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Comparative analysis of drivers of energy consumption in China, the USA and India – A perspective from stratified heterogeneity

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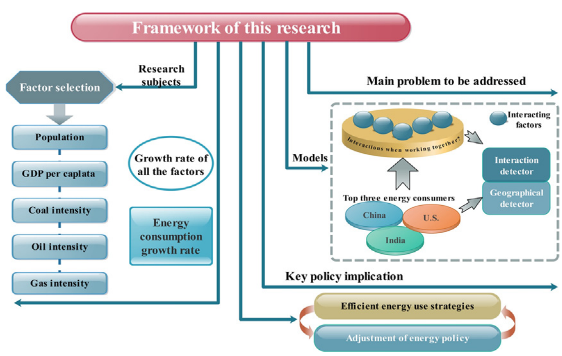
HIGHLIGHTS

- All factors have interactions and enhance each other when influencing total energy consumption growth rate.
- India has the strongest factor interactions when influencing the energy consumption growth rate.
- All interactions between factors in US is not significant as those in China and India.
- Coal consumption intensity is the biggest driver in China and India.
- The leading drivers in US are the individual incomes and oil consumption intensity.

GRAPHICAL ABSTRACT



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ABSTRACT

With the limited amount of resources, developing effective strategies to make full use of them and decrease the energy consumption without too much sacrifice of economic output requires identifying key drivers of energy consumption growth rate as a prerequisite. Meanwhile, as top three consumers of primary energy of the world, China, the United States of America, and India burn over 45% of global fuels in 2016. Conducting an empirically comparative analysis of them can also set up pilot scheme for other economies to develop more efficient strategies for energy consumption. The paper modified the original Geographical Detector model with a different sampling method to detect the key driver of energy consumption growth rate, which filling the gap that there are possible interactions of potential factors. The results show that coal intensity is the biggest driver to change overall energy consumption growth rate in China and India. In comparison, for the United States, the leading drivers of energy use are the factors of individual incomes and oil intensity. In addition, all factors have interactions and enhance each other when influencing total energy consumption growth rate. India has the strongest factor interactions when influencing the energy consumption growth rate among the three economies, all interactions between factors in US is not significant as those in China and India. Besides providing outcomes that can contribute towards developing new strategies to use energy more efficiently, this research offers a pilot example of analyzing energy issues from the perspective of stratified heterogeneity in consideration the characteristic differences of each factor.

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1. Introduction

Energy consumption is a fundamental issue which has gaining increasing focus all around the world. Due to the limited source while population is growing, learning the suitable and practical ways to make efficient use of primary energy is in desperate need. To cut the energy consumption to an appropriate degree globally, it is an essential prerequisite to investigate the key drivers of energy consumption growth rate and the influencing mechanism. By developing deeper knowledge of the change rate of primary energy can adjust the corresponding policies to make efficient use of the limited energy we share worldwide. Moreover, as top three consumers of world's primary energy with distinct development patterns, China, USA and India can be representative of other economies with less energy consumption. As a result, the analysis of energy consumption of these three countries can be vital to the top three consumers as well as the rest of the rest regions for its pilot impact.

The share of top three consumers of the whole world for primary energy is demonstrated in Fig. 1, the proportion of them (yellow sector in Fig. 1) in the world's total primary has increased from 39.42% in 1965 to 45.57% in 2017, the increment is mainly brought from the dramatic increase in China, who has become the biggest consumer for primary energy in 2017.

China, the largest developing country and the biggest consumer of primary energy globally, accounted for 23% of the total primary energy consumption around the world (Fig. 1). Comparatively, the United States of America (USA), the world's largest developed country and the world's second-largest energy consumer globally, accounted for 17% of global total energy consumption (Fig. 1). While, India, the world's fastest-growing major economy, one of the fastest-growing in energy consumption and the world's third greatest energy consumer, accounted for 9% of global total energy consumption (BP, 2017; WorldBank, 2017). As a result, a deeper understanding of the driving factors in those three countries can offer insight towards the development of new, more effective strategies to curb energy consumption in those three countries, and, by extension, in the world.

Various studies have been conducted concerning energy consumption for its link with economic growth. Overall, the relationship between energy consumption and economic growth is a widely discussed in previous literatures via various techniques such as multivariate cointegration (Ghali and El-Sakka, 2004) and bivariate cointegration (Granger, 1969). As is pointed out by IPCC, countries with different development patterns and historic stages have different incentives for energy consumption. For developing countries, they may have more practical thoughts such as focusing more on how to seek for more employment opportunities, however, for developed economies, energy insecurity or climate change mitigation are heated topics (IPCC, 2014). Since all countries are keen on boosting their economy, meanwhile, the close relationship between energy consumption and economic growth, clarifying the key driver of energy consumption is significant to various countries at different economic development stages. To be more specific, most research are carried out via the decomposition methods and the econometric tools to identify the main causes of energy consumption.

Decomposition methods consist of two main techniques: Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA). The SDA approach was primarily based on national or regional input-output (I-O) tables. Original I-O model in economics studies was adopted to carry out researches in environmental analysis since 1970s (W. Leontief, 1970). In recent SDA studies, Wang and Zhou decomposed aggregate carbon intensity change by multiplicative SDA along with input–output analysis (Wang and Zhou, 2019). Meanwhile, SDA has been used in energy-related carbon emission researches, Yuan et al. (2015), on the other hand, proposed a new SDA to investigate the effects of indirect, residential carbon emissions in China from 2002 to 2007. Zhao et al. (2016) used the SDA approach to explore the effects of carbon emissions in China-USA trade between 1995 and 2009. Cansino et al. (2016) investigated CO_2 emissions changes in Spain for the period of 1995 to 2009, based on an improved SDA. The results conclude that Kyoto's Protocol, as well as European Directives, played positive roles in emission reduction. Lan et al. (2016) provided an SDA on energy footprints among 186 nations from 1990 to 2010 by using a comprehensive, multi-regional, I-O database. This study indicates that affluence and population drove up energy footprints. Ang et al. conducted a multi-region SDA of emission performance (Wang et al., 2019b) and India's coal consumption (Wang and Song, 2019), based on an I-O analysis. Chen et al. (2017) employed multi-region, I-O analysis to explore the spatial and inter-sectoral linkages of carbon emissions, in Melbourne and Sydney. With regard to the energy studies via the SDA technique, Rose and Chen (1991) analyzed sectoral energy consumption changes in the USA. Zhang et al. (Zhang and Lahr, 2014) employed the SDA method to decompose energy consumption change in China from 1987 to 2007. Lenzen (1998) analyzed requirements of direct and indirect primary energy and GHGs with final consumption in

