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A Study on the Effect of Socioeconomic and Demographic Factors on Energy Consumption in Residential, Commercial, and Industrial Settings: A Case Study of West Virginia

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Abstract: This research investigates the effects of socioeconomic and demographic factors on energy consumption across residential, commercial, and industrial settings. The study was done using multiple linear regression and data from national surveys and the census. The results indicate that poverty, educational attainment, and race, significantly influence energy consumption in the residential and commercial sectors. Specifically, Poverty and areas with higher Hispanic Populations are positive predictors of energy use, while Illiteracy is a negative predictor. Similar trends are observed in commercial electricity consumption; however, industrial energy use does not appear to be affected by these factors. This suggests that other elements, such as geographical location, scale of production, operational practices, and governmental policies, could play a role in industrial energy consumption. By identifying the connections between socioeconomic and demographic factors and energy consumption, this research contributes to the broader discussion on energy equity and sustainability and highlights the urgent need for energy policies for reliable and affordable energy for all communities.

Keywords: Energy Consumption; Electricity; Natural Gas; Socioeconomic Factors; Demographic Factors.

Introduction

Energy consumption is fundamental to economic development and societal well-being (Stern, 2004). However, disparities in energy access and affordability create significant challenges, particularly for low-income and minority populations. The strong correlation between per capita income and energy consumption highlights how economic status influences access to reliable, high-quality energy sources (Hosier & Dowd, 1987). Moreover, energy accessibility is a key factor in poverty alleviation, as a lack of clean and affordable energy perpetuates economic deprivation and limits opportunities for social mobility (Pachauri & Spreng, 2004; GEA, 2011).

In the United States, low-income households allocate nearly three times more of their income to energy expenses than the median-income population, disproportionately impacting Black and Hispanic communities (Low, 2016; Ross et al., 2018). Despite federal programs such as the Low Income Home Energy Assistance Program (LIHEAP) and the Weatherization Assistance Program (WAP), one in three households still struggles to secure adequate energy access (U.S. Energy Information Administration, 2015). This burden is further exacerbated by a shift toward a capital-intensive economy, which has led to a decline in personal savings and increased vulnerability to energy poverty (Berman et al., 2016; Zheng et al., 2022).

The consequences of energy insecurity extend beyond financial strain. Households facing high energy costs often adopt compensatory behaviors, such as reducing heating and cooling, which can negatively affect health and well-being (Liu et al., 2017). Furthermore, low-income and minority communities frequently experience greater exposure to environmental hazards, compounding their socioeconomic disadvantages (He et al., 2020). Research also suggests that lower educational attainment correlates with poverty, reinforcing cycles of economic hardship and limited access to essential resources, including energy (Patel et al., 2018). Given the critical role of energy in financial stability and public health, policymakers could prioritize equitable energy access as a social justice issue (Chester & Morris, 2011). Targeted interventions such as expanded subsidies, improved energy efficiency initiatives, and enhanced infrastructure for low-income households can alleviate energy burdens and promote sustainable access to quality energy services (Rogulj et al., 2023; Vega-Perkins et al., 2023).

West Virginia exemplifies these challenges, ranking among the poorest U.S. states. It is the 10th smallest and 12th least populated state, with 51% of its 1.79 million residents living in rural areas (U.S. Census Bureau, 2020). Approximately 16.7% of its population, about 300,000 residents, live below the poverty line, and 11 counties experience persistent poverty. The state's median household income is $55,217, with a per capita income of $31,462 (Benson et al., 2023). Energy consumption patterns in West Virginia reflect broader economic trends, with the industrial sector consuming the largest share (384 trillion Btu in 2022), followed by the residential (154 trillion Btu) and commercial (107 trillion Btu) sectors (U.S. Energy Information Administration, 2021).

This study examines how socioeconomic and demographic factors influence energy consumption in West Virginia across residential, commercial, and industrial sectors. We explore the impact of poverty, illiteracy, and minority populations on electricity and natural gas (NG) consumption. This research provides insights for West Virginia policymakers by identifying key disparities and consumption trends. The findings can inform targeted energy policies, such as enhancing affordability programs, expanding infrastructure in underserved areas, and developing energy-efficient housing initiatives. Addressing these issues is essential for reducing energy poverty, promoting economic equity, and ensuring sustainable energy access for all West Virginians.

