Residential Consumer Understanding of Electricity Bills: The Case of the Indian Consumer

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ABSTRACT

The neoclassical model of economics assumes that the greater the information available, the easier it is for a consumer to make decisions. In the context of electricity usage, overwhelming amounts of information presented on energy bills and a lack of real-time information deter consumers from understanding their own energy usage and developing personalized strategies to reduce it. This study assesses the literacy levels regarding electricity bills amongst consumers in India. Regression results indicate that homes with stronger beliefs in energy conservation minimize their usage. The size of the dwelling, demographics, and the ownership of the dwelling influence literacy levels regarding electricity bills. The study had a counterintuitive finding, as the respondents were found reluctant to receive a normative comparison of their electricity bills—strange for a collectivistic cultured society like India. The study recommends making electricity bills more visually appealing and increasing their frequency to increase awareness of energy usage.

KEYWORDS

Electricity, Electricity Bill, Information Feedback, Normative Comparison, Ordinal Regression, Residential Energy Conservation

1. INTRODUCTION

Residential electricity consumption has increased by a factor of more than 50 since 1971 in India (Chunekar & Sreenivas, 2019). The increased pace of urbanization coupled with rapid electrification and rising incomes has resulted in increased appliance ownership and, thereby, increased electricity usage in India (Chunekar & Sreenivas, 2019). Despite consuming less than one-third of the world's average electricity, India still ranks third in carbon emissions, after USA and China as per the Intergovernmental Panel on Climate Change, 2015. While on the one hand, there is progress towards meeting United Nations Sustainable Goal 7 of energy access to all, on the other hand, there is a conscious drive towards reducing energy-related environmental pollution (International Energy Agency, 2020). The energy demand in India is poised to double by 2040 (International Energy Agency, 2020), indicating increased energy generation and carbon emissions even further. India has contributed a 5% growth in CO₂ emissions with the rise in its GDP (Azevedo, Sartori, & Campos, 2018). This necessitates energy conservation to reduce the impacts of climate change. Conservation efforts can start

with the residential energy sector, which contributes 25–30% of all energy consumption worldwide, while also contributing to 17% of total CO₂ emissions (Nejat et al., 2015; Swan & Ugursal, 2009).

Providing consumers relevant, timely and symmetric information can enable them to participate in conserving their residential energy. The electricity bill is intended to provide usage-related information to increase energy consciousness amongst consumers and encourage them to reduce consumption (Trotta, 2020). It is received periodically and the included price and quantity information offers consumers an opportunity to modify their consumption in response to external feedback (Wichman, 2017). A well-drafted energy bill serves as an effective tool in facilitating consumers on their electricity usage (Brühl, Smith, & Visser, 2019). Consumers need to receive adequate and transparent information on electricity pricing, consumption and complaint redressal procedure from their energy providers to enable energy conservation (Balani, Ramesh, & Aggrawal, 2021).

Gathering such robust information on energy consumption is possible with the help of smart meters, that enable electricity consumption tracking in 15 minute intervals and transmit energy consumption information to the user and the utility provider. However, in India, smart meters are yet not widely installed. As of current practices, data on residential energy consumption is not recorded till the utility provider completes the physical examination of electricity meters in residential premises. The nation wide lockdown enforced between March and May 2020, ensued by the COVID-19 crisis, showed the urgency for installation of smart meters which can enable in monitoring energy usage and also recommend ways to conserve the energy.

The need for residential energy conservation is more pressing in the post-COVID-19 world. Data suggests that during the COVID-19 lockdown residential consumption of electricity increased significantly (Elavarasan, et al., 2020), while that of large industrial and commercial units was reduced (Aruga, Islam, & Jannat, 2020). While literature is well documented in other facets of energy literacy amongst electricity consumers (DeWaters et al., 2013; Martins et al., 2019), this study seeks to understand the following from the consumer's monthly electricity bills

1. Consumer's interpretation of their bills
2. Consumer's perception of their bills
3. Impact of socio demographic factors on electricity usage
4. Electricity consciousness of the consumers

The motivation behind this study was to understand the consumer's interpretation and perception of a detailed utility bill (in this case electricity) so as to facilitate in designing consumer friendly utility bills in future. This will enable the local utility bodies to design easy, comprehensible bills in future like the renewable energy bills, water bills etc.

