Do Nudges and Prepaid Electricity Token Lead to Electricity Savings? Analysis of Urban Consumption Behaviour in Indonesia

Eka Sudarmaji(✉) and Sri Ambarwati

Faculty of Economics and Business, University of Pancasila, Jalan Srengseng Sawah, Pasar Minggu, Jakarta 12640, Indonesia
esudarmaji@univpancasila.ac.id

Abstract. In order to determine how nudging could affect Indonesians' energy use habits, we ran a pilot experiment. The pilot study provided compelling evidence in favor of utilizing nudging to encourage increased energy use that is more ecologically friendly. It is mainly used to offer real-time information utilizing prepayment meters (smart electricity) to display energy usage and to provide transparency about the effects of current energy use and costs to lower peak consumption. By contrasting and showing their own and their peers' energy consumption habits, the authors minimized consumption by using social norms established by peer comparisons. Between December 2021 and April 2022, the research was conducted in urban areas of Bantul, Jogjakarta. Sixty-two respondents are divided into two groups of households: observe (self-selected) and control families (randomly selected). Both observer and control families must have had an active electricity account for at least one year and owned a dwelling ranging in size from 50 to 200 square meters. The model employed a t-paired sample using the "Non-Equivalent Groups Design" (NEGD) framework for the comparisons and the Logit model. The result found a significant difference in energy saving between the two groups for three months of the experiment. The research discovered that Prepaid Meter and Social Norm & Feedback could decrease energy bills. The results showed that every change in the Nudging Social Norm variable could increase energy saving and had a significance value at the 95% significance level.

Keywords: NEGD · energy-saving · logit · nudges · household energy behaviour

1 Introduction

Because so many technologies are used in our everyday lives and demand electricity, Indonesia's electricity usage is rising. The increase in electricity rates every year causes household costs also to increase [1]. One of the efforts to save is through cutting electricity consumption (curtailment) and replacing old equipment that requires a large amount of energy with new technology equipment that requires less energy or is energy efficient. The decision to replace the old-tech equipment with new-technology equipment that

S. Jahroh et al. (Eds.): BIEC 2022, AEBMR 236, pp. 225–237, 2023.
https://doi.org/10.2991/978-94-6463-144-9_22

saves energy and uses "Smart Electricity" prepaid electricity service is seen as behavior to adopt technological innovations [2].

Using a prepaid electricity system, users may control their energy consumption as intelligently as possible, tailoring it to their demands and financial situation, mainly if that information includes other household energy usage. That information might also trigger energy-saving social norms [3]. The experimental team put information at their door for research on energy use [4]. The data indicates that a household's consumption level is higher or lower than the average. Measurements of the data were made both before and after the experiment. The negatively informed household will spend less energy in the following time if their home uses more than the average household.

Prepaid electricity system similarly to credit (also known as "pulsa") on the mobile phones. Credit (in the form of vouchers or tokens) must be purchased by customers at the merchants. Customers can utilize the quota provided by this credit indefinitely; there is no time restriction placed on it. Customers are required to purchase more credit in order to replace the electricity allotment after it has been used up. The Prepaid Meter Machine (MPB) will sound an alarm to alert the customer of impending quota depletion. Customers that use prepaid electricity may quickly and readily determine how much energy they have used. Customers may thus define their own deadlines and quotas, giving them the flexibility to modify their expenditure and budget as needed. On the other hand, prepaid electricity cannot be isolated from its flaws. Many have complained that the meter is easily broken because it is frequently handled when filling tokens. Moreover, must often manage the remaining pulses in case the power does not go off. Similarly, postpaid electricity has been around for a long time. Customers will benefit from being able to use the power they require first. Only then will the payment be modified to reflect the electricity used at the end of each month.

