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Consumption Behaviour and Conservation of Household Electricity in Delhi: A Factor Analysis Approach

Nidhi Tewathia[1]

[1]*Assistant Professor, Department of Economics, Gargi College, Delhi University, New Delhi, India*
Email: tewathian@gmail.com

Abstract

Electricity has attained a very important place in every household on this planet. It is a major contributor towards improvement of the standard of living of any individual, family and society at large. The primary focus for this research is to demonstrate the viability of Factor Analysis as a statistical tool for use in exploratory research. This tool not only offers the possibility of attaining a clear view of the data but also the possibility of utilizing the output in further analyses. In this light, the paper aims to find the latent variables which explain the factors behind consumer behavior and awareness in context of household electricity consumption. A questionnaire based study for 395 Delhi households was undertaken wherein the sample households were selected on the basis of stratified random sampling technique. The exploratory factor analysis (EFA) is conducted with a principal components extraction method and varimax rotation method. The factors are identified which stand valid to be included and targeted in further research on the electricity consumption and its conservation.

Keywords: Awareness; Behaviour, Electricity, Factor analysis, Household.
JEL Classification: D11, D12, Q44.

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Contents

1. Introduction

Electricity has attained a very important place in every household on this planet. It is a major contributor towards improvement of the standard of living of any individual, family and society at large. The task of understanding energy-consuming behaviors has presented substantial complexities. The complexities as per Ritchie *et al.* (1981) involve determining both the factors that influence electricity-consuming behaviors and the nature of each influence. The potential factors which influence electricity consuming behaviors include climatic conditions, house/product/vehicle characteristics, household demographics, and attitudinal variables**.** In fact, it has been observed by Collins (2010) that households could also increase their use of electricity if they see that their neighbors are using substantially more than they are[1].

Delhi is one of the biggest and most populous metropolitans in the world. The growth in the population, density and the number of households in Delhi over the past four decades (Table 1) makes it an appropriate subject for this study.

Table-1. Population of Delhi (1981-2011)

S.No	Item	1981	1991	2001	2011
1	Total population	6220406	9420644	13850507	16753235
2	Density of Population	4194	6352	9340	11297
3	Number of households	1211784	1860748	2554149	3340538

Source: Directorate of Census operations, Delhi

Along with population and income of Delhi, the domestic electricity consumption and the number of domestic consumers has also increase steadily over the period of 2009 to 2016 (Table 2). Over the period of 2000 to 2011, the share of domestic electricity consumption out of the total electricity consumption of Delhi has gone up from 23 per cent to 25.2 per cent[2]. Over the period of 2006 to 2012, the annual per capita electricity consumption has increased from 671.9 kWh to 879.22 kWh[3].

Table-2. Domestic Consumption of Electricity in Delhi

S.No	Period	Domestic consumers	Domestic Electricity Consumption (in million units)
1	2009-10	3000383	8753
2	2010-11	3258647	9723
3	2011-12	3464611	10396
4	2012-13	3616611	10796
5	2013-14	3954019	11609
6	2014-15	4094647	12386
7	2015-16	4289124	12560

Source: Delhi Statistical Handbook, 2016

The literature suggests that attitude of the consumers and their approach towards the consumption of electricity molds the consumption pattern of electricity. Awareness towards the scarcity of electricity is one of the factors which determine the attitude of a household for conservation of electricity. Consumer behavior towards the consumption of a good or service is greatly affected by the family culture, habits, lifestyle and awareness. Though, electricity has emerged as a major source of improvement of the living standard of the residents of Delhi, no study exists which provide information on the factors that determine the electricity consumption behaviour of a household in terms of awareness, attitude, habits and conservation. Many scientific studies are featured by the fact that "numerous variables are used to characterize objects" (Rietveld and Hout, 1993). Because of such big numbers of variables that are into play, the study can become quite complicated. Besides, it is possible that some of the variables measure different aspects of a same underlying variable. The present paper utilises the tool of exploratory factor analysis to identify the latent variables which can be of use for further research in the area of household electricity consumption behaviour in Delhi.

2. Literature Review

The investigations on consumers' willingness to change habits and undertake energy savings are relevant for the present study. In the literature, attitudes have been found to correlate with electricity conservation behavior. Psychology-based studies show mixed results. "Mass information has limited success. Targeted information campaigns can be more effective" (International Energy Agency, 2002). Gatersleben *et al.* (2002) through the results of two large-scale surveys of Dutch households, showed that, among other things, households with high pro-environmental attitudes were often not aware of the environmental impacts of their energy consumption, both directly and indirectly.

Gardner and Ashworth (2007)[4] came out with substantial results from their study in the context of consumer behavior and attitude. People who already use less electricity, women, and people with more pro-environmental beliefs, attitudes and past behavior have stronger intentions to reduce their energy consumption. People with higher levels of knowledge tended to polarize, reporting either very high or very low intentions to reduce consumption. These results are in line with previous findings and with psychological theory. The findings for acceptance of both demand management and distributed generation were fairly similar, even though individual survey respondents only assessed one technology. Younger, more educated, working people, with moderate size households including children and higher income levels, were more likely to accept these technologies. People

[1]This phenomenon has been termed as the "Demonstration effect" in the fundamentals of economics. The consumers feel peer pressure to remain in sync with the neighborhood and hence have to maintain a status level similar to the neighbors.
[2]Ministry of Power/ Central Electricity Authority
[3]August Report 2013, CEA
[4] The survey was developed with reference to psychological theory.
[5] They can be automatically generated in SPSS by selecting the Anderson and Rubin option in the Factor Analysis.
[6] A group of persons normally living together and taking food from common kitchen constitute a household. The word 'normally' means that the temporary visitors are excluded. 'Living together' is usually given more importance than 'sharing food from a common kitchen' in drawing the boundaries of a household (NSS 66th round).
[7]Gurgaon, Faridabad and Noida.
[8] The sample is said to be adequate if the value of KMO is greater than 0.5.
[9] Eigenvalues indicate the amount of variance explained by each principal component or each factor.
[10] The scree test is only reliable when you have a sample size of at least 200.
[11] Factor rotation is analogous in that it attempts to provide a "vantage point" from which the data's organizational structure—the ways in which items share

scoring higher on pro-environmental beliefs and behaviors, those with positive attitudes and subjective norms towards energy reduction, and those with higher levels of knowledge about energy/environment issues were also more likely to accept both technologies. In direct demand management applications, air conditioners and pool pumps are the two high-load appliances most likely to be controlled.

Collins (2010) says that the behavioral patterns for using appliances progress from knowledge based to skill-based more rapidly when operation is less complex. Once a person is operating an appliance using skill-based behavior, the behavior is harder to change. Another thing pointed by him is that the people use instruction manuals less when the appliance is less complex. "Encouraging the electricity efficiency through an alteration of 'lifestyles' could be difficult as this would involve changing how people live (which is a difficult and questionable task for a government or any group to undertake), but also because changing lifestyles means changing socialized ideas of taste and norms, which does not happen quickly" (McMichael, 2007).

