Study of Household Energy Consumption Pattern Due to Usage of Electronic Gadgets before and During Pandemic

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Abstract

One key aspect of green computing is reducing greenhouse gas (GHG) emissions, which are gases that trap heat in the Earth's atmosphere and contribute to global warming and climate change. COVID-19 has introduced significant challenges to the energy industry. Potentially new practices and social forms developed during the pandemic have created an impact on energy demand and consumption. As there is an adverse effect on the global environment, it is time to improve the working habits of computer and business users. The aim of this study is to show the increased household energy consumption during the COVID-19 pandemic due to the rapid rise in the purchase and usage of electronic gadgets in Indian households. Due to the widespread adoption of the "work from home" mentality by businesses even after the epidemic, it has been noted that this has persisted. The study utilized the non-experimental quantitative research design specifically, the survey method which employs a descriptive questionnaire to the respondents. Information was gathered through a survey of 101 families in the Indian state of Maharashtra's three districts, Mumbai, Thane, and Palghar. A supervised machine learning model called regression analysis is used to verify the predictions. Investigation reveals that energy consumption is not only dependent on age, area, number of people, and number of gadgets owned by people but on various other factors.

Keywords: Green Computing, Greenhouse Gas (GHG), Supervised Machine Learning, Regression Analysis. COVID-19

1. Introduction

Economic development and technological innovations in India during the past decades have been accompanied by an increase in energy consumption. This has taken up a sharp shoot during the COVID-19 pandemic. The coronavirus (COVID-19) pandemic has impacted every field of life globally and has drastically stimulated environmental change. After Covid-19, schools and colleges started functioning physically, but most IT industries adopted the work-from-home culture and permitted their employees to continue working from home. This has seen a rapid increase in the purchase and usage of electronic gadgets in every household. In addition to that, cooling equipment was also in demand to maintain the room temperature of the home. Considering the green computing factors, optimal usage of all electrical and electronic equipment is necessary to keep the home environment healthy. Energy costs can be drastically reduced by reducing energy consumption. (Le & Pitts, 2019)

The highest proportion of energy consumption is due to families' subsistence needs; consumption increases as income increases and family size is inversely related to it. In order to develop effective strategies, it is necessary to understand better the energy usage in households, including the ownership of electrical appliances and user behaviour, in addition to the concern for improving housing design. The identification of the key factors contributing to household energy consumption will be useful in directing appropriate energy efficiency solutions in terms of building design and energy policy formulation. It has been found that research in this field is interdisciplinary and more depth is needed at the city and individual levels. (Zarco-Periñán *et al*., 2022). Energy costs can be drastically reduced by reducing energy consumption. Knowing the sources beforehand is crucial in order to implement strategies that reduce them. As a result, actions can be taken to lower consumption and consequently, carbon emissions.

This study aims to provide significant knowledge of household energy utilized in Mumbai, Thane, and Palghar districts in terms of actual energy consumption due to electronic gadgets, appliance ownership, and usage behaviour during the pandemic. This study will provide valuable information on actual energy consumption, appliance ownership, and usage behaviour to supplement the currently insufficient data sources on household energy use in India. Knowledge and understanding of appliance use will aid efforts to improve not only energy efficiency but also a better understanding of the means to create comfort in buildings.

1.1 Literature Review

Researchers in different countries are keen to study household energy consumption patterns and Greenhouse gas emissions in order to promote low-carbon lifestyles. A carbon footprint is the total amount of greenhouse gas emissions caused by individuals, organizations, or products, both directly and indirectly. According to the World Economic Forum, the ICT, Entertainment, and Media sectors have a significant environmental impact due to their carbon footprint, energy consumption, and energy supply (Tomitsch, M, 2022).

Jens *et al.* (2016), reported that smartphone use produces the highest carbon footprint of any device. It is possible to conclude that using technology is more harmful than manufacturing the device (Jens, M & Dag, L, 2018). As per le Quéré *et al*., 2020, though GHG emissions decreased during the pandemic across various sectors, a reverse impact was seen in household sectors. This was mainly due to increased activity resulting in increased energy demand in the household sector. In 2025, the number of devices will increase by 50%, and the digital footprint will double or triple (Bordage, F, 2019). Teehan & Kandlikar, 2013, predicted that in the personal computing (PC) sector, operational impacts are estimated to account for roughly 60% of greenhouse gas emissions, with the remaining 40% due to manufacturing.

