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Socio-technical drivers of energy use in low-income housing in Jordan: insights from a regression-based study

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ABSTRACT
The residential sector in Jordan accounts for 61% of national primary energy consumption, with low-income households contributing substantially to this demand. However, empirical evidence on household energy use remains scarce. This study draws on survey data from nearly 400 households in Amman to identify key determinants of energy consumption. Data on building attributes, household characteristics, and energy-related behaviours were collected through interviewer-administered questionnaires. Descriptive statistics and stepwise multiple linear regression were employed to assess how these factors influence energy consumption. Four regression models were tested: building characteristics (e.g. floor area, thermal performance); household attributes (e.g. household size, age composition); energy-related behaviour (e.g. heating-and-cooling patterns, sociocultural practices); and a combined model, against energy expenditure as the dependent variable. Building factors explained 9.6% of the variance in energy expenditure, while household characteristics and behavioural factors accounted for 40.2% and 30.3%, respectively. Air-conditioner ownership emerged as the strongest predictor, followed by the presence of young adults, heating-and-cooling duration, number of cooling devices, and daylight quality. This study represents one of the first empirical assessments of how building and occupant-related factors collectively influence household energy demand, providing an evidence-based foundation for future research and policy in Jordan and comparable contexts across the Global South.

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KEYWORDS
Energy consumption; low-income housing; household survey; Jordan; stepwise multiple linear regression

Introduction

Residential building operations account for 22% of global final energy consumption (IEA, 2022). In response, governments worldwide are intensifying efforts to reduce energy use in this sector by implementing various measures and policies. However, despite these efforts, Jordan has witnessed a marked increase in residential energy demand over the past 15 years, with the sector accounting for nearly 61% of the national energy consumption (Dar-Mousa & Makhamreh, 2019; MEMR, 2017, 2018, 2021; NEPCO, 2016). This trend poses substantial challenges in light of the country's rapid population growth and escalating housing demand (Alnsour, 2016; MEMR, 2018; NEPCO, 2022; Sammour et al., 2024). Such a rise is largely driven by low-income households, which comprise 50.8% of urban households and 44% of overall housing demand (DOS, 2022; UN-Habitat et al., 2022). Compared to their more affluent counterparts, these households face distinctive constraints shaped by inefficient buildings, sociocultural dynamics and limited financial and spatial resources (Malik & Bardhan, 2023; Santamouris et al., 2007). These interconnected challenges drive everyday energy behaviours, appliance usage, and adaptive living practices, often leading to higher energy consumption (Gupta et al., 2024).

Addressing this issue requires context-sensitive interventions and evidence-based policy frameworks that accurately reflect the realities of low-income housing. However, the lack of comprehensive data on such households in Jordan impedes progress toward enhancing both thermal comfort and energy efficiency. Effective policy development necessitates a nuanced understanding of the drivers of residential energy consumption within Jordan's unique socio-economic and cultural context (Howden-Chapman et al., 2009; Huebner et al., 2015; Kavousian et al., 2013; Šćepanović et al., 2017). Existing research on energy use in Jordan

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remains limited and is primarily dominated by technical studies that depend on non-empirical data and small-scale analysis (Albatayneh et al., 2020; Ali & Alzu'bi, 2017; Mari et al., 2020; Younis et al., 2017). These studies often neglect critical occupant-related determinants, such as socio-demographic characteristics and behavioural practices (Ioannou & Itard, 2015; Kane et al., 2015; Love & Cooper, 2015). Consequently, the absence of comprehensive, empirically grounded data leaves a significant gap, hindering the effectiveness of policy interventions to reduce residential energy consumption (Bai et al., 2018; Nagendra et al., 2018; Steg, 2018).

Building on and complementing our earlier qualitative investigation (Maaith et al., 2025), which revealed that the complex interplay of sociocultural practices (e.g. privacy, family dynamics) and physical conditions shapes spatial adaptations and energy practices, this paper extends that inquiry through a quantitative lens. The present study examines their broader socio-technical patterns across 392 low-income households, focusing on building characteristics, adaptive behaviours, and comfort perceptions that collectively reflect and quantify these underlying sociocultural influences.

This study addresses these gaps by examining energy consumption patterns among low-income households in Amman and identifying key building and occupant-related factors that determine energy use. It introduces a novel, integrated questionnaire that captures both technical (e.g. design and resident-led modifications) and social dimensions, including socio-cultural practices, behavioural adaptations, and perceptions of comfort and affordability. Data collected from 392 surveyed low-income households in Amman during July and August 2024 constitute one of the most extensive socio-technical empirical datasets in Jordan.

Understanding the multifaceted drivers of residential energy demand in resource-constrained urban contexts is vital for promoting energy efficiency, affordability, and environmental sustainability in Jordanian housing and comparable contexts across the Global South. By addressing these challenges, this study contributes to progress toward several key Sustainable Development Goals, notably SDG 1 (No Poverty), SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action).

Previous studies

Residential energy consumption emerges from a dynamic interaction between buildings and occupants over time (Chen et al., 2021). This study draws upon three perspectives, adaptive comfort, socio-materiality, and energy cultures, to explain how material, behavioural, and cultural elements co-shape energy demand. The adaptive comfort model (De Dear & Brager, 1998; Yao et al., 2022) emphasises behavioural responses to thermal conditions, the socio-materiality perspective (Shove et al., 2012) underscores the inseparability of social practices and material infrastructures, while the energy cultures framework (Stephenson et al., 2010) links energy use to shared social norms and material contexts. Together, these frameworks inform a socio-technical perspective that integrates building and occupant dimensions to provide a holistic understanding of this complexity (Khosla et al., 2019; Sharmin & Khalid, 2022). Guided by this framing, the following review synthesises key determinants of residential energy use.

Impact of building characteristics on energy consumption

Building characteristics, such as floor area, building envelope airtightness and insulation, and glazing-type, remain among the strongest determinants of household energy use, explaining approximately 39–54% of the observed variance (Guerra Santin et al., 2009; van den Brom et al., 2019). Evidence from low-income and vulnerable contexts confirms the significant impact of building attributes on households' energy demand. Floor area consistently emerges as a dominant determinant, with larger homes requiring more energy for heating, cooling, and lighting (Gao et al., 2019; Wang et al., 2023). However, the effect of the number of rooms remains inconsistent. While Romero-Jordán and del Río (2022) and Vosoughkhosravi et al. (2024) reported a positive association when floor area was excluded, Tokam and Ouro-Djobo (2025) observed an opposite effect when floor area was controlled for.

The thermal performance of the building envelope is equally pivotal. Poor insulation and inadequate envelope conditions substantially increase energy expenditure, particularly in low-income settings (Hernández & Phillips, 2015; Larrea-Sáez et al., 2023). Guerra Santin et al. (2009) identified wall insulation as the most influential building factor, followed by ceiling insulation and window performance. In Jordan, improving airtightness was found to be as effective as enhancing roof insulation in reducing energy demand (Albatayneh et al., 2020). Furthermore, glazing type, primarily single-versus double-glazing, has been widely associated with heating and cooling loads (Bournas et al., 2019; Xu et al., 2023).

Impact of occupants on energy use

Occupant-related factors contribute 10.7–50% of the variance in energy use (van den Brom et al., 2019; Xu et al., 2020). These encompass household characteristics, such as household size (occupant number), occupant age composition, householder head characteristics, and income, as well as behavioural factors, including energy use practices and lifestyle (Xu et al., 2020).

Household characteristics

Household characteristics significantly influence residential energy consumption, though their effects are often complex. Household size or the number of individuals in the household is one of the strongest determinants, with larger households typically consuming more energy but less per capita due to shared appliance use and economies of scale (Hu et al., 2020; Xie & Noor, 2022). Age composition of household members also matters. Aslam and Ahmad (2018) found that Pakistani households with elderly individuals or children tend to have higher consumption. Teenagers and young adults can similarly elevate demand, driven by electricity-intensive activities (Khosla et al., 2019). Gender dynamics introduce nuanced patterns, as demonstrated by Kostakis (2020), who found that male-dominated households in Greece typically consume more energy, whereas Mashhoodi and Bouman (2023) observed that female-dominated households in the Netherlands display greater conservation-oriented behaviour.

The influence of householder head characteristics, particularly age, shows mixed patterns, positive, negative, or nonlinear, depending on contextual factors (Bardazzi & Pazienza, 2020; Estiri & Zagheni, 2019; Inoue et al., 2022). Such variability partly stems from methodological differences in defining age, whether based on the reference person or the oldest household member, leading to inconsistent results across studies (Huebner et al., 2016). Educational attainment is another relevant factor, with higher education levels generally associated with greater energy use, possibly reflecting higher income (Taale & Kyeremeh, 2019). Moreover, Lenzen et al. (2006) suggest that the householder's influence often parallels household size. While income remains a robust predictor of higher consumption (Debs et al., 2021), it alone may be insufficient; integrating it with household structure yields stronger explanatory power (Yust et al., 2002). Beyond direct energy consumption, studies in rural South Africa and Iran found that higher-income households are more likely to own energy-intensive appliances, such as air conditioners (AC) and washing machines, thereby amplifying consumption (Han et al., 2022; Koch et al., 2024; Soltani et al., 2019).

Energy-related behaviour

While building and household characteristics explain part of residential energy use, occupant behaviour remains a critical determinant of how and when energy is consumed (Krishnan et al., 2022). Evidence consistently shows that energy-related behaviours are largely driven by the pursuit of indoor thermal comfort, with heating-and-cooling practices accounting for much of the demand, particularly in low-income and hot-climate settings (Nahmens et al., 2015). This demand is commonly met through mechanical cooling, including fans and ACs (Olatunde et al., 2024; Ryu & Kim, 2021). Appliance usage also plays a crucial role, as higher frequency and longer operation durations correspond with greater consumption (Rouleau et al., 2018; Xu et al., 2020). Conversely, energy-conscious behaviours, such as turning off unused lights, can reduce household energy use by 20–30% (Sundah et al., 2024). Awareness and the use of energy-efficient appliances further contribute to long-term reductions in energy expenditure (Sundah et al., 2024). In high-density, low-income housing, constraints such as limited space and variable occupancy patterns encourage adaptive energy practices that significantly shape electricity demand (Sarkar & Bardhan, 2020).

Sociocultural norms further mediate energy-related behaviours, particularly in communities with strong cultural identities. Despite their substantial influence, these factors remain underrepresented in empirical research (Gupta et al., 2024; Khalid & Sunikka-Blank, 2017). For instance, Debnath et al. (2020) and Maina (2023) observed that social expectations, security concerns, and privacy preferences shape behavioural and spatial adaptations, affecting how occupants regulate indoor conditions and manage energy use, ultimately driving up cooling demand in contexts such as India and Nigeria. Similarly, Razem et al. (2025) highlight that privacy adaptations in Jordanian households constrain natural ventilation and lead to greater reliance on mechanical cooling, which is consistent with energy cultures and socio-materiality mechanisms. Likewise, guest-hosting traditions, common in Arab societies, result in higher energy use due to increased occupancy loads, comfort standards, and spatial preparation (Aldossary et al., 2015).

The literature demonstrates that residential energy consumption is shaped by building and occupant-related factors. While measurable factors, such as house floor area, appliance ownership, and thermal practices clearly affect demand, the influence of household composition, behavioural, and sociocultural factors remains less well understood. Despite the growing recognition of these interdependencies, the impact of

Figure 1. Study area – locations of the surveyed public housing in Amman.

sociocultural practices remains underexplored, highlighting the need for further investigation.

Methodology

Case study area

Amman, Jordan's capital, accommodates 42% of the national population and 46% of dwellings, with 94% of its housing stock consisting of multi-family apartments predominantly occupied by middle-and low-income households (DOS, 2015; Halme et al., 2024; UNDP, 2013). Residential energy consumption constitutes 49% of the city's demand (Dar-Mousa & Makhamreh, 2019), making Amman a representative context for low-income energy investigations. The research covered all four low-income public housing developments in Amman: Abu-Alanda, Mostanada, Princess Iman, and Marka Al-Dyar (Figure 1), established in 2008 by the Housing and Urban Development Corporation (HUDC). These projects exemplify the spatial and construction characteristics of low-income housing in Jordan (Al-Homoud & Is-Haqat, 2019), comprising eight apartment typologies ranging from 90 to 160 m^2 (Figure 2).

Survey questionnaire

The survey comprised 53 primary and sub-questions systematically organised into six key sections (Table 1). The questionnaire was developed based on previously validated surveys, including those by the Jordan Green Building Council (Nazer, 2019), and international benchmarks such as the Residential Energy Consumption Survey from the US Department of Energy and the Energy Information Administration (EIA, 2024) and the Energy Follow-Up Survey conducted by the UK Department of Energy and Climate (BRE, 2013). Furthermore, the survey questions and parameters were refined through a critical review of relevant literature to ensure alignment with established research and suitability for the study's specific context. To ensure content validity and cultural appropriateness, the questionnaire was reviewed by two experts in housing and energy studies. A pilot test was conducted with a small group of non-sampled low-income households to refine clarity, relevance, and cultural appropriateness. Based on participant feedback, modifications were made before finalising the survey. The questionnaire was initially drafted in English and then translated into Arabic, Jordan's official language, to ensure cultural relevance, accessibility, and clear understanding among respondents.

