



Identifying contributing factors to China's declining share of renewable energy consumption: no silver bullet to decarbonisation

Muhammad Jawad Sajid¹ · Syed Abdul Rehman Khan¹ · Ernesto D. R. Santibanez Gonzalez²

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Abstract

Renewable energy consumption (REC) holds the key to sustainable development. Therefore, many studies have considered the role of REC. However, the factors influencing the REC share in total energy usage (SREC) are not well investigated. Especially, the factors of China's fast-shrinking SREC are understudied. This research void on the world's largest renewable energy producer and consumer, i.e., China's decreasing SREC, is alarming and requires thorough investigation. Our study intends to fill this gap by analyzing the factors of China's decreasing SREC. The study uses both the conventional (descriptive and directional correlational analyses) and some unconventional (automatic linear modeling (ALM) and Artificial neural network (ANN) multilayer perceptron (MLP)) approach to investigate the factors of China's decreasing SREC. The initial hypothesis testing and most reliable model validation were achieved via directional correlational (Pearson and Spearman) and ALM analyses. The ANN MLP (two hidden layers) indicated that the most critical factor is "Combustible renewables and waste," with a 100% normalized importance. It was followed by "urbanization (64.2%), gross savings (56.1%), and alternative and nuclear energy (38%)," respectively. It is suggested that the Chinese government and private investors prioritize their investments based on factors' importance ranking.

Keywords Artificial neural network (ANN) · Automatic linear modeling (ALM) · Environment · Sustainability; IBM SPSS · Pearson and Spearman rank correlation · Regression analysis

Background

China is currently the world's largest energy consumer (ChinaPower: Center for Strategic and International Studies 2021). Coal consumption accounts for nearly 58% of this energy requirement (U.S. EIA 2021). This excessive reliance on unclean fossil fuels made China the world's largest carbon emitter (Sajid et al. 2020, 2021; Sajid 2021; Sajid and Gonzalez 2021). Despite this significant contribution

to global carbon emissions, China was the world leader in renewable energy production capacity in 2020 (Jaganmohan 2021a). Furthermore, the country's consumption of renewable energy has increased significantly. Between 2010 and 2020, China's renewable energy consumption grew at a compound annual growth rate (CAGR) of nearly 23.41% (estimations based on Statista (Jaganmohan 2021b)). However, the Chinese SREC in total energy consumption decreased at a CAGR of approximately 7.1% between 1999 and 2020 and by 6.26% between 2010 and 2020 (estimations based on the World Bank's "World development indicators" (The World Bank 2021)). That means that the country's overall achievements in increasing the total volume of renewable energy production and consumption may not impact the country's CO₂ emission reduction targets. Notably, the 2030 net-zero emissions target may become unachievable if its SREC continues to decline at this alarming rate. As a result, understanding the factors influencing China's SREC's constant decline may aid in improving the SREC in the long run following COVID-19.

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✉ Muhammad Jawad Sajid
jawad.jaws@outlook.com; 11910@xzit.edu.cn

¹ School of Engineering Management, Xuzhou University of Technology, Management Building, Xuzhou 221000, Jiangsu, China

² Department of Industrial Engineering, Faculty of Engineering, University of Talca, Los Niches Km 1, CES4.0 Curicó, Chile

Generally, various types of regression analyses are used in the related literature to understand better the effects of various variables on energy consumption and carbon emissions. For example, using the “pooled mean group estimators (PMG),” Sadik-Zada and Ferrari (2020) discovered a strong correlation between the pollution heaven and the environmental Kuznets curve (EKC) hypotheses. Godil et al. (2020) used the quantile autoregressive distributed lag (QARDL) to examine the asymmetric impact of freight and passenger transport on establishing EKC in the US economy. Sadik-Zada and Loewenstein (2020) studied the income-environment (EKC) linkage in oil-producing nations and the other factors contributing to air pollution using the PMG and nonparametric panel analyses. Sadik-Zada and Gatto (2021) used the PMG to examine oil’s net greenhouse gas (GHG) footprint in oil-rich settings. They developed a three-sector decision model that served as a commonality for evaluating the interaction of structuralist and institutional factors affecting pollution in oil-dependent economies. Sajid (2020) used nonlinear and linear regression analyses to examine the relationship between China’s production and consumption-based carbon emissions and various socioeconomic drivers. Using the panel QARDL, Yu et al. (2022) assessed the effects of different socioeconomic factors on CO₂ emissions in developing nations. Khan et al. (2021a) used regression analyses such as the “generalized method of moments, fully generalized least squares, and OLS” to investigate the relationship between green supply chain management (in terms of decarbonization) and various macroeconomic factors. In particular, the importance of renewable energy has prompted numerous studies on its environmental, economic, and political/policy implications. Table 4 summarizes some of the pertinent literature by categorizing it according to REC’s environmental, economic, and political/policy aspects. In this regard, the table provides a brief overview of some of the most recent and most relevant research articles on REC.

(1) Despite extensive research on various aspects of REC, the factors influencing the SREC in a country’s or region’s total energy mix have received little attention. (2) The factors influencing China’s (the world’s leader in renewable energy production and consumption) shrinking SREC are particularly understudied in the related literature. (3) In addition, due to a general lack of literature, a suitable scale presenting the key factors of progress (both positive and negative growth rates) of SREC is mostly lacking. (4) Finally, as shown in Table 4, most of the available literature on various economic, environmental, and political/policy dimensions of REC has primarily focused on traditional manual regression-related methods. However, automated methods such as ALM and ANN are rarely used in these studies.

This study addresses the above research gaps in the following ways. First, the study hypothesizes the relationship between various key factors and the SREC based on relevant literature and economic theory/insight. Second, China was chosen as a case study because its SREC is declining rapidly, which adds to the practicality and significance of our research. Our study also offers some methodological innovations compared to other related studies. (1) ALM was used to determine whether the factor selection based on directional relationship presents the most important predictors (independent variables) of China’s declining SREC. In other words, we ran the ALM analysis to find the most stable (reliable) model for the ANN analysis. The ALM was introduced in IBM SPSS Version 19 and enabled researchers to automatically select the best subset (Oshima and Dell-Ross 2016), i.e., the ALM assists us in choosing the best model for subsequent ANN (or regression) analyses (Yakubu et al. 2019). ALM has several computational and technical advantages over traditional linear regression approaches. Researchers frequently collect many independent variables, each of which could predict the dependent variable (Yang 2013). As a result, deciding which subset (s) of a large pool of potential predictors to include in a linear regression model is a common and potentially challenging aspect of regression modeling (Ratner 2012; Yang 2013). At least one small sample of candidate predictors that provides appropriate prediction accuracy at a reasonable cost should be chosen (Yang 2013). (2) Instead of the regression-based tools mentioned above and in Table 4, ANN MLP analysis is conducted in this study. An ANN is a set of non-linear data modeling tools that includes input and output layers and one or two hidden layers. The training method iteratively modifies the weights of the connections between neurons in each layer to reduce errors and produce accurate predictions (IBM Corporation 2012). One of the main advantages of ANNs over standard statistical techniques (e.g., regression) is their versatility and lack of distributional assumptions (Smart Vision Europe 2021). Figure 1 depicts the model selection and essential factor identification procedure used in our study. Meanwhile, Table 1 provides the full names of the abbreviations used in this study.