Collins (2010) also suggests that a household may have at least three motivations for changing their energy use habits: a) Financial: saving money on their monthly utility bill, b) Environmental: reducing their carbon footprint, c) Competitive: outperforming neighbors in saving energy. Initially he looked at three mechanisms in particular: offering people cash rebates for reducing use, providing them with more frequent feedback, and giving them tips on how to conserve energy. Not surprisingly, the cash payments tended to work best, while the conservation tips showed the smallest impact**.** The present study has attempted a probe in this direction.

As per Jensen *et al.* (2011) "Small investments typically involve purchasing and installing the gadget and a change of habits requiring time and effort, whereas the financial cost of the investment itself is often small". It is this kind of change in habits that the electricity saving programs is designed to induce. But the results from the literature are much more inconclusive. According to Jensen *et al.* (2011) some studies find that willingness to change habits depends on income, age, education, and household size, but most studies have not found these effects. The only consistent result seems to be that the ownership status of the dwellings has no effect.

Reiss and White (2002) recognised that each household faces private costs of reducing consumption in response to the public appeals. Through individual efforts, there remains a virtually zero possibility of bringing about any tangible benefit with respect to the electricity crisis. But what works for individuals is that there exists a considerable incentive to free-ride on whatever efforts are made by others. The nature of individuals' free-rider problem here and the lack of private incentives for electricity conservation leave largely "moral suasion"- type arguments to explain their behavior: consumers individually wanting to "do their part" to mitigate the electricity crisis, and so forth.

It is generally observed that the family members sit and decide whether to purchase an appliance or not, but there remain many factors which are considered less often or not considered at all while deciding to purchase the appliances. In case of an appliance like an AC or a refrigerator, the thought process gets influenced by the ownership of big refrigerators and high load AC by the neighboring households. This reflects the demonstration effect as the families feel the need of buying a certain appliance only because it exists in the friends" or relatives" house. In case of TV and computer, the stand-by power, on-mode power, cost of running, energy efficiency are the factors which are rarely considered.

Chitnis *et al.* (2014) and Tukker *et al.* (2010) have suggested that environmental policies aiming at changing the behaviours and patterns of electricity consumption are necessary and Dresner and Ekins (2006) say that improving energy efficiency is useful. The prevailing demographic and socio-economic trends which characterize many societies, like increasing proportion of people living in small families and in comparatively larger accommodations are likely to increase electricity consumption via ownership of electrical appliances. This will have a negative impact on a country's carbon footprint which may be larger than the positive impact of policies in existence in order to improve a citizen's pro-environmental behavior. This will make it harder to design policies that can effectively reduce the electricity consumption and carbon footprint of a country only by addressing the citizen's pro-environmental behavior.

3. Methodology and Database

In this section, I describe how the factors are estimated using asymptotic principal component analysis, the appropriate sample size and the data collection. Factor analysis was originated in Psychology theory. Spearman (1904) started his research on factors of intelligence, based on Pearson (1901) works. Spearman enhanced a two-sector model which was further researched and developed in to multi-factor model. This multi-factor model was later termed as "factor analysis" by Thurstone in 1931.

3.1. Factor Model and the Estimation of Factors

Factor analysis uses mathematical procedures for the simplification of interrelated measures to discover patterns in a set of variables (Child, 2006). Attempting to discover the simplest method of interpretation of observed data is known as parsimony, and this is essentially the aim of factor analysis (Harman, 1976). It summarizes a set of variables by constructing a few "common factors" related to all of the variables and "specific factors" related to each individual observed variable only. The basic idea is to summarize a large amount of information in a relatively small number of estimated factors. A provisional assertion is made that a model having a single latent variable (i.e., a single factor), with a separate path emanating from it to each of the items, is an accurate representation of causal relationships (Figure 1). But, before undertaking the factor analysis, Cronbach's alpha and Kaiser-Meyer-Olkin (KMO-test) measures are applied to check the reliability of data and sample size adequacy.

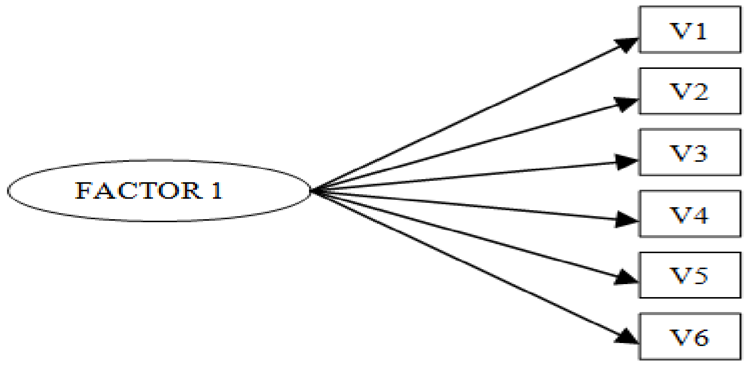

Figure-1. Single-factor Model

3.1.1. Static Factor Model

Econometric theory for the determination of the number of factors has recently been developed for both the dynamic factor framework (Stock and Watson, 2005; Bai and Ng, 2007; Hallin and Liška, 2007) as well as for the static factor framework (Bai and Ng, 2002). The methodology is based on very classical principles. A set of p observed variables shall be summarized by a small number of latent variables k (such that k < p) called common factors. The linear relationship between factors and observed variables are modelled theoretically as follows:

$$\left.\begin{aligned} x_1 &= a_{11} f_1 + a_{12} f_2 + \dots + a_{1k} f_k + \varepsilon_1 \\ x_2 &= a_{21} f_1 + a_{22} f_2 + \dots + a_{2k} f_k + \varepsilon_2 \\ x_3 &= a_{31} f_1 + a_{32} f_2 + \dots + a_{3k} f_k + \varepsilon_3 \\ &\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ x_p &= a_{p1} f_1 + a_{p2} f_2 + \dots + a_{pk} f_k + \varepsilon_p \end{aligned}\right\} \quad (1)$$

where

x_i is the ith observed variable, i = 1, 2, 3,…., p.

f_j is the jth factor, j = 1, 2, 3,…, k.

a_{ij} is the coefficient of the ith indicator and the jth factor, and a_{ij} is also called factor loading

ε_i is the unobserved error for the ith variable, i = 1, 2, 3,…, p.

