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The effects of governance quality on renewable and nonrenewable energy consumption: An explainable decision frame

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Abstract

This study analyzes the effect of governance quality (six aspects: government effectiveness; control of corruption; voice and accountability; regulatory quality; political stability and absence of violence; and rule of law) on the renewable and nonrenewable energy consumption prediction based on the SHapely Additive exPlanations method for model analysis and interpretability. The empirical findings indicate that the time-varying contributions of six aspects of governance quality on nonrenewable (renewable) energy consumption predicting vary greatly in E-7 and G-7 countries. The time-varying contribution of governance quality within countries is heterogeneous and asymmetrical, especially India (Germany) in E-7 countries (G-7 countries). The prediction contribution distribution of governance quality between countries is more discrete in G-7 countries than E-7 countries. Our results are of great importance to policymakers and investors for enhancing the renewable energy consumption level in overcoming environmental challenges based on the country itself through governance quality.

KEYWORDS

E-7 countries and G-7 countries, energy consumption, governance quality, SHapely Additive exPlanations

1 | INTRODUCTION

As an important national strategic resource, energy is significant for the development and stability of economies and society. However, fossil energy takes up a great proportion of energy consumption and drives a series of environmental degradation (Dietz et al., 1998), because the carbon dioxide released by fossil energy would facilitate or increase the frequency of cataclysmic events, such as extreme weather events and reducing biodiversity (Abid et al., 2021). Faced with such challenges, countries around the world are taking various solutions in the light of the 2015 Paris Climate Agreement to optimize energy consumption structure, such as increasing renewable energy consumption (Chiu & Chang, 2009). However, fossil energy consumption has continued to rise recently, while renewable energy consumption has not increased significantly (Sun et al., 2023). Additionally, floods, cyclones, high temperatures, and other events occur frequently, as stated in "World Disasters Report 2020: Come Heat or High Water." With the serious and special occasions, it is important in exploring the factors that determine renewable energy consumption. Meanwhile, it is feasible to formulate and implement policies on adjusting energy consumption structure and increasing the share of renewable energy consumption in the structure of energy consumption by comparing these factors. Therefore, this research tries to discover the possible factors.

The influencing factors of energy consumption have been widely explored in the literature, especially economic growth being the main driving force. Besides, economic growth is the main performance of institutional quality based on the new institutional economics (Rodrik, 2004). It is reasonable to consider the factor of governance quality. This paper considers that governance quality mainly affects energy consumption through two channels based on summarizing the existing research, as shown in Figure 1. On the one side, good governance increases the amount of energy consumption through the promotion contribution. With the improvement of the governance quality, economic growth would be increased sharply by increasing customers' purchasing (Bornemann et al., 2018; Glad, 2017), expanding product scale (Bah et al., 2021), stimulating market investment (Barro, 1996; Cowell et al., 2017), and optimizing industrial structure (Davies et al., 2018). And without a doubt, economic growth results in an increase in energy demand and accelerates energy consumption (Alsaleh et al., 2021). On the other hand, a good governance decreases the amount of energy consumption through the inhibition contribution. As governance quality improves, innovative technology would be greatly improved, such as energy development technology (Gaspari & Lorenzoni, 2018; Pakseresht et al., 2020), product production technology (Bekhet & Latif, 2018), and machine operation technology (Clarke, 2001). The improvement of technology promotes energy efficiency and decreases energy consumption. Specifically, this study attempts to analyze and discuss the first question: (1) How does governance quality predict energy consumption, especially renewable and nonrenewable energy consumption?

Although it is theoretically reasonable for governance quality to act on energy consumption, relatively few studies consider the impact of all dimensions of governance quality. World Bank seeks to measure the governance quality from six aspects covering all domains of governance, such as voice and accountability, control of corruption (CC), government effectiveness (GE), regulatory quality, rule of law, and political stability and absence of violence (PSAV), as shown in Table 1 with a detailed description (Guliyeva et al., 2018). For each indicator, the higher the score, the stronger of government in the corresponding dimension (Haq et al., 2006). Some scholars commonly consider a single aspect in the contribution of governance quality, such as corruption (Ahlin & Pang, 2008; Glaeser & Saks, 2006; Li et al., 2000; Mo, 2001; Robinson et al., 2017), political instability (Agyemang et al., 2018), and institutional quality. These existing researches provide a great valuable reference to this issue. Notably, as governance quality represents many dimensions, it is essential to clearly clarify the impact mechanism in such a diversified and comprehensive framework. Specifically, this study attempts to answer and discuss the second question: (2) Does contributions of such predictors vary with different dimensions of governance quality on energy consumption, especially renewable and nonrenewable energy consumption?

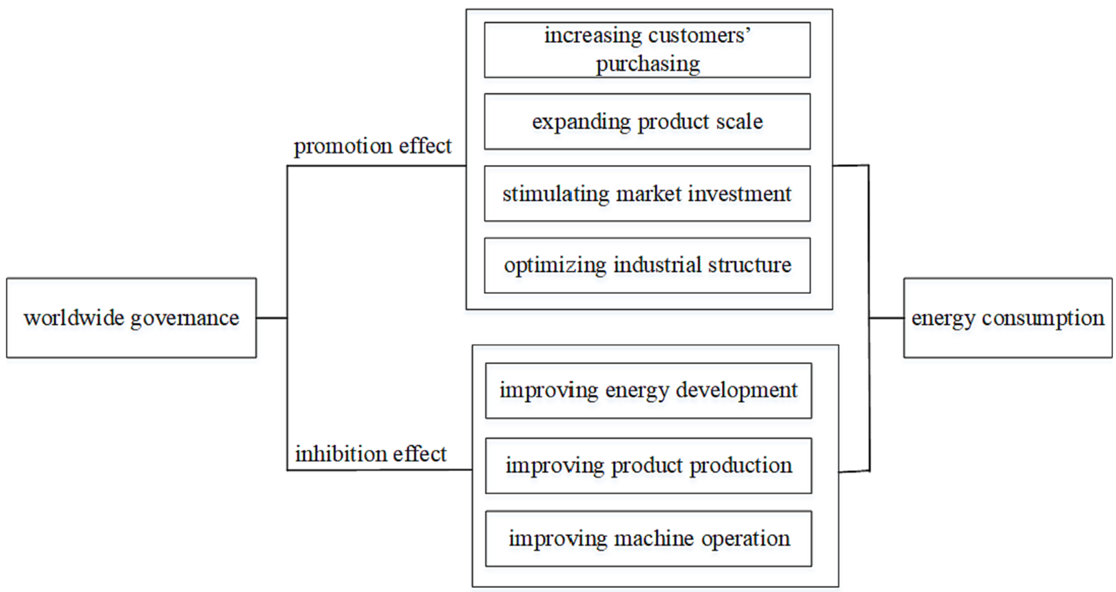

FIGURE 1 The influencing mechanism of governance quality affecting energy consumption.

TABLE 1 The description of worldwide governance.

Definition variable	Description
Voice and accountability	Capturing the degree of freedom in selecting their government, mainly specific in three aspects: freedom in social media, freedom in social association, and freedom in social expression
Political stability and absence of violence	Capturing the degree of stability in politics and society, mainly specific in three aspects: social violence, political stability, and terrorism
Government effectiveness	Capturing the degree of quality in social services, mainly specific in three aspects: policy formulation, policy implementation, and government commitment
Regulatory quality	Capturing the degree of ability in promoting social development, mainly specific in two aspects: formulating policies and regulations and implying policies
Rule of law	Capturing the degree of confidence in and abide by the rules of society, mainly specific in three aspects: contract enforcement, property rights, and crime and social power
Control of corruption	Capturing the degree of corruption in society, mainly specific in two aspects: citizens and civil servant

Source: The Worldwide Governance Indicators.

The level of national economic development would generate the different impacts of governance quality on renewable and nonrenewable energy consumption. Generally, the level of national economic development of a country is closely related to its industrial structure, urbanization, international trade, technological development level, labor market structure, market supervision, and government subsidies, which would contribute energy consumption structure (Chen et al., 2019; Feng et al., 2009; Liu & Li, 2011; Yang et al., 2023). However, whether the governance quality will have different contributions on renewable and nonrenewable energy consumption is unclear. It can be inferred that different levels of national economic development under different aspects of governance may have different impacts on the energy consumption structure. Specifically, this study attempts to answer and discuss the third question: (3) Does the importance of governance quality on energy consumption is different in developed and emerging countries, represented by the E-7 countries and G-7 countries?