Methods

Materials sources and processing

This study uses the World Bank’s “World development indicators” (The World Bank 2021) to compile annual data for most socioeconomic variables from 1990 to 2020, including FDI, GDP, GCF, PAs, CRW, EPRS, EPOGC, urbanization, ANE, GS, and SREC. However, due to the non-availability of the EFs annual data, the

Fig. 1 A conceptual framework for identifying key factors. Depending on the normality tests (skewness and kurtosis), the initial hypotheses are tested using directional (one-tailed) Pearson correlation and/or Spearman rank correlation. The most reliable model depicting the relationship between dependent (target) and independent (predictor) variables is accepted using ALM analysis. Finally, the ANN MLP analysis ranks the variables based on their predictive power of the dependent variable SREC

Key factor identification process

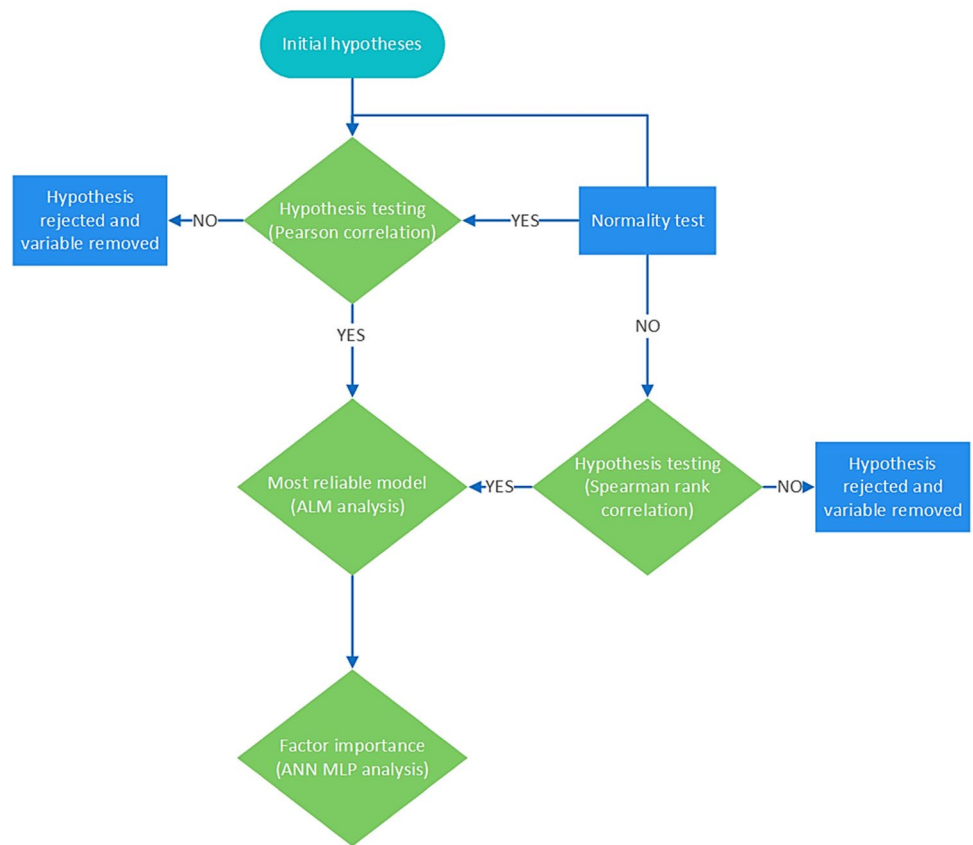


Table 1 List of abbreviations

Abbreviation	Full name
ANN	Artificial neural network
ALM	Automatic linear modeling
APR	Annual percentage growth
CAGR	Compound annual growth rate
MLP	Multilayer perceptron
REC	Renewable energy consumption
REP	Renewable energy production
r_p or PCC	Pearson correlation coefficient
r_s or SRCC	Spearman rank correlation coefficient
SREC	Share of REC in total energy usage
FDI	Foreign direct investment
GDP	Gross domestic product
GCF	Gross capital formation
P.A.s	Patent applications
EFs	Education funds
CRW	Combustible renewables and waste
EPRS	Electricity production from renewable sources
EPOGC	Electricity production from oil, gas, and coal sources
ANE	Alternative and nuclear energy
GS	Gross saving

“National Bureau of Statistics of China” was consulted (National Bureau of Statistics of China 2020). Additionally, some variables’ missing values were estimated using linear forecasting. Supplementary Table S1 contains additional information about the historical and forecasted data.

Hypotheses development

A hypothesis is an assumption based on prior studies or existing information about a subject (John A. Dutton e-Education Institute 2014). A clearly defined and specific research topic and hypothesis will almost certainly aid in guiding the direction and breadth of the study, as well as how data is collected (Farrugia et al. 2010; Sajid et al. 2021). We have relied on the previously published literature, economic theory, and intuition to develop high-quality hypotheses.

FDI

Many recent studies have examined the negative and positive effects of FDI on the environment (Li et al. 2019; Demena

and Afesorgbor 2020). Additionally, studies have established a causal relationship between energy consumption and FDI (Rahman 2021). Several studies have found that FDI positively impacts REC (Amri 2016; Doytch and Narayan 2016). As a result, a positive relationship between the SREC and FDI in China is hypothesized.

H1: Positive relationship between FDI and China's SREC.

GDP

Renewable energy production and consumption have been linked to economic growth in the literature. According to studies, renewable energy production leads to economic development (GDP growth) in developed and developing countries (Singh et al. 2019). Many studies, in particular, have found that GDP growth (economic growth) has a positive effect on REC in the EU-28 (Akadiri et al. 2019; Sahlian et al. 2021), South Asia (Rahman and Velayutham 2020), and OECD countries (Dogan et al. 2020). Furthermore, it has been estimated that there is a positive relationship between economic development and REC (Fan and Hao 2020; Vo and Vo 2021). As a result, it is hypothesized that GDP and SREC have a positive linear relationship.

H2: Positive relationship between GDP and China's SREC.