Customers may monitor their daily power use with prepaid electronic meters at any time. The meter displays the final remaining kWh use figure. Customers can reduce their power use if they feel it is excessive. Electricity use may be tailored to fit the budget. With the value of Electricity Credit (vouchers), customers have the flexibility to buy electricity based on their abilities and needs (more control in managing the family budget), there will be no late fees, no additional costs for paying electricity due to being burdened with late fees due to forgetting to pay electricity bills, privacy will be more secure. Customers who desire greater convenience will not have to wait. It will not be subjected to meter recording officers because prepaid meters automatically record customer power use (accurately and without meter recording mistakes), and a broad network of token or credit purchases electricity. Smart tokens or pulses (vouchers) may now be purchased at over 30,000 ATMs in Indonesia. It can also be accessed via online power payment counters. This prepaid electricity system is become appropriate for consumers with a rented house business or a rented room (boarding house). Customers who own a house or rent a room no longer have to worry about unpaid power bills because electricity consumption has become their responsibility and has been tailored to the demands of the renters.

The prepaid system is also widely used in urban households. Through this prepaid, how urban households can control the use of their electricity costs. The information on the electricity meter can encourage people's behavior to be more energy efficient. One aspect of the 'Nudge idea' is how smart electricity is used to encourage energy-saving behavior in urban communities. Understanding consumer behavior in lowering energy usage, especially adopting the prepaid meter system technology in household, is one of many critical issues to consider. This research will look at the most critical elements that motivate and inhibit technology adoption for various technologies. It is critical to investigate the behavior of adopting prepaid meter stechnologies since technological acceptance or rejection can occur at individual levels, and consumer participation is frequently required to appreciate the full benefits of this technology.

This research investigates the technologies that impact 'Nudge Idea' in the Indonesian household sector. Nudge theory is used to frame constrained choices (framing) to lower the cost of household energy use. The aim is precise for energy efficiency, energy conservation, and carbon emission reduction. The primary issue that this research must address is how probable the Nudge principle can be applied. The goal of nudging is to influence people's behavior and prompt them to do specific actions without taking away their freedom of choice. Numerous nudges change people's behavior predictably without considerably limiting options or altering economic incentives. An alternative approach to attaining policy goals is provided by nudging, which can replace or supplement conventional policy tools. The "Nudge" idea can be used for modifying people's behavior [5]. "Nudge" theory proposes incentives to modify people's behavior in various areas.

2 Literature Review

Many previous researchers namely motivation that is economic, which predicts that almost all individuals or companies wish to save costs. The economic motivations that best predict actual intention to act in adopting home energy innovations - that is, that best characterize early adopters. [6] first classified adopters into five categories in his diffusion of innovation theory: innovators, early adopters, early majority, late majority, and laggards. According to Rogers' perspective, innovators might be community leaders or people who accept innovation in the future. Individuals in the group may make diverse decisions to accept the technology and act differently. They may use one technology but not another. According to Rogers's theory, adopters have less variety in the value or requirement for the target technology [7].

Other empirical findings, however, show that predictions based on economic behaviour face many challenges. The priority, practicability, and environmental motivation are also essential factors that are widely discussed and are characteristics of conservatism energy adopters [7]. Numerous studies were driven by various variables, including environmental values and views that are society's moral duty to lower emissions, or in other words, as part of pro-environmental behaviour [8, 9]. Environmental behavior is primarily tied to energy consumption and is defined as any action that contributes directly or indirectly to environmental conservation and sustainability [10].

Conservatism energy research takes many diverse ways among academics worldwide, particularly in research based on behaviour theory. Most of this empirical research on conservatism energy divided into two categories: research based on internal or endogenous variables and research based on external factors [11]. The empirical research based on internal and non-economic elements is observed in terms of age, gender, education, and energy efficiency information, the majority of which are vague, resulting in an information gap [11, 12] distinguishes energy efficiency behaviour from non-economic motivation in two parts: 1) curtailment behaviour, i.e., behaviour patterns in which individuals reduce activities that harm the environment and choose pro-environmental or pro-environmental behaviour (turn off lights when leaving the room), and 2) efficiency behaviour, i.e., reduce environmental impact by adopting more efficient technology (using energy-efficient equipment).