The study is based in the Tier 2 urban city of Pune, in the state of Maharashtra, which has one of the highest domestic power tariffs in India and is expected to be a key electricity demand center between 2019 and 2029 (Ministry of Power, Government of India, 2015-16). This study assesses energy cost literacy levels (taken as a proxy for electricity bill literacy) amongst 130 affluent residential households in the city. It considers correct identification of energy costs in the bill to indicate level of energy cost literacy. A higher number of correctly identified costs indicated higher energy cost literacy levels. Given the ordinal nature of this variable, ordinal regression was used to identify factors impacting energy cost literacy levels amongst sampled respondents. Factors such as direct information experience of electricity bills (e-bills), information feedback perception of e-bills, residential electricity consciousness and respondent socio-demographic profiles were included as possible impacting factors. Polytomous Universal Model (PLUM) procedure in SPSS was used to conduct ordinal regression analysis. Data collection was done in the immediate time period (in the months of August and September 2020) following the first wave of COVID-19 induced lockdown in India (imposed during March – May 2020). The lockdown resulted in inflated electricity bills for

residences, and the study aimed at capturing residential e-bill literacy during in this context. Hence this study suffers from a small sample size limitation.

This paper is structured in six sections. Section 1 sets the context for the study at hand. Section 2 reviews the literature on information feedback provided through electricity bills in various countries. Section 3 introduces the research methodology and conceptual model of the study. Section 4 presents the data analysis and key takeaways. Conclusions and managerial implications are presented in section 5, and section 6 concludes the paper by discussing study limitations.

2. LITERATURE REVIEW

Literature published between 2015 and 2020 was studied to ensure recency of relevant literature on energy information feedbacks, which increase consumer's knowledge on own energy consumption, and perceptions around it. Keywords included energy literacy, energy cost literacy, information feedback on end-user of electricity consumption, direct and indirect information feedback on residential electricity consumption, information-seeking behavior, and electricity bill awareness. Publications were selected from the Scopus indexed database. Additionally, grey literature like energy reports and IEA reports were also studied.

Residential energy consumption accounts for more than 20% of annual emissions (Environmental Protection Agency, 2011) thus becoming the prime audience for receiving energy information feedbacks – which is the process of giving people information about their behavior, such that it can be used to reinforce and/or modify future actions (Karlin, Zinger, & Ford, 2015). In the words of Kluger and DeNisi (1996), the provision of information referred to as *feedback intervention* is the “actions taken by (an) external agent to provide information regarding some aspect(s) of one's task performance” (p. 255).

Information feedback on energy consumption has attracted research attention for many years now, and some of the earliest studies can be traced back to the 1970s and 1980s (Seligman & Darley, 1977; Winkler & Winett, 1982; (Van Houwelingen & Van Raaij, 1989); Bandura, 1977). In developed economies, energy feedback mechanisms have gained speedy attention, keeping pace with energy infrastructure changes such as the introduction of In-House Display (IHD) systems, sensing technologies and smart meters – all of which provide real-time information to consumers (Chopra, 2011). Energy information feedback can be direct or indirect (Bertoldi, Serrenho, & Zangheri, 2016). Direct feedbacks provide appliance-level disaggregated consumption and cost information through in-house displays(IHDs) whereas Indirect feedback is relayed through text messages, emails, and electricity bills. While indirect feedbacks can be more cost effective, they are usually less effective than direct feedback systems such as IHDs and TV relayed messaging (Vassileva, Dahlquist, Wallin, & Campillo, 2013).

Energy feedbacks can greatly alter the reducible component of residential energy consumption, more effectively than energy prices and energy-efficiency labels (Yu & Guo, 2016; Zainudin & Ramli, 2017). Feedbacks can be monetary, informational, or behavioral (Buckley, 2020), and can reduce residential electricity demand by up to 20% (Yu & Guo, 2016). Effective designing of feedbacks must take into account the design, content, medium of sharing, and format in which information is shared, where each of these parameters hold equal importance in defining the success of the feedback (Canfield et al., 2016). Feedback should also be frequent, understandable and relatable (Vine, Laurie, & Morris, 2013) and latest research on the subject now explores the role of text based feedbacks or a “conversational” feedback agents (Gnewuch, Heckmann, Morana, & Maedche, 2018).

