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The impact of high-tech industry development on energy efficiency and its influencing mechanisms

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In responding to climate change, energy efficiency is one of the key factors for sustainable development, where the high-tech industry can play an important role. However, whether the development of high-tech industry impacts energy efficiency as well as the mechanisms behind still remain unclear. Thus, based on the dynamic spatial Durbin model, this study aims to investigate: 1) the impact of high-tech industry development on energy efficiency from three perspectives of high-tech industry development, i.e., scale, productivity, and agglomeration, and 2) the mechanisms behind such impact especially through technological innovation and industrial structure. The results confirm the influence of high-tech industry development on energy efficiency both directly and indirectly. On the one hand, our analysis contributes on the existing body of scientific knowledge by expounding the relationship between scale, productivity, and agglomeration of high-tech industry development and energy efficiency. On the other hand, it further deepens the understanding on such relationship by revealing two underlying mechanisms behind, i.e., through promoting technological innovation, the productivity and agglomeration of high-tech industries can either completely or partially improve energy efficiency, while the scale and agglomeration of high-tech industries can hinder energy efficiency to a certain level through the industrial restructuring. Based on these findings, this paper provides some policy implications, which are believed to facilitate the practices of energy conservation and emission reduction in China.

KEYWORDS
high-tech industry development, energy efficiency, influencing mechanism, technological innovation, Industrial structure

1 Introduction

Carbon dioxide (CO_2) emissions from energy consumption are considered as the main source of global warming (Marra et al., 2015; Xu and Lin, 2018; Yu et al., 2020a; Jiang et al., 2022), which further lead to serious changes in global climate. Along with the exploitation and utility of fossil fuel, there have been simultaneously dual pressure of resource exhaustion and environmental pollution (Shao et al., 2019; Chishti et al., 2020; Ullah et al., 2020; Noureen et al., 2022). Against this background, improving energy efficiency is considered as one of the most critical steps to achieve carbon emission reduction without necessary economic decline (Yuan et al., 2012). To improve energy efficiency, high-tech industries have been playing a significant role in implementing innovation-driven development and high-quality economic strategy (Tsai et al., 2009). Thus, most countries have been promoting High-Tech Industry Development (HTID) to achieve positive potentials (Bregman et al., 1991). For example, China attaches great importance to the development of digital, high-tech and modern service industries to improve energy efficiency rapidly and control the total energy consumption growth, for reaching the peak of CO_2 emissions by 2030 and achieving carbon neutrality by 2060 (75th UN General Assembly, 2020).

Despite its rising practical importance, the extant research on HTID still suffers from two major gaps. First, most studies have focused on a central question of "*does HTID have the positive effect on economic growth* (Coad and Rao, 2008; Delgado et al., 2014; Wolf & Terrell, 2016; Goldschlag & Miranda, 2020) *or does it promote high-quality economic development*" (Li et al., 2019). Only handful studies pay attention to the relationship between HTID and energy efficiency. However, it is also shown in the extant research that the development of high-quality economics has to depend on energy efficiency (Bieri, 2010; Cieslik and Ghodsi, 2015; Chen et al., 2018a), as energy efficiency provides the specific and visible sources of competitive advantages to build friendly environments and energy security critical for high quality economics (Zhang et al., 2017; Chishti et al., 2021; Zhu & Chishti, 2021; Chishti et al., 2022). Therefore, it is essential to take a closer examination the effects of HTID on energy efficiency (Goldschlag & Miranda, 2020). The second research gap is that the existing studies have scarcely examined the mechanism about how HTID influences energy efficiency and accordingly provided limited insight into "how does it contribute to energy efficiency" (Marra et al., 2015). In other words, it remains unclear what factors can be caused by HTID that in turn facilitate the improvement of energy efficiency (Zandiatashbar et al., 2019). Therefore, both theoretically and practically, the questions remain: what impacts HTID has on energy efficiency; and if so, through what mechanisms it works (Cao et al., 2020).

To fill two research gaps, this paper aims to explore the HTID's impact on energy efficiency in terms of the HTID's scale, productivity, and agglomeration, following the conventions of the existing studies such as Drucker & Feser (2012), Chen et al. (2018b), and Gui (2018), among others. Besides, it is generally agreed that high-tech industries are different from traditional industries, in terms of the facts that their competitiveness lies in technological innovation (Aydalot & Keeble, 2018); and their enabling ecological environment is industrial cluster (Wanzenböck & Piribauer, 2018). Thus, this paper further pays specific attention to technological innovation and industrial structure and examines their mediating roles on the relationship between HTID and energy efficiency.