The researchers had focused on several forms of social factors (normative and informational), moral norms and informational impacts (i.e., trust in friends/relatives and neighbours), and attitudes about target behaviour as predictors of intention toward energy saving. The most often used and supervised theories are 'Theory Plan Behaviour (TPB)' [9, 13] [14, 16]. The TPB was discovered to be a feasible model for describing energy consumption intentions and actions by these researchers.

Previous research indicated that adopting energy-efficient items was more prominent than general societal norms [17]. As a result, generic societal norms have little direct influence and are dominating in influencing individual behaviour to conduct energy efficiency [18, 19] propose harmonizing conceptions of a healthy environment by adding social variables within community groups, such as government regulations that give incentives and educational initiatives. Government involvement in educational programs or campaigns to raise awareness of the use of energy efficiency in adopting green technologies can boost community efforts to protect the environment while also achieving cost-effectiveness [20]. The results of energy education experiments, energy information system seems to be helpful for governments and policy makers. The social norm method of modifying behaviour about the use of energy efficiency items, mainly those directly tied to the success of a clean and healthy environmental campaign, is heavily influenced by the presence of government backing [21]. This is in contrast to the situation in China, where [22] discovered that government initiatives did not affect the decision of Chinese homeowners to use energy-saving measures. Energy cost-effectiveness determined by various aspects, including energy performance, climate, and, most critically, power pricing [23].

3 Method

The following variables affect total home power consumption: 1) dwelling features, such as size; 2) equipment characteristics, and 3) the intensity of equipment utilized for domestic and leisure activities. Climate, cost, and individual traits like brand all impact these selections. This study employed an experimental methodology using the Non-Equivalent Groups Design (NEGD), the most popular research methodology in social science [24–27]. NEGD happens when program participants are handled differently. The main goal of this study is to provide the intervention household group, which is used as a "observe" variable compared to other "control" groups, with more information and training. The experimental group was given the following information as well as additional training on limiting behavior and effectiveness: 1) Shutting off lights when people leave the room, 2) Watching for old, low-energy light bulbs at home, 3) Washing clothes only when there are enough and during pick-up hours, 4) Changing out high energy-consumption electrical appliances with more energy-efficient ones, such dishwashers, and irons; 5) shutting off laptops and screens when not in use.

This research aims to determine differences in the tendency of energy saving in urban households in Indonesia. The dependent variable in this research is energy saving, while the independent variables are Smart Electricity - Prepaid Meter and Nudge - Social Norm & Feedback. Authors used the most common nudge is information provision, frequently employed in conjunction with modifications in the default option. A potential method for increasing pro-environmental decisions is to provide trustworthy and accessible information that minimizes choice complexity. According to the literature study, most examples where information is utilized as a nudging tool target energy consumption and efficiency. There is also the providing of real-time information. Using in-house smart meters, for example, to show energy usage and give transparency about the impact of current energy use and pricing yields intriguing outcomes in terms of lowering peak energy consumption.

Suppose people are unaware of the costs associated with using energy-consuming devices. In that case, they may find it difficult to fully comprehend the effects of their actions, such as choosing between two different light bulbs or energy sources or timing when to run the washing machine. Providing up-to-date information in the form of, say, in-home displays, which act as both a continual reminder of energy use and learning aid, enabling people to progressively learn to discriminate between the energy usage of various appliances, is one method to get through this information barrier. In a randomized-control experiment, sixty-two residential dwellings in Bantul, Jogyakarta, Indonesia, were divided into two treatment groups and one control group. An energy consumption monitor was put in each treatment group's house, with the first group having it for the whole three-month investigation. The control group did not get any prodding. Social nudges that employ peer comparisons to leverage social norms are noteworthy because they may be applied at different points in time and space. According to various studies conducted in the United States, the United Kingdom, and Ireland, sharing information in the form of social feedback and regular updates on current energy usage patterns can cut energy consumption by up to 7%, [28].

