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The role of electricity access in promoting industrialization in developing countries: Utilizing machine learning algorithms

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Abstract

This study investigates the influence of industrial employment and access to electricity on manufacturing value-added (MVA) in five emerging economies: Brazil, Nigeria, Egypt, Pakistan, and India. It aims to assess the relative importance of these two factors in driving industrial output, with a focus on identifying patterns that can inform policy development. The study relies on five machine learning algorithms: Random Forest, Gradient Boosting, K-Nearest Neighbors, Decision Trees, and Support Vector Machines to model and investigate the relationship between manufacturing value-added, industrial employment, and electricity access. Correlation studies are carried out by country to better understand the results. According to the study, in each of the five countries, manufacturing value-added is far more impacted by power availability than by industrial employment. Industrial employment only contributed 0.7% to 36.8% of the influence on manufacturing value-added, but availability to power accounted for 63.2% to 99.3%. Strong negative correlations between electricity access and manufacturing value-added were found in Brazil ($r = -0.803$), Nigeria ($r = -0.722$), and India ($r = -0.682$), whereas Pakistan showed a weak positive correlation ($r = 0.22$) and Egypt a weak inverse correlation ($r = -0.382$). The correlation between MVA and industrial employment varied: weak positive in Brazil ($r = 0.384$) and Pakistan ($r = 0.11$), strong negative in India ($r = -0.568$), and weak negative in Egypt ($r = -0.097$) and Nigeria ($r = -0.031$). The results imply that increasing industrial employment or extending access to electricity does not ensure increased manufacturing production. The impacts vary from nation to nation and are probably influenced by more general sectoral and structural factors, including rival industries, legal systems, and the standard of infrastructure. Emerging country policymakers should prioritize investments in grid resilience, worker skill development, and supply chain modernization. Governments can strengthen evidence-based policy planning by using machine learning as an evaluation and forecasting tool to better match industrial strategy with actual performance indicators.

Keywords: Electricity access, Gradient boosting, Machine learning, Random forest, Manufacturing value-added.

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1. Introduction

Access to reliable electricity is a cornerstone of economic development and industrial transformation. Electricity enables modern industries to operate efficiently, facilitates the use of advanced technologies, and fosters economic diversification. In developing countries, however, the lack of universal electricity access continues to constrain industrial growth, reducing the competitiveness of manufacturing sectors and impeding sustainable development. This study investigates the interplay between electricity access, industrial employment, and manufacturing value-added in five developing countries: India, Pakistan, Nigeria, Egypt, and Brazil. These countries, representing different regions and industrial contexts, provide a valuable lens through which to analyze the challenges and opportunities associated with electricity-driven industrialization.

Manufacturing value-added is a critical metric for assessing the health and growth of the industrial sector. It reflects the contribution of manufacturing to gross domestic product (GDP) and serves as an indicator of industrial productivity and efficiency. Higher manufacturing value-added is pivotal for economic transformation and job creation in developing economies. However, the extent to which electricity access contributes to manufacturing value-added varies significantly depending on industrial employment, infrastructure development, and economic policies. This study aims to unravel these complex relationships, offering insights into how electricity and industrial employment jointly influence manufacturing outcomes.

Electricity access, measured as the percentage of the population with reliable electricity, plays a fundamental role in industrialization. Reliable electricity enables the continuous operation of machinery, supports the integration of digital technologies, and reduces production costs. For instance, studies have shown that countries with high electricity access tend to experience more rapid industrial growth. However, electricity access remains uneven in many developing countries, with rural areas often lagging behind urban centers. In Nigeria, for example, frequent power outages force manufacturers to rely on costly generators, which increase production costs and reduce competitiveness [1]. Similar challenges are observed in Pakistan, where electricity shortages have disrupted industrial productivity.

Industrial employment is another critical factor in driving manufacturing value-added. A skilled and adequately employed industrial workforce enhances production efficiency, promotes innovation, and supports the adoption of advanced manufacturing technologies. However, the interplay between industrial employment and electricity access is particularly significant in shaping the value-added of manufacturing. In Egypt, for instance, a growing industrial workforce has struggled to fully capitalize on its potential due to intermittent electricity supply and outdated infrastructure [2]. Conversely, Brazil has demonstrated how investments in electricity infrastructure and workforce development can contribute to sustained industrial growth, highlighting the importance of an integrated approach.

