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What drove electricity consumption in the residential sector during the SARS-CoV-2 confinement? A special focus on university students in southern Spain

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1. - Introduction

The home confinement of people all around the world due to the SARS-CoV-2 pandemic [1] has had an impact on the habits of families and people living together in the same household. One of the most important changes has been the shift of part of the energy consumption, mainly electricity, away from places of work, study and leisure and into family dwellings. Global oil demand fell by 30% while people were working at home [2]. These changes have sparked growing interest in the analysis of the behaviour of residential energy consumption, particularly electricity consumption.

In countries such as Spain, the energy consumption of the residential sector represents 17.07% of the total [3]). In the region of Andalusia, southern Spain, residential buildings alone required 1821.5 ktoe in 2019 (13.4% of regional final energy consumption) and the residential electricity consumption was 12,761,560 MWh in the same year (37.72% of the total regional electricity consumption [4].

From the pollution perspective, as a member of the European Union (EU), Spain made a commitment to reduce primary energy consumption in 2020, pledging to keep it below 123.4 Mtoe or 87.2 Mtoe for final energy consumption [5]. This reduction is part of the EU's roadmap for compliance with the Paris Agreement in 2030 and for achieving carbon neutrality by 2050. In Spain, the residential sector alone is responsible for 14% of greenhouse gas (GHG) emissions [6]. Although residential consumption also includes the commercial sector and public administrations, this figure explains why reducing electricity consumption in the residential sector has been part of the Spanish roadmap to carbon neutrality since long before the pandemic.

The specialized literature focusing on the analysis of the determinants of electricity consumption in the residential sector has highlighted the role played by i) socio-economic variables of the inhabitants, ii) technical specifications of the dwellings (surface area, number of floors, and age), iii) equipment, and iv) climate.

In order to reduce energy consumption and emissions, most measures focused on residential energy consumption have been aimed at improving the energy efficiency of dwellings. In the EU, the Energy Efficiency Directives prompted a change in building codes to ensure the construction of nearly zero-emission buildings through a combination of thermal insulation and the use of renewable energy [7]. For older dwellings, countries such as Spain have developed public subsidy programmes to encourage investments in the improvement of the thermal envelope of dwellings and the replacement of conventional windows with insulated ones [6]. The replacement of lighting systems with LEDs and the energy rating of large household appliances are also aimed at reducing electricity consumption in homes. In addition to all of the above, citizens must be educated on the need to reduce energy consumption in order to cut polluting emissions.

The lockdown of the population in response to the SARS-CoV-2 pandemic represents an opportunity to better understand the determinants of energy consumption in general and electricity consumption in particular, both in exceptional situations and in future scenarios where teleworking and e-learning may be more commonplace. Furthermore, lockdown offers an opportunity to test the effectiveness of some measures that have been implemented in recent years to reduce energy consumption in the residential sector.

Along with teleworking, the replacement of face-to-face teaching by e-learning during the months of confinement has led to a shift in electricity consumption away from schools and into family homes and other student accommodation. Although several vaccines against SARS-CoV-2 infection are currently being administered to the population, possible resurgences of the pandemic due to variants in the virus strain cannot be ruled out. Moreover, it is also possible that future regional pandemics

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similar to SARS (China, 2003) or MERS-CoV (Saudi Arabia, 2012) could lead to further confinement of the population. The results obtained allow to identify the areas of action that have the greatest impact on electricity consumption in the residential sector, even in normal scenarios in which people are not confined to their homes, but in which a substantial share of workers are working from home and students are using alternative learning modes such as flipped classrooms.

Recently, some studies have emerged analysing energy consumption during the pandemic in non-residential buildings facilities [8,9]. However, there is no literature analysing the determinants of electricity consumption in the residential sector in situations as exceptional as pandemic-induced lockdowns. Thus, the contribution of this work is threefold. First, it contributes to filling the gap in the literature by analysing the determinants of electricity consumption during lockdown (the research conducted offers an unusually rich database for this type of research, in that it provides data on 46 different variables). Second, because the data collected are from students, this work provides information on how increased leisure time and e-learning activities impact electricity consumption. The third contribution of the study is the chosen case study: Southern Spain.

In order to carry out this research, an anonymous online survey was administered to university and pre-university students who were confined to their homes between March and June 2020. The period corresponds to the hard lockdown during which people were only allowed to leave home for food supplies or healthcare needs. The machine learning regression methodology used allowed sequentially subtracting variables until no further variables can be deleted without a statistically significant loss of fit. The analysis of these drivers and inhibitors of household energy consumption in the exceptional scenario of lockdown is the novelty of this study, as soon as the value of the results would be founded on the need for knowledge in the face of the increasing development and often irruptive behaviour of teleworking and e-learning in the aftermath of the pandemic.

The rest of the article is structured as follows. After this introduction, a thorough literature review is presented in Section 2 together with a description of the variables used. The methodology and the data are described in Section 3, while Section 4 details and discusses the main results. Section 5 presents the main conclusions and provides policy recommendations.

2. - Literature review and selected key variables

2.1. - Literature review

The scientific literature identifies four groups of determinants of energy consumption in the residential sector: i) socio-economic, ii) technical characteristics of the dwelling, iii) equipment and iv) climate. Table A.1 in Annex 1 offers a detailed list of relevant literature grouped into these sets of determinants of energy consumption.

The group of socio-economic factors has received the most academic attention to date, particularly the number of residents in the household ([10–12]). Special attention has also been given to the influence of the composition of the family or group of cohabitants on electricity consumption [13,14]. There has also been a focus on the age of the family members [15–18] as well as their level of education [19–22]. A final set of papers analyse the impact of income and work activity of family members [11,12,22].

The second group of determinants of energy consumption in the residential sector encompasses the technical characteristics of the dwelling. Most of these studies focus on the liveable area [23,24] and the dwelling type [25,26]. The layout of the dwelling has also attracted the interest of researchers, who have analysed both the number of rooms [17,21,27,28] and the number of bedrooms [28–31]. Another variable that has been analysed is the age of the dwelling [24,32]. The literature has also examined the tenure status [17,19,28,31] and the presence of air-conditioning and heating systems [14,27,34–36].