The pilot experiment was conducted in an urban setting. Information about the impact of information and social norms were two different types of nudges employed in the experiment. The field study examines the relative effects of two different nudges on energy use. The interventions use nudges, which do not change economic incentives or forbid particular behavior. In our pilot field study, we looked at the relative impacts of two alternative nudges on energy conservatism. The results, therefore, imply that small-scale interventions might affect ecologically advantageous behavior in energy conservation, such as appealing to social norms or disseminating knowledge. The results of the pilot experiment analysis suggest that these little nudges may have a significant impact on household urban conservative energy policy.

Authors performed the descriptive statistics were used in logistic regression to explain the description of the variables in the research. Descriptive statistics in research transform research data into a tabulated form, making it easy to understand and interpret. Tabulation presents a summary, arrangement, or arrangement of data in the form of tables and graphs. Meantime the data Analysis Techniques and Hypothesis Testing include the Differential Test. The test used the different test approach with Independen Sample Test to show the significance of the difference in the average value of the variables based on the categories of gender, experience, and investment products as well as the level of expenditure on the respondents. In conducting a different test with Independen Sample Test, it must meet the parametric criteria. Namely, the population has a normal distribution.

4 Result

A descriptive statistical strategy to defining the independent variables' features. Table 1 displayed descriptive statistical information from the sample data investigated (N), specifically the sample data of 62 respondents. The Table 1, displays each variable's lowest, maximum, average, and standard deviation values. Individual characteristic variables of the home area have a minimum value of 36sqm and a maximum value of 147sqm, an average value of 107.7 sqm, and a standard deviation of 32.69 in descriptive statistics. Other individual characteristics include the number of responder members, denoted by dummy = 1 for household members residing in a house with fewer than five individuals. Dummy = 2 was assigned to household members with more than five people living in the house. Dummy = 1 represents 450 watts of power, whereas dummy = 2, dummy = 3, and dummy = 4 represent 900, 1300, and above 1300 watts, respectively. The average value of electrical capacity is 1.7 7 with a standard deviation of 0.76, implying that the average installed electrical capacity in urban neighbourhoods is 450 watts or 900 watts. In the variable kind of power payment, the number dummy = 1 represents monthly payments, while dummy = 2 represents token payments. It is characterized by the average usage of conventional lights or bulbs, as much as 82.71 h for numerous light bulbs installed and turned on for one day, for varied use of electrical equipment installed inside and outside the house. Fans and refrigerators come in second and third place. Because of the hot heat in the Bantul region, fans outnumber room temperature controls. Simultaneously, the refrigerator is tagged with constantly placed for 24 h. The average refrigerator usage is less than a fan and almost a light bulb, and the Bantul urban neighbourhood lacks it. Meanwhile, TV is the fourth most often used technology in metropolitan areas, with average utilization of 15.10 h per day.

Table 2 displays each energy saving that happened every month from January to March for households that got the nudging framing with mean and standard deviation values. Individual characteristic variables of energy saving in January have a mean value of 0,19 and a standard deviation of 0,402. On the other hand, the household with no nudging framing has a mean value of 0,00 and a standard deviation of 0,00. In February and March, energy saving with nudging framing rose to a mean value of 0,61 and 0,84 with a standard deviation of 0,495 and 0,374, respectively. It implied that the average energy saving in February and march was higher than in January.