Studies exploring the role of energy information feedback in India, has been developing only in the recent years. The power of indirect information feedback, as “nudges” to reduce electricity consumption at homes was studied and reported by (Sudarshan, 2017), which reported that pure non monetary informational strategies can nudge energy saving at Indian homes more than monetary incentives. The effectiveness of non-monetary messaging for energy saving in a developing country

setting like India was also highlighted by (Chen, Delmas, Locke, & Singh, 2017). Further, (Jain, Chhabra, & Singh, 2015) found that daily reporting of energy consumption patterns, and a normative comparison helped in 20% energy savings in a student dormitory setup, signifying the importance of normative comparisons in energy feedback systems.

The literature analysis shows that while recent studies are exploring the efficacy of energy feedback systems in the Indian context, very few studies have explored how this information feedback has translated into electricity cost literacy amongst residences. Energy cost literacy, is an understudied subject and needs to be understood better, especially in Indian homes. The Indian electricity sector proposes to undergo radical reforms in view of dwindling financial health of power supplying utilities – one of which is to end the era of electricity subsidies for the residential sector (Bhattacharyya & Ganguly, 2017). With At-cost pricing of power being introduced soon, Indian residences will encounter increase cost of electricity consumption, and hence elevated level of energy cost literacy is necessary, such that energy conservation can begin at homes. This study aims to address the research gaps on the subject and focuses on understanding how cost literate residential consumers are and what changes can be made to indirect feedback, to increase energy cost literacy and energy conservation.

3. RESEARCH METHODOLOGY AND CONCEPTUAL MODEL

3.1. Research Methodology

To assess the level of energy cost literacy in residential consumers, based on information provided in their monthly electricity bills, the study presented an online questionnaire to sample respondents, chosen from Pune city in the state of Maharashtra, India. The choice of Pune city was due to the anticipated growth in residential electricity consumption at a Compound Annual Growth Rate (CAGR) of 6.4% between 2019 and 2029 (Central Electricity Authority, 2020). Survey questionnaire was designed to gather information on consumer demographics, appliance ownership, energy conservation activities practiced at home, perceptions electricity bills, levels of cost literacy, and finally, preferred modes of presenting information. A typical sample respondent belonged to Socio-Economic Classification categories A1, A2, A3, and B1, defined as per the new Socio-Economic Classification scale developed by BARC India. Within that, a stratified purposive sampling method was adopted. The choice of respondents was made basis their level of education, ownership of the appliances, and their ability to complete the survey online. The survey was mailed to 150 respondents, of which 130 respondents completed it correctly. Study areas within the city were chosen based on publicly accessible data made available by the local power supplying utility – Maharashtra State Electricity Distribution Company Limited (MSEDCL, 2019). Data was collected within a short period of time, between the months of August and September 2020, to capture consumer sentiments around consumption costs in the immediate aftermath of the COVID-19 lockdown (first wave).

The study uses correct identification of energy costs in the bill to indicate the level of energy cost literacy. A higher number of correctly identified costs indicated higher energy cost literacy levels. This ordinal nature of the variable was then coded into low literacy, moderate literacy, and high literacy levels. More specifically, respondents who could not identify any cost elements or could identify only one of the six cost components (Indian residential households incur costs under 6 large components), were categorized as having *low literacy*. Correct identification of 2–3 cost elements was categorized as *medium literacy*, and respondents identifying 4–6 cost elements reflected *high literacy* levels. As the response variable (i.e., level of electricity-bill cost literacy) was ordinal in nature, ordinal regression using the Polytomous Universal Model (PLUM) procedure in SPSS was chosen as a data analysis technique. This choice of statistical technique aligns with the literature, wherein the dependent variable is considered ordinal in nature (DeCarlo, 2003; Chen & Hughes, 2004; Lal et al., 2017).

3.2. Conceptual Model

This study aimed to understand the level of energy consumption cost literacy amongst sampled residential consumers. Some factors that were conceptualised to influence the level of cost literacy in households and were tested in the study model, are detailed as follows.