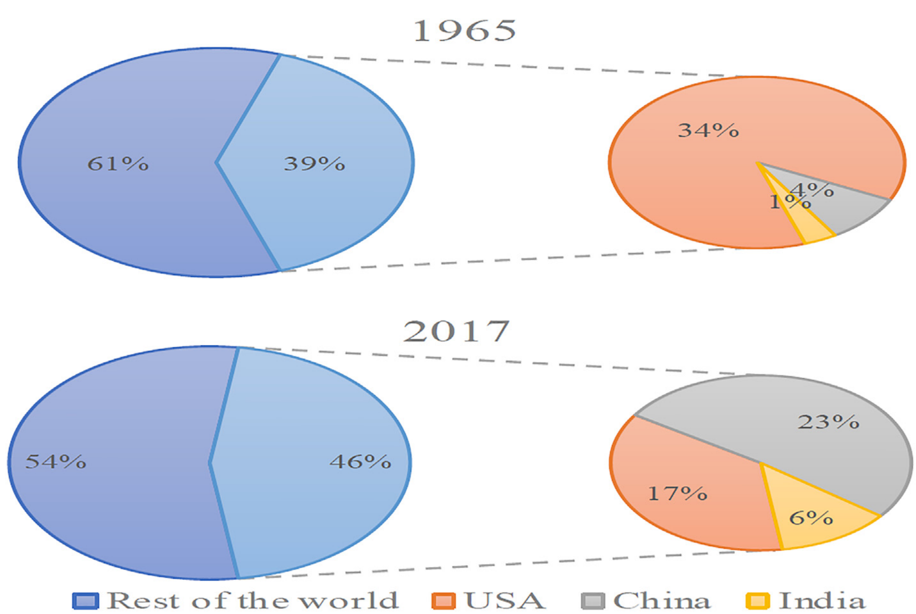

Fig. 1. Proportion changes of primary energy in 1965 and 2017. Ref.(BP, 2017).

Australia. Román-Collado et al. (2018) discussed whether electricity turned green or black in Chile and identified the main drivers, sectors and energy sources by applying SDA. Zhong (2018) identified the main influencing factors of energy consumption from the perspectives of the supply side and demand side of energy consumption from different economies.

The IDA technique was also widely used for its characteristic of easy to handle in energy-related studies. The method was originated from energy studies and have been developed into various Laspeyres based and Divisia based decomposition techniques (Ang, 2004) to study the changes in energy consumption, energy intensity and energy-related emissions. The Logarithmic Mean Divisia Index (LMDI), which was first introduced by Ang (Ang et al., 1998), is one of the most popular techniques in recent energy studies after modifying the negative values (Ang and Liu, 2007b) and zero values (Ang and Liu, 2007a). For example, Fernández et al. (2014) applied the LMDI method to analyze the factors of aggregate energy consumption change in the EU-27 for the period 2001 to 2008. Results reveal that energy efficiency improvements cannot overcome the effect of economic activity in terms of aggregate energy consumption. Xu et al. (2014) used LMDI to identify factors influencing carbon emissions in China. The results show that the economic output was the major driver, followed by population and energy mix. The energy intensity was the main inhibitory driver. Wang et al. combined the C-D production function with LMDI to investigate the factors affecting carbon emission in China (Wang and Jiang, 2019), and the factors affecting energy consumption in China and India (Wang et al., 2019a). The results show that the investment and labor effect were critical in the increase of energy use. Cansino et al. (2015) employed LMDI to assess the drivers of Spain's CO_2 emissions from 1995 to 2009. Findings demonstrate that renewable energy sources were detrimental to CO_2 emissions. Lyu et al. (2016) applied the LMDI method to study the changes of air pollution emissions in China for the period 1997 to 2012. Results manifest that economic growth and energy intensity were key drivers influencing air pollutant emissions. In addition, Ang et al. (2015) proposed a spatial-IDA framework according to the multiplicative IDA and studied energy consumption performance across 30 regions in China. Román-Collado and Morales-Carrión (2018) found that the key drivers are the activity and the population effect in the Latin America region, the intensity effect is the only inhibiting factor. Li et al. (2017) studied both national and regional emissions performance in China during 2000 to 2014, based on the LMDI model and an improved M-R spatial decomposition method, respectively. The spatial decomposition results indicate that differences in carbon emissions among Chinese regions were expanding. Liu et al. (2017b) applied temporal and spatial index decomposition—the LMDI model and the single-region EIO model—to explore the influencing factors of emissions in China's exports during 2002 through 2011.

The aforementioned representative literature on energy spatial decomposition analysis in the last two years are listed in Table 1.