Integrating machine-learning algorithms into this study provides a robust analytical framework for uncovering complex patterns and relationships between electricity access, industrial employment, and manufacturing value-added. Machine learning enables the processing of large datasets across diverse variables, facilitating predictive modeling to assess the impact of policy changes or infrastructure improvements. For example, this study can use regression-based algorithms to quantify the relative importance of electricity access and workforce dynamics in driving manufacturing growth. Clustering algorithms can also identify regional trends and disparities among the studied countries, offering actionable insights for targeted policy interventions. By leveraging these advanced tools, this research ensures data-driven accuracy and enhances the capacity to design effective industrialization strategies tailored to the specific needs of developing economies.

The countries under study present diverse yet comparable challenges and opportunities in advancing industrialization. In India and Pakistan, rapid population growth and urbanization have led to rising electricity demand, putting pressure on existing infrastructure. Nigeria and Egypt, as leading economies in Africa, face similar challenges related to electricity reliability and infrastructure limitations, which hinder their ability to attract investment in manufacturing. Brazil has made significant strides in industrial diversification in South America, but regional disparities in electricity access remain a concern. These varied contexts underscore the importance of tailored policy interventions to address specific national and regional challenges.

By focusing on these five countries, this study seeks to provide a comprehensive analysis of how electricity access and industrial employment impact manufacturing value-added. The findings are expected to offer actionable policy recommendations to governments, development agencies, and stakeholders aiming to promote sustainable industrialization. Beyond the economic implications, improving electricity access has social and environmental benefits, contributing to poverty alleviation, education, and the achievement of Sustainable Development Goals (SDGs).

In conclusion, the role of electricity access in advancing industrialization cannot be overstated. It is a prerequisite for enhancing productivity, fostering innovation, and driving economic growth. When combined with strategic investments in industrial employment, access to electricity has the potential to transform developing economies, enabling them to compete more effectively in global markets. This study sheds light on the challenges faced by developing countries and emphasizes the opportunities for prioritizing electricity-driven industrial policies.

2. Literature Review

Reliable access to energy is crucial for the industrialization and economic development of emerging countries. Several studies have examined this connection, demonstrating how access to power improves industry productivity, creates jobs, and encourages economic diversity. This review highlights key findings from relevant studies on the topic.

[3] examined the macroeconomic effects of electricity access, emphasizing its essential role in promoting industrial growth in emerging markets. In a related study, Bhattacharyya and Palit [4] addressed the problem of inconsistent electricity distribution, which hinders rural industrial development. Furthermore, World Bank [5] indicated that improvements in the power sector enhance electricity reliability and attract foreign direct investment, especially in energy-intensive sectors. Raghutla and Chittedi [6] investigated the connection between electricity access and economic development, identifying a unidirectional causal link between financial growth and electricity access in the BRICS nations.

Electricity access significantly influences industrial productivity. Shahbaz et al. [7] demonstrated that reliable electricity supports economic growth by enabling uninterrupted manufacturing operations. Studies in sub-Saharan Africa, including those by International Energy Agency (IEA) [1] have documented how power outages negatively affect industrial productivity, forcing industries to rely on expensive diesel generators and decreasing profitability. Similarly, Rao [8] examined the economic consequences of electricity access on enterprises and discovered an 18% increase in family enterprise revenue, with significant effects observed for up to 16 hours of electricity provision. Emeka et al. [9] investigated the impacts of industrialization on productive capacity in Africa, concluding that electrification increases productivity, labor force participation, and institutional quality. Furthermore, Perez-Sebastian et al. [10] examined the influence of grid electrification on economic transformation. They discovered that the industrial sector benefited the most, with power infrastructure accounting for 17% of structural transformation.

Electrification also plays a crucial role in employment and regional development. Dinkelman [11] found that rural electricity increased employment in labor-intensive businesses in South Africa. Similarly, Nguyen and Bui [12] demonstrated that reliable energy encourages foreign direct investment in Southeast Asia's manufacturing sectors. Abid et al. [13] investigated the impact of industrialization on economic development in both developed and developing countries, indicating a U-shaped relationship: the effects of the labor force are positive in developed countries but negative in developing ones.