3.2.1. Direct Information Experience

Information and decision making go hand in hand, observed for energy consumption related decision making at homes (Hilorme, Tkach, Dorenskyi, Katerna, & Durmanov, 2019). It is seen that when consumers perceive the information experience to be sub-optimal, it can lead to rational inattention – for energy consumption related decision making as well (Niederberger & Champniss, 2017). Hence for this study, it was of interest to check if the information provided in the current electricity bills is being processed adequately, and if it influences the cost literacy levels amongst residences or otherwise. To objectively study this, the following null hypothesis was framed:

H1: Direct information does not influence the level of electricity cost literacy in households.

3.2.2. Electricity Consciousness

Energy/Electricity consciousness is seen vital to promote energy saving practices amongst consumers (Porwal, Bora, & Jha, 2020). The objective of this study was to explore the relationship between the level of energy/electricity consciousness and electricity cost literacy. Respondents were asked to indicate practices at home, such as switching off appliances, buying energy-efficient appliances, ensuring no appliances are in standby mode, and not taking any steps at all. To test the relevance of this construct, second study hypothesis was framed as follows:

H2: Belief in energy conservational practices does not impact electricity cost literacy in households.

3.2.3. Information Feedback Perception

While it is well documented that energy information feedback help in encouraging energy saving behaviour (Karlin, Zinger, & Ford, 2015), but if the information feedback is not perceived to be enough/appropriate, results can be slow/counter intuitive (Fredericks, Fan, Woolley, Quincey, & Streeton, 2020). In this study, we tested the respondent's perceptions of the content and tone of information feedback in current e-bills. Two questions were presented to test this construct: The first one tested the ease of understanding the e-bill (1=*veryhard* and 4 = *very easy*), and the second question tested the relevance of the information presented in energy conservation actions at home (1 = *not very effectively at all* and 4 = *very helpful*). A four-point Likert scale was adopted instead of a five-point scale in both questions, to get a non-neutral response. The third hypothesis was framed as follows, so as to test the influence of consumer perception on current information feedback and electricity cost literacy:

H3: Perception of information feedback does not influence electricity cost literacy in households.

3.2.4 Socio-Demographic Variables

Literature suggests that demographic variables such as age, income and education, carry significant influences in energy literacy and subsequent energy behaviors (Martins et al., 2019). While the study chose only the affluent consumers (socio-economic classification A1,A2,A3, and B1), it yet investigated the impacts of socio-demographic variables such as *respondent age, household income, gender, educational profile, nature of dwelling of the respondent, and size of dwelling on e-bill literacy*. Thus the 4th study hypothesis was thus framed as follows:

H4: Respondent's socio-demographic variables do not influence electricity cost literacy in households.

Based on the above constructs, the proposed conceptual model for this study is presented in Figure 1.

Figure 1. Conceptual model

4. DATA ANALYSIS AND KEY FINDINGS

Data was collected from 130 residential respondents. Sample statistics appended in Table 1 indicate that a typical respondent is on average 40 years of age, earns between Rs. 10 and Rs. 20 Lakhs per annum, has at least a graduation or post-graduation academic degree and lives in smaller family sizes. The sample observes an equal split of male and female respondents (57% and 43%, respectively), thus avoiding any gender bias in the data. As for energy consumption, more than 90% of the sample paid less than Rs. 5,000 per month in e-bills, and for 82% of the sample, e-bill amounts are less than 5% of the monthly household income. Such low electricity consumption costs can be attributed to cross-subsidies extended to Indian residential and agricultural consumers (Jain & Nandan, 2019). Finally, approximately 50% of the sample came to be categorized under *low e-bill literacy*, with only 28% of the sample households correctly identifying all six cost components.