Sample size and selection

A representative sample of low-income households in Amman's public housing was selected using Cochran's formula (Eq 1; Cochran, 1977). The sample size was calculated based on prior research insights and response reliability, applying a 95% confidence level and a 5% margin of error to ensure the survey's validity and

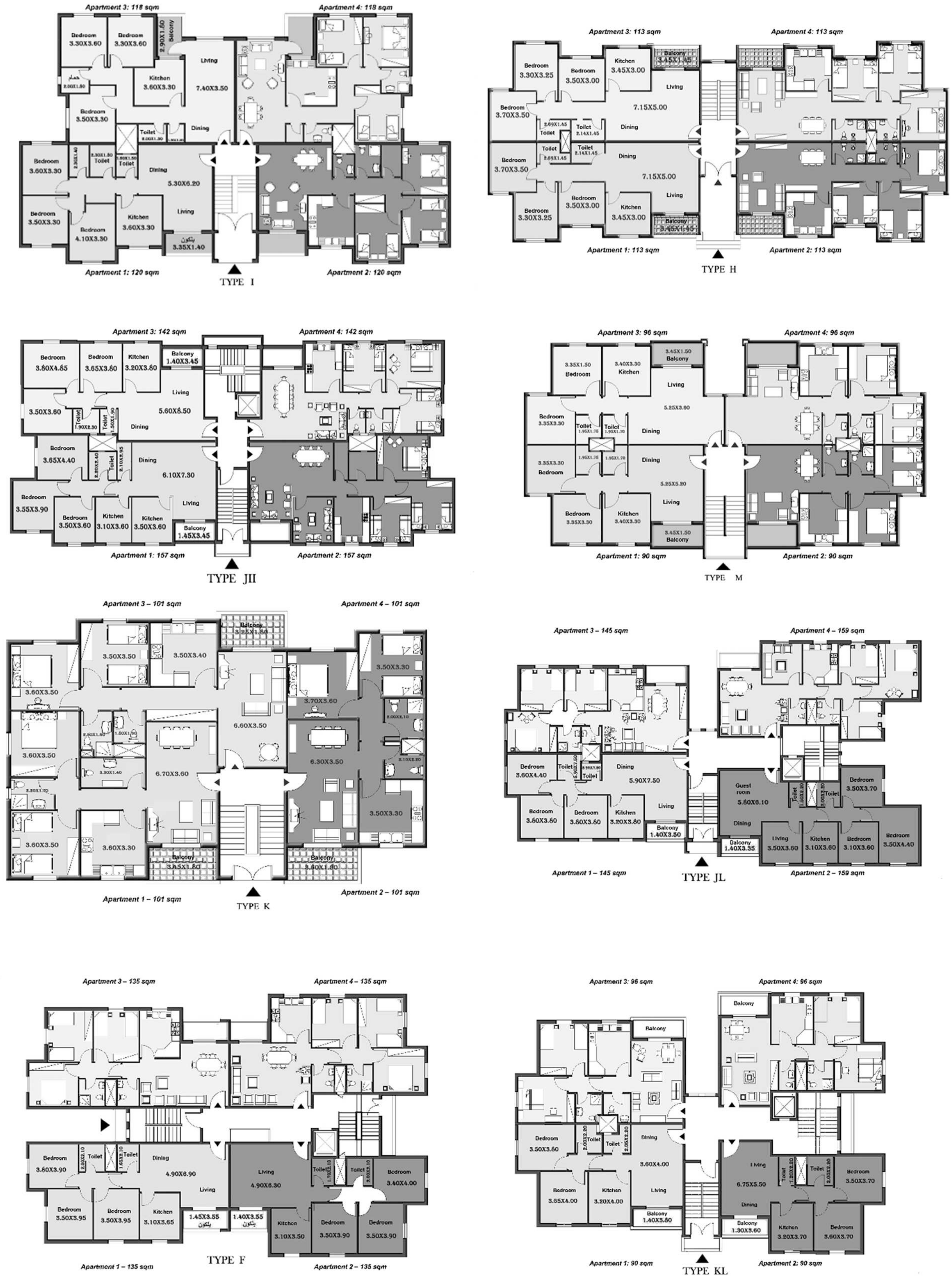


Figure 2. Surveyed household housing typologies.

Table 1. Questionnaire structure.

Item	Content
Household social-demographics profile	Total household income, household structure, household size, household members' age band and gender, primary householder's employment status and educational level.
Building form and characteristics	The floor level and orientation of the house, floor area (m^2), number of bedrooms, guestroom and balcony availability and usage frequency, renovation/modification work and its main driver, the performance of wall and ceiling insulation, window glazing and performance, and availability of window shading.
Space heating, cooling, and ventilation	Type, number, age, operation, capacity, and efficiency of heating and cooling devices/ systems, cooled/heated spaces, setpoints and schedules for heating, cooling, and ventilation, fuel sources, and window opening behaviour in winter and summer.
Occupancy pattern	Main occupancy pattern on weekdays and weekends.
Lighting, appliances, and hot water	Primary lighting type, daylight quality, lighting usage and behaviour, appliance ownership and usage frequency, availability and efficiency of electrical appliances, and type, fuel, and control of domestic hot water (DHW) systems.
Energy bills and usage	Seasonal electricity and fuel costs, affordability, and alternative energy sources.

generalisability (Smithson, 2003).

$$n = \frac{z^2(pq)}{e^2} \tag{1}$$

Where n is the sample size, z is the z-score for a 95% confidence level (1.96), p is the estimated proportion of the population, with $q = 1{-}p$, and e is the margin of error (0.05). Based on an estimated 1.04 million low-income households in Amman (DOS, 2017), the required minimum sample size was 384. The study achieved 392 valid responses, exceeding this threshold for representativeness.

A proportionate stratified random sampling strategy was employed to ensure the representative coverage of low-income households across Amman's public housing districts. Stratification by geographic location enables proportional inclusion of diverse household characteristics and building typologies while improving estimate precision across homogeneous strata (Qian, 2010). However, due to safety concerns in the Princess Iman district, data collection was limited, and the sample was reallocated to other strata to maintain overall representativeness.

The questionnaire was administered through face-to-face interviews with the households conducted by the principal researcher with support from six trained assistants. This approach was chosen to ensure a high response rate, especially given the varying literacy levels among the target population; it allowed respondents to seek clarification when needed (Hox & De Leeuw, 1994). Households were reached door-to-door and in local public spaces, including mosques and supermarkets. Eligible respondents were residents aged 18 or older from low-income families, as locally defined, typically earning around 500 Jordanian dinars[1] (JOD) or less monthly (DOS, 2024; UN-Habitat, 2023). Data collection was conducted during July and August 2024.

The data collection process encountered several challenges, including participants' reluctance to share detailed energy-related information due to privacy concerns and cultural norms that limited access to in-home surveys in conservative settings. These challenges required adaptive, culturally-sensitive strategies to maintain methodological integrity, uphold ethical standards, and foster participants' trust and engagement. All study protocols and survey instruments were reviewed and pre-approved by the relevant institutional research ethics committee. Ethical procedures followed institutional and national guidelines, ensuring informed and voluntary participation, verbal consent documentation, and strict confidentiality in accordance with Jordanian Law No. 24 of 2023 (MODEE, 2023).

Data processing and analysis

Data processing was conducted to ensure the dataset's accuracy, reliability, and readiness for analysis. This process involved systematic data cleaning, coding, and imputation of missing values using RStudio (RStudio Team, 2020). Given the minimal rate of missingness (0.36%) and the absence of any variable exceeding 5%, missing numerical values were imputed using the mean, while categorical variables were replaced with the mode. This approach minimised biases and ensured missing values did not significantly affect the results (Guerra Santin et al., 2009). Diagnostic checks confirmed that the missingness pattern was random and that coefficient estimates remained stable relative to complete-case results, indicating the robustness of the imputation procedure. Sample balance across housing districts was also examined, and post-stratification weighting was deemed unnecessary due to consistent representation across strata.

Data analysis consisted of two key components: descriptive statistics and Multiple Linear Regression (MLR), both conducted in RStudio. Descriptive analysis summarised the dataset, providing an overview of the survey sample's characteristics and the key energy consumption patterns by calculating percentages, means, and standard deviations. MLR was performed to examine the relationships between household energy consumption and building attributes, household characteristics, and behavioural factors identified from survey data, along with their associated impacts. MLR is an effective method in empirical studies to assess the influence of multiple independent predictors, including categorical and continuous variables, within a single analytical framework, enabling a comprehensive assessment of the simultaneous effects of diverse predictors (Ellsworth et al., 2023; Mao, 2021; Marill, 2004; Plonsky & Ghanbar, 2018; Wondola et al., 2020). In empirical energy research, MLR has been widely used for its statistical rigour, transparency, interpretability, and efficiency when working with structured micro-level datasets (Al-Kassab et al., 2024; Bansal & Singh, 2023; Moumen et al., 2024). While more advanced techniques, such as ridge regression or structural equation modelling, can address complex or high-dimensional data, they often prioritise prediction over explanation and reduce interpretability (Rajan, 2022; Rožman et al., 2024; Zhang & He, 2025). Given the dataset's structured nature and the explanatory goals of this research, MLR offers a theoretically sound and methodologically appropriate approach. It enables a clear comparison of the relative importance of each factor, aligning with this study's aim to provide actionable insights into the socio-technical determinants of energy use in low-income housing.

In many low-income Global South contexts, including Jordan, the unavailability of metered electricity consumption data, as well as the decentralised and manual use of diverse energy sources, limits access to accurate consumption data (Koepke et al., 2021; Lemanski et al., 2025; Wiese & van der Westhuizen, 2024; Younis et al., 2016). Such infrastructural and governance challenges make expenditure data a more reliable and context-sensitive proxy for actual household energy use. Accordingly, annual household energy expenditure was adopted as an integrated indicator, consolidating spending on electricity, gas, and other fuels to capture total energy use across end-uses (Younis et al., 2016) (Besagni & Borgarello, 2018; Klassert et al., 2015; Salari & Javid, 2017). Empirical studies confirm that expenditure reliably approximates actual consumption when detailed metered data are unavailable, and energy prices are relatively stable (Besagni & Borgarello, 2018; Dubois et al., 2024; Meechai & Wijesinha, 2022; Oliveira Panão, 2021; Piao & Managi, 2023; Taale & Kyeremeh, 2019; Taneja & Mandys, 2022). It also reflects both technical and behavioural aspects of energy use, allowing concurrent analysis of consumption intensity, energy burden, and household welfare (Longhi, 2015; Scheier & Kittner, 2022). In Jordan, residential electricity tariffs are heavily subsidised for consumption below 600 kWh/month (0.05–0.10 JOD/kWh), covering all surveyed households (MEMR, 2019; NEPCO, 2022; Rahahleh & Hani, 2024). Hence, variation in expenditure primarily represents differences in consumption volume rather than price, ensuring comparability and consistency across the sample. Annual household energy expenditure was derived by summing seasonal electricity and fuel costs reported by each household. Average monthly expenditures for winter, summer, and transitional periods were multiplied by the corresponding months and aggregated to obtain annual totals. This approach ensured consistency across households and comparability in reflecting overall energy use.

A bidirectional stepwise regression approach, guided by the Akaike Information Criterion (AIC), was applied to refine the selection of predictor variables within the MLR. This approach balances model complexity and explanatory power by automatically selecting from numerous independent variables and discarding those with less significance, thereby enhancing efficiency and interpretability (Darnius et al., 2019; Kimura & Waki, 2018). This simplification not only enhances statistical robustness but also increases the model's practical applicability in contexts with constrained data collection. Predictors were screened using correlation and multicollinearity diagnostics. Variables with weak explanatory power ($p > 0.10$) or high collinearity (VIF > 5) were excluded to improve model stability. The final integrated model retained statistically significant ($p \leq 0.05$) and theoretically relevant predictors to ensure interpretability and robustness.

Most variables exhibited a normal distribution; however, the dependent variable was positively skewed. Accordingly, a logarithmic transformation was applied to normalise residuals and stabilise variance. Beyond its corrective role, the log-linear specification serves as a widely adopted functional form in applied regression analysis, implicitly validating model robustness and enabling coefficient interpretation in percentage terms (Motta, 2019; Rittmann et al., 2025). Coefficients were exponentiated to revert the results to the original scale, facilitating the interpretation of changes in energy expenditure. For i = 1,2,3, … n, the regression model is expressed as:

$$\log(Y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + \epsilon_i \qquad (2)$$

Where $\log(Y_i)$: represents the natural logarithm of the annual household energy expenditure for household i, X_{ij}: represents the j-th independent variable for household i, β_0: is the intercept term, β_j: the estimated coefficients for each predictor variable, measuring their effect on energy expenditure and ϵ_i: the error term is assumed to be normally distributed.

Additionally, to ensure that the regression results were not influenced by extreme values, a sensitivity analysis was conducted by excluding the top and bottom 5% of households based on annual energy expenditure. While the dependent variable was log-transformed to mitigate the influence of outliers, this test further confirmed the robustness of the models. Additional verification employed ridge (L2), LASSO (L1), and elastic-net ($\alpha = 0.5$) regularised regressions with 10-fold cross-validation (CV) for all models. Ridge regularisation reduced multicollinearity and overfitting by penalising large coefficients, while CV assessed predictive accuracy (He, 2024; Sztepanacz & Houle, 2024). A 10-fold CV OLS model was also estimated for the integrated specification (Lewis et al., 2023). Comparable CV root mean square errors (RMSEs) and consistent coefficient signs across all models confirmed the robustness of the model selection and penalisation choices.

Nominal and ordinal variables were transformed into dummy variables to prepare categorical data for regression analysis (Appendix D). Nominal variables included ownership of heating and cooling devices, house floor area, type and behaviour of lighting, renovations, and domestic hot water (DHW) system. Ordinal variables, like age composition, householder head employment and education, income, heating and cooling duration, heating and cooling device age, adaptive thermal behaviours, and DHW use, were also dummy-coded to capture potential non-linear effects. This ensured that all categorical variables were properly structured for the reliable estimation of energy expenditure in relation to occupant and building factors.