GCF

China has made significant investments in long-term (fixed-capital) renewable energy projects in recent years. In 2020, China more than quadrupled its new wind and solar power plant development from the previous year (Xu and Stanway 2021). According to the National Energy Administration, China will install 71.67 gigatonnes of wind power capacity in 2020, the most ever and nearly double the amount added in 2019 (Xu and Stanway 2021). Furthermore, studies have shown that fixed capital formation positively affects REC (Abbas et al. 2020). As a result, it is hypothesized that GCF and China's SREC have a positive linear relationship.

H3: Positive relationship between GCF and China's SREC.

PAs

China holds the most renewable energy patents in the world. In 2016, China accounted for nearly 29% of global

renewable energy patents (Jaganmohan 2021c). China's contribution to global patents increased to more than 57%, with 7544 renewable energy patents (estimation based on Statista (Jaganmohan 2021d)). There is also evidence that renewable energy patents positively impact renewable energy production (Tee et al. 2021). As a result, it is logical to assume a positive relationship between China's PAs and the SREC.

H3: Positive relationship between PAs and China's SREC.

EFs

According to studies, environmental awareness and societal acceptance of renewable energy and REC are high in highly educated cultures. On the supply side, higher levels of scientific knowledge and know-how have been observed to promote the development and dissemination of renewable energy technology. Secondary education, in particular, has been shown to increase both long-term and short-term REC (Mahmood 2020). Other findings suggest that education level is related to participation in renewable energy production and consumption (Özçiçek and Ağpak 2017). As a result, it is assumed that there is a positive correlation between the Chinese EFs and the SREC.

H4: Positive relationship between EFs and China's SREC.

CRW

CRW is defined as "industrial waste, solid biomass, biogas, liquid biomass, and municipal waste" and is expressed as a percentage of total energy consumption (IEA Statistics 2014). CRWs are considered a critical component of renewable energy (Ali et al. 2021). Based on this definition, it is reasonable to assume that China's SREC positively correlates with the CRW.

H5: Positive relationship between CRW and China's SREC.

EPRS

Electricity demand has been shown to affect renewable energy generation in China (Ma and Xu 2021). As a result, it seems natural to assume that the EPRS positively correlates with REC.

H6: Positive relationship between EPRS and China's SREC.

EPOGC

If a given country’s energy/power demand is met by fossil fuels, it is reasonable to assume that renewables’ role (consumption) will suffer. As a result, it is taken that there is a negative relationship between EPOGC and the Chinese SREC.

H7: Negative relationship between EPOGC and China’s SREC.

Urbanization

Many studies have found a link between overall energy consumption and urbanization (Avtar et al. 2019; Nuta et al. 2021). In particular, it has been demonstrated that Urbanization positively impacts the growth of China’s REC (Yang et al. 2016). As a result, urbanization is hypothesized to have a positive relationship with China’s SREC.

H7: Positive relationship between urbanization and China’s SREC.

ANE

While alternative and renewable energy seek to reduce carbon emissions, they are not the same (Sol-Up 2021). Compared to renewable energy, alternative energy does not have an infinite supply, whereas renewable energy, as the name implies, is always available, comparable to solar energy (Sol-Up 2021). It is reasonable to believe that in the country’s effort to reduce carbon emissions, ANE can be considered a renewable energy substitute. As a result, a negative relationship between ANE and China’s SREC can be hypothesized.

H7: Negative relationship between ANE and China’s SREC.

GS

Previous research has shown that GS has a significant negative long-term and short-term impact on energy consumption (Faisal et al. 2016). Aside from this decrease in energy consumption, other evidence revealed that the OECD’s net savings had a negative impact on total factor energy efficiency (Ziolo et al. 2020). Based on this evidence, it is assumed that there is a negative correlation between GS and SREC.

H8: Negative relationship between GS and China’s SREC.

Directional relationship analysis

The PCC and SRCC were used to test the preliminary hypotheses in this study. Correlation analysis will help determine whether the dependent variable (SREC) and the independent variables have a statistically significant (directional) relationship? And (2) whether the relationship’s trajectory corresponds to the hypothesized directions? Researchers frequently use the correlation coefficient to determine the direction of a relationship between two variables (Schober et al. 2018). PCC and SRCC are commonly used in hypothesis testing to determine the directionality of a relationship between dependent and independent variables (Sajid et al. 2021). The PCC is widely used for normally distributed continuous data, whereas the SRCC can be used for ordinal and non-normal distributions. The estimates for the SPSS-based skewness and kurtosis tests for normality should be between + 1 and – 1 (Sajid et al. 2021). Furthermore, one-tailed significance is preferable to traditional two-tailed significance for directional hypothesis testing (Sajid et al. 2021).

PCC analysis

The PCC, which shows how the dependent and independent variables are linked together, can be calculated using the following equation:

$$r_{p(SREC,F^k)} = \frac{\sum_{t=1}^b (SREC_t - \overline{SREC})(F_t^k - \overline{F}^k)}{\sqrt{\sum_{t=1}^b (SREC_t - \overline{SREC})^2} \sqrt{\sum_{t=1}^b (F_t^k - \overline{F}^k)^2}} \tag{1}$$

where $r_{p(SREC,F^k)}$ represents the value of PCC between the Chinese SREC and different independent factors $F^k(k = 1, 2, 3, \dots, n)$. $t = 1, 2, 3, \dots, b$ presents the time or, in other words, the yearly data. And \overline{SREC} and \overline{F}^k denote the arithmetic means.

SPCC analysis

Compared to the PCC’s linear relationship, the SPCC analysis is based on the monotonic relationships between dependent and independent variables. As the independent variable rises, a monotonic function either never increases or never drops. The following equation is used the estimate the value of SPCC:

$$r_{s(SREC,F^k)} = 1 - \frac{6 \sum r_t^2}{b(b^2 - 1)} \tag{2}$$

where $r_{s(SREC, F^k)}$ presents the value of SPCC between the dependent $SREC$ and independent F^k . r_t^2 represents the difference between each observation's two ranks and b represents the number of observations (years).

ALM analysis

Under ALM, the stepwise and all-possible-subset (i.e., best-subsets) methods are two standard variable selection procedures. In contrast to the stepwise approach, which saves computational effort by only exploring a subset of the model space, the all-possible subsets approach searches the entire model space by considering all possible regression models from the pool of potential predictors (Yang 2013). Many researchers appear to prefer the all-possible-subsets method to the stepwise approach in terms of popularity (Yang 2013). Because the process of evaluating all possible subsets can provide the best subsets after considering all possible regression models, the researcher can then select an appropriate final model from the most promising subsets (Yang 2013). As a result, in this study, we used the “best-subsets (all-possible-subsets)” option to select the most stable (reliable) model. Our study's main ALM execution criteria are presented in Supplementary Table S3. Based on the directional analysis, the finalized predictor variables in line with the hypotheses are considered for ALM testing to decide the most stable (reliable) model.

$$SREC = f(FV_p) \quad (3)$$

where $SREC$ is the dependent variable. FV_n ($p = 1, 2, 3, \dots, n$) presents the finalized dependent variables that have passed the directional correlation analysis, i.e., the hypothesis testing.