The third group of factors focuses on the equipment in the dwelling, with the literature primarily analysing the impact on energy consumption of household appliances [21,27], entertainment devices [14,37], and appliances for cooking [17,38] and for food preservation [16,21]. More recently the literature has started to pay attention to equipment for heating, comfort [39] and laundry [11,27]. Finally, there is an emerging literature exploring the role of small electronic devices in energy consumption [40,41], which is of particular relevance when it comes to students.

Lastly, the growing concern about climate change has prompted research on the influence of the climate on energy consumption in the residential sector, separately from that of heating and cooling systems [11,19].

2.2. - Selected key variables

The research has defined 46 variables based on the previous subsection (for more details, see also Table A.1).Table 1 presents the description of these variables and their expected impact on household consumption, *ceteris paribus*. The expected sign of the relationship is easily interpretable in the case of numerical variables. In the case of categorical variables, the impact will depend both on the level taken as a reference and on the other levels that make up the variable (more details in Section 3.2). A positive impact means higher energy consumption, while a negative impact would indicate the opposite.

3. - Methodology and data

3.1. - Methodology

3.1.1. - Two relevant stages

In order to identify the variables that influence household electricity consumption during the strictest lockdown, a multiple linear regression (MLR) model was built (see Supplementary Materials). The model is developed in two stages. In the first stage, a test is carried out to check the homogeneity of the database.

The second stage involves four steps. As Fig. 1 shows, the first step is to select the most explanatory variables for the MLR model. In the second step, the model is built with the variables selected in the previous step. The third step consists of validation and checking model assumptions. Finally, the analysis of the model is carried out in the fourth step.

3.1.2. Stage 1: database homogeneity

The database was obtained from surveys administered to university and pre-university students in December 2020 and March 2021 (details in Section 3.2). The only characteristic that differentiates the two samples is that, in the period to which the survey refers, some students (university students) were already studying at university, while those in the other group (pre-university students) were at high school doing the preparatory course that allows them to enter university. Stage 1 involves applying a homogeneity test to the data on household energy consumption during lockdown, differentiating between the two samples (university and pre-university students). Specifically, the non-parametric Mann-Whitney test [42] was used since household energy consumption during lockdown did not follow a normal distribution according to the Shapiro-Wilk normality test [43].Finally, the database adaptation was carried out.

3.1.3. Stage 2, first step: variable selection

The first step is to select the most explanatory variables for the subsequent creation of the MLR model, to which end it is first necessary to decide which selection criteria to use. While there are many criteria that can be used [44,45], the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are the two most popular criteria used in regression analysis, as they allow a balance between prediction accuracy and the principle of parsimony [46,47]. The literature review

Table 1
Variables and expected impact on electricity consumption during lockdown.

Nº	Variable	Description	Type (Reference category if applies)	Expected impact on electricity consumption	
1	TypeHouse	Dwelling type	Categorical (Flat or apartment in building with 2–4 dwellings)	Flat or apartment in building with more than 4 dwellings	Uncertain impact
				Semi-detached single-family home	Positive impact
				Detached single-family home	Positive impact
2	m^2	Square metres of the home	Ordered categorical	Positive impact	
3	Floors	Number of floors	Numeric	Uncertain impact	
4	Property	Ownership of the home	Categorical (Rented)	Occupied without rent payment	Positive impact
				Owned or acquired by someone in the family	Positive impact
5	Year	Year of construction of the dwelling	Ordered categorical	Uncertain impact	
6	Bedrooms	Number of bedrooms	Numerical	Positive impact	
7	Rooms	Total number of rooms	Numerical	Positive impact	
8	RyCSystem	Cooling and heating systems in the dwelling	Categorical (Mostly)	No, only some rooms	Uncertain impact
				Yes, the entire dwelling	Uncertain impact
9	LightSystem	Main lighting system of the dwelling	Categorical (Energy-saving light bulbs)	Incandescent bulbs	Positive impact
				Fluorescent tubes	Positive impact
10	ThermalInsulationWindows	Thermal insulation windows	Categorical (Yes)	No	Positive impact
11	ElectricityContract	Type of electricity contract in the dwelling	Categorical (Flat rate)	PVPC (voluntary pricing for small consumers) or regulated market	Uncertain impact
				Self-consumption system	Uncertain impact
				Variable hourly rates	Uncertain impact
12	HouseholdMembers	Number of household members	Numerical	Positive impact	
13	AgeCategory	Age range of members of the household	Ordered categorical	Uncertain impact	
14	Teleworking	Number of persons teleworking or studying at home	Numerical	Positive impact	
15	EmploymentStatus	Employment status of household breadwinners	Categorical (Unemployed)	Full-time employees	Positive impact
				Part-time employees	Positive impact
				Included in ERTE (temporary layoff scheme)	Positive impact
				Retired	Uncertain impact
16	AnnualIncome	Annual household income	Ordered categorical	Positive impact	
17	ConfinementConsumption	Energy consumption during lockdown (kWh)	Numerical	Dependent variable	
18	GrowthConsump	Perceived growth in energy consumption during lockdown	Categorical	Uncertain impact	
19	WinterConsumption	Energy consumption during a winter month (kWh)	Numerical	Uncertain impact	
20	UseStudyDevice	Use of devices for studying	Ordered categorical	Positive impact	
21	UseLeisureDevice	Use of devices for leisure	Ordered categorical	Positive impact	
22	UseCookDevice	Use of cooking devices	Ordered categorical	Positive impact	
23	UseHyCDevice	Use of heating and cooling devices	Ordered categorical	Positive impact	
24	TVhours	TV hours	Ordered categorical	Uncertain impact	
25	HeatingDegrees	Temperature for using the heating system	Categorical (Below 15 °C)	Below 18 °C	Positive impact
26	CoolingDegrees	Temperature for using the cooling system	Categorical (Above 26 °C)	Above 30 °C	Negative impact
27	UseCoolingSystems	Use of the cooling system	Categorical (None)	Splits	Positive impact
				Splits and fans	Positive impact
				Fans	Positive impact
28	UseHeatingSystems	Use of the heating system	Categorical (Electric heaters)	Other	Negative impact
				Electric radiators	Negative impact
				Splits	Negative impact
				Splits and electric heaters	Uncertain impact

(*continued on next page*)

Table 1 (*continued*)

