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KEYWORDS

Nudge interventions | Electricity consumption | Pro-environmental behavior | Randomized controlled trial

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C93, D12, D91

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This report presents the scientific activities carried out for the implementation of the field experiment within the BAC project "Riduzione delle emissioni da consumo elettrico attraverso interventi comportamentali personalizzati: uno studio controllato e randomizzato sul campo (TAILNUD)", BAC, PE GRINS – "GRINS – Growing Resilient, Inclusive, and Sustainable" (project code PE0000018, CUP: C93C22005270001), Spoke 6. The report aims to situate the experimental study's research question within the relevant literature, present the pre-registered testable predictions, describe the study plan, the experimental design and the resulting datasets uploaded on AMELIA, and outline the initial and preliminary statistical analysis conducted on the data.

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The “TAILNUD” project: A Scientific Report on the Study Plan and the Datasets Uploaded on AMELIA

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Abstract. This report presents the scientific activities carried out for the implementation of the field experiment within the BAC project *“Riduzione delle emissioni da consumo elettrico attraverso interventi comportamentali personalizzati: uno studio controllato e randomizzato sul campo (TAILNUD)”*, BAC, PE GRINS – *“GRINS – Growing Resilient, Inclusive, and Sustainable”* (project code PE0000018, CUP: C93C22005270001), Spoke 6. The report aims to situate the experimental study’s research question within the relevant literature, present the pre-registered testable predictions, describe the study plan, the experimental design and the resulting datasets uploaded on AMELIA, and outline the initial and preliminary statistical analysis conducted on the data.

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1. Introduction

Residential electricity consumption represents a significant share of global CO_2 emissions and an increasingly important challenge for electricity systems as electrification expands. The widespread diffusion of electric heat pumps, air-conditioning, and electric vehicles is raising residential loads and increasing the frequency of local peak-demand events. These trends amplify the need for effective demand-side management strategies capable of reducing emissions and improving grid stability. While economic incentives — such as time-of-use pricing or rebates — remain fundamental policy tools, a substantial share of household electricity use depends on behavioral routines that can at least in principle be modified through low-cost informational interventions. Understanding how to design such interventions effectively, and for whom they work best, is therefore a central question for both researchers and policymakers.

Over the past fifteen years, behavioral interventions have become a core component of energy-efficiency programs. A large body of evidence shows that households respond to social comparisons, feedback, reminders, and framing cues, often reducing electricity use by 1–4% on average (Karlin et al., 2015, Nisa et al., 2019). Yet these averages conceal wide heterogeneity: some users respond strongly while many others hardly react. This heterogeneity reflects differences in habits, technological constraints, daily routines, environmental preferences, and sensitivity to financial savings. As highlighted in Atzori et al. (2025), consumption patterns themselves also exhibit high variability: households differ markedly in their volatility, daily peak timing, and responsiveness to external signals. These insights motivate the idea that *personalized* interventions that are aligned with the specific motivations and consumption patterns of users may outperform generic, one-size-fits-all approaches. In this context, the increasing availability of smart-meter data offers an unprecedented opportunity to design more targeted behavioral strategies.

This paper presents the results of a field experiment where we combine high-frequency energy consumption data, granular information on individual attitudes and behavioral interventions that are tailored to these attitudes.. In collaboration with Koala, a company managing energy communities in Southern Italy, we conducted a large-scale randomized controlled trial involving more than 3,100 households equipped with smart meters and linked survey data. Participants received a series of messages via WhatsApp containing concrete tips on how to reduce daily electricity use. The content of the tips was held constant, while the *framing* of the message varied across three conditions: an environmental frame emphasizing ecological benefits, an economic frame highlighting potential monetary savings, and a neutral frame presenting the information without motivational emphasis. A fourth group served as a pure control, receiving no messages. This design allows us to evaluate not only the average effectiveness of informational nudges but also the comparative performance of frames that appeal to different behavioral motivations.

A key feature of the experiment is the integration of behavioral indicators collected prior to treatment. In particular, we collect data that allow us to classify participants according to their environmental sensitivity and monetary orientation. This enables a direct test of the “match hypothesis”: whether messages are more effective when their framing aligns with the user’s intrinsic preferences (e.g., environmental messages for environmentally oriented users). Prior literature suggests that such alignment should strengthen motivation and reduce psychological reactance, yet empirical tests remain scarce in the context of energy consumption.

The study contributes to the literature and policy debate in two main ways. First, it provides causal evidence on the effectiveness of message framing using high-frequency consumption data, allowing for precise identification of treatment effects. Second, it evaluates the impact of *tailored* behavioral interventions, an area where empirical evidence remains limited despite growing theoretical attention. The high-frequency data allows to evaluate not only if a certain message is effective, but also at when exactly it is effective during the day, allowing for inference on peak-use effects of the interventions. The hypotheses were pre-registered and the pre-registration can be found at: https://osf.io/7qgex.

The results show that the interventions have no significant effect on energy consumption. This holds both when looking during the period of the intervention and in theone that immediately follows. The interventions also show non-significant interactions with the individual attitudes toward money and the environment. Similarly null effects are reproduced throughout the hours of the day. Overall our results highlight the limits of behavioral interventions to reduce electricity demand. We study a context where electricity demand is already low by western standards and where prices had increased substantially in the three years prior to the experiment. Such a situation is unfavorable to behavioral interventions as the room for further increasing demand without substantially changing one's habits is limited.

The paper proceeds as follows. Section 2 locates our contribution in the related literature. Section 3 presents the experimental design and implementation details. Section 4 presents the empirical strategy and the results. Section 5 discusses the results and possible future research pathways.

2. Related Literature

Behavioral approaches to reducing residential energy consumption have received extensive attention in recent years, complementing traditional economic instruments. Early large-scale randomized controlled trials, such as the Opower Home Energy Reports, demonstrated that providing households with social-comparison feedback and conservation tips leads to persistent reductions in consumption of approximately 1.5–3% (Allcott, 2011, Allcott and Rogers, 2014). Subsequent replications across different countries confirm that informational nudges can promote energy savings even in the absence of monetary incentives (Karlin et al., 2015, Andor and Fels, 2018, Nisa et al., 2019). Meta-analyses summarizing more than one hundred experimental studies report average reductions of 2–4%, while highlighting substantial heterogeneity in effect sizes across contexts, households, and intervention types (Mertens et al. 2022). This heterogeneity has important welfare implications: Allcott and Kessler (2019) show that the welfare gains from informational treatments could almost double if reports were targeted to the most responsive users instead of being sent uniformly.

A growing literature examines sources of heterogeneity in responsiveness to behavioral interventions. Ideological orientation, environmental preferences, and sensitivity to financial savings influence how households respond to different types of messages. For example, Costa and Kahn (2013) find that politically conservative households reduce consumption less in response to social-comparison reports, while Tiefenbeck et al. (2018) show that real-time feedback and timely, action-oriented tips induce stronger reductions among environmentally motivated users. The broader psychological literature similarly emphasizes that the effectiveness of behavioral interventions depends on addressing the specific determinants of behavior Van Valkengoed et al. (2022). These findings have motivated increasing interest in *tailored* interventions, where the content or framing of the message is adapted to the recipient's characteristics or preferences.