Although the study focuses on public-housing typologies within a single city, it captures a substantial and diverse population. This narrower geographical scope enables a more contextually grounded understanding of socio-cultural dynamics that broader comparisons may overlook (Booth et al., 2019; Halme et al., 2024). Using expenditure as the dependent variable is methodologically appropriate in such settings, as it reflects actual household behaviour and resource allocation while accounting for the influence of cultural and economic factors (Charron-Chénier, 2018; Eika et al., 2020). Despite its local focus, the study's insights are transferable to other MENA and Global South contexts with comparable cultural and climatic conditions (Agarwal et al., 2024).

Results

Survey data description

Respondents and household socio-demographic profile

Table A1 summarises the socio-demographics of the surveyed households. Most respondents were middle-aged (45–54 years) and resided in Abu Alanda, the largest surveyed district. Households were typically nuclear, averaging six members with balanced gender and age composition (5–65 years), with a monthly income between 301–500 JOD, consistent with the national low-income profiles (DOS, 2024). Nearly half of the household heads had only primary or secondary education, and 59% were fully employed. This diverse yet economically vulnerable sample provides a robust foundation for analysing variation in household energy practices.

Building characteristics and socio-cultural adaptations

Table A2 presents the main physical characteristics of the surveyed dwellings. Most surveyed buildings were four-story structures, with households predominantly occupying middle floors. Floor area typically ranged between 90 and 120 m^2 (87%), mainly three-bedroom units (55%). About 90% featured a balcony or yard, and 44% featured a guest area. Notably, 67% of households received weekly visitors, reflecting sociocultural norms that influence spatial layout and energy use.

Thermal performance was generally poor. Approximately 61% of households reported inadequate wall and ceiling insulation, and over one-third rated the quality of their windows as low, despite the widespread use of double-glazing (90%), highlighting notable disparities in comfort and efficiency. These deficiencies prompted frequent home modifications, reflecting the inability of the original design and quality to meet residents' basic needs (Maina, 2023). As illustrated in Figure 4(a,b), moisture treatment was the most common intervention (71%), followed by balcony enclosures (48%) and interior partitions (35%). Additional modifications included installing window films or curtains (31%) and extending floor area (24%). Privacy was the dominant motivation for these changes (68%), reflecting its cultural centrality, followed by aesthetic upgrades (50%), thermal improvements (38%), and accommodations for guests and large families. Consistent with these trends, privacy (63%) and large family size (46%) were the most influential self-reported energy drivers (Figure 4(c)). Overall, these results highlight the interplay between persistent physical deficiencies and deeply rooted sociocultural values, driving ongoing household investment in modifications that directly shape energy use and comfort patterns.

Space heating, cooling, and ventilation

Thermal discomfort was widespread across surveyed households. 85% of respondents described their homes as cold in winter, while 87% reported excessive heat in

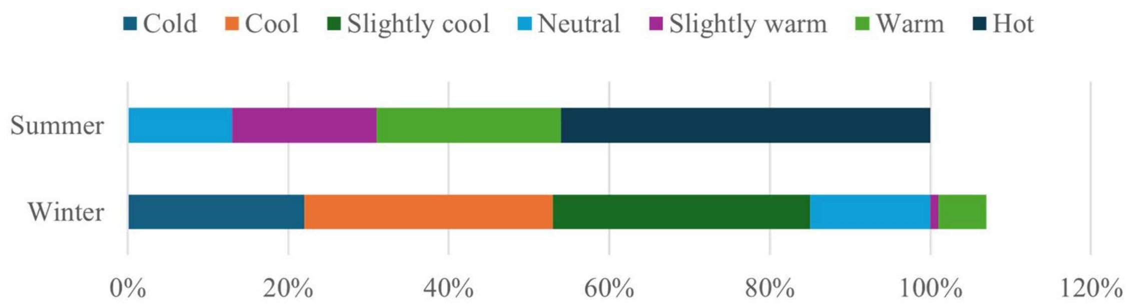


Figure 3. Respondents' thermal comfort in their houses.

summer (Figure 3). As detailed in Table A3, electric stand fans were the dominant cooling method (95%), while Air-conditioners (ACs) were used by 27% of households. On average, households owned two to three cooling appliances, nearly half of which were between one and five years old; however, 65% of these appliances were energy inefficient. Among AC users, 28% had split-unit systems, with an average capacity of approximately 1.5 tons, typically set to 22.8°C. Cooling was generally used for four months (June-September), with some extending use into May or October (Figure 4(d)). Heating, conversely, was primarily provided by liquefied-petroleum-gas (LPG) portable heaters (71%), followed by kerosene heaters (32%). Households reported an average of one-to two heating devices; most were six-to-ten years old (86%) and were energy-inefficient. Only 27% of AC users employed their units for heating, usually set at 27.9°C. Heating was mainly used for five months (November-March), with 56% extending operation into April (Figure 4(e)).

The living room was the most conditioned space, typically heated for up to 15 h daily in 59% of households and cooled in 55% of households. Bedrooms received less conditioning (heated in 43% and cooled in 29%), while kitchens were rarely heated or cooled (Figure 4(f,g)). Thermal thresholds were moderate, cooling was activated when slightly warm (54%), and heating was activated when slightly cool (43%). To maintain warmth, most households closed windows (88%), added clothing layers (86%), or increased appliance power (36%) (Figure 4(h)). In summer, common cooling measures included removing clothing (75%), lowering shutters or curtains (74%), increasing appliance power (38%), and opening windows (31%) (Figure 4(i)). Only a minority relied on additional devices (13% for cooling, 9% for heating), reflecting a preference for low-cost behavioural regulation. Natural ventilation remained central to thermal management, with a distinct seasonal pattern in window-opening behaviours (Table A3).

Occupancy pattern

Occupancy trends showed greater home presence on weekends than on weekdays (Figure 4(k)). On weekends, 48% of households stayed home all day and 36% for most of the day, compared to 27% and 50% on weekdays, respectively. This variation in presence significantly influences daily energy use rhythms and the durations of appliance operations.

Lighting, DHW, and appliances

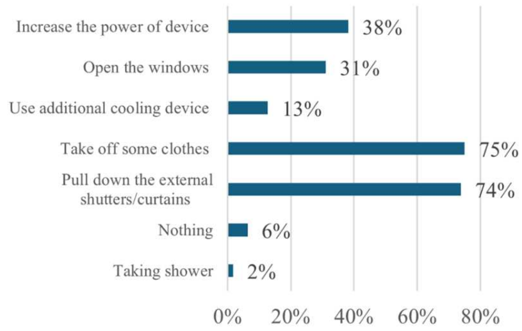
Daylight satisfaction was evenly divided, influencing lighting usage patterns. About half relied mainly on night-time lighting, while others used it throughout the day. Energy-efficient lighting was prevalent, with 84% using Light-Emitting Diode (LED) bulbs, and 62% habitually switching off lights in unoccupied rooms. Similar adaptive behaviour characterised DHW practices. In winter, 86% relied on electric heaters, while most discontinued use in summer. Nearly half (44%) used hot water daily, while others did so less frequently (Table A4).

Appliance ownership and usage varied widely (Figure 5). Households owned an average of eight appliances, with refrigerators (100%), TVs (90%), and receivers (88%) being universally owned and used daily. Moderate-use appliances, such as kettles (72%), water coolers (68%), and washing machines (84%), exhibited variable usage patterns, ranging from daily to weekly operation. Less common appliances, including irons (55%), vacuum cleaners (42%), microwaves (36%), and dryers (9%), were used infrequently. Importantly, 78% of households reported using energy-efficient appliances, particularly refrigerators (68%) and washing machines (54%), indicating growing awareness of energy conservation practices across socio-economic strata.

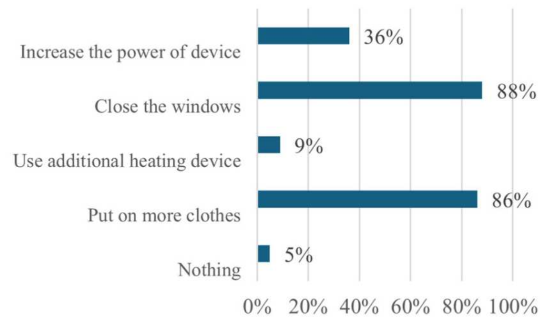
Energy expenditure and affordability

Table A5 summarises household energy expenditure, perceptions of affordability. The mean annual energy expenditure per household was 562.7 JOD, with marked seasonal variation. Winter electricity and energy

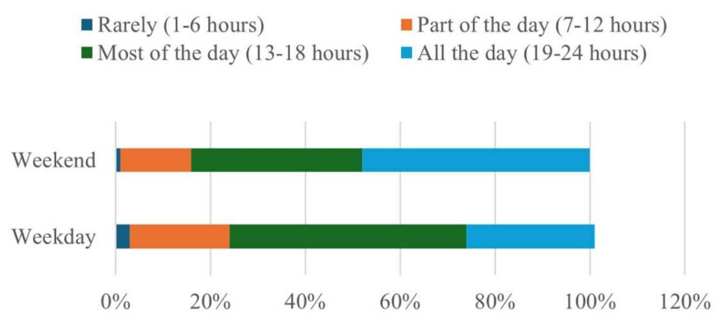
Figure 4. Descriptive statistics on renovations and their motivation, cooling and heating months, heated and cooled spaces, thermal comfort strategies, and occupancy patterns.



(i) Behaviour to cool down.



(h) Behaviour to get warm.



(k) Household occupancy pattern.

Figure 4 *Continued*

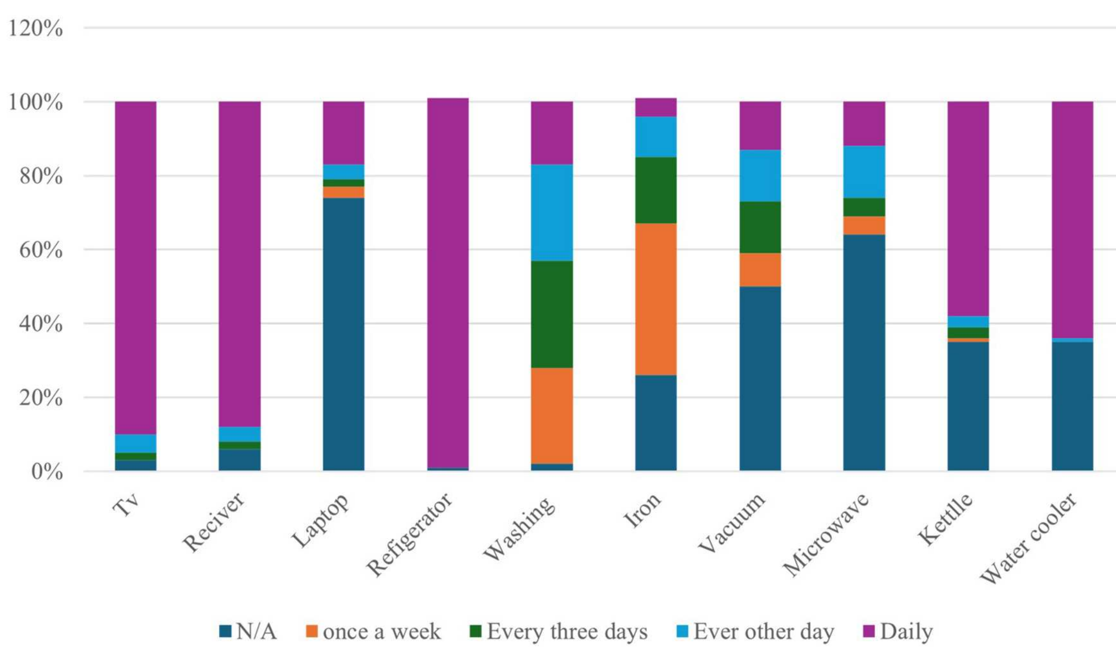


Figure 5. Appliance usage pattern.

expenditure were the highest, averaging around 30 JOD monthly, compared with lower spending during summer and transitional months. Adoption of alternative energy sources was minimal (7%), and among these, nearly all relied on solar water heating systems. Affordability perceptions reflected widespread financial strain: 67% of respondents were dissatisfied with their energy expenses, 27% were neutral, and only 6% were satisfied.

Table 2. Estimated regression results of Model-1 building characteristics.

	Coefficient	Exponential coefficient	95% CI	Standard error	Significance t – statistic	Significance p-value	Collinearity VIF
Intercept	6.233	509.281	6.117, 6.349	0.0588	105.932	< 0.0001	–
House floor area between 121–160 m^2	0.2364	1.2667	0.148, 0.325	0.0451	5.2413	< 0.0001***	1.0117
Double-glazed windows	0.1142	1.1210	0.024, 0.204	0.0458	2.4938	0.0131**	1.0029
Daylight quality	−0.0431	0.9578	−0.072, −0.014	0.0147	−2.9375	0.0035***	1.0090

Model evaluation and diagnostics: $R^2 = 0.105$; Adjusted $R^2 = 0.09573$. 95% confidence intervals for β are reported in the table. * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

This indicates persistent economic pressure from household energy costs and limited capacity for investing in efficiency upgrades or renewable alternatives.

Regression analysis

MLR was conducted to examine the extent to which various factors contribute to the variance in annual household energy expenditure. Given the socio-technical complexity of energy consumption, four MLR models were developed to systematically assess distinct predictor categories: building attributes, household characteristics, and behavioural dimensions of energy use. This approach enabled more precise interpretation of each domain's contribution and the unique explanatory power of each set of factors. A final integrated model then incorporated the most influential predictors, clarifying cross-domain interactions and offering a rigorous framework for identifying determinants of residential energy demand (Guerra Santin et al., 2009; Huebner et al., 2016; Lee & Song, 2022).