The underlying model supposes that each of the p observed variables (x_i) results from the linear combination of both a small number of common factors f_j and an idiosyncratic component ε_i . In simple words, like regression model, a factor is a linear combination of a group of variables combined to represent a scale measure of a concept. We can write Equation (1) in matrix form:

$$X = a f + \varepsilon \quad (2)$$

where

X is a $p\times 1$ vector of measured/observed variables

f is a $k\times 1$ common factors

a is a $p\times k$ matrix of weights (factor loadings)

ε is a $p\times 1$ vector of unique factors, error variation

Factor analysis essentially describes the factor structure of the data. The factor loadings are $a_{i1}, a_{i2},\dots,a_{ik}$ which denotes that a_{i1} is the factor loading of i_{th} variable on the first factor. The specific or unique factor is denoted by ε_i. We can estimate the actual values of the factors for every observation after linear transformation. These values are known as factor scores which are very useful when we want to rank the individual observation. From Equation (1) we can generate Equation (3) by using regression in order to obtain the factor scores.

$$\left.\begin{aligned} f_1 &= \beta_{11} x_1 + \beta_{12} x_2 + \dots + a_{1p} x_p \\ f_2 &= \beta_{21} x_1 + \beta_{22} x_2 + \dots + a_{2p} x_p \\ f_3 &= \beta_{31} x_1 + \beta_{32} x_2 + \dots + a_{3p} x_p \\ &\dots\dots\dots\dots\dots\dots \\ f_k &= \beta_{k1} x_1 + \beta_{k2} x_2 + \dots + a_{kp} x_p \end{aligned}\right\} \quad (3)$$

where

β_{ij} are the coefficients of regression

We can write Equation (3) in matrix form:

$$f = \beta^T X \quad (4)$$

where

X is a $p\times 1$ vector of observed variables

f is a $m\times 1$ vector of common factors

β is a $p\times m$ matrix of coefficients of regression, and is also called factor score coefficient matrix,

β^T is the transpose of β, hence β^T is m×p matrix

The integrated scores are the weighted arithmetic mean of each factor with the weight of variance contribution ratio which is the contribution of each factor to the cumulative variance after rotation, shown by Equation (5):

$$F = w^T f \quad (5)$$

where

F is the integrated score for each sample point
w is a $m\times1$ vector of the variance contribution ratio
w^T is the transpose of w, hence is 1×m vector
f is a $m\times1$ vector of factor scores of sample point

One of the limitations of this technique is naming the factors. Factor names may not accurately reflect the variables within the factor. Further, some variables are difficult to interpret because they may load onto more than one factor which is known as split loadings.

3.1.2. Anderson and Rubin Scores

The method proposed by Anderson and Rubin (1956) is a variation of the Bartlett procedure, in which the least squares formula is adjusted to produce factor scores that are not only uncorrelated with other factors, but also uncorrelated with each other. Computation procedures are more complex than the Bartlett method and consist of multiplying the vector of observed variables by the inverse of a diagonal matrix of the variances of the unique factor scores, and the factor pattern matrix of loadings for the observed variables. Results are then multiplied by the inversion of the symmetric square root of the matrix product obtained by multiplying the matrices of eigenvectors (characteristic vectors of the matrix) and eigenvalues (characteristic roots of the matrix). The resulting factor scores[5] are orthogonal, with a mean of 0 and a standard deviation of 1.

3.2. Sample Size

The recommended sample size is at least 300 participants, and the variables that are subjected to factor analysis each should have at least 5 to 10 observations (Comrey and Lee, 1992). A larger sample size diminishes the error in the data and so factor analysis generally works better with larger sample sizes. However, Guadagnoli and Velicer (1988) proposed that if the dataset has several high factor loading scores (> .80), then a smaller small size ($n > 150$) should be sufficient. For the present study, electricity consumption data of 395 households[6] is collected through stratified random sampling technique. The households were asked about their electricity consumption behavior. The responses were also collected in order to assess their awareness about the conservation of electricity. Likert scale is used to record such responses.

3.3. Data

The data presented and utilise in this study is collected from a number of sources. The respondents, i.e., the households were selected on the basis of stratified random sampling technique. The data on lifestyle choices, electricity use habits of the households and various socio-demographic variables is collected in order to draw a valid database. The present study is undertaken for Delhi wherein the National Capital Region[7] has been excluded. The data on all the variables is collected through primary survey of households. The basic statistics available with census reports, statistical abstracts by the government of NCT of Delhi, CMIE reports, NSS rounds, reports by various government agencies like CEA, DERC, government budgets, economic survey, reports made by NGOs and research institutions have been referred to. Statistical software STATA 11 and SPSS 13 are used to conduct the factor analysis and other statistical operations.

4. Household Electricity Consumption Behaviour: Descriptive Statistics

To examine the attitude of Delhi consumers or households towards the usage of electricity, 14 questions were asked from the respondents (See Appendix A). Likert scale was utilized with the following choices of options to respond from: Always, Mostly, Occasionally, Rarely, Never. The descriptive results are as follows:

1. 83 per cent of families mostly or always switch off the lights and fans when no one is in the room.
2. 75 per cent families mostly or always switch off the TV from power plug after switching off from remote.
3. 68.6 per cent of households rarely or occasionally leave switch on after laptop/mobile is fully charged.
4. 40 per cent of households leave geyser on even after the light of geyser goes off automatically.
5. 65 per cent of households mostly or always use them on power saving mode while 28.6% households occasionally use appliance on power saving mode.
6. 75.7 per cent of households never or rarely talk on phone while TV is on or hold long conversations with the family.
7. 53.2 per cent households never use TV for listening while doing household chores.
8. 24.3 per cent of the families always iron all the pending clothes in one go, while 24.6 per cent mostly do that and 25.6 per cent only occasionally iron all clothes at one stretch.
9. 49.1 per cent of the households rarely keep warm food in the fridge but a good proportion of the households i.e., 39.2 per cent never store hot or warm food in the refrigerator.
10. 69 per cent of households mostly or always see BEE label on the appliance before buying it.
11. 21 per cent households occasionally use manuals for appliances while 71.7 per cent mostly or always use manuals.

On the other hand, it was observed that the households still have individuals who indulge in wasteful practices like 1) leaving the switch of the TV, laptop charger and geyser "on" when these appliances are not in active use 2) do not refer to the manuals of the appliances before using them 3) switch on the TV and talk over phone or keep doing household chores 4) leaving the fans and lights on in the room when there is no one in that room. It is important to probe the awareness level of the households for it may be the reason behind the power consuming attitude of the households (refer appendix C).

[5] They can be automatically generated in SPSS by selecting the Anderson and Rubin option in the Factor Analysis.
[6] A group of persons normally living together and taking food from common kitchen constitute a household. The word 'normally' means that the temporary visitors are excluded. 'Living together' is usually given more importance than 'sharing food from a common kitchen' in drawing the boundaries of a household. (NSS 66th round)
[7] Gurgaon, Faridabad and Noida.

Awareness in general means knowing or being informed. To understand the dynamics of electricity consumption by households, it is important that the consumers of electricity have a certain level of awareness about the generation and use of electricity. In order to assess the awareness level of the households in general and specific to electricity certain statements were provided to the respondents and they were asked to give their responses in terms of agree, strongly agree, disagree, strongly disagree and cannot say (See Table 3 for results). Likert scale was applied to the responses. Mean score on the likert scale was obtained to find the household trend.