Parallel developments in energy data availability and machine-learning techniques have enabled increasingly sophisticated segmentation of households. Many studies use smart-meter data to identify distinct usage profiles based on daily load shapes, volatility, or seasonal patterns. For instance, Räsänen et al. (2008) use Self-Organizing Maps (SOM) and K-means to classify Finnish households into consumption profiles and to inform personalized feedback strategies. Liu et al. (2012) apply a similar approach to detect four distinct user profiles with implications for tariff design, while McLoughlin et al. (2015) compare clustering algorithms and link cluster membership to socio-demographic characteristics. More recent work introduces hybrid machine-learning approaches that combine SOM with deep-learning or genetic algorithms to improve classification accuracy and prediction of load profiles (Majidi and Smith, 2023, Abdelaziz et al., 2024). Reviews such as Michalakopoulos et al. (2024) provide comprehensive overviews of clustering methods applied to residential electricity data. These studies collectively underscore the potential of segmentation for designing targeted behavioral and demand-response interventions.

Atzori et al. (2025) contributes to this literature by proposing a robust clustering methodology that combines a discrete wavelet transformation with SOM and K-means. It focuses on *changes* in consumption (volatility), rather than levels, which helps address the scale-invariant nature of electricity use and provides behaviorally meaningful clusters. The clusters identified reflect recurring usage patterns and correlates such as heating technology, dwelling characteristics, and tariff structures.

However, segmentation alone does not establish whether tailored strategies outperform generic ones. Evidence directly testing this hypothesis remains limited. Some studies find that aligning message framing with individual motivations increases effectiveness, while mismatched frames can reduce engagement or even backfire; yet empirical results remain mixed and context-dependent. Thus, field experiments explicitly testing tailored interventions remain crucial for clarifying the mechanisms through which behavioral messages operate.

This paper contributes to this research agenda by combining household segmentation, motivational profiling, and a randomized controlled trial. By testing the effectiveness of environmental, economic, and neutral message framings — and by measuring individual sensitivity to environmental and financial motives prior to treatment — the study provides rare causal evidence on whether tailored messaging improves energy-saving outcomes. Moreover, the setting of energy communities represents a novel and policy-relevant context, as these groups are expected to play an increasing role in decentralized generation, peer-to-peer trading, and community-based demand-response programs.

3. Experimental design

In this section, we describe all the activities carried out within the TAILNUD project during the period from May to November 2025, which led to the collection of the datasets uploaded to AMELIA. This detailed account also helps users understand the structure and composition of the datasets now publicly available on the platform.

The figure below provides a graphical representation of the study plan timeline.

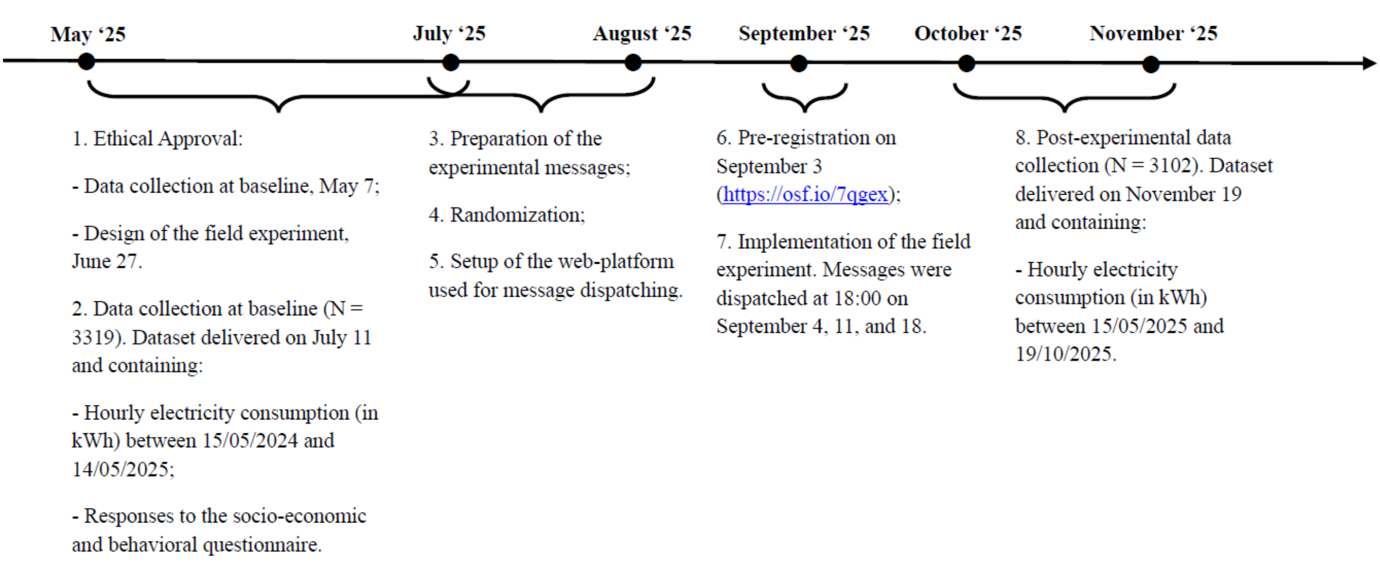

Figure 1. The timeline of the study plan within the TAILNUD project

Ethical approval. The study received approval from the Ethics Committee of the University of Milan-Bicocca on April 30, 2025 (document n. 0189703, transmitted on May 6, 2025) for the distribution of the questionnaire through Koala. Approval for the amendment extending the scope to the field experiment was granted on June 25, 2025 (n. 0295118, transmitted on July 2, 2025).

Data collection at baseline. Between May and July 2025, we worked closely with our partner company, Koala S.r.l. SB, to conduct the baseline data collection. The entire procedure was carried out through a dedicated web platform owned and managed by Koala.

Upon registering on the platform, participants were first presented with an informed consent form (see Appendix A1) describing the study and the data collection procedures. The form also informed them that their identities would remain anonymous throughout all phases of the study, and that their anonymized data would be uploaded to AMELIA. Participants were required to explicitly provide consent before proceeding.

After completing the consent form, participants entered a screen instructing them to complete two tasks. First, they were asked to provide their electricity consumption data for the previous 18 months by independently downloading them from either ARERA’s “Portale dei Consumi” or from the websites of their respective Distribution System Operators (DSOs), in standard XML or CSV format, following Koala’s operational instructions.