- **Model-1** assessed the impact of building characteristics, including house floor area, house floor level, number of bedrooms, orientation, thermal performance, and daylight quality.
- **Model-2** explored household characteristics, such as household size, age composition, income, and appliance ownership, to understand their contribution to energy consumption.
- **Model-3** examined occupant behaviour, focusing on energy use patterns, cooling and heating practices and sociocultural behaviours.
- **Model-4** integrated statistically significant predictors (p-value ≤ 0.05) from the previous models, providing insight into the most robust determinants and highlighting the combined effect of building and occupant-related factors.

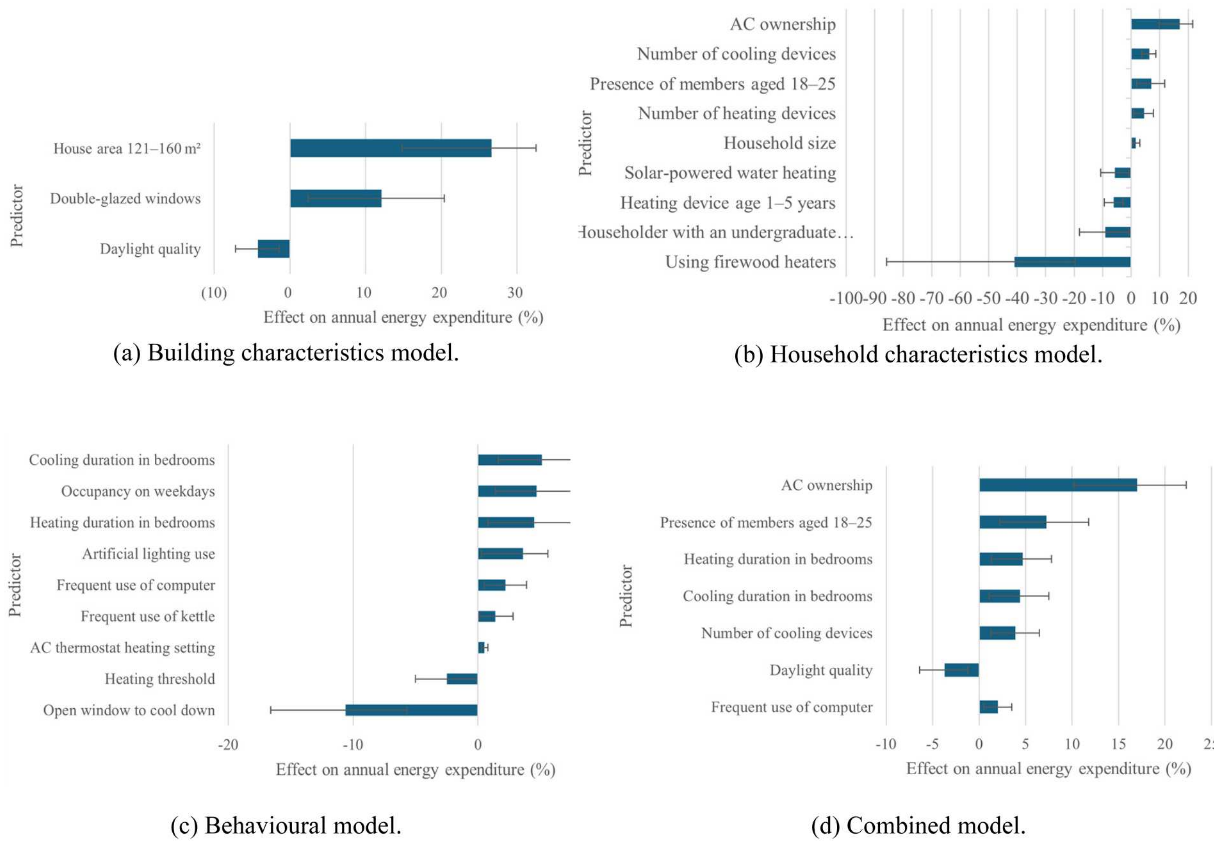
Building characteristics model

Model-1 (Table 2; Figure 6(a)) examined the influence of building characteristics on household energy expenditure. The model was statistically significant and explained approximately 9.6% of the variance in energy expenditure (Adjusted $R^2 = 0.0957$). Houses with floor areas between 121 and 160 m^2 appear to be the most important predictors of building characteristics (p-value < 0.001), associated with a 26.67% increase in energy expenditure compared to smaller dwellings. Similarly, houses with double-glazed windows exhibited a 12.10% increase in energy expenditure (p-value = 0.0131). In contrast, better daylight was linked to a 4.22% lower expenditure (p-value = 0.0035), likely reflecting reduced reliance on artificial lighting.

Household characteristics model

Model-2 (Table 3; Figure 6(b)) explained 40.2% of the variance in energy expenditure (Adjusted $R^2 = 0.4017$). Using firewood heaters had the largest effect, reducing annual energy expenditure by 41.0% (p-value = 0.0018). In contrast, AC ownership was associated with a 16.98% increase in energy expenditure (p-value< 0.0001). Each additional cooling and heating device increased energy expenditure by 6.39% (p-value < 0.0001) and 4.59% (p-value = 0.0108), respectively. Device characteristics also mattered; households with newer heating devices (1–5 years old) consumed 6.0% less energy (p-value = 0.0002). Similarly, solar-powered water heating reduced energy use by 5.57% (p-value = 0.0241), indicating that houses with solar water systems rely less on electricity for hot water.

Demographic characteristics showed smaller but significant effects. Each additional household member was associated with a 1.57% increase in mean energy expenditure (p-value = 0.03), while the presence of household members aged 18–25 was linked to a 7.03% increase (p-value = 0.0064), indicating higher consumption patterns among young adults. Householder head educational level was another factor, with householders with undergraduate-level education spending 9.03% less (p-value = 0.0317), potentially reflecting conscious behaviours associated with higher educational attainment. While several factors significantly influence energy expenditure, some exhibit marginal significance at the 10%



(a) Building characteristics model.

(b) Household characteristics model.

(c) Behavioural model.

(d) Combined model.

Figure 6. Effect size (±95% confidence intervals) and partial dependence estimates (Average Marginal Effects, AMEs) of statistically significant predictors (p-value < 0.05) on annual household energy expenditure across the four regression models. Bars indicate the percentage change in mean energy expenditure associated with each variable, while error bars represent the 95% confidence intervals.

level, suggesting potential trends worth further exploration. For instance, the use of stand fans was linked to lower expenditure (−9.13%), while nuclear households consumed slightly less energy (a 6.92% decrease). In contrast, greater appliance ownership was marginally associated with higher consumption (+1.29%).

Behavioural model

Model-3 (Table 4; Figure 6(c)) explained 30.3% of the variance in energy expenditure (Adjusted $R^2 = 0.3034$). The results demonstrate the crucial role of heating and cooling habits, appliance usage patterns, and lighting behaviour in shaping residential energy demand.

Table 3. Estimated regression results of Model-2 household characteristics.

		Exponential			Significance		
	Coefficient	Coefficient	95% CI	Standard error	t − statistic	p-value	Collinearity VIF
Intercept	6.1514	469.3741	5.9298, 6.374	0.1132	54.325	< 0.0001	–
Using firewood heaters	−0.5274	0.5901	−0.858, −0.197	0.1679	−3.141	0.0018***	1.1538
AC ownership	0.1568	1.1698	0.098, 0.216	0.03	5.2214	< 0.0001***	1.4254
Using a stand fan for cooling	−0.0957	0.9087	−0.202, 0.010	0.0539	−1.7757	0.0766*	1.1866
A householder with an undergraduate-level education	−0.0946	0.9097	−0.181, −0.008	0.0439	−2.1567	0.0317**	1.3859
Presence of members aged 18–25	0.0679	1.0703	0.019, 0.117	0.0248	2.7398	0.0064***	1.2177
Number of cooling devices	0.0619	1.0639	0.037, 0.087	0.0128	4.8276	< 0.0001***	1.6398
Nuclear family structure	−0.0717	0.9308	−0.1525, 0.0090	0.0411	−1.7464	0.0816*	1.1064
Heating device age: 1–5 years	−0.0616	0.9403	−0.094, −0.029	0.0166	−3.7138	0.0002***	1.2326
Solar-powered water heating	−0.0573	0.9443	−0.107, −0.008	0.0253	−2.2645	0.0241**	1.2863
Number of heating devices	0.0449	1.0459	0.0104, 0.0794	0.0175	0.0108	0.0108**	1.4433
Household size	0.0156	1.0157	0.002, 0.030	0.0072	2.1784	0.0300**	1.2808
Appliances ownership	0.0128	1.0129	−0.002, 0.028	0.0075	1.7027	0.0895*	1.6804

Model evaluation and diagnostics: $R^2 = 0.4262$; Adjusted $R^2 = 0.4017$. 95% confidence intervals for β are reported in the table. * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Among the behavioural factors, relying on natural ventilation as a cooling strategy was the strongest energy-saving behaviour, resulting in a 10.5% reduction in expenditure (p-value < 0.0001). In contrast, prolonged cooling in bedrooms (p-value = 0.004) and weekday occupancy (p-value = 0.005) significantly increased energy expenditure. Extended heating durations in bedrooms resulted in a 4.48% increase (p-value = 0.0172), highlighting the energy demand associated with thermal comfort in sleeping areas. The AC thermostat setting for heating had a minor but significant effect, contributing to a 0.53% increase (p-value < 0.001), which underscores the impact of occupant preferences on heating loads. Meanwhile, a warmer heating threshold was associated with 2.51% lower expenditure (p-value = 0.046). Appliance and lighting behaviour also contributed to energy consumption. Increased lighting use was associated with a 2.97% increase (p-value = 0.0314), while frequent use of computers and kettles increased expenditure by 2.22% (p-value = 0.0097) and 1.45% (p-value = 0.0377), respectively. Several variables showed a marginal effect (p-value < 0.10), including weekend occupancy (+3.13%), cooling hours in living areas (+2.29%), frequency of vacuum use (+1.63%), and efficient lighting behaviour (−4.75%).

Combined model

The final model (Table 5; Figure 6(d)) explained 43.96% of the variance in annual energy expenditure (Adjusted $R^2 = 0.4396$). AC-ownership was the strongest predictor, associated with a 17% increase (p-value < 0.001). This was followed by the presence of members aged 18–25, which was associated with a 7.26% increase (p-value < 0.01), and extended bedroom heating and cooling durations by 4.7% and 4.44% (p-value < 0.01 for both), respectively. Each additional cooling device added 3.95% (p-value < 0.01). As observed in model-1, better daylight remained negatively associated with energy use (−3.71%; p-value < 0.01). Frequent computer use was linked to a 2.0% increase (p-value < 0.01), underscoring the impact of everyday device use. Meanwhile, several variables had a marginal significance effect (p-value < 0.10), including weekday occupancy (+2.70%), heating threshold (−2.22%), householder head education at the college level (+8.74%), and household size (+1.34%).

As shown in Figure 7, the explanatory power varied considerably across the regression models. The household characteristics model had the highest explanatory power among the individual domains (Adjusted R^2 = 40.2%), followed by the behavioural (Adjusted R^2 = 30.3%) and the building model (Adjusted R^2 = 9.6%). These results underscore the central influence of household structure and everyday practices over purely physical attributes in shaping energy demand. The integrated model achieved the greatest explanatory strength (Adjusted R^2 = 43.96%), reinforcing the value of a socio-technical approach that captures the interplay between the physical building and occupant (characteristics and behaviours).

All Variance Inflation Factors (VIFs) were below the accepted threshold of 5, indicating low multicollinearity and stable parameter estimates (Kim, 2019). Furthermore, diagnostic plots (residuals versus fitted values, Q–Q plots, scale–location plots, and residuals versus leverage; see Figure B. 1–4), confirmed that key model assumptions, such as linearity, normality of residuals, and the absence of influential outliers, were largely satisfied. A minor indication of heteroscedasticity was observed in model-3; therefore, heteroscedasticity-consistent robust standard errors (HC3) were applied, and the results remained statistically robust. Sensitivity analysis excluding the top and bottom 5% of households by annual energy expenditure confirmed the robustness

Table 4. Estimated regression results of Model-3 behavioural.

	Coefficient	Exponential coefficient	95% CI	Standard error	Significance t − statistic	p-value	Collinearity VIF
Intercept	5.5259	251.1122	5.286, 5.766	0.1222	45.2183	< 0.0001	–
Open the window to cool down	−0.1113	0.8947	−0.166, −0.057	0.0276	−4.0334	< 0.0001***	1.1299
Cooling duration in bedrooms	0.0496	1.0509	0.016, 0.083	0.0172	2.8867	0.0041***	1.4711
Efficient lighting behaviour	−0.0487	0.9525	−0.099, 0.002	0.0256	−1.9062	0.0574*	1.0599
Occupancy on weekdays	0.0456	1.0467	0.014, 0.077	0.0162	2.8154	0.0051***	1.0527
Heating duration in bedrooms	0.0438	1.0448	0.008, 0.080	0.0183	2.3933	0.0172**	1.2527
Occupancy on the weekend	0.0308	1.0313	−0.002, 0.064	0.0167	1.8465	0.0656*	1.0936
Artificial lighting use	0.0293	1.0297	0.003, 0.056	0.0136	2.1597	0.0314**	1.2303
Cooling duration in the living	0.0293	1.0297	−0.001, 0.059	0.0153	1.9144	0.0563*	1.1358
Frequent use of a computer	0.0220	1.0222	0.005, 0.039	0.0084	2.5997	0.0097***	1.2094
Heating threshold	−0.0254	0.9749	−0.050, 0.000	0.0127	−2.0016	0.0460**	1.1810
Frequent use of the vacuum	0.0162	1.0163	−0.0008, 0.0333	0.0087	1.870	0.0622*	1.1925
Frequent use of the kettle	0.0144	1.0145	0.001, 0.028	0.0069	2.085	0.0377**	1.1574
AC thermostat heating setting	0.0053	1.0053	0.003, 0.008	0.0013	3.9688	< 0.0001***	1.3213

Model evaluation and diagnostics: $R^2 = 0.3301$; Adjusted $R^2 = 0.3034$. 95% confidence intervals for β are reported in the table. * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

Table 5. Estimated regression results of model-4 combined the most influential factors at the 5% level ($p < 0.05$).