Governance quality does play a role in predicting renewable and nonrenewable energy consumption. This study finds several noteworthy and valuable conclusions, which are essential to understanding the relationship between governance quality and energy consumption structure, especially in G-7 and E-7 countries. First, each indicator of governance quality has a time-varying contributions on renewable and nonrenewable energy consumption predicting, and different countries show different time-varying importance characteristics among G-7 and E-7 countries. For example, each indicator of governance quality on nonrenewable energy consumption predicting fluctuates slightly (greatly) over time for Turkey, Mexico, Italy, and Canada (Indonesia, India, USA, Germany, and England). However, each indicator of governance quality on renewable energy consumption predicting fluctuates slightly (greatly) over time for Turkey, Russia, Mexico, and Italy (India, Brazil, France, and England). Second, at any point in time, the contribution of each indicator of governance quality on nonrenewable (renewable) energy consumption predicting varies greatly among G-7 or E-7 countries. For example, compared with other E-7 (G-7) countries, China (USA) has significant heterogeneity in the impact of each indicator of governance quality on predicting nonrenewable (renewable) energy consumption. However, several countries have shown a similar contribution of one indicator of governance quality on nonrenewable (renewable) energy consumption. For example, for nonrenewable energy consumption, the importance of the rule in China, India, and Brazil (Japan and France) is relatively consistent in E-7 (G-7) countries; for renewable energy consumption predicting, the contribution of GE in China, India, and Brazil (the USA and France) is relatively consistent in E-7 (G-7) countries. Therefore, the importance of governance quality on predicting renewable and nonrenewable energy consumption are heterogeneous in both timeline and countries. These findings reveal that governance quality does not necessarily have a decisive importance on optimizing energy consumption structure, which depends on the development and stage of the country itself.

The contributions of this study are threefold. First, this research validates the importance of governance quality on energy consumption predicting. To our knowledge, existing research had illustrated the critical of governance quality on energy consumption (Naqvi et al., 2021; Psychogios et al., 2019). However, few studies have focused on a comprehensive description of the contribution of governance quality. Governance is a multidimensional issue, which ranges from the degree of democracy to the rule of law in a country. Focusing on the part dimension of governance quality may be misleading. The study strives and expands the existing literature from the six dimensions of governance quality. Additionally, the research analyzes the different contributions of governance quality on renewable and nonrenewable energy consumption so as to optimize energy consumption structure. Second, in addition to the impact contributions, we also analyze the time-varying contributions and compare the heterogeneity among E-7 and G-7 countries. This research is in line with the fact that social constructions on energy consumption predicting may vary widely depending on the national economy structure and social culture (Dietz et al., 1998; Granovetter, 1992; Stephenson et al., 2021). These findings indicate the optimal path of energy consumption structure varies from country to country. Third, we use the explainable machine learning method, which provides the explanatory power of each indicator. The explainable machine learning method could solve the questions about the nonlinear and nonstationary time series and takes the asymmetries into account. Additionally, these findings provide a helpful tool for policymakers to prioritize which institutional optimization to pay close attention on based on their country characters.

2 | EMPIRICAL MODELS AND DATA

2.1 | Methodology framework

Machine learning methods are widely applied in many fields (Liu et al., 2023; Su et al., 2023; Weng et al., 2021), especially the energy consumption literature, as they are capable to deal with critical problems, such as data missing and the optimization of hyperparameters. For example, Ulucak (2021) used bootstrap auto-regressive distributive lag to verify the relationship between financial development and energy consumption. Adaboost, K-nearest neighbor, support vector regression (SVR), multilayer perceptron (MLP), decision tree, and so forth are used for energy consumption forecasting by Jain et al. (2014) and Robinson et al. (2017). Nabavi et al. (2020) performed power forecasting by hybrid approach, which combines MLP, SVR, and CatBoost algorithms. However, the explainability of predictive factors is not known, which is important in practice by developing optimization strategies. Then, we search extensively and found further breakthroughs in machine learning in terms of explainability. For instance, Jin and Zhu (2015) came up with a relative variable importance in predicting by MLP and decision tree method. Similarly, Li et al. (2018) analyzed a feature importance analysis by XGBoost and deep neural networks. Additionally, Lundberg and Lee (2017) put forward explanation capacity with the SHapely Additive exPlanations (SHAP) method, which could work with complex models.

This research aims to unveil the heterogeneous impacts of governance quality on renewable and nonrenewable energy consumption in the SHAP method for explaining machine learning model. On the one hand, the SHAP method obtains a global explanation rather than a local explanation, which could give the accurate explanation about each indicator of good governances. On the other hand, the SHAP method takes into account all sequential combinations in an efficient model to evaluate feature importance, which could accurately obtain the relative weight between indicators of good governances. In summary, we employ the SHAP method for explaining machine learning models to quantify the contribution of worldwide governance on renewable and nonrenewable energy consumption in G-7 and E-7 countries. In detail, Figure 2 display the overview of the proposed framework using the SHAP method for explaining machine learning models. Specifically, first, the energy consumption is used as a target and the worldwide

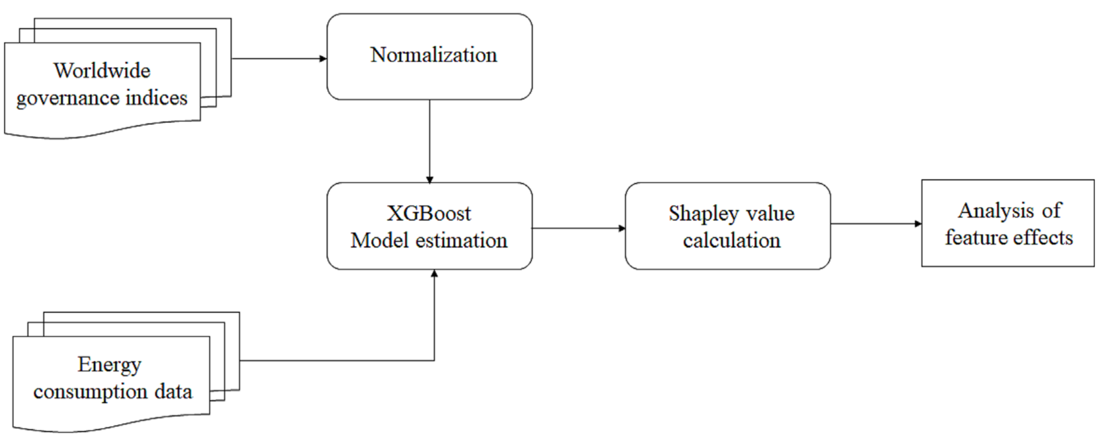

FIGURE 2 The methodology framework.

governance index is utilized for machine learning model input. Second, the XGBoost model is used to capture the complex relationship between worldwide governance indices and energy consumption data. Third, the Shapley value is calculated by the SHAP method. Finally, we can analyze the feature contribution based on the Shapley value. In the following section, we give the description of the key ideas of the XGBoost algorithm and SHAP method, as well as the feature contribution.

2.2 | Model

Suppose $D=\{x_i,y_i\}$ as the input data sample of this study, x_i denote the worldwide governance indices and y_i indicates the energy consumption data. In detail, $x_i=\left\{x_i^{(1)},x_i^{(2)},\cdots x_i^{(p)}\right\}$ is the data instance of input world governance indices; p represents the number of its features. $y_i=\left\{y_i^{(1)},y_i^{(2)},\cdots y_i^{(q)}\right\}$ is the data instance of input energy consumption variable; q is the dimension of corresponding features.

First, we normalize the data in the range of $[0,1]$ to eliminate the differences in variable dimension, which could increase model fitting reliability. Then, the standardized data are used as the input of the model. The regression problem is measured and evaluated using the mean square error as the loss function.

In this paper, we introduce the XGBoost method as the prediction model of energy consumption because XGBoost is a scalable tree boosting method proposed by Chen and Guestrin (2016). Regression problems and classification problems could be solved in parallel by XGBoost (Dong et al., 2023; Friedman, 2001, Weng et al., 2022). Specifically, there are two key optimization improvements. On the one hand, to prevent overfitting problems, regularization terms are added to the objective function of XGBoost (Chen et al., 2015). On the other hand, to get a more accurate performance, XGBoost conducts a second-order Taylor expansion. The related detail information of XGBoost is listed as follows.

In the training process of the energy consumption prediction model, the XGBoost model with regularization objective is as follows:

$$\mathrm{Obj}(\phi)=\sum_{i=1}^{n} l(\widehat{y}_i,y_i)+\sum_{k}\Omega(f_t), \tag{1}$$

where y_i is true value of energy consumption and $\widehat{y}_i$ denotes the output value predicted by the model. l is a loss function which measures the predicted values and true energy consumption. Penalty term $\Omega(f)=\gamma T+\frac{1}{2}\lambda\|w\|^2$ is used to prevent model overfitting.

Second, the SHAP method is employed to explain the governance quality indicators in the energy consumption prediction model. SHAP, a feature analysis method based on cooperative game theory, can explain the machine learning model by calculating the contribution of each variable to the predicted energy consumption (Lundberg et al., 2020). The Shapley (1953) value of the feature contribution estimated by this method is consistent and fair.

SHAP method defines the explanation as

$$g(z')=\phi_0+\sum_{j=1}^{M}\phi_j z'_j, \tag{2}$$

where g denotes the explanation model; $z'\in\{0,1\}^M$ is the alliance vector; and M is the number of the largest alliance. The Shapley value of feature j is denoted as $\phi_j\in\mathbb{R}$.

Finally, we can extract the feature contribution of governance quality on the relationship between energy consumption by analyzing the Shapley values. The absolute value of Shapley indicates the importance of the feature, that is, the effect intensity of the variable on the outcomes. The positive and negative of Shapley value denote the direction of feature effect. Among them, a positive value means it pushes up the predicted result, which means it has a positive influence. On the contrary, a negative value indicates a negative effect on the consequence variable (energy consumption).