Table-3. Statistics on Household Awareness

S. No	Statement	SA (%)	A (%)	CS (%)	D (%)	SD (%)	Mean score of likert scale
1	I am aware of the adverse effects of electricity generation.	22.5	69.9	6.3	1.3	0	1.14
2	Electricity is not scarce and should not be conserved.	1.5	1.8	2.5	51.4	42.8	-1.32
3	The raw material required for electricity generation is readily available.	0.8	3.8	36.7	38.5	20.3	-0.74
4	Renewable/non-conventional sources are not available for electricity generation.	7.1	20	57.2	9.9	5.8	0.13
5	Electricity generation has a direct impact on the climate.	13.7	51.4	31.6	2.3	1	0.74
6	High consumption level of electricity does not increase the average temperature of our environment.	0.8	3.8	32.7	51.1	11.6	-0.69
7	Reducing the electricity wastage will help protect the environment.	52.9	41.3	5.1	0.3	0.3	1.47
8	Presence of sunlight in the house saves electricity.	51.6	45.8	2	0.5	0	1.49
9	Walls of the house should not be painted with light colors.	2.8	4.8	7.1	36.2	49.1	-1.24
10	Home with BEE labelled appliances does not consume less electricity.	0.5	2.8	19.5	44.6	32.7	-1.06

Note: Scores and full forms; SA=Strongly Agree (2), A=Agree (1), CS=Cannot Say (0), D=Disagree (-1) and SD=Strongly Disagree (-2)

Over the past few years, electricity being scarce and power failures still prevalent, some households have taken steps to reduce the electricity consumption or at least to reduce the wasteful usage of electricity. When consumers make decisions to conserve energy – such as; by using less hot water or turning lights off around the house – it is likely they lose some utility by having to expend the extra effort in the conservation. With perfect information relating consumption to cost, they will only conserve when the utility of lowering their bill (and reducing their Green House Gases footprint) outweighs the disutility of using less energy.

It was observed during the data collection that the people who already use less electricity, women, and people with more pro-environmental beliefs, attitudes and past behavior have stronger intentions to reduce their electricity consumption. On the other hand, households with highly educated family head do not necessarily have low electricity consumption (Tewathia, 2014). They report either very high or very low intentions to reduce consumption. These results are found in sync with the findings of Gardner and Ashworth (2007).

5. Empirical Results & Discussion

This paper used Exploratory Factor Analysis, which tries to uncover complex patterns by exploring the dataset and testing predictions (Child, 2006). Cronbach's Alpha test tells us about how much variance a group of items had in common. It was found to be greater than 0.7 which indicates good reliability of the data. But, it should be emphasized that a relatively high alpha is no guarantee that all the observed variables reflect the influence of a single latent variable. Correlations based on two items representing primarily the same latent variable should be high, and those based on items primarily influenced by different latent variables should be relatively low. To check whether the considered sample is big enough, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy[8] was undertaken.

Factor Analysis provide a means of explaining variation among relatively many original variables using relatively few newly created variables (i.e., the factors). This amounts to condensing information so that variation can be accounted for by using a smaller number of variables. Factor analysis can help us determine empirically how many constructs, or latent variables, or factors underlie a set of observed variables. Extracting too many factors may present undesirable error variance but extracting too few factors might leave out valuable common variance. So it is important to select which criterion is most suitable to your study when deciding on the number of factors to extract. Two widely used non-statistical guidelines for judging when enough factors have been extracted are the eigenvalue[9] rule (Kaiser, 1960) and the scree test[10] (Cattell, 1966). A factor that achieves an eigenvalue of 1.0 contains the same proportion of total information as does the typical single observed variable. The eigenvalue rule (Kaiser, 1960) asserts that factors with eigenvalues less than 1.0 (and, thus, containing less information than the average item) should not be retained as the eigenvalue represents the strength of the factor. Eigenvalue used to establish a cut off of factors is a value like R square in regression.

Before trying to interpret factors—to ascertain what the constructs or latent variables corresponding with factors are, based on the items identified with each factor—it is usually necessary to perform a factor rotation[11].

[8] The sample is said to be adequate if the value of KMO is greater than 0.5.
[9] Eigenvalues indicate the amount of variance explained by each principal component or each factor.
[10] The scree test is only reliable when you have a sample size of at least 200.
[11] Factor rotation is analogous in that it attempts to provide a "vantage point" from which the data's organizational structure—the ways in which items share certain characteristics— becomes apparent. It increases interpretability by identifying clusters of variables that can be characterized predominantly in terms of a single latent variable (i.e., items that are similar in that they all have a strong association with, and thus are largely determined by, only one and the same factor).

Methods such as 'varimax', is applied in order to maximize the variance of the squared loadings for each item. So, depending on how the vectors are oriented, the loadings will vary. Factor loadings[12] are correlations between each item and each factor based on the orientation of the vectors (i.e., reference lines) defining the factors. We are seeking a specific type of unevenness in which one loading is substantial while all other loadings for that variable are small. The results in Table 4 reflect that a simple structure[13] is achieved.

Table-4. Factors Loadings on Electricity Consumption Behavior Variables

Observed Variables	F1	F2	F3
x_1: Do you switch off the fans, ACs and lights when no one is in the room?	*0.8138*	-0.0488	-0.1742
x_2: Do you switch off the power plug of TV after switching it off by the remote control?	*0.7232*	-0.0131	-0.1021
x_3: Does the switch remain "on" even after the laptop/mobile/camera is fully charged?	- 0.3673	0.0366	*0.6946*
x_4: Do you keep the water geyser on after its light turns off on its own after reaching at the maximum temperature?	-0.3196	0.0978	*0.6294*
x_5: Do you indulge in long conversations in person or on phone while the TV is on?	-0.1128	*0.7177*	0.2340
x_6: Is TV used only for listening while doing the household chores?	0.2093	*0.7145*	0.0374
x_7: Do you use the electrical appliances such as ACs and refrigerators at their power saving mode?	*0.5626*	-0.2588	-0.1924
x_8: Do you use the lights in the room during daytime when the room has enough sunlight?	0.2399	*0.7117*	-0.1685
x_9: Do you consider the BEE label while purchasing electrical appliances?	0.3538	-0.2216	-0.1723
x_{10}: Do you refer the instruction manual for all the electrical appliances?	*0.5881*	-0.1546	-0.4042
x_{11}: Do you get the walls of your house painted in dark colors?	0.0504	0.0916	*0.7158*
x_{12}: Do you store hot/ warm food in your refrigerator?	-0.2382	*0.5978*	0.2691
x_{13}: Do you pay the electricity bill on time?	0.1154	-0.0116	0.0433
x_{14}: Do you iron all the pending clothes in one go?	*0.5220*	-0.1035	0.2667

Cronbach's alpha: 0.7919
KMO value: 0.8029
Total Variance explained: 58.35%
Determinant[14]: 0.030
Bartelett's Test of Sphericity[15]: sig. .000
Rotation method: Varimax with Kaiser Normalization

Each factor is defined by the items that load most heavily on it. To determine the cut-off for a statistically meaningful rotated factor loading, a general rule to determine the reliability of the factor is to be looked upon i.e., the relationship between the individual rotated factor loading and the magnitude of the absolute sample size. The larger the sample size, smaller loadings are allowed for a factor to be considered significant (Stevens, 2002). According to Costello and Osborne (2005) a factor with fewer than three items is generally weak and unstable; 5 or more strongly loading items (.50 or better) are desirable and indicate a solid factor. Table 4 shows such loadings in bold. The items with the highest loadings are the ones that are most similar to the latent variable. A global assessment of the correctness or incorrectness of the factor structure[16] was made and it was found that the analysis was considered to have produced the correct factor structure.