Materials and Methods

Data Collection and Integration

The data for this study were gathered from publicly available sources for the state of West Virginia, as summarized in Table 1.

Energy consumption and emissions data were obtained from the National Renewable Energy Laboratory (NREL)'s City and County Energy Profiles, which provide information on county-level fuel consumption, CO_2 emissions, and total population (Ma et al., 2019). This dataset includes details on electricity and Natural Gas (NG) consumption across residential, commercial, and industrial sectors and their respective greenhouse gas emissions (measured in metric tons of CO_2 equivalent).

Demographic data, including population estimates, were sourced from the 2016 American Community Survey (ACS) (U.S. Census Bureau,

Table 1. Data and Their Sources

Data	Source	Description
County Fuel and CO_2 Emission	Ma et al., 2019	County-level data on fuel consumption with associated CO_2 emissions in metric tons
Poverty Rates	U.S. Census Bureau, *Poverty and Median Household Income Estimates 2016*	County-level estimates of the percentage of residents living below the poverty line
Black and Hispanic Population	U.S. Census Bureau, *ACS Demographics and Housing Estimates 2016*	Minority population in U.S. Counties
Illiteracy Rate	U.S. Department of Education, *PIACC SAE 2016*	Literacy levels at or below Level 1 for counties across the U.S.

2016). Information on poverty levels came from the 2016 Small Area Income and Poverty Estimates (SAIPE) dataset (U.S. Census Bureau & Program, 2016).

Literacy rates were derived from the Program for the International Assessment of Adult Competencies (PIAAC) Small Area Estimation (SAE) dataset, which measures the proportion of adults with literacy proficiency at or below Level 1 (U.S. Department of Education, 2016).

A structured merging process was implemented to integrate data from multiple sources into a unified dataset. Since the datasets varied in format and granularity, the first step was standardizing county names to ensure consistency across all sources. All the collected data were merged to form a single matrix. A unique column label named 'County Name_State Abbreviation' was created and used as a common column to combine data using the 'XLOOKUP' function in Excel software.

Data Analysis

Once the data was gathered from diverse sources, it underwent a comprehensive merging process to consolidate all relevant information into a single dataset. Subsequently, the data was cleaned to eliminate any inconsistencies. Before constructing linear regression models, the assumptions of linearity, independence, homoscedasticity, and normality of residuals were examined. A normality test was conducted on the original data, and it was found that the data was not normally distributed. To achieve normality, a log base 10 transformation was applied. After transformation, the data was again checked for normality using the Shapiro-Wilk normality test and Q-Q Plot in JAMOVI (The Jamovi project, 2024)- an open-source statistical software. Most variables demonstrated normality, with p-values greater than 0.05. However, commercial NG consumption showed a significant deviation from normality ($p < 0.001$), indicating potential skewness or outliers in the dataset. Similarly, the Variance Inflation Factor (VIF) for each factor was calculated to examine the likely presence of multicollinearity. A VIF value of 5.0 or higher indicates potential multicollinearity issues. In this study, all calculated VIF values are below the threshold of 5.0, suggesting that multicollinearity is not a concern among the constructs (Duong et al., 2023; Joo & Han, 2021). The value obtained from the multicollinearity test and Shapiro-Wilk normality test is reported in Table 2 below.

Six multiple linear regression models were developed for the residential, commercial, and industrial electricity and natural gas consumption where electricity and natural gas consumption in residential, commercial, and industrial settings was taken as a dependent variable, whereas socioeconomic factors (Illiteracy and Poverty) and minority population as a demographic factor (Black and Hispanic Population) were taken as an input variable. The model's relevance was assessed using the adjusted R^2 to evaluate explanatory power, Root Mean Square Error (RMSE) to measure prediction error, and the p-value to determine statistical significance (Hair et al., 2010).