Furthermore, to empirically examine the heterogeneous impacts of worldwide governance on renewable and nonrenewable energy consumption among G-7 and E-7 countries, as well as the different effect of worldwide governance between countries. Based on this, considering the 14 countries, $C=\{E-7,G-7\}$, $E-7=\{e_1,\cdots e_7\}$, and $G-7=\{g_1,\cdots g_7\}$. The time $T=\{t_1,\cdots t_k\}$. The feature effect of index $x_i^{(p)}$ is

$$I=\left|\phi_{it}^{(k)}\right|, \tag{3}$$

where $t\in T=\{1996,\cdots 2019\}$ and $k\in C$ denotes the index of country.

2.3 | Data and variables

This paper employs an explainable machine learning framework to reveal the relationship between worldwide governance and energy consumption for a sample of E-7 and G-7 countries in the period 1996–2019. That is, we aim to explore whether energy consumption is associated with high-quality governance countries. Further, the different dimensions of worldwide governance allow us to study the heterogeneous reactions to energy consumption. Additionally, the sufficiently long-time dimension could make us analyze how energy consumption reacts to governance quality changes. What is more, the samples of E-7 and G-7 countries help us to deeply examine the differentiation roles of worldwide governance on energy consumption. Focused on this analysis, this research contains two datasets: (1) data on energy consumption and (2) data on worldwide governance.

In the context of this study, it is a major issue to define an appropriate and the availability explained variable of energy consumption. Fortunately, the EIA and BP Statistical Review of World Energy sources[1] had collected related data from more than 200 countries from 1996. Energy mainly consists of two parts, such as renewable energy and nonrenewable energy. Our analysis uses data about the annual time series of renewable energy and nonrenewable energy consumption from G-7 countries[2] and E-7 countries[3] covering the period 1996–2019. Using terabyte joule measures energy consumption. Generally, nonrenewable energies are fuel oil, petroleum, coal, kerosene, diesel, natural gas, and gasoline (Khan et al., 2020). Renewable energies are solar, tide, wave hydro, wind, geothermal, and so forth (Guo et al., 2021; Li et al., 2020; Shahzad et al., 2021).

Governance contains a series of formal informal constraints or rules. The effectiveness of governance is determined by governmental executive ability. The World Bank researchers use 340 variables obtained from the survey, public sector data, commercial business information sources, and so on (Desbordes & Koop, 2016; Langbein & Knack, 2010; Thomas, 2010). The governance quality could be described in six aspects, such as voice and accountability (VOA), control of corruption (CC), government effectiveness (GE), rule of law (RL), regulatory quality (RQ), and political stability and absence of violence (PSAV), which are measured from −2.5 to 2.5.

2.4 | Evaluation metrics

To evaluate the predictive performance of the regression model, we choose four different criteria, including root mean square error (RMSE), mean absolute error (MAE), median absolute error (MdE), and maximum absolute error (MAxE). These criteria are commonly used indicators for assessing the predictive performance of regression models (Niu et al., 2023; Sun et al., 2023; Yang et al., 2023). The specific formulas for calculating these criteria are shown below:

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_i-\widehat{R}_i\right)^2}, \tag{4}$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|R_i-\widehat{R}_i\right|, \tag{5}$$

$$MdE=\text{median}\left(\left\{R_i-\widehat{R}_i\right\}_{i=1}^{N}\right), \tag{6}$$

$$MAxE=\max\left(\left|R_i-\widehat{R}_i\right|_{i=1}^{N}\right), \tag{7}$$

where N denotes the number of samples and R_i and $\widehat{R}_i$ indicate the true value and predicted value, respectively.

3 | EMPIRICAL ANALYSIS AND RESULTS

An analysis according to worldwide governance and energy consumption in the period 1996–2019 is measured. This study mainly analyzed the heterogeneity effect of worldwide governance on energy consumption, emphasizing the time-varying effect of each indicator of worldwide governance within countries and the heterogeneity effect of each indicator of worldwide governance between countries. In addition, in the heterogeneity effect analysis, we distinguish the difference of nonrenewable and renewable consumption.

3.1 | Overall predictive performance

In this section, we selected a range of benchmark regression models for fitting governance quality and two energy consumption variables, including linear regression, SVR, random forest, LightGBM, CatBoost, and XGBoost. These models cover both traditional linear regression and nonlinear machine learning methods, providing broad applicability. To effectively test the predictive performance of the models, we split the samples from each country into training and testing sets with a ratio of 6:4. Tables 2 and 3 present the predictive performance of different models on the testing set. All models were implemented using the scikit-learn library in Python.

The results show that machine learning models outperform traditional statistical learning methods on these evaluation criteria, demonstrating the superiority of machine learning in capturing complex nonlinear relationships. For the prediction of primary energy consumption, XGBoost achieves scores of 14.999, 8.4689, 4.2981,

TABLE 2 Overall performance of different regression models in primary energy consumption prediction.

Model	RMSE	MAE	MdE	MAxE
LR	23.5011	16.8939	12.5854	72.2138
SVR	17.5551	11.5106	7.5187	78.1869
RF	18.3329	9.9181	4.9080	76.3065
LightGBM	15.7005	9.6359	6.8477	**71.1425**
CatBoost	18.0026	10.3669	5.4370	78.4667
XGBoost	**14.9999**	**8.4689**	**4.2981**	71.1948

Note: The bold font in the table indicates that the model performs best under this metric.
Abbreviations: LR, linear regression; MAE, mean absolute error; MAxE, maximum absolute error; MdE, median absolute error; RF, random forest; RMSE, root mean square error; SVR, support vector regression.

TABLE 3 Overall performance of different regression models in renewable consumption prediction.

Model	RMSE	MAE	MdE	MAxE
LR	0.8903	0.5701	0.4739	4.6826
SVR	0.5095	**0.2849**	0.1560	3.0044
RF	0.7567	0.4520	0.2888	3.8522
LightGBM	0.6343	0.3826	0.1563	2.4745
CatBoost	0.6333	0.4373	0.2700	2.6888
XGBoost	**0.4845**	0.2862	**0.1482**	**2.3423**

Note: The bold font in the table indicates that the model performs best under this metric.
Abbreviations: LR, linear regression; MAE, mean absolute error; MAxE, maximum absolute error; MdE, median absolute error; RF, random forest; RMSE, root mean square error; SVR, support vector regression.

and 71.1848 on RMSE, MAE, MdE, and MAxE, respectively. Among these, XGBoost performs slightly worse than LightGBM on MAxE. In the case of renewable consumption prediction, XGBoost demonstrates the best performance on RMSE, MdE, and MAxE, scoring 0.4845, 0.1482, and 2.3423, respectively. The SVR model achieves a score of 0.2849 on MAE. Overall, XGBoost emerges as a competitive model for predicting both types of energy consumption. Consequently, we apply the SHAP method to explain the XGBoost model and obtain the feature contributions, which will be used for further experimental analysis.

3.2 | The time-varying contribution of worldwide governance within countries

Figures 3 and 4 report the results of the contribution of each indicator of worldwide governance on nonrenewable energy consumption predicting among E-7 countries and G-7 countries. At the same time, the results of the contribution of each indicator of worldwide governance on renewable energy consumption predicting among E-7 countries and G-7 countries are reported in Figures 5 and 6. Below, this analysis is mainly carried out from two perspectives. On the one hand, this research verifies whether the influence of each indicator of worldwide governance on nonrenewable (renewable) energy consumption predicting has time-varying contribution. On the other hand, this study further gives evidence of heterogeneity in the time-varying contributions among indicators of worldwide governance for each country.

The time-varying contribution of VOA is heterogeneous. Overall, the influence of VOA on nonrenewable or renewable energy consumption predicting has a significant strengthening trend over time in E-7 countries, as shown in Figures 3 and 5. However, among G-7 countries, the influence of VOA tends to weaken over time, as shown in Figures 4 and 6. In particular, the time-varying contribution of VOA on nonrenewable (renewable) energy consumption predicting has a small fluctuation range in Turkey. Additionally, for Indonesia (Brazil; USA; and Italy), the time-varying effect of VOA on nonrenewable energy consumption fluctuates greatly (slightly). However, for Indonesia (Brazil; USA; and Italy), the time-varying effect of VOA on renewable energy consumption fluctuates slightly (greatly).

The time-varying effect of PSAV is heterogeneous. On the whole, the influence of PSAV on nonrenewable (renewable) energy consumption has a slight fluctuation range over time in E-7 and G-7 countries, as shown in Figures 3–6. In particular, the time-varying contribution of PSAV on nonrenewable energy consumption has a great fluctuation range in Indonesia, India, and Japan. However, for renewable energy consumption, the time-varying contribution of PSAV fluctuates greatly in Russia. Additionally, for China, the time-varying contribution of PSAV on renewable energy consumption prediction fluctuates slightly. What is more, for France and Japan, the effect of PSAV on predicting nonrenewable energy consumption decreases in 2005 and 2010.