	Coefficient	Exponential coefficient	95% CI	Standard error	Significance t – statistic	p-value	Collinearity VIF
Intercept	5.8655	352.6584	5.639, 6.092	0.115	51.0033	< 0.0001	–
AC ownership	0.1629	1.1769	0.102, 0.223	0.0307	5.3006	< 0.0001***	1.2967
A householder with a college-level education	0.0838	1.0874	−0.004, 0.172	0.0446	1.8783	0.0611*	1.8253
Presence of members aged 18–25	0.0701	1.0726	0.022, 0.118	0.0244	2.8766	0.0043***	1.2563
Heating duration in bedrooms	0.0457	1.0468	0.013, 0.078	0.0166	2.7527	0.0062***	1.2797
Cooling duration in bedrooms	0.0434	1.0444	0.011, 0.075	0.0163	2.6529	0.0083***	1.6528
Number of cooling devices	0.0387	1.0395	0.013, 0.065	0.0132	2.9372	0.0035***	1.8478
Daylight quality	−0.0378	0.9629	−0.064, −0.012	0.0131	−2.8832	0.0042***	1.2967
Occupancy on weekdays	0.0268	1.027	−0.003, 0.056	0.0150	1.7872	0.0747*	1.1210
Heating threshold	−0.0225	0.9778	−0.046, 0.001	0.0117	−1.9138	0.0564*	1.2544
Frequent use of a computer	0.0201	1.0203	0.005, 0.035	0.0076	2.6315	0.0089***	1.2243
Household size	0.0133	1.0134	0.000, 0.027	0.007	1.9112	0.0567*	1.2924

Model evaluation and diagnostics: $R^2 = 0.4697$; Adjusted $R^2 = 0.4396$. 95% confidence intervals for β are reported in the table. * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level.

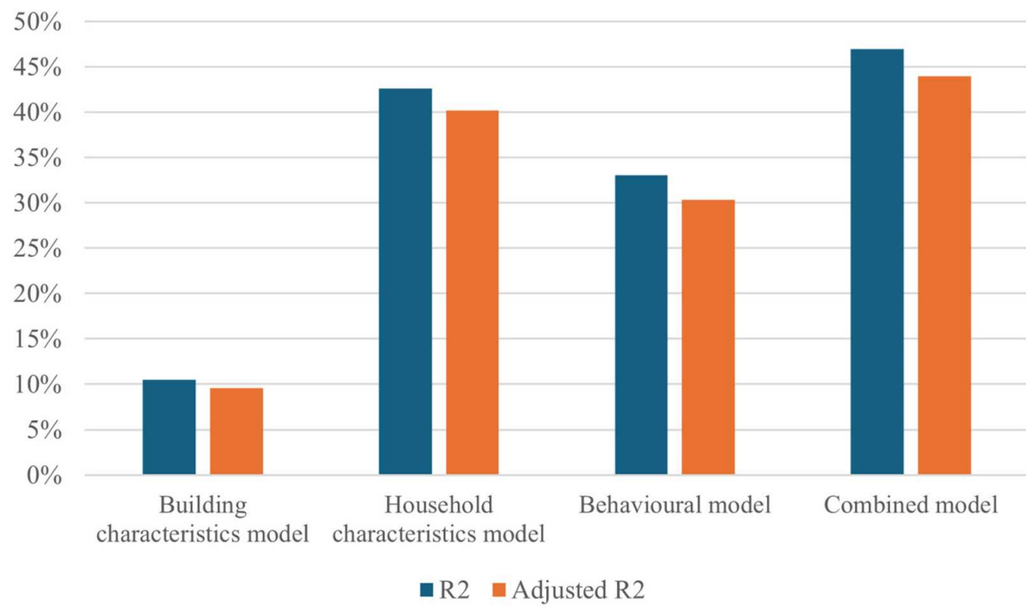


Figure 7. The R^2 and Adjusted R^2 for four regression models.

of all models (Table C. 1–2). The Adjusted R^2 values declined moderately ($\Delta R^2 \approx 0.03$–0.15) and AIC values became more negative, indicating stable relationships and reduced outlier influence. Cross-validated ridge, LASSO, and elastic-net regressions produced comparable CV RMSEs (≈ 0.22–0.28) and nearly identical coefficient magnitudes and directions, reinforcing the robustness and generalisability of the regression models (Table C. 3).

Discussion

This study provides critical insights into the primary determinants of energy consumption in low-income households in Jordan and assesses their relative importance. The findings reveal that occupant-related factors, including household characteristics and behavioural patterns, are the most influential predictors, collectively explaining 70.5% of the variance in energy use. This dominance highlights the greater explanatory power of social and behavioural factors compared to building-related attributes in low-income contexts. While prior research has identified building characteristics, such as house floor area, as a strong predictor of residential energy use (Huebner et al., 2015; Kavousian et al., 2013; Theodoridou et al., 2011), the present analysis reveals that AC-ownership, a household-level attribute, emerges as the most substantial determinant of energy use in low-income households. Although only 27% of surveyed households owned an AC, ownership was correlated with significantly higher expenditure, reflecting the high operational cost. Similar patterns have been reported in Hong Kong, Malaysia, India, and Australia, where AC-ownership consistently emerges as a key driver of energy consumption (Fan et al., 2017; Ramapragada et al., 2022; Sena et al., 2021; Tso & Yau, 2007).

Several additional household characteristics significantly influenced energy use. Household size exhibited a positive association with energy expenditure, consistent with prior findings by Druckman and Jackson (2008), Huebner et al. (2015), and Jaffar et al. (2018). Larger families are likely to use appliances more frequently for cooking, washing, and cleaning, thereby increasing their overall energy use. The age composition of households also influenced consumption patterns; the presence of young adults (aged 18–25) was consistently positively correlated with higher energy expenditure, likely reflecting extended occupancy hours and intensive use of electronic devices. The positive link between computer usage frequency and energy expenditure further supports this interpretation (Lusinga & de Groot, 2019; Pothitou et al., 2017), emphasising how socio-demographic structure intersects with behavioural practices to shape household energy dynamics.

Another significant determinant was the household head's education. Households led by individuals with a university education recorded lower expenditure, indicating greater energy efficiency awareness, consistent with findings from other low-income contexts in the Global South (Taale & Kyeremeh, 2019). Nevertheless, over half of the respondents reported only primary, secondary, or non-formal education, which may limit the diffusion of energy-saving knowledge in this context. Other characteristics, including householder head employment status and age, were not statistically significant predictors, diverging from results in earlier research in the Netherlands and the United States (Abrahamse & Steg, 2009; Guerra Santin et al., 2009; Liao & Chang, 2002).

Although income was not directly determined, several indirect variables exhibited substantial effects. Ownership of multiple cooling and heating appliances significantly increased energy expenditure, underscoring the cumulative burden of device proliferation. The age of heating devices also proved relevant; newer devices were associated with lower energy costs, reflecting improved efficiency. This pattern extends to energy sources, where the ownership of traditional and renewable systems produced distinct impacts. Using firewood heaters yielded the greatest reduction in energy expenditure, underscoring the cost-effectiveness of traditional heating methods compared to fuel-based alternatives. Similarly, solar water heaters yielded average savings of 5.6% in expenditure; however, their adoption rate remained low (7%), highlighting significant potential for policy interventions to promote affordable renewable technologies in low-income settings.

Behavioural practices revealed a clear distinction between energy-saving and energy-intensive behaviours. Natural ventilation emerged as the most impactful energy-saving strategy, associated with a 10.5% reduction in annual energy use. This finding underscores the significance of low-tech adaptive comfort practices in reducing cooling-related energy demand. A higher heating threshold temperature complemented these behaviours, indicating a willingness to tolerate cooler indoor conditions before activating heating. These adaptive practices appear to be shaped by cost-conscious decision-making, whereby limited income encourages residents to accept thermal discomfort to reduce expenditure. Descriptive findings reinforce this interpretation, showing high adoption rates of non-energy-based thermal practices, including adjusting clothing layers (86%) and closing windows (88%). Collectively, these behaviours illustrate how socio-economic realities drive context-specific thermal practices that diverge from those of more affluent households, pointing to the need for locally grounded models of energy behaviour.

Conversely, certain behavioural patterns significantly elevated energy demand. Extended operation of cooling and heating in bedrooms increased consumption by 4–6%, mirroring evidence from Indian low-income housing (Gupta et al., 2024). Similarly, higher AC thermostat settings during heating increased energy expenditure, consistent with a wide range of studies linking temperature preferences to energy variation (Guerra Santin et al., 2009; Jaffar et al., 2018; Steemers & Yun, 2009). Weekday occupancy was also associated with higher energy use, contrasting with patterns in Western contexts, where weekend peaks are typical (Hiller, 2012; Soheilian et al., 2019). This discrepancy likely reflects sustained weekday use of lighting and appliances. In line with Firth et al. (2008), frequent use of kettles, lighting, and computers further contributed to elevated consumption, demonstrating that even low-wattage devices can cumulatively drive energy demand when used frequently. These results reaffirm that energy use depends not only on the availability of technologies but also on the intensity, duration, and contextual patterns of their operation.

Sociocultural practices, such as guest-hosting, privacy-driven spatial modifications, and multigenerational living, were not statistically significant predictors. However, descriptive analysis revealed a range of behavioural and spatial practices driven by these factors, such as balcony enclosures, partitioning, or space extensions for guests, that can unintentionally affect ventilation, lighting, and thermal conditions, indirectly impacting energy use (Maaith et al., 2025; Muianga et al., 2022;

Qtaishat et al., 2020). Their weak statistical representation may stem from the challenges of quantifying complex socio-cultural behaviours in structured surveys and the inherent limitations of regression-based models (G. M. Huebner et al., 2015; Shipworth, 2005). Although these sociocultural factors were not strongly reflected in quantitative models, they remain important contextual influences that mediate household energy behaviour and design adaptations. Beyond quantitative evidence, complementary qualitative findings from our prior study, Maaith et al. (2025), further contextualise the results, revealing that sociocultural norms surrounding privacy, gendered spaces, and hospitality drive spatial modifications, such as balcony enclosures, that inadvertently increase cooling demand. Design strategies that integrate privacy-compatible cross-ventilation, adjustable screening, and external shading could therefore reconcile cultural expectations with energy-efficient design, extending the practical and policy relevance of these findings.

While building characteristics played a comparatively minor role, they remained meaningful. Floor area was the most significant predictor, corroborating prior research findings of Jones and Lomas (2015) and Kelly (2011). Conversely, daylight quality consistently demonstrated an energy-saving effect (3.6–4.2% reduction), underscoring the value of passive design in reducing artificial lighting demand, an essential consideration for cost-sensitive households. Nonetheless, the descriptive data revealed that approximately 50% of households rated their daylight as poor to average, and 44% relied heavily on artificial lighting, reinforcing the need to improve daylight access. Interestingly, despite being present in 90% of homes, double-glazed windows were associated with higher expenditure. This counterintuitive relationship likely reflects quality (air leakage, thermal bridging), insufficient envelope insulation elsewhere, and usage patterns, rather than an inherent inefficiency of glazing, suggesting that technical efficiency must be coupled with proper implementation and user awareness.

Some observed relationships may partially reflect endogeneity or self-selection. Factors such as AC-ownership and house floor area may be simultaneously shaped by income and perceived thermal discomfort, complicating causal interpretation. Similarly, appliance ownership and educational level may covary with unobserved socio-economic attributes that influence energy behaviour. These associations reflect the socio-technical reality that several predictors represent interconnected household decisions rather than entirely independent drivers. Nevertheless, the robustness diagnostics, including regularised regression, sensitivity analysis, and multicollinearity testing, confirmed stable coefficient signs and magnitudes, reinforcing the internal validity of the results. Collectively, these insights highlight the intertwined socio-technical nature of residential energy use, particularly in complex contexts such as low-income housing.

Consistent with prior studies (Lee & Song, 2022; Xie & Noor, 2022), the integrated model, which combines building- and occupant-related variables, achieved the highest explanatory power, accounting for approximately 44% of the variance in household energy expenditure. Although modest, this value is reasonable given the complexity of residential energy consumption dynamics. Similar studies report comparable or even lower explanatory capacity. For instance, Huebner et al. (2016) found that socio-demographic and behavioural factors together explained 45% of household energy use in the UK, Jaffar et al. (2018) reported 32% in Kuwait, while Besagni and Borgarello (2018) found that combined household and building factors explained 38% in Italy. These consistent findings across diverse contexts highlight the challenge of fully capturing the dynamic and multifaceted nature of household energy use, even when a wide range of relevant variables is considered.

Conclusion

This study presents one of the first large-scale empirical investigations into the determinants of residential energy consumption among low-income households in Jordan. Through a socio-technical lens, this study situates energy consumption within the lived experiences of low-income households and challenges dominant building-centric assumptions about residential energy use in a rapidly urbanising, resource-constrained context.