The following equation provides the basic linear multiple-regression equation presenting the finalized predictor variables after the hypotheses testing:

$$SREC = c + b_1FV_1 + b_2FV_2 + b_3FV_3 + \dots + b_nFV_n + \epsilon \quad (4)$$

where $SREC$ presents the dependent variable. c represents the y-intercept, also known as the constant of the regression equation and ϵ is the residual of the regression analysis. In this study, the Akaike information criterion with correction for small sample sizes (AICC) is used to develop the most reliable model. The model (presenting a set of predictors) with the minimum value of AICC is the final model for the subsequent ANN MLP analysis.

$$AIC = 2p - 2\ln(H) \quad (5)$$

where AIC represents the Akaike information criterion, $p = 1, 2, 3, \dots, n$ presents the number of the estimated

parameters of our study, and H represents the highest value of the model's likelihood function. Form the AIC the $AICC$ can be easily calculated as below:

$$AICC = AIC + \frac{2p^2 + 2p}{l - p - 1} \quad (6)$$

where l presents our sample size, and p represents the number of model parameters.

ANN analysis

IBM SPSS ANNs provide an alternative advanced predictive capability to regression or classification trees (Smart Vision Europe 2021). IBM SPSS ANNs offer nonlinear data modeling processes that enable you to identify more complex data associations (Smart Vision Europe 2021). Of the many models available, the multilayer feed-forward model owing to its formidable modeling capability is the most common method for prediction under ANN (Hornik et al. 1989; Liu et al. 2009). The three-layer feed-forward model (used in this study) consists of three layers: (1) a single input layer, (2) a few hidden layers (in our case, two hidden layers based on model overfitting and underfitting criteria), (3) and a single output layer (Nakhaei et al. 2012). All neurons belonging to a layer are linked to every other neuron of the preceding layer (Mosavi 2011). The model is a “teacher training network” (Nakhaei et al. 2012), which shows that there should be a train and a test set. The model validates the data based upon the train set, and once it is done, the test set is used to check how effective the model is (Jangidin 2019). The model sends the signal from the input layer, which passes across the hidden layer to the output layer; in case of differences between obtained and correct output values, the error is sent back (backward propagation), and some minor corrections are made to the weights in all the layers (Nakhaei et al. 2012). The train and test sets are proportioned in this study as 0.70 and 0.30, which is the usual ratio in ANN (Jangidin 2019). Figure 2 depicts a typical ANN three-layer feed-forward model with two hidden layers.

MLP ANN analysis

SPSS ANNs can be used under the MLP or radial basis function (RBF) technique. These approaches are supervised learning, which means they map the suggested relationships in the data (IBM Corporation 2012). Both use feed-forward architectures, which means that data only travels in one direction, from the input nodes to the output nodes via nodes' hidden layer (s). While the MLP procedure can uncover more complex relationships, the RBF procedure is

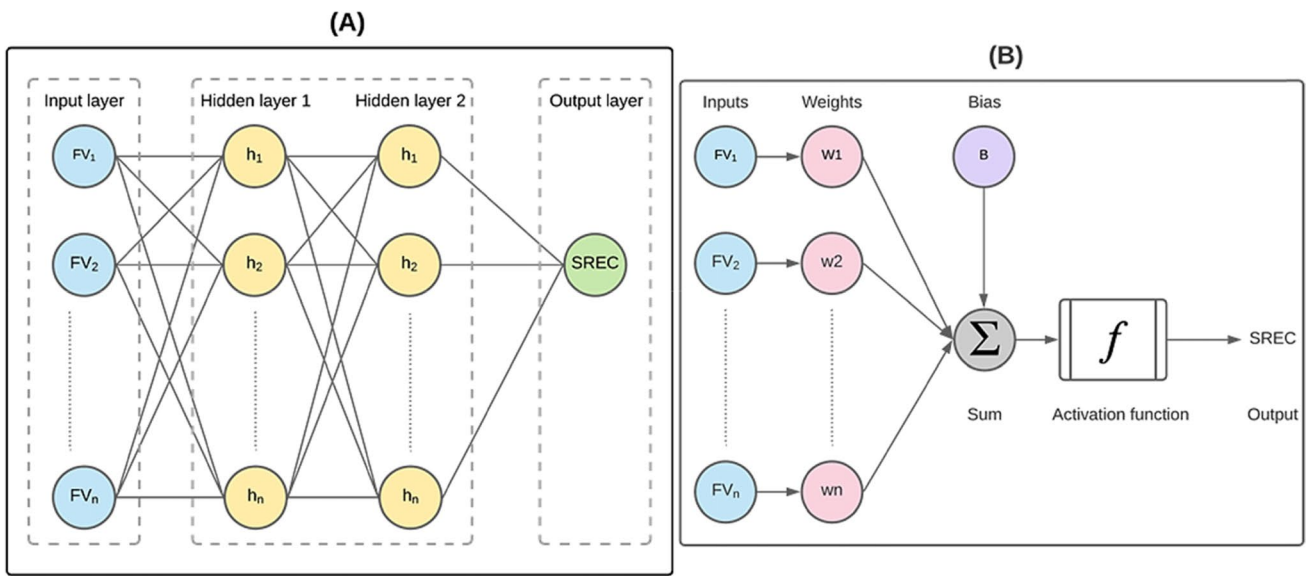


Fig. 2 A typical ANN three-layer feed-forward model with two hidden layers. **A** ANN architecture. **B** Neural activation

typically faster. When the dataset is nonlinear, the perceptron-based model is expanded to a more complex structure, especially MLP (Bekesiene et al. 2021). The MLP allows the usage of nonlinear activation functions (for example, sigmoid or hyperbolic tangent). As a result, the MLP procedure was used in this study to identify important factors affecting China’s SREC. Based on the trial and test basis, the specifications from Table S4 are used for this study to minimize the “sum of squares errors (SSE)” for both training and testing samples (while keeping the model’s over and under-fitting in check). It has been discovered that more than two hidden layers are unnecessary (Bekesiene et al. 2021). Typically, one hidden layer is adequate, but in some cases, the required hidden units must be split across two hidden layers to satisfy the required number of network restrictions (Bekesiene et al. 2021). Supplementary Table S5 summarizes the results obtained using a single-hidden-layer model while keeping all other criteria constant. The following equation can be used to represent the SSE:

$$SSE = D^2 = (O_M - O_R)^2 \tag{7}$$

where D presents the difference between the measured (O_M) and the real (O_R) values. Meanwhile, the relative error (RE) can be presented with the following equation:

$$RE = \frac{|D|}{O_R} = \frac{|O_M - O_R|}{O_R} \tag{8}$$

where $|D|$ presents the absolute difference between O_M and O_R .