Nº	Variable	Description	Type (Reference category if applies)	Expected impact on electricity consumption	
				Splits and radiators	Negative impact
				None	Negative impact
29	Use_tablet	Used the tablet to study	Categorical (Yes)	No	Negative impact
30	Use_desktopPC	Used desktop computer to study	Categorical (Yes)	No	Negative impact
31	Use_laptop	Used laptop to study	Categorical (Yes)	No	Negative impact
32	Use_Smartphone	Used smartphone to study	Categorical (Yes)	No	Negative impact
33	Use_none	No devices used to study	Categorical (Yes)	No	Positive impact
34	P_TV	Owns TV	Categorical (Yes)	No	Negative impact
35	P_OvenEH	Owns oven with extractor hood	Categorical (Yes)	No	Negative impact
36	P_OvenWEH	Owns oven without extractor hood	Categorical (Yes)	No	Negative impact
37	P_ElectricCooker	Owns electric cooker	Categorical (Yes)	No	Negative impact
38	P_Fridge	Owns refrigerator	Categorical (Yes)	No	Negative impact
39	P_Wmachine	Owns washing machine	Categorical (Yes)	No	Uncertain impact
40	P_Freezer	Owns freezer	Categorical (Yes)	No	Negative impact
41	P_microwave	Owns microwave oven	Categorical (Yes)	No	Uncertain impact
42	P_vacuum	Owns vacuum cleaner	Categorical (Yes)	No	Negative impact
43	MoreUse_Dstudy	More use of devices for studying	Categorical (Yes)	No	Negative impact
44	MoreUse_Dcooking	More use of cooking appliances	Categorical (Yes)	No	Negative impact
45	MoreUse_Dleisure	More use of devices for leisure	Categorical (Yes)	No	Negative impact
46	NoMoreUse	No increased use of devices or appliances	Categorical (Yes)	No	Positive impact

Note: Categorical variables show the expected impact on electricity consumption as it moves from the reference category (shown in parentheses in the Type column) to another category. Ordered categorical variables show the expected impact on electricity consumption when advancing to higher levels.
Source: Own elaboration

shows how the AIC has been widely used and is appropriate for the analysis of energy consumption [48,49]. Therefore, in line with the relevant literature, the AIC was used for the variable selection.

The AIC compares different models, allowing the researcher to establish the best fit between the information needed and model performance [50]. It may be written as follows:

$$AIC = -2 * ln(L) + 2 * k \quad (1)$$

where k is the number of explanatory variables used to build the MLR model and L is the value of the likelihood (how well the model reproduces the data). The best MLR model is the one with the greatest explanatory power using the fewest possible independent variables (minimum AIC value).

AIC is applied in this analysis through the Stepwise Algorithm (stepAIC function) implemented in the R software [51]. The algorithm offers two ways of creating stepwise models: either forward selection or backward elimination. This paper uses the latter approach, starting with the full model, which offers the advantage of considering the effects of all variables simultaneously. This is especially important in cases where multicollinearity is detected, since backward stepwise may mean all the variables are retained in the model, whereas with forward selection it may be the case that none of them are entered into the model [52]. In backward elimination, the starting point is a model that incorporates all the explanatory variables, with predictors gradually being eliminated until the AIC indicates that further elimination of variables does not improve the model [53]. This procedure helps to prevent overfitting by eliminating the less significant explanatory variables. Finally, the independent variables not eliminated in the stepwise algorithm will be incorporated into the MLR model in the next step.

3.1.4. Stage 2, second step: building the MLR model

This second step focuses on the construction of the MLR model with the predictors that survived the stepwise procedure in step one. The model is built according to the concepts described in Supplementary Materials (S.1) and using the Fitting Linear Model (lm function) implemented in the R software [54,55].

The quality of the model is measured through the coefficient of determination (R^2), adjusted coefficient of determination (R^2_{adj}) and the root mean square error (RMSE), as described in Supplementary Materials (S.1).

3.1.5. Stage 2, third step: validation and checking model assumptions

The third step is MLR model validation. To be accepted, the regression model must satisfy several assumptions. More details on MRL model assumptions can be found in Williams et al. (2013) [56]. Table 2 summarizes assumptions and the testing procedure.

3.1.6. Stage 2, fourth step: interpretation and analysis of the model

Finally, the fourth step is the interpretation and analysis of the MLR model. Here, the regression coefficients will be discussed in detail, considering the value itself, the impact (negative or positive) and the