Through descriptive statistics and bidirectional stepwise MLR analysis based on data from almost 400 low-income households, this study reveals that while building factors contribute modestly to energy variation, occupant-related variables, particularly behavioural patterns and socio-demographics, play a significant role in shaping household energy demand. Notably, AC-ownership emerged as the most influential predictor of energy expenditure, followed by the presence of young adult members, heating- and cooling-duration, and the number of cooling devices. These findings underscore the significant impact of thermal comfort demand on energy consumption in this context. Additionally, passive design features, particularly access to daylight, were associated with reduced energy use, underlining their potential as cost-effective, energy-saving strategies. Notably, although sociocultural factors, including privacy concerns and guest-hosting traditions, did not emerge as direct predictors in the regression analysis, the descriptive findings highlight their indirect yet meaningful influence on spatial adaptations and energy behaviours.

The insights generated offer practical implications for policy and design interventions. Strengthening appliance and air-conditioning efficiency standards and labelling should be a policy priority to manage the growing cooling-related energy demand. Prioritising envelope design, including insulation, fenestration, and integrated shading, in low-income housing is essential to improving thermal comfort and energy efficiency. Incorporating passive design strategies during the early stages of design and construction can reduce reliance on AC and heating, aligning with affordability and energy efficiency objectives. Furthermore, expanding access to renewable solutions, such as solar water heating, could provide long-term economic relief for energy-burdened households. Government-backed incentives, including tax reductions and installation subsidies, are crucial to support the adoption of these measures, complemented by targeted subsidies for energy-efficient appliances. To reinforce physical upgrades, culturally sensitive energy awareness campaigns, delivered through local NGOs or trusted community organisations, can promote responsible energy use and thermal adaptation without undermining comfort or sociocultural norms. More broadly, policymakers and designers must recognise that household energy demand results from a dynamic interaction between occupants and physical building, necessitating contextually informed socio-technical energy policies.

While survey results have advanced the understanding of energy consumption among low-income households and filled a key gap in regional literature, they remain indicative in nature, and further in-depth research is essential. Although this study incorporated seasonal data to capture household conditions, adaptations, and expenditures, it did not adopt a full longitudinal design that tracked changes across multiple years. Long-term longitudinal studies are important for revealing evolving behavioural patterns, yet are challenging to implement in low-income settings due to a lack of standardised metering infrastructure and sociocultural sensitivities, such as privacy and trust concerns. These contextual and logistical constraints pose challenges to sustained data collection. Advancing this work through a mixed-methods approach, combining in-depth qualitative interviews to explore the indirect pathways that affect energy consumption, with environmental monitoring tools (e.g. temperature, humidity), would deepen our understanding and enhance the robustness and applicability of the findings.

Although fieldwork was conducted in July and August, the survey incorporated seasonally disaggregated expenditure data and behavioural recall questions, enabling the representation of winter, summer, and transitional energy use patterns. Consequently, the analysis reflects annual household energy dynamics rather than just summer conditions. While findings are contextually grounded in Amman's public housing developments, these typify the design, construction, and socio-economic conditions of low-income urban settlements across Jordan, supporting cautious but meaningful generalisation to comparable national and regional contexts.

Although self-reported energy expenditure is commonly used in similar studies, actual metered consumption data are more appropriate (Gouveia & Seixas, 2016). However, collecting metered data in household surveys is extremely challenging and unreliable due to practical constraints, especially in low-income, mixed-fuel, and nuanced sociocultural contexts within developing countries. Given the absence of precise metered data on electricity consumption in kilowatt-hours and detailed quantification of other fuel usage, annual energy expenditure served as a pragmatic proxy in this study. Future research should ideally incorporate actual metered energy data where feasible.

This study also did not incorporate analytical techniques, such as structural equation modelling, computational social science techniques, or machine-learning-based causal models at this stage, which are more suitable for capturing complex, multi-directional relationships and uncovering underlying causal pathways. These techniques typically require large, high-quality longitudinal datasets, often spanning multiple years, as well as the validation of strong theoretical assumptions regarding the interdependence and structure of variables. These requirements exceed the scope of this exploratory stage. Instead, MLR was purposefully selected for its methodological transparency, statistical robustness, and interpretive accessibility, making it appropriate for identifying key associative patterns within the data. MLR allows the examination of relationships between variables without imposing a predefined structural framework, which is well-suited to the initial identification of influential predictors. The findings provide a robust empirical foundation for future theory-driven research involving causal modelling and more complex inferential techniques.

Finally, despite being grounded in the Jordanian context, this study's methodological approach, combining a large-scale household survey design with empirical regression modelling, offers an adaptable framework applicable to other low-income urban settings. The study's insights contribute directly to global debates on equitable energy transitions, energy justice, and the interplay between social and physical determinants of residential energy use.

Note

1. One Jordanian Dinar is equivalent to 1.41 U.S. Dollars as of August 2025. This conversion is provided for reference purposes only, as exchange rates are subject to fluctuations.

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Author contributions

CRediT: **Nowf Maaith:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft; **Tania Sharmin:** Supervision, Writing – review & editing.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used [ChatGPT and Grammarly] in order to improve the readability and language of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Data availability statement

The data that support the findings of this study, as well as the bilingual (Arabic–English) questionnaire and R analysis scripts, are available from the corresponding author, N.M., upon reasonable request. The data are not publicly available as they contain information that could compromise the privacy of research participants.

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References

Abrahamse, W., & Steg, L. (2009). How do socio-demographic and psychological factors relate to households' direct and indirect energy use and savings? *Journal of Economic Psychology*, *30*(5), 711–720. https://doi.org/10.1016/j.joep.2009.05.006

Agarwal, N., Nagpure, A., & Ramaswami, A. (2024). Studying extreme heat and social inequality in Global South cities: Recommendations for cross-cultural research. *One Earth*, *7*(8), 1324–1329. https://doi.org/10.1016/j.oneear.2024.07.021

Albatayneh, A., Assaf, M. N., Jaradat, M., & Alterman, D. (2020). The effectiveness of infiltration against roof insulation aimed at low income housing retrofits for different climate zones in Jordan. *Environmental and Climate Technologies*, *24*(3), 11–22. https://doi.org/10.2478/rtuect-2020-0082

Aldossary, N. A., Rezgui, Y., & Kwan, A. (2015). An investigation into factors influencing domestic energy consumption in an energy subsidized developing economy. *Habitat International*, *47*, 41–51. https://doi.org/10.1016/j.habitatint.2015.01.002

Al-Homoud, M., & Is-Haqat, H. (2019). Exploring the appropriateness of the royal initiative for housing for the low-income group in Jordan. *IOP Conference Series: Materials Science and Engineering*, *471*(7), 072001. https://doi.org/10.1088/1757-899X/471/7/072001

Ali, H. H., & Alzu'bi, S. N. (2017). Design optimization of sustainable affordable housing model in hot-arid climate-case of Jordan. *International Journal of Housing Markets and Analysis*, *10*(5), 607–627. https://doi.org/10.1108/IJHMA-01-2017-0009

Al-Kassab, M. M., Al-Hasawi, M. A., & Mohyaldeen, S. Y. (2024). Methods of obtaining the ridge parameter K in multiple linear regression analysis. In *Springer proceedings in mathematics and statistics* (Vol. 466, pp. 579–584). https://doi.org/10.1007/978-981-97-4876-1_40

Alnsour, J. A. (2016). Managing urban growth in the city of Amman, Jordan. *Cities*, *50*, 93–99. https://doi.org/10.1016/j.cities.2015.08.011

Aslam, M., & Ahmad, E. (2018). Impact of ageing and generational effects on household energy consumption behavior: Evidence from Pakistan. *Energies*, *11*(8), 2003. https://doi.org/10.3390/en11082003

Bai, X., Dawson, R. J., Ürge-Vorsatz, D., Delgado, G. C., Salisu Barau, A., Dhakal, S., Dodman, D., Leonardsen, L., Masson-Delmotte, V., Roberts, D. C., & Schultz, S. (2018). Six research priorities for cities and climate change. *Nature*, *555*(7694), 23–25. https://doi.org/10.1038/d41586-018-02409-z

Bansal, S., & Singh, G. (2023). Multiple linear regression based analysis of weather data: Assumptions and limitations. In

Amlan Chakrabarti, Amit Kumar Singh, & Naveen Chilamkurti (Eds.), *Communications in computer and information science* (pp. 221–238. https://doi.org/10.1007/978-3-031-45121-8_19

Bardazzi, R., & Pazienza, M. G. (2020). When I was your age: Generational effects on long-run residential energy consumption in Italy. *Energy Research & Social Science*, *70*, 101611. https://doi.org/10.1016/j.erss.2020.101611

Besagni, G., & Borgarello, M. (2018). The determinants of residential energy expenditure in Italy. *Energy*, *165*, 369–386. https://doi.org/10.1016/j.energy.2018.09.108

Booth, A., Mshelia, S., Analo, C. V., & Nyakang'o, S. B. (2019). Qualitative evidence syntheses: Assessing the relative contributions of multi-context and single-context reviews. *Journal of Advanced Nursing*, *75*(12), 3812–3822. https://doi.org/10.1111/jan.14186

Bournas, I., Dubois, M.-C., & Laike, T. (2019). Relation between occupant perception of brightness and daylight distribution with key geometric characteristics in multifamily apartments of Malmö, Sweden. *Journal of Physics: Conference Series*, *1343*(1), 012161. https://doi.org/10.1088/1742-6596/1343/1/012161

BRE. (2013). *Energy Follow-Up Survey (EFUS), 2011*. https://assets.publishing.service.gov.uk/media/5a74a7d540f0b61df4777659/11_Methodology.pdf

Charron-Chénier, R. (2018). Spending bundles: Incorporating household expenditures in the sociology of consumption. *Socius: Sociological Research for a Dynamic World*, *4*. https://doi.org/10.1177/2378023117752834

Chen, S., Zhang, G., Xia, X., Chen, Y., Setunge, S., & Shi, L. (2021). The impacts of occupant behavior on building energy consumption: A review. *Sustainable Energy Technologies and Assessments*, *45*, 101212. https://doi.org/10.1016/j.seta.2021.101212

Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.

Dar-Mousa, R. N., & Makhamreh, Z. (2019). Analysis of the pattern of energy consumptions and its impact on urban environmental sustainability in Jordan: Amman city as a case study. *Energy, Sustainability and Society*, *9*(1), 1. https://doi.org/10.1186/s13705-019-0197-0

Darnius, O., Normalina, & Manurung, A. (2019). Model selection in regression linear: A simulation based on akaike's information criterion. *Journal of Physics: Conference Series*, *1321*(2), 022085. https://doi.org/10.1088/1742-6596/1321/2/022085

Debnath, R., Simoes, G. M. F., Bardhan, R., Leder, S. M., Lamberts, R., & Sunikka-Blank, M. (2020). Energy justice in slum rehabilitation housing: An empirical exploration of built environment effects on socio-cultural energy demand. *Sustainability*, *12*(7), 3027. https://doi.org/10.3390/su12073027

Debs, L., Kota, B. R., & Metzinger, J. (2021). Recent energy consumption trends in American homes. *EPiC Series in Built Environment*, *2*, 606–596. https://doi.org/10.29007/dx6k

De Dear, R., & Brager, G. S. (1998). Developing an adaptive model of thermal comfort and preference. ASHRAE Transactions, 104(1), 145–167.

DOS. (2015). *National Census*. https://memr.gov.jo/En/List/Studies_and_Statistics

DOS. (2017). *Jordan statistical yearbook*. www.dos.go

DOS. (2022). *Annual report*.

DOS. (2024). *Estimated Population of 2023*.

Druckman, A., & Jackson, T. (2008). Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy*, *36*(8), 3177–3192. https://doi.org/10.1016/j.enpol.2008.03.021

Dubois, F., Zabaloy, M. F., & Ibánez Martín, M. M. (2024). Modeling energy consumption to measure energy poverty in households in Buenos Aires (Argentina), 2017–2018. *Regional Statistics*, *14*(2), 374–400. https://doi.org/10.15196/RS140207

EIA. (2024). *Residential Energy Consumption Survey (RECS)*. https://www.eia.gov/survey/form/eia_457/RECS%20457%20A_Questionnaire%20Content.pdf

Eika, L., Mogstad, M., & Vestad, O. L. (2020). What can we learn about household consumption expenditure from data on income and assets? *Journal of Public Economics*, *189*, 104163. https://doi.org/10.1016/j.jpubeco.2020.104163

Ellsworth, S. G., van Rossum, P. S. N., Mohan, R., Lin, S. H., Grassberger, C., & Hobbs, B. (2023). Declarations of independence: How embedded multicollinearity errors affect dosimetric and other complex analyses in radiation oncology. *International Journal of Radiation Oncology*Biology*Physics*, *117*(5), 1054–1062. https://doi.org/10.1016/j.ijrobp.2023.06.015

Estiri, H., & Zagheni, E. (2019). Age matters: Ageing and household energy demand in the United States. *Energy Research & Social Science*, *55*, 62–70. https://doi.org/10.1016/j.erss.2019.05.006

Fan, H., MacGill, I. F., & Sproul, A. B. (2017). Statistical analysis of drivers of residential peak electricity demand. *Energy and Buildings*, *141*, 205–217. https://doi.org/10.1016/J.ENBUILD.2017.02.030

Firth, S., Lomas, K., Wright, A., & Wall, R. (2008). Identifying trends in the use of domestic appliances from household electricity consumption measurements. *Energy and Buildings*, *40*(5), 926–936. https://doi.org/10.1016/J.ENBUILD.2007.07.005

Gao, J., Zhong, X., Cai, W., Ren, H., Huo, T., Wang, X., & Mi, Z. (2019). Dilution effect of the building area on energy intensity in urban residential buildings. *Nature Communications*, *10*(1), 4944. https://doi.org/10.1038/s41467-019-12852-9