In Tables 3 and 4, the author used tabular analysis here is a method to analyze quantitatively the relationship between several variables 'Prepaid Meter and Energy Saving' and 'Social Norm & Feed-back and Energy Saving (3 Months)' with the variable of 'Nudging' and ' prepaid meters. The cross-tabulation here is used to understand the

Table 1. Descriptive analysis

	Minimum	Maximum	mean		Std. Deviation
	Statistics	Statistics	Statistics	Std. Error	Statistics
Respondent Status	1.00	2.00	1.06	0.04	0.25
House Area	36.00	147.00	107.77	5.87	32.69
Number of Family Members	1.00	2.00	1.94	0.04	0.25
Home Status	1.00	2.00	1.65	0.09	0.49
HOME Directions	1.00	4.00	1.61	0.13	0.72
Electric Capacity	1.00	4.00	1.77	0.14	0.76
Electricity Payment	1.00	2.00	1.29	0.08	0.46
Bulb/(Hours X Amount)	-	216.00	82.71	10,20	56.82
LEDs/(Hours X Amount)	-	48.00	9.68	2.94	16.36
Neon /(Hours X Amount)	-	28.00	7.74	1.84	10.23
AC /(Hours X Amount)	-	16.00	0.52	0.52	2.87
Refrigerator /(Hours X Amount)	-	48.00	19.35	2.34	13.03
TV /(Hours X Amount)	-	72.00	15,10	2.60	14.49
Fan /(Hours X Amount)	-	96.00	22.84	3.65	20,30
Iron /(Hours X Amount)	2.00	4.00	2.06	0.06	0.36
Machine /(Hours X Amount)	-	2.00	1.55	0.15	0.85
Savings (Jan-Mar)	-	0.34	0.16	0.02	0.10

Table 2. Nudge - Social Norm and Feed-back and Energy Saving (3 Months)

Nudge - Social Norm and Feed-back		N	Mean	Std. Deviation	Std. Error Mean
Energy Saving (January)	Nudging	31	0,19	0,402	0,072
	No Nudging	31	0,00	0,000	0,000
Energy Saving (February)	Nudging	31	0,61	0,495	0,089
	No Nudging	31	0,26	0,445	0,080
Energy Saving (March)	Nudging	31	0,84	0,374	0,067
	No Nudging	31	0,32	0,475	0,085

Table 3. Cross Tabulation - Smart Electricity & Energy Savings (3months)

		Energy Saving (3months)		Total
		Yes	No	
Smart Electricity - Prepaid: Meter	No Prepaid Meter	10 (27,78%)	**26 (72,22%)**	36 (58,06%)
	Prepaid Meter	**16 (61,54%)**	10 (38,46%)	26 (41,94%)
Total		26 (41,93%)	36 (58,06%)	62 (100%)

Table 4. Cross Tabulation: Social Norm & Feed-back and Energy Saving (3 Months)

		Energy Saving (3months)		Total
		No	Yes	
Nudge - Social Norm & Feed-back	No Nudging	21 (67,74%)	10 (32,25%)	31 (50%)
	Nudging	5 (16,13%)	26 (83,87%)	31 (50%)
Total		26 (41,94%)	36 (58,06%)	62 (100%)

correlation between the above variables and to show how the correlation changes from one grouping of variables, ‘prepaid meter’ to ‘energy saving,’ ‘social norm and feedback’ to ‘nudging.’ From Table 3, the results of the cross-tabulation above showed that the probability of Smart Electricity - Prepaid: Meters that can occur energy saving is 61.54%. In comparison, energy saving cannot occur in 38.46% of 26 respondents, or 41.94%, who use the smart prepaid meter. Meanwhile, there were 36 respondents, or 58.06%, who did not use a smart prepaid meter, with 72.22% no energy saving accumulated in 3 months during the research conducted by the authors. In Table 4, the results of the cross-tabulation above show that the probability of Nudge - Social Norm & Feedback that energy saving can occur is 83.87%. In comparison, energy saving cannot occur in 16.13% of 31 respondents, or 50.00% of whose framing is done using ‘nudging.’ Meanwhile, the remaining 31 respondents, or 50.00%, who did not do ‘nudging’ framing could only produce an energy saving of 32.25%, so the remaining 67.74% did not occur in the accumulation of energy saving for three months during the research carried out. In order to see a significant difference in energy saving in January, February, and march between the observed and the control groups. The authors used The Levene test shown in Table 5. The results are significant at statistical levels below 5% for variables of energy saving in January, February, and March.