Results

Data Description

The dataset includes a total sample size of 55, representing all 55 counties in West Virginia (U.S. Census Bureau, 2020). The missing samples are due to the unavailability of county data, and the software automatically omits invalid rows. Table 2 presents the descriptive statistics for the variables used in this study, including mean, Standard Deviation (SD), minimum and maximum values, Variance Inflation Factor (VIF), and results from the Shapiro-Wilk normality test. Among the socio-economic and demographic factors, the percentage of Poverty has a mean value of 1.252 (SD = 0.1095), while Illiteracy and the Hispanic Population have means of -0.649 (SD = 0.0962) and 2.384 (SD = 0.5268), respectively. The Black Population has the highest variation, with a standard deviation of 0.7278. The VIF values for these factors range from 1.94 to 4.88, indicating no severe multicollinearity concerns.

The results from Table 2 show that the Residential Electricity and NG consumption were relatively similar, with mean values of 5.064 (SD=0.3972) and 5.386 (SD=0.4872), respectively, suggesting a balanced reliance on both energy sources in the residential sector. In the commercial sector, electricity consumption had a lower mean of 4.820 (SD=0.5332) compared to residential use, while NG consumption showed greater variability (SD = 1.57), possibly reflecting diverse heating and operational demands across different commercial buildings. The industrial sector exhibited slightly

Table 2. Data Description table (n=49)

Factors	Mean	SD	Min	Max	VIF	Shapiro-Wilk	
						W	p
% Poverty	1.252	0.1095	0.968	1.575	2.01	0.978	0.390
Illiteracy	-0.649	0.0962	-0.886	-0.377	1.94	0.984	0.663
Hispanic Population	2.384	0.5268	1.431	3.644	4.88	0.983	0.654
Black Population	2.583	0.7278	0.903	4.117	4.48	0.992	0.983
Residential Electricity Consumption	5.064	0.3972	4.402	6.039		0.976	0.324
Residential NG Consumption	5.386	0.4872	4.418	6.533		0.985	0.738
Commercial Electricity Consumption	4.820	0.5332	3.934	6.045		0.963	0.092
Commercial NG Consumption	4.659	1.5741	0.477	6.783		0.827	< 0.001
Industrial Electricity Consumption	5.050	0.6059	3.219	6.057		0.970	0.181
Industrial NG consumption	5.165	0.9540	2.029	6.777		0.937	0.006

Note. All factors are transformed using a log base 10.
n=sample size, SD=Standard Deviation, Min=Minimum, Max=Maximum, VIF=Variance Inflation Factor, W=Test Statistic

lower electricity consumption (mean = 5.05) than residential, but higher NG use (mean = 5.17), indicating a stronger dependence on natural gas for industrial processes

Four demographic and socioeconomic factors across counties in West Virginia are shown in Figure 1, with darker shades indicating higher values for each factor. Panel A displays the Hispanic population, where counties in the eastern panhandle, particularly Jefferson County, show the highest Hispanic populations, while much of the state has relatively sparse Hispanic representation. Panel B illustrates poverty levels, with the southern counties, especially McDowell and Mingo, exhibiting the highest poverty rates, exceeding 30%. Panel C maps illiteracy rates, revealing that the highest rates are concentrated in south-central West Virginia, with counties like McDowell and Logan showing illiteracy rates above 0.4%. Panel D depicts the Black population, with Kanawha County standing out prominently for having a significantly higher Black population than surrounding counties. Collectively,