Though GHG emissions decreased during the pandemic across various sectors, a reverse impact was seen in household sectors. This was mainly due to increased activity resulting in increased energy demand in the household sector (le Quéré *et al*., 2020). Staying in quarantine and being isolated at home during a coronavirus pandemic will increase the home's electricity bills (Qarnain *et al*., 2020).

1.2. Objectives

- To analyse the relationship between the demographic characteristics of households and their electricity usage patterns.
- To identify the most common appliances and electronic devices contributing to household electricity consumption.
- To provide insights into the potential for reducing household electricity consumption through behavior change and the adoption of energy-efficient technologies.
- To develop recommendations for policymakers and energy providers on how to encourage energy conservation and reduce household electricity consumption.

Hypothesis H0: Household Operational Energy Consumption by electronic gadgets during the pandemic largely depends on the demographic characteristics of households and the number of gadgets respondents own.

Hypothesis H1: Household Operational Energy Consumption by electronic gadgets during the pandemic depends on various factors rather than the demographic characteristics of households and the number of gadgets respondents own.

1.3. Scope

The scope of this study is limited to Households of Mumbai, Thane, and Palghar districts of Maharashtra State, India. Data analysis on energy consumption is limited to basic electronic products such as Air-conditioners, Televisions, Desktop PC, laptops, Smart mobile phones, Network Devices, Digital Notebooks, DVD Players, etc. used during the pandemic.

2. Research Methodology

2.1 Exploratory Data Analysis

Primary data is collected from the online survey of 101 respondents residing in the Mumbai, Thane, and Palghar districts. Secondary data such as the Power rating of electronic gadgets are taken from the device manuals. The total power consumption of all 8 devices is calculated by adding power consumption from each device.

The power consumption of each device is calculated by the following formula –

Power Consumption of a device (in watts) = (Number of such devices × Usage in Hours × Power rating in watts per Hour)

Machine Learning technique is used for quantitative data analysis. A supervised Machine Learning Model called Regression analysis is used to train and test the target variable -Total power consumption. Python and various python built-in libraries are used such as Pandas, NumPy, Matplotlib, Seaborn, SciPy, SciKit Learn, Min-Max Scaler, etc for data analysis. Furthermore, one-way ANOVA analysis was performed to understand the significant variations in electricity consumption patterns before and during the pandemic.

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2.2 Demographic Data of Respondents

Figure 1: % of Respondents from Various Districts

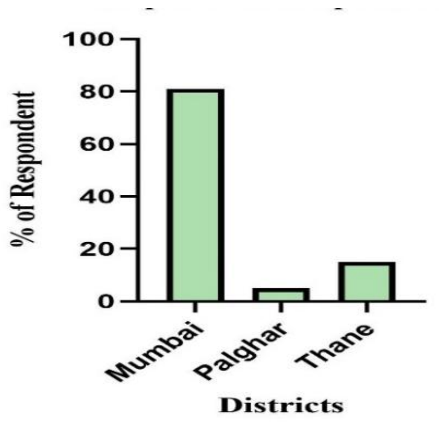

Figure 2: Age Group of Respondents

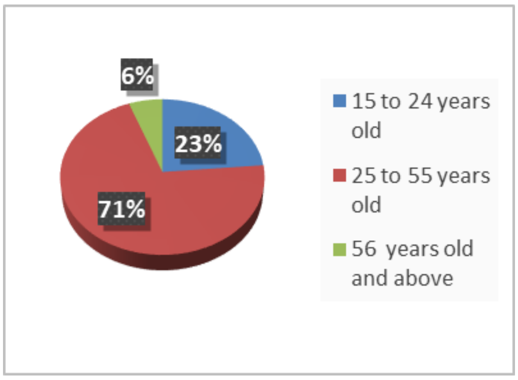

Figure 1: A total of 101 responses were analyzed from three districts of Maharashtra and they were 81 from Mumbai, 15 from Thane, and 5 from Palghar.
Figure 2: 23% of respondents were from the age group 15-24 years, 71% of respondents were from the age group 25 to 55 years, and 6% of respondents were 56 years old and above.