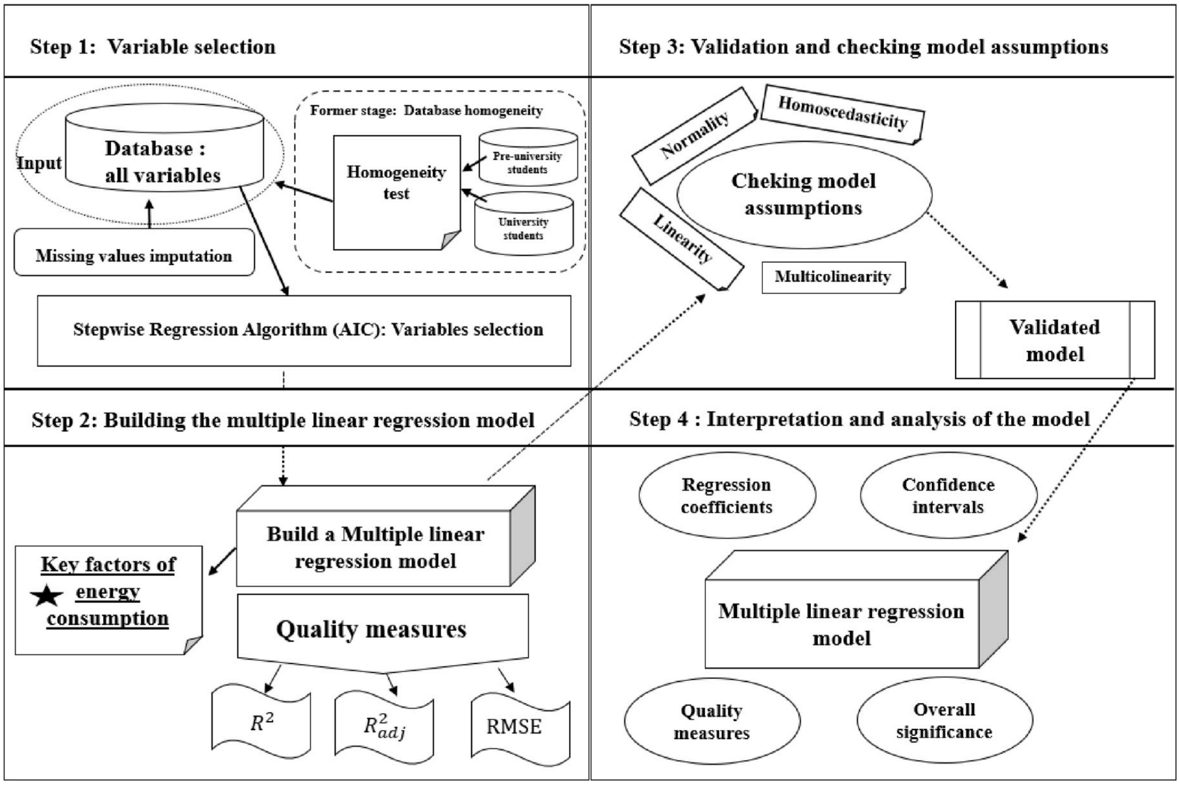

Fig. 1. Schematic diagram of the development of multiple linear regression model (stage 2) Source: Own elaboration.

Table 2
Assumptions and testing procedure.

Assumptions	Testing procedure	Detailed plot and test
1. Linearity	Test	Ramsey Regression Equation Specification Error Test
2. Normality	Plot	QQ Plot of Residuals
	Test	Shapiro-Wilk Normality Test
3. Homoscedasticity	Plot	Scale-location plot
	Test	Breusch-Pagan Test for Homoscedasticity
4. Multicollinearity	Matrix	Correlation Matrix

Source: Own elaboration

significance (p-value). In addition, the confidence intervals will be constructed, the quality measures will be reviewed again (see section 3.1.4), and the overall significance of the model will be tested.

3.2. Data

The data used come from an anonymous online survey complete by students of the University of Seville (Spain). The sample includes information about households of university and pre-university students who were confined to their homes in Spain between the months of March and June 2020. The period corresponds to the strict lockdown during which they were only allowed to leave the home for food supplies or healthcare needs. The survey initially targeted 478 households, but after the pre-processing, 311 surveys were considered valid (124 for university students and 187 for pre-university students). In order to avoid the loss of information from a series of surveys, a small number of missing values (34 values in categorical predictors, representing 0.2% of the total) have been imputed. This percentage (0.2%) is less than 1%, below the level that is considered statistically non-significant [57]. The imputation of missing values in predictors has been carried out using Random Forest [58].The proximity matrix from the Random Forest is used to impute the NAs (rfImpute function in R software). For categorical predictors, the imputed value is the category with the largest average proximity.

The anonymous questionnaire included a series of items related to socio-economic factors, technical characteristics of the dwelling, equipment in the dwelling and use of devices, climate change behaviour and other specific variables. Table 3 shows a summary of the variables and results obtained from the questionnaire (more details in Supplementary Materials (0 S.2.1)).

The survey results are representative of the Andalusia region. It observes the predominance of the single-family home (54%) over other types, in line with the statistics for this region [59]. The most numerous group of households report a living area of between 76 and 100 m^2, which are values similar to those given by the official statistics on Andalusia [60]. There is a clear predominance of home ownership in the sample (91.96%), similar to the value provided by Ref. [61]. When asked about the age of the dwelling, the most numerous group reports an age of between 20 and 30 years. In this regard, it should be noted that the residential housing stock in Andalusia amounted to 4,353,146 in 2011, of which 3,087,222 were primary residences, 628,703 were secondary residences and 637,221 were unoccupied. More than 82% of main residences were built before 1970 and the same is true for 15% of secondary residences [60]. In line with the above, the high representation in the sample of dwellings over 10 years old (more than 95% of the observations) is due to students living with their parents during

Table 3
List of variables and survey results.

Variable Description	Most observed level/[range]	Values	Variable Description	Most observed level/[range]	Values
Dwelling type	Semi-detached single-family home	103 (33.12%)	TV hours	3–6 h	105 (33.8%)
Square metres of the home	76–100 m^2	101 (32.48%)	Temperature for using the heating system	Below 15 °C	167 (53.7%)
Number of floors	[1–5]	1.95 (0.95)	Temperature for using the cooling system	Above 30 °C	170 (54.7%)
Ownership of the home	Owned or belongs to someone in the family	286 (91.96%)	Use of the cooling system	Splits and fans	96 (30.9%)
Year of construction of the dwelling	1990–1999	126 (40.5%)	Use of the heating system	Electric radiators	96 (30.9%)
Number of bedrooms	[2–6]	3.40 (0.7590)	Used the tablet to study	No	225 (72.3%)
Total number of rooms	[3–15]	8.32 (2.3704)	Used the desktop computer to study	No	256 (82.3%)
Cooling and heating systems in the dwelling	No, only some rooms	134 (43.1%)	Used laptop to study	Yes	273 (87.8%)
Main lighting system of the dwelling	Energy-saving light bulbs	252 (81.00%)	Used smartphone to study	No	162 (52.1%)
Thermal insulation windows	Yes	139 (44.70%)	No devices used to study	No	308 (99.0%)
Type of electricity contract in the dwelling	Voluntary pricing for small consumers or regulated market	174 (55.9%)	Owns TV	Yes	311 (100%)
Number of household members	[1–7]	3.29 (1.0509)	Owns oven with extractor hood	Yes	208 (66.9%)
Age range of members of the household	26–50 years	195 (62.7%)	Owns oven without extractor hood	No	225 (72.3%)
Number of persons teleworking or studying at home	[0–7]	1.58 (1.21)	Owns electric cooker	Yes	205 (65.9%)
Employment status of household breadwinners	Full-time employees	189 (60.80%)	Owns refrigerator	Yes	311 (100%)
Annual household income	20.000–39.999 €	112 (36.00%)	Owns washing machine	Yes	310 (99.7%)
Energy consumption during lockdown (kWh)	[54–900]	395.6 (182.76)	Owns freezer	Yes	282 (90.7%)
Perceived growth in energy consumption during lockdown	0–25% more	190 (61.10%)	Owns microwave oven	Yes	276 (88.7%)
Energy consumption during a winter month (kWh)	[60–996]	395.6 (189.46)	Owns vacuum cleaner	Yes	198 (63.7%)
Use of devices for studying	50–75% more	147 (47.3%)	More use of devices for studying	Yes	260 (83.6%)
Use of devices for leisure	50–75% more	124 (39.9%)	More use of cooking appliances	No	211 (67.8%)
Use of cooking devices	0–25% more	128 (41.2%)	More use of devices for leisure	No	158 (50.8%)
Use of heating and cooling devices	0–25% more	153 (49.2%)	No increased use of devices or appliances	No	299 (96.1%)