Second, they were asked to complete an online socio-economic and behavioral questionnaire consisting of 20 sequential questions presented across five screens, with no possibility to revise answers provided on previous screens. The full list of questionnaire items is provided in Appendix A2. The questions were selected by screening relevant sources, specifically:

i. **Sociodemographic questions:** *Residential Energy Consumption Survey (RECS) 2024 Household Survey Questionnaire*;

ii. **Environmental attitudes:** PEBS Scale, as discussed in Menardo et al. (2020), Markle (2013), and Larson et al. (2015);

iii. **Habits:** Lavelle (2015);

iv. **Money attitudes:** Klontz et al. (2011) and Ertz et al. (2016).

Koala matched the electricity consumption data with the questionnaire responses and prepared anonymized datasets for transfer to our research team. The IT procedures implemented by Koala ensured full anonymity. At all stages of the research, the link between questionnaire responses, consumption data, and personal information was obscured by the platform and inaccessible to any third party, including the platform operator. This allowed the datasets to be matched without enabling either Koala or the researchers to identify participants. Koala ensured that all data collection and transfer procedures were fully GDPR-compliant and aligned with the GRINS personal data processing guidelines.

On July 11, 2025, we received hourly electricity consumption data from 3,319 households in Campania (15/05/2024–14/05/2025), along with socio-economic variables and survey responses. These data were used for randomization and baseline consumption analysis.

Two CSV datasets were produced during this phase of the study and uploaded to AMELIA for public access (subject to a formal request to the authors):

- **split_file_1, split_file_2, split_file_3** – hourly electricity consumption data for 3,319 users (15/05/2024–14/05/2025);

- **socio_dem** – socio-demographic, economic, housing, attitudinal, and behavioral data, including environmental attitudes (PEBS scale) and respondents' willingness to pay or reduce comfort for sustainability.

Experimental conditions. The experiment was designed to test the effects of sending different types of messages on electricity consumption savings, as well as to assess how these effects interact with behavioral dimensions elicited in the initial questionnaire. Specifically, we employed three types of messages (see Appendix for the full transcripts):

- **Neutral messages (T_neu)**: These messages simply highlighted the possibility of reducing electricity consumption by following simple tips.

- **Environmental messages (T_env)**: These messages emphasized the potential pro-environmental consequences of reducing electricity consumption by following simple tips.

- **Economic messages (T_econ)**: These messages focused on the positive economic consequences—expressed in terms of monetary savings—associated with reducing electricity consumption by following simple tips.

For each of the three treatments described above, we developed a set of four distinct messages. The first message included a logo image corresponding to the treatment, a brief description of the study, a statement informing participants that they would receive tips in the near future that could potentially help them reduce electricity consumption by 1 kWh per day, and, for T_env and T_econ, information on how such savings would translate into environmental benefits or monetary gains, respectively. The second message, sent together with the first, contained the first set of four tips and reiterated the potential treatment-specific consequences. The third and fourth messages, sent in the following two weeks, each contained an additional set of four tips along with reminders of the corresponding potential consequences.

In addition to these treatments, we included a control group (**Control**) in which participants did not receive any messages throughout the entire experiment.

The messages were sent through an automated system integrating the Koala's proprietary web-platform with the WhatsApp Business API, which made it possible to centrally and systematically manage the distribution of messages to the different user groups.

Randomization. We leveraged the initial data collection to randomly assign participants to treatments using stratified randomization based on the following variables:

- the province in which the participant's dwelling was located (either Avellino, Benevento, or Naples);

- whether the participant scored above or below the median of an environmental attitude index, computed as the simple average of responses to the environmental attitude questions in the questionnaire. In this respect, we relied on the Pro-Environmental Behaviors Scale (PEBS), adapted to the Italian context by Menardo et al. (2020), focusing exclusively on the "Conservation" dimension. Participants responded on a 5-point Likert scale, and the index was computed as the arithmetic mean of the items included in this subscale (specifically, questions 15.1, 15.2, 15.3, and 15.4 in the socio-economic and behavioral questionnaire; see Appendix A.2);
- whether the participant scored above or below the median of a money attitude index, computed as the simple average of responses to the economic/monetary attitude questions. Similarly, to measure attitudes toward money, we employed the "Money Worship" factor from the Klontz-Money Script Inventory (Klontz et al., 2011). Responses were provided on a 6-point Likert scale, and the corresponding index was calculated as the arithmetic mean of the relevant items (questions 20.1, 20.2, 20.3, 20.4, 20.5, 20.6, 20.7, 20.8, 20.9, 20.10).

As a robustness check, we also conducted a confirmatory principal component analysis for both the environmental and economic attitude measures, which yielded identical results.

Randomization assigned 829 subjects to the control group, 829 to *T_neu*, 830 to *T_env*, and 831 to *T_econ*. As shown in Table 1, the treatment groups resulting from the randomization were well balanced not only with respect to the stratification variables, but also across several other important characteristics: whether the dwelling was equipped with a heat pump, an air conditioning system, or an electric water heater; whether the participant belonged to an Energy Community; annual income; full-time versus part-time employment status; the number of household occupants; whether the subject lived in an apartment rather than a house; and whether the subject owned the dwelling rather than rented it.

Table 1. Balancement checks of the sub-populations assigned to the four experimental treatments.

	Naples	Benevento	Avellino	Above the median of the environmental attitude index	Above the median of the money attitude index	Heat pump	Air conditioner	Electric water heating	Energy community	Annual income	Full-time job	Part-time job	Number of household occupants	Owner	Apartment
T_neu	.001	$-3.77e^{-16}$	-.001	.001	-.001	-.007	.007	-.016	.001	.058	.022	-.031	.051	.013	.040
	(.012)	(.024)	(.025)	(.025)	(.024)	(.013)	(.025)	(.021)	(.018)	(.090)	(.024)	(.024)	(.061)	(.025)	(.024)
T_env	.001	-.001	-.001	.002	-.002	-.006	-.025	.012	.025	-.092	-.001	.006	-.035	.009	$.042^{*}$
	(.012)	(.024)	(.025)	(.024)	(.024)	(.013)	(.025)	(.021)	(.018)	(.090)	(.024)	(.024)	(.061)	(.025)	(.024)
T_econ	$-1.394e^{-4}$	$1.176e^{-4}$	$2.18e^{-5}$	.001	$1.408e^{-4}$	.003	.002	.020	-.026	.129	-.020	-.008	.023	.002	.022
	(.012)	(.024)	(.025)	(.024)	(.024)	(.013)	(.025)	(.021)	(.018)	(.090)	(.024)	(.024)	(.061)	(.025)	(.024)
Constant	$.058^{***}$	$.451^{***}$	$.491^{***}$	$.462^{***}$	$.441^{***}$	$.076^{***}$	$.484^{***}$	$.739^{***}$	$.154^{***}$	3.075^{***}	$.426^{***}$	$.393^{***}$	2.830^{***}	$.485^{***}$	$.390^{***}$
	(.008)	(.017)	(.017)	(.017)	(.017)	(.009)	(.017)	(.015)	(.013)	(.064)	(.0172)	(.017)	(.043)	(.017)	(.017)
N.	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319	3319
F-test	0.01	0.00	0.00	0.00	0.00	0.31	0.68	1.05	2.74	2.16	1.00	0.93	0.71	0.12	1.29
p>F-test	0.999	1.000	1.000	1.000	1.000	0.817	0.567	0.368	0.042	0.091	0.393	0.428	0.544	0.947	0.278