The time-varying contribution of GE is heterogeneous. On the whole, the contribution of GE on nonrenewable (renewable) energy consumption has a significantly weakened (strengthening) trend over time in E-7 and G-7 countries, as shown in Figures 3 (2) and 4 (4). In particular, the time-varying contribution of GE on nonrenewable renewable energy consumption predicting has a strengthening (weakened) trend in 2006 (2005 and 2010) for India (England and Japan).

The time-varying contribution of renewable energy consumption is heterogeneous. On the whole, the contribution of renewable energy consumption on

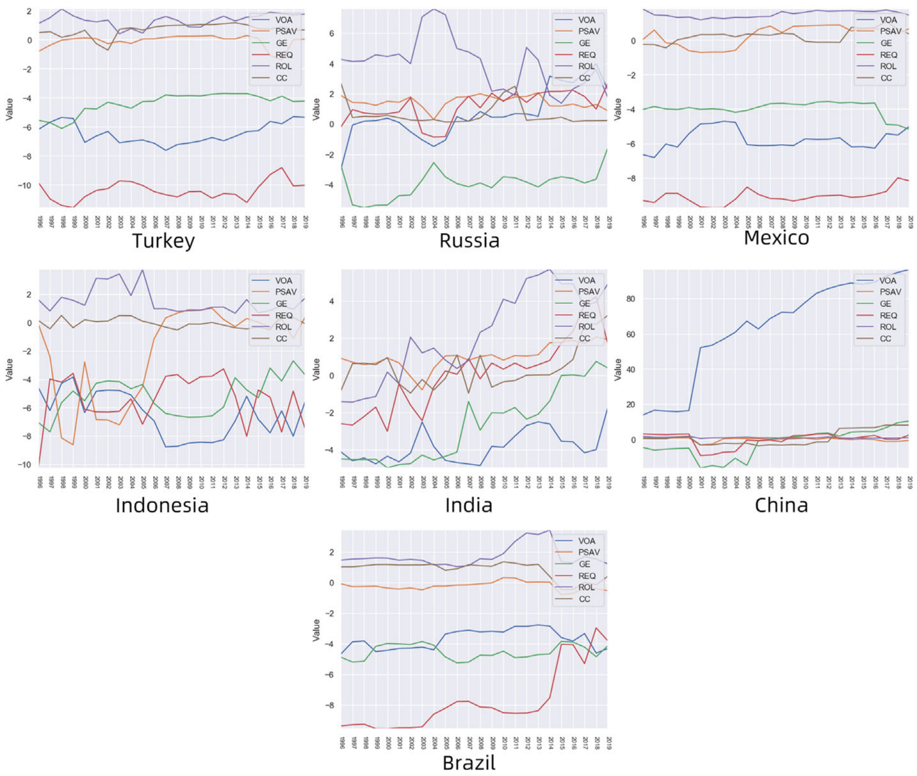

FIGURE 3 The time-varying contribution of worldwide governance on nonrenewable energy consumption predicting among E-7 countries.

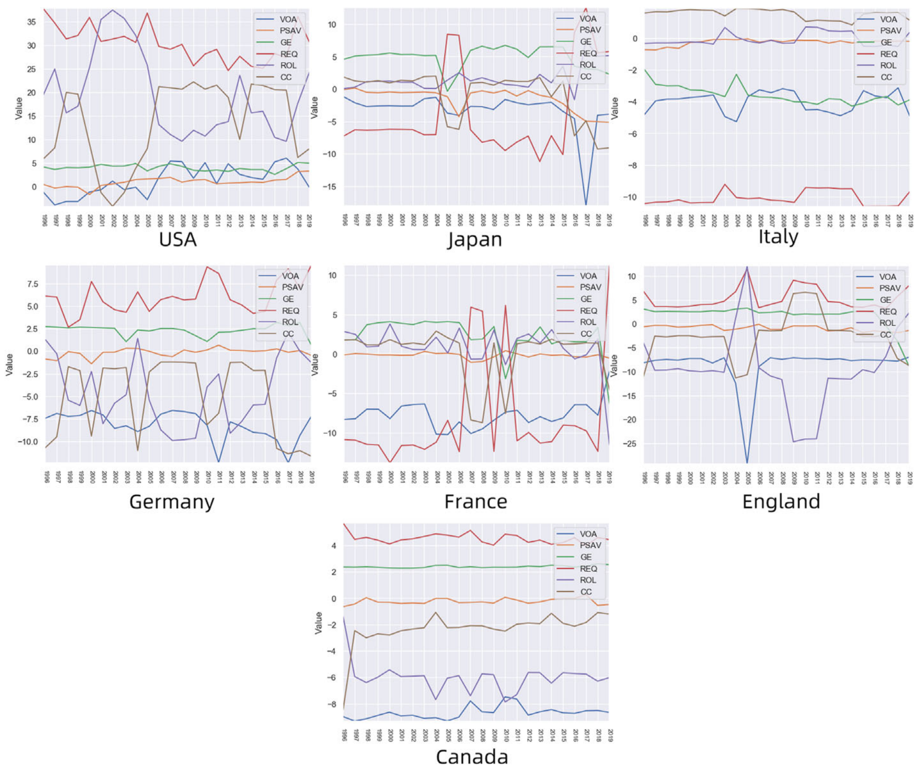

FIGURE 4 The time-varying contribution of worldwide governance on nonrenewable energy consumption predicting among G-7 countries.

nonrenewable energy consumption predicting has a significant strengthening (weakened) trend over time in E-7 (G-7) countries, as shown in Figure 3 (2). However, whether it is E-7 or G-7 countries, the contribution of renewable energy consumption on renewable energy consumption predicting has a significant strengthening trend over time. In particular, the time-varying contribution of renewable energy consumption on nonrenewable (renewable) energy consumption predicting has a great fluctuation range in Russia, Indonesia, India, and France

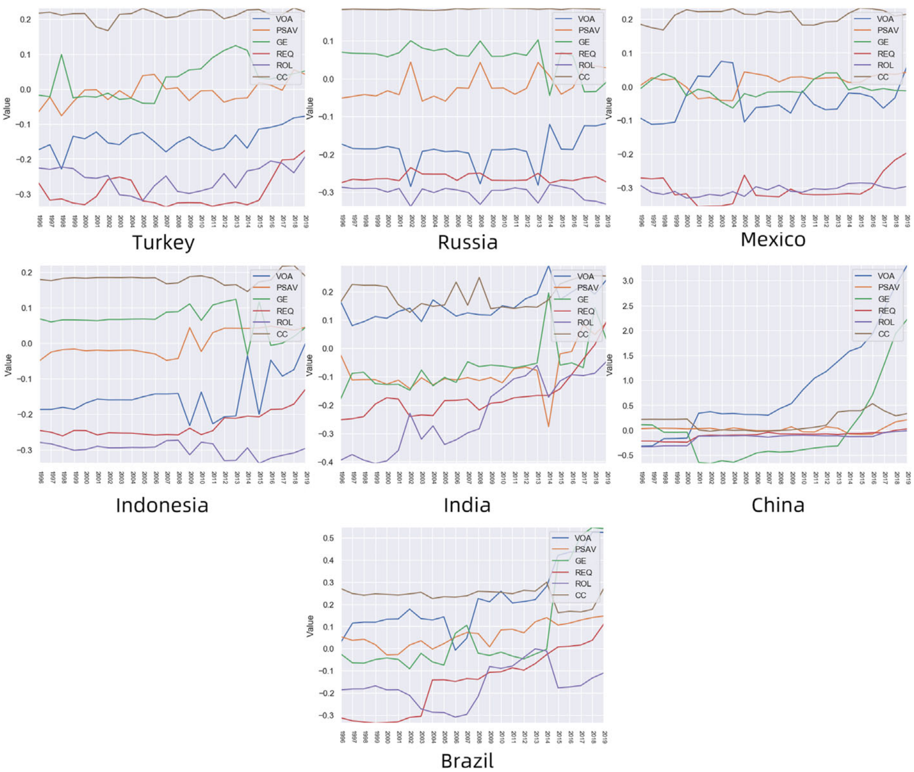

FIGURE 5 The contribution of worldwide governance on renewable energy consumption predicting among E-7 countries.

