Energy for sustainable development, factor productivity and technological progress in the manufacturing process of China's textile sector

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ABSTRACT

Textile manufacturing plays an imperative role in the economic development of several countries. Among the world's top ten textile exporters, China reported positive growth. To achieve factor output, substitution and technological progress among energy and non-energy factors, the current study uses the trans-log production function from 1990 to 2022 to cope with continuing energy-economy-related possibilities. The empirical findings confirm that all the energy inputs are substitutes in which energy and capital play a significant role in the production process. The factor's substitutability provides a rising trend between labor-energy and capital-energy with average elasticities of 0.50 and 0.67, showing a sign of increasing capital and labor to energy for further development. The factor's technological progress falls between -1.89 and +1.91, in which capital-energy and labor-energy show positive convergence; however, labor presents substitutability with technological advancement. Finally, textiles determining the future of fashion, sustainability, and functionality as technology should align with environmental and social goals in which energy substitution possibilities are the best fit.

Keywords: Textile manufacturing, inter-factors, trans-log production function, technological progress, China

1. Introduction

Energy plays an imperative role in the global economy because numerous goods and services normally rely on energy consumption. The social, sustainable and economic progress of industrializing nations requires sustainable energy. The textile sector is a key contributor to different countries, encircling small and large-scale processes globally [1]. Global fiber production has grown quickly with the increasing utilization of textiles and clothing. The global textile market size arrived at 985 billion US$ in 2022, which is expected to arrive at 1268 billion US$ by 2028 [2]. Hence, due to the changing behavior of consumers, population growth, technological progress, and managerial regulations are the main factors pushing the market.

China has ranked as one of the world's biggest manufacturers since 2010, and it is the only country contributing a key role in industrial groups [3]. Also, five of China's twenty-six manufacturing industries are the world's most advanced industries, of which the textile industry is the leading one. China's textile sector is the biggest in the world in total production, trade and exports, with a productivity of 58 million tons annually in the fiber types alone, adding for higher than 50% of the total world, with textile and garment exports of more than a 3rd of global shipments. Thus, this sector adds practically to motivating the market, engaging labor, growing income, quickening urbanization, and encouraging societal advancement.

Moreover, due to rapid development and economic sustainability, the Chinese textile sector has had a continuous growth in energy consumption, capital investment, and output. As per the World Development Indicators [4], the textile industry of China added 9.99% of the value-added of the total manufacturing industry in 2022, presenting that the textile sector plays and an imperative role in the manufacturing process. Meanwhile, the textile sector has some challenges (i.e., low-carbon energy efficiency, pollution and energy resources) in environmental regulations. Regarding economic progress, the energy demand for textiles is gradually rising, leading to possible deficits in the overall quantity of energy. For this, China's textile sector will certainly face strong energy limitations [5]; thus, energy efficiency, technological progress, skilled labor, and capital development are becoming priorities. Under production processes and economic development in different sectors, several studies paid attention to the possibility of energy, environment and productivity [6-8]. Assessment of energy efficiency, factor substitution and their differences in technological progress is the major goal within the textile industry. Due to the severe limitations of unusual energy sources and ecological issues, obtaining energy productivity has become progressively serious for textile manufacturing in industrialized countries. Energy is an important input for every process along with the industrial manufacturing chain of textiles because of a lot of plants, which together utilize a substantial energy amount. Moreover, it is an effective process for encouraging economic and environmental sustainability in China [9]. Thus, it is clear that energy-efficiency policies should be performed in the textile industry, minimizing energy utilization and energy imports.

Several studies have examined energy, economy and environmental issues in different aspects; for example, Lin and Bai [10] employed the global meta-frontier method to examine China's textile sector using fossil fuels and carbon emissions from 1985 to 2016; Tushar et al. [11] used the Intuitionistic fuzzy technique for Bangladesh's textile sector using the energy price and economic sustainability factors; and de Oliveira et al. [12] used the supercritical carbon emissions and economic development for a sustainable textile future in the United States. Though, the total factors to encourage energy efficiency seeing the energy stage of textile manufacturing, especially in the developing countries to attain sustainable development in the current literature. Furthermore, studies on China's textile sector's inter-factor and inter-fuel substitution have achieved little attention. To the best of our understanding, there are only a few researches on China's industries; for example, Smyth et al. [13] for the iron and steel sector; Lin and Wesseh [14] for China's chemical industry; Li and Lin [15] for carbon intensity and CO_2 emissions as a whole; Lin and Tan [16] for the light industry; and Xie and Hawkes [17] for the transport industry. However, the current study contributes to the literature by examining inter-factor and inter-fuel substitution possibilities in the textile sector of China.

As per Amankwah-Amoah [18], technological advances have escorted a new era for businesses and governments. This is because much of the world is associated with rapid growth and promising areas of business [19]. Similarly, the Chinese government made a new assertion in 2015 in the Paris Agreement to lessen carbon intensity by 60-65% in 2030 compared to 2005 [20]. (i) To achieve this goal, the government has made a series of measures, such as fuel substitution possibilities, technological advancements and renewable energy technologies (RETs), to sustain the environment and economic growth. Therefore, the authors proposed the need for sector-specific goals, which presents in current research. (ii) Regarding policy perspectives, it is compulsory to follow a comparable line of studies as mentioned above, which will analyze factors substitution possibilities of factors in a specific sector, mainly those that have huge energy intensity and value-addition in the country's economy, like the textile sector. This will not only aggregate bias but also assist as an imperative base for sectoral-related policies and predictions. Also, with the growing demand for energy-economic inputs, as the textile sector rises and extends, predations are necessary to be done so as to compare current demand with the essential supply. This study not only estimates the overall energy and non-energy input trends, but also measures the degree of inter-factor and inter-fuel substitution possibilities. Also, this might be useful for China's textile manufacturing process and to see the factor's contribution to the cost of growth. (iii) This study also estimates that only a few scholars have examined the effect of energy and economic factors in China, as stated above, on different sectors. Those studies had little study duration by 2016; however, a recent study used the most current data from 1990 to 2022, applying different variables, such as labor, capital, energy and output of the textile sector. These factors (i.e., energy and non-energy) investigate the country's efficiency and technological progress among these inputs. Therefore, study applied a trans-log production function, which is more suitable for analyzing the economy of a country, energy, technology, and future policies. For instance, Christensen et al. [21] proposed that this function is more appropriate in estimating factor's elasticities, substitution and technological progress, which was further employed by several authors (e.g., Kim [22]; Pablo-Romero and Gómez-Calero [23]; Lin et al. [24]). Finally, based on these backgrounds, the present study supports contributing to the literature regarding the Chinese textile sector's energy and economic framework, which has not been discussed in previous studies.

Section 1.1 presents a summary of China's textile industry. Section 2 provides the relevant literature and gaps. Section 3 provides data and variables. Section 4 provides a method and measurement process. Consequences and discussion are given in Section 5. Conclusion and policy recommendations are given in Section 6.

1.1. Summary of China's textile industry

The textile manufacturing plays a dynamic role in the economic development of numerous developing countries. In order to achieve energy proficiency and sustainability, technology is decisive for the textile sector to achieve national and international targets. China has been the world's huge textile manufacturer and exporter since 1994 [25], which describes that China's fiber production increased by greater than 50% of the worldwide fiber production [26]. Therefore, this industry is known as the traditional support industry in China because it plays an imperative role in increasing employment, urbanization, economic development, and social development. During the 14th Five-Year Planning period, for instance, 2021-2025, the value-added, energy, labor productivity, exports, research and development (R&D), manufacturing, and CO_2 emission reduction are the major concerns, as described in Table 1.

Table1

China's textile sector and its performance under the Five-Year Economic Plan.

Major indicators	Goals for 2021-2025	Conclusions
Annual industrial growth	Previous goals were to achieve 6-7% annual growth, which was also influenced by COVID-19 and declined by 4520 billion renminbi in 2020. However, a reasonable growth was achieved.	The COVID-19 epidemic was the major factor in stopping huge potential, which declined industrial energy consumption by more than 18%.
Fiber manufacturing	Fiber arrived at 58 million tons in 2020, which was estimated at 50% of the world's productivity. The achievement was estimated at more than 50%.	China has concentrated on increasing the textile size and industry, including its fiber production in the coming five years.
Annual labor productivity	Planned to increase 8% yearly, which is seen as faster growth during current times.	China's textile industry is going to be more mature with the improvement of labor productivity; hence, it needs more investments.
Textile export	Textile exports arrived at 32.9% of the total world textiles, which is expected to increase by more than 30% of the world during 2025.	It expects to lessen textile export share in the world and plans to sell a major share in the domestic market in the coming five years.
R&D expenditure	Increased from 1% to 1.3% in the current planning period.	Planned to raise the R&D budget in each planning period to achieve target, quality and industrial upgrades.
Manufacturing recycled fiber	11.3% of fiber was recycled during 2015, and it is expected to manufacture recycling by 15% in the current planning period.	It will concentrate more on the circular economy, value-added and environment.
Carbon mitigation	It was not mentioned; however, it declined by 18% aggregately during the planning period.	Trying to focus on building less pollutant infrastructure based on recycled material and China's climate change policy.