Notes. This table reports estimates (standard errors in parentheses) from OLS models. T_neu, T_env, and T_econ are treatment dummies (the reference is the baseline group of subjects who did not receive any message during the experiment). Naples, Benevento, Avellino, Above the median of the environmental attitude index, Above the median of the money attitude index, Heat pump, Air conditioner, Electric water heating, Energy community, Full-time job, Part-time job, Owner, and Apartment are dummies assuming a value of 1 when the variable label applies for the subject and 0 otherwise. Number of household occupants is the number of household occupants from 1 to 6 (with 6 indicating “six or more occupants”). Annual income is a categorical variable indicating the household’s yearly income, ranging from 1 (“up to 15,000 euros”) to 7 (“more than 150,000 euros”). Significance levels: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Pre-registered hypotheses. The following hypotheses were pre-registered on OSF (https://osf.io/7qgex) on September 3, 2025, the day before the first block of messages was sent to participants:

H1: Informational treatments (environmental, economic, neutral) lead to greater reductions in energy consumption relative to the control group (T_all > Control).

H2: Environmental framing leads to a greater reduction in energy consumption than the neutral message, which in turn outperforms the control (T_env > T_neu > Control).

H3: Economic framing leads to a greater reduction in energy consumption than the neutral message, which in turn outperforms the control (T_econ > T_neu > Control).

H4: The treatment effect is stronger when the message framing matches the individual's sensitivity (i.e., a positive Treatment × Sensitivity_match interaction), compared to cases of mismatch.

H4.1: This pattern is expected to hold both when considering overall match/mismatch and when examining specific types of sensitivity (environmental or economic) separately.

Implementation of the field experiment. The field experiment took place over the first three weeks of September 2025. Messages were sent at 18:00 on September 4, 11, and 18. Koala continuously monitored procedures and delivered a detailed implementation report at the end of the experiment.

Post-experimental data collection. On November 19, 2025, Koala delivered the final post-experimental dataset including hourly consumption records (15/05/2025–19/10/2025) for 3,102 households, along with complete attrition information. The dataset was assembled via the same proprietary web platform.

Seven CSV datasets were produced during the last phase of the study and uploaded to AMELIA for public access (subject to a formal request to the authors):

1. **k_energy_part_1, k_energy_part_2, k_energy_part_3, k_energy_part_4, k_energy_part_5, k_energy_part_6** – post-experimental hourly consumption data for 3,102 households.
2. **energy_attrition** – attrition dataset comparing the initial 3,319 households with the final 3,102.

The relatively low attrition rate resulted from the promotional activities carried out by Koala together with its partner company, ART S.r.l. – Centro Ricerche, to incentivize participants' engagement in the study. At the start of the first data collection phase, participants were informed that by completing all stages of the study they would be eligible to enter a lottery offering several prizes in the form of Amazon Gift Cards and other promotional items.

4. Results

4.1 Empirical strategy

Data Selection and Time Windows. We selected hourly electricity consumption data for two comparable periods across 2024 and 2025. Specifically, we defined three distinct time windows around the experimental intervention period (September 4-18):

- **PRE period**: August 28 – September 3 (7 days before treatment onset)
- **EXP period**: September 4 – September 18 (during treatment exposure)
- **POST period**: September 19 – September 25 (7 days after treatment conclusion)

This temporal structure allows us to examine treatment effects in the immediate post-intervention period while using the pre-treatment period as a baseline comparison. The 2024 data serve as a placebo test, as no intervention was administered in that year.

Econometric Framework: Panel Random Effects Model, Given the panel structure of our data, repeated hourly observations for each individual, we employed a panel random effects model. This specification accounts for unobserved individual heterogeneity while allowing treatment effects to be estimated across the population.

The baseline random effects model can be expressed as:

$$y_{it} = \alpha + X_{it}\beta + u_i + \varepsilon_{it}$$

where: - y_{it} denotes electricity consumption (kWh) for individual i at time t, X_{it} represents a vector of explanatory variables (treatment indicators and covariates) , u_i captures time-invariant individual-specific effects (random effects) and ε_{it} is the idiosyncratic error term

The random effects specification assumes $u_i \sim N\left(0, \sigma_u^2\right)$ and $\varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right)$, with u_i uncorrelated with the regressors. Standard errors are clustered at the individual level to account for serial correlation within individuals.

Direct Treatment Effect Estimation (POST Period Only). Our primary analysis focuses on the POST period, where we expect treatment effects to manifest. We estimated a sequence of increasingly saturated models:

Model (a) – Treatment Effects Only:

$$y_{it} = \alpha + \beta_1 T_{env,i} + \beta_2 T_{econ,i} + \beta_3 T_{neu,i} + u_i + \varepsilon_{it}$$

where T_{env}, T_{econ}, and T_{neu} are dummy variables indicating assignment to the environmental, economic, and neutral treatment arms, respectively. The Control group serves as the reference category. The coefficients β_1, β_2, and β_3 represent the average treatment effects relative to Control.

Model (b) – With Sociodemographic Controls:

$$y_{it} = \alpha + T_i\beta + Z_i\gamma + u_i + \varepsilon_{it}$$

where Z_i includes individual-level covariates: household size, presence of air conditioning, heat pump, electric water heating, energy community membership, apartment dwelling, part-time employment status, and province indicators (Naples, Benevento, being Avellino the reference category).

Model (c) – With Behavioral Mechanisms:

$$y_{it} = \alpha + T_i\beta + Z_i\gamma + M_i\delta + \left(T_i \times M_i\right)\theta + u_i + \varepsilon_{it}$$

We introduce two mechanism variables derived from the baseline questionnaire:

a. **above_m_env**: Binary indicator equal to 1 if the individual's Pro-Environmental Behavior Scale (PEBS) score exceeds the sample median, capturing environmental attitudes and propensity for sustainable behaviors.
b. **above_m_money**: Binary indicator equal to 1 if the individual's money consciousness index exceeds the sample median, measuring sensitivity to financial considerations and saving propensity.

The interaction terms $\left(T_i \times M_i\right)$ allow treatment effects to vary by these behavioral predispositions. A significant interaction coefficient indicates treatment effect heterogeneity: for instance, a negative coefficient on $T_{env} \times$ *above_m_env* would suggest that environmentally-framed messages are particularly effective among individuals with stronger pro-environmental attitudes.