The *level of e-bill literacy* exhibited by the respondent formed the dependent variable. Thirteen covariates were included as independent variables, which were hypothesized to influence the level of e-bill literacy amongst respondents. Details of the covariates and nature of the variables appear in Table 2 below:

To conduct ordinal regression using PLUM in SPSS, an appropriate link function was chosen. *Link functions* enable forming linear relationships between the covariates and the probability of the dependent variable (the probability of fitting into one of the e-bill literacy categories). The choice of the most efficient link function to predict the most accurate model and parameter estimates was based on the frequency distribution of the dependent variable (level of e-bill literacy). Since 50% of the respondents fell in the *low literacy* category, the negative log-log (nloglog) link function was

Table 1. Sample statistics

Variable	Frequency	% of sample
Number of cost components correctly identified	0 = 57 1 = 3 2 = 9 3 = 25 4 = 12 5 = 11 6 = 5	46.7% 2.5% 7.4% 20.5% 9.8% 9.0% 4.1%
Level of e-bill literacy		
Low (correctly identified < 2 e-bill cost components)	65	50%
Moderate (correctly identified 3–4 e-bill cost components)	29	22%
High (correctly identified 5–6 e-bill cost components)	36	28%
Age		
<30 years	43	33.1%
30–40 years	17	13.1%
40–50 years	44	33.8%
50–60 years	17	13.1%
>60 years	9	6.9%
Monthly electricity bill		
< Rs. 2,000/month	63	51.6%
Rs. 2,000–5,000/month	51	41.8%
Rs. 6,000–10,000/month	7	5.7%
>Rs. 10,000/month	1	0.8%
E-bill as a percentage of monthly income		
< 5%	100	82.0%
6–10%	19	15.6%
11–20%	3	2.5%
Gender of the respondent		
Male	69	56.6%
Female	53	43.4%
Annual household income		
<Rs. 10 lacs per annum	39	32.0%
Rs. 11–20 lacs per annum	51	41.8%
>Rs. 21 lacs per annum	32	26.2%
Educational attainment		
School degree	1	0.8%
Graduate	18	14.8%
Post-graduation	87	71.3%
Higher education	16	13.1%
Household size		
2 members	0	0.0%
3–5 member	108	88.5%

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Table 1. Continued

Variable	Frequency	% of sample
> 5 members	14	11.5%
House ownership		
Owned	99	81.1%
Rented	23	18.9%
Area of house		
<1000 square feet (sqft)	42	34.4%
1000–1500 sqft	58	47.5%
>1500 sqft	22	18.0%

Table 2. List and nature of covariates included in the study

S. No.	Co-variate	Variable type	Details
1	Direct information experience	Scale	Number of items in the electricity bill read by the respondent before paying every month.(Higher numbers indicate higher information experience.)
2	Electricity consciousness	Scale	Measure of electricity-saving practices conducted at home. A larger number indicated more activities adopted,such as switching off lights and usingenergy-efficient appliances(EETs).
3	Information feedback perception	Scale	Perception of the content and tone of information in the bill. A larger number indicates higher ease with which the information is received by consumers
4	Age	Scale	Age of the respondent
5	Appliance usage	Scale	Number of appliances used at home
6	Monthly electricity bill	Ordinal	< Rs.2,000/month = 1 Rs. 2,000–5,000/month = 2 Rs. 6,000–10,000/month = 3 > Rs. 10,000/month = 4
7	Bill as a % of monthly income	Ordinal	< 5% = 1 6–10% = 2 11–20% = 3
8	Gender	Nominal	Male = 1 Female = 2
9	Household income	Ordinal	< Rs. 10 lacs per annum = 1 Rs. 11–20 lacs per annum = 2 >Rs. 20 lacs per annum = 3
10	Educational attainment	Ordinal	School degree =1 Graduation degree =2 Post-graduation degree =3 Higher education =4
11	Family size	Ordinal	Couple occupancy =1 3–5 members =2 >5 members =3
12	House ownership	Nominal	Owned =1 Rented =2
13	Area of house	Ordinal	<1000 squarefeet (sqft) =1 1000–1500 sqft =2 >1500 sqft =3

chosen, as recommended by Garson (2012) and Smith et al. (2019). Next, the model fit diagnostics (presented in Table 3) were studied to test if including the 13 independent variables increased model accuracy. The null hypothesis framed here was that models created with and without additional covariates are equally accurate and hold the same predictive abilities. As the chi-square test value had a significance level of less than .05, the final model (including specified covariates) was better than the model with no covariates.

Table 3. Model fit information

Model	-2 log likelihood	Chi-square	df	Sig.
Intercept only	254.464			
Final	209.589	44.875	22	0.003
<i>Link function: negative log-log</i>				

To adjudge the goodness of fit of the model at hand, the pseudo- R^2 values were considered. The included covariates explained between 30–35% of the variation in the outcome variables. The goodness of fit measures appears in Table 4.