As per the China Statistical Yearbook [27], the particular figure of energy consumption in the textile sector of China was 3034 10^4tec in 1990, while arriving at 3020 10^4tec in 2000. After that, it rapidly increased to 7268 10^4tec in 2022. Since 1990, textile energy consumption has grown by 139.55%. Thus, the annual average growth of energy use grew by 3.18%, which increased the value-added of the textile sector by 48.55% during 1990-2022. Figure 1 shows the sudden growth of textile energy consumption after 2000. Together with the invaluable chance to enter the World Trade Organization, the energy consumption rate in the textile sector of China continued to grow. However, a decline in energy utilization seemed during 1996-2000, and similarly, there was little decline in value-added, which was majorly because of the recession in which industry efficiency was reduced by 1.8% annually. This is also consistent with the previous findings of Lin and Moubarak [28].

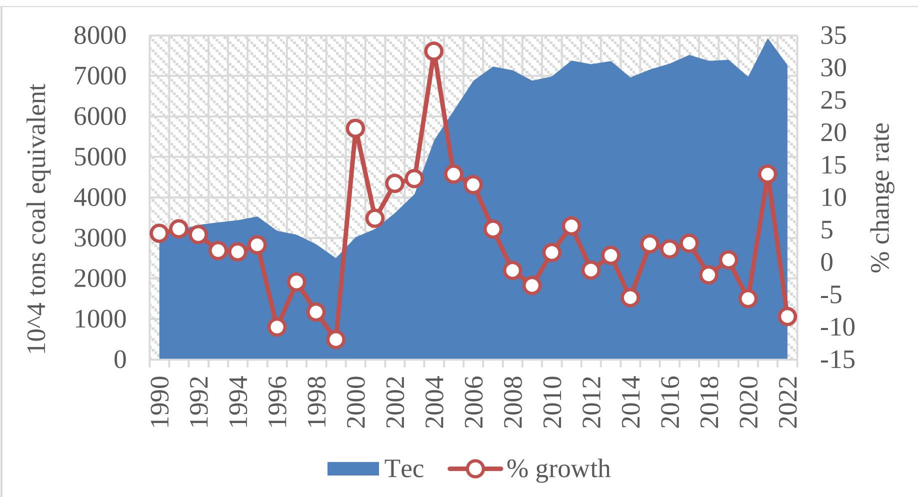

Fig. 1. China's textile industry and its annual growth rate from 1990 to 2022.

Regarding energy structure, China's textile sector is the major consumer of natural gas and electricity, which have contributed 91.45% and 8.26% during 2022. However, coal and oil consumption in the textile sector were reduced by 0.99%, as shown in Fig. 2[1]. Thus, overall natural gas consumption plays a vital role in the manufacturing process of the textile sector. Recently, this sector has been in a transformation process with huge international proficiency and investments. Finally, textile products are becoming more and more cultured in the current era, which will substantially continue to impact the energy mix in the future.

[1] The textile sector consumes several fuel data, which is not continuously available during the estimated period. However, based on overall energy, we have analyzed the sectorial production. It includes, such as EC, electricity consumption; NC, natural gas consumption; OC, oil consumption; CC, coal consumption.

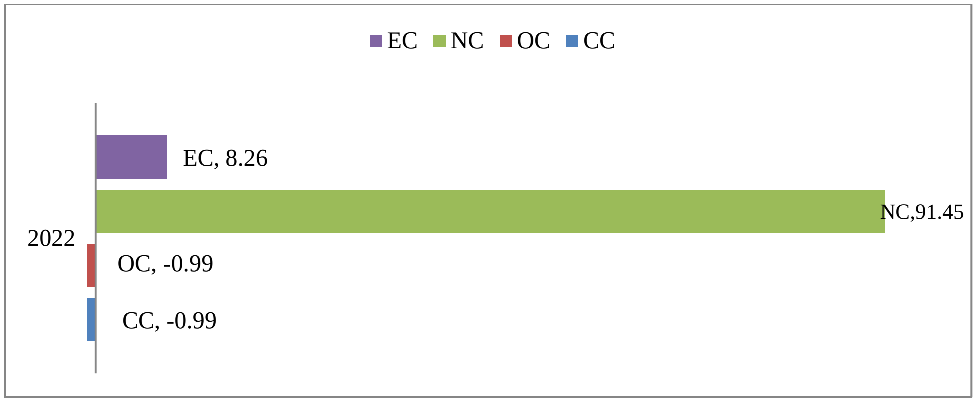

Fig. 2. Textile fuel consumption during 2022. (Unit: %).

2. Review and research gaps

Energy consumption and its efficiency are becoming very important; the studies on various factors impacting energy security and conservation with various methods are found in abundance. Old-styled energy efficiency factors have failed to consider the impact of individual inefficient market factors on energy-related inputs, such as energy substitutability influenced by a relative price variation, which also impacts energy productivity. Using the ordinary least squares (OLS) method, the endogeneity issues may arise if energy efficiency is applied as the input variable. Recently, study found that several scholars inside and outside China have tried to investigate China's energy efficiency by employing various techniques. For example, Zhang et al. [29] proposed that China's high-tech industry is significant impacted by the digital economic development under the improvement of total factor productivity; Santos et al. [30] analyzed that the enhancement in energy efficiency can majorly be ascribed to the enhancement in total-factor productivity in Portugal; Chanda and Umetsu [31] estimated the index of total-factor productivity of Agro-industry by using Malmquist index method for Zambia; Lin and Wesseh [14] employed the trans-log production model to check inter-fuel substitution for China's chemical industry and then divided energy into several aspects, such as technological progress and technical efficiency; Zhao and Lin [5] assessed the productivity of China's textile industry using Biennial Malmquiste-Luenberger productivity index under carbon constraints from 2000-2012; Lin et al. [7] used the co-integration and scenario analysis to check China's technology and intensity from 1990-2015 to check environmental variations. Similarly, few scholars employed the production function to investigate national level energy substitution under specific constraints; for instance, Zhang and Raza [48] analyzed the traditional energy substitution with low-carbon energy in Saudi Arabia from 1990-2023 under carbon-neutrality plan 2060, Zhao et al. [49] examine the impacts of electricity demand with power energy substitution in China, Williams and Yang [50] examined the fossil fuel substitution in the cement production process with solar energy to mitigate carbon emissions in the US, China and Brazil by employing simulation method, and Raman et al. [51] employed the multi objective functions for investigating energy sources to fulfil the electricity demands of a residential community. These studies have tried to check the substitution possibilities under low-carbon transition under technical and economic consideration for a particular sector or a country. However, this study designed to sightseeing and identifying the most effective pathways for a most energy consuming sector in China under the degree of inter-factor and inter-fuel substitution possibilities. Thus, this study will provide useful information into the possibility for supportable practices and energy productivity enhancements in the textile and relevant industrial sectors.

Based on past and appropriate literature, the subsequent research gaps were found: first, several studies have investigated the results of energy efficiency using popular factors in measuring textile efficiency; however, no one has estimated inter-factor substitution and technological progress in the textile sector in China. Second, research couldn't find an analysis based on inter-factor substation, especially in the textile sector, that can help to investigate the energy-economy, input elasticity, output substitution, and technological progress from 1990-2022. However, generally, the existing literature falls short of data formulation, limited studies for multiple countries, and driving factors with the lowest technological impacts. Thirdly, the current studies failed to promote factor's efficiency and how they support to economic sustainability. Thus, the current research goals to fill these shortcomings as: what are the production factors that are promoting the energy and non-energy factors in textile manufacturing, especially in a huge penetrating economy like China? How are these factors interrelated with each other in terms of substitution, output and technical soundness? Thus, it is clear evidence from the past literature review that no research has certainly been completed on China employing the energy and non-energy factors and their technological progress in the current era. Moreover, this study on China's textiles just not only fills the study gap on inter-factor substitution but also provides important energy and sustainability policies, which are useful for China's future.