Several studies have looked into different electrical supply models. Buwa and Rao [14] investigated the relationship between energy access and development, contrasting centralized and decentralized supply systems. Mainali and Silveira [15] investigated rural electrification options in Nepal and Afghanistan and concluded that micro-hydro mini-grids offer the most cost-effective solution, although individual household technologies are preferable for widely dispersed households. Bonan et al. [16] reviewed impact evaluations related to electricity access and cooking facilities, demonstrating the significant effect of electricity access on well-being indicators.

Public-private partnerships (PPPs) and multinational enterprises (MNEs) are essential for constructing electrical infrastructure. Foster and Rana [17] show that PPPs increase investments in energy infrastructure, ensuring a dependable electricity supply for African companies. Similarly, D'Amelio et al. [18] examined MNEs' role in electricity access, finding that they effectively deploy infrastructure in institutionally weak environments. Sambodo et al. [19], highlighting the increasing energy demand in developing economies, particularly in the Asia-Pacific region, emphasize the need for sustainable energy solutions to support urbanization and economic growth.

Access to electricity has a tremendous impact on education and human capital development. Kelly et al. [20] investigated how access to power affects primary education and discovered that increased electricity availability improves school enrollment and achievement. Furthermore, Emeka et al. [9] found that human capital, healthcare spending, and a rise in institutional quality affect African productivity.

While earlier research has explored the relationship between power access and industrialization, this study adopts a novel approach by utilizing machine-learning techniques to investigate these relationships. Unlike previous research, which primarily relied on descriptive or regression analyses, this study employs predictive modeling techniques, including clustering, decision trees, and regression-based algorithms, to identify patterns in electricity access, industrial employment, and manufacturing value addition. Furthermore, while many studies focus on individual regions or countries, such as Lipscomb et al. [21] on Brazil and Khandker et al. [22] on Bangladesh, this study conducts a comparative analysis of regions in Asia (India and Pakistan), Africa (Nigeria and Egypt), and South America (Brazil), thereby increasing the findings' generalizability.

This study addresses a significant gap in the literature by integrating machine learning and employing a comparative multi-regional approach. It provides innovative methods to assess and improve the contribution of electricity access to industrialization in developing countries.

3. Empirical Framework

This paper explores the relationship between manufacturing value added (% of GDP) as the dependent variable and access to electricity (% of population) and employment in industry (% of total employment) as independent variables. This is demonstrated by the equation below:

MVA= AC+EN

Where,

MVA: manufacturing value added.

AC: Access to electricity as a percentage.

EN: Employment in industry as a percentage.

4. Data and Methodology

4.1. Data

The research variables are specific to the group of countries under study, which were selected based on the availability of the necessary data for the research. Therefore, the research relied mainly on India and Pakistan from the Asian continent, Egypt and Nigeria from the African continent, and Brazil from Latin America as emerging industrial countries located within the developing countries. The data were obtained from the World Bank database, and the periods covered by the research differed from one country to another according to the availability of data. For example, the study relied on the period from 1993 to 2022 in India, 1998 to 2022 in Pakistan, 1992 to 2022 in Egypt, and 1999 to 2022 in Nigeria and Brazil. The following table shows the statistical description of the variables under study:

Table 1.
Data Statistics.

Variables	Country	Source of data	Mean	Mode	Median	Dispersion	Min.	Max.
Access to electricity (% of population	India	World Bank	73.62	49.81	73.2	0.21	49.81	99.6
	Pakistan	World Bank	84.36	70.26	87.1	0.098	70.26	95
	Egypt	World Bank	98.33	100	99	.018	93.4	100
	Nigeria	World Bank	48.3	55.4	39	0.15	35.23	60.5
	brazil	World Bank	96.88	99.7	97.85	0.034	88.8	100
Employment in industry (% of total employment)	India	World Bank	20.41	14.75	20.13	0.19	14.7	26.12
	Pakistan	World Bank	22.28	20.11	21.41	0.079	20.11	25.51
	Egypt	World Bank	23.63	19.75	22.9	.10	19.75	28.6
	Nigeria	World Bank	11.7	10.14	11.38	.098	10.14	14.56
	brazil	World Bank	22.66	20.25	22.96	0.05	20.25	24.02
Manufacturing value added (% of GDP)	India	World Bank	15.77	13.12	15.76	0.071	13.12	17.86
	Pakistan	World Bank	12.1	9.09	12.48	.12	9.09	14.62
	Egypt	World Bank	16.49	15.36	16.35	0.046	15.36	18.49
	Nigeria	World Bank	12.6	6.55	11.66	0.34	6.55	20.9
	brazil	World Bank	13.83	10.33	13.03	.29	10.33	28.04

4.2. Methodology

The research relied on five machine-learning algorithms: random forest, gradient boosting, k-nearest neighbor, decision tree, and support vector machine to determine the most accurate prediction algorithm. The random forest and gradient boosting algorithms will identify the independent variables that most significantly impact the dependent variable. Table 2 shows a brief description of these algorithms.