Results

Descriptive analysis of historical data

Figure 3 depicts the growth patterns of the various independent variables and the dependent variable SREC, and Supplementary Table S2 presents detailed descriptive statistics. As can be seen, the Chinese SREC has a noticeable, sharp downward trend, with an APR of more than -2.6% . Other factors with a clear downward trend included EFs, CRW, urbanization, and EPOGC. Despite a rapid increase between 1990 and 1993, FDI declined in 1994. In contrast, GDP, GCF, PAs, EPRS, ANE, and GS indicated an overall positive growth trend.

Hypothesis testing with directional PCC and SRCC analyses

PCC and SRCC analyses were used to accept or reject the hypothesized directional relationships between independent variables and the dependent variable of Chinese SREC. The normality tests “skewness and kurtosis” were used to determine whether the data was suitable for the PCC analysis. As shown in Table 2, some variables have values for both tests between the recommended values of 1 and -1 for PCC, while others have values greater than ± 1 . The dependent variable SREC, in particular, had a kurtosis value of -1.70 . To reconcile the normality of some variables and the non-normality of others, we used both the PCC and SRCC for hypothesis testing. Both tests produced roughly the same results in precisely identical directions. Except for

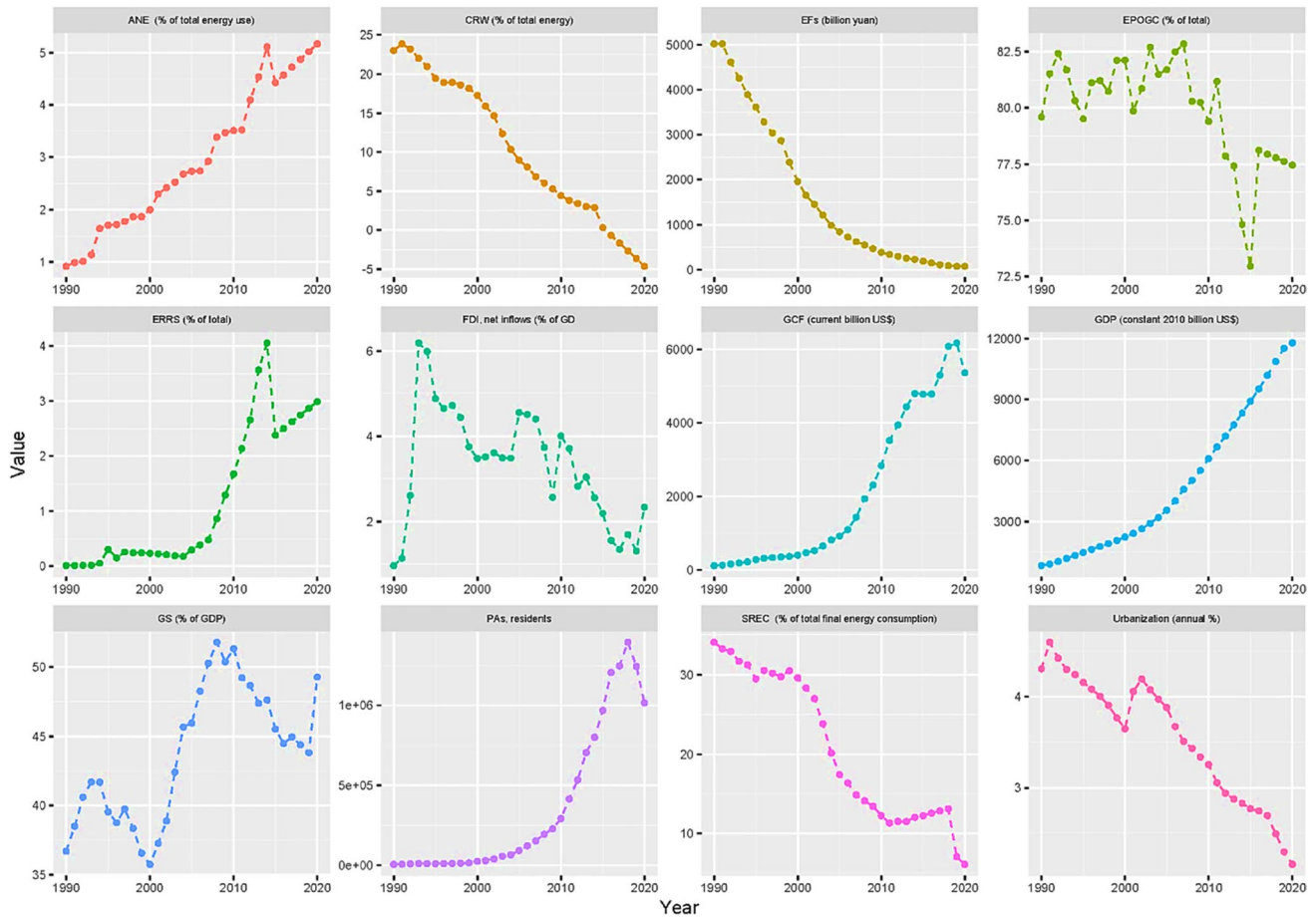


Fig. 3 The historical trend of the selected socioeconomic factors. The author’s construct is based on the World Bank’s “World Development Indicators” and the data from the “National Bureau of Statistics of China”

Table 2 Normality, PCC, and SRCC for hypothesis testing

Items	PCC (r_p)	SRCC (r_s)	Significance $p(1\text{-tailed})$	Skewness	Kurtosis	Sample (N)	Initial hypothesis
FDI	0.36	0.343	<0.05	0.05	-0.50	31	Accept
GDP	-0.907	-0.951	<0.01	0.67	-0.90	31	Reject
GCF	-0.87	-0.948	<0.01	0.72	-1.13	31	Reject
PAs	-0.758	-0.923	<0.01	1.16	-0.18	31	Reject
EFs	0.917	0.951	<0.01	0.87	-0.68	31	Accept
CRW	0.975	0.949	<0.01	-0.02	-1.39	31	Accept
EPRS	-0.827	-0.925	<0.01	0.83	-0.83	31	Reject
EPOGC	0.56	0.605	<0.01	-1.15	1.35	31	Reject
Urbanization	0.9	0.906	<0.01	-0.43	-1.01	31	Accept
ANE	-0.938	-0.956	<0.01	0.22	-1.24	31	Accept
GS	-0.847	-0.737	<0.01	0.00	-1.29	31	Accept
SREC	-	-	-	0.09	-1.70	31	-