Table 4. Pseudo- R^2 Indicators

Cox and Snell	0.308
Nagelkerke	0.351
McFadden	0.176
<i>Link function: negative log-log</i>	

Next, parameter estimates were assessed to identify independent variables with significant influences on the response variable (level of e-bill literacy), which are reproduced in Table 5.

Six independent variables in the analysis emerge as statistically significant, namely *electricity consciousness*, *information feedback perception*, *age*, *dwelling type*, *dwelling area*, and *gender of the respondent*. First, a significant positive relationship is noted between electricity consciousness and energy cost literacy levels. More specifically, a unit increase in electricity consciousness increased the log of odds of carrying higher energy cost literacy levels increased by 0.619. This indicates that respondents that practice more energy conservation steps at home are in fact paying more attention to their energy consumption costs.

Second, respondents with a positive perception towards the information characteristic of the feedback information provided in an e-bill have a higher probability of being in higher bill literacy levels ($\beta = 0.20$; $p = 0.09$). The ease of reading the electricity bill directly impacts the level of understanding of energy consumption costs. Third, higher age translates to higher literacy ($\beta = 0.02$; $p = 0.04$). Fourth, respondents staying in owned accommodations are more likely to have lower bill literacy ($\beta = -0.99$; $p = 0.01$). This finding contradicts literature evidence. Literature suggests that individuals dwelling in owned homes are more likely to own a higher number of appliances (due to the surety of tenure of stay), and higher appliance ownership translates into higher energy consumption (Leahy & Lyons, 2010). This in turn activates the need to know more about household energy consumption. However, increasing urbanization has led to migration, owing to which rental

Table 5. Model parameter estimates

		Estimate	Std. error	Wald	df	Sig.	95% confidence interval	
							LB	UB
Threshold	Bill literacy = 1	1.618	2.485	0.424	1	0.515	-3.253	6.488
	Bill literacy = 2	2.871	2.494	1.326	1	0.250	-2.017	7.760
Location	Direct Information experience	0.110	0.204	0.293	1	0.588	-0.289	0.509
	Electricity consciousness	0.619	0.222	7.737	1	0.005*	0.183	1.054
	Information feedback perception	0.205	0.121	2.880	1	0.090#	-0.032	0.442
	Age	0.025	0.013	4.057	1	0.044*	0.001	0.050
	Appliance usage	-0.043	0.166	0.065	1	0.798	-0.368	0.283
	Monthly e-bill: < Rs. 2,000	-1.522	1.337	1.295	1	0.255	-4.142	1.099
	Monthly e-bill: Rs. 2,000–5,000	-1.348	1.306	1.066	1	0.302	-3.908	1.212
	Monthly e-bill: Rs. 6,000–10,000	-2.108	1.550	1.850	1	0.174	-5.145	0.930
	Monthly e-bill: > Rs. 10,000	0 ^a			0			
	Bill as a % of monthly income: < 5%	0.708	1.192	0.353	1	0.552	-1.628	3.044
	Bill as a % of monthly income: 6–10%	0.653	1.232	0.281	1	0.596	-1.762	3.068
	Bill as a % of monthly income: > 11%	0 ^a			0			
	HHincome: < Rs. 10 lacs p.a.	0.002	0.470	0.000	1	0.997	-0.920	0.924
	HHincome: Rs. 11–20 lacs p.a.	-0.012	0.375	0.001	1	0.974	-0.747	0.723
	HHincome: < Rs. 21 lacs p.a.	0 ^a			0			
	Edu: school degree	-19.732	0.000		1		-19.732	-19.732
	Edu: under-graduation	-0.076	0.656	0.013	1	0.908	-1.361	1.210
	Edu: post-graduation	0.211	0.452	0.218	1	0.641	-0.675	1.097
	Edu: higher education	0 ^a			0			
	HH members: 3–5	0.215	0.571	0.142	1	0.706	-0.903	1.333
	HH members: >5	0 ^a			0			
	Dwelling ownership: owned	-0.990	0.385	6.605	1	0.010*	-1.745	-0.235
	Dwelling ownership: rented	0 ^a			0			
	Dwelling area: < 1,000 sqft	-0.838	0.496	2.856	1	0.091#	-1.810	0.134
	Dwelling area: 1,000–1,500 sqft	-0.365	0.464	0.619	1	0.431	-1.274	0.544
	Dwelling area: > 1,500 sqft	0 ^a			0			
	Gender: male	0.954	0.322	8.768	1	0.003*	0.323	1.586
	Gender: female	0 ^a			0			