Note: Results are expressed as mean ± SD for numerical variables and N (%) for ordered categorical/categorical variables (for these variables only the most representative category is shown).
Source: Own elaboration

lockdown, reflecting the high average age (29.5 years) at which young Spaniards leave the parental household [62].

Most households have already installed energy-saving light bulbs, although less than half have installed thermally insulated windows. The most common type of electricity supply contract is PVPC (voluntary pricing for small consumers) [63]. Socio-economic variables indicate that even in the period of strict home confinement, 60.8% were in full-time employment and 13.2% were protected by an ERTE (temporary layoff scheme) [64]. The largest income group was between 20,000 and 40,000 €/year.

The majority stated that their perception was that electricity consumption increased by 0–25% compared to the same period the previous year. Electronic devices were used 50–75% more for studying, with the smartphone being the least often used for this task. The increase in the use of devices for leisure was in the same range. Regarding cooking, 41.2% responded that they had used the kitchen up to 25% more.

When asked about the standard comfortable temperature, almost half of the respondents put up with temperatures as low as 15 °C without turning on the heating, while the other half turn on the heating when it drops to 18 °C. Similar behaviour for cooling systems is observed, with households activating them from 26 °C or 30 °C. The largest group of households uses both splits and fans for cooling, while relatively few uses electric radiators for heating.

4. - results and Discussion

4.1. - Results

4.1.1. Stage 1: homogeneity of the database

Stage 1 entails testing the homogeneity of household energy consumption during home confinement, differentiating between the two samples obtained (university and pre-university students). Table 4 shows average consumption as a summary measure for each sample. Non-parametric tests were carried out here, since the values for household energy consumption during lockdown did not follow a normal distribution. Table 5 shows the results of the Shapiro-Wilk normality test applied to household energy consumption during lockdown. The Mann-Whitney test revealed no evidence to suggest the need to address the two

Table 4
Average household energy consumption during lockdown.

Sample	Mean of household energy consumption during lockdown	N	Standard deviation
University	403.69	124	187.96
Pre-university	418.22	187	179.50
Total	412.43	311	182.76

Source: Own elaboration.

Table 5
Shapiro-Wilk normality test applied to household energy consumption during lockdown.

Variable	w	p-value
Household energy consumption during lockdown	0.98	0.006

Source: Own elaboration.

samples separately; the results are shown in Table 6.

As a result of this test, data from university and pre-university students were merged and considered a single dataset. Further analysis (or steps in the study) was then carried out on this dataset, including the descriptive statistics in Table 3 above.

Before starting Stage 2, a final adaptation of the database was carried out, reducing the number of variables incorporated in the backward stepwise multiple regression analysis to 39. The dummy variables Use_none, P_TV, P_Fridge, P_Wmachine, NoMoreUse were not introduced in the process due to the imbalance between their two categories (one of the categories captured more than 95% of the responses). Furthermore, the variable Floors was not included as an error was detected in the interpretation of the question by the students surveyed, who confused the number of floors in their home with the number of floors in their block of flats. Finally, the variable GrowthConsump was not included in the process as it was considered only as a parameter to gather useful information for drawing conclusions.

4.1.2. Stage 2, first step: variables selection

Once the homogenization of the dataset is validated, the second stage consists in selecting the variables to be incorporated into the MLR model. Backward stepwise regression analysis was carried out, starting with a model that incorporates all the explanatory variables and gradually eliminating predictors until the AIC criterion indicates that any further elimination of variables does not result in an improvement of the model. Results of the stepwise regression analysis are shown in Table 7. It can be seen that eliminating some variables that appear in the table leads to an increase in the AIC criterion (ΔAIC).

Thus, the 15 critical predictors listed in Table 7 have been identified. Specifically, this procedure identified two socio-economic predictors related to ownership and the household members; four technical characteristics of the dwelling, including dwelling type, number of bedrooms, lighting systems and the size of the dwelling; six equipment predictors related to the use of leisure devices, heating systems, tablet, cooking device, increased use of leisure devices and owning an electric cooker; two climate change behaviour variables (cooling and heating degrees); and the household electricity consumption in the previous winter.

Table 6
Homogeneity Test: Mann-Whitney test.

Variable	Homogeneity Test: Mann-Whitney[a]	p-value
Education level, university and pre-university	12,034	0.571

Source: Own elaboration.
[a] Mann-Whitney Test.

Table 7
Stepwise regression analysis results. Selected predictors according to AIC.

Predictor	ΔAIC
UseLeisureDevice	+0.04
Bedrooms	+3.34
LightSystem	+4.34
HeatingDegrees	+5.84
UseHeatingSystems	+6.44
CoolingDegrees	+7.14
Property	+7.74
P_ElectricCooker	+9.04
MoreUse_Dleisure	+10.24
HouseholdMembers	+13.44
Use_Tablet	+14.84
m2	+16.34
UseCookDevice	+24.54
TypeHouse	+26.24
WinterConsumption	+511.94

Source: Own elaboration.