Table 2.
Description of several different machine-learning algorithms.

Algorithm	Description
Random Forest (RF)	The model of random forests uses a tree operation to sample the dataset. We fit the trees with bootstrapped samples to reduce error and average the results. The dataset is randomly sampled before the trees are built to reduce the chance of output correlation. Because each tree in a random forest model is architecturally distinct and randomly selects a portion of the sample to minimize the likelihood of providing identical predictions, this method is ideal for detecting missing data. We discovered that averaging the less accurate forecasts from many trees produces the most accurate results Sen and Mehtab [23].
Gradient Boosting (GB)	Boosting is an ensemble method of classification that employs a continuous classification approach based on the features used by the following model. Weight-average boosting approaches increase the performance of an underperforming learner model. Several weakly trained models provide support for a considerably better-trained model. A weak learner has a low correlation with the correct classification. Still, as the learning process progresses, the correlation between the accurate classifier and the resulting weak learner improves Abd El-Aal [24].
K-nearest Neighbor (KNN)	According to the KNN notion of label consistency, the label of each given instance must match the associated KNN instance. Regarding forecasting accuracy, KNN is a simple algorithm that makes no assumptions about the data's structure. Cumulative learning provides universal benefits because it is based on cases that do not require training before making predictions. KNN is commonly used to solve regression and classification learning problems Kang [25].
Decision Tree (DT)	This is a tree-based machine learning technique that uses if-then conditions, so-called because it functions as a conditional. The root node of the decision tree is generated first, followed by the branch nodes. The information is divided into categories based on the features of the nodes that serve as decision points. The branches linking the nodes at different levels represent distinct choices defined by the state of the node's attributes, Sen and Mehtab [23].
Support vector machine (SVM)	Classification applications that use a novel machine learning algorithm require an independent and identically distributed dataset. In contrast to other machine learning approaches that calculate probability distributions, SVM allocates x to a single classification out of several. Less effective discriminatory tactics are adopted only when blueprints must be created to save time and energy, especially in a multifaceted sector. An ideal surface equation for separating multiple classes necessitates a discriminating function that accurately forecasts new occurrence labels. In contrast to evolutionary approaches or perceptions, SVM's convex optimization issues always offer consistent optimal space values. Perceptions are highly rigorous for an SVM's starting and termination stages Abd El-Aal [26].

5. Empirical Results

5.1. Model Evaluation

To determine the algorithms' performance, we must rely on the values of each (MSE, RMSE, MAE, MAPE, R2), shown in Tables 3, 4, and 5.

Table 3.
The ML accuracy in Asia.

Country	Model	MSE	RMSE	MAE	MAPE	R2
India	RF	0.43	0.66	0.51	.033	65.8
	KNN	0.46	0.67	0.55	.035	64.1
	DT	0.511	0.71	0.55	0.35	60.1
	SVM	0.55	0.742	0.59	0.038	57.1
	GB	0.57	0.758	0.60	0.038	55.2
Pakistan	DT	1.3	1.14	.87	.70	.457
	RF	1.32	1.15	.815	0.065	.449
	GB	1.79	1.33	.812	0.073	.254
	KNN	2.45	1.56	1.13	0.095	0.023
	SVM	3.16	1.77	1.28	.11	.31

Table 3 shows that the most accurate algorithm for India is Random Forest, while for Pakistan, it is a Decision Tree.

Table 4.
The ML accuracy in Africa.