3. Variables and data description

This study uses the three major factors, i.e., output, labor, capital, and textile energy consumption from 1990-2022. The sample period was taken based on maximum availability of data, which primarily structured for China's textile sector, which providing reliable information of related inputs. All the energy-related information is collected from the China Statistical Yearbook, which is based on several fuels, as shown in Note 2[2]. Output, labor and capital data are also composed of data from the China Statistical

[2] Energy consumption in the textile sector of China.

Textile fuel consumption	Fuel components
Coal consumption	Coal and coke
Oil consumption	Crude oil, gasoline, kerosene, diesel oil and fuel oil
Natural gas consumption	Total natural gas
Electricity consumption	Total electricity

Yearbook, while data concerning Gross Capital Formation (GCF) is collected from World Development indicators. The data relating to energy were originally collected in 10^4 tons of coal equivalents (tce). The data related to capital, GCF and output are collected in billions of dollars, while data relating to labor is transformed into billions. In respect of selection of energy and non-energy factors, the technological progress enhances efficiency at the micro and macro levels. The employed variables in the study under theoretical relationship between output and inputs serve as the best option. It measures the substitution possibilities between energy and non-energy factors that establish a definite theoretical relationship between them. Against this background, it could be said that the present study adds to literature not only in terms of textile sector, but also output efficiency of other sectors. Hence, the employed variables assist as the basis for future study to be done. Data on different energy and non-energy factors, including mean, median, maximum, minimum, std. dev., skewness, kurtosis, and units are provided in Table 2. In addition, the pictorial representation of all the variables is presented in Fig. 3, which presents that all the variables correlate.

Table 2
Data description.

Variables	Capital	Labor	Textile energy consumption	Output
Mean	7.0771	-0.293	8.530	7.979
Median	7.001	-0.256	8.836	7.920
Maximum	8.950	-0.246	8.978	9.791
Minimum	4.814	-0.435	7.825	5.888
Std. Dev.	1.370	-0.060	0.404	1.292
Skewness	-0.100	-1.143	-0.347	-0.106
Kurtosis	1.537	2.866	1.318	1.603
Abbreviation	k	l	tec	y
Unit	Billion $	Billion	10^4tec	Billion $
Observations	33	33	33	33

Note: all measures are logarithmic

In order to avoid the biases in the data, study converted all data into possible and equal units, and then converted all data into natural logarithmic form, which may stabilize the variance and thus improve the statistical properties. To evade the spurious outcomes of further elasticities of substitution, several transformations of the dataset were made. To remove the impact of inflation, we estimated output and capital stock at constant prices (2015). However, 1990 is the base year while 2022 is considered as current year. This measurement process is important for the parametric analysis, which is consistent with Raza et al [32]. Thus, based on the analysis, the perpetual inventory method was employed, as followed in Eq. (1).

$$K_t = K_{t-1}.(1-\delta)+I_t \quad (1)$$

Where K_t is the present capital stock, K_{t-1} is the previous capital stock, δ is the depreciation rate of capital, I_t is the capital stock present investment, and t is the time.

As per Smyth et al. [13] and Lin and Wesseh [14], the study considers that the δ for the China's transport and chemical sector is 5%; hence, suppose that it is logical to employ the similar capital δ rate in China's textile sector. As per the Chinese National Bureau of Statistics, the fixed asset of depreciation rate for enterprise is 5.5% and the loan interest rate between 3 and 5 years is 5.58% [57]. Thus, we suppose that the annual depreciation rate for Chinese textile industry is 5%. Thus, the base year capital stock (K_0) can be assessed as follows in Eq. (2).

$$K_0 = I_0/(g+\delta) \tag{2}$$

Where g expresses the average increase of capital expenditures from 1990-2022, and I_0 implies the capital expenditure of textiles in 1990.

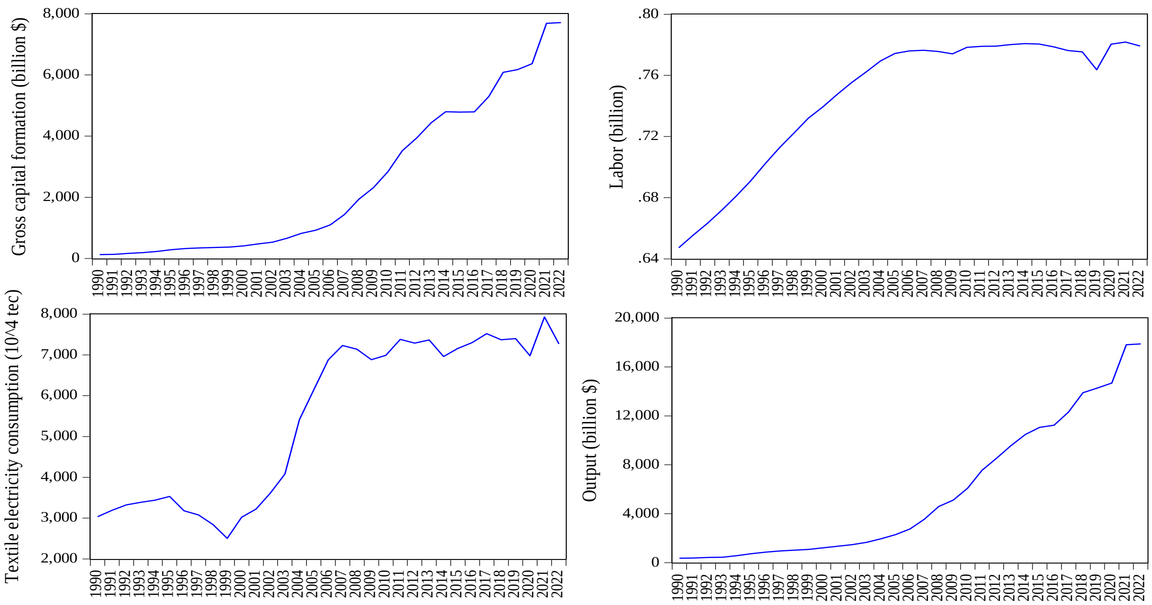

Fig. 3. Plot of main variables from 1990-2022.

4. Method and estimation process

To check the elasticity of substitution and output of various factors, different scholars have chosen properties of cost and production function, for example, Hall [46] for OECD countries; Serletis et al. [33] for the United States; Bölük and Koç [34] for Turkey's manufacturing industry; Lin and Tian [16] for China's light industry; Lin and Atsagli [35] for South Africa; and Raza and Lin [36] for Pakistan's renewable energy substitution. Thus, study found mixed results related to inter-factor and inter-fuel changeover potentials in different republics. Hence, this study employs the second-order Taylor valuation series, which is known as trans-log production function [37]. This function aims to investigate the relationship between inputs and outputs at a particular point. Moreover, it is the process where functional forms levy no limitations or restrictions on the production process. Given that the marginal rate of technical substitution in China may be impacted over time, it is made-up that technical distinction is non-neutral and scale-changing. Therefore, to see the productive factor's calculation, the specified general production function is as in Eq. (3):

$$\ln Y_t = \ln \beta_0 + \sum_i \beta_i \ln A_{it} + \frac{1}{2}\sum_i \sum_j \beta_{ij} \ln A_{it} \ln A_{jt} \tag{3}$$

Where Y_t signifies output, β_0 specifies the technical knowledge state, β_i and β_{ij} expresses technologically determined constraints i and j, A_{it} and A_{jt} shows the inputs i and j, and t is time. $\ln$ is the natural logarithm. Selecting the Chinese textile sector, the basic assumption is that there is a dual differentiable aggregate trans-log production function linked with the labor, capital, and energy inputs. As per Pavelescu [38], this process enables one to evade the imposition of molds, i.e., perfection or perfect substitution of given inputs. Moreover, quadratic terms allow for nonlinear associations between these factors. Therefore, these assumptions made the trans-log production function useful to many scholars because of its elasticity as compared to other techniques. Based on inter-factors, the function of China's textile sector can be stated as in Eq. (4).

$$\begin{aligned}\ln Y_t = {} & \beta_0 + \beta_k \ln k_t + \beta_l \ln l_t + \beta_{tec} \ln tec_t + \\ & \beta_{k.l} \ln k_t . \ln l_t + \beta_{k.tec} \ln k_t . \ln tec_t + \beta_{l.tec} \ln l_t . \ln tec_t + \\ & \beta_{k.k} \left(\ln k\right)^2 + \beta_{l.l} \left(\ln l\right)^2 + \beta_{tec.tec} \left(\ln tec\right)^2\end{aligned} \tag{4}$$