Moreover, the feasibility analysis of the regression model was carried out to assess the feasibility of the logistic regression model to be used. The test is carried out using the goodness of fit test measured by the Hosmer and Lemeshow Test, where the Chi-Square is 7.619, and the significant value is 0.472. Based on this value, because the significance value is more significant than 0.05, it can be concluded that the regression model is feasible for further analysis because there is no real difference between the predicted clarification and the observed classification.

Table 5. Independen Sample Test

		Levene's Test for Equality of Variances	
		F	Sig.
Saving January	Equal variances assumed	49.861	0.000
	Equal variances not assumed		
Saving February	Equal variances assumed	4.419	0.040
	Equal variances not assumed		
Saving March	Equal variances assumed	9.282	0.003
	Equal variances not assumed		

The coefficient of determination is used to determine how much the independent variables' variability can explain the dependent variability. The coefficient of determination in logistic regression can be seen in the value of the Nagelkerke R Square model; Nagelkerke R Square can be interpreted as the value of R Square in multiple regression in multiple regression. Based on the results for the coefficient of determination. The value of Nagelkerke R Square was 0.574. It means that the variability of the dependent variable that can be explained is 57.40%, while other variables outside the research model explain the remaining 42.60%. It showed that Smart Electricity – Prepaid Meter and Nudge - Social Norm & Feed-back could explain energy-saving variables by 57.40%.

The omnibus test was conducted to test whether the independent variables had a simultaneous effect on the dependent variable, namely auditor switching. Measurements can be made by looking at the significance value; if the significance value shows a value < 0.05, then the variable. The independent variables together have a significant effect on the dependent variable. However, if the significant value shows a value > 0.05, the independent variables together have no significant effect on the dependent variable. In the test results, the authors found that the significance level of 0.000 or below 0.05, so it can be concluded that together the research variables, namely Smart Electricity – Prepaid Meter and Nudge - Social Norm & Feed-back have a significant effect on energy-saving variables.

The Table 6 above showed the results of logistic regression testing at a significance level of 5%. The equation of the above test was:

$\log\_\sqrt{\log_e}\left(\frac{\pi i}{1-\pi}\right)$ (energy saving) = -5,194 Nudging-Social Norm -1,890 Prepaid Meter + 0,210 Washing-machine usage + 4.261 Iron Usage – 0.038 Fan Usage + 0.017 TV Usage – 0.028 Refrigerator Usage + 1.274 AC Usage – 0.065 fluorescent lamps Usage – 0.019 LED Usage – 0.006 Bulbs ssUsage – 2.414 Electricity Capacity + 0.416 House Direction + 1.701 House Status – 0.446 Number of family – 0.012 House Size + 0.197 Respondence Status.

The Table 6 showed that every change in the Nudging Social Norm variable could increase energy saving by 5.194. Meanwhile, for the prepaid meter variable, every increase in the prepaid meter variable will reduce energy costs and increase energy

Table 6. Logistics Regression Result

	B	S.E.	Wald	df	Sig.	Exp(B)
Respondences Status	0.197	1.132	0.030	1.000	0.862	1.218
House Size	(0.012)	0.022	0.317	1.000	0.573	0.988
Number of Family	(0.446)	1.007	0.196	1.000	0.658	0.641
House Status	1.701	1.302	1.706	1.000	0.192	5.480
House Direction	0.416	0.463	0.807	1.000	0.369	1.515
Electricity Capacity	(2.414)	1.299	3.454	1.000	**0.063**	**0.089**
Bulbs Lamps Hours Usage	(0.006)	0.014	0.187	1.000	0.665	0.994
LED Lamps Hours Usage	(0.019)	0.019	0.988	1.000	0.320	0.981
A fluorescent lamps Usage	(0,065)	0.046	2.010	1.000	0,156	0.937
AC Usage	1.274	2,512.061	0,000	1.000	1,000	3.576
Refrigerator Usage	(0.028)	0.036	0.611	1.000	0.434	0.972
TV Usage	0.017	0.055	0.099	1.000	0.753	1.017
Fan Usage	(0.038)	0.037	1.054	1.000	0.305	0.963
Iron Usage	4.261	2.315	3.388	1.000	**0.066**	**70.910**
Washing Machine Usage	0.210	0.484	0.187	1.000	0.665	1.233
Prepaid Meter	(1.890)	1.581	1.429	1.000	0.232	0.151
Nudge-Social Norm	(5.194)	2.314	5.039	1.000	**0.025**	**0.006**