Country	Model	MSE	RMSE	MAE	MAPE	R^2
Egypt	KNN	0.403	0.635	0.497	0.03	0.327
	SVM	0.464	0.681	0.578	0.035	0.226
	GB	0.476	0.690	0.575	0.035	0.205
	RF	0.510	0.714	0.571	0.034	0.148
	DT	0.685	0.828	0.60	0.035	0.144
Nigeria	RF	2.11	1.453	1.12	0.095	0.889
	GB	2.95	1.71	1.31	0.107	0.845
	KNN	3.22	1.79	1.39	0.122	0.830
	SVM	3.8	1.95	1.56	0.13	0.80
	DT	3.8	1.95	1.43	0.121	0.80

Table 4 shows that the most accurate algorithm for Egypt is k-nearest neighbor, while for Pakistan, it is a random forest.

Table 5.
The ML accuracy in Latin America.

Country	Model	MSE	RMSE	MAE	MAPE	R^2
Brazil	RF	5.35	2.31	1.37	0.088	0.671
	KNN	7.07	2.65	1.7	0.109	0.565
	DT	7.65	2.76	1.54	0.100	0.530
	GB	9.92	3.15	1.7	0.113	0.390
	SVM	13.72	3.71	2.32	0.141	0.153

5.2. Feature Importance

Recognizing the relevance of features will only reveal the dark side of ML models. We evaluate the model's forecasts or classifications by quantifying the influence of each input variable or feature. Prioritizing these attributes using significance ratings helps data scientists better understand how their models function. This information enables users to enhance their models, accelerate progress, and make more precise decisions. Tables 6, 7, and 8 show how crucial the algorithm's characteristic is:

Table 6.
Feature importance for the Asian region.

Variables	India	Pakistan
	Random forest features	**Random forest features**
Access to electricity (% of population)	0.632	0.80
Employment in industry (% of total employment)	0.368	0.20

From Table 6, we find that the most influential variable on the added value of the manufacturing sector in India and Pakistan is the percentage of the population with access to electricity, at 63% and 80%, respectively. In comparison, employment in the industrial sector contributed 36% and 20% in each of the two countries.

Table 7.
Feature importance for the African region.

Variables	Egypt	Nigeria
	Gradient boosting features	**Random forest features**
Access to electricity (% of population)	0.705	0.824
Employment in industry (% of total employment)	0.295	0.176

The same situation in India and Pakistan is repeated in Egypt and Nigeria, where the percentage of access to electricity was the most influential variable on the added value of the manufacturing sector, at 70% in Egypt and 82% in Nigeria. The remaining contribution percentages were for the other variables.

Table 8.
Feature importance for the Latin America region.

Variables	Brazil
	Random Forest Features
Access to electricity (% of population)	0.993
Employment in industry (% of total employment)	0.007

Brazil did not differ from the previous countries, as shown in Table 8. However, the electricity access variable accounted for more than 99% of the total impact on the added value of the industrial sector.

To clarify whether the relationship between the dependent and independent variables is direct or inverse, we can explore this through Tables 9, 10, and 11 and more clearly in Figures 1, 2, and 3.

Table 9.
Pearson correlation for the Asian region.

Country	Independent Variables	Dependent Variable	Pearson Correlation
India	Manufacturing, value added (% of GDP)	Access to electricity (% of population)	-0.682
		Employment in industry (% of total employment)	-0.568
Pakistan	Manufacturing, value added (% of GDP)	Access to electricity (% of population)	0.22
		Employment in industry (% of total employment)	0.11