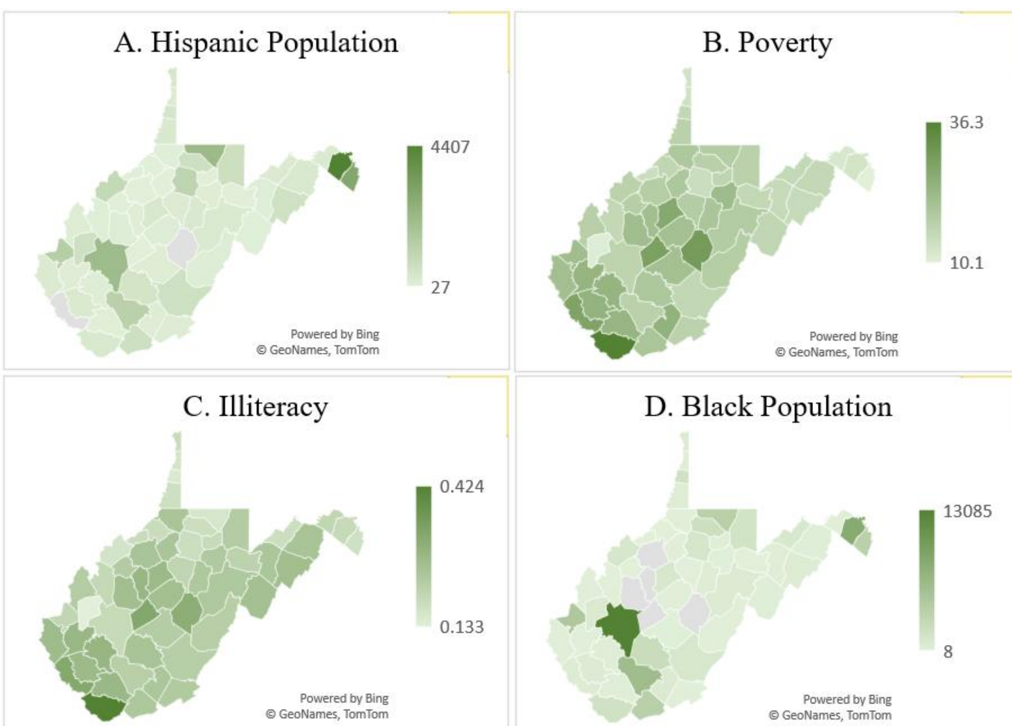

Figure 1. Heatmap Plot of Factors in West Virginia. ***The darker color represents the higher values for each factor.***

Table 3. Model Summary and Result from the Linear Regression for Residential Electricity and NG Consumption.

Factors	Electricity Consumption		NG Consumption	
	Estimate (SE)	p-value	Estimate (SE)	p-value
(Intercept)	1.8162 (0.778)	0.024	-1.144 (1.158)	0.329
Hispanic Population	0.5430 (0.1352)	< 0.001	0.313 (0.202)	0.128
Black Population	0.0753 (0.0895)	0.405	0.115 (0.134)	0.393
% Poverty	0.9266 (0.4145)	0.031	2.402 (0.620)	< 0.001
Illiteracy	-0.9386 (0.4728)	0.053	-3.827 (0.707)	< 0.001
Adjusted R^2	0.700		0.563	
RMSE	0.204		0.305	
F	29.0		16.4	
p	< 0.001		< 0.001	

Note. SE=Standard Error, RMSE=Root Mean Square Error, F=F-test, p=p-value

these maps reveal clear geographic disparities in demographic and socioeconomic conditions within West Virginia, identifying regions that may benefit from focused policy intervention and resource allocation.

Residential Setting

Table 3 presents the results from two linear regression models predicting residential electricity and NG consumption. The model for electricity consumption explains 70.0% of the variance (*Adjusted* $R^2 = 0.70$, $F = 29.0$, $p < 0.001$), while the model for residential NG consumption accounts for 56.3% of the variance (*Adjusted* $R^2 = 0.56$, $F = 16.4$, $p < 0.001$). For residential electricity consumption, the Hispanic Population ($\beta = 0.543$, $SE = 0.1352$, $p < 0.001$) and percentage of poverty ($\beta = 0.9266$, $SE = 0.4145$, $p = 0.031$) have significant positive associations, suggesting that areas with a higher Hispanic Population and Poverty levels contribute to increased electricity consumption. Illiteracy is negatively associated with electricity consumption ($\beta = -0.9386$, $SE = 0.4728$, $p = 0.053$), though the effect is only marginally significant. The Black Population has no statistically significant effect ($p = 0.405$) on electricity consumption. For residential NG consumption, the percentage of poverty exhibits a strong positive relationship (β = 2.402, SE = 0.620, p < 0.001), suggesting that higher poverty rates in a county lead to greater NG consumption. In contrast, Illiteracy is negatively associated (β = -3.827, SE = 0.707, p < 0.001) with NG consumption, suggesting that areas with higher illiteracy rates consume less natural gas. Neither the Hispanic nor the Black Population was correlated with NG consumption (p > 0.10).