From Table 4 we can find the factor matrix which shows the linear relationship between observed variables (x) and factors (f). For example, we take arbitrary three observed variables and use the form of Equation (2) to get the following factor structure[17]:

$$\begin{Bmatrix} x_1 \\ x_3 \\ x_5 \end{Bmatrix} = \begin{Bmatrix} 0.8138 & -0.0488 & -0.1742 \\ 0.3673 & 0.0336 & 0.6946 \\ -0.1128 & 0.7177 & 0.2340 \end{Bmatrix} \begin{Bmatrix} f_1 \\ f_2 \\ f_3 \end{Bmatrix} \tag{6}$$

where
x_1 is 'Do you switch off the fans, ACs and lights when no one is in the room?'
x_3 is 'Does the switch remain "on" even after the laptop/mobile/camera is fully charged?'
x_5 is 'Do you indulge in long conversations in person or on phone while the TV is on?'
f_i is the ith factor

From Equation 6, we find strong positive correlation between switching off the fans, ACs and lights when no one is in the room and factor 1, switch remaining "on" even after the laptop/mobile/camera is fully charged and factor 3 and indulging in long conversations in person or on phone while the TV is on and factor 2.

Furthermore, each factor has different effects on the household electricity consumption behavior, which can be reflected by factor scores. The factor scores are the products of the observed data and the factor score coefficient matrix[18]. Equation (3) is used to calculate factor scores (see appendix for factor scores). For example, factor 1 can be written as follows[19]:

$$f_1 = 0.379x_1 + 0.330x_2 + \dots\dots - 0.106x_8 + \dots\dots + 0.292x_{14}$$

where

x_1 is 'Do you switch off the fans, ACs and lights when no one is in the room?'
x_2 is 'Do you switch off the power plug of TV after switching it off by the remote control?

[12] In regression terms, it is the standardized regression coefficient between the observed values and common factors.
[13] It is a circumstance when the variable is being influenced primarily by the single factor on which it loads substantially.
[14] Determinant score indicates an absence of multi-collinearity if the score is above the rule of thumb of .00001.
[15] This test shows that we do have patterned relationships amongst the variables ($p < .001$).
[16] The factor analysis for this sample produced three factors, and the items loaded on the correct factors (all conservation items loaded together on a single factor, all usage behavior items loaded together on a single factor, all wastage items loaded together on a single factor). A researcher drawing that sample, and performing such an analysis, would draw the correct conclusions regarding the underlying factor structure for those items.
[17] This 3×3 matrix in Equation (6) is a part of the factor matrix presented in Table 4.
[18] A negative number implies that the score is under the average.
[19] For further information on factor score coefficient matrix, see Appendix A.

x_8 is 'Do you use the lights in the room during daytime when the room has enough sunlight?
x_{14} is 'Do you iron all the pending clothes in one go?'

It is clear that 'Do you switch off the fans, ACs and lights when no one is in the room?', 'Do you switch off the power plug of TV after switching it off by the remote control?' and 'Do you iron all the pending clothes in one go?' have a strong positive influence on factor 1. 'Do you use the lights in the room during daytime when the room has enough sunlight? (x_8), has a negative linear relation to factor 1. We name the factors after the commonness of the explanatory variables. After carefully observing the Table 4, factors are named as: factor 1; *Electricity saving habits*, factor 2; *Electricity wasting practices* and factor 3; *Disguised Wastage of Electricity*.

From Equation (5), we can find the integrated scores which measure the household electricity consumption behavior of 395 Delhi households objectively and synthetically. The weights are the ratios of the contribution of each factor to the cumulative variance. Contribution of factor 1 is 18.27 per cent, of factor 2 is 14.56 per cent and of factor 3 is 14.37 per cent which gives us the cumulative variance as 47.210 per cent (refer appendix A). Hence, we can write the integrated score of first household as:

$$f = 0.182f_1 + 0.145f_2 + 0.143f_3$$

Same procedure was applied for identifying the latent variables and factor loadings for electricity conservation variables. The questionnaire (refer Appendix B) carried ten variables which were ranked by the respondents on a Likert scale. After conducting Factor Analysis, three factors were retained (see Table 5). The factor loadings which are greater than 0.5 are shown in Table 5 (for details see appendix B). It is evident that a simple factor structure is obtained.

Table-5. Factor Loadings on Electricity Conservation variables

Observed Variables	F1	F2	F3
v_1: I am an informed and aware citizen of the state.		0.8364	
v_2: I am aware of the adverse effects of electricity generation.		0.8265	
v_3: I will prefer pre-informed power cuts.		0.6711	
v_4: Reducing the electricity wastage will help protect the environment.			0.6300
v_5: I am not aware of different ways to reduce the wastage of electricity in my household.			(-)0.7583
v_6: It would save me money to reduce my household's electricity consumption.			0.7691
v_7: Reducing my household's electricity consumption would cause me inconvenience.	(-)0.7817		
v_8: I know people who have taken steps to reduce their household's electricity consumption.	0.7825		
v_9: During the past year I have taken steps to reduce my household's electricity consumption.	0.8782		
v_{10}: I have complete control over whether I reduce my household electricity consumption.	(-)0.6125		
Cronbach's alpha: 0.7113 KMO value: 0.704 Total Variance explained: 63.92% Determinant: 0.046 Bartelett's Test of Sphericity: sig. .000 Rotation method: Varimax with Kaiser Normalization			

The signs of the loadings show the direction of the correlation and do not affect the interpretation of the magnitude of the factor loading or the number of factors to retain (Kline, 1994).
Equation 2 can be re-written, with a small replacement of notation, as

$$V = a\,f + \varepsilon \qquad (7)$$

In form of Equation 7, the 3×3 matrix[20] can be written as follows:

$$\begin{Bmatrix} v_1 \\ v_4 \\ v_8 \end{Bmatrix} = \begin{Bmatrix} -0.0387 & \mathit{0.8364} & 0.1115 \\ 0.3027 & 0.3715 & \mathit{0.6300} \\ \mathit{0.7825} & 0.0982 & 0.1568 \end{Bmatrix} \begin{Bmatrix} f_1 \\ f_2 \\ f_3 \end{Bmatrix} \qquad (8)$$

where
v_1 is 'I am an informed and aware citizen of the state'
v_4 is 'Reducing the electricity wastage will help protect the environment'
v_8 is 'I know people who have taken steps to reduce their household's electricity consumption'
f_i is the ith factor