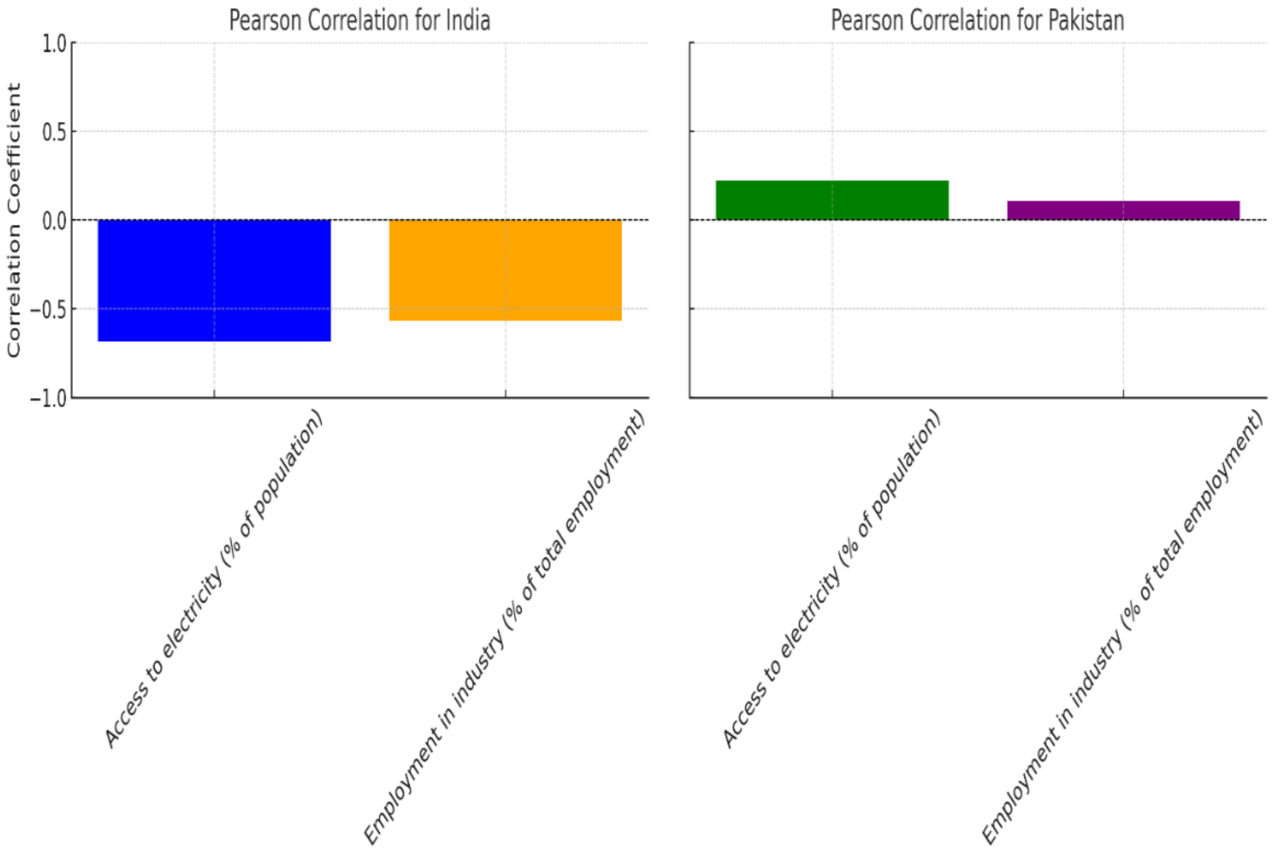

Figure 1.
Pearson correlation for the Asian region.

Table 10.
Pearson correlation for the African region.

Country	Independent Variables	Dependent Variable	Pearson Correlation
Egypt	Manufacturing, value added (% of GDP)	Access to electricity (% of population)	-0.382
		Employment in industry (% of total employment)	-0.097
Nigeria	Manufacturing, value added (% of GDP)	Access to electricity (% of population)	-0.722
		Employment in industry (% of total employment)	-0.031