Commercial Setting

Table 4 summarizes the results of two linear regression models predicting Commercial Electricity and NG Consumption. The model for Commercial Electricity Consumption demonstrates strong explanatory power, accounting for 76.2% of the variance (Adjusted $R^2 = 0.76$, F = 39.5, p < 0.001).

Table 4. Model Summary and Result from the Linear Regression for Commercial Electricity and NG Consumption.

Factors	Electricity Consumption		NG Consumption	
	Estimate (SE)	p-value	Estimate (SE)	p-value
(Intercept)	0.0067 (0.924)	0.994	-13.148 (5.315)	0.018
Hispanic Population	0.6663 (0.161)	< 0.001	1.659 (0.908)	0.076
Black Population	0.1068 (0.107)	0.322	-0.554 (0.586)	0.351
% Poverty	1.1704 (0.494)	0.022	7.663 (2.787)	0.010
Illiteracy	-2.2999 (0.564)	< 0.001	-8.740 (3.200)	0.010
Adjusted R^2	0.762		0.240	
RMSE	0.243		1.18	
F	39.5		4.16	
p	< 0.001		0.007	

Note. SE=Standard Error, RMSE=Root Mean Square Error, F=F-test, p=p-value

Table 5. Model Summary and Result from the Linear Regression for Industrial Electricity and NG Consumption.

Factors	Electricity Consumption		NG Consumption	
	Estimate (SE))	p-value	Estimate (SE)	p-value
(Intercept)	3.3532 (2.184)	0.132	0.271 (3.393)	0.937
Hispanic Population	0.3767 (0.381)	0.328	1.026 (0.592)	0.090
Black Population	0.0949 (0.252)	0.709	-0.516 (0.392)	0.194
% Poverty	0.3367 (1.169)	0.775	1.400 (1.815)	0.445
Illiteracy	-0.1797 (1.333)	0.893	-2.984 (2.070)	0.157
Adjusted R^2	0.0817		0.0674	
RMSE	0.575		0.894	
F	2.07		1.87	
p	0.101		0.133	

Note. SE=Standard Error, RMSE=Root Mean Square Error, F=F-test, p=p-value

In contrast, the model for commercial NG consumption explains only 24.0% of the variance (Adjusted $R^2 = 0.24$, $F = 4.16$, $p = 0.007$), indicating a weaker fit. For Commercial Electricity Consumption, the Hispanic Population ($\beta = 0.6663$, SE = 0.161, $p < 0.001$) and the percentage of Poverty ($\beta = 1.1704$, SE = 0.494, $p = 0.022$) are significantly positively associated, suggesting that areas with higher Hispanic populations and greater poverty levels tend to exhibit increased commercial electricity use. Illiteracy has a strong negative effect ($\beta = -2.2999$, SE = 0.564, $p < 0.001$), indicating that areas with higher illiteracy rates consume less electricity. The Black Population does not significantly impact electricity consumption ($p = 0.322$).

For Commercial NG Consumption, the percentage of Poverty exhibits a strong positive association ($\beta = 7.662$, SE = 2.787, $p = 0.010$), suggesting that commercial establishments in poverty-stricken areas consume more NG. Similarly, illiteracy shows a significant negative effect ($\beta = -8.740$, SE = 3.200, $p = 0.010$). The intercept is negative and significant ($\beta = -13.148$, SE = 5.315, $p = 0.018$), suggesting a potential baseline reduction in NG consumption. However, neither the Hispanic ($p = 0.076$) nor the Black ($p = 0.351$) Population significantly affects Commercial NG Consumption.