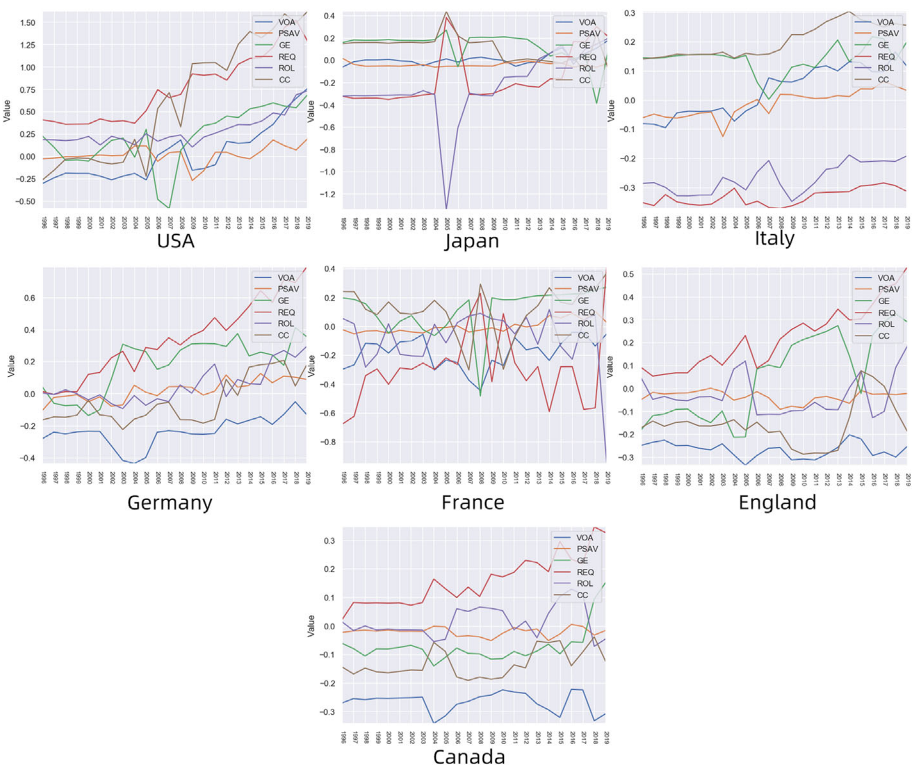

FIGURE 6 The contribution of worldwide governance on renewable energy consumption predicting among G-7 countries.

(Turkey and France). Additionally, since 2014 (2014), the contribution of renewable energy consumption on nonrenewable (renewable) energy consumption continues to rise in Brazil (India and Brazil). What is more, for Japan, the contribution of renewable energy consumption on nonrenewable (renewable) energy consumption predicting increases significantly in 2005. However, the contribution of renewable energy consumption on renewable (renewable) energy consumption predicting decreases significantly in 2007.

The time-varying contribution of ROL is heterogeneous. On the whole, the contribution of ROL on nonrenewable (renewable) energy consumption predicting has a significantly weakened (strengthen) trend over time in E-7 and G-7 countries, as shown in Figures 3 (3) and 4 (4). In particular, the time-varying contribution of ROL on nonrenewable (renewable) energy consumption predicting has a great fluctuation range in Russia, Indonesia, and Germany (India, Brazil, England, and Canada). What is more, for Japan (England), the effect of ROL on nonrenewable energy consumption predicting increases significantly from 2003 and 2006 and decreases from 2008 to 2012. However, for England and Japan, the contribution of ROL on renewable energy consumption predicting decreases significantly in 2005. For Canada, the contribution of ROL on renewable energy consumption predicting increases from 2013 to 2016.

The time-varying contribution of CC is heterogeneous. Overall, the contribution of CC on nonrenewable (renewable) energy consumption predicting has a slight fluctuation range over time in E-7 countries, as shown in Figures 3 and 5. However, the influence of CC on predicting nonrenewable (renewable) energy consumption has a significantly weakened (strengthen) trend over time in G-7 countries, as shown in Figure 4 (4). In particular, the time-varying contribution of ROL on nonrenewable (renewable) energy consumption predicting has a great fluctuation range in India and Germany (India, USA, England, and France). What is more, for the USA and France, the effect of CC on nonrenewable energy consumption predicting decreases significantly in 2002 and 2007 and increases significantly in the next stage. However, for the USA, the contribution of CC on renewable energy consumption predicting continuously increases significantly.

In summary, the heterogeneity in the time-varying contribution of each indicator of worldwide governance on nonrenewable (renewable) energy consumption predicting is little fluctuation for Turkey, Mexico, Italy, and Canada (Turkey, Russia, Mexico, and Italy) over time. However, the heterogeneity in the time-varying contribution of each indicator of worldwide governance on nonrenewable (renewable) energy consumption predicting is large fluctuation for Indonesia, India, USA, Germany, and England (India, Brazil, France, and England) over time. In particular, for China (Brazil; Russia; Japan; and France), among indicators of worldwide governance, the time-varying contribution of VOA (renewable energy consumption; renewable energy consumption and ROL; renewable energy consumption; and renewable energy consumption and CC) on nonrenewable energy consumption predicting is greatly heterogeneous. Since 2013, the time-varying contribution of each indicator of worldwide governance on renewable energy consumption predicting makes changed in E-7 countries.

3.3 | The heterogeneity contribution of worldwide governance between countries

Figures 7 and 8 (Figures 9 and 10) report the results of the heterogeneity contribution of each indicator of worldwide governance on predicting nonrenewable energy

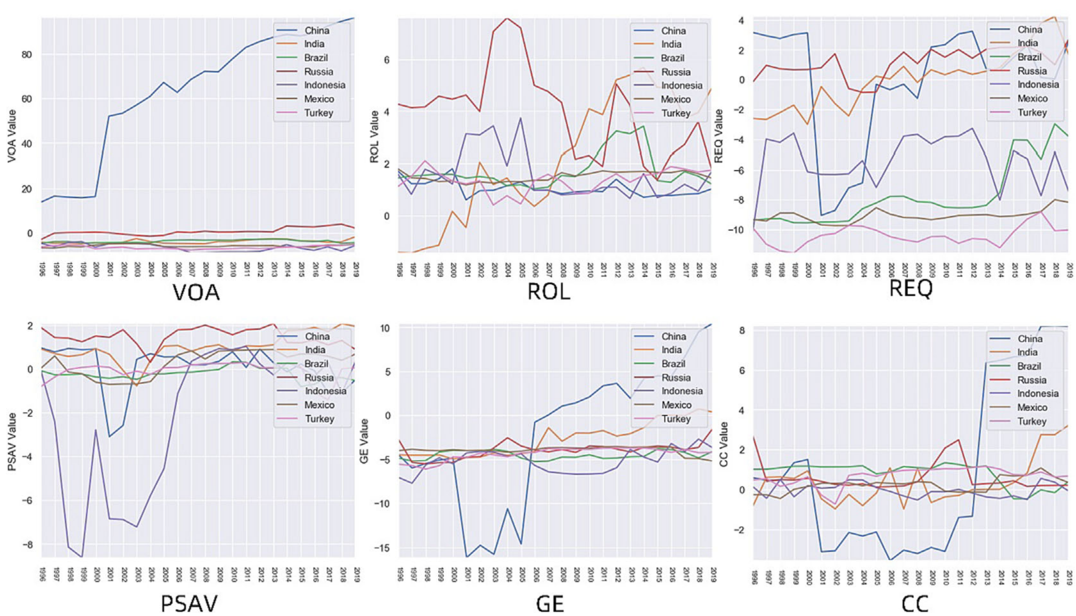

FIGURE 7 The contribution of each indicator of worldwide governance on nonrenewable energy consumption predicting among E-7 countries. CC, control of corruption; GE, government effectiveness; PSAV, political stability and absence of violence.

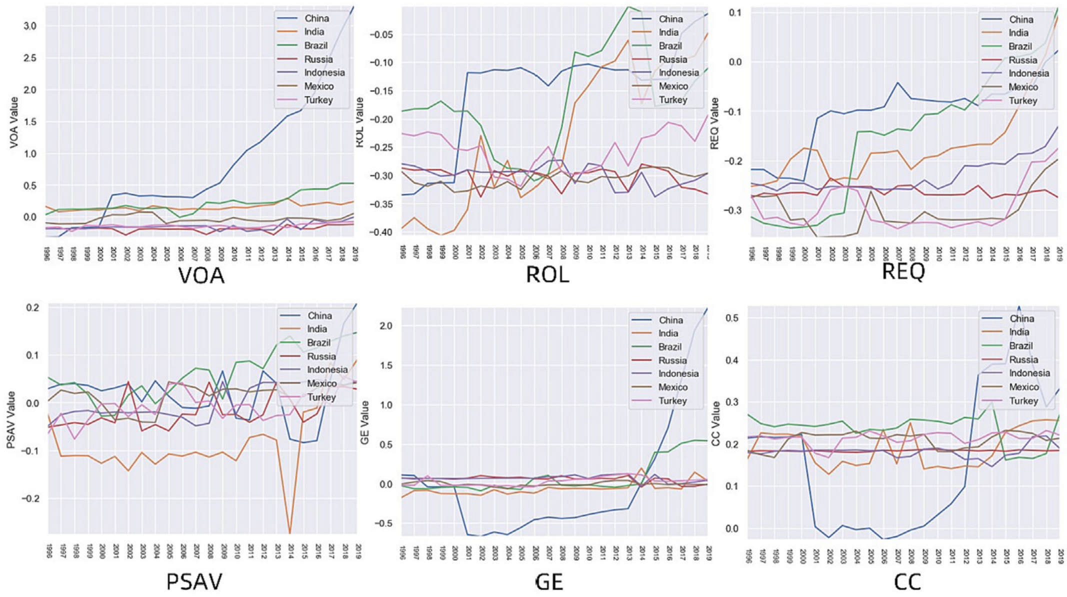

FIGURE 8 The contribution of each indicator of worldwide governance on renewable energy consumption predicting among E-7 countries. CC, control of corruption; GE, government effectiveness; PSAV, political stability and absence of violence.