Where Y_t is the textile output. l_t, k_t, tec_t represents the inputs of labor, capital and textile energy consumption. β_t is the input parameter to be estimated in time t. Relating the economic sector of a linear homogenous production function, it is likely to analyze the output elasticities of the *ith* inputs, which are considered to be firmly positive marginal outputs of all inputs, which are calculated in Eq. (5).

$$\psi_{it} = \frac{\partial \ln Y_t}{\partial \ln X_{it}} = \beta_i + \sum_j \beta_{ij} \ln X_{jt} > 0 \tag{5}$$

Based on Eq. (5), the factor's output elasticity can be calculated by Eqs. (6)-(8).

$$\psi_{k_t} = \frac{d \ln Y_t}{d \ln k_t} = \beta_k + \beta_{k.l} \ln l_t + \beta_{k.tec} \ln tec_t + 2\beta_{k.k} \ln k_t > 0 \tag{6}$$

$$\psi_{l_t} = \frac{d \ln Y_t}{d \ln l_t} = \beta_l + \beta_{k.l} \ln k_t + \beta_{l.tec} \ln tec_t + 2\beta_{l.l} \ln l_t > 0 \tag{7}$$

$$\psi_{tec_t} = \frac{d \ln Y_t}{d \ln tec_t} = \beta_{tec} + \beta_{k.tec} \ln k_t + \beta_{l.tec} \ln tec_t + 2\beta_{tec.tec} \ln tec_t > 0 \tag{8}$$

However, ψ_t represents the output elasticity of employed factors, which can be further substituted between the energy and non-energy factors. Thus, the substitutability can be stated as it is the relative difference in the portion of input factors to the percent change in the marginal rate of technical substitution of the inputs, as provided in Eq. (9).

$$\varpi_{ij} = \%\Delta\left(\frac{X_{it}}{X_{jt}}\right) \Big/ \%\Delta\left(\frac{P_{jt}}{X_{it}}\right) \tag{9}$$

Where ϖ_{ij} is the factor's substitutability between i and j. Δ is the change. The substitution theory evidences that the factor's elasticities should be greater than zero, and can be estimated as in Eq. (10).

$$\varpi_{ij} = \frac{\%\Delta\left(X_{it}/X_{jt}\right)}{\%\Delta\left(P_{jt}/X_{it}\right)} = \left(\frac{d\left(X_{it}/X_{jt}\right)}{d\left(MP_{jt}/MP_{it}\right)}\right)\left(\frac{\left(MP_{jt}/MP_{it}\right)}{d\left(X_{it}/X_{jt}\right)}\right) \tag{10}$$

Where MP_{it} and MP_{jt} are the marginal productivity of inputs i and j. Thus, the substitution between pairs of factors, such as capital-labor (k-l), capital-energy (k-tec) and labor-energy (l-tec) can be measured as in Eqs. (11).

$$\varpi_{ij} = \left[1 + \frac{-\beta_{ij} + \left(\psi_i/\psi_j\right)\beta_{jj}}{-\psi_i + \psi_j}\right]^{-1} \tag{11}$$

Furthermore, each factor's substitution between (k-l), (k-tec) and (l-tec) can be measured using Eqs. (12)-(13).

$$\varpi_{k.l} = \left[1 + \frac{-\beta_{k.l} + \left(\psi_k/\psi_l\right)\beta_{l.l}}{-\psi_k + \psi_l}\right]^{-1} \tag{12}$$

$$\varpi_{k.tec} = \left[1 + \frac{-\beta_{k.tec} + \left(\psi_k/\psi_{tec}\right)\beta_{tec.tec}}{-\psi_k + \psi_{tec}}\right]^{-1} \tag{13}$$

$$\varpi_{l.tec} = \left[1 + \frac{-\beta_{l.tec} + \left(\psi_l/\psi_{tec}\right)\beta_{tec.tec}}{-\psi_l + \psi_{tec}}\right]^{-1} \tag{14}$$

In addition, to measure the technological progress among the pairs of factors, the relative differences in the technological progress (ϕ_{ij}) process based on Eq. (4). This method has been employed by Lin and Wesseh [14] and Lin et al. [24] by combining all the output elasticities and parameters. To see the factor's ϕ_{ij}, the specific function, as seen in Eq. (15).

$$\phi_{ij} = \left(\beta_i / \psi_i\right) - \left(\beta_j / \psi_j\right) \tag{15}$$

Where ϕ_{ij} indicates the technological progress between i and j factors. β_i, β_j, ψ_i, and ψ_j are the coefficients and output states of technical knowledge. As per the rule of thumb, if the $\phi_{i>j}$, it means i is quicker than j factor. If the $\phi_{i<j}$, it means j is quicker than i. If the $\phi_{ij} = 0$, which shows there is no progress between the factors i and j.

To design the study's framework and process for evaluating the substitution elasticities between energy and non-energy factors are provided in Fig. 4. The substitution of each factor provides mixed effects, which is called inter structural effects, which have not been discussed before. Moreover, the pair of each factor, such as k-l, k-tec and l-tec give the valuation of both energy and non-energy substitution at the level of aggregation.

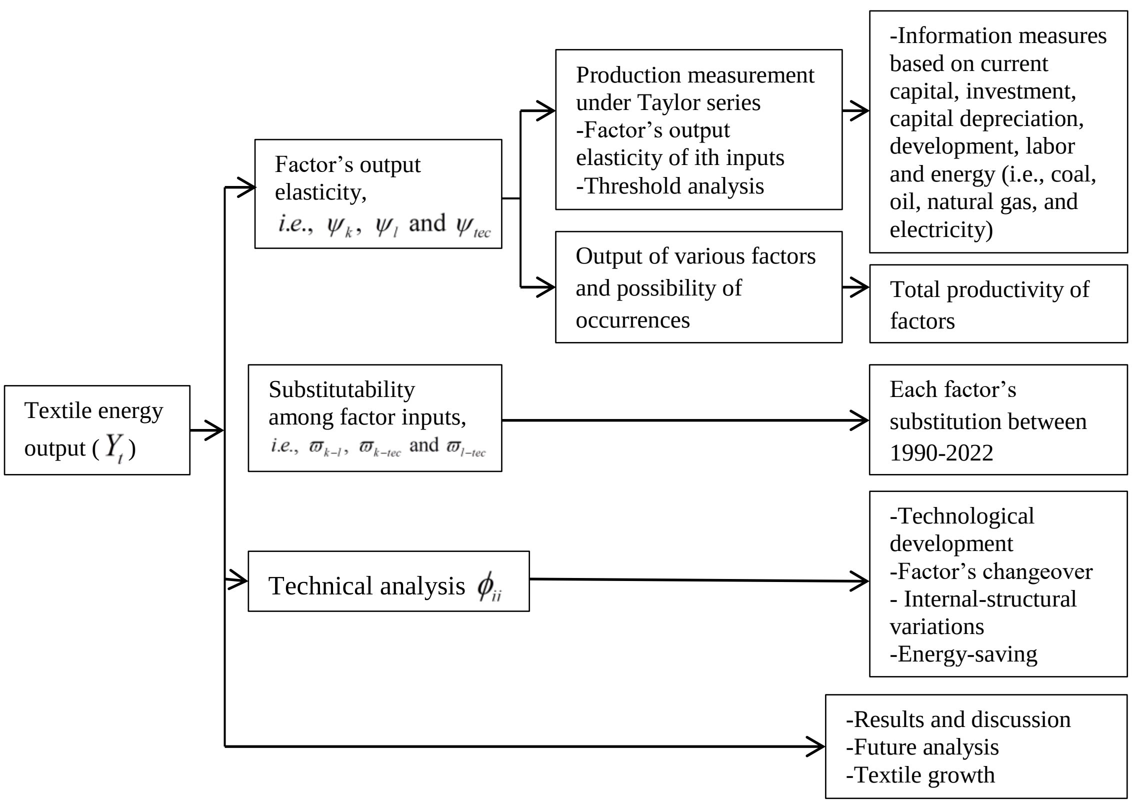

Fig. 4. Design mechanism of textile manufacturing of China.