Gouveia, J. P., & Seixas, J. (2016). Unraveling electricity consumption profiles in households through clusters: Combining smart meters and door-to-door surveys. *Energy and Buildings*, *116*, 666–676. https://doi.org/10.1016/j.enbuild.2016.01.043

Guerra Santin, O., Itard, L., & Visscher, H. (2009). The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings*, *41*(11), 1223–1232. https://doi.org/10.1016/j.enbuild.2009.07.002

Gupta, V., Sarkar, A., Saxena, A., Jana, A., & Bandyopadhyay, S. (2024). Appliance utility in low-income housing: On the relation between socio-economic characteristics, thermal comfort and appliance usage pattern. *Energy and Buildings*, *323*, 114849. https://doi.org/10.1016/j.enbuild.2024.114849

Halme, M., Piekkari, R., Matos, S., Wierenga, M., & Hall, J. (2024). Rigour vs. Reality: Contextualizing qualitative research in the low-income settings in emerging markets. *British Journal of Management*, *35*(1), 36–51. https://doi.org/10.1111/1467-8551.12690

Han, X., Poblete-Cazenave, M., Pelz, S., & Pachauri, S. (2022). Household energy service and home appliance choices in urban China. *Energy for Sustainable Development*, *71*, 263–278. https://doi.org/10.1016/j.esd.2022.09.021

He, Y. (2024). Ridge regression under dense factor augmented models. *Journal of the American Statistical Association*, *119*(546), 1566–1578. https://doi.org/10.1080/01621459.2023.2206082

Hernández, D., & Phillips, D. (2015). Benefit or burden? Perceptions of energy efficiency efforts among low-income housing residents in New York City. *Energy Research & Social Science*, *8*, 52–59. https://doi.org/10.1016/j.erss.2015.04.010

Hiller, C. (2012). Influence of residents on energy use in 57 Swedish houses measured during four winter days. *Energy and Buildings*, *54*, 376–385. https://doi.org/10.1016/j.enbuild.2012.06.030

Howden-Chapman, P., Viggers, H., Chapman, R., O'Dea, D., Free, S., & O'Sullivan, K. (2009). Warm homes: Drivers of the demand for heating in the residential sector in New Zealand. *Energy Policy*, *37*(9), 3387–3399. https://doi.org/10.1016/j.enpol.2008.12.023

Hox, J. J., & De Leeuw, E. D. (1994). A comparison of nonresponse in mail, telephone, and face-to-face surveys. *Quality and Quantity*, *28*(4), 329–344. https://doi.org/10.1007/BF01097014

Hu, Z., Wang, M., Cheng, Z., & Yang, Z. (2020). Impact of marginal and intergenerational effects on carbon emissions from household energy consumption in China. *Journal of Cleaner Production*, *273*, 123022. https://doi.org/10.1016/j.jclepro.2020.123022

Huebner, G., Shipworth, D., Hamilton, I., Chalabi, Z., & Oreszczyn, T. (2016). Understanding electricity consumption: A comparative contribution of building factors, socio-demographics, appliances, behaviours and attitudes. *Applied Energy*, *177*, 692–702. https://doi.org/10.1016/j.apenergy.2016.04.075

Huebner, G. M., Hamilton, I., Chalabi, Z., Shipworth, D., & Oreszczyn, T. (2015). Explaining domestic energy consumption – The comparative contribution of building factors, socio-demographics, behaviours and attitudes. *Applied Energy*, *159*, 589–600. https://doi.org/10.1016/j.apenergy.2015.09.028

IEA, P. (2022). *World energy outlook 2022*. International Energy Agency (IEA).

Inoue, N., Matsumoto, S., & Mayumi, K. (2022). Household energy consumption pattern changes in an aging society: The case of Japan between 1989 and 2014 in retrospect. *International Journal of Economic Policy Studies*, *16*(1), 67–83. https://doi.org/10.1007/s42495-021-00069-y

Ioannou, A., & Itard, L. C. M. (2015). Energy performance and comfort in residential buildings: Sensitivity for building parameters and occupancy. *Energy and Buildings*, *92*, 216–233. https://doi.org/10.1016/j.enbuild.2015.01.055

Jaffar, B., Oreszczyn, T., Raslan, R., & Summerfield, A. (2018). Understanding energy demand in Kuwaiti villas: Findings from a quantitative household survey. *Energy and Buildings*, *165*, 379–389. https://doi.org/10.1016/j.enbuild.2018.01.055

Jones, R. V., & Lomas, K. J. (2015). Determinants of high electrical energy demand in UK homes: Socio-economic and dwelling characteristics. *Energy and Buildings*, *101*, 24–34. https://doi.org/10.1016/j.enbuild.2015.04.052

Kane, T., Firth, S. K., & Lomas, K. J. (2015). How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling. *Energy and Buildings*, *86*, 817–832. https://doi.org/10.1016/j.enbuild.2014.10.011

Kavousian, A., Rajagopal, R., & Fischer, M. (2013). Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. *Energy*, *55*, 184–194. https://doi.org/10.1016/j.energy.2013.03.086

Kelly, S. (2011). Do homes that are more energy efficient consume less energy?: A structural equation model of the English residential sector. *Energy*, *36*(9), 5610–5620. https://doi.org/10.1016/j.energy.2011.07.009

Khalid, R., & Sunikka-Blank, M. (2017). Homely social practices, uncanny electricity demands: Class, culture and material dynamics in Pakistan. *Energy Research & Social Science*, *34*, 122–131. https://doi.org/10.1016/j.erss.2017.06.038

Khosla, R., Sircar, N., & Bhardwaj, A. (2019). Energy demand transitions and climate mitigation in low-income urban households in India. *Environmental Research Letters*, *14*(9), 095008. https://doi.org/10.1088/1748-9326/ab3760

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, *72*(6), 558–569. https://doi.org/10.4097/kja.19087

Kimura, K., & Waki, H. (2018). Minimization of Akaike's information criterion in linear regression analysis via mixed integer nonlinear program. *Optimization Methods and Software*, *33*(3), 633–649. https://doi.org/10.1080/10556788.2017.1333611

Klassert, C., Sigel, K., Gawel, E., & Klauer, B. (2015). Modeling residential water consumption in Amman: The role of intermittency, storage, and pricing for piped and tanker water. *Water*, *7*(7), 3643–3670. https://doi.org/10.3390/w7073643

Koch, S. F., Nkuna, B., & Ye, Y. (2024). Income elasticity of residential electricity consumption in rural South Africa. *Energy Economics*, *131*, 107405. https://doi.org/10.1016/j.eneco.2024.107405

Koepke, M., Monstadt, J., Pilo', F., & Otsuki, K. (2021). Rethinking energy transitions in southern cities: Urban and infrastructural heterogeneity in Dar es Salaam. *Energy Research & Social Science*, *74*, 101937. https://doi.org/10.1016/j.erss.2021.101937

Kostakis, I. (2020). Socio-demographic determinants of household electricity consumption: Evidence from Greece using quantile regression analysis. *Current Research in Environmental Sustainability*, *1*, 23–30. https://doi.org/10.1016/j.crsust.2020.04.001

Krishnan, D., Kelly, S., & Kim, Y. (2022). A meta-analysis review of occupant behaviour models for assessing demand-side energy consumption. *Energies*, *15*(3), 1219. https://doi.org/10.3390/en15031219

Larrea-Sáez, L., Cuevas, C., & Casas-Ledón, Y. (2023). Energy and environmental assessment of the Chilean social housing: Effect of insulation materials and climates. *Journal of Cleaner Production*, *392*, 136234. https://doi.org/10.1016/j.jclepro.2023.136234

Lee, S.-J., & Song, S.-Y. (2022). Determinants of residential end-use energy: Effects of buildings, sociodemographics, and household appliances. *Energy and Buildings*, *257*, 111782. https://doi.org/10.1016/j.enbuild.2021.111782

Lemanski, C., Haque, A. N., de Groot, J., & McAskill, N. (2025). The false optimism of electrification: Why universal electricity access has not delivered urban energy transformation in South Africa. *Energy Policy*, *198*, 114506. https://doi.org/10.1016/j.enpol.2025.114506

Lenzen, M., Wier, M., Cohen, C., Hayami, H., Pachauri, S., & Schaeffer, R. (2006). A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. *Energy*, *31*(2-3), 181–207. https://doi.org/10.1016/j.energy.2005.01.009

Lewis, M. J., Spiliopoulou, A., Goldmann, K., Pitzalis, C., McKeigue, P., & Barnes, M. R. (2023). Nestedcv: An R package for fast implementation of nested cross-validation with embedded feature selection designed for transcriptomics and high-dimensional data. *Bioinformatics Advances*, *3*(1). https://doi.org/10.1093/bioadv/vbad048

Liao, H.-C., & Chang, T.-F. (2002). Space-heating and water-heating energy demands of the aged in the US. *Energy Economics*, *24*(3), 267–284. https://doi.org/10.1016/S0140-9883(02)00014-2

Longhi, S. (2015). Residential energy expenditures and the relevance of changes in household circumstances. *Energy Economics*, *49*, 440–450. https://doi.org/10.1016/j.eneco.2015.03.018

Love, J., & Cooper, A. C. G. (2015). From social and technical to socio-technical: Designing integrated research on domestic energy use. *Indoor and Built Environment*, *24*(7), 986–998. https://doi.org/10.1177/1420326X15601722

Lusinga, S., & de Groot, J. (2019). Energy consumption behaviours of children in low-income communities: A case study of Khayelitsha, South Africa. *Energy Research & Social Science*, *54*, 199–210. https://doi.org/10.1016/J.ERSS.2019.04.007

Maaith, N., Sharmin, T., & Bk, S. (2025). Socio-technical dynamics of energy consumption in low-income housing in Amman, Jordan. *Habitat International*, *163*, 103485. https://doi.org/10.1016/J.HABITATINT.2025.103485

Maina, J. J. (2023). Factors influencing transformation of prototype public housing in Northern Nigeria. *Covenant Journal of Research in the Built Environment (CJRBE)*, *11*(1), 65–81.

Malik, J., & Bardhan, R. (2023). A localized adaptive comfort model for free-running low-income housing in Mumbai, India. *Energy and Buildings*, *281*, 112756. https://doi.org/10.1016/j.enbuild.2022.112756

Mao, S. (2021). Statistical derivation of linear regression. *Proceedings of SPIE - The International Society for Optical Engineering*, *12163*, 141. https://doi.org/10.1117/12.2628017

Mari, T., Odat, S., & Al-Shammari, A. (2020). Energy performance analysis of passive design strategies for the green affordable homes project in Jordan. *Journal of Engineering and Architecture*, *8*(2), 81–92. https://doi.org/10.15640/jea.v8n2a10

Marill, K. A. (2004). *Advanced statistics:* Linear regression, part II: Multiple linear regression. *Academic Emergency Medicine*, *11*(1), 94–102. https://doi.org/10.1197/j.aem.2003.09.006

Mashhoodi, B., & Bouman, T. (2023). Gendered geography of energy consumption in The Netherlands. *Applied Geography*, *154*, 102936. https://doi.org/10.1016/j.apgeog.2023.102936

Meechai, J., & Wijesinha, M. (2022). Household energy expenditure and consumption patterns in the United States. *Computational Statistics*, *37*(5), 2095–2127. https://doi.org/10.1007/s00180-022-01255-y

MEMR. (2017). *Ministry of energy & mineral resources, annual report*.

MEMR. (2018). *Ministry of energy & mineral resources, annual report*.

MEMR. (2019). *Ministry of energy & mineral resources, annual report*.

MEMR. (2021). *Ministry of energy & mineral resources, annual report*.

MODEE. (2023). *Personal data protection law*. https://www.modee.gov.jo/ebv4.0/root_storage/en/eb_list_page/pdpl.pdf

Motta, V. (2019). Estimating poisson pseudo-maximum-likelihood rather than log-linear model of a log-transformed dependent variable. *RAUSP Management Journal*, *54*(4), 508–518. https://doi.org/10.1108/RAUSP-05-2019-0110

Moumen, I., Rafalia, N., & Abouchabaka, J. (2024). A machine learning approach to residential energy prediction using large-scale datasets in MongoDB. In *2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM)* (pp. 1–6). IEEE. https://doi.org/10.1109/WINCOM62286.2024.10656645

Muianga, E. A. D., KnatzKowaltowski, D. C. C., Silva, V. G. d., Granja, A. D., Moreira, D. d. C., & Ruschel, R. C. (2022). Housing transformations and their impacts on the well-being of dwellers. *Ambiente Construído*, *22*(4), 255–274. https://doi.org/10.1590/s1678-86212022000400639

Nagendra, H., Bai, X., Brondizio, E. S., & Lwasa, S. (2018). The urban south and the predicament of global sustainability. *Nature Sustainability*, *1*(7), 341–349. https://doi.org/10.1038/s41893-018-0101-5

Nahmens, I., Joukar, A., & Cantrell, R. (2015). Impact of low-income occupant behavior on energy consumption in hot-humid climates. *Journal of Architectural Engineering*, *21*(2), A4014004. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000162

Nazer, H. (2019). Developing an energy benchmark for residential apartments in amman.

NEPCO. (2016). *Annual Report 2016. National Electric Power Company (NEPCO)*. https://www.nepco.com.jo/store/docs/web/2016_en.pdf

NEPCO. (2022). *National electric power company, annual report*.