However, due to the limitations of the decomposition method, the analyzing factor (such as energy consumption, energy-related carbon dioxide emission and energy intensity) must be decomposed into the multiplication of the potential influencing factors, as a result, the potential influencing factors that can be analyzed are limited. In addition, another main stream of methods widely used are econometric tools. Raeeni et al. (2019) identified whether the agriculture policies had worked and brought sectoral economic increase by applying causality and cointegration tests, providing valuable policies for policy makers. Hao and Peng (2017) using panel data analysis of thirty provinces in China between 1994 and 2014 to discuss convergence of per capita energy consumption, which is an indirect coefficient of energy consumption. Liu Y. et al. (2017a) developed a spatial econometric analysis on the basis of the SPIRPAT model, aiming to detect the impacts brought from Chinese typical new-type urbanization. Si et al. (2018) employed econometric method by analyzing instruments, comparing the impacts of various energy policies and compared their effectiveness.

Those models can sometimes discuss the product term of two factors, however, the two-factor interaction is not necessarily the multiplication relationship, other kinds of interactions should be detected to fill the gap. Besides, neither decomposition tools nor econometric methods can reveal the universal interactions of various influencing factors when they work together to change the dependent variable. In this case, we apply the interaction detector from the modified geographical detector to fill the gap.

In order to better show the energy consumption research in China (Crompton and Wu, 2005; Gu et al., 2019; Ma and Stern, 2008; Song et al., 2019), the US (Carmona et al., 2017; Harris et al., 2018; Mahalingam and Orman, 2018; Wang et al., 2018) and India (Ghosh, 2009; Mahalingam and Orman, 2018; Wang et al., 2019c), we have reviewed the research and list some in the table below (see Table 2).

With regard to the geographical detector model, Wang first proposed four Geographical Detector Models based on spatial variation

Table 1
Representative literature for energy spatial decomposition analysis in recent years.

Authors	Study object	Study period	Methodology	Main findings
Lan et al. (2016)	Energy footprints among 186 nations	1990–2010	SDA	Affluence and population growth are driving energy footprints worldwide
Su and Ang (2016)	Emission performance in China	2002	Spatial-SDA analysis	Imports assumptions are found to have no influence on the emission intensity effect, but they can affect other decomposition effects
Wang et al.	Global CO_2 emission intensity	2000–2009	Spatial-SDA analysis	Sectoral emission efficiency improvement was the main contributor to the slight decrease in global emission intensity during the period, while international trade marginally hampered improvement of global emission intensity
Chen et al. (2017)	Carbon emissions in Melbourne and Sydney	2009	Multi-region I—O analysis	Imported emissions make up more than 50% of the city carbon footprints, with most of them attributable to goods (excluding food) and services (excluding electricity)
Ang et al. (2015)	Energy consumption performance across 30 regions in China	2002	Spatial-IDA analysis	They propose a new model known as the M-R model, the decomposition results it gives pass the circularity test in index number theory.
Li et al. (2017)	National and regional emissions performance in China	2000–2014	LMDI model and an improved M-R spatial decomposition method	Economic output and energy efficiency are important factors leading to the differences in CO_2 emissions among regions.
Liu et al. (2017a, 2017b)	The influencing factors of emissions in China's exports	2002–2011	LMDI model and the single-region EIO model	The differences in the economy-wide emission intensities between China and its major trade partners were the biggest contribution to this reality, and the trade balance effect played a less important role
Román-Collado and Morales-Carrión (2018)	The driving forces behind CO_2 emissions changes in Latin America	1990–2013	Multiplicative LMDI	The main drivers for the Latin America region are the activity and the population effect, the intensity effect is revealed as the only inhibitor

analysis of the geographical strata to assess health risks (Wang et al., 2010). To detect gene-environment interactions, Wen-Chung Lee proposed a general approach to testing for sufficient-cause, gene-environment interactions in case-control studies (Lee, 2015). Recently, the Geographical Detector Model has been used in various fields to a wide extent: human health, agriculture, environmental pollution and so on. Lou analyzed the accumulation phase of $PM_{2.5}$ during the pollution episode (PMAE) in the Yangtze River Delta in China by exploring the spatial variations of PMAE and its links to the socioeconomic factors using a geographical detector (Lou et al., 2016). Yilan Liao applied geographical detectors based on spatial variation analyses of identified factors, in order to establish connections between regional features and the disability employment rate and to identify city groups with significantly higher and lower percentage rates of disability employment (Liao et al., 2016). Liang studied the distribution of sand dunes in the Maowusu (Mu Us) Sandy Land in the southern Ordos Plateau, northern China, through the Geographical Detector Model. They came to the conclusion that the climatic potential productivity, local relief, and drainage, are the key factors in shaping the landscape spatial pattern (Liang and Yang, 2016). In order to understand the relationship between the incident rates of infectious diseases and gross domestic product (GDP) growth in China, Tao Zhang proposed several models including the Geographical Detector (Zhang et al., 2016). Zhu He used the Geographical Detector Model to collect and analyze data from three types of urban RBDs in Beijing and thereby analyzed spatial-temporal changes (Zhu et al., 2015). Yin Ren conducted an analysis using the Geographical Detector Model in urban areas to reveal interactions between human activities, ecological factors, and LST (Ren et al., 2016). Du examined the individual and combined influences of physiographic factors on dryland vegetation greenness changes, identifying the most suitable characteristics of each principal factor for stimulating vegetation growth, finding that dryland greenness was affected, primarily, by precipitation, soil type, vegetation type, and temperature, either separately or in combination (Du et al., 2017). Goudarzi identified more sensitive regions of Qazvin aquifer in Iran, indicating that 9% of the area of the aquifer is categorized under the high-risk level. This indicates a need for an emergency recovery action plan and sensitivity analysis on the parameters of the aquifer vulnerability to show the effect of the soil media more than other parameters (Goudarzi et al., 2017). As aforementioned, the Geographical Detector Model has been used in a wide range of areas from natural to social science. Because of the clear physical meaning of the q value of the Geographical Detector Model, there is no linear assumption and the Geographical Detector Model is successfully used to analyze the driving forces from the perspective of stratified heterogeneity.