savings by 1.890. From the significance value, we can conclude that only the Nudging Social Norm variable affects energy saving with a significance value of 0.006 and 0.151 (at the 95% significance level). So it can be said that the first hypothesis (H1) and the second hypothesis (H2) are both accepted.

The classification matrix shows the predictive power of the regression model to predict energy saving for urban Jogyakarta society by treating Smart Electricity – Prepaid Meter and Nudge - Social Norm & Feedback. The variable's operational definition shows the dependent variable's predictive value. In this case, energy-saving occurs with code 1, and energy saving does not occur with code 0. To find out the results of the predictive power of the regression model can be seen by comparing the results of the percentage of energy saving and energy saving. Here is the presentation of the clarification model.

The cut value is 0.500.

The Table 7 above describes the information regarding the accuracy of the energy saving with a cut-off value of 0.500. In aggregate, the above model has an accuracy rate of 80.645%. If it is seen that the distribution tends to increase, it can be seen in the percentage correct, whose value is not too far between 76.923% and 83.333%. Thus, this model can be considered good because the distribution is slightly more even.

Table 7. Classification Matrix

		Predicted		
		"Saving Happened (3months)		Percentage Correct
		No Saving happened (0)	Saving Happened (1)	
Saving Happened (3months)	No Saving happened (0)	20	6	76,923
	Saving Happened (1)	6	30	83,333
Overall Percentage				80,645

5 Conclusion

A previous study investigates the nudge effects and Provides real-time information by using prepaid meters (smart electricity) to display energy usage and to provide transparency about the impact of current energy use and prices to reduce peak consumption. Also, this research looks at how their impacts change depending on standard features like house attributes and socioeconomic traits of their owners. One of the study's unique characteristics is the focus on urban family environments as a significant factor in how urban society responds to well-intentioned new information. This study stresses the "nudge" idea, frequently utilized in many nations, using architectural possibilities for energy efficiency. Our initial hunch is that urban culture, which consumes much energy, tends to listen to and agree with the general population. For the government or authority to reach the same conclusion, a group in a rural setting may have the same similarities. Similar to how public opinion or social norms with a general behavior will undoubtedly be more prominent in obtaining energy efficiency items and energy conservation. The "nudge" campaign to promote energy efficiency or conservation is new, on the rise, and is widely used by various governments. The relevant Ministries can collaborate with district governments on energy efficiency initiatives to promote energy savings and make them more appealing to the public aesthetically. Incentives for the larger community might be framed using the concept of "nudge." The "Nudge" theory of energy consumption reduction might lead to numerous energy-saving initiatives and lower carbon emissions in the future. Overall, the pilot experiment findings provide a solid case for employing nudging to promote more environmentally friendly behavior in areas such as energy consumption. Several of the nudges we described are simple to decrease the energy bill. To deal with energy conservatism, nudge mechanisms might be utilized. Social nudges, or the use of social norms to provide information and peer comparisons, have also increased electricity savings. We propose Smart Electricity – Prepaid Meter and Nudge - Social Norm & Feedback on the urban household energy saving. Smart meters are particularly intriguing owing to their potential for dynamic feedback on energy usage and the possibility that this push will be successful for electricity use.

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