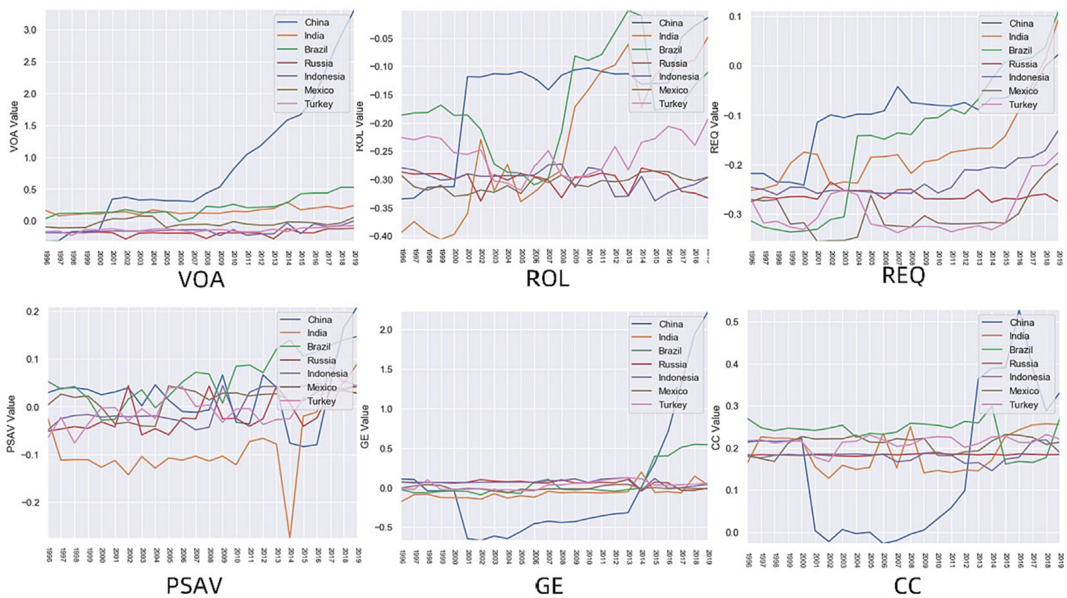

FIGURE 9 The contribution of each indicator of worldwide governance on nonrenewable energy consumption predicting among G-7 countries. CC, control of corruption; GE, government effectiveness; PSAV, political stability and absence of violence.

(renewable energy) consumption among E-7 and G-7 countries. Below, this analysis is mainly carried out from three perspectives, such as country, time, and indicators.

The effect of VOA on predicting nonrenewable (renewable) energy consumption among E-7 and G-7 countries is heterogeneous. For the nonrenewable (renewable) energy consumption predicting, the heterogeneity contribution on China (USA and England) among E-7 (G-7) countries is the largest. Additionally, for the nonrenewable energy consumption predicting, the effect on Germany and England is relatively consistent. Especially, after 2005, the heterogeneity contribution of VOA on nonrenewable energy consumption predicting among E-7 countries increased.

The contribution of ROL on nonrenewable (renewable) energy consumption predicting among E-7 and G-7 countries is heterogeneous. For the nonrenewable energy consumption predicting, the heterogeneity effect on

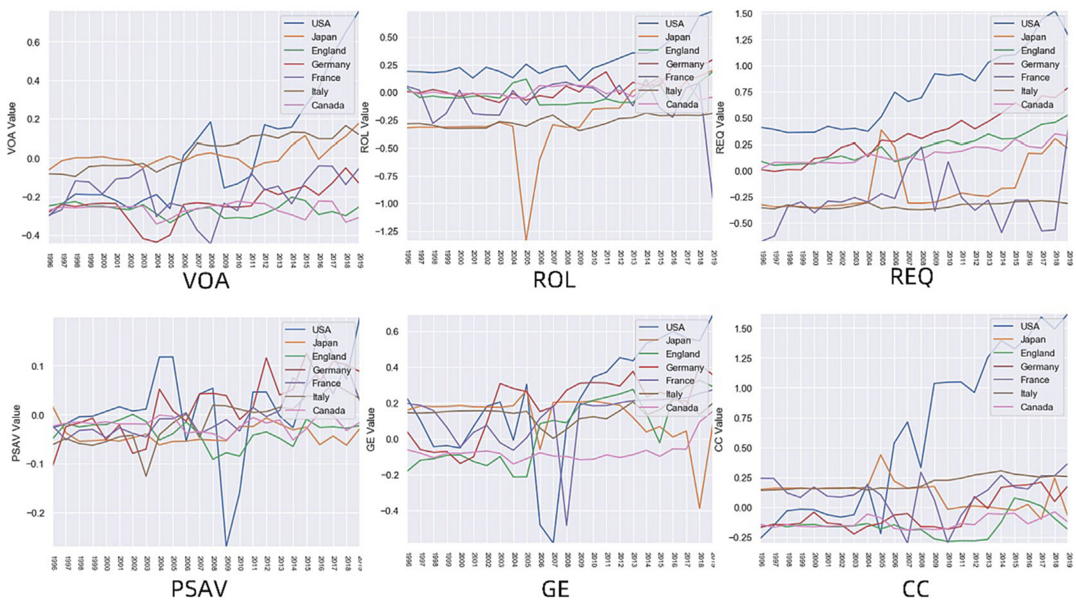

FIGURE 10 The contribution of each indicator of worldwide governance on renewable energy consumption predicting among G-7 countries. CC, control of corruption; GE, government effectiveness; PSAV, political stability and absence of violence.

Russia and India (USA and England) among E-7 (G-7) countries is the largest. For renewable energy consumption predicting, the heterogeneity contribution on China, India, and Brazil (Japan) among E-7 (G-7) countries is the largest. Additionally, for the nonrenewable energy consumption predicting, the contribution on China, Indonesia, and Turkey (Japan and France) is relatively consistent in E-7 (G-7) countries. For renewable energy consumption predicting, the contribution on Germany and Canada is relatively consistent in G-7 countries. Especially, after 2010 (2007), the heterogeneity contribution of ROL on nonrenewable (renewable) energy consumption predicting among E-7 countries increased.

The contribution of renewable energy consumption on predicting nonrenewable (renewable) energy consumption among E-7 and G-7 countries is heterogeneous. For the nonrenewable (renewable) energy consumption, the heterogeneity effect on China and Indonesia (USA) among E-7 (G-7) countries is the largest. Additionally, for the nonrenewable energy consumption predicting, the effect on India and Russia (Japan, England, and Canada) is relatively consistent in E-7 (G-7) countries. Especially, after 2004 (2005), the heterogeneity effect of renewable energy consumption on renewable energy consumption predicting among E-7 (G-7) countries increased.

The contribution of PSAV on predicting nonrenewable (renewable) energy consumption among E-7 and G-7 countries is heterogeneous. For the nonrenewable energy consumption predicting, the heterogeneity contribution on China and Indonesia (USA and Japan) among E-7 (G-7) countries is the largest. For renewable energy consumption predicting, the heterogeneity contribution on China and India (USA) among E-7 (G-7) countries is the largest. Additionally, for the nonrenewable energy consumption predicting, the contribution on India and Russia (France and Canada) is relatively consistent in E-7 (G-7) countries. For renewable energy consumption predicting, the contribution on Japan and Canada is relatively consistent in G-7 countries. Especially, after 2007 (2010), the heterogeneity contribution of PSAV on nonrenewable energy consumption predicting among E-7 (G-7) countries increased. After 2014, the heterogeneity contribution of PSAV on renewable energy consumption predicting among E-7 countries increased.

The contribution of GE on nonrenewable (renewable) energy consumption predicting among E-7 and G-7 countries is heterogeneous. For the nonrenewable energy consumption predicting, the heterogeneity contribution on China (Italy) among E-7 (G-7) countries is the largest. For renewable energy consumption predicting, the heterogeneity contribution on China (USA and France) among E-7 (G-7) countries is the largest. Additionally, for the nonrenewable (renewable) energy consumption predicting, the contribution on Russia and Turkey (Indonesia, Mexico, and Turkey) is relatively consistent in E-7 countries. Especially, after 2006, the heterogeneity contribution of GE on nonrenewable energy consumption predicting among E-7 and G-7 countries increased. From 2005 and 2009, the heterogeneity contribution of GE on renewable energy consumption predicting among G-7 countries is the largest.

The contribution of CC on nonrenewable (renewable) energy consumption predicting among E-7 and G-7 countries is heterogeneous. For the nonrenewable (renewable) energy consumption predicting, the heterogeneity effect on China (USA) among E-7 (G-7) countries is the largest. Additionally, for renewable energy consumption predicting, the contribution on England and Canada is relatively consistent in G-7 countries.