On the basis of the existing literatures (more detailed information please see the appendices), there are some new contributions that we are aiming to make, (1) since most energy studies have not put the possible interactions of different factors into consideration, these may cause distinct results when finding the key drivers of energy consumption, we modified the geographical detector model to fill this gap. (2) When analyzing the influencing factors, the characteristic differences are not well handled, thus we take the stratified heterogeneity into consideration by addressing the differences of each stratum for each potential influencing factor. (3) Unlike most previous detect main driver of the energy consumption, we identify the contributions and mechanism of each factor by discussing the growth rate of primary energy consumption, which can not only reveal the change trend of energy consumption but also eliminate the impacts from the orders of magnitude from each detecting factor. (4) After reviewing the literatures of the geographical model, it has a wide use in spatial heterogeneity by applying raster data which containing spatial characteristics for in certain time (for example, in a day or a year). However, since the change of energy consumption is a long-term process which contains time-series characteristics, apart from the base year and the final year, the evolution process should also be considered. As a result, the original Geographical Detector model should be modified to be applied in energy studies. A year-to-year stratified sampling method is conducted to compare the energy consumption changes in different years and the various influencing factors. In order to improve the pertinence of the model in energy studies, the original Geographical Detector model is modified in this paper to investigate the key drivers of energy consumption growth in China, the USA and India.

Our research motive is to compare the drivers of world's top three consumers for primary energy after putting the possible interactions of the influencing factors into consideration, which is new in related energy analysis. Besides, instead of just applying the Geographical Detector model, the long-term characteristic for energy consumption has been considered, meanwhile, differences of various strata for each potential factor by modifying the original Geographical Detector model.

2. Materials and methodology

2.1. Research framework

A geographical detector is a tool to test the spatial stratified heterogeneity of a variable and the driving forces of the changes of a given region. Generally speaking, a geographical detector contains four detectors: the factor detector, the interaction detector, the ecological

Table 2
The energy consumption research of China, the US and India.

Authors	Study region	Methodology	Main findings
Crompton and Wu (2005)	China	Bayesian vector autoregressive	Overall energy consumption increased to 2173 Mtce in 2010 with the annual growth rate of 3.8%.
Ma and Stern (2008)	China	Logarithmic mean Divisia index (LMDI)	Technological change is the dominant contributor to the decline in energy intensity
Song et al. (2019)	China	Structural decomposition analysis (SDA)	From 1997 to 2015, China's total metal consumption increased, China's high-speed economic growth has come at the expense of high-intensity metal consumption, especially in industry
Gu et al. (2019)	China	Double-logarithmic dynamic panel model	An inverted U-shaped relationship between energy technological progress and carbon emissions is detected
Carmona et al. (2017)	The US	Granger causality analysis	the impact of GDP on primary energy consumption is heterogeneous and energy source-specific, and an asymmetric behavior appears among cycles
Mahalingam and Orman (2018)	The US	Panel cointegration and panel causality tests	In the Rocky mountain region energy consumption Granger causes state GDP and in the Southwest it is opposite, GDP Granger causes energy consumption.
Harris et al. (2018)	The US	Four-parameter multi-cycle logistic growth curve models	ongoing increases in total US energy production dominated by crude oil and natural gas production will likely peak in 2017.
Mukherjee (2008)	India	Data envelopment analysis	Neither relative pricing of energy nor power sector reforms provide the appropriate incentives for improving energy intensity.
Ghosh (2009)	India	Autoregressive distributed lag (ARDL)	Electricity demand and supply side measures can be adopted to reduce the wastage of electricity, which would not affect future economic growth of India

detector and risk detector. In order to figure out the main driving factors of energy consumption growth rate in various regions, the interaction detector and the ecological detector was applied after testing the spatial stratified heterogeneity. The framework of this research is shown in the following figure (see Fig. 2).

2.2. Data source and processing

According to most of previous consumption decomposition studies, energy consumption can be decomposed into population, GDP per capita, and energy intensity. Furthermore, energy intensity can be sub-divided into coal intensity, oil intensity, and gas intensity to reveal specific reasons in different regions. The annual time-series data on primary energy consumption, population, and GDP in China, the USA, and India, between 1965 and 2015, used in this study, was obtained from the World Bank and BP Statistical Review of World Energy (BP, 2017; WorldBank, 2017). It should be noted that constant US dollar (2010) was used as the GDP indicator to eliminate the influence of inflation. Energy consumption was converted to Million tonnes oil equivalent (Mtoe). It should be noted that energy intensity (energy consumption per unit of economic growth, the ratio of national energy consumption to national output given by GDP, $EI = \frac{energy\ consumption}{GDP}$) X_1-X_5 denotes the growth rate of five influencing factors to energy consumption, to be more specific, they are: population of one given country (P); Gross Domestic Product (GDP) per-capita ($Q = \frac{GDP}{P}$); coal intensity ($CI = \frac{coal\ consumption}{GDP}$); oil intensity ($OI = \frac{oil\ consumption}{GDP}$); gas intensity ($GI = \frac{gas\ consumption}{GDP}$). Since we aim to detect the key driver of energy consumption growth rate instead of energy consumption, X1-X5 are then addressed as the growth rate of the factors stated above.

Based on studies of energy consumption, influencing factors can be split into: population, GDP per capita and energy intensity.

* Per capita GDP (G): is calculated as GDP (in 2010 USD) divided by population per capita. GDP is an indicator of a region's standard of living and one of the drivers of energy consumption (Kaya decomposition).
* Energy intensity (EI) comprises three parts of the type of the fossil fuels. In this case, energy can be divided into coal intensity (CI), oil intensity (OI) and gas intensity (GI). The influencing factors are divided into five aspects: population effect, human activity effect (GDP per capita), coal intensity effect, oil intensity effect and gas intensity effect (energy intensity).