For validation purposes, we replicated the same model specifications on:

- **PRE period data**: As a placebo test, we expect null treatment effects since observations precede the intervention. Significant coefficients in this period would indicate pre-existing differences between treatment groups, potentially threatening internal validity.

- **EXP period data**: To examine immediate behavioral responses during active treatment exposure.

ANCOVA-Style Specification (PRE + POST Combined)

To increase statistical power and control for baseline consumption patterns, we estimated an ANCOVA model pooling PRE and POST observations:

$$y_{it} = \alpha + \beta_{POST} POST_t + T_i\beta + \left(POST_t \times T_i\right)\phi + u_i + \varepsilon_{it}$$

where: - $POST_t$ is a dummy variable equal to 1 for observations in the POST period and 0 for PRE period observations - The coefficients β on treatment indicators capture baseline (PRE) differences between treatment groups - The interaction terms $\left(POST_t \times T_i\right)$ represent the **difference-in-differences** estimator: the change in consumption from PRE to POST for each treatment group relative to the Control group

Interpretation of coefficients: - β_{POST}: Average change in consumption from PRE to POST for the Control group - $\phi_{T_{env}}$ (coefficient on $POST \times T_{env}$): Additional change for the environmental treatment group beyond the Control group's change, i.e., the causal treatment effect under parallel trends assumption.

Model with Triple Interactions: To examine whether treatment effect heterogeneity by behavioral mechanisms emerges specifically in the post-treatment period, we estimated:

$$y_{it} = \alpha + \beta_{POST} POST_t + T_i\beta + \left(POST_t \times T_i\right)\phi + M_i\delta + \left(T_i \times M_i\right)\theta + \left(POST_t \times T_i \times M_i\right)\psi + u_i + \varepsilon_{it}$$

The triple interaction coefficients ψ test whether the moderation effect of behavioral mechanisms (environmental attitude and money attitude indices) on treatment efficacy is specific to the post-intervention period. A significant coefficient on $POST \times T_{env} \times$ *above_m_env* indicates that the differential treatment effect for environmentally-conscious individuals emerges only after treatment exposure, rather than reflecting pre-existing heterogeneity.

4.2 Results

Tables 2 and 3 present the estimation results across all model specifications for the POST, PRE, EXP periods and the combined PRE+POST analysis, respectively, while Table 4 summarizes the coefficient interpretations.

Table 2. Preliminary results. PRE, POST and EXP regressions.

	Model								
	PRE (a)	PRE (b)	PRE (c)	EXP (a)	EXP (b)	EXP (c)	POST (a)	POST (b)	POST (c)
Constant	0.312***	0.213***	0.214***	0.312***	0.212***	0.204***	0.326***	0.231***	0.227***
	(0.005)	(0.010)	(0.011)	(0.004)	(0.008)	(0.009)	(0.004)	(0.008)	(0.009)
T_env	0.006	0.008	0.013	0.005	0.007	0.017*	0.001	0.003	0.012
	(0.007)	(0.007)	(0.011)	(0.006)	(0.005)	(0.009)	(0.006)	(0.005)	(0.010)
T_econ	-0.001	-0.002	-0.004	0.003	0.002	0.009	-0.003	-0.003	0.0003
	(0.007)	(0.006)	(0.010)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.009)
T_neu	-0.001	-0.003	0.006	0.003	0.002	0.017**	-0.001	-0.002	0.011
	(0.007)	(0.006)	(0.010)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)
above_m_env			-0.009			0.013*			0.002
			(0.009)			(0.007)			(0.007)
above_m_money			0.006			0.004			0.006
			(0.009)			(0.007)			(0.007)
T_env x above_m_env			0.014			-0.005			0.001
			(0.013)			(0.011)			(0.011)
T_econ x above_m_env			0.018			-0.001			0.006
			(0.012)			(0.010)			(0.010)
T_neu x above_m_env			0.001			-0.020**			-0.012
			(0.013)			(0.010)			(0.010)
T_env x above_m_money			-0.027**			-0.017			-0.022**
			(0.013)			(0.010)			(0.011)
T_econ x above_m_money			-0.016			-0.015			-0.015
			(0.012)			(0.010)			(0.010)
T_neu x above_m_money			-0.021*			-0.012			-0.018*
			(0.013)			(0.010)			(0.010)
Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Obs.	521136	521136	521136	1116720	1116720	1116720	521136	521136	521136
N.	3102	3102	3102	3102	3102	3102	3102	3102	3102

Notes. This table reports GLS random effect models (standard errors in parentheses). Reference categories: Control (treatment). Negative coefficients indicate consumption reduction relative to the reference category. T_econ, T_env, and T_neu are treatment dummies. above_m_env is a dummy that takes a value of 1 if the subject's environmental attitude index is above the median in the population. above_m_money is a dummy that takes a value of 1 if the subject's money attitude index is above the median in the population. T_env x above_m_env, T_econ x above_m_env, T_neu x above_m_env, T_env x above_m_money, T_econ x above_m_money, T_neu x above_m_money are interaction terms. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Preliminary results. Regressions on PRE and POST periods.

	Model		
Variable	PRE POST (a)	PRE POST (b)	PRE POST (c)
Constant	0.312***	0.312***	0.312***
	(0.005)	(0.007)	(0.007)
T_env	0.006	0.015	0.016
	(0.007)	(0.011)	(0.011)

T econ	-0.001	0.003	0.003
	(0.007)	(0.010)	(0.011)
T neu	-0.001	0.016	0.012
	(0.007)	(0.010)	(0.010)
POST	0.013***	0.013***	0.013***
	(0.004)	(0.004)	(0.004)
POST T env	-0.005	-0.005	-0.007
	(0.006)	(0.006)	(0.008)
POST T econ	-0.002	-0.002	-0.002
	(0.006)	(0.006)	(0.008)
POST T neu	-0.000	-0.000	-0.001
	(0.006)	(0.006)	(0.008)
above_m_env		-0.002	-0.002
		(0.007)	(0.007)
above_m_money		0.004	0.004
		(0.007)	(0.007)
T env x above m env		0.005	0.005
		(0.011)	(0.013)
T econ x above m env		0.008	0.008
		(0.010)	(0.012)
T neu x above m env		-0.007	-0.007
		(0.011)	(0.012)
T env x above m money		-0.025**	-0.028**
		(0.011)	(0.012)
T econ x above m money		-0.017	-0.017
		(0.010)	(0.012)
T neu x above m money		-0.021**	-0.023*
		(0.011)	(0.012)
POST x T env x above m env			-0.001
			(0.008)
POST x T econ x above m env			-0.000
			(0.008)
POST x T neu x above m env			-0.002
			(0.008)
POST x T env x above m money			0.005
			(0.008)
POST x T econ x above m money			0.002
			(0.009)
POST x T neu x above m money			0.004
			(0.008)
Obs.	1042272	1042272	1042272
N. subjects	3102	3102	3102

Notes. Same remarks of Table 2 apply.