In order to enhance the feasibility, the research scope of this study is set as HTID in China due to two considerations: 1) the research on HTID and energy efficiency is focused more on the Western countries than on the Asian ones (Bakouros et al., 2002; Goldschlag & Miranda, 2020); 2) China calls for such research to provide scientific foundation for policy making. In fact, China with its rapid economic growth over the past 40 years has become the largest energy consumer in the world (World Energy Statistical Yearbook, 2021), as illustrated in Figure 1. Besides, as the world's largest developing country, it is in the stage of deepening industrialization and urbanization. The demand for energy continues to grow, and the task of ecological and environmental protection is arduous. In this case, improving energy efficiency is the key measure that China can take for energy conservation and emission reduction. Therefore, it has more motivations to improve energy efficiency for energy saving and emission reduction. Meanwhile, it has regarded HTID as one of the most important forces for adjusting the industrial structure, transforming the economic growth mode, and improving innovation capability for national sustainability (Johansson et al., 2015). More recently, "Made in China 2025" was initiated as an important program to improve HTID and was expected to result in significant improvement of energy efficiency (Li et al., 2019). All these in turn make China a suitable context for this study.

The remainder of this paper is organized as follows. Section 2 provides a literature review on the relevant topics. Section 3 develops the hypotheses and outlines the theoretical framework. Section 4 explains the research methodology and data sources. The empirical analysis and results are presented in Section 5 and further discussed in Section 6. Finally, Section 7 provides a conclusion by highlighting the theoretical contributions and the policy implications of the paper and suggesting the future research directions.

2 Literature review

2.1 Research on HTID and energy efficiency

The Organization for Economic Cooperation and Development (OECD) uses the strength of research and development (R&D) to define high-tech industries (Bierly &

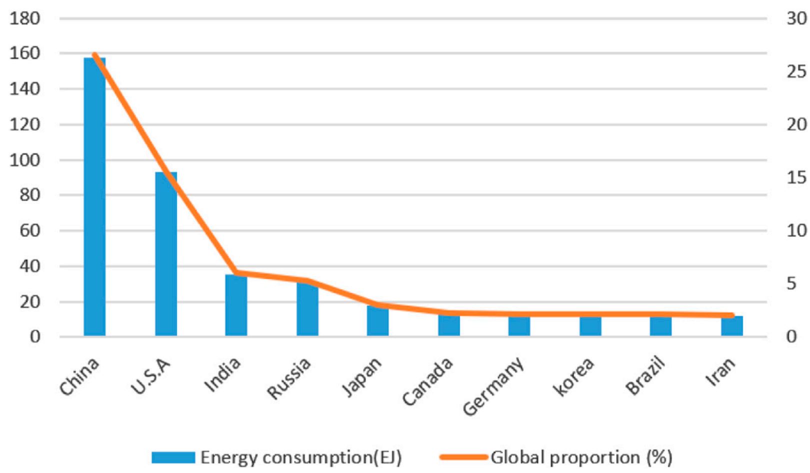

FIGURE 1
Top ten energy consuming countries in the world in 2021.

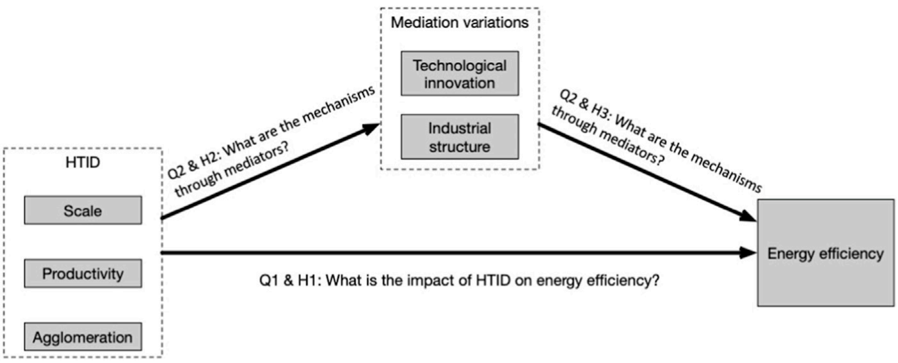

FIGURE 2
The research conceptualized framework.