Link function: negative log-log

*: Significant at 99% Confidence Interval; #: Significant at 95% Confidence Interval

Abbreviations: HH: household; p.a.: per annum; sqft: square feet; Edu: educational level; e-bill: electricity bill; LB: lower bound; UB: upper bound

dwelling are on the rise. Affluence, status, and need for comfort and convenience (Sovacool, 2011) have increased appliance usage in rented homes (Walia et al., 2015) as well.

Fifth, the area of the household also appears to hold a negative impact on literacy levels—respondents dwelling in smaller homes are less likely to have higher energy cost literacy ($\beta = -8.38$; $p = 0.09$) due to lower energy consumption levels (Jones et al., 2015). Finally, male respondents are more likely to exhibit higher literacy levels ($\beta = 0.95$; $p = 0.003$), which aligns with the widely documented gender disparity in energy literacy (Brounen et al., 2013; (Nakai, Okubo, & Kikuchi, 2017). Separation in household tasks and responsibilities results in energy-related decisions being male-driven (Pachauri & Rao, 2013), which feeds the gender disparity or gap.

As the last step in data analysis, a test of parallel lines, also alternatively known as the test of proportional odds, was conducted in order to test if the slope coefficients of independent variables are the same for all the ordered response categories. Since the p -value of the test came out larger than .05 ($-2 \log \text{likelihood} = 195.13$; $p\text{-value} = 0.885$), the null hypothesis that all slope coefficients are the same across all response categories holds true. The test results are reproduced in Table 6. Based on the study findings, the final model can be summarized in Figure 2.

To better understand the preferred information feedback characteristics related to monthly electricity consumption, respondents were asked to choose between 5 options. The objective was to check how households would prefer to receive their electricity bills to ease their understanding. Options included *last six months consumption data presented graphically*, *last six months consumption data presented in a tabular format*, *comparison of current month consumption in the same month last year*, *cost break-up of current month consumption graphically*, and *color-coded comparison of household consumption with area average*. Results suggest that 78% of the sampled households prefer to understand their own historical consumption in a visually appealing format. Interestingly, only 26.2% of the samples were interested in receiving household consumption in comparison to area average. This

Table 6. Test of parallel lines

Model	-2 log likelihood	Chi-square	df	Sig.
Null hypothesis	209.589			
General	195.133 ^b	14.456 ^c	22	0.885

Link function: negative log-log

*: Significant at 99% Confidence Interval; #: Significant at 95% Confidence Interval

Figure 2. Final conceptual model

clearly indicates the lack of want for normative messaging in the sample, contradicting study results in other economies (Nolan et al., 2008; Komatsu & Nishio, 2015). This is a counterintuitive finding as in a high-context collectivistic culture like India, people's energy consumption is influenced by other's behavior and social comparison (Mi et al., 2019), as by definition, collectivist occupants care not only about themselves but also about their social networks. Altering individual energy consumption behavior is often a signal to contribute to the environment shared by others (Jing et al., 2016).

On the frequency of information feedback, 42% of the sample opined that they were satisfied with it. However alongside, 23% of the households would like to receive bi-monthly information updates, and 25% of the sample would like a text alert when household consumption goes over a certain unit level. This indicates that a higher frequency of information is a useful behavioral nudge that can activate energy conservation norms.

5. DISCUSSION AND MANAGERIAL IMPLICATIONS

This study was undertaken to assess the level of understanding of monthly energy consumption costs amongst residential consumers of electricity, along with identifying the most significant factors impacting them. Respondent were selected from the socio-economic classes of A1,A2 and A3 representing affluent households where electricity bills form less than 5% of monthly income. For such affluent households, attention to the detail could be missing as found by (Schleich, Klobasa, Gözl, & Brunner, 2013). This could be one of the reasons for limited or no literacy of the cost components on the electricity bill. Another factor to bill inattention could be the form of bill receipt. If most of the consumers have opted for an e-bill or have opted for an auto payment facility the possibility of them going through various cost components on the bill are lesser. This results in e-bill illiteracy.