4.1. Measurement procedure

Using Eq. (4), there are several terms that show that the model has multicollinearity issues. This presents that two or higher than two explanatory variables in the ordinary least squares (OLS) method are highly linked. On the basis, coefficient measures may change arbitrarily due to small changes in the model or statistics. The group of parameters can be estimated using $n(n+3)/2$, if each input has a trans-log component. Thus, existing parameters are offset with employed inputs, presenting the parameterization [13]. Employing the trans-log production function, the research estimates the factor inputs and their substitutability might face multicollinearity issues. If there is a multicollinearity problem in the existing statistics, then ridge regression will be employed, which was suggested by Hoerl and Kennard. [39]. As shown in Fig. 5, the ridge regression results can be attained employing $(X'X+kI)\hat{\beta}=h$ offers $\hat{\beta}=(X'X+kI)^{-1}h$, where $h=X'Y$, k is the ridge parameter, which is $k\geq 0$. The k can be assessed at all levels, for instance, [0-1]. If the std. Dev. is minimum or optimistic, the subject is continuing and lessens the variances. I show the identity matrix, i.e., $I=\begin{pmatrix}1 & 0\\ 0 & 1\end{pmatrix}$. This method is useful in the econometric literature that has been employed by several researchers, for example, Lin and Wesseh [14] for China and Raza et al. [32] for Pakistan. Using the ridge trace plot, the suitable value of $\hat{\beta}$ is selected. In this study, the ridge trace k is employed at the optimum value of ridge regression because it reduces the multicollinearity issues by incorporating a minimum value to the diagonal of the number that is in the form of a correlation. Hence, it can be considered that minimum variance looks at the OLS estimators with declination in the coefficients towards zero. The ridge threshold is description is provided in Appendix A-Table A1.

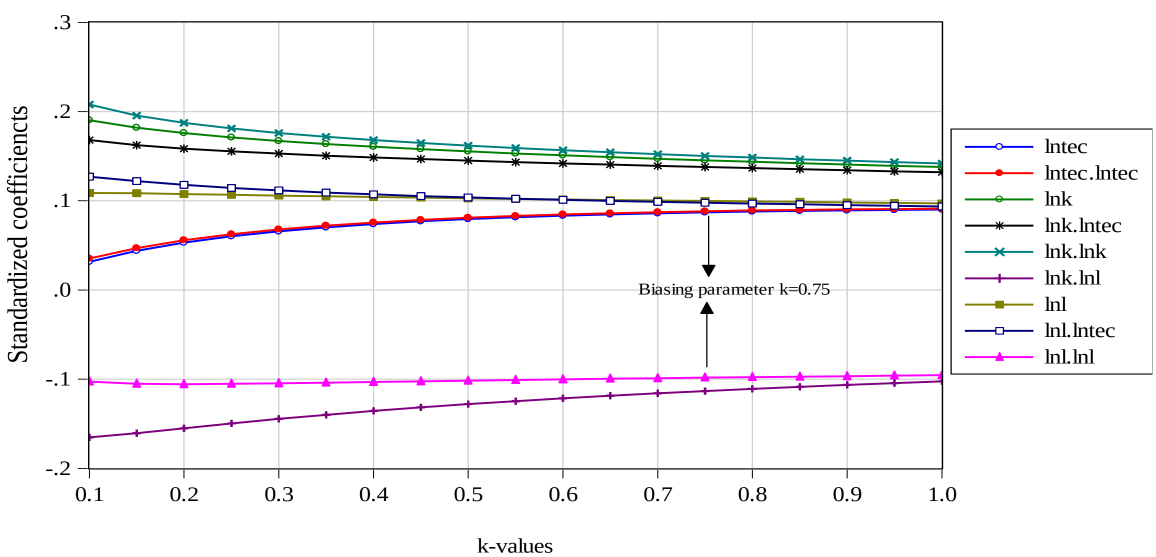

Fig. 5. Ridge threshold based on different coefficients.

5. Empirical findings and discussion

The results are based on Eqs. (4)-(8) estimates output elasticities and Eqs. (12)-(14) estimates the substitution possibilities over the specified period. The Eq. (15) estimates the relative differences int technological progress among the various factors. The results based on multicollinearity issues, input elasticity, output substitution, and technological progress of China's textile sector from 1990 to 2022 are explained in this section.

First, the study tried to conceal the methodology for the current study; the Pearson's correlation test was employed for the individual predictor variables, as described in Table 3. Being a predominant technique in the literature, its scientific evidence is not mentioned in the method section to save the space. The correlation coefficients measure the linear reliance between 1 and -1, which is consistent with the several studies (e.g., Xie and Hawkes [17]; Lin and Atsagli [35]). Also, unlike relevant correlation techniques, for instance, the cosine of Salton and McGill [40], Pearson's correlation coefficient is bounded by multivariate statistics due to normalization implied by measuring the negative values. The detailed results of correlation coefficients are provided in Table 3, presenting that all the factor values fall between 0.6 and 0.9. However, the variance inflation factor (VIF) shows huge values, which are higher than ten, evidencing the level of multicollinearity issue between explanatory variables. It proposes that the ridge regression employed in the current study is a better econometric technique since various coefficient estimations for multiple regression methods are extremely reliant on the independence of the model terms. Hence, the study employed the ridge trace plot to check the accurate value of model significance, as shown in Fig. 5. It estimated that when the k-value equals 0.75, all the coefficients become stable, enlightening the multicollinearity issue and reducing the variance. Consequently, the outcomes from Table 3 verify that the ordinary least squares (OLS) are not suitable for estimating the functional parameters.

Table 3

Correlation and variance inflation factor (VIF) analysis.

Variables	Capital	Labor	Textile energy consumption	Output	VIF
Capital	1				173094
Labor	0.6480	1			51192.1
Textile energy consumption	0.8157	0.8135	1		95911.9
Output	0.9990	0.6451	0.8070	1	-

Second, the study strongly considers that there is a high correlation between the independent variables (see Table 3), which represents a high multicollinearity issue. This proves that this phenomenon can give inconsistent outcomes and challenges in our model. Moreover, our empirical results estimates the stationarity of individual variables by Augmented Dickey-Fuller (ADF) and Philips and Perron (PP) unit root tests [52,53], as shown in Table 4. We measure the stationarity property of existing data. Yet, it is necessary to show that all the estimated factors in the model are stationary. Table 4 represents that all the variables employed in model are stationary and each variable is stationary after taking the first difference (I(1), respectively. For instance, Lin and Tian [54] employed the unit root tests using the similar methods to reflect the clarity of data.

Table 4
Unit root test.

Variables	ADF	PP	Variables	ADF	PP
	I(0)	I(0)		I(1)	I(1)
$\ln y$	0.3274	0.7204	$\Delta \ln y$	0.0000*	0.0169*
$\ln l$	0.0001	0.0005*	$\Delta \ln l$	0.0231**	0.0163*
$\ln k$	0.7740	0.6724	$\Delta \ln k$	0.0480**	0.0426**
$\ln tec$	0.7618	0.7147	$\Delta \ln tec$	0.0082*	0.0059*

Note: I(0) represents the unit root at level; I(1) represents the unit root at first difference; *,** represents the significance level at 1% and 5%. Δ is the first-order difference of a variable ~ I (0) represents that the variable is stationary, while ~ I(1) shows that the variable has a unit root.

To estimate the structural breaks, we shadowed the research of Aue and Horváth [56], who investigated the tome series internal and external breaks. The results are presented in Table 5. The outcomes in Table 5 presents that all the analyzed variables (i.e., labor, capital, output, and energy) are stationary at I(1) with structural breaks in the periods 1999, 2005 and 2015, respectively. However, it is observed that none of series is integrated of order 2. Hence, the long-run relationship happens, and therefore, the variables relationship is effective by the cointegration test.

Table 5
Unit root test under structural break.

ADF	I(0)	I(0)		Variables	I(0)	I(0)	
	t-value	p-value	Break point		t-value	p-value	Break point
$\ln y$	-3.42276	>0.01	2003	$\Delta \ln y$	-4.07785	<0.01	2015
$\ln l$	-5.62125	<0.01	1994	$\Delta \ln l$	-6.77768	<0.01	2005
$\ln k$	-3.76079	>0.01	2002	$\Delta \ln k$	-4.39052	<0.01	2015
$\ln tec$	-4.390878	<0.01	2003	$\Delta \ln tec$	-5.68116	<0.01	1999

Third, using a high number of parameters to be measured in the proposed production function, and hence the potential threat of high linear association between the independent variables, such as multicollinearity. Hence, we start our analysis by formulating or identifying the linear association among the major independent variables by employing the model suggested by Kmenta [55]. According to this method, a simple estimation of the degree of association between the independent variable can be achieved by regressing individual variables on the enduring explanatory variables. The conforming coefficient of determination (R^2) from individual regression model can then be employed as an estimation of the degree of linear relationship. If the R^2 is higher, we get a higher linear relationship among independent variables. The current study represents that the R^2 for each model based on labor, capital and energy as dependent variables is 0.988, 0.999 and 0.989, respectively. Furthermore, the Variance Inflation Factor-VIF for each variable of the stated model (see Eq. 4) is also high, such as more than ten, representing that there is a multicollinearity issue. The estimated results are provided in Table 6. As shown in Table 5, when we measure our production model in Eq. 4 with the common OLS method, we find unreliable outcomes. Though all the variables in the model have a mutually significant impact on the textile output, 6 out of 9 individual measures have a statistically insignificant effect because of their high Std. Err. (S.E) on textile sector output. Also, four out of nine measures show negative signs, which cannot be supported by economic theory. These outcomes are the signs of high multicollinearity that have severely influenced the parameter estimates. Thus, the OLS regression measures have proved the severity of the multicollinearity identified by the method suggested by Kmenta [55].