All the ten variables have been found heavily loaded on three factors. It is observed that v_7 and v_{10} have negative correlation with factor 1 while the variables indicating taking conservation steps by the household as well as the neighborhood, i.e., v_8 and v_9 have positive correlation with factor 1. Factor scores are calculated with the help of SPSS and are presented in the component score coefficient matrix in appendix B. For example, factor 1 can be written as follows:

$$f_1 = -0.19v_1 - 0.36v_2 + \ldots + 0.144v_4 \ldots + 0.319v_8 + \ldots - 0.234v_{10}$$

Observed variables, 'I am an informed and aware citizen of the state', 'I am aware of the adverse effects of electricity generation' and 'I have complete control over whether I reduce my household electricity consumption', have negative influence on factor 1 namely 'conservation of electricity'. While variables, 'Reducing the electricity wastage will help protect the environment' and 'I know people who have taken steps to reduce their household's

[20]This 3×3 matrix in Equation (7) is a part of the factor matrix presented in appendix B.

electricity consumption' have strong positive influence on factor 1. Factor 1 is named as '*Conserving Electricity*', factor 2 as '*Awareness of the consumer*' and factor 3 as '*Electricity Conservation Benefits*'.

The integrated score of a given household is again calculated on the basis of contribution of each factor in the cumulative variance. The weights are the ratios of the contribution of each factor (25.28 per cent, 20.62 per cent and 18.01 per cent) to the cumulative variance (63.927 per cent), which are 0.252, 0.206 and 0.18 (refer Appendix B). The integrated score of first household is calculated as follows:

$$f = 0.252f_1 + 0.206f_2 + 0.18f_3$$

When interpreting the factors, one needs to look at the loadings to determine the strength of the relationships. Factors can be identified by the largest loadings, but it is also important to examine the zero and low loadings in order to confirm the identification of the factors (Gorsuch, 1983). Each factor in Table 4 and 5 is defining a distinct cluster of interrelated variables as the cross-loadings[21] were found to be very few and low in value (see factor matrix presented in appendix A and B).

6. Conclusion

Electricity has become an invisible source of energy for us. The ever-rising electricity consumption is a clear indicator of the derived demand for the electrical appliances. The consumers of such appliances are and will increase with rising income, changing lifestyle, modernization, and in broader terms, development of the country. This paper utilized a large cross-section (395 households) primary data on the households residing in Delhi. Exploratory factor analysis was conducted for the household electricity consumption behavior and their awareness level towards electricity usage and its conservation. These are the two major areas for which the policy makers need to ponder carefully. Three factors i.e., Electricity saving habits, Electricity wasting practices and Disguised wastage of electricity could be targeted at the very beginning when the survey questionnaire is being conceptualized to lessen the complications in computation. Similarly, the factors; Conserving electricity, Awareness of the consumer and Electricity conservation benefits shall be addressed in the questionnaire in order to capture the consumer intentions with respect to their future actions or plans. We can say that the factor analysis utilized for this study has presented some relevant implications for policy makers. It was realized that many households are aware that the electricity is scarce but still, much is to be done in order to conserve it. Policies designed to have a direct influence on family size and the type of house that individuals live in, will go a long way in addressing the environmental and energy issues. More campaigns and awareness programs need to be conducted so that the citizens understand the importance of electricity in their lives. Such awareness programmes must not be simply an eye-wash but should be able to make a difference in the electricity consumption behaviour.

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[21] A cross-loading is when an item loads at .32 or higher on two or more factors Costello, A.B. and J.W. Osborne, 2005. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Practical Assessment, Research & Evaluation, 10(7): 1-9. Cross loadings are also called split loadings.

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Appendix-A

22. Electricity consumption behavior:
Please put a (*) under the appropriate response.

S.No	Question	Always	Mostly	Occasionally	Rarely	Never
1	Do you switch off the fans, ACs and lights when no one is in the room?					
2	Do you switch off the power plug of TV after switching it off by the remote control?					
3	Does the switch remain “on” even after the laptop/mobile/camera is fully charged?					
4	Do you keep the water geyser on after its light turns off on its own after reaching at the maximum temperature?					
5	Do you indulge in long conversations in person or on phone while the TV is on?					
6	Is TV used only for listening while doing the household chores?					
7	Do you use the electrical appliances such as ACs and refrigerators at their power saving mode?					
8	Do you use the lights in the room during daytime when the room has enough sunlight?					
9	Do you consider the BEE label while purchasing electrical appliances?					
10	Do you refer the instruction manual for all the electrical appliances?					
11	Do you get the walls of your house painted in dark colors?					
12	Do you store hot/ warm food in your refrigerator?					
13	Do you iron all the pending clothes in one go?					
14	Do you pay the electricity bill on time?					

22. Factor loadings

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
q22:1	0.8138	-0.0488	-0.1742	0.0477	0.3028
q22:2	0.7232	-0.0131	-0.1021	0.1984	0.4270
q22:3	-0.3673	0.0336	0.6946	-0.0468	0.3793
q22:4	| -0.3196	0.0978	0.6294	0.1265	0.4761
q22:5	-0.1128	0.7177	0.2340	-0.0315	0.4164
q22:6	0.2093	0.7145	0.0374	-0.3969	0.2867
q22:7	0.5626	-0.2588	-0.1924	0.0392	0.5779
q22:8	-0.2399	0.7117	-0.1685	-0.0240	0.4069
q22:9	0.3538	-0.2216	-0.1723	0.6296	0.3996
q22:10	0.5881	-0.1546	-0.4042	0.3569	0.3395
q22:11	0.0504	0.0916	0.7158	-0.0866	0.4691
q22:12	-0.2382	0.5978	0.2691	0.2541	0.4489
q22:13	0.1154	-0.0116	0.0433	0.8352	0.2871
q22:14	0.4954	-0.1035	0.2667	0.2360	0.6171

#Factor 4 was found to be measured by less than three variables (A solution is less satisfactory if a given factor is measured by less than three variables) and hence was dropped.