Table 4. Coefficient Interpretation Guide

Coefficient	Interpretation
T_{env}	Average consumption difference between Environmental treatment and Control
$POST$	Change in consumption from PRE to POST for Control group
$POST\times T_{env}$	Difference-in-differences: treatment effect of Environmental arm
$above\_m\_env$	Consumption difference for subjects with high- vs. low- environmental attitude
$T_{env} \times above\_m\_env$	Treatment effect heterogeneity: additional effect for subjects with high environmental attitude
$POST\ \times T_{env} \times above\_m\_env$	Whether the heterogeneous treatment effect emerges post-intervention

Our analysis reveals that none of the treatment coefficients achieve conventional levels of statistical significance across model specifications. This pattern holds consistently for the POST period analysis, the ANCOVA-style PRE+POST specification, and persists regardless of the inclusion of sociodemographic controls or behavioral mechanism interactions. The estimated treatment effects are not only statistically insignificant but also substantively small in magnitude.

Several theoretical and contextual factors may account for these null findings.

Treatment Salience. The informational treatments delivered through messaging may have lacked sufficient salience to induce measurable behavioral change. Energy consumption decisions are often habitual and automatic, requiring substantial cognitive engagement to override established patterns. Brief informational interventions, even when well-designed, may fail to penetrate the behavioral inertia characterizing routine household electricity use. The treatment messages—whether emphasizing environmental benefits, economic savings, or neutral information—may have been insufficiently prominent or memorable to trigger sustained attention and subsequent action.

Baseline Consumption Levels: A Floor Effect. A more fundamental constraint emerges from the baseline consumption patterns observed in our sample. Italian households, particularly in the southern regions represented in our study, already exhibit relatively low per-capita electricity consumption by European standards. Critically, this consumption restraint appears to be driven predominantly by economic necessity rather than environmental consciousness.

Households facing budget constraints have already implemented the most accessible conservation measures—turning off lights, limiting appliance use, moderating heating and cooling. The marginal opportunities for further reduction are therefore limited. When baseline consumption is already near a practical minimum, even effective treatments have little room to produce detectable effects. This floor effect represents a structural barrier to identifying treatment impacts, regardless of experimental design quality.

Electricity Tariff Structure and Incentive Dilution. Perhaps most consequentially, the architecture of Italian residential electricity tariffs substantially attenuates the financial incentives for consumption reduction. The total electricity bill comprises multiple components:

1. **Variable consumption charges** (€/kWh consumed)

2. **Fixed capacity charges** (based on contracted power capacity, typically 3-6 kW)
3. **System charges and levies** (partially fixed, partially consumption-based)
4. **Taxes** (VAT and excise duties)
5. **Network and distribution fees** (largely fixed)

For typical Italian households, the fixed components represent a substantial share of the total bill—often exceeding 40-50% depending on consumption levels and contract terms. This tariff structure implies that a given percentage reduction in electricity consumption translates into a considerably smaller percentage reduction in the total bill amount.

This incentive dilution has profound implications for behavioral interventions emphasizing economic benefits. The economically-framed treatment arm (T_{econ}) explicitly appealed to financial savings from reduced consumption. However, when the actual monetary savings are modest—perhaps a few euros per month—the effort required to modify consumption behavior may exceed the perceived benefit. Rational consumers, even if responsive to the message, may conclude that the behavioral costs of conservation outweigh the attenuated financial returns.

5. Discussion

These findings suggest that informational interventions alone may be insufficient to reduce electricity consumption in contexts characterized by already constrained baseline consumption driven by economic factors, tariff structures that decouple consumption changes from bill impacts and low treatment salience relative to habitual behavior

More effective approaches might include tariff reforms that increase the marginal price visibility of consumption, interventions targeting high-consumption households with greater reduction potential, real-time feedback mechanisms that enhance the salience of consumption decisions, structural interventions (e.g., appliance efficiency programs) that reduce consumption without requiring sustained behavioral effort.

The null results, while disappointing from an intervention effectiveness standpoint, provide valuable information about the boundary conditions under which informational nudges operate. They underscore the importance of considering baseline consumption levels, economic constraints, and tariff structures when designing and evaluating energy conservation programs.

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APPENDIX

A.1. Consent form

[The consent form was originally written in Italian and appeared on the first screen of the web-interface at the first log-in of the subject. Since all the phases of the study were administered online, informed consent to participate was obtained by clicking on the "I consent" option in the first screen.]

We greatly appreciate your participation in our study on Italians' energy consumption, approved by the Ethics Committee of the University of Milano-Bicocca. During the study, you will be asked to fill an initial questionnaire of approximately 30 questions. Some questions do not have right or wrong answers: we are interested in your honest opinions, perceptions, and viewpoints. We assure you that your responses will be treated with the utmost confidentiality.

The data are anonymous (researchers will receive your responses and the data associated only with the alphanumeric code that we ask you to enter at the beginning of the questionnaire as your sole identifier) and will be analyzed exclusively in aggregate form and for academic research purposes.

The same alphanumeric code will be used to match your survey responses with the electricity consumption data you have agreed to upload to the Koala company platform. By consenting to participate, you also consent to this matching, always carried out anonymously and solely for scientific research purposes.

The University of Milano-Bicocca is the data controller for the responses you provide. Joint controllers for the processing of your data are Koala company, for the consumption data and their matching with your survey responses, and Fondazione GRINS, a PNRR-funded institution that manages the Amelia platform on which the data, in aggregated and anonymous form, will be stored.

The study will take approximately 10 minutes to complete.

Your participation does not involve any risk for you.

Your participation in this research is voluntary. You have the right to withdraw from the study at any time, for any reason, and without any consequences. If you wish to contact a researcher responsible for the study to discuss this research, you may write to:

- luca.corazzini@unimib.it
- marco.mantovani@unimib.it

By clicking the button below, you acknowledge that your participation in the study is voluntary, that you are at least 18 years old, and that you are aware you may withdraw from participation at any time.

- I consent
- I do not consent

A.2. The socio-economic and behavioral questionnaire

[The questionnaire was originally written in Italian. The questions were presented sequentially across five screens: Screen 1 displayed questions 1–6; Screen 2, questions 7–10; Screen 3, questions 11–14; Screen 4, questions 15–19; and Screen 5, question 20. After completing the questions on each screen, participants proceeded to the next one and were not able to return to previous screens to modify their responses.]