Table 6

Model results of the OLS outcome estimations.

Variables	Coefficients	Std. Err. (S.E)	T-values	P-values	VIF	1/VIF
$\ln l$	-5.337175	27.20628	-0.196174	0.8462	51192.15	0.000020
$\ln k$	-2.614469	2.190140	-1.193745	0.2447	173094.0	0.000006
$\ln tec$	1.204967	5.519313	0.218318	0.8291	95911.92	0.000010
$\ln k . \ln l$	-4.176224	1.745388	-2.392719	0.0253	1548.347	0.000646
$\ln k . \ln tec$	0.116687	0.255872	0.456035	0.6526	256400.6	0.000004
$\ln l . \ln tec$	6.404528	3.684033	1.738456	0.0955	43390.98	0.000023
$\ln l . \ln l$	30.28865	19.98668	1.515442	0.1433	11908.18	0.000084
$\ln k . \ln k$	0.093159	0.033681	2.765966	0.0110	8083.935	0.000124
$\ln tec . \ln tec$	-0.018601	5.519313	-0.051330	0.9595	118412.3	0.000008
Constant	8.869467	21.32703	0.415879	0.6814		
R-square	0.9992					
Adj. R-square	0.9990					
K-value	0.0000					
F-value	3564.300			0.0000		

Fourth, the study coefficients become stable when parametric values are 0.75. It can be stated that the minimum value of k reduces the variances and ultimately resolves the model issue. Table 7 represents that the adjusted R^2 of the model is 0.9899, the Std. Err. of each factor is not more than 0.06, and the VIF subsequently, which are suggesting the constancy of the model. The model's F-value is 63.311 and is significant at 0.0001. Overall, we found that the ridge regression Std. Err. is smaller, while over 95% of the coefficients are optimistic and falls in between the range of zero to one, which is in line with the economic theory. Therefore, the analysis relies on the ridge trace and the VIF to limit the accurate k-value. At the specified value (k=0.75), the ridge regression was used, factor's output elasticity, substitution and technological progress. The results based on ridge regression are described in Table 7. One can simply see that all main parameters have the projected sign, and all parameters are statistically valid. In addition, the VIFs of all the parameters are optimistic, which are less than 10. Seeing from the conventional statistics, nonentity seems to be wrong with the recent method condition. Furthermore, based on Table 7 outcomes, the factor's output elasticities are discussed below.

Table 7
Ridge regression-based estimations.

Variables	Coefficients	Std. Err. (S.E)	T-values	P-values	VIF
$\ln l$	0.099780	0.058322	1.710851	0.062742	0.041826
$\ln k$	0.145400	0.048314	3.009495	0.008414	0.031274
$\ln tec$	0.087000	0.062459	1.392919	0.100568	0.106730
$\ln k.\ln l$	-0.113200	0.054756	2.067363	0.036266	0.108506
$\ln k.\ln tec$	0.137800	0.049628	2.776648	0.012025	0.023478
$\ln l.\ln tec$	0.097800	0.058909	1.660180	0.067737	0.075242
$\ln l.\ln l$	-0.098300	0.058759	1.672928	0.066443	0.056719
$\ln k.\ln k$	0.150200	0.047535	3.159744	0.006701	0.040886
$\ln tec.\ln tec$	0.088200	0.062032	1.421837	0.096438	0.103915
Constant	2.023261			0.02000	
R-square	0.9829				
Adj. R^2	0.9899				
K-value	0.75				
F-value	63.311			0.0001	

Table 8 represents the results of different diagnostic tests, which were employed to observe the reliability of the model. Durbib Watson and Breusch-Godfrey Serial Correlation LM tests suggest the model did not suffer any serial relationship. Jarque-Bera estimation represent that the residuals of the model are normal. Also, the heteroscedasticity issue was measured using the Heteroscedasticity: Breusch-Pagan-Godfrey and ARCH tests, represents that there is no issue of heteroscedasticity in the model. Thus, the diagnostic tests show that about 90% of the explanatory variables are quantified by R^2. Hence, employing the key driving indicators in the model, this is highly contributing to the economy of China's textile sector.

Table 8
Diagnostic estimation.

Tests	Probability	Results
Jarque-Bera	0.3879	Residuals are normally distributed.
Durbin Watson stat	2.071218	There is no serial correlation.
Breusch-Godfrey Serial Correlation LM	0.0571	No serial correlation is seemed.

Heteroscedasticity: Breusch-Pagan-Godfrey	0.2285	No heteroscedasticity issue is seemed.
ARCH	0.2357	No heteroscedasticity issue is seemed.

Fifth, based on previous results derived from Eqs. (6)-(8), the output elasticities of each factor. These factors are labor (ψ_{l_t}), capital (ψ_{k_t}) and textile energy consumption (ψ_{tec_t}) from 1990 to 2022. All the relevant results of ψ_{l_t}, ψ_{k_t} and ψ_{tec_t} are described in Table 9, presenting that all the factors' output elasticities are optimistic. Also, it can be seen that the increasing trends in the energy consumption are enhancing the non-energy factor, such as ψ_{k_t} in the textile sector, the output grows. As shown in Table 9, the output elasticity of ψ_{tec_t} is about 2.54, while ψ_{l_t} and ψ_{k_t} are 0.2 and 2.3, respectively. This presents that the energy utilization in the textile industry of China is rising maximally with the rising trend of capital, which is reliable with the findings of Lin et al. [7] However, the study estimated that the ψ_{l_t} is optimistically elastic but presents the minimum output over the estimated period. This is because the China's textile industry has declined labor employment and growing trend of technical level, which is consistent with the study of Zhu et al. [9] and Lin et al. [7]. Furthermore, the study found that the labor productivity in 2013-2014 was the highest level in the history. Noticeably, enhancing labor output is an imperative path for the textile sector of China to reach the maximum energy efficiency level. Thus, it was found that labor productivity has the lowest impact on energy. With the continuous growth of ψ_{tec_t} annually, the output energy elasticity is rising, which is embodiment of the economic scale. Furthermore, the average elasticity of ψ_{k_t} and ψ_{tec_t} are close to each other and greater than one, presenting that when ψ_{tec_t} and ψ_{k_t} elasticities rise by 1%, the revenue of textile sector will increase by greater than 1%. The output elasticity for capital and energy consumption remained relatively constant; hence, the output elasticity of labor has grown overtime. Thus, the production function of energy and capital is at maximum scale because labor output variability is under 0.19, which concludes that when labor grows by 1%, the productivity will transform by 0.19%. Thus, it is obvious that the function is diminishing for labor when each additional unit of labor adds minimum to output, holding all other inputs (i.e., capital and energy) constant. As a result, the development in the textile sector of China's output is showing a rising trend of capital and technological enhancement. Thus, there is a probability to reduce energy intensity and improve energy efficiency.

Table 9

The substitution elasticity of alternative textile energy inputs in China from 1990-2022.