2.3. Analysis model

Spatial stratified heterogeneity is a universal driver of biological diversity and evolution, environmental patterns and tyranny, and inter-regional conflicts and cooperation. The geographical detector was originally applied in the epidemiology research, consisted of factor detector, ecological detector, risk detector and interaction detector. Factor detector mainly focused on testing the spatial stratified heterogeneity and the main driver detection; ecological detector explored whether a stratum i (associated with one suspected determinant) is more significant than another stratum j (associated with another suspected determinant); risk was mainly used to search for areas with potential health hazards and interaction were applied to test whether two influencing factors Xi and Xj had an impact on each other, in other words, whether they enhanced or weaken each other, or just independent from each other.

GeoDetector software is originally based on spatial variation analysis of the geographical strata of variables to assess the environmental risks to human health: the ecological detector compares the importance degree of the factors; the risk detector indicates where the risk areas are; the factor detector identifies which factors have contributed more to the risk; and the interaction detector reveals whether the risk factors interact or lead independently to the variable Y. (Wang et al., 2010) The Geo-detector tool can be easily accessed (GeoDetector Software).

2.3.1. Factor detector

Environmental factors can pose significant impacts on the specific area when the geographical things have significant consistency, making

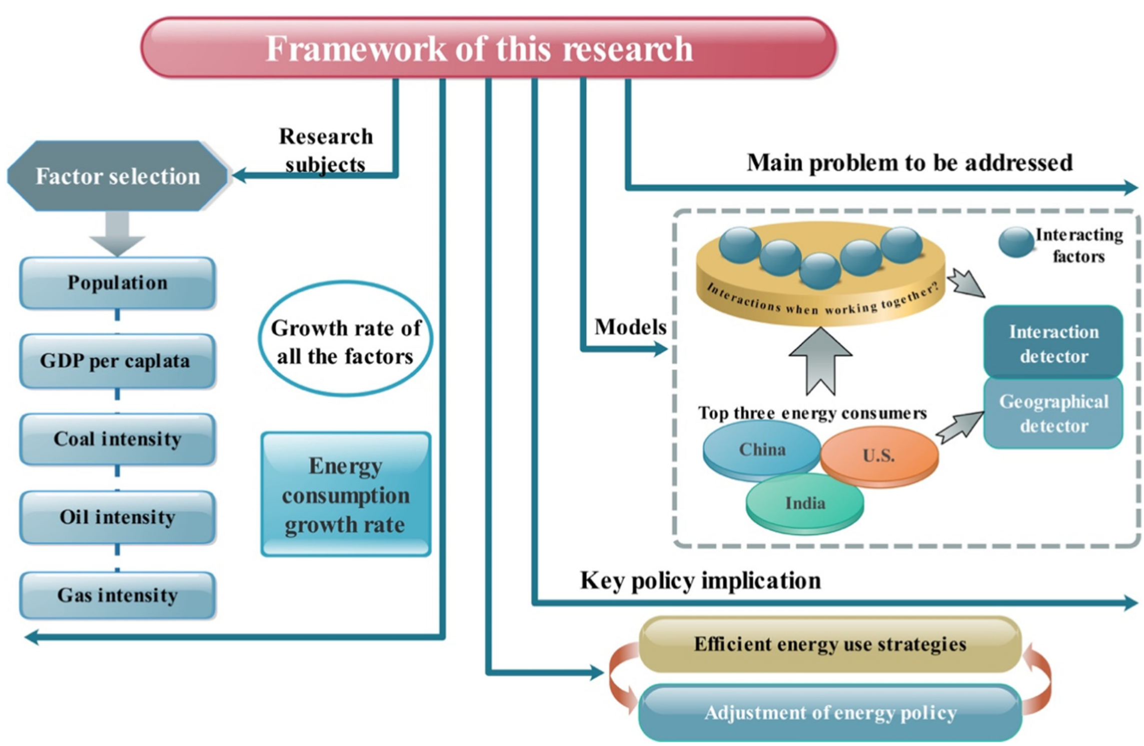

Fig. 2. Framework of this research.

them the driving force for the region. Factor detector identifies the degree to which a variable accounted for the prevalence of energy consumption growth rate. In this case, the association between Y and X can be measured by the q-statistic. To figure out whether there is a significant difference between two variances, the F-test is applied:

$$F = \frac{SSW_{Xi}}{SSW_{Xj}} = \frac{ms_1^2(n-1)}{ns_2^2(m-1)} \tag{1}$$

The statistic is approximately distributed as F(m − 1,n − 1), whose degrees of freedom was df = (m − 1,n − 1). To test whether the variances are significantly different, the null hypothesis H_0: $SSW_{Xi} = SSW_{Xj}$ is made at the significant level α (0.05), and by checking the distribution table or comparing the *p* value, if F(m − 1,n − 1) > $(f_\alpha)_{max}$, the null hypothesis is rejected, the alternative hypothesis: H_0: $SSW_{Xi} \neq SSW_{Xj}$ is chosen. In this case, the stratified determinants brought about significant differences in energy consumption in different regions. Then the power of determinants can be defined as q-statistic. The calculation method is shown in Eq. (2):

$$q = 1 - \sum_{h=1}^{L} \frac{N_h {\sigma_h}^2}{N\sigma^2} = 1 - \frac{SSW_{Xi}}{SSW_{Xj}} \tag{2}$$

where N stands for the population of the sample (the size of the study area) and σ^2 represents the variance of the study area. It should be noted that the region studied can be divided into different strata (h) on the basis of different determinants, which ranges from 1 to L. The q-statistic shows the association concerning the consistency of their spatial distributions. SSW_{Xi} and SSW_{Xj} represent the summary of the within the variance of each sample, respectively. When the variance of each sub-region is small, whereas the variances between sub-regions is large (which means that such a division explains most or even all of the dependent variable changes). Thus, q = 1 indicates a perfectly stratified heterogeneous result, whereas if q = 0, there is not a stratified heterogeneous sign of the study sample. In addition, the strata stated above is not limited to a geographical aspect, it can also be seen from the aspect of time or similar. It has a similar meaning to the mathematical space (see Fig. 3).