FDI, whose PCC and SRCC with SREC were statistically significant at $\alpha = 0.05$, all relationships were statistically significant at $\alpha = 0.01$. The statistically significant (one-tailed) directional relationships between FDI, EFs, CRW,

urbanization, ANE, and GS and the dependent variable SREC were consistent with the hypothesized relationships and were thus accepted for further analysis. However, the directional relationship of the remaining five factors, such



Fig. 4 Results of the ALM analysis with enhanced model stability: **A** model summary; **B** predictor importance (independent variable); **C** component model accuracy; and **D** component model details

as GDP, GCF, PAs, EPRS, and EPOGC, did not match the hypothesis and were thus excluded from further analysis.

The most reliable model selection based on ALM

The ALM model was run to maximize model stability (reliability). In other words, the analysis was carried out to find the most reliable model for the subsequent ANN MLP analysis. Figure 4A shows that the ensemble (mean) model’s accuracy (98.8%) and quality were slightly better than the reference model (98.6%). According to predictor importance, the CRW, ANE, and EFs

were the top three predictors for predicting the values of the target SREC variable. FDI, on the other hand, was the least essential predictor variable. Figure 4D depicts the best model for predicting the value of the dependent variable at the component level. It is clear that model number ten, with an accuracy of 98.7%, is the best model, or, in other words, it presents the best group of predictors for predicting the value of the dependent variable. Model 10 comprises the top five predictors in terms of predictor importance (as shown in Fig. 5B). This model includes CRW, ANE, EFs, urbanization, and GS independent variables.

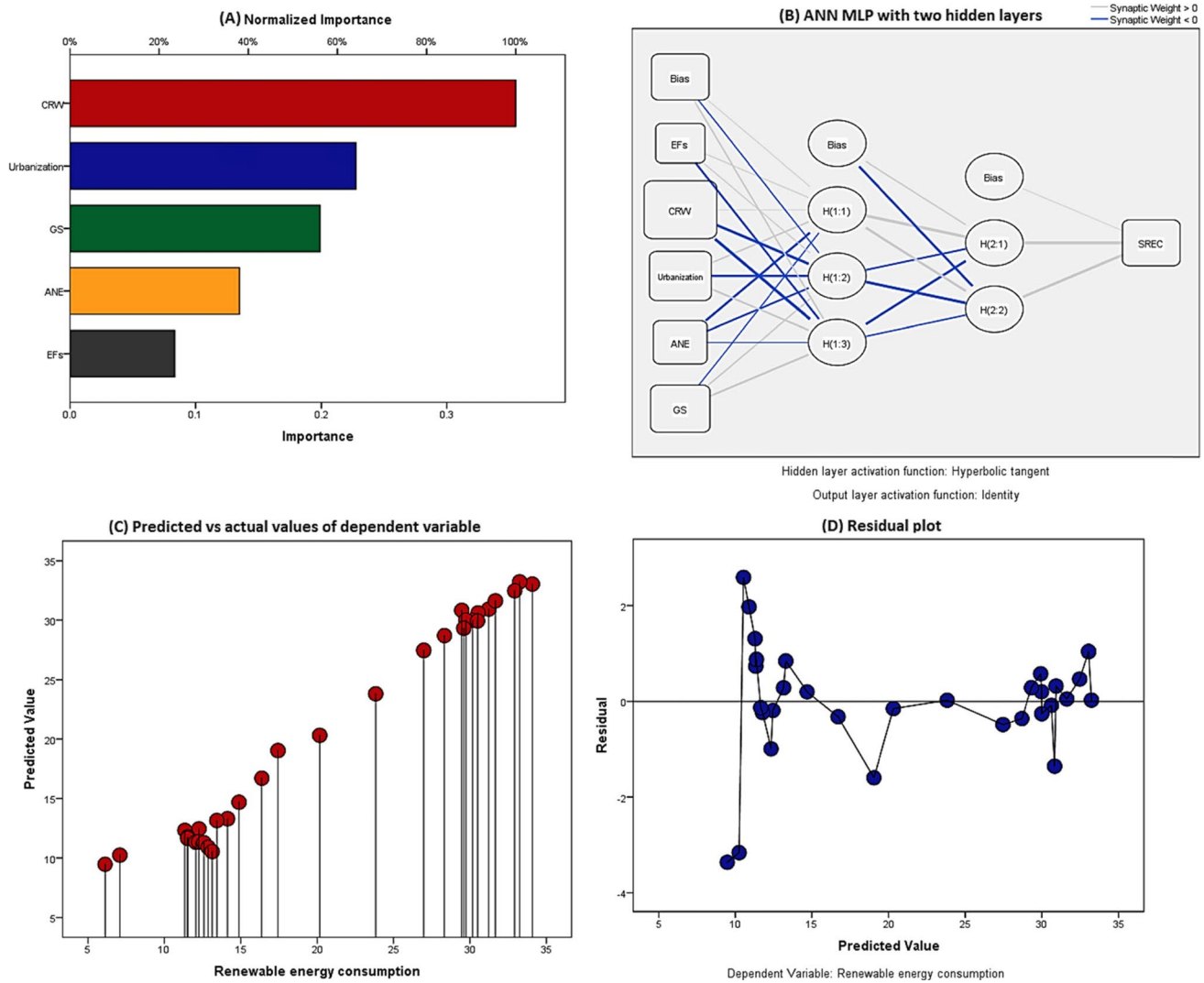


Fig. 5 The ANN MLP analysis of factor importance includes **A** importance and normalized importance; **B** an ANN MLP network with two hidden layers; **C** predicted vs. actual dependent variable values; **D** a residual plot of predicted values

Analysis of factor importance based on ANN MLP approach

The finalized predictors from the ALM analysis were ranked using ANN MLP analysis. The final ANN MLP model was

Table 3 The ANN MLP analysis's model summary (two hidden layers)

Item ^a	Training	Testing
Sample <i>N</i>	20	11
% Sample <i>N</i>	64.5%	35.5%
Sum of squares error	0.105	0.135
Relative error	0.010	0.065

^aError computations are based on the testing sample

chosen with the over and underfitting model in mind. The analysis is summarized in Table 3. The training and testing sum of squares errors and relative errors were not excessively large, indicating that the model was not underfitted. At the same time, the difference between training and testing errors is not very large, meaning that the model is not overfitted. Figure 5A depicts the independent variables' importance and normalized importance values.