Year	ψ_{l_t}	ψ_{k_t}	ψ_{tec_t}	Year	ψ_{l_t}	ψ_{k_t}	ψ_{tec_t}
1990	0.424454	1.598404	2.122176	2007	0.195601	2.333403	2.631657
1991	0.416516	1.625728	2.144874	2008	0.160475	2.423832	2.670775

1992	0.394357	1.688897	2.182411	2009	0.137458	2.476505	2.688287
1993	0.377365	1.731727	2.206561	2010	0.114896	2.537318	2.719406
1994	0.358051	1.779735	2.232833	2011	0.095411	2.602732	2.759099
1995	0.331418	1.849442	2.270973	2012	0.081436	2.636594	2.772506
1996	0.303452	1.887697	2.271586	2013	0.068769	2.672197	2.790804
1997	0.291555	1.903097	2.274714	2014	0.054271	2.695585	2.79167
1998	0.275699	1.917198	2.268418	2015	0.05747	2.694467	2.796054
1999	0.256045	1.929239	2.2529	2016	0.059731	2.69491	2.799521
2000	0.262711	1.954922	2.298869	2017	0.0518	2.725144	2.818185
2001	0.249106	2.002058	2.33318	2018	0.034384	2.766933	2.833765
2002	0.245805	2.035088	2.36965	2019	0.036018	2.771637	2.834957
2003	0.231751	2.098903	2.421271	2020	0.022619	2.780559	2.831109
2004	0.23278	2.164326	2.501976	2021	0.013441	2.837036	2.879713
2005	0.230419	2.200181	2.541531	2022	0.005132	2.83816	2.864463
2006	0.221258	2.252633	2.585785	**Average**	**0.190656**	**2.275948**	**2.538233**

Sixth, using Eqs. (12)-(14), derived the elasticity of substitution between capital-labor ($\varpi_{k.l}$), capital-textile energy consumption ($\varpi_{k.tec}$) and labor-textile energy consumption ($\varpi_{l.tec}$), are described in Table 10. The consequences given in Table 10 present that all the pairs of factors are substitutes. In our case, the elasticity of substitution is the ratio of two inputs to a production process concerning the proportion of their marginal products and so evaluates the curvature of an isoquant. This substitution between pairs varies from zero to infinity. Zero expresses that two factors cannot substitute for each other, while infinity shows that two factors are varying and have the possibility of substitution between them. As shown in Table 10, all the factors' elasticities are close to unity, rejecting the null hypothesis, showing that the average elasticities are almost close to one of the best levels, which are reliable with the findings of Lin and Wesseh [14] and Raza and Lin [41].

The results between $\varpi_{k.tec}$ and $\varpi_{l.tec}$ show maximum average substitution elasticities of 0.67 and 0.50, while $\varpi_{k.l}$ looking to be minimum by 0.13, which shows that capital and energy have the highest substitution possibility. Moreover, it can be said that energy utilization can be substituted by capital and labor in textile production, which is reliable with the findings of Lin and Moubarak [28]. It can be noted that during the study analysis, $\varpi_{k.l}$ has slowly declined to the other pairs, which clears that the textile sector is in the phase of technical development in the technical labor process. This also measures that China's textile industry is labor-intensive, a rise in technological progress and labor productivity can rouse textile initiatives to lessen energy intensity [7,42]. In addition, as the textiles and apparel industry chain changes, the major challenge is the skilled labor and bounded employment opportunities [43]. Within these encounters, the study found plentiful employment coming from technological advancements and digital upgradation in the major sections. Moreover, they observe that digitalization and mechanization will alleviate the labor dearth, create modest benefits, and enable the cost-effective growth of the textile industry. The results proved that the rising capital investment in the textile sector can make-up for the reduction in the labor force.

Also, the $\varpi_{l.tec}$ reduction shows that technical development and energy intensity may reduce textile labor. As shown in Table 10, capital and labor can obviously substitute for energy or conserve energy, which may also impact ecological sustainability. Due to the maximum trade and services, the textile sector is of maximum $\varpi_{k.tec}$, thus, it is imperative to understand that $\varpi_{k.l}$ and $\varpi_{k.tec}$ are necessary factors; thus, the information linked to capital can be enhanced. In addition, the textile technology has become an imperative issue around the globe, especially in the production process. This is because the textile industry adds to enhancing the market, absorbing technical labor, hurrying urbanization, and helping societal progress [5]. Also, energy is a significant resource for textile manufacturing, allowing each process phase and considerably influencing working efficiency, price structure and ecological sustainability [44]. Consequently, the critical technologies-related to the intelligence of the Chinese textile industry are developing rapidly, and big data technology for the whole textile production process is also being applied rapidly, for example, digital-twin technology for garment design [45]. Thus, automated equipment is replacing physical labor in distinctive textile processes; robots in this sector have become a necessary part of intelligent production.

Table 10

Output elasticity of alternative textile energy inputs in China from 1990-2022.

Year	$\varpi_{k.l}$	$\varpi_{k.tec}$	$\varpi_{l.tec}$	Year	$\varpi_{k.l}$	$\varpi_{k.tec}$	$\varpi_{l.tec}$
1990	0.348787	0.633881	0.528848	2007	0.119243	0.668194	0.499462
1991	0.337843	0.635046	0.527411	2008	0.094944	0.673899	0.496338
1992	0.310895	0.638964	0.52411	2009	0.079991	0.677691	0.494393
1993	0.292088	0.641686	0.521767	2010	0.065569	0.681002	0.492479
1994	0.271619	0.644767	0.51921	2011	0.053294	0.68391	0.490838
1995	0.244268	0.649164	0.515792	2012	0.045026	0.686089	0.48973
1996	0.220907	0.653443	0.5129	2013	0.037606	0.687957	0.488727
1997	0.211233	0.654905	0.511642	2014	0.029498	0.690286	0.48763
1998	0.199105	0.657135	0.51011	2015	0.031232	0.689733	0.487865
1999	0.184667	0.660075	0.5083	2016	0.032443	0.689434	0.488029
2000	0.186846	0.658504	0.508443	2017	0.027864	0.690693	0.487407
2001	0.173772	0.660536	0.50673	2018	0.018273	0.693434	0.486097
2002	0.168962	0.660731	0.506041	2019	0.019104	0.693799	0.486216
2003	0.155181	0.662869	0.50423	2020	0.011986	0.69511	0.485232
2004	0.151353	0.662386	0.503629	2021	0.006992	0.696001	0.48454
2005	0.147566	0.662558	0.503096	2022	0.002672	0.697663	0.483943
2006	0.138808	0.664018	0.501957	**Average**	**0.133928**	**0.669562**	**0.501307**

Finally, using Eq. (15), study used energy and non-energy factors to check the relative differences in technological progress (ϕ_{ij}), such as $\phi_{k.l}$, $\phi_{k.tec}$ and $\phi_{l.tec}$ from 1990-2022. This attempt has been made to get the relative differences in textile factor's technological progress taken in this study. This was considered by making application of aggregate translog production function of the China's textile industry and combining the output elasticities and calculated coefficients from Eq. (3). In addition, we draw inferential statistics of the technological pairs of factors, as shown in Table 11. The results show that each model (i.e., $\phi_{k.l}$, $\phi_{k.tec}$ and $\phi_{l.tec}$) clarifies a significant portion of the variations. As shown in Table 11, the p-values are all less than 1%, for below the conventional 5% threshold, representing that the technological progress is significantly contributing. This analysis further indicates that the textile sector accounts for at least 95% of the variations in these technological progress measures.

Table 11

The technological models based inferential statistics under variance analysis.

Technical inputs		DF	Sum of Squares	Mean Square	F Value	Prob>F
φk.l	Model	1	12.363	12.3636	191.7571	<0.0001
	Error	31	1.9987	0.0644		
	Total	32	14.3623			
φk.tec	Model	1	0.0024	0.0024	596.3105	<0.0001
	Error	31	0.0001	0.000004		
	Total	32	0.0025			
φl.tec	Model	1	12.0211	12.0211	184.8849	<0.0001
	Error	31	2.0156	0.0650		
	Total	32	14.03675			

All the ϕ_{ij} results are described in Fig. 6, showing that all the inputs are positive (i.e., $\phi_{k.tec}$ and $\phi_{l.tec}$) except $\phi_{k.l}$. In addition, Fig. 6 presents that the capital-labor are progressive and can be technologically substituted in the future; however, $\phi_{k.tec}$ and $\phi_{l.tec}$ are more than zero, presenting that ϕ_{ij} is the main input driven and changes between 2% and 19%, respectively. It can be seen that all the factors continued to be stable until 2005. Though, $\phi_{k.tec}$ provided a stable change during the period while $\phi_{l.tec}$ and $\phi_{k.l}$ fluctuating due to the labor employment in the textile manufacturing process, which is consistent with the China Energy Yearbook (various issues). Generally speaking, recent outcomes propose that the $\phi_{l.tec}$ is faster than $\phi_{k.tec}$, presenting that labor and capital are associated with energy consumption. However, textile sector-related production accepts technology in reflection of reducing the textile production cost because China has major concerns in the import and export of various products [5]. Thus, energy consumption is the main concern, which may provide more technological labor and production.