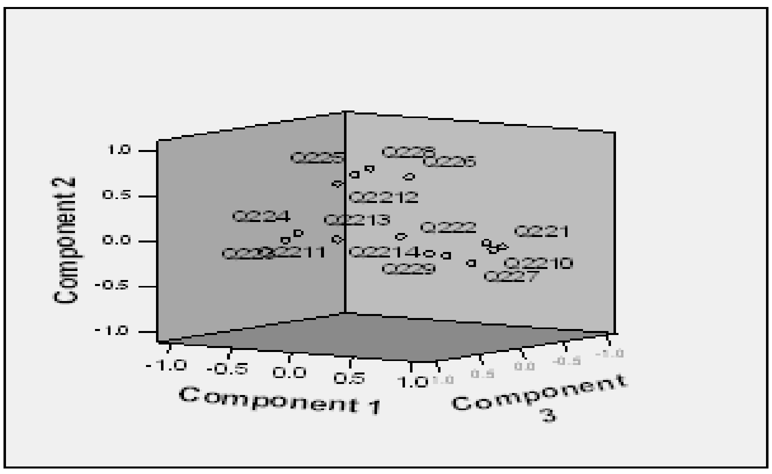
Component Score Coefficient Matrix

	Component			
	1	2	3	4
Q221	.379	.053	.042	-.136
Q222	.330	.081	.063	-.007
Q223	-.001	-.087	.379	-.007
Q224	-.014	-.016	.333	.120
Q225	.072	.367	.053	.030
Q226	.248	.356	-.001	-.297
Q227	.221	-.081	.007	-.098
Q228	-.106	.399	-.231	.097
Q229	.027	.008	-.043	.388
Q2210	.139	.047	-.148	.156
Q2211	.240	-.034	.466	-.128
Q2212	-.041	.328	.056	.259
Q2213	-.056	.116	.022	.590
Q2214	.292	-.019	.268	.036

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Component Scores.

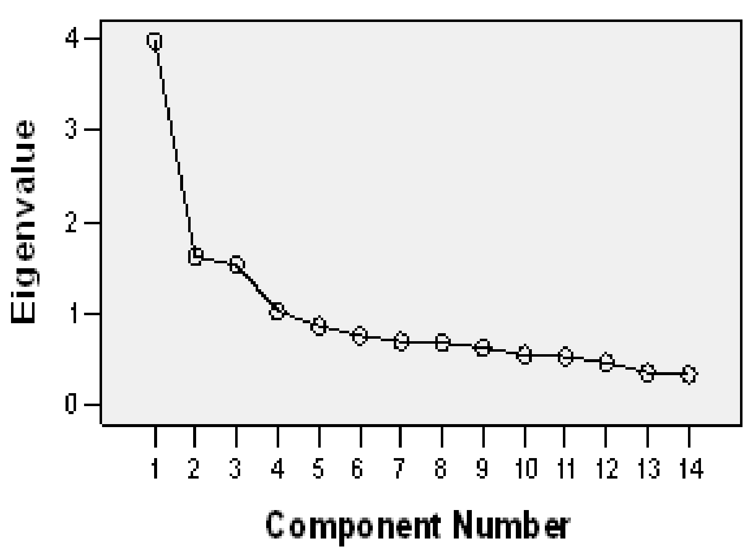
22. Component Space: Factors Loadings on Electricity Consumption behavior

Component Plot in Rotated Space



22. Scree Plot: Factors Loadings on Electricity Consumption Behavior Variables

Scree Plot



Appendix-B

24. Electricity Conservation Behavior
Put a (*) under the appropriate response.

S.No	Statement	Strongly agree	Agree	Cannot say	Disagree	Strongly disagree
1	I am an informed and aware citizen of the state.					
2	I am aware of the adverse effects of electricity generation.					
3	I will prefer pre-informed power cuts.					
4	Reducing the electricity wastage will help protect the environment.					
5	I am not aware of different ways to reduce the wastage of electricity in my household.					
6	It would save me money to reduce my household's electricity consumption.					
7	Reducing my household's electricity consumption would cause me inconvenience.					
8	I know people who have taken steps to reduce their household's electricity consumption.					
9	During the past year I have taken steps to reduce my household's electricity consumption.					
10	I have complete control over whether I reduce my household electricity consumption.					

24. Factor loadings

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Uniqueness
q24:1	-0.0387	0.8364	0.1115	0.2865
q24:2	-0.0869	0.8265	0.1687	0.2809
q24:3	0.0964	0.6711	0.1028	0.5297
q24:4	0.3027	0.3715	0.6300	0.3735
q24:5	0.0392	-0.0933	-0.7583	0.4147
q24:6	-0.1848	0.1274	0.7691	0.3580
q24:7	-0.7817	0.1014	0.2050	0.3366
q24:8	0.7825	0.0982	0.1568	0.3534
q24:9	0.8782	0.0122	0.0290	0.2279
q24:10	-0.6125	0.2534	0.3386	0.4460

Component Score Coefficient Matrix

	Component		
	1	2	3
Q241	-.019	.463	-.148
Q242	-.036	.440	-.109
Q243	.036	.369	-.103
Q244	.144	.050	.349
Q245	-.015	.153	-.493
Q246	-.043	-.138	.483
Q247	-.305	-.006	.072
Q248	.319	.024	.123
Q249	.353	.009	.063
Q2410	-.234	.050	.132

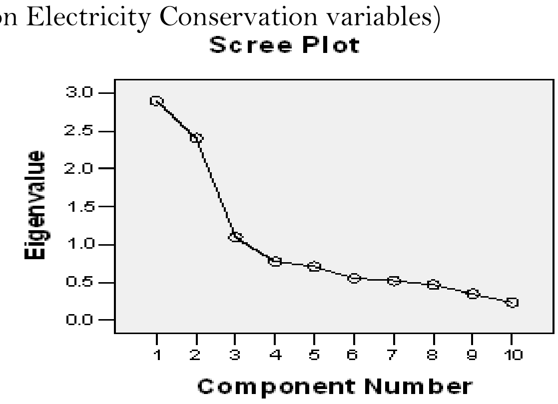
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Component Scores.

Total Variance Explained

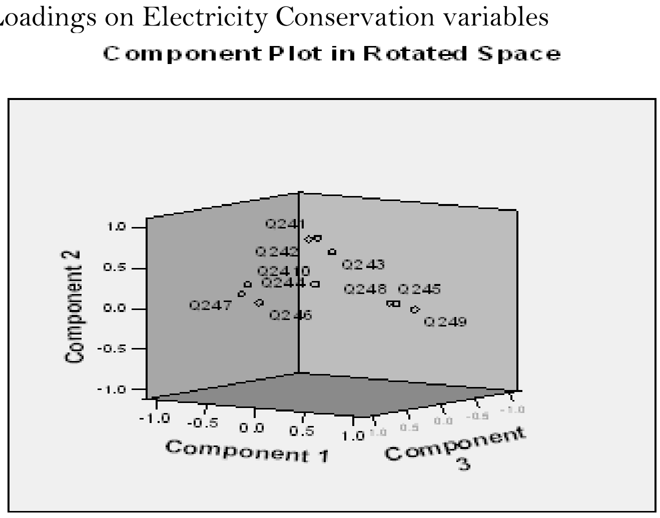
Componer	Initial Eigenvalues			xtraction Sums of Squared Loading			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.897	28.974	28.974	2.897	28.974	28.974	2.528	25.281	25.281
2	2.402	24.020	52.994	2.402	24.020	52.994	2.063	20.628	45.909
3	1.093	10.933	63.927	1.093	10.933	63.927	1.802	18.019	63.927
4	.772	7.720	71.648						
5	.706	7.055	78.703						
6	.555	5.548	84.251						
7	.524	5.239	89.490						
8	.466	4.663	94.153						
9	.346	3.464	97.617						
10	.238	2.383	100.000						

Extraction Method: Principal Component Analysis.