In summary, the heterogeneity contribution of each indicator of worldwide governance on nonrenewable (renewable) energy consumption predicting is significant. Compared with other E-7 countries, China (Russia; India; and Indonesia) has the biggest difference in the impact of VOA, renewable energy consumption, PSAV, GE, and CC (ROL; ROL; and renewable energy consumption and PSAV) on nonrenewable energy consumption predicting; compared with other E-7 countries, China (India; Brazil; and Indonesia) has the biggest difference in the impact of VOA, renewable energy consumption, PSAV, GE, and CC (ROL and PSAV; ROL; and renewable energy consumption) on renewable energy consumption predicting; compared with other G-7 countries, USA (England; Japan; and Italy) has the biggest difference in the contribution of VOA, renewable energy consumption, PSAV, and CC (VAO and ROL; PSAV; and GE) on nonrenewable energy consumption predicting; and compared with other G-7 countries, USA (England and France) has the biggest difference in the impact of VOA, renewable energy consumption, PSAV, GE, and CC (VOA and GE, respectively) on renewable energy consumption predicting. However, for nonrenewable energy consumption predicting, the contribution of ROL (renewable energy consumption; PSAV; and GE) in China, India, and Brazil (Russia and India; Russia and India; and Russia and Turkey) is relatively consistent in E-7 countries; for renewable energy consumption predicting, the contribution of GE in Indonesia, Mexico, and Turkey is relatively consistent in E-7 countries; for nonrenewable energy consumption predicting, the contribution of VOA (ROL; renewable energy consumption; and PSAV) in Germany and England (Japan and France; Japan, England, and Canada; and France and Canada) is relatively consistent in G-7 countries; and for renewable energy consumption predicting, the effect of ROL (PSAV; GE; and CC) in Germany and Canada (Japan and Canada; USA and France; and England and Canada) is relatively consistent in G-7 countries.

4 | CONCLUSION AND POLICY IMPLICATIONS

This research fully explores the relationship between governance quality and energy consumption. A novel set of governance qualities is offered in the first systematically empirical exploration on the prediction of energy consumption by explainable machine learning method across E-7 and G-7 countries from 1996 to 2019. The research framework reconciles divergent views on the role of governance quality and aims to report helpful conclusions regarding government and energy consumption structure.

Main findings report that the role of governance quality on energy consumption predicting in E-7 or G-7 countries is different. On the one hand, the impact of each indicator of governance on energy consumption predicting varies considerably over time. Especially, the trend of contribution among each indicator of governance varies enormously. On the other hand, the contribution of each indicator on energy consumption predicting in different countries varies greatly. Especially, the difference is evident across different indicators of governance effect on energy consumption predicting in E-7 or G-7 countries. Therefore, the heterogeneity for the contribution of governance on energy consumption predicting about both each indicator of governance and each country in E-7 or G-7 countries exists. Therefore, notably, our paper adds to researches on energy consumption predicting and argues that governance can emerge as a valuable tool to optimize energy consumption structure.

Our study has several recommendations. First, the heterogeneity contribution of governance on energy consumption predicting indicates the different governance strategies on energy consumption predicting in E-7 and G-7 countries. Achieving the targets set about CO_2 emissions and addressing the environmental externalities, renewable energy consumption should be improved among countries around the world. What is more, increasing the proportion of renewable energy consumption predicting would not affect economic progress. According to the research findings of the article, it can be achieved by encouraging building governance system and strengthening policy implementation. It is important to mention here that governance strategies should be in synergy with the specifics of the country itself, such as different stages of energy consumption; it is necessary to take matching tools and adjust the governance policy intensity correspondingly. Second, policymakers can take appropriate initiatives to disseminate information about the destructive effects of nonrenewable energy consumption and make customer-friendly policies for companies and organizations to employ renewable energy. It is best for governments to provide corresponding freedom and democracy environment, such as opening supervision management information system, advocating freedom of speech, and encouraging sharing of information. The policymakers can make regulations to enhance social stability and avoid politically motivated violence, including terrorism.

However, this research is subject to certain limitations. First, this study examines the isolated predictive power of governance quality on renewable and nonrenewable energy consumption yet omits an exploration of combined index in analyzing the energy transition. Previous studies have pointed out the independent effector of governance quality on energy consumption. However, limited attention has been given to examining how these factors interact and influence energy consumption. Subsequent research could analyze that how distinct factors combination of governance quality on energy consumption, adopting a configurational approach. Second, this study constructs a systematic framework to elucidate the influence of governance quality on renewable and nonrenewable energy consumption. Subsequently, prospective investigations could employ integrated approach to assess mediation encompassing different index of governance quality. Given the diverse dimensions and attributes of governance quality, forthcoming research could explore mediation mechanisms through path analysis. Third, future studies could consider increasing the sample size by including more countries to obtain more comprehensive and novel results. Additionally, incorporating other factors that influence energy consumption can provide a more comprehensive understanding of the relationship between governance quality and energy consumption. As for the method, this paper proposes a decision framework based on interpretable machine learning to explore the relationship between governance quality and energy consumption. However, the accuracy of the fitted model has a significant impact on the calculation of contributions. Therefore, future research could explore regression models with better performance for fitting the relationship between the two variables. Moreover, alternative interpretable machine learning methods could be explored to validate and compare the robustness of the results.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in EIA and BP Statistical Review of World Energy (http://www.bp.com/). These data were derived from the following resources available in the public domain: BPSRWE (http://www.bp.com/statisticareview).

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ENDNOTES

[1] It can be found on the internet (http://www.bp.com/statisticalreview).

[2] The G-7 countries include Canada, France, Germany, Italy, Japan, United Kingdom, and USA.

[3] The E-7 countries include Brazil, China, India, Indonesia, Mexico, Russia, and Turkey.

REFERENCES

Abid, N., Ikram, M., Wu, J., & Ferasso, M. (2021). Towards environmental sustainability: Exploring the nexus among ISO 14001, governance indicators and green economy in Pakistan. *Sustainable Production and Consumption*, *27*, 653–666. https://doi.org/10.1016/j.spc.2021.01.024

Agyemang, O. S., Gatsi, J. G., & Ansong, A. (2018). Institutional structures and financial market development in Africa. *Cogent Economics & Finance*, *6*, 1488342. https://doi.org/10.1080/23322039.2018.1488342

Ahlin, C., & Pang, J. (2008). Are financial development and corruption control substitutes in promoting growth? *Journal of Development Economics*, *86*, 414–433. https://doi.org/10.1016/j.jdeveco.2007.07.002

Alsaleh, M., Abdul-Rahim, A., & Abdulwakil, M. M. (2021). The importance of worldwide governance indicators for transitions toward sustainable bioenergy industry. *Journal of Environmental Management*, *294*, 112960. https://doi.org/10.1016/j.jenvman.2021.112960

Bah, M., Ondoa, H. A., & Kpognon, K. D. (2021). Effects of governance quality on exports in sub-Saharan Africa. *International Economics*, *167*, 1–14. https://doi.org/10.1016/j.inteco.2021.05.003

Barro, R. J. (1996). Democracy and growth. *Journal of Economic Growth*, *1*, 1–27. https://doi.org/10.1007/BF00163340

Bekhet, H. A., & Latif, N. W. A. (2018). The impact of technological innovation and governance institution quality on Malaysia's sustainable growth: Evidence from a dynamic relationship. *Technology in Society*, *54*, 27–40. https://doi.org/10.1016/j.techsoc.2018.01.014

Bornemann, B., Sohre, A., & Burger, P. (2018). Future governance of individual energy consumption behavior change—A framework for reflexive designs. *Energy Research & Social Science*, *35*, 140–151. https://doi.org/10.1016/j.erss.2017.10.040

Chen, S., Jin, H., & Lu, Y. (2019). Impact of urbanization on CO_2 emissions and energy consumption structure: A panel data analysis for Chinese prefecture-level cities. *Structural Change* *and Economic Dynamics*, *49*, 107–119. https://doi.org/10.1016/j.strueco.2018.08.009

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM. https://doi.org/10.1145/2939672.2939785

Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., et al. (2015). Xgboost: Extreme gradient boosting. *R Package Version 0.4-2 1*, 1–4.

Chiu, C. L., & Chang, T. H. (2009). What proportion of renewable energy supplies is needed to initially mitigate CO_2 emissions in OECD member countries? *Renewable and Sustainable Energy Reviews*, *13*, 1669–1674. https://doi.org/10.1016/j.rser.2008.09.026

Clarke, R. (2001). Person location and person tracking-technologies, risks and policy implications. *Information Technology and People*, *14*, 206–231. https://doi.org/10.1108/09593840110695767

Cowell, R., Ellis, G., Sherry-Brennan, F., Strachan, P. A., & Toke, D. (2017). Rescaling the governance of renewable energy: Lessons from the UK devolution experience. *Journal of Environmental Policy & Planning*, *19*, 480–502. https://doi.org/10.1080/1523908X.2015.1008437

Davies, M., Swilling, M., & Wlokas, H. L. (2018). Towards new configurations of urban energy governance in South Africa's renewable energy procurement programme. *Energy Research & Social Science*, *36*, 61–69. https://doi.org/10.1016/j.erss.2017.11.010

Desbordes, R., & Koop, G. (2016). Should we care about the uncertainty around measures of political-economic development? *Journal of Comparative Economics*, *44*, 752–763. https://doi.org/10.1016/j.jce.2015.08.002

Dietz, T., Stern, P. C., & Guagnano, G. A. (1998). Social structural and social psychological bases of environmental concern. *Environment and Behavior*, *30*, 450–471. https://doi.org/10.1177/001391659803000402

Dong, Y., Wang, J., Niu, X., & Zeng, B. (2023). Combined water quality forecasting system based on multiobjective optimization and improved data decomposition integration strategy[J]. *Journal of Forecasting*, *42*(2), 260–287. https://doi.org/10.1002/for.2905