Figure 3: Category of Respondents

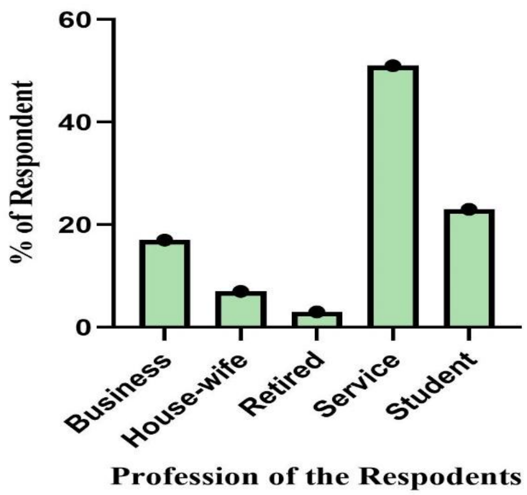

Figure 4: Electricity Bill Range Before and During Covid-19

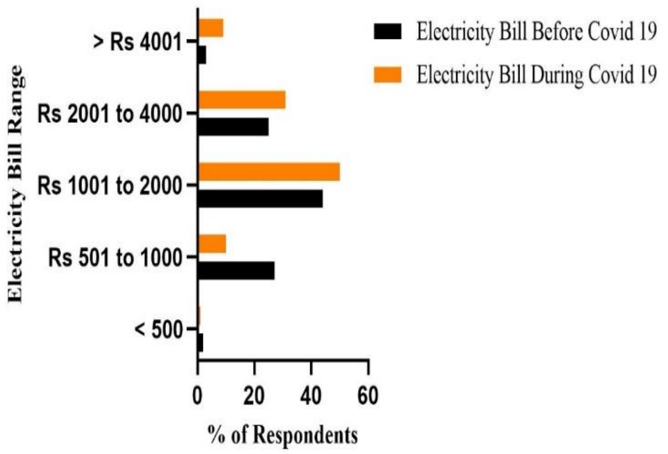

Figure 3: Out of 101 respondents, 3% were retired, 7% were housewives, 17% were business people, 23% were students, and 51% were a service background.
Figure 4: Electricity bills of more than Rs. 4,001, Bills between Rs.2,001 to Rs. 4,000, and Bills between Rs. 1,001 to Rs. 2,000 have increased during the pandemic than before the pandemic.

Table 1: Number of Electronic Gadgets Owned by Respondents

No. of Devices owned	AC	DVD	Laptop	Smartphone	Network Device	Desktop PC	TV	Digital tablets
1	39	13	50	62	50	6	38	15

2	48	12	40	29	27	10	28	15
3	18	5	11	6	12	5	9	1
More than 3	0	7	12	3	9	2	13	6
None	0	3	27	38	31	9	24	3

Table 2: Details of Respondent's Electronic Gadgets Usage Pattern

Range of Hours engaged by device	**AC**	**DVD**	**Laptop**	**Smartphone**	**Network Device**	**Desktop PC**	**TV**	**Digital Tablets**
Less than 5 Hrs	66	67	43	23	24	54	51	60
5 Hrs to < 8 Hrs	8	4	21	34	11	8	32	12
8 Hrs to < 12 Hrs	5	3	20	30	20	11	9	3
12 Hrs or Greater	1	0	5	11	39	4	2	2