QUESTIONNAIRE – Questions and Answers (English Version)

1. How many people live in your household (including yourself)?

- 1
- 2
- 3
- 4
- 5
- 6
- More than 6

2. What type of home do you live in?

- Detached single-family house
- Attached single-family house (duplex, terraced house, townhouse)
- Apartment in a building with 2–4 units
- Apartment in a building with 5 or more units

3. What best describes your current housing situation?

- I own my home
- I rent my home
- I live in the home for free (e.g., with family or friends)

4. What is the size of your home?

- Less than 50 m²
- 50–100 m²
- 101–150 m²
- 151–200 m²
- More than 200 m²

5. What is the energy efficiency class of your home?

- A4
- A3
- A2
- A1
- B
- C
- D
- E

- F
- G
- Don’t know

6. How many rooms does your home have?

- 1
- 2
- 3
- 4
- 5 or more

7. Which of the following appliances are present and regularly used in your home?

- Refrigerator
- Oven
- Microwave
- Induction cooktop
- Dishwasher
- Food processor
- Coffee machine
- Fan
- Freezer
- Blender
- Toaster
- Washing machine
- Dryer
- Air conditioner
- Heat pump
- Water heater
- Vacuum cleaner
- Iron
- Other (specify)

8. Do you own an electric car or motorcycle?

- Yes
- No

If Yes: How often do you charge it using your household’s power source (POD)?

- Never
- A few times a week
- Every day
- Multiple times a day

9. Which of the following systems or devices does your home have?

- External wall insulation (thermal coat)

- Energy-efficient lighting
- Double or triple glazing
- Programmable thermostat
- Solar photovoltaic panels
- Solar thermal panels
- Underfloor heating
- Condensing boiler
- Mechanical ventilation system (MVHR)
- Solar energy storage battery
- Thermally insulated roof
- None of the above

10. Have you changed electricity provider in the past two years?

- Yes
- No

If Yes: What was the main reason?

- Better economic conditions
- Poor customer service
- Billing or transparency issues
- Environmental sustainability of the new provider
- Other (specify)

11. What was the total gross household income last year (before taxes and deductions)?

- Up to €15,000
- €15,001–€28,000
- €28,001–€50,000
- €50,001–€75,000
- €75,001–€100,000
- €100,001–€150,000
- Over €150,000

12. What best describes your current employment status?

- Full-time paid work (30+ hours per week)
- Part-time paid work (8–29 hours per week)
- Part-time paid work (less than 8 hours per week)
- Retired
- Student
- Full-time higher education
- Unemployed (seeking work)
- Not seeking work

13. On a typical working day, how many hours (out of 24) do you spend at home?

(Numerical answer)

14. On a typical non-working/holiday day, how many hours do you spend at home?

(Numerical answer)

15. How often do you perform the following actions?

15.1 Turning off standby modes on appliances/electronic devices

- Never
- Rarely
- Sometimes
- Usually
- Always

15.2 Reducing heating or air conditioning to save energy

- Never
- Rarely
- Sometimes
- Usually
- Always

15.3 Limiting shower time to save water

- Never
- Rarely
- Sometimes
- Usually
- Always

15.4 Using washing machine or dishwasher only with a full load

- Never
- Rarely
- Sometimes
- Usually
- Always

16. Please indicate how much you agree or disagree with the following statements:

16.1 I would be willing to lower my standard of living to protect the environment.

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

16.2 I would be willing to pay higher prices for goods and services to protect the environment.

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

16.3 I would sacrifice some personal comfort to save energy.

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

16.4 My personal behavior can make a positive difference for the environment.

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

17. How concerned are you about environmental issues?

- Very concerned
- Quite concerned
- No opinion
- Not concerned
- Not concerned at all

18. Have you engaged in any of the following behaviors in the past month?

- Bought reusable products instead of disposable ones
- Reduced energy consumption
- Reduced water consumption
- Paid bills or made purchases online
- Avoided products with excessive packaging
- Repaired items instead of buying new ones
- None of the above

19. Have you done any of the following in the past five years?

19.1 Bought energy-efficient appliances

- Yes
- No

19.2 Installed thermal insulation

- Yes
- No

19.3 Switched to a renewable energy provider

- Yes
- No

19.4 Purchased a low-energy-consumption vehicle

- Yes
- No

20. Please indicate how much you agree or disagree with the following money-related statements:

20.1 Things would be better if I had more money.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.2 More money would make me happier.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.3 There will never be enough money.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.4 It is difficult to be poor and happy.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.5 You can never have too much money.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.6 Money is power.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.7 I will never be able to afford what I truly want.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.8 Money would solve all my problems.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.9 Money buys freedom.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.10 If you have money, someone will try to take it from you.

- Strongly agree
- Agree
- Partially agree

- Partially disagree
- Disagree
- Strongly disagree

20.11 I am wealthy.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.12 I always have enough money to make it to the end of the month.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.13 I have a lot of money.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

20.14 I can afford to buy expensive things.

- Strongly agree
- Agree
- Partially agree
- Partially disagree
- Disagree
- Strongly disagree

A.3. The text of the messages used in the field experiment

[Messages were originally in Italian. Messages were delivered through Koala's proprietary system integrated with the WhatsApp Business API. Messages were sent at 18:00 on September 4 (the first two messages in a treatment), September 11 (the third message), and September 18 (the forth message), 2025.]

[NEUTRAL MESSAGES - T_neu]

[Message 1 – First message in the chat with the user]

👋 Hello from KOALA 🐨! As part of a research project in collaboration with the University of Milano-Bicocca ☘️, we will send you some tips to help you save electricity. By following them, you can save more than 1 kWh of electricity per day without giving anything up!

[Message 2 – Immediately after the previous message containing the image]

👋 Hello! Did you know that you can save more than 1 kWh of electricity per day without giving anything up? Here are the first 4 tips to help you reach this goal:

1️⃣ Unplug chargers for electronic devices when not in use and avoid leaving TVs and PCs on standby;

2️⃣ Close the refrigerator and freezer quickly and remember to defrost them at least once a year;

3️⃣ Try to use the washing machine and dishwasher only when fully loaded, preferably at night and at moderate temperatures (40°C for the washing machine and 50°C for the dishwasher);

4️⃣ If you have an air conditioner, set it to 26°C in dehumidifier mode and close doors and windows, and lower the shutters during the hottest hours.

We wish you a great day!

[Message 3]

👋 Hello! Here are 4 more tips to help you save more than 1 kWh of electricity per day easily and without giving anything up:

5️⃣ Hang your clothes outside instead of using the dryer;

6️⃣ Avoid setting very low temperatures in the fridge and freezer. 4°C for the fridge and −18°C for the freezer are sufficient to store food correctly;

7️⃣ Turn off the modem/router at night or when you're not at home or on vacation;

8️⃣ If you have an electric water heater, remember to turn it off when not needed and set the thermostat to 50–55°C.

We wish you a great day!