2.3.2. The interaction detector

Another kind of geographical detector identifies the interaction effect between the factor X_i and the factor X_j. In other words, it presents a method to test whether the interactions between influencing factors will change the ability or degree to reveal the overall characteristic. Moreover, it can detect whether different factors are independent of each other. After a calculation of q (X_i), q (X_j) and the interactions between them, the degree of the interaction was established. The types of interactions between various covariates are shown in Table 3. "∩" denotes the intersection between X_i and X_j. When q ($X_i \cap X_j$) > Max [q ($X_i \cap X_j$)), it denotes that the interaction between factor X_i and X_j is the bilinear strengthening. The interaction between factor X_i and X_j is weak and nonlinear when q ($X_i \cap X_j$) < Min [q ($X_i \cap X_j$)). If q ($X_i \cap X_j$) is between the minimum and maximum of it, the uni-directionally weakened status is defined. When q ($X_i \cap X_j$) > q (X_i) + q (X_j) is tested, the nonlinear but enhanced status occurred, however, if they are equal, the independent interaction degree is defined.

A sub-model of the geographical detector model, the interaction detector can be applied to reveal the possible interactions. To be more specific, interactions between different influencing factors when changing the overall energy consumption growth rate change may exist if they are not independent from each other, this phenomenon can enhance or weaken the detection of the key driver to the total energy consumption change need to be clarified. Unfortunately, most energy studies have not put the possible interactions of different factors into consideration, this may cause distinct results when finding the key drivers of energy consumption, we modified the geographical detector model to fill this gap.

2.3.3. The ecological detector

Mainly, the ecological detector identifies the impact difference between two factors. In order to detect which factor tends to be the most significant of the various effects, the F-statistic is applied, shown in Eq. (3):

$$F = \frac{N_{Xi}(N_{Xj}-1)SSW_{Xi}}{N_{Xj}(N_{Xi}-1)SSW_{Xj}} \tag{3}$$

The statistic is approximately distributed as F(N_{Xi} − 1, N_{Xj} − 1) where F denotes the F test value in the statistical test, N_{Xi} and N_{Xj} stand for the population of sample i and j, SSW_{Xi} and SSW_{Xj} mean the

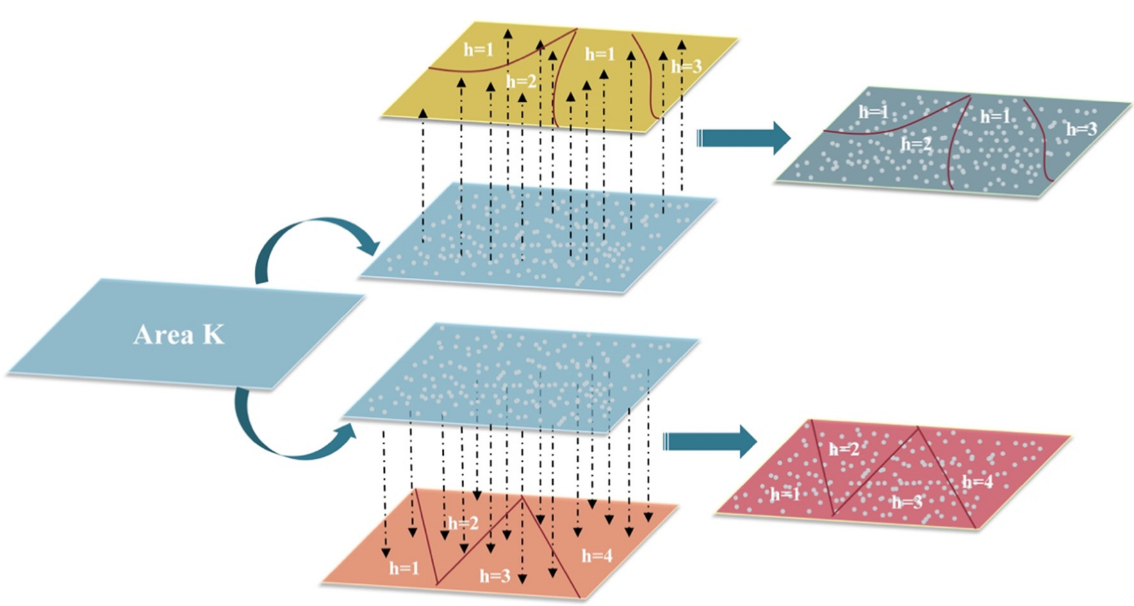

Fig. 3. Schematics of the geographical detector model q-statistic.

Table 3
Types of interactions between two covariates.

State	Interaction degree
$q(X_i \cap X_j) < \mathrm{Min}(q(X_i \cap X_j))$	Weaken, nonlinear
$\mathrm{Min}(q(X_i \cap X_j)) < q(X_i \cap X_j) < \mathrm{Max}(q(X_i \cap X_j))$	Weaken, univariate, nonlinear,
$q(X_i \cap X_j) > \mathrm{Max}(q(X_i \cap X_j))$	Enhance, linear, bilinear
$q(X_i \cap X_j) = q(X_i) + q(X_j)$	Independent
$q(X_i \cap X_j) > q(X_i) + q(X_j)$	Enhance, nonlinear

summary of the within the variance of each sample. In addition, the null hypothesis (H_0) is constructed as: $SSW_{Xi} = SSW_{Xj}$. The F test was processed at a confidence level of 95%. When the p value is smaller than 0.05, the null hypothesis is rejected. In other words, the factors posed distinct driving effects on the result.