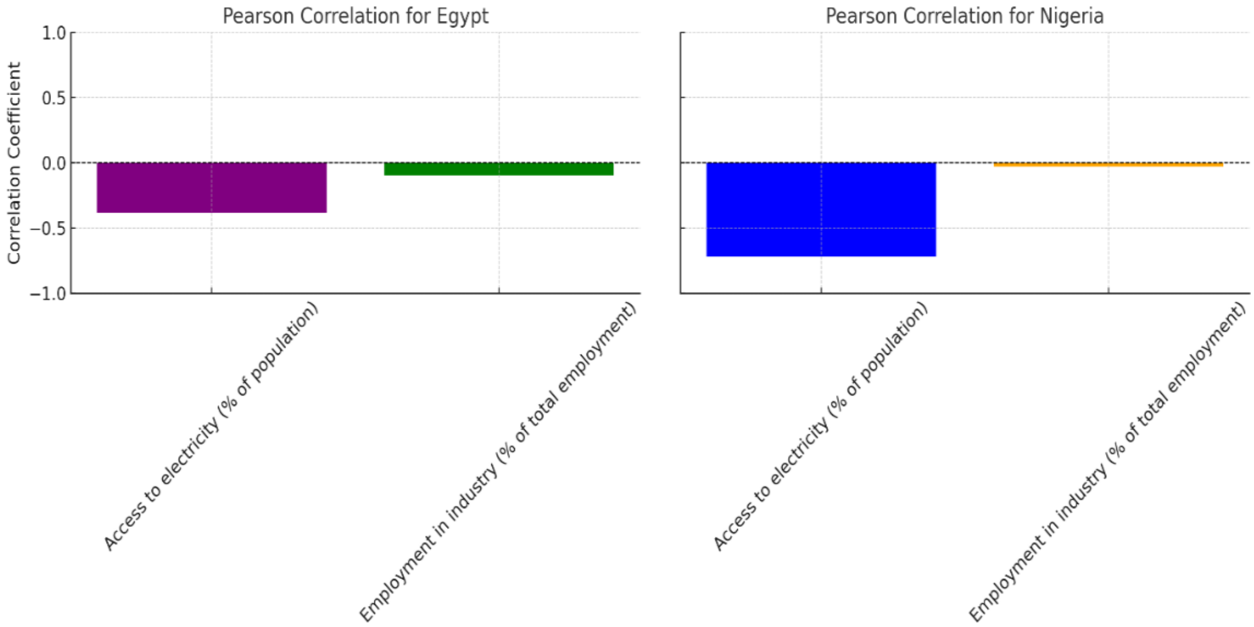

Figure 2.
Pearson correlation for the African region.

Table 11.
Pearson correlation for the Latin America region.

Country	**Independent Variables**	**Dependent Variable**	**Pearson Correlation**
Brazil	Manufacturing, value added (% of GDP)	Access to electricity (% of population)	-0.803
		Employment in industry (% of total employment)	0.384

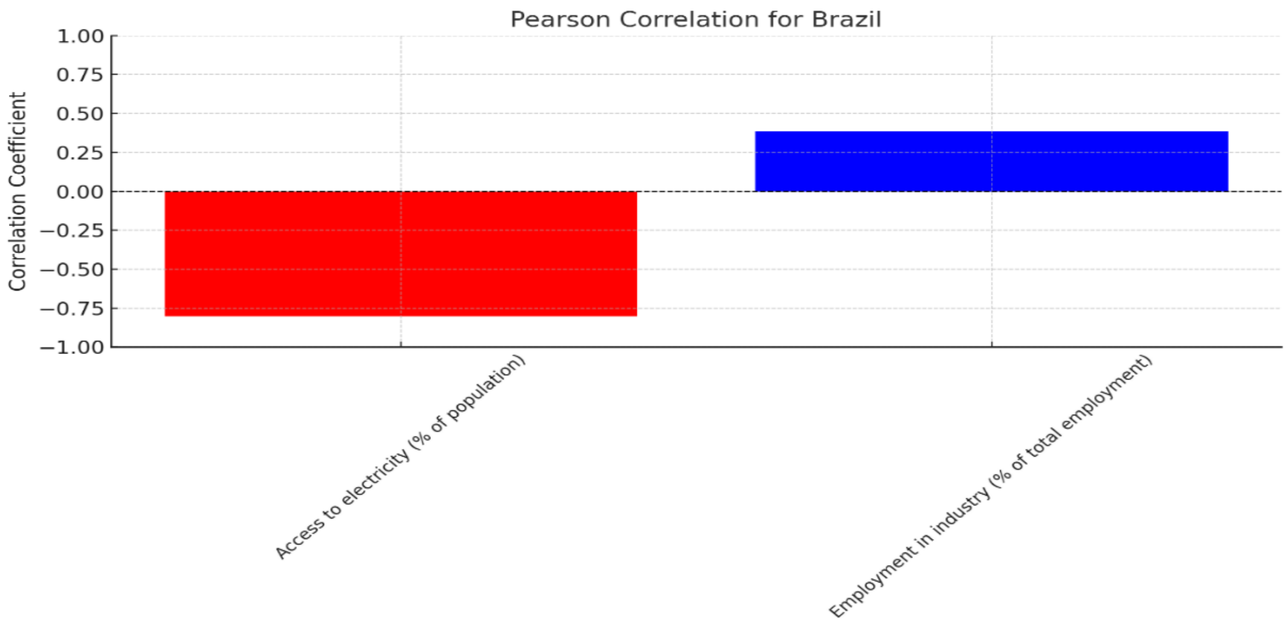

Figure 3.
Pearson correlation for the Latin America region.