Meanwhile, Fig. 5B depicts the neural network, with darker colors indicating more significant relationships. Figures 5C and D show the plots for actual vs. predicted values and the residual plot. The most important predictor of the Chinese SREC was CRW, with a 100% normalized value (0.355 importance score out of a total of 1). CRW was followed by urbanization, GS, and ANE,

with normalized importance scores of 64.2%, 56.1%, and 38.0%, respectively. According to the ANN MLP analysis, EFs was the least important, with a normalized importance score of 23.5% (0.083 importance value).

Discussion

1. This study concentrated on the factors influencing the decline of SREC in China's total energy consumption. Many previous studies have estimated various aspects of REC, such as economics and finance (Akadiri et al. 2019; Anton and Nucu 2020; Rahman and Velayutham 2020), the environment and carbon emissions (Destek and Sinha 2020; Sharif et al. 2020; Yuping et al. 2021), and policy and politics (Mahmood 2020; Uzar 2020; Chen et al. 2021). However, few studies have focused on identifying the main drivers of SREC growth, particularly the drivers of China's decreasing SREC. Our study addressed this critical research gap by identifying the key factors contributing to the decline of Chinese SREC using techniques such as PCC, SRCC, ALM, and ANN MLP.
2. The validated finalized factors (FVs) were considered for the ANN MLP analysis based on the correlational and ALM analyses. The availability or growth of CRW with a 100% normalized importance (0.355 importance score), according to our findings, was the most critical factor in the growth of Chinese SREC. Previously, several studies examined the relationship between CRW and CO₂ emissions in general (Ben Jebli and Ben Youssef 2015; Ali et al. 2021) and country-specific CO₂ releases (Ben Jebli et al. 2015; Ben Jebli and Ben Youssef 2019). Although the previous research has identified CRW as an essential component of the renewable energy mix (Ali et al. 2021), few studies have looked at CRW as a factor in the growth of renewable energy in general, specifically SREC. As a result, CRWs and their role in the growth of renewable energy in general, particularly SREC, remain an unexplored area. That also increases the significance of our CRW findings for policy and future research issues. Based on our findings, it is recommended that the Chinese government and private investors invest more in CRWs to address China's decreasing SREC.
3. Urbanization was the second most influential factor on Chinese SREC, according to ANN MLP, with normalized importance of 64.2% (importance = 0.228). Urbanization is now well established to increase energy consumption (Avtar et al. 2019; Nuta et al. 2021). For China, urbanization contributed 94.1% of REC in 2001 and 11.8% in 2012, implying that urbanization increased REC (Yang et al. 2016). Our directional relationship analysis found a positive relationship between urbanization and Chinese SREC. In general, the urban population in China is more aware of the health effects of pollution than the rural population (Yang 2020). Thus, educating the newly migrated rural population can amplify the positive impact of urbanization on the Chinese SREC.
4. GS was the third most important factor in determining the Chinese SREC, with a normalized importance score of 56.1% (importance = 0.199). A negative relationship between GS and Chinese SREC was hypothesized and tested via the directional correlation analysis. There is little literature on the relationship between GS and REC. As a result, it is not easy to compare our findings to those of other related studies. However, using energy consumption and savings as a proxy, we can see that previous studies have also reported a negative relationship between energy consumption/energy efficiency and gross (or net) savings (Faisal et al. 2016; Ziolo et al. 2020). The general public and banks must be encouraged to eventually use the savings on long-term renewable energy production and consumption projects (e.g., solar panels, small wind turbines, and solar water heaters).
5. ANEs are sometimes taken as a substitute for renewable energy. However, ANE presents energy consumption sources (such as natural gas) that are less polluting than coal and oil. Unlike renewable energy sources, these resources are not limitless (Sol-Up 2021). Our findings revealed a strong inverse relationship between the Chinese ANE and SREC. As per our ANN analysis, ANE, with a 38% normalized score (importance = 0.135), was the fourth most crucial factor in China's SREC. Although ANEs are generally cleaner sources of energy than traditional fossil fuel sources (Sol-Up 2021), primary ANEs such as natural gas are far dirtier (in terms of lifecycle GHG emissions) than primary renewable energy sources such as biomass, hydropower, wind, and solar (Ritchie 2020). As a result, it is suggested that the government prioritize increasing the share of REC over ANE, which has a negative relationship with SREC. That can be accomplished by redirecting funds and investments from ANE to renewable energy production and consumption.
6. EFs refer to the total investment in education financing, including public school funding, private school funding, contributions, tuition, and other educational costs (National Bureau of Statistics of China 2020). Our findings indicate a positive correlation between the EFs and the Chinese SREC. Additionally, ANN MLP analysis revealed EFs as the least influential factor determining China's SREC value. As a result, EFs' direct impact

on Chinese SREC will be minimal compared to other factors. However, EFs can aid in developing technical know-how (or personnel) and innovations related to the production and consumption of renewable energy. Furthermore, EFs can indirectly affect China's SREC by increasing public awareness of environmental issues. Consequently, the Chinese government, private institutions, and non-governmental organizations must increase their investment in EFs in the coming years.

7. Many previous studies have shown that GDP has a positive impact on REC in various regions such as the EU-28 (Akadiri et al. 2019; Sahlian et al. 2021), South Asia (Rahman and Velayutham 2020), and the OECD (Dogan et al. 2020). Furthermore, some studies have linked economic growth and REC in China (Fan and Hao 2020; Vo and Vo 2021). In the case of China's SREC, however, our findings revealed a statistically significant strong negative linear relationship between SREC and GDP. Similarly, it has been reported that the GCF has a positive impact on Chinese REC (Abbas et al. 2020). Our findings, however, revealed a negative correlation between China's SREC and GCF.
8. Furthermore, based on economic theory and intuition, PAs (Tee et al. 2021), EPRS (Ma and Xu 2021), and EPOGC were hypothesized to have a positive relationship with Chinese SREC. However, our findings show that these variables and SREC have inverse correlations. The main reason for this disparity between previous findings and our results is that previous literature has mainly focused on REC in China and other regions. Over study, however, focused on the relatively understudied but critical SREC, which is constantly declining in comparison to China's constant growth in REP and REC. Our findings can thus shed new light on the relationships between key factors and SREC growth in general. Our results can be instrumental in mitigating the critical problem of China's declining SREC.