24: Scree Plot (Factor Loadings on Electricity Conservation variables)

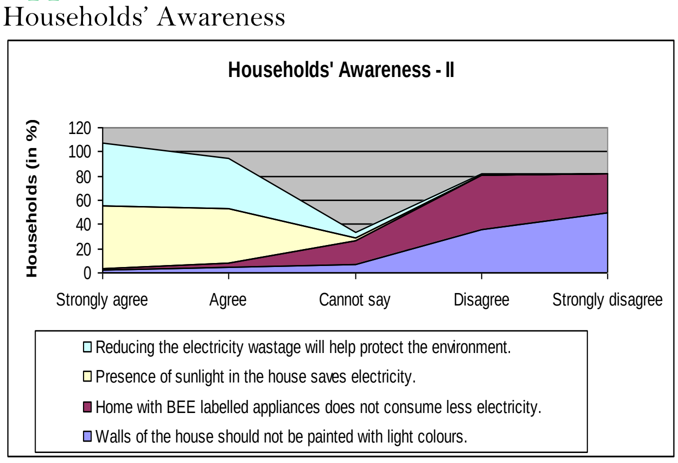


24. Component space Factor Loadings on Electricity Conservation variables

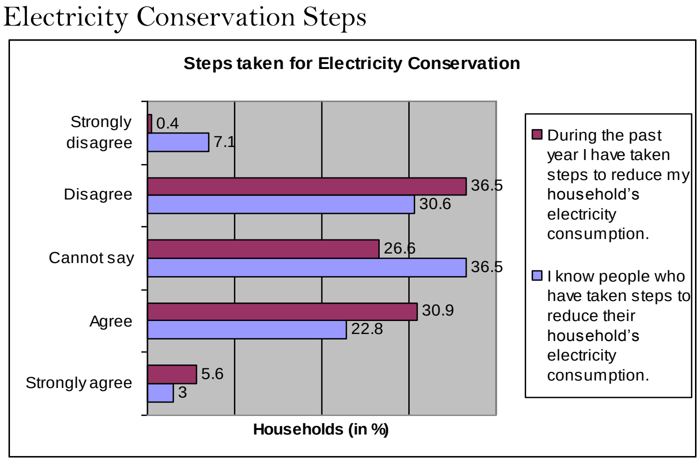


Appendix-C

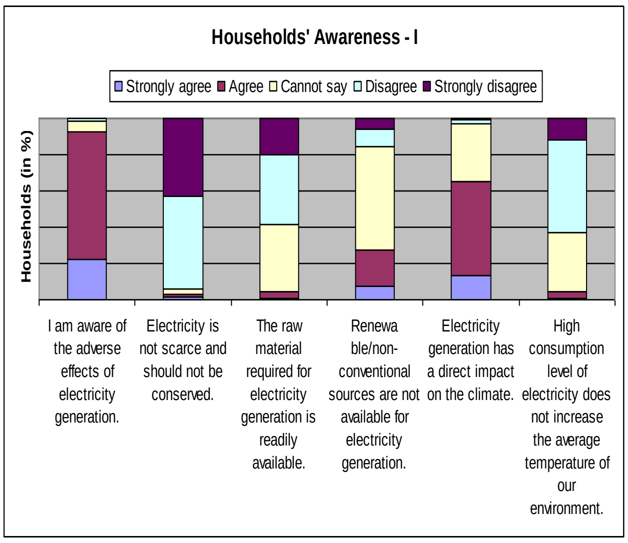
Households' Awareness



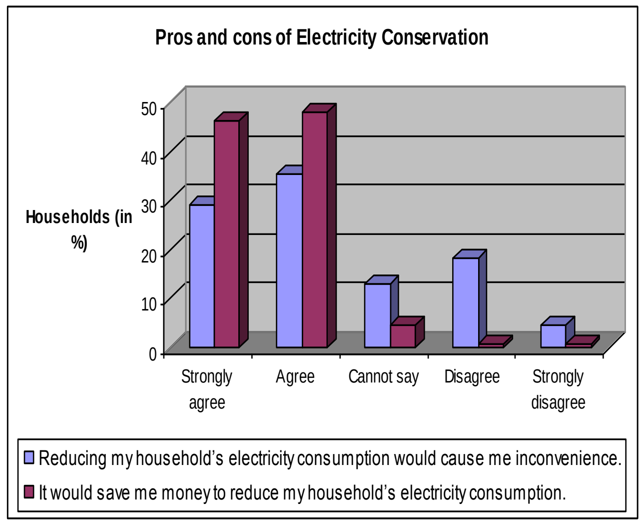
Electricity Conservation Steps



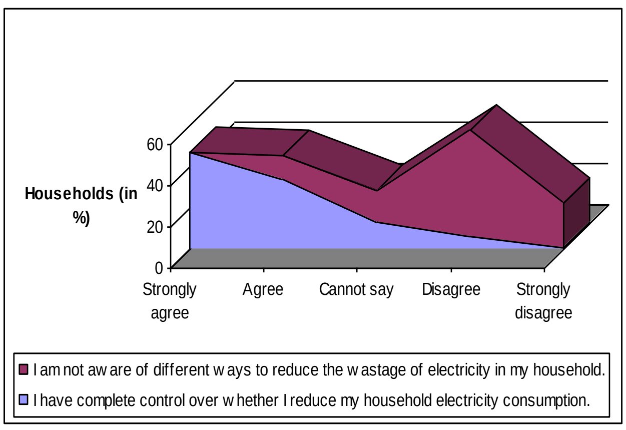
Households' Awareness



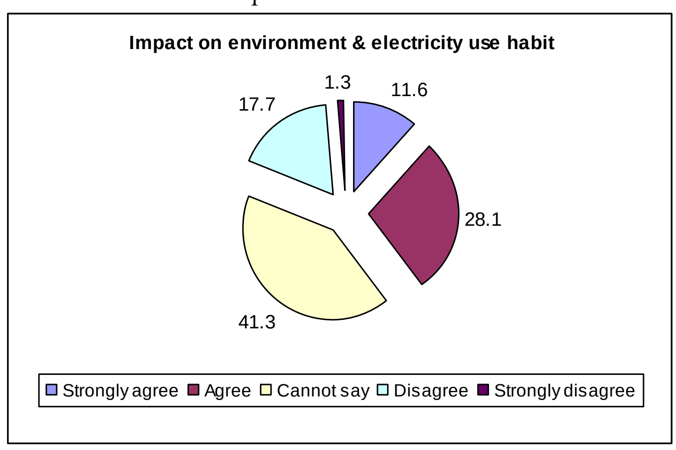
Pros & Cons of Electricity Conservation



Control and Awareness



Environnemental Impact as Motivation



Willingness to pay for Energy Efficient Home