The study is significant in light of the impending reforms in the Indian electricity sector that will result in higher energy consumption costs for the residential consumers (by ending the practice of cross-subsidies in the electricity sector), which calls for higher energy consumption cost literacy, on the part of households. Ordinal regression results suggest that households with electricity consciousness (by adopting several energy-conserving practices at homes), and those who find the content and tone of information feedback presented in monthly e-bills easy to interpret carry, higher levels of energy cost literacy. Higher literacy is also more likely in older and male respondents. Thus, an age disparity and gender gap are evident. On the other hand, respondents living in owned accommodation and smaller homes are more likely to exhibit lower literacy levels.

This study presents six policy recommendations for consideration which are enumerated as follows:

- First, there is a need to make information feedback more visually appealing. The energy consumption data could be presented in colorful graphs, with color-coded indications for higher consumption months (e.g., indicated in red or orange) for easier understanding of the information. It could also pictorially depict the increased emissions due to higher consumption.
- Second, frequent informational nudges to increase energy consumption awareness should be practiced. At present, neither the information on consumption quantity nor the resulting cost is known to residences before the end of the month when the e-bills are generated. A bi-monthly information alert (every 15 days) or a text or email alert when household consumption crosses benchmark unit consumption would be a nudge in the right direction. Since it is observed that an average household consumes around 300 units of electricity per month (Chunekar et al., 2016), this alert can be activated once a household exceeds 150 units in the month.
- Third, the study results indicate a dichotomy in energy cost literacy when it comes to home sizes. This is due to the perception that smaller homes lead to smaller consumption, which may not necessarily be true. This can be remedied by including the merits of adopting Energy Efficient Appliances (EEAs) and presenting residential carbon footprint calculations (Jones & Kammen,

2011) in monthly e-bills. Such non-monetary messaging is helpful in changing residential electricity consumption (Chen et al., 2017) and can be considered. EEA and smart appliance adoption expedite providing appliance level direct information feedback on energy consumption, but suffer from low adoption rates in India, due to low penetration of smart grid (Kappagantu & Daniel, 2017).

- Fourth, the information content of the bill should be reduced. Excess content leads to information overload fatigue, which discourages consumers from analyzing the bill. The bill could add in some interactive features like appreciation for energy conserved in the form of positive bill messages using emoticons, and framing increased energy usage as missed targets. Such nudges can be used for other types of bills too.
- Fifth, the study presents a counterintuitive finding – which is the lack of want of normative reporting in energy bills (comparison of own consumption with neighbours/consumers in the same area). In a high context collectivistic culture, this finding is indeed surprising. This can be due to the fact that the study sample belong to the affluent families, for whom electricity bills form less than 5% of monthly income levels, and hence are not influenced by the normative appeal. Moreover as there is no reward associated with the energy savings, the social comparisons of the same might not be very lucrative or considered ‘cool’.
- Sixth and finally, there is an urgent need of widespread installation of the smart meters amongst residences. This will ensure live tracking of energy consumption, both to consumers and to the utility. This information can effectively nudge residences to switch to Energy Efficient Appliances (EEAs) faster. The installation of smart meters will ease the billing process and will also reveal multiple aspects on energy conservation.

6. LIMITATIONS

This study was undertaken in the immediate months following the COVID-19 lockdown in India. Since the lockdown resulted in higher electricity consumption at homes (due to staying home and working from home), many residential consumers suffered from price shocks in energy bills generated in the months of July–September 2020, when retrospective bills were raised. Bill-related information was gathered from SEC classes A1, A2, A3, and B1, and samples from lower social strata were not gathered. Data was gathered from homes that were used to higher levels of thermal comfort and had airconditioners, refrigerators, and other comfort-inducing appliances.

The study was focused on assessing energy cost understanding in abnormally high consumption periods, which mandated data collection in a short period of time. Thus, while the results cannot be generalized, they provide useful insights for framing nudges to encourage higher energy conservation in residences.

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