Feng, T., Sun, L., & Zhang, Y. (2009). The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy*, *37*, 5475–5483. https://doi.org/10.1016/j.enpol.2009.08.008

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*, 1189–1232. https://doi.org/10.1214/aos/1013203451

Gaspari, M., & Lorenzoni, A. (2018). The governance for distributed energy resources in the Italian electricity market: A driver for innovation? *Renewable and Sustainable Energy Reviews*, *82*, 3623–3632. https://doi.org/10.1016/j.rser.2017.10.100

Glad, W. (2017). Everyday governance of domestic energy systems. *Procedia Engineering*, *180*, 1612–1621. https://doi.org/10.1016/j.proeng.2017.04.324

Glaeser, E. L., & Saks, R. E. (2006). Corruption in America. *Journal of Public Economics*, *90*, 1053–1072. https://doi.org/10.1016/j.jpubeco.2005.08.007

Granovetter, M. (1992). Economic institutions as social constructions: A framework for analysis. *Acta Sociologica*, *35*, 3–11. https://doi.org/10.1177/000169939203500101

Guliyeva, A., Rzayeva, U., & Guliyeva, G. (2018). The mpact of worldwide governance indicators on renewable energy production in Caspian Sea countries. *International Journal of Energy, Environment and Economics*, *26*, 97–114.

Guo, Y., Yu, C., Zhang, H., & Cheng, H. (2021). Asymmetric between oil prices and renewable energy consumption in the G7 countries. *Energy*, *226*, 120319. https://doi.org/10.1016/j.energy.2021.120319

Haq, R., Zia, U., & Arif, G. (2006). Governance and pro-poor growth: Evidence from Pakistan [with comments]. *The Pakistan Development Review*, *45*, 761–776. https://doi.org/10.30541/v45i4IIpp.761-776

Jain, R. K., Smith, K. M., Culligan, P. J., & Taylor, J. E. (2014). Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Applied Energy*, *123*, 168–178. https://doi.org/10.1016/j.apenergy.2014.02.057

Jin, Y., & Zhu, Y. (2015). A data-driven approach to predict default risk of loan for online peer-to-peer (P2P) lending. In *2015 Fifth International Conference on Communication Systems and Network Technologies* (pp. 609–613). IEEE. https://doi.org/10.1109/CSNT.2015.25

Khan, Z., Malik, M. Y., Latif, K., & Jiao, Z. (2020). Heterogeneous effect of eco-innovation and human capital on renewable & non-renewable energy consumption: Disaggregate analysis for G-7 countries. *Energy*, *209*, 118405. https://doi.org/10.1016/j.energy.2020.118405

Langbein, L., & Knack, S. (2010). The worldwide governance indicators: Six, one, or none? *The Journal of Development Studies*, *46*, 350–370. https://doi.org/10.1080/00220380902952399

Li, H., Xu, L. C., & Zou, H. F. (2000). Corruption, income distribution, and growth. *Economics and Politics*, *12*, 155–182. https://doi.org/10.1111/1468-0343.00073

Li, J., Zhang, X., Ali, S., & Khan, Z. (2020). Eco-innovation and energy productivity: New determinants of renewable energy consumption. *Journal of Environmental Management*, *271*, 111028. https://doi.org/10.1016/j.jenvman.2020.111028

Li, W., Ding, S., Chen, Y., & Yang, S. (2018). Heterogeneous ensemble for default prediction of peer-to-peer lending in China. *IEEE Access*, *6*, 54396–54406. https://doi.org/10.1109/ACCESS.2018.2810864

Liu, M., Choo, W. C., Lee, C. C., & Lee, C. C. (2023). Trading volume and realized volatility forecasting: Evidence from the China stock market[J]. *Journal of Forecasting*, *42*(1), 76–100. https://doi.org/10.1002/for.2897

Liu, W., & Li, H. (2011). Improving energy consumption structure: A comprehensive assessment of fossil energy subsidies reform in China. *Energy Policy*, *39*, 4134–4143. https://doi.org/10.1016/j.enpol.2011.04.013

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, *2*(1), 56–67. https://doi.org/10.1038/s42256-019-0138-9

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Advances in neural information processing systems* (Vol. 30, pp. 4768–4777). NIPS.

Mo, P. H. (2001). Corruption and economic growth. *Journal of Comparative Economics*, *29*, 66–79. https://doi.org/10.1006/jcec.2000.1703

Nabavi, S. A., Aslani, A., Zaidan, M. A., Zandi, M., Mohammadi, S., & Hossein Motlagh, N. (2020). Machine learning modeling for energy consumption of residential and commercial sectors. *Energies*, *13*(19), 5171. https://doi.org/10.3390/en13195171

Naqvi, I., Poorthuis, A., & Govind, A. (2021). Urban governance and electricity losses: An exploration of spatial unevenness in Karachi, Pakistan[J]. *Energy Research & Social Science*, *79*, 102166. https://doi.org/10.1016/j.erss.2021.102166

Niu, Z., Demirer, R., Suleman, M. T., & Zhang, H. (2023). Cross-sectional return dispersion and stock market volatility: Evidence from high-frequency data[J]. *Journal of Forecasting*, *42*, 1309–1328. https://doi.org/10.1002/for.2959

Pakseresht, M., Shirazi, B., Mahdavi, I., & Mahdavi-Amiri, N. (2020). Toward sustainable optimization with Stackelberg game between green product family and downstream supply chain[J]. *Sustainable Production and Consumption*, *23*, 198–211. https://doi.org/10.1016/j.spc.2020.04.009

Psychogios, A., Nyfoudi, M., Theodorakopoulos, N., Szamosi, L. T., & Prouska, R. (2019). Many hands lighter work? Deciphering the relationship between adverse working conditions and organization citizenship behaviours in small and medium-sized enterprises during a severe economic crisis[J]. *British Journal of Management*, *30*(3), 519–537. https://doi.org/10.1111/1467-8551.12245

Robinson, C., Dilkina, B., Hubbs, J., Zhang, W., Guhathakurta, S., Brown, M. A., & Pendyala, R. M. (2017). Machine learning approaches for estimating commercial building energy consumption[J]. *Applied Energy*, *208*, 889–904. https://doi.org/10.1016/j.apenergy.2017.09.060

Rodrik, D. (2004). Institutions and economic performance-getting institutions right[J]. *CESIfo DICE Report*, *2*(2), 10–15.

Shahzad, U., Radulescu, M., Rahim, S., Isik, C., Yousaf, Z., & Ionescu, S. (2021). Do environment-related policy instruments and technologies facilitate renewable energy generation? Exploring the contextual evidence from developed economies[J]. *Energies*, *14*(3), 690. https://doi.org/10.3390/en14030690

Shapley, L. S. (1953). A value for n-person games.

Stephenson, R. L., Hobday, A. J., Allison, E. H., Armitage, D., Brooks, K., Bundy, A., Cvitanovic, C., Dickey-Collas, M., Grilli, N. M., Gomez, C., Jarre, A., Kaikkonen, L., Kelly, R., López, R., Muhl, E. K., Pennino, M. G., Tam, J. C., & van Putten, I. (2021). The quilt of sustainable ocean governance: Patterns for practitioners[J]. *Frontiers in Marine Science*, *8*, 630547. https://doi.org/10.3389/fmars.2021.630547

Su, M., Cheng, D., Xu, Y., & Weng, F. (2023). An improved BERT method for the evolution of network public opinion of major infectious diseases: Case study of COVID-19[J]. *Expert Systems with Applications*, *233*, 120938. https://doi.org/10.1016/j.eswa.2023.120938

Sun, Y., Ding, J., Liu, Z., & Wang, J. (2023). Combined forecasting tool for renewable energy management in sustainable supply chains[J]. *Computers & Industrial Engineering*, *179*, 109237. https://doi.org/10.1016/j.cie.2023.109237

Thomas, M. A. (2010). What do the worldwide governance indicators measure?[J]. *The European Journal of Development Research*, *22*, 31–54. https://doi.org/10.1057/ejdr.2009.32

Ulucak, R. (2021). A revisit to the relationship between financial development and energy consumption: Is globalization paramount?[J]. *Energy*, *227*, 120337.

Weng, F., Zhang, H., & Yang, C. (2021). Volatility forecasting of crude oil futures based on a genetic algorithm regularization online extreme learning machine with a forgetting factor: The role of news during the COVID-19 pandemic[J]. *Resources Policy*, *73*, 102148. https://doi.org/10.1016/j.resourpol.2021.102148

Weng, F., Zhu, J., Yang, C., Gao, W., & Zhang, H. (2022). Analysis of financial pressure impacts on the health care industry with an explainable machine learning method: China versus the USA[J]. *Expert Systems with Applications*, *210*, 118482. https://doi.org/10.1016/j.eswa.2022.118482

Yang, C., Abedin, M. Z., Zhang, H., Weng, F., & Hajek, P. (2023). An interpretable system for predicting the impact of COVID-19 government interventions on stock market sectors[J]. *Annals of Operations Research*, 1–28. https://doi.org/10.1007/s10479-023-05311-8

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