From Tables 9, 10, and 11, we find that the relationship between the rate of access to electricity and the value added of the manufacturing sector is a strong inverse relationship in India, Nigeria, and Brazil, and a weak inverse relationship in Egypt. The matter differed in Pakistan, as it was a weak direct relationship. The relationship between employment in the industrial sector and the value added to the manufacturing sector was associated with a strong inverse relationship in India and a weak inverse relationship in Egypt and Nigeria, while in Pakistan and Brazil, it was a weak direct relationship. From here, we can assert that both the increase in access to electricity and the rise in employment in the industrial sector do not control growth in the manufacturing sector. However, it is possible in industries that crowd out the manufacturing sector, as shown in the cases of the five countries under study.

6. Conclusion

This study explores how access to electricity influences the industrial sector's value addition in five emerging nations: India, Pakistan, Egypt, Nigeria, and Brazil. Access to power emerged as the most critical factor in all countries, though its effects varied significantly. A disturbing inverse link was discovered in India, Nigeria, and Brazil, indicating that improved electrical access does not always correlate with higher manufacturing value addition. Egypt had a modest negative correlation, whilst Pakistan had a weak positive association. These findings call into question the premise that better energy availability immediately promotes industrial growth, emphasizing the importance of addressing underlying structural difficulties within each country's industrial environment.

The relationship between industrial employment and manufacturing value-added complicates this situation further. In India, industrial employment displayed a strong inverse relationship with manufacturing growth, while Egypt and Nigeria showed weak inverse correlations. On the other hand, Pakistan and Brazil indicated weak positive relationships, implying that growth in industrial employment might support the manufacturing sector in these countries. These findings suggest that access to electricity or labor participation alone cannot ensure long-term industrialization. Instead, fundamental factors such as infrastructure quality, technological innovation, and economic diversity are critical for the sector's performance. Additionally, competing industries in these economies may divert resources from manufacturing, limiting growth potential.

This study emphasizes the need for personalized, country-specific strategies to manage the complex link between energy access, industrial employment, and manufacturing outcomes. Investing in renewable energy infrastructure, particularly in countries like Nigeria and India, might reduce power outages and increase industrial competitiveness. Furthermore, encouraging worker development through skill-building programs and updating industrial processes can enhance the benefits of increasing employment. Policymakers should adopt a holistic approach that balances increasing energy availability with initiatives to improve industrial efficiency, promote technological innovation, and address sector-specific issues. This approach enables developing economies to fully realize their industrial sectors' potential while strengthening their position in the global market.

7. Implications and Future Work

The study's findings have important policy and practical implications for emerging economies seeking to boost industrial growth. First, since access to electricity affects manufacturing value added more than it affects industrial employment, governments should prioritize investment in reliable and sustainable energy infrastructure. National policies must include not only expanding access but also improving electricity quality, reducing outages, and supporting renewable energy sources. Furthermore, the inverse relationship observed in some countries necessitates a more nuanced understanding of electricity utilization efficiency, implying that access alone is insufficient unless combined with industrial readiness and infrastructure quality.

Second, the weak or negative correlation between industrial employment and manufacturing performance in several countries implies a need to shift focus toward workforce productivity, automation readiness, and upskilling rather than solely increasing employment numbers. Policymakers must integrate industrial policy with education, vocational training, and technological adaptation strategies.

Future studies can take this analysis in a variety of directions. One approach is to refine the model by including new explanatory variables such as infrastructure quality indices, innovation indicators, or trade openness. Another promising approach is to conduct sectoral-level analyses to determine how electricity access affects various manufacturing sub-sectors (for example, textiles, heavy industry, and food processing).

In the future, deep learning algorithms or hybrid machine learning methods may improve forecasting accuracy and pattern detection. Finally, qualitative studies, such as expert interviews or case studies, can complement quantitative models by providing more detailed insights into country-specific processes that influence the relationship between the electricity sector and industry.

Abbreviations:

The following abbreviations are used in this manuscript:

MVA	Manufacturing value-added
ML	Machine Learning
AC	Access electricity
EN	Employment in industry
RF	Random Forest
DT	Decision Tree
GB	Gradient Boosting
KNN	k-nearest neighbor
SVM	Support Victor Machine

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