3. Results and discussion

3.1. Factor detection

As is shown in Table 4, the order of contribution to energy consumption in China is: $X_3 > X_2 > X_5 > X_4 > X_1$. The key determinant factors on energy consumption are coal consumption intensity growth rate and per-capital GDP growth rate. In comparison, the order of contribution to energy consumption in the USA is: $X_2 > X_4 > X_3 > X_1 > X_5$. The key determinant factors in the USA are per-capital GDP growth rate and oil consumption intensity growth rate. The order of contribution to energy consumption in India is: $X_3 > X_5 > X_4 > X_2 > X_1$. The key determinant factor on energy consumption is coal consumption intensity growth rate.

3.2. Interaction detector

In China, all factors were found to enhance each other to increase the energy consumption (Table 5). To be more specific, $X_1 \cap X_2$ is a nonlinear relationship, which can also be found for $X_1 \cap X_3$, $X_1 \cap X_4$, $X_2 \cap X_3$, $X_2 \cap X4$, $X_2 \cap X_5$ and $X_4 \cap X_5$. Bilinear relationship and nonlinear relationship are two types of relationship that reveal the degree of the interaction of two factors. Compared with bilinear relationship, the nonlinear relationship shows a more significant enhancing relationship, to be more specific, the connection of two factors in nonlinear relationship can enhance each other more when changing the overall energy consumption growth rate. However, it turned out to be a bilinear relationship for the rest combinations, exerting a synergistic effect on the energy consumption growth in China. The interactions of population and gas intensity, coal intensity and oil intensity as well as coal intensity and gas intensity are not as strong as those interactions of other factors.

As for the USA (Table 6), the relationship between X_1 and X_3 is nonlinear and they also enhance each other to increase the energy consumption growth rate, which is the same as $X_1 \cap X_4$, $X_1 \cap X_5$, $X_3 \cap X_4$ and $X_3 \cap X_5$. While the relationship between the other factors is bilinear, indicating a synergistic impact on the energy consumption in the USA. Population change rate has a more significant combing effect with energy intensity effect to the aggregate energy use and coal intensity also shows a closer connection with oil intensity and gas intensity effects when they work together to change the energy consumption.

Table 4
The contribution of each factor and the determinant power.

Region	X_1	X_2	X_3	X_4	X_5
China	0.0559	0.2463[b]	0.5613[c]	0.1272	0.1558[a]
US	0.0704[a]	0.4939[c]	0.1252	0.3057[c]	0.0556
India	0.0010	0.0187	0.2660[b]	0.0383	0.0515

[a] Means rejecting the null hypothesis at the 90% confidence level.
[b] Means rejecting the null hypothesis at the 95% confidence level.
[c] Means rejecting the null hypothesis at the 99% confidence level.

Table 5
Interaction relationship of each factor on energy consumption in China.

Factor combination	Graphical representation	Interaction relationship
$X_1 \cap X_2$		Enhance, nonlinear
$X_1 \cap X_3$		Enhance, nonlinear
$X_1 \cap X_4$		Enhance, nonlinear
$X_1 \cap X_5$		Enhance, bilinear
$X_2 \cap X_3$		Enhance, nonlinear
$X_2 \cap X_4$		Enhance, nonlinear
$X_2 \cap X_5$		Enhance, nonlinear
$X_3 \cap X_4$		Enhance, bilinear
$X_3 \cap X_5$		Enhance, bilinear
$X_4 \cap X_5$		Enhance, nonlinear

Note: denotes $\mathrm{Min}(q(X_i),q(X_g))$; represents $\mathrm{Max}(q(X_i),q(X_g))$; means $q(X_i) + q(X_g)$; denotes $q(X_i \cap X_g)$.

As is shown in Table 7, all factors were found to enhance each other, apart from X_1 and X_2, which have a bilinear relationship. The rest of the factors tended to show a nonlinear relationship in India, indicating that the interactions are stronger than the population and GDP per capita growth rates in affecting the energy consumption changes. Except the growth rate of population and GDP per capita, India has the strong interactions between the rest of the factors to influence the total energy consumption growth rate.

Overall, the interactions between factors in US is not significant as those in China and India, also, India has the strongest interactions of the three economies.

3.3. Ecological detector

The results of the ecological detection focused on whether there were significant differences in the effects of detection factors on the spatial distribution of energy consumption. The results show that the

Table 6
Interaction relationship of each factor on energy consumption in the USA.

Factor combination	Graphical representation	Interaction relationship
$X_1 \cap X_2$		Enhance, bilinear
$X_1 \cap X_3$		Enhance, nonlinear
$X_1 \cap X_4$		Enhance, nonlinear
$X_1 \cap X_5$		Enhance, nonlinear
$X_2 \cap X_3$		Enhance, bilinear
$X_2 \cap X_4$		Enhance, bilinear
$X_2 \cap X_5$		Enhance, bilinear
$X_3 \cap X_4$		Enhance, nonlinear
$X_3 \cap X_5$		Enhance, nonlinear
$X_4 \cap X_5$		Enhance, bilinear

Note: denotes $\mathrm{Min}(q(X_i),q(X_g))$; represents $\mathrm{Max}(q(X_i),q(X_g))$; means $q(X_i) + q(X_g)$; denotes $q(X_i \cap X_g)$.

Table 7
Interaction relationship of each factor on energy consumption in India.

Factor combination	Graphical representation	Interaction relationship
$X_1 \cap X_2$		Enhance, bilinear
$X_1 \cap X_3$		Enhance, nonlinear
$X_1 \cap X_4$		Enhance, nonlinear
$X_1 \cap X_5$		Enhance, nonlinear
$X_2 \cap X_3$		Enhance, nonlinear
$X_2 \cap X_4$		Enhance, nonlinear
$X_2 \cap X_5$		Enhance, nonlinear
$X_3 \cap X_4$		Enhance, nonlinear
$X_3 \cap X_5$		Enhance, nonlinear
$X_4 \cap X_5$		Enhance, nonlinear

Note: denotes Min(q(X_i),q(X_g)); represents Max(q(X_i),q(X_g)); means q(X_i) + q(X_g); denotes q($X_i \cap X_g$).

incidence of energy consumption between X_1 and X_3, X_2 and X_3, respectively, are significantly different at the 95% confidence level in China. While in the USA, the incidence of energy consumption between X_1 and X_2 are significantly different. In India, there is no statistical significance in the difference for explanatory power between the detection factors.