4.1.3. Stage 2, second step: building the multiple linear regression model

The second step is the construction of the MLR model using the critical predictors identified. The MLR model is formulated as follows:

$$\text{ConfinementComsumption} = \alpha + \beta_1\text{TypeHouse} + \beta_2\text{m2} + \beta_3\text{Property} + \beta_4\text{Bedrooms} +$$

$$\beta_5\text{LightSystem} + \beta_6\text{HouseholdMembers} + \beta_7\text{WinterConsumption} + \beta_8\text{UseLeisureDevice} +$$

$$\beta_9\text{UseCookDevice} + \beta_{10}\text{HeatingDegrees} + \beta_{11}\text{CoolingDegrees} + \beta_{12}\text{UseHeatingSystems} +$$

$$\beta_{13}\text{Use}_{\text{Tablet}} + \beta_{14}\textbf{ElectricCooker} + \beta_{15}\,\textbf{MoreUse}_{\textbf{Dleisure}} + \varepsilon \tag{2}$$

As expected, the number of significant variables (minimum 0.05 significance) in the MLR model is equal to 15 (all the predictors). The *F*-statistic = 48.81 (*p*-value < 0.001), indicating that the MLR model produces statistically satisfactory and reliable results. The quality of the model is measured through the coefficient of determination ($R^2 = 0.84$), adjusted coefficient of determination ($R^2_{adj} = 0.82$) and the root mean square error (RMSE = 76.01).

4.1.4. Stage 2, third step: validation and checking model assumptions

The third step involves checking the assumptions of MLR model that must be met to ensure correct validation. This process has validated the proposed MLR model (the detailed procedure and results are described in Supplementary Materials (S.3).

4.1.5. Stage 2, fourth step: analysis of the model

The fourth step is the analysis of the MLR model. Table 8 shows the statistics for the regression coefficients and the quality measures.

The impact column indicates whether the relationship is positive or negative, as determined by the sign of the corresponding weight. Along with the p-value column, this enables the interpretation of the influence of each variable on electricity consumption. This interpretation depends on the nature of each variable:

All the quantitative variables (WinterConsumption, Bedrooms, and Household Members) have a statistically significant impact on electricity consumption. For these variables, a negative direction displayed in the Impact column should be interpreted as an inverse relationship between electricity consumption and these variables; that is, an increase in such variables corresponds to a decrease in electricity consumption and vice-versa. On the other hand, a positive direction displayed in the

Table 8
MLR regression coefficients (value, confidence interval, impact and significance) and quality measures.

Predictors	β-Weights	95% CI	Impact	p-value
Intercept	49.57	−12.02, 111.17	Positive	0.114
TypeHouse: Flat or apartment in building with more than 4 dwellings	19.79	−8.40, 47.99	Positive	0.168
TypeHouse: Semi-detached single-family home	−39.30	−67.41, −11.19	Negative	0.006 **
TypeHouse: Detached single-family home	10.15	−21.62, 41.93	Positive	0.529
m^2 : 76–100 m^2 (L)	22.66	−4.99, 50.32	Positive	0.107
m^2 : 101–125 m^2 (Q)	−13.84	−39.28, 11.59	Negative	0.284
m^2 : 126–150 m^2 (C)	−27.96	−50.17, −5.75	Negative	0.013 *
m^2 : 151–200 m^2 (^4)	−21.99	−43.41, −0.58	Negative	0.044 *
m^2: > 200 m^2 (^5)	−36.24	−58.96, −13.53	Negative	0.001 **
Property: Owned or belongs to someone in the family	53.90	19.21, 88.59	Positive	0.002 **
Bedrooms	−14.33	−27.15, −1.50	Negative	0.028 *
LightSystem: Incandescent bulbs	30.74	7.56, 53.93	Positive	0.009 **
LightSystem: Fluorescent tubes	77.66	−79.74, 235.07	Positive	0.332
HouseholdMembers	17.82	8.86, 26.78	Positive	<0.001 ***
WinterConsumption	0.82	0.78, 0.87	Positive	<0.001 ***
UseLeisureDevice: 25 to 50% more (L)	13.65	−9.51, 36.81	Positive	0.247
UseLeisureDevice: 50 to 75% more (Q)	−20.11	−40.06, −0.16	Negative	0.048 *
UseLeisureDevice: 75 to 100% more (C)	9.87	−6.25, 26.01	Positive	0.229
UseCookDevice: 25 to 50% more (L)	20.93	−6.30, 48.17	Positive	0.131
UseCookDevice: 50 to 75% more (Q)	−35.43	−58.82, −12.04	Negative	0.003 **
UseCookDevice: 75 to 100% more (C)	−33.59	−52.96, −14.22	Negative	<0.001 ***
HeatingDegrees: Below 18°C	−22.83	−41.50, −4.16	Negative	0.016 *
CoolingDegrees: Above 30°C	−23.97	−42.93, −5.02	Negative	0.013 *
UseHeatingSystems: Other	−30.58	−60.45, −0.70	Negative	0.044 *
UseHeatingSystems: Electric radiators	−18.17	−42.09, 5.74	Negative	0.135
UseHeatingSystems: Splits	34.75	−3.88, 73.38	Positive	0.077
UseHeatingSystems: Splits and electric heaters	−13.47	−45.96, 19.00	Negative	0.414
UseHeatingSystems: Splits and radiators	−42.52	−79.43, −5.61	Negative	0.024 *
UseHeatingSystems: None	−60.47	−107.44, −13.50	Negative	0.011 *
Use_Tablet: Yes	40.04	19.77, 60.32	Positive	<0.001 ***
P_ElectricCooker: Yes	32.14	12.51, 51.77	Positive	0.001 **
MoreUse_Dleisure: Yes	−32.13	−51.04, −13.22	Negative	<0.001 ***
MSE	5177.36			
RMSE	71.95			
Residual Standard Error	75.97			
R2	0.84			
R2 adjusted	0.82			
Overall significance	<0.001 ***			

Note: Significance codes: '***' 0.001 '**' 0.01 '*' 0.05. Ordered categorical levels [L, Q, C, ^4, ^5] were created by R Software to carry out the polynomial test.
Source: Own elaboration.

Impact column should be interpreted as a direct relationship between electricity consumption and these variables.

For multinomial variables—UseHeatingSystems, LightSystem, and TypeHouse—each category is displayed, and the result shown in the Impact column should be interpreted as the effect of the presence (positive impact) or absence (negative impact) of the category in question on electricity consumption. It can be seen that there is at least one category in these variables in which presence or absence is statistically relevant. In dichotomous categorical variables (e.g., Property, among others), the result displayed in the Impact column should be interpreted as the effect of the presence (positive impact) or absence (negative impact) of the reference category on electricity consumption.