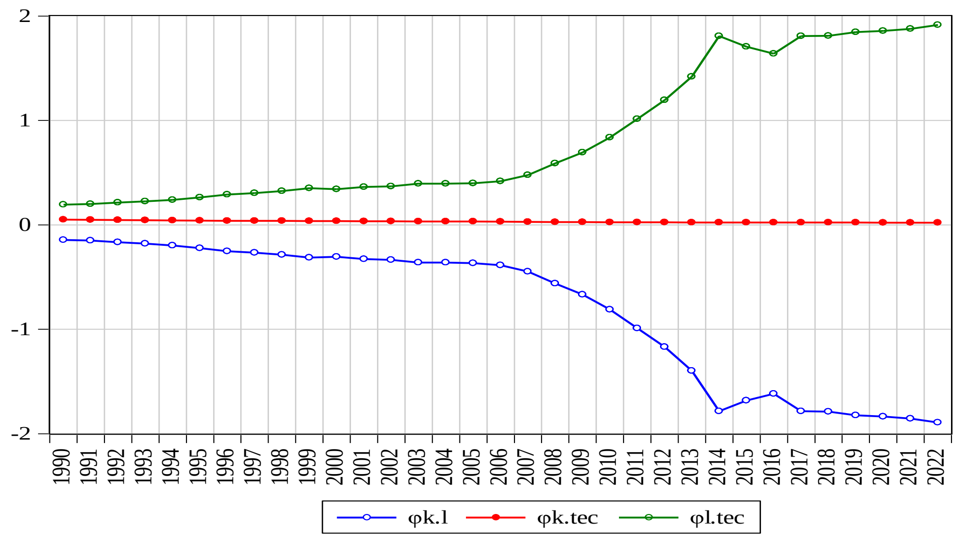

Fig. 6. Differences in technical change between energy and non-energy inputs in the textile sector.

6. Conclusion and policy suggestions

6.1. Conclusion

Applying the trans-log production function, the current study analyzes the output elasticity, elasticity of substitution and technological progress between energy and non-energy factors from 1990-22022, for the textile sector of China. Furthermore, the ridge regression technique to check the multicollinearity problem in the estimated data. Based on the method and recent data application, the study found the following outcomes:

First, the textile sector output is positively and significantly associated with labor, capital and energy. The results give intuitions that energy works as an element for growth for the textile sector of China. Thus, it adds to the literature on the energy-economic development process. Furthermore, labor contribution is not astonishing since we have observed in the assessment period due to technological advancements.

Second, results observed in the current study that capital-energy and labor-energy are highly substitutes in the manufacturing process of the Chinese textile sector, which means the possibility for this sector to substitute technological labor and advanced capital without imperiling output. This means that these factors have the possibility in the manufacturing process without any negative impact on the economy of the country. Hence, lessening energy in lieu of skilled labor and advanced capital gives the outcome of main interest. These outcomes also look to give proof of the significant role of textile energy manufacturing substitutes in the future.

Consequently, the outcomes related to labor-energy and capital-energy present a robust convergence difference in technological progress between 0.02 and 1.91, presenting a positive influence. The technological progress between labor and energy shows the determined involvement during the studied period, particularly after 2005.

Moreover, with the development of research and development in energy technology and capital development, the textile sector can be further improved.

6.2. Policy suggestions

The study outcomes give significant policy recommendations for China's textile industry in context of energy, economy and technical sustainability. As China see itself in a state of dilemma and has to accurately regulate its upcoming energy policies. It is clear that the issue of sustainable development and technological innovation would be the foundation for these policies. In general, 15th Five-Year Plan (2026-2030) in March 2026, plan sets the Chinese economic and social development until 2030 in which textile industry has an obviously concentrated on high-quality growth. Thus, the victory in this view will rely on the ability of the textile sector to confront with the goals of government.

First, since energy and non-energy inputs seemed to be substitutes, policies proposed to encourage the huge consumption of marginal energy sources can provide opportunities. With capital and energy being substitute, for example, Chinese government can inspire relevant industries to employ more energy and investment in technical capital.

Second, recalling from Table 9, to sustain economic growth is to guarantee that policies directed at motivating growth of the energy consumption (i.e., renewable electricity) market should be highlighted. The government should guarantee that the proportion of capital investment in advanced machinery is increased and that the technological mechanism is enhanced. Moreover, the government should guarantee a particular degree of dependence on advanced technology, skilled labor and renewable energy because China is a big economy with growing energy demand.

Third, a switch from capital to energy would need a definite level of elasticities in technology. This can bring about huge capital expenditures on novel technologies, machine upgradation, fresh production equipment, etc. Also, the costs linked with these variations, the government policies may be useful in future in order to apply strategies to reduce capital expenditures. For example, minimum taxes, capital subsidies and door-to-door access can be applied for prompt implications.

Finally, with the development of new textile frameworks and textile technologies, renewable energy substitution possibilities (i.e., solar, wind, etc.) can be added in further studies in the future. This is because China's textile sector is still hugely reliant on the coal and oil consumption. As per the China's National Energy Administration[47] (2024), China's energy installed capacity reached by 14.6% in 2024 in in which solar capacity increased by 277 to 887 gigawatts, while wind power capacity grew by 80 to 521 gigawatts. This presents that country has the ability to substitute fossil fuel energy to cleaner energy with sustainable results. Ultimately, the supply-side energy transition and investment in modern machines will create several jobs in the renewable energy industry. Also, machine learning and artificial intelligence in further study can support upcoming research and enhance the precision of past results. In addition, the current study employs input substitution possibilities to check production and technological progress using translog production model; however, future study can apply cause and effect relationship among various inputs. This will predict, explain factors and solve issues by knowing the relationship between cause and effect and factor costing, which will helpful for future policies. Moreover, sustainability and green-transition can be discussed on the availability of individual fuel information for textile sector.

Availability of data and materials

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Appendix A

Table A1

Ridge threshold based on ridge trace analysis.

k	R^2	$\ln tec$	$\ln tec.\ln tec$	$\ln k$	$\ln k.\ln tec$	$\ln k.\ln k$	$\ln l.\ln l$	$\ln l$	$\ln l.\ln tec$	$\ln l.\ln l$
0.05	0.9972	0.9340	0.8952	0.3626	0.2517	0.9720	1.1220	0.1829	0.3427	0.9981
0.10	0.9960	0.6852	0.6608	0.1701	0.0995	0.3667	0.5232	0.1130	0.2637	0.3902
0.15	0.9947	0.5351	0.5171	0.1160	0.0638	0.2173	0.3451	0.0916	0.2192	0.2405
0.20	0.9934	0.4320	0.4180	0.0901	0.0494	0.1542	0.2035	0.0801	0.1883	0.1772
0.25	0.9920	0.3574	0.3460	0.0746	0.0418	0.1200	0.1564	0.0725	0.1653	0.1426
0.30	0.9907	0.3013	0.2920	0.0641	0.0371	0.0987	0.1043	0.0667	0.1474	0.1208
0.35	0.9893	0.2581	0.2503	0.0565	0.0340	0.0841	0.1002	0.0621	0.1331	0.1056
0.40	0.9879	0.2241	0.2174	0.0508	0.0316	0.0735	0.0868	0.0583	0.1214	0.0943
0.45	0.9864	0.1967	0.1910	0.0462	0.0298	0.0655	0.0832	0.0550	0.1116	0.0855
0.50	0.9850	0.1744	0.1694	0.0426	0.0283	0.0592	0.0754	0.0522	0.1033	0.0785
0.55	0.9836	0.1560	0.1516	0.0395	0.0271	0.0541	0.0735	0.0497	0.0961	0.0727
0.60	0.9821	0.1405	0.1366	0.0370	0.0260	0.0500	0.0689	0.0474	0.0899	0.0678
0.65	0.9806	0.1275	0.1240	0.0348	0.0251	0.0464	0.0558	0.0454	0.0844	0.0636
0.70	0.9791	0.1163	0.1132	0.0329	0.0242	0.0435	0.0524	0.0435	0.0796	0.0599
0.75	0.9775	0.1067	0.1039	0.0313	0.0235	0.0409	0.0521	0.0418	0.0752	0.0567
0.80	0.9759	0.0984	0.0958	0.0298	0.0228	0.0386	0.0456	0.0403	0.0713	0.0539
0.85	0.9743	0.0911	0.0888	0.0285	0.0222	0.0367	0.0425	0.0388	0.0678	0.0513
0.90	0.9727	0.0847	0.0826	0.0274	0.0216	0.0349	0.0326	0.0375	0.0646	0.0490
0.95	0.9711	0.0790	0.0771	0.0263	0.0211	0.0333	0.0311	0.0362	0.0617	0.0469
1.00	0.9694	0.0740	0.0722	0.0254	0.0206	0.0319	0.0252	0.0351	0.0590	0.0449

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