Industrial Setting

Table 5 presents the results of the regression analysis for Industrial Electricity and NG consumption. The electricity and NG consumption models exhibit low explanatory power, with adjusted R^2 values of 0.081 and 0.067, respectively. Neither model is statistically significant ($p = 0.101$ for electricity consumption, $p = 0.133$ for NG consumption), indicating that the selected socioeconomic and demographic factors do not strongly predict industrial energy consumption. None of the independent variables shows a statistically significant association with industrial electricity consumption. The Hispanic Population ($\beta = 0.3767$, SE = 0.381, $p = 0.328$), Black Population ($\beta = 0.0949$, SE = 0.252, $p = 0.709$), percentage of Poverty ($\beta = 0.3367$, SE = 1.169, $p = 0.775$), and Illiteracy ($\beta = -0.1797$, SE = 1.333, $p = 0.893$) all show non-significant effects on electricity and NG consumption. The intercept is also non-significant ($p = 0.132$), further confirming the weak explanatory power of the model.

Similar patterns emerge for Industrial NG Consumption. While the Hispanic Population shows a marginally significant positive relationship ($\beta = 1.026$, SE = 0.592, $p = 0.090$), the effect is not strong enough to be considered statistically significant. The Black Population ($\beta = -0.516$, SE = 0.392, $p = 0.194$), percentage of Poverty ($\beta = 1.400$, SE = 1.815, $p = 0.445$), and Illiteracy ($\beta = -2.984$, SE = 2.070, $p = 0.157$) were not statistically significant. The model intercept is also not significant ($p = 0.937$).

Discussion

The results highlight significant relationships between socio-economic and demographic factors and energy consumption across residential, commercial, and industrial sectors. The Hispanic Population and Poverty percentage positively impact residential electricity consumption. This means that areas with higher Hispanic populations and poverty tend to consume more electricity. These findings are consistent with previous studies indicating that African American and Hispanic groups are more likely to come from socioeconomically disadvantaged backgrounds (Bednar & Reames, 2020). Lower-income households face increased energy demands due to inefficiencies in home insulation and appliance usage (Reames, 2016).

Additionally, Black and Hispanic communities often face systemic barriers that contribute to disparities in educational attainment, poverty, and employment opportunities when compared to other demographic groups (Alcendor, 2020; Evans & Chapman, 2024). As a result, lower-income households, including many Black and Hispanic families, often spend a larger share of their income on energy bills compared to wealthier households. Nationally, the median wealth for white families is approximately $184,000, while it is about $23,000 for Black families and around $38,000 for Hispanic families, highlighting broader economic disparities across the United States (Kent & Ricketts, 2021). This wealth gap is exacerbated by limited access to energy-efficient housing and appliances, as well as a lack of investment in infrastructure, primarily in minority neighborhoods ("Energy justice towards racial justice," 2020). Research shows that poverty is a significant factor in energy consumption, particularly in developing regions. Limited financial resources often hinder access to energy-efficient technologies and services, increasing the energy bill compared to households with energy-efficient equipment. As income rises, households change to cleaner and more efficient energy sources (Ross et al., 2018). In contrast, households in economically disadvantaged areas frequently depend on cheaper, less efficient energy options, aggravating energy poverty and restricting overall energy consumption (Xia et al., 2022). As income declines, families struggle to meet their basic energy needs, leading to reduced energy consumption and potential health risks linked with inadequate heating or cooling (Charlier & Kahouli, 2019).

In this study, only socioeconomic factors were correlated with residential NG consumption. Poverty exhibits a positive effect, while Illiteracy negatively impacts consumption. Poverty is a positive contributor because of the affordability of NG over electricity and other residential energy sources. Government data show that NG is three times more affordable than electricity (U.S. Department of Energy, 2023). The negative association with illiteracy may reflect limited awareness of natural gas as a cost-effective energy source, as suggested by energy literacy research. However, it could also signal deeper challenges associated with extreme poverty, such as financial constraints, limited access to information, or difficulties in navigating the processes required to switch to natural gas, including the ability to establish the necessary service connections (DeWaters & Powers, 2011).