Figure 5: Electronic Devices Owned by Respondents

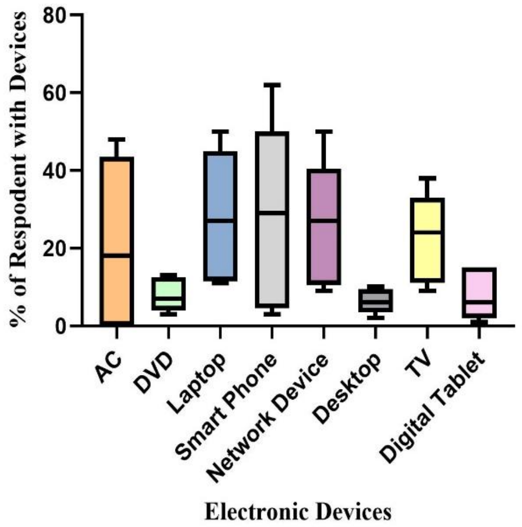

Figure 6: Duration spent with Electronic Devices

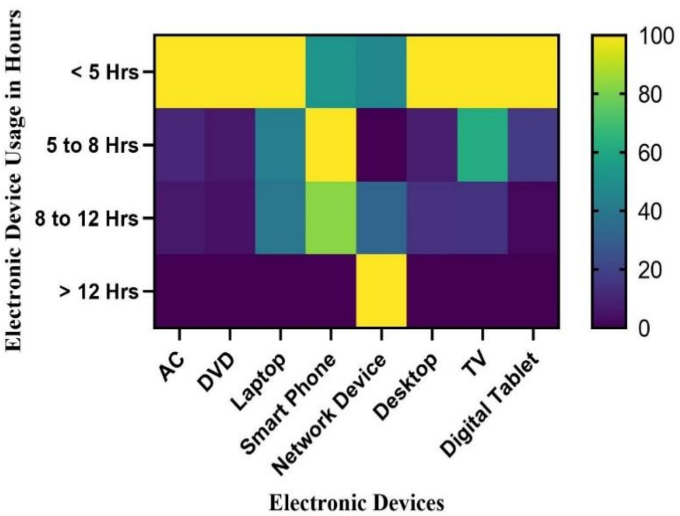

Figure 5: Electronic devices such as Smartphones, laptops, AC, TV, and Network devices are more in number in every household and they are used for longer hours.

Figure 6: It shows that the majority of devices usage hours are less than 5 hours, whereas, smartphones, TV, and Laptop are used between 5 to 8 hours. Network devices are being used for more than 12 hours in a few households.

3. Research Findings

Household electricity consumption is one of the major contributors to greenhouse gas (GHG) emissions, which are gases that trap heat in the Earth's atmosphere and contribute to global warming. Electronic gadgets, such as smartphones, laptops, and tablets, are a major source of greenhouse gas

(GHG) emissions. Based on the results of the one-way ANOVA analysis with a p-value = 0.999, there is no significant difference in electricity consumption before and during the Covid-19 pandemic. This suggests that the pandemic did not have a significant impact on electricity consumption. While it may have been expected that the lockdowns and changes in work and travel patterns would have led to changes in electricity usage, this study did not find evidence to support this hypothesis.

Results of the Machine learning technique called regression metrics show that MAE (Mean Absolute Error), MSE (Mean Squared Error), and RMSE (Root Mean Square Error) values are very less than the acceptance range.

MAE: 0.09884655444483528
MSE: 0.018745409280430305
RMSE: 0.1369138754123566

T-test is conducted on Power_Consumption (target variable) to check the null hypothesis. T-test gives the statistics and p-value.

Statistic = 3.9481607 and p-value = 0.00013326

As the p-value is very less than the significance level of 0.05 which indicates that the null hypothesis H0 – Household operational energy consumption by electronic gadgets during the pandemic largely depends on the demographic characteristics of households and the number of gadgets respondents own is not true. This is because household power consumption is not only dependent upon these four input variables. There are various other factors such as income level, education level, living habits, home characteristics, weather conditions, etc., and collecting these many data from respondents was out of the scope. Therefore, the alternate hypothesis H1- 'Household operational energy consumption by electronic gadgets during the pandemic depends on various factors rather than the demographic characteristics of households and the number of gadgets respondents own' may be true. Hence alternate hypothesis is accepted.

However, it is important to note that this conclusion is based solely on the data analysed and does not take into account potential variations in electricity consumption across different regions, time periods, or demographic groups. Therefore, further research is needed to gain a more comprehensive understanding of the effects of the Covid-19 pandemic on electricity consumption. The increase in electricity bills during lockdown can be attributed to various factors, such as increased use of electronics and appliances due to work-from-home arrangements, higher levels of cooking and food storage at home, and increased indoor heating or cooling needs. These factors have all contributed to a higher demand for electricity, leading to an increase in electricity bills. It is important for individuals and households to take measures to reduce their electricity consumption during the lockdown period, such as turning off appliances when not in use, using energy-efficient appliances, and adjusting their heating and cooling systems to more sustainable levels. This can help to reduce the impact of the lockdown on their electricity bills, while also contributing to a more sustainable future.