For ordered categorical variables (see Table 1), R fits a series of polynomial functions or contrasts to the levels of the variable. The first is linear (.L), the second is quadratic (.Q), the third is cubic (.C), etc. R fits one fewer polynomial function than the number of available levels. The specific weight values themselves hold no real meaning since they are computed by R to make all predictors orthogonal, but their sign shows the effects on the electricity consumption of a trend through the different levels of the variable, recorded in the Impact column. For example, because predictors for "m2: 76–100 m2 (L)" and "m2: 101–125 m2 (Q)" are nonsignificant, a change from less than 76 to 76–100 m2 and from 76 to 100 to 101–125 m2 has no statistical effect on electricity consumption, but since predictors for "m2: 126–150 m2 (C)", "m2: 151–200 m2 (^4)", "m2: >200 m2 (^5)" are significant and negative, this suggests a reduction pattern in electricity consumption as there is an increase in surface (a move from a lower to an upper level of the variable).

In light of these results and their interactions, the mechanisms through which the variables exert an effect on electricity consumption are discussed in the following sections (4.2 Discussion and limitations of the study, and 5 Conclusions).

4.2. - Discussion and limitations of the study

4.2.1. Discussion

The results indicate that families and groups of cohabitants who spent the hard lockdown in semi-detached single-family homes registered lower electricity consumption. This expected consumption was 39 kWh lower than households in the reference category (flat or apartment in a building with 2–4 dwellings). Households in the other categories did not show significantly different electricity consumption behaviour. Single-family semi-detached houses tend to have open spaces where their inhabitants can compensate for mobility restrictions by engaging in recreational activities in these areas. The shorter time spent indoors may explain this lower electricity consumption.

The results show that there is a direct relationship between the liveable area and the income of the occupants. Of those who live in a semi-detached single-family home, 36% have an annual income of more than 40,000 €/year. This relationship may explain the more efficient equipment in larger dwellings, which enables lower electricity consumption. This is particularly the case from 126 m^2 of floor area upwards.

Home ownership seems to have a wealth effect on electricity consumption, with an expected increase of 53.9 kWh [65].

Contrary to what has been claimed in the literature, the model shows the influence of the number of bedrooms as an inhibitor of energy consumption. In line with the results related to dwelling type, when inhabitants of a dwelling had the possibility of engaging in recreational activities in spaces separate from the rest of the home during lockdown, this seems to have enabled lower electricity consumption.

The use of energy-saving light bulbs proves to be an effective energy-saving measure. Dwellings that did not use this lighting system showed a significantly higher average consumption, by 30.74 kWh.

The number of household members has a clear influence on electricity consumption. For each additional household member, the expected increase in energy consumption is 17.82 kWh.

Household energy consumption during a winter month is revealed as one of the key determinants that can explain energy consumption during lockdown. Each kWh consumed during the winter month corresponded to 0.82 kWh during the month of the strictest home confinement.

Among the occupants of the dwelling,there are very different profiles in terms of the use of leisure time. The results show that there is no clear evidence of a relationship between the intensity of use of electrical devices for leisure and energy consumption. Only those who registered an increase in consumption intensity of between 50 and 75% show some difference with respect to the rest. Surprisingly, those who perceived the greatest increase in their intensity of use of cooking devices showed lower consumption than those who saw a moderate or lesser increase of these devices during lockdown.

It is interesting to analyse the behaviour of households with different sensitivities to standards of indoor temperature comfort. Households who are more demanding when it comes to the standard of comfort (they turn on heating devices when the indoor temperature drops below 18 °C) consumed less energy than the less demanding ones (those who turn on the heating only when the indoor temperature drops below 15 °C). This result is consistent with households' knowledge of the consumption requirements of this type of equipment, as households with an indoor temperature comfort standard below 15 °C showed a higher use of heating devices with higher electricity consumption requirements (e.g. electric heaters). Households reduced their comfort standard during lockdown. A similar result was observed for households that turned on cooling devices from 30 °C and up. Again, it seems that they raised their tolerance threshold, as their expected consumption was lower by 23.9 kWh.

Households equipped with an electric cooker had higher electricity consumption than those without it.

Finally, the use of tablets for both study and leisure is found to be a driver of household electricity consumption [66]). Tablets and similar devices were used between 50 and 75% more for leisure by the largest group of respondents (39.9%), while within this same range 47.3% of respondents used them for studying. However, despite these increases in intensity of use, tablets were only used for studying by 27.7% of respondents. This is probably due to the fact that not all online tasks were prepared to be done with these devices and they were used in addition to another electrical device for studying, such as a laptop or desktop computer. The combination of face-to-face and online classes can contribute to a balanced use of electronic equipment. In this respect, the flipped classroom offers an interesting possibility for such a mix [67,68].

4.2.2. Limitations of the study

This study has some limitations in its design, mainly due to the surprise factor of the first lockdown. The first limitation is the small number of participants. The sample size was determined by our access to students that could be trained to ensure their correct understanding of the electricity bill and a proper understanding of the variables. Although this limitation has indeed produced a smaller sample than desirable, the sample was representative of the Andalusian reality (Section 3.2), and it is considered adequate for our statistical analysis. Also, data were self-reported and could not be directly verified. However, each questionnaire was checked for reliability. As a result, the variable Floors, which intuitively impacts electricity consumption, was eliminated from the analysis due to a lack of available and/or reliable data. In addition, 167 questionnaires with a lot of missing data and/or inconsistent answers were discarded. To avoid problems with self-reported data, experts could have directly read the electricity bill, but this would have given rise to privacy concerns. Also, better survey design could have prevented survey respondent burnout, leading to nonresponses or implausible responses.

In terms of the statistical analysis, nonlinearity in the regression model could be assumed using a neural network approach or another least-squares approach. Although this might yield better predictions, the influence of the variables, which is the main scope of this study, would be indirectly estimated through experimental methods that are not widely accepted. Nevertheless, it is difficult to isolate cause and effect in 15 significant variables, even in a linear model. An attempt has been made in this section and contrasted with the impact expected on the basis of the previous literature (Table 1).

Finally, it is important to point out Andalusia's distinctive socio-economic, cultural, climate and geographical characteristics, meaning the results cannot be directly extrapolated to other regions without further consideration. A comparison with other regions with different cultural customs and at different latitudes would help identify the mechanisms through which these variables influence electricity consumption.