The result from the commercial electricity consumption shows that the Hispanic Population, Poverty, and Illiteracy are the factors that affect the consumption. The Hispanic Population and Poverty are positive predictors, and Illiteracy is a negative predictor of electricity consumption. The significance of the Hispanic population in commercial electricity consumption can be attributed to various socio-economic and business-related factors. Hispanic-owned businesses are increasingly recognized for revitalizing local economies, particularly in dying and small towns in rural America (Lichter et al., 2016). One possible explanation for the higher commercial electricity demand in areas with larger Hispanic populations could be the growth of commercial activities, such as small retail shops and service-oriented enterprises, which have been documented in national trends (Maples & Bradley, 2021). However, further data would be needed to confirm this relationship within the context of this study. Similarly, our results indicate a negative correlation between Illiteracy and energy consumption. This may be because illiteracy can limit individuals' ability to access and interpret information related to energy efficiency and sustainable practices, which may contribute to lower adoption of efficient technologies and result in higher energy costs (Bohvalovs et al., 2023; Gómez-Navarro et al., 2021). This lack of understanding, particularly regarding energy-efficient technologies, billing structures, and conservation strategies, affects energy consumption and limits individuals' engagement in energy-saving practices, which alleviate energy poverty. Households lacking literacy often have limited energy usage information and rely on inefficient equipment (DeWaters & Powers, 2011; U.S. Department of Energy, 2016). Ortiz et al. suggest that initiatives addressing energy poverty usually depend on changing consumer habits and behaviors, which are significantly influenced by levels of education and awareness regarding energy use (Ortiz et al., 2021).

In contrast, the results of the Shapiro-Wilk test indicate that the distribution of commercial natural gas consumption deviates significantly from normality ($W=0.827$, $p<0.001$), suggesting potential violations of the normality assumption for residuals in the regression model. Non-normality in the dependent variable can lead to biased standard errors, affecting the reliability of p-values and confidence intervals (Osborne & Waters, 2019). Despite this, the multiple linear regression model identifies Poverty and the Illiteracy rate as statistically significant predictors of commercial natural gas consumption. Specifically, Poverty exhibits a positive relationship, while the Illiteracy rate is negatively associated with commercial natural gas consumption. The statistical significance of these factors should be interpreted with great caution as the reliability of p-values diminishes when normality is violated, increasing the likelihood of Type I or Type II errors (Schmidt & Finan, 2018). Further robustness checks and alternative modeling techniques are recommended to ensure the validity of statistical inferences.

Unlike the residential and commercial sectors, the regression model for industrial energy consumption shows no statistically significant predictors, with all p-values exceeding 0.05. The adjusted R^2 values of 0.081 for electricity and 0.067 for NG indicate little explanatory power of these variables in predicting industrial energy consumption. For industrial energy consumption, other factors such as geographical location, production quantity, operational practices, regulatory framework, governmental policies, economic growth, etc., can play a larger role in impacting energy consumption (Katunský et al., 2011; Qing et al., 2021; Zhang et al., 2023). Socioeconomic and demographic factors might not affect industrial energy use as much as they do in residential and commercial settings.

Limitations

The research is constrained by the availability and precision of socioeconomic and demographic data in West Virginia, which limits the extent to which various influencing factors could be incorporated. Many other variables, such as building characteristics, energy efficiency measures, climate variations, and policy interventions, also play a crucial role in shaping energy consumption patterns but were not included due to data limitations. Despite these constraints, the findings of this study remain relevant and offer meaningful conclusions that can help policymakers develop targeted strategies to address energy access, efficiency, and affordability challenges. Future research should integrate a broader range of factors and leverage more precise data to enhance the robustness and applicability of the findings.

Conclusion

In conclusion, this study underscores the significant influence of socioeconomic and demographic factors—particularly poverty, Hispanic population density, and illiteracy—on residential and commercial energy consumption in West Virginia, while industrial consumption remains unaffected by these variables. The findings reveal that energy use in vulnerable communities is intertwined with economic instability and educational disparities, necessitating targeted interventions to reduce energy insecurity. Policymakers should prioritize educational outreach, infrastructure investment, and financial support for low-income and minority households to alleviate the disproportionate energy burden and promote equitable access to efficient and affordable energy resources.

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