4. Discussion

Factors played different roles in various areas. Generally, coal consumption intensity accounted most in the change of the primary energy consumption, which is a serious question in China. The use of coal caused the growth of energy consumption for its characteristic of high pollution and low conversion efficiency. As a consequence, the adjustment of energy mix is in desperate need. China is developing with a surprising speed and more energy has been put into use than ever before. More environmental problems have been accompanied by the heavy use of energy. In addition, all factors were found to enhance each other. The relationship of the power of determinant of population and gas consumption intensity is bilinear, the same as the power of determinant of coal consumption intensity and oil consumption intensity, as well as coal consumption intensity and gas consumption intensity.

When it comes to the USA, the most significant factor is the GDP per capita. In other words, economic growth was the greatest contributor to energy use. As the world's first largest economy, the USA always consumes a large amount of energy to satisfy the need to increase the domestic product. In other ways, human activities, especially in terms of the economic aspect, have a strong connection with energy use to maintain industrial and daily life. In addition, the USA's oil consumption was 19,396 Barrels in 2015, which contributed a 19.7% share of the world's oil consumption. The use of oil rendered the oil consumption intensity factor an important force to influence the change of energy consumption. All factors were found to enhance each other, and the relationship between the power of determinant of population and coal consumption intensity is nonlinear.

As for India, coal consumption intensity played a significant role in increasing the total energy consumption. Finding ways to optimize the energy mix and improve the use and conversion efficiency is also of vital importance in India. All factors were found to enhance each other; the relationship between the power of determinant of population and GDP per capita is bilinear, while the relationship of the other factors is nonlinear.

5. Conclusions and policy implications

5.1. Conclusions

This paper examines the determinant factors of energy consumption by means of geographical detector methods in China, the USA, and India. Also, the main drivers in these three countries were compared. Several conclusions are formulated:

1. The two developing economies-China and India, coal use contributed the most towards the growth of energy consumption growth rate, while GDP per capita in the United States is the most significant impact when changing total energy consumption growth rate. India has the strongest factor interactions when influencing the energy consumption growth rate among the three economies, all interactions between factors in US is not significant as those in China and India.
2. In China, coal consumption intensity accounted for the most in the change of energy consumption growth rate. GDP per capita also played an important role in increasing energy use. The order of contribution to energy consumption is: coal consumption intensity, GDP per capita, gas consumption intensity, oil consumption intensity and population. As such, the key determinant factors on energy consumption are coal consumption intensity and GDP per capita. In China, all factors were found to enhance each other to increase the energy consumption. As for energy consumption mix, China should focus more on the limit of coal use and the search for renewable fuels to replace traditional coal consumption, especially in sectors like electricity. Meanwhile, rapid economic development has also brought related environmental pollution. Thus, in addition, policy should highlight possibilities to obtain a pattern to decouple economic increase and energy consumption.
3. In the USA, GDP per capita contributed the most towards the growth of energy use change. Oil consumption intensity proved to be the second largest driving factor in the change of energy consumption. A massive switch to oil consumption contributed to the energy consumption change rate. In addition, the most significant driver, economic effect, poses a substantial threat to the growth of energy consumption in terms of price and investment change. All factors enhance each other when change energy consumption while the joint impacts of population change rates with that of energy intensity and coal intensity with oil intensity and gas intensity are more significant.
4. In India, the key determinant factor on energy consumption is coal consumption intensity. As another large developing country, which is similar to China, coal consumption growth contributed the most to the total energy consumption increase. All the factors influencing each other and have an enhanced impact, however, the growth rate of population and GDP per capita did not remain at the same level of the rest interaction relationship of other factors.

5.2. Policy implications

The proportion and growth rate of fossil energy will be further reduced with the help of the rapid development of renewable energy after the Paris Agreement. Since the determinant power of the factors of energy intensity varies from one country to another, corresponding adjustments must be made in accordance. Since coal consumption intensity is the biggest driver to increase energy consumption in China and India. The adjustment of energy mix is fundamental to energy consumption growth rate change in China and India, especially in terms of coal intensity. In addition, sensible choices for China include developing a low-carbon economy and adjusting industry structure. For the United States, the leading drivers of energy use are the factors of individual incomes and oil intensity, the growth rate change of GDP per capita have significant impacts to overall energy consumption growth rate change. Meanwhile, since the effect from oil intensity change can also pose comparatively substantial impacts on energy consumption growth rate in the US, the shift from coal to renewable fuels can make its contribution, however, the high price of renewables still hinders the energy switch, what the US focus to control the energy consumption growth rate can be resources and technology improvement. The effect of human activities played a significant role in China and the USA, which is because using primary energy is a direct way to prompt economic growth. Since all factors are detected to enhance other, policy makers should balance the impacts from all factors when proposing feasible polices or measures. In general, high-carbon energy approaches should be transformed to low-carbon energy. For example, coal can be replaced by renewable fuels such as natural solar and nuclear power. Energy intensity effect should be treated as a key issue because it has a direct link with energy efficiency. Scientific research on improving the usage and conversion efficiency of energy should be encouraged. Also, for developing countries like China and India, the dependence of coal consumption is primarily for the reason of low price of the traditional fossil fuels, however, in the long run, government can link the switch to a more sustainable energy consumption development pattern and environment-friendly society with offering more job opportunities. To be more specific, the development of renewable energy industries is not quite sophisticated, as a result, to deliver better energy services with secure impacts, more jobs can be accompanied. However, the government need initially pour more funds to these sustainable industries to speed up the process of building a more sustainable energy system with lower environment impacts.

Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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