Conclusions

COVID-19 has provided a reprieve to the global atmosphere by halting the carbon release rate. However, post-COVID-19 sustainable growth options are required to capitalize on COVID-19's positive environmental gains (Sajid and Gonzalez 2021). Increasing the SREC is one such critical factor for environmentally sustainable growth. China is the world's largest source of carbon emissions. China is also the world leader in REP and REC. Over the last decade, China's REP and REC have increased by more than 13% (estimations based on

Statista (Jaganmohan 2021e)) and 23% CAGR, respectively, indicating that the country is on track to reduce carbon emissions and achieve net-zero emissions by 2030. However, China's rapid growth in REP and REC comes with a catch. The Chinese SREC has been declining in recent years. That implies that all efforts to promote the REP and REC may not yield the desired results (in terms of GHG emissions reductions). And it may be pointless if the Chinese government cannot raise the SREC in the coming years. Despite the gravity of the situation, few studies have focused on determining the underlying causes of China's declining SREC. Furthermore, most studies that examine the drivers of REC use traditional regression approaches. Our study filled these research gaps. Based on previous literature and economic theory/intuition, our study (1) identified several factors that could influence the Chinese SREC. (2) Furthermore, in contrast to traditional regression approaches, this study used the ALM and ANN approaches, which have some additional advantages (see "Background" and "Methods"). Our findings revealed that the SREC, EFs, CRW urbanization, EPOGC, and FDI have historically shown a decreasing growth trend. However, indicators such as GDP, GCF, PAs, EPRS, ANE, and GS showed an upward trend. The statistically significant PCC and SRCC analyses confirmed the hypothesized relationships between the dependent SREC and the independent variables FDI, EFs, CRW, Urbanization, ANE, and GS. While the directional relationships hypothesized between the dependent SREC and the independent GDP, GCF, PAs, EPRS, and EPOGC were rejected. The ALM analysis, which sought to identify the most reliable model, revealed that a model comprised of the five predictors of EFs, CRW, urbanization, ANE, and GS with an accuracy score of 98.7% was the most reliable. As a result, the FDI factor was not included in the subsequent ANN MLP analysis. Finally, the ANN MLP analysis revealed that the CRW (100% normalized importance) was the most critical factor for the Chinese SREC. Urbanization (64.2%), GS (56.1%), and ANE (38%) followed it. EF (23.5%) was the least important factor according to our ANN MLP analysis. By identifying and ranking the key factors contributing to China's declining SREC, our research can help policymakers improve the Chinese SREC. Furthermore, our study's key factor identification method can be used or modified in future research. Based on our findings, utmost priority should be given to improving CRW's availability. Meanwhile, based on the remaining validated factors' importance ranking, the Chinese government and private investors can prioritize their investments to help slow the fast-shrinking rate of Chinese SREC.

Appendix

Table 4

Table 4 Categorization and summary of relevant literature on the socioeconomic aspects of REC

Category	Reference	Study	Main methods
Economics and finance	Rahman and Velayutham (2020)	The relationship between “renewable and non-renewable energy” consumption and economic growth in a panel of five South Asian nations from 1990 to 2014 was examined in this research	“Panel Fully Modified Ordinary Least Squares (FMOLS) plus panel Dynamic Ordinary Least Squares (DOLS)“
	Akadiri et al. (2019)	The study examined a positive and substantial long-run relationship between environmental sustainability, “renewable energy” use, and economic development in the “EU-28” countries	“Autoregressive distributed lag (ARDL)”
	Anton and Nucu (2020)	The article analyzed the impact of “financial development” on using “renewable energy” sources in the EU’s 28 member states	“Fixed-effect panel model”
	Fan and Hao (2020)	The study calculated the connection between “renewable energy” usage, GDP, and foreign direct investment in China	“Vector error-correction model (VECM) and Granger causality test”
	Dogan et al. (2020)	The study calculated the economic effect of “renewable energy” use on the economies of “Organisation for Economic Co-operation and Development (OECD)” countries	“Panel quantile regression”
	Godil et al. (2021a, b)	This study examined the relationship between India’s “financial development, R&D expenditures, internationalization, institutional quality, and energy usage” using quarterly data from 1995 to 2018	“QARDL regression”
Environment and carbon emissions	Yuping et al. (2021)	The authors quantified the dynamic impacts of “renewable energy usage, globalization, economic growth, and non-renewable energy” usage on Argentina’s CO ₂ emissions from 1970 to 2018	“ARDL regression”
	Destek and Sinha (2020)	This study assessed the validity of the Environmental Kuznets Curve hypothesis of environmental footprint, taking into account the effect of “renewable energy” use and several other socioeconomic aspects	“FMOLS and DOLS”
	Sharif et al. (2020)	The authors re-examined the effect of “renewable and non-renewable energy” use on Turkey’s environmental footprint	“QARDL regression”
	Alola et al. (2019)	The research calculated the connection between ecological footprint, real GDP, openness to trade, birth rate, and “renewable and non-renewable energy use.”	“ARDL regression”
	Nathaniel and Iheonu (2019)	The authors investigated the impact of “renewable and non-renewable energy” use on Africa’s CO ₂ emissions	“Augmented Mean Group (AMG)”
	Sarwat et al. (2022)	The authors validated the EKC hypothesis after considering “natural resources, renewable energy sources, and globalization”	“Method of Moments Quantile Regression (MMQR), FMOLS, DOLS, and heterogeneous panel causality test”
	Godil et al. (2021b)	The authors used annual data from 1990 to 2018 to examine the impact of “economic growth, technological innovation, and renewable energy” on CO ₂ emissions in China’s transportation sector	“QARDL regression”
	Khan et al. (2021b)	This study looked into carbon-free economic development and international tourism in developed countries using improved logistics infrastructure and “renewable energy”	“Fixed effect, Random effect, and Ordinary least square regression (OLS)”
Policy and politics	Uzar (2020)	The study looked at the impact of institutional quality on “renewable energy” used in 38 different nations	“ARDL-PMG (Pooled mean group estimation)”
	Chent et al. (2021)	This study examined the role of democratic institutions in consuming “renewable energy”	“Panel threshold model”
	Mahmood (2020)	This study investigated the effects of education and economic development on Saudi Arabia’s “renewable energy” usage	“Cointegration and Bound testing values”
	ÖZÇİÇEK and AĞPAK (2017)	The authors evaluated the impact of education on using “renewable energy”	“Pseudo Poisson maximum likelihood method”
	Yang et al. (2016)	The study looked at the effect of Urbanization on the increase of “renewable energy” use	“Logarithmic mean Divisia index”

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Data availability The socioeconomic data related to various factors is available freely from the World Bank's data bank (<https://databank.worldbank.org/source/world-development-indicators>) and from the National Bureau of Statistics of China (国家数据 (stats.gov.cn)). Furthermore, data related to the main estimations is provided within the manuscript's tables and figures.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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