[Message 4]

👋 Hello! Here are the last 4 tips to help you save more than 1 kWh of electricity per day easily and without giving anything up:

9️⃣ When buying new appliances, choose the most efficient ones in class A or higher;

1️⃣0️⃣ Defrost food in the refrigerator;

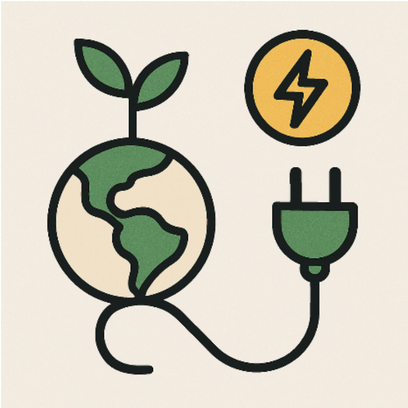
1️⃣1️⃣ Turn off the lights in empty rooms and use natural light as much as possible by keeping curtains open and placing your desk near a window;

1️⃣2️⃣ Use the oven to cook multiple dishes at once and avoid opening it frequently during cooking.

We wish you a great day!

[ENVIRONMENTAL MESSAGES - T_env]

[Message 1 – First message in the chat with the user]



👋 Hello from KOALA 🐨! As part of a research project in collaboration with the University of Milano-Bicocca ☘️, we will send you some tips to help you save electricity. By following them, you can save more than 1 kWh of electricity per day without giving anything up!

👉 In terms of environmental sustainability, this corresponds to reducing about 150 kg of CO_2, which equals:

🌳 The emissions absorbed by 10 adult trees in one year through their oxygen production;

💧 The consumption of over 150 showers lasting 7 minutes;

🚗 1200 km driven by a newly registered car.

[Message 2 – Immediately after the previous message containing the image]

👋 Hello! Did you know you can save more than 1 kWh of electricity per day without giving anything up while promoting environmental sustainability? Remember: it's like saving 1200 km driven by a newly registered car 🚗!

Here are the first 4 tips to help you reach this goal:

1️⃣ Unplug chargers for electronic devices when not in use and avoid leaving TVs and PCs on standby;

2️⃣ Close the refrigerator and freezer quickly and remember to defrost them at least once a year;

3️⃣ Try to use the washing machine and dishwasher only when fully loaded, preferably at night and at moderate temperatures (40°C for the washing machine and 50°C for the dishwasher);

4️⃣ If you have an air conditioner, set it to 26°C in dehumidifier mode and close doors and windows, and lower the shutters during the hottest hours.

With mindful choices, you can actively contribute to protecting the environment and combating climate change!🌍

We wish you a great day!

[Message 3]

👋 Hello! Here are 4 more tips to help you save more than 1 kWh of electricity per day easily and without giving anything up while promoting environmental sustainability.

Remember: it's like saving the consumption of over 150 showers lasting 7 minutes 💧!

5️⃣ Hang your clothes outside instead of using the dryer;

6️⃣ Avoid setting very low temperatures in the fridge and freezer. 4°C for the fridge and -18°C for the freezer are sufficient to store food correctly;

7️⃣ Turn off the modem/router at night or when you're not at home or on vacation;

8️⃣ If you have an electric water heater, remember to turn it off when not needed and set the thermostat to 50-55°C.

With mindful choices, you can actively contribute to protecting the environment and combating climate change!🌍

We wish you a great day!

[Message 4]

👋 Hello! Here are the last 4 tips to help you save more than 1 kWh of electricity per day easily and without giving anything up while promoting environmental sustainability.

Remember: this corresponds to the emissions absorbed by 10 adult trees in one year during their oxygen-producing activity 🌳!

9️⃣ When buying new appliances, choose the most efficient ones in class A or higher;

1️⃣0️⃣ Defrost food in the refrigerator;

1️⃣1️⃣ Turn off the lights in empty rooms and use natural light as much as possible by keeping curtains open and placing your desk near a window;

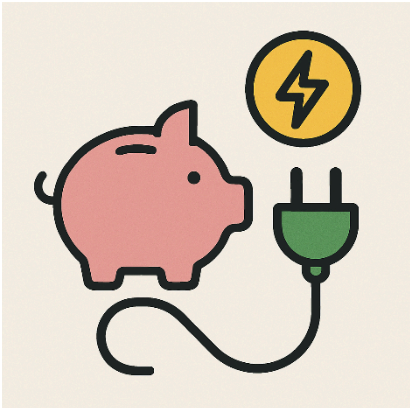
1️⃣2️⃣ Use the oven to cook multiple dishes at once and avoid opening it frequently during cooking.

With mindful choices, you can actively contribute to protecting the environment and combating climate change!🌍

We wish you a great day!

[ECONOMIC MESSAGES - T_econ]

[Message 1 – First message in the chat with the user]



👋 Hello from KOALA 🐨! As part of a research project in collaboration with the University of Milano-Bicocca ☘️, we will send you some tips to help you save electricity. By following them, you can save more than 1 kWh of electricity per day without giving anything up!

👉 In economic terms, this corresponds to annual savings of €90–€110, which equals:

🧾 About one free bimonthly electricity bill per year;

🛒 A weekly grocery shop for a representative Italian family;

📰 An annual subscription to a newspaper or an online multimedia platform.

[Message 2 – Immediately after the previous message containing the image]

👋 Hello! Did you know you can save more than 1 kWh of electricity per day without giving anything up and improve your household budget? Remember: it's like getting a free bimonthly bill every year 🧾!

Here are the first 4 tips to help you reach this goal:

1️⃣ Unplug chargers for electronic devices when not in use and avoid leaving TVs and PCs on standby;

2️⃣ Close the refrigerator and freezer quickly to avoid thermal dispersion and remember to defrost them at least once a year to increase efficiency;

3️⃣ Try to use the washing machine and dishwasher only when fully loaded, preferably at night (using delayed start programs) and at moderate temperatures (40°C for the washing machine and 50°C for the dishwasher);

4️⃣ If you have an air conditioner, set it to 26°C in dehumidifier mode and close doors and windows, and lower the shutters during the hottest hours.

Through mindful choices, you can gain economic benefits and give your wallet some relief! 💰

We wish you a great day!

[Message 3]

👋 Hello! Here are 4 more tips to help you save more than 1 kWh of electricity per day easily and without giving anything up while improving your household budget.

Remember: it's equivalent to a weekly grocery shop for a representative Italian family 🛒!

5️⃣ Hang your clothes outside instead of using the dryer;

6️⃣ Avoid setting very low temperatures in the fridge and very high ones in the freezer. 4°C for the fridge and −18°C for the freezer are sufficient to store food correctly;

7️⃣ Turn off the modem/router at night or when you're not at home or on vacation;

8️⃣ If you have an electric water heater, remember to turn it off when not needed and set the thermostat to 50–55°C.

Through mindful choices, you can gain economic benefits and give your wallet some relief! 💰

We wish you a great day!

[Message 4]

👋 Hello! Here are the last 4 tips to help you save more than 1 kWh of electricity per day easily and without giving anything up while improving your household budget:

Remember: this corresponds to an annual subscription to a newspaper or an online multimedia platform 📰!

9️⃣ When buying new appliances, choose the most efficient ones in class A or higher;

🔟 Defrost food in the refrigerator;

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Remember: through mindful choices, you can gain economic benefits and give your wallet some relief! 💰

We wish you a great day!