Olatunde, T. M., Okwandu, A. C., & Akande, D. O. (2024). Reviewing the impact of energy-efficient appliances on household consumption. *International Journal of Science and Technology Research Archive*, *6*(2), 001–011. https://doi.org/10.53771/ijstra.2024.6.2.0038

Oliveira Panão, M. J. N. (2021). Lessons learnt from using energy poverty expenditure-based indicators in a mild winter climate. *Energy and Buildings*, *242*, 110936. https://doi.org/10.1016/j.enbuild.2021.110936

Piao, X., & Managi, S. (2023). Household energy-saving behavior, its consumption, and life satisfaction in 37 countries. *Scientific Reports*, *13*(1), 1382. https://doi.org/10.1038/s41598-023-28368-8

Plonsky, L., & Ghanbar, H. (2018). Multiple regression in L2 research: A methodological synthesis and guide to Interpreting R^2 Values. *The Modern Language Journal*, *102*(4), 713–731. https://doi.org/10.1111/modl.12509

Pothitou, M., Hanna, R. F., & Chalvatzis, K. J. (2017). ICT entertainment appliances' impact on domestic electricity consumption. *Renewable and Sustainable Energy Reviews*, *69*, 843–853. https://doi.org/10.1016/J.RSER.2016.11.100

Qian, J. (2010). Sampling. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International encyclopedia of education* (pp. 390–395). Elsevier. https://doi.org/10.1016/B978-0-08-044894-7.01361-0

Qtaishat, Y., Emmitt, S., & Adeyeye, K. (2020). Exploring the socio-cultural sustainability of old and new housing: Two cases from Jordan. *Sustainable Cities and Society*, *61*, 102250. https://doi.org/10.1016/j.scs.2020.102250

Rahahleh, H., & Hani, M. (2024). *Tackling Jordan's chronic electricity deficit: New tariff sparks debate*. www.dohainstitute.org

Rajan, M. P. (2022). An efficient ridge regression algorithm with parameter estimation for data analysis in machine learning. *SN Computer Science*, *3*(2), 171. https://doi.org/10.1007/s42979-022-01051-x

Ramapragada, P., Tejaswini, D., Garg, V., Mathur, J., & Gupta, R. (2022). Investigation on air conditioning load patterns and electricity consumption of typical residential buildings in tropical wet and dry climate in India. *Energy Informatics*, *5*(S4), 61. https://doi.org/10.1186/s42162-022-00228-1

Razem, M., Khalid, R., & Sunikka-Blank, M. (2025). Unveiling women's ventilation practices and comfort in Jordan: Video diaries as method for post-occupancy evaluation. *Building Research & Information*, *53*(1-2), 56–76. https://doi.org/10.1080/09613218.2024.2387289

Rittmann, O., Neunhoeffer, M., & Gschwend, T. (2025). How to improve the substantive interpretation of regression results when the dependent variable is logged. *Political Science Research and Methods*, *13*(1), 203–211. https://doi.org/10.1017/psrm.2023.29

Romero-Jordán, D., & del Río, P. (2022). Analysing the drivers of the efficiency of households in electricity consumption. *Energy Policy*, *164*, 112828. https://doi.org/10.1016/j.enpol.2022.112828

Rouleau, J., Gosselin, L., & Blanchet, P. (2018). Understanding energy consumption in high-performance social housing buildings: A case study from Canada. *Energy*, *145*, 677–690. https://doi.org/10.1016/j.energy.2017.12.107

Rožman, M., Kišić, A., & Oreški, D. (2024). Comparative analysis of nonlinear models developed using machine learning algorithms. *WSEAS Transactions on Information Science and Applications*, *21*, 303–307. https://doi.org/10.37394/23209.2024.21.29

RStudio Team. (2020). *RStudio: Integrated development for R*. RStudio, PBC. http://www.rstudio.com/

Ryu, J., & Kim, J. (2021). Effect of different HVAC control strategies on thermal comfort and adaptive behavior in high-rise apartments. *Sustainability*, *13*(21), 11767. https://doi.org/10.3390/su132111767

Salari, M., & Javid, R. J. (2017). Modeling household energy expenditure in the United States. *Renewable and Sustainable Energy Reviews*, *69*, 822–832. https://doi.org/10.1016/j.rser.2016.11.183

Sammour, F., Alkailani, H., Sweis, G. J., Sweis, R. J., Maaitah, W., & Alashkar, A. (2024). Forecasting demand in the residential construction industry using machine learning algorithms in Jordan. *Construction Innovation*, *24*(5), 1228–1254. https://doi.org/10.1108/CI-10-2022-0279

Santamouris, M., Kapsis, K., Korres, D., Livada, I., Pavlou, C., & Assimakopoulos, M. N. (2007). On the relation between the energy and social characteristics of the residential sector. *Energy and Buildings*, *39*(8), 893–905. https://doi.org/10.1016/j.enbuild.2006.11.001

Sarkar, A., & Bardhan, R. (2020). Socio-physical liveability through socio-spatiality in low-income resettlement archetypes – A case of slum rehabilitation housing in Mumbai, India. *Cities*, *105*, 102840. https://doi.org/10.1016/j.cities.2020.102840

Šćepanović, S., Warnier, M., & Nurminen, J. K. (2017). The role of context in residential energy interventions: A meta review. *Renewable and Sustainable Energy Reviews*, *77*, 1146–1168. https://doi.org/10.1016/j.rser.2016.11.044

Scheier, E., & Kittner, N. (2022). A measurement strategy to address disparities across household energy burdens. *Nature Communications*, *13*(1), 288. https://doi.org/10.1038/s41467-021-27673-y

Sena, B., Zaki, S. A., Rijal, H. B., Alfredo Ardila-Rey, J., Yusoff, N. M., Yakub, F., Ridwan, M. K., & Muhammad-Sukki, F. (2021). Determinant factors of electricity consumption for a Malaysian household based on a field survey. *Sustainability*, *13*(2), 818. https://doi.org/10.3390/su13020818

Sharmin, T., & Khalid, R. (2022). Post occupancy and participatory design evaluation of a marginalized low-income settlement in Ahmedabad, India. *Building Research & Information*, *50*(5), 574–594. https://doi.org/10.1080/09613218.2021.2018286

Shipworth, D. (2005). Synergies and conflicts on the landscape of domestic energy consumption: Beyond metaphor. In P. Bertoldi, A. Ricci, & B. Unseld (Eds.), *Proceedings of the 7th European council for an energy efficient economy summer study* (pp. 1381–1392). European Council for an Energy Efficient Economy (ECEEE).

Shove, E., Watson, M., & Pantzar, M. (2012). *The dynamics of social practice: Everyday life and how it changes*. SAGE Publications.

Smithson, M. (2003). *Confidence intervals (No. 140)*. Sage.

Soheilian, M., Moadab, N. H., Fischl, G., & Aries, M. B. C. (2019). Comparison of simulated energy consumption by smart and conventional lighting systems in a residential setting. *Journal of Physics: Conference Series*, *1343*(1), 012155. https://doi.org/10.1088/1742-6596/1343/1/012155

Soltani, M., Rahmani, O., Beiranvand Pour, A., Ghaderpour, Y., Ngah, I., & Misnan, S. H. (2019). Determinants of variation in household energy choice and consumption: Case from mahabad city, Iran. *Sustainability*, *11*(17), 4775. https://doi.org/10.3390/su11174775

Steemers, K., & Yun, G. Y. (2009). Household energy consumption: A study of the role of occupants. *Building Research & Information*, *37*(5-6), 625–637. https://doi.org/10.1080/09613210903186661

Steg, L. (2018). Limiting climate change requires research on climate action. *Nature Climate Change*, *8*(9), 759–761. https://doi.org/10.1038/s41558-018-0269-8

Stephenson, J., Barton, B., Carrington, G., Gnoth, D., Lawson, R., & Thorsnes, P. (2010). Energy cultures: A framework for understanding energy behaviours. *Energy Policy*, *38*(10), 6120–6129. https://doi.org/10.1016/j.enpol.2010.05.069

Sundah, J., Sofie Pongoh, D., Pinangkaan, A. J. J., Majampoh, W. V., Gerung, A., & Otavianus Angka, O. (2024). Electric energy savings for household appliances: Small steps, Big impact. *Jurnal Syntax Admiration*, *5*(11), 4826–4836. https://doi.org/10.46799/jsa.v5i11.1767

Sztepanacz, J. L., & Houle, D. (2024). Regularized regression can improve estimates of multivariate selection in the face of multicollinearity and limited data. *Evolution Letters*, *8*(3), 361–373. https://doi.org/10.1093/evlett/qrad064

Taale, F., & Kyeremeh, C. (2019). Drivers of households' electricity expenditure in Ghana. *Energy and Buildings*, *205*, 109546. https://doi.org/10.1016/j.enbuild.2019.109546

Taneja, S., & Mandys, F. (2022). Drivers of UK household energy expenditure: Promoting efficiency and curbing emissions. *Energy Policy*, *167*, 113042. https://doi.org/10.1016/j.enpol.2022.113042

Theodoridou, I., Papadopoulos, A. M., & Hegger, M. (2011). Statistical analysis of the Greek residential building stock. *Energy and Buildings*, *43*(9), 2422–2428. https://doi.org/10.1016/j.enbuild.2011.05.034

Tokam, L., & Ouro-Djobo, S. S. (2025). Identification of factors influencing electricity consumption in yaoundé city, Cameroon. *African Journal of Science, Technology, Innovation and Development*, *17*(2), 263–276. https://doi.org/10.1080/20421338.2025.2460227

Tso, G. K. F., & Yau, K. K. W. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, *32*(9), 1761–1768. https://doi.org/10.1016/J.ENERGY.2006.11.010

UN-Habitat. (2023). *Jordan: Housing and slum upgrading*. https://unhabitat.org/jordan-housing-and-slum-upgrading?utm

UN-Habitat, Swiss State Secretariat for Economic Affairs (SECO), & Greater Amman Municipality. (2022). *Amman spatial profile*.

UNDP (2013). Jordan poverty reduction strategy, final report. In *Jordan poverty reduction strategy*. United Nations Development Programme (UNDP) and Ministry of Planning and International Cooperation (MOPIC), Government of Jordan.

van den Brom, P., Hansen, A. R., Gram-Hanssen, K., Meijer, A., & Visscher, H. (2019). Variances in residential heating consumption – Importance of building characteristics and occupants analysed by movers and stayers. *Applied Energy*, *250*, 713–728. https://doi.org/10.1016/j.apenergy.2019.05.078

Vosoughkhosravi, S., Sheikh, S., Kamel, E., & Jafari, A. (2024). Analyzing energy performance in American low income households: A DataDriven approach with machine learning insights. *Journal of Building Engineering*, *89*, 109305. https://doi.org/10.1016/j.jobe.2024.109305

Wang, Y., Hou, L., Cai, W., Zhou, Z., & Bian, J. (2023). Exploring the drivers and influencing mechanisms of urban household electricity consumption in China – Based on longitudinal data at the provincial level. *Energy*, *273*, 127191. https://doi.org/10.1016/j.energy.2023.127191

Wiese, M., & van der Westhuizen, L.-M. (2024). Impact of planned power outages (load shedding) on consumers in developing countries: Evidence from South Africa. *Energy Policy*, *187*, 114033. https://doi.org/10.1016/j.enpol.2024.114033

Wondola, D. W., Aulele, S. N., & Lembang, F. K. (2020). Partial least square (PLS) method of addressing multicollinearity problems in multiple linear regressions (case studies: Cost of electricity bills and factors affecting it). *Journal of Physics: Conference Series*, *1463*(1), 012006. https://doi.org/10.1088/1742-6596/1463/1/012006

Xie, Y., & Noor, A. I. M. (2022). Factors affecting residential end-use energy: Multiple regression analysis based on buildings, households, lifestyles, and equipment. *Buildings*, *12*(5), 538. https://doi.org/10.3390/buildings12050538

Xu, X., Xiao, B., & Li, C. Z. (2020). Critical factors of electricity consumption in residential buildings: An analysis from the point of occupant characteristics view. *Journal of Cleaner Production*, *256*, 120423. https://doi.org/10.1016/j.jclepro.2020.120423

Xu, X., Xie, J., Zhou, H., & Liu, J. (2023). Effect of different window types on energy rating based on the survey data in China. In J. Zhang, Y. Yang, & S. Zhang (Eds.), *Proceedings of the 5th international conference on building energy and environment* (pp. 807–810). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-9822-5_86

Yao, R., Zhang, S., Du, C., Schweiker, M., Hodder, S., Olesen, B. W., Toftum, J., Romana d'Ambrosio, F., Gebhardt, H., Zhou, S., Yuan, F., & Li, B. (2022). Evolution and performance analysis of adaptive thermal comfort models – A comprehensive literature review. *Building and Environment*, *217*, 109020. https://doi.org/10.1016/j.buildenv.2022.109020

Younis, A., Taki, A., & Bhattacharyya, S. (2016). Low-Middle income apartments in urban Amman/Jordan: Energy challenges and motivations. In *Proceedings of the 2016 2nd international conference on civil, environment and waste management (ICEWM'16)* (pp. 1–6). Universal Researchers in Science and Technology (URST).

Younis, A., Taki, A., & Bhattacharyya, S. (2017). Towards resilient low-middle income apartments in Amman, Jordan: A thermal performance investigation of heating load. In *Proceedings of the CIBSE ASHRAE Technical Symposium 2017* (pp. 1–8). Chartered Institution of Building Services Engineers (CIBSE).

Yust, B. L., Guerin, D. A., & Coopet, J. G. (2002). Residential energy consumption: 1987 to 1997. *Family and Consumer Sciences Research Journal*, *30*(3), 323–349. https://doi.org/10.1177/1077727X02030003001

Zhang, G., & He, Y. (2025). A general procedure for evaluating models and ensemble support vector regression. *Communications in Statistics - Simulation and Computation*, *54*(11), 4574–4585. https://doi.org/10.1080/03610918.2024.2384569