5. - conclusions

This work advances the present state of knowledge by identifying the areas of action with the greatest impact on electricity consumption under lockdowns scenarios. The conclusions can help inform decision-making in areas where a substantial share of the workforce is working from home and students are using alternative learning modes such as flipped classrooms, as well as in potential scenarios that accentuated these trends.

A multiple linear regression model was built to identify drivers and inhibitors of electricity consumption in the residential sector in southern Spain during the home confinement associated with the SARS-CoV-2 pandemic. A total of 15 variables were validated as predictors of electricity consumption: two socio-economic predictors; four technical characteristics of the dwelling; six equipment predictors; two climate change behaviour variables and the household electricity consumption the previous winter.

From the results obtained, it can be concluded that the demand pressure on the electricity system is lower in residential areas where there is an abundance of single-family dwellings. The expected consumption was 39 kWh lower than flat or apartment in a building with 2–4 dwellings. Our first policy recommendation therefore concerns the urban planning of residential areas to promote this type of building, which, as well as helping to reduce electricity consumption, can also be more easily adapted for effective decarbonization and the introduction of renewable elements and alternative energy sources (e.g. photovoltaic self-consumption and storage).

On the other hand, when it comes to flats or apartments, it is recommended the introduction of subsidies and the universalization of existing to improve energy efficiency. Concrete measures such as replacing fossil fuel electricity generation with renewable thermal energy or photovoltaics, as well as the digital monitoring of energy consumption in buildings.

Furthermore, our results show the importance of having household equipment that improves the efficiency of electricity consumption. However, achieving the widespread use of such equipment would require a huge drop in prices brought about either through direct subsidies or tax incentives. The literature suggests that subsidies are more effective, although both measures would require appropriate communication and publicity policies. The latter suggestion is quite important as our results reveal considerable misunderstanding among citizens concerning the political measures in force to promote energy-saving. Since the results show that the wealth effect associated with home ownership is a driver of electricity consumption, increasing the expected energy consumption by 53.9 kWh, the awareness-raising campaigns should particularly target homeowners.

Additionally, the results show that households are well informed about the electricity consumption of their cooling and heating equipment, allowing them to reduce their standard of comfort so as not to increase their consumption despite spending more time in the dwelling due to lockdown. The good outcomes for LED lights show that bulb replacement policies have contributed to reducing household electricity consumption. Dwellings that did not use LED lights showed a significantly higher average consumption, by 30.74 kWh. The data from the survey show that there is scope for similar success with the installation of thermal insulated windows in dwellings, as over 65% of the households surveyed did not have this system in place. More government assistance is recommended to encourage the retrofitting of households and to facilitate the transition to full energy-efficient lighting and effective external insulation of dwellings.

The increased leisure (cooking or using of small electronic devices) time associated with the lockdown period does not translate into higher electricity consumption; on the contrary, it proves to be an inhibitor. In households where lockdown increased cooking time by more than 50% relative to the situation where they were not confined to their homes, electricity consumption was lower compared to households that did not increase cooking time. At the same time, the increased use of small electronic devices for leisure (50–75% more than in the pre-lockdown situation) has an impact in terms of lower electricity consumption. As such, more teleworking and e-learning could even be expected to reduce total electricity consumption in the residential sector.

Finally, the conclusion most directly related to student behaviour and the intensive use of e-learning is the positive impact of tablet use on electricity consumption. On average, using a tablet to study increases consumption by 40 kWh. The related recommendation that can be made is to design educational activities that can be done on a desktop PC or smartphone.

Future research should focus on checking the progress of energy saving and energy efficiency measures in households, especially those with intensive daily teleworking and e-learning, while comparing the differences with the results obtained from a similar analysis in other European regions/countries with different socio-economic, cultural, climate and geographical characteristics.

Credit author statement

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Declaration of competing interest

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

Data availability

Data will be made available on request.

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Annex 1

Table A.1
Systematic literature review on determinants of energy consumption in the residential sector.

Socio-economic determinants	
Number of residents in the household	[11–13,16–23,25,27,34,36,38,41,69–72,74]
Composition of the family or group of cohabitants	[10,13–15,21,24,26,30–32,40,41,69,75,76]
Family members	[10,11,13,15–19,21,22,25,30,31,69,73]
Level of education	[11,17,19–21,40,41,73]
Income and work activity of family members	[11,12,20–22,26]
Technical characteristics of the dwelling	
Liveable area	[11,16,18,19,23,24,26,28,32,36,38,41,69,73]
Dwelling type	[11,12,16–18,21,23–25,30,31,33,69,73]
Number of rooms	[12,17,21,25,27,28]
Number of bedrooms	[12,23,24,28–31,73]
Age of the dwelling	[12,17,21,23,24,32,69,73]
Tenure status	[11–13,15,18,19,21,23,24,31,33,38,73]
Presence of air-conditioning and heating systems	[12,14,16,17,19,21,25–27,32,34–38,41,72,73,77]
Equipment	
Household appliances	[10,13,21,23,25,27,34,78]
Entertainment devices	[11,13–16,21,25–27,30,31,37]
Appliances for cooking	[9,13,14,16,17,19,21,27,30,32,38]
Appliances for food preservation	[10,12–14,16,17,19,21,26,27,30,31,36,37,41]
Equipment for heating, comfort and laundry	[10,11,13–17,19,26,27,29–31,36,37,39,73]
Small electronic devices in energy consumption	[10,13–15,19,26–28,30,31,35,40,41]
Climate	
Heating and cooling systems	[11,19]

Source: Own elaboration.

Annex 2

Nomenclature

AIC Akaike Information Criterion
BIC Bayesian Information Criterion
ERTE Temporary layoff scheme
EU European Union
GHG Greenhouse gas
kWh kilowatt hours
LED Light-emitting diode
Mtoe million tonnes of oil equivalent
MLR Multiple linear regression
PVPC Voluntary pricing for small consumers
RMSE Root mean square error
SARS Severe acute respiratory syndrome
SARS-CoV-2 Severe acute respiratory syndrome coronavirus 2
MERS-CoV Middle East Respiratory Syndrome coronavirus

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.energy.2022.125467.

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