Table 3: Comparison of Electricity Bill Before and During Pandemic

Range of Electricity Bill	Average monthly electricity bill BEFORE COVID-19 Pandemic	Average monthly electricity bill DURING COVID-19 Pandemic
< Rs 500	2	1
Rs 501 to 1000	27	10

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Rs1001 to 2000	44	50
Rs 2001 to 4000	25	31
> Rs 4001	3	9

Figure 7: Analysis of Electricity Bill Before and During Pandemic

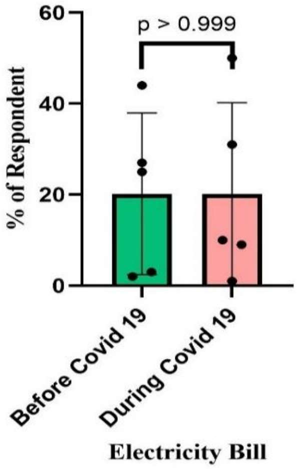

Figure 8: Duration spent with Electronic Devices

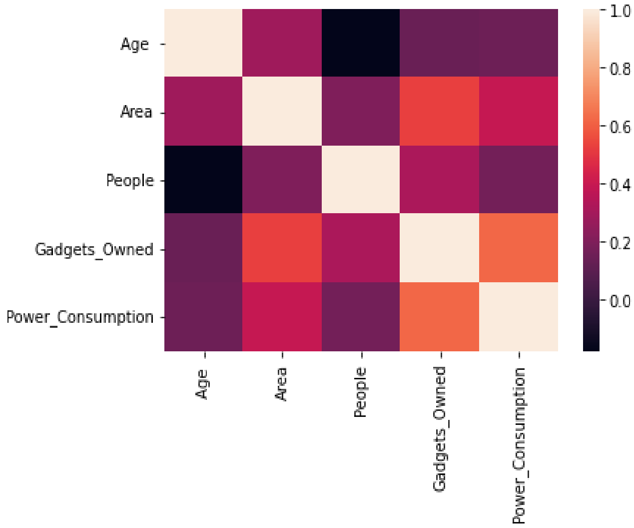

Figure 7: One-way ANOVA analysis was performed to understand the significant variations in electricity consumption patterns before and after the pandemic.

Figure 8: Heat Map showing the Correlation between independent (Age, Area, People, and Gadgets_owned) and dependent (Power_Consumption) variables. The heat map is a 2-Dimesional graphical representation of data to analyze complex data sets. Here values are represented as colors. It is observed that Power Consumption is better correlated with Gadgets Owned.

4. Suggestions

1. In India as household income is rising, ownership of electronic appliances and gadgets also rising dramatically. Higher living standards also continue to increase ownership of residential appliances, and as a result, appliances are expected to consume more electricity. Considering all these measures it is essential to improve the energy efficiency of the housing sector. Therefore, more energy-star-rated products must be produced for residential sectors.
2. More consumer awareness programs by service providers on the energy star rating of the products are to be conducted to encourage the purchase of the most efficient available technologies.
3. Optimal use of power management settings of equipment will help to reduce electronic equipment energy use.
4. Internet access and networking also influence typical computer energy consumption which must be cut down.
5. Configuring computers with built-in power-management capability by activating sleep mode and optimal use of power-management settings, such as automatic standby and decreased brightness on notebook or laptop screens, can cut energy consumption.

6. Video calls can be efficiently handled by inviting fewer people, switching cameras when not needed, and by avoiding artificial backgrounds.
7. Population growth, economic development, diversified energy sources, and migration from rural to urban areas are the factors resulting in many changes in energy consumption in housing sectors. Hence, a good plan of action is required in these sectors.
8. From the study it is observed that people purchased gadgets to fulfil their job/study requirements during the pandemic. More gadgets will result in more e-wastes. If the e-wastes are not disposed of properly, it will make the environment unhealthy. Hence, gadgets must be purchased only when there is a need.
9. This research study conducted on household energy consumption patterns during the Covid-19 pandemic will be helpful as a valuable reference for policymakers, energy planners, students, research scholars, or other agencies and to implement a further plan of action to work towards saving the environment. Thus, cumulative action from all individuals will help to keep the environment safe and healthy. When every individual becomes environmentally and socially conscious, rapid economic growth would be expected in this country.

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