Chakrabarti, 1996). Similarly, the European Union (2016) also states that high-tech industries are based on high and new technology and engaged in R&D, new production, and technical services with greater economic and social benefits. In short, high-tech industries invest heavily in R&D and advance technology rapidly (Alsleben, 2005). These knowledge- and technology-intensive industries are normally with higher efficiency, more added value, and relatively lower resource consumption than traditional industries (Adams, 2005; Bauer et al., 2012). Therefore, the research tended to reach a consensus that high-tech industry can be considered as green and low-carbon (Bieri, 2010; Li & Lin, 2018) and HTID could lead to sustainable economics by developing innovation, improving efficiency, and reducing pollution (Delgado et al., 2014).

However, the current studies have mainly focused on HTID's impact on energy consumption and the consequent CO_2 emission, other than on energy efficiency. For example, Xu and Lin (2018) applied nonlinear and panel models to study the positive impact of HTID on CO_2 emissions. Li et al. (2019) confirmed the spatial agglomeration and spillover effect of HTID, while showing carbon emission is negatively correlated with HTID in local and adjacent regions. Chen et al. (2019) argued that the scale of HTID has a lagging effect on improving green economy efficiency in the Yangtze River economic belt. Liu et al. (2019) found that R&D investment in some high-tech industries can reduce regional energy consumption. In addition, instead of taking HTID as a whole, researchers tended to explore one specific industry's impact on energy consumption (Bonilla-Camposab et al., 2020), e.g., renewable energy (Weber & Cabras, 2017), electric vehicle (Haddadian et al., 2016), or information and communication (Zhang & Liu, 2015).

2.2 Research on HTID and technological innovation/industrial structure

It is generally agreed that HTID has become an important symbol of the level of scientific progress and productivity development in a country or a region (Shahzad et al., 2022). However, its relationship with technological innovation has not been confirmed. Some studies have suggested the role of high-tech industrial development (such as high-tech industrial agglomeration) in promoting technological innovation (Murshed et al., 2021). Furthermore, these studies tend to argue technological innovation is the key source for enterprises to survive in high-tech industries (Shahzad et al., 2022). In contrast, other studies believe that high-tech industrial agglomeration hinders its access to external knowledge and results in the phenomenon of "free riding" (Yang et al., 2021), which implies a negative relationship between HTID and technological innovation.

Meanwhile, it is also indicated in the existing studies that high tech industries have become the most dynamic growth point of the world economy, the leading industry (Song & Ding, 2019; Dong et al., 2021) to promote economic development, and the backbone to promote the optimization and adjustment of industrial structure. Accordingly, the role of HTID in boosting the development of industrialization and the adjustment of industrial structure has received more academic attention. The findings are generally two-fold. On the one hand, the regional scale differences in the development of high-tech industries will inevitably affect the allocation of regional high-tech industrial resources and the upgrading of industrial structure (Ze-Lei et al., 2017). On the other hand, high-tech industrial agglomeration is conducive to have a spillover effect on the development of other industries, thus promoting the upgrading of industrial institutions and realizing economic transformation (Wolf & Terrell, 2016; Yin & Guo, 2021). Nevertheless, there also exist studies that report no impact of HTID on industrial structure. For example, Zhang (2016) believed that HTID strengthens China's financial structure dominated by indirect finance but fails to promote the upgrading of industrial structure. Furthermore, Jin et al. (2017) found for regions with relatively backward economic development level, HTID has a long lag period, and its role in promoting the upgrading of industrial structure is not obvious.

2.3 Research on technological innovation/industrial structure and energy efficiency

Scholars use to decompose the influencing factors of energy efficiency from two aspects of technological and structural changes, proving that these two aspects play an important role in improving energy efficiency (Sun et al., 2021; Chishti & Sinha, 2022; Dogan et al., 2022; Jahanger et al., 2022). On the one hand, as the main source of technological progress, it has become a common sense that technological innovation helps to improve energy efficiency (Chen & Liu, 2021), although the extent to which technological innovation improves energy efficiency might be affected by factors such as energy price (Cheng & Li, 2010), environmental regulation (Fisher-Vanden et al., 2006), and foreign direct investment (Zhang & Fu, 2022). In contrast to such main-stream understanding, Luo et al. (2015) showed that technological progress has a negative effect on energy efficiency, which stems from the impact of energy rebound effect. Similarly, Chen & Liu, (2021) believe that technological progress has different effects on energy intensity, in which biased technological progress has a more significant impact through factor substitution.

On the other hand, it is normally believed that the optimization of industrial structure is closely related to the improvement of energy efficiency (Dong et al., 2021). Lewis (1954) put forward the "structural dividend hypothesis," which was the first to study the relationship between industrial structure and energy efficiency. Since then, a large number of scholars started to explore this topic, but they reached different conclusion. Most scholars believe that industrial structure adjustment has a significant and positive impact on energy efficiency (Yu et al., 2020b); while other scholars show that the contribution of industrial structure change to energy efficiency is not obvious (Zhou and Lin, 2005; Yuan et al., 2012; Liu & Tian, 2019), or even has a reverse effect (Wang, 2003; Wu and Cheng, 2006).

2.4 Literature analysis

The literature review above provides strong supports to two research gaps proposed in the introduction. On the one hand, there are few studies specifically focusing on the relationship between HTID and energy efficiency. While more research like Dong et al. (2021) that investigated how the development of traditional industries affects the energy efficiency, we are only able to identify two studies, i.e., Jia and Zhang (2013) and Chen et al. (2019), which specifically focused on HTID and energy efficiency. In other words, the effect of HTID on energy efficiency has yet fully clarified and verified. On the other hand, it can also be seen from the above literature review that scholars tend to discuss the relationships between HTID, technological innovation, industrial structure, and energy efficiency two-by-two, rather than building an analytical framework to understand these relationships in a more systematic manner. Besides, the results are rather inconsistent. Corresponding to these gaps, the research questions of this study can further be illustrated in Figure 2 and specified as:

RQ1: Whether does HTID have the impact on energy efficiency?

RQ2: Whether do technological innovation and industrial structure play a role in the impact of HTID on energy efficiency?

3 Hypothesis development and research framework

In this Section, we aim to develop theoretical understandings about the two research questions. Accordingly, three hypotheses and a conceptualized framework regarding the relationships between HTID, technological innovation, industrial structure, and energy efficiency are developed, which will be elaborated below in detail.

3.1 HTID and energy efficiency

In order to understand the relationship between HTID and energy efficiency, it is important to examine three characteristics of high-tech industries. First, high-tech industries compose production factors different from traditional manufacturing (Gil et al., 2019). With their key elements being intellectual resources rather than fixed assets, it is possible for high-tech industries to replace the inputs of energy factors with non-energy ones (Diwan & Chakraborty, 1990). Besides, HTID can facilitate to attract foreign direct investment and other advanced capital, along with a large number of professional and technical personnel, hence leading to higher labor productivity (Bregman et al., 1991). These together reduce energy consumption and improve energy efficiency through factor substitution. Besides, through its rapid flow and integration of resources, HTID can also improve the productivity of industry machinery and equipment, thus leading to less input of energy and other resource (Weber & Cabras, 2017) and further the improvement of energy efficiency (Rogers, 2001). Second, with the competitive advantage of technological innovation, products manufactured by high-tech industries should be highly efficient. Thus, HTID promotes a low-carbon lifestyle among the adopters of high-tech products (Haschka, & Herwartz, 2020), such as solar water heaters and new energy vehicles. Therefore, energy efficiency is improved through advanced technologies. Third, in the ecological environment of industrial agglomeration, new technologies, processes, and management methods used in high-tech industries provide a good environment for local enterprises through external spatial overflow (Fallah et al., 2014). In other words, high-tech companies in the clusters might share infrastructure, including energy and power, pollution control, and other facilities (Fosfuri & Thomas, 2004; Li et al., 2019). Additionally, the clusters might also provide potential knowledge spillover, as employees from different companies or departments could learn from each other (Autant-Bernard & LeSage, 2011), which hence improves energy efficiency. Accordingly, Hypothesis 1 is proposed as:

Hypothesis 1: HTID has a positive impact on energy efficiency.

3.2 Mediating roles of technological innovation and industry structure

Although the existing studies have scarcely addressed the mechanisms of how HTID contributes to energy efficiency, they have indeed proved that HTID can promote technological innovation and industrial transformation (Merchant, 1997), which can further improve energy efficiency (Gerstlberger et al., 2014). This implies that the HTID may have not only a direct impact on energy efficiency but also indirect mediating impacts through technological innovation and industrial structure. In other words, promoting technological innovation and optimizing industry structure might be the underlying mechanisms, which can facilitate HTID positively influencing energy efficiency. Therefore, it is also relevant to examine the potential mediating effects of technological innovation and industry structure on the relationship of HTID and energy efficiency.

3.2.1 Technological innovation

The HTID promotes the generation and diffusion of technological innovation (Perry-Smith & Mannucci, 2017) through technology innovation network to strengthen the learning effect, stimulate the overflow (Feldman & Kelley, 2006), and reduce the cost of information, transactions, and finance among enterprises (Franzen et al., 2007). The high-tech industries not only promote and spread their own industrial technological innovation (Artz et al., 2010), but also provide a foundation for subsequent