policies, technological disruptions, and energy price volatility, which are critical for a comprehensive understanding of energy consumption patterns. Incorporating these variables into future models would enhance the robustness and applicability of predictions. Furthermore, the study's focus on static scenarios limits its ability to account for evolving societal behaviors and technological advancements over time. Longitudinal studies or adaptive models that consider real-time changes in household preferences, policy impacts, and technological adoption could provide more dynamic insights into energy demand trends.

The study's use of high-frequency data is a strength but also poses challenges in terms of scalability and data availability for other regions. Future research should explore methods for integrating high-frequency data with other types of datasets, such as qualitative surveys or macroeconomic indicators, to provide a more holistic understanding of energy consumption drivers. Additionally, while the models employed effectively capture correlations between household characteristics and energy patterns, they may not fully address causality or the complex interactions between variables. Advanced modeling techniques, such as causal inference or agent-based simulations, could be employed in future studies to better understand these dynamics.

Lastly, the study does not explicitly address the long-term cohort effects, where individuals' consumption patterns are shaped by the socio-economic environment of their formative years. Future research should investigate how these effects influence energy behaviors over time, particularly in rapidly aging societies. By addressing these limitations and exploring new directions, future studies can build on this research to develop more comprehensive, transferable, and actionable insights into household energy consumption in a rapidly changing world.

CRediT authorship contribution statement

Yan Zou: Conceptualization, Methodology, Writing – original draft, Formal analysis. **Chen Wang:** Data curation, Validation, Writing – review & editing, Visualization. **Hina Najam:** Software, Investigation, Writing – review & editing, Resources. **Abdelmohsen A. Nassani:** Project administration, Methodology, Writing – review & editing, Funding acquisition. **Gozal Djuraeva:** Supervision, Project administration, Validation, Writing – review & editing, **David Oscar:** Methodology, Writing – review & editing.

Declaration of competing interest

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

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Data availability

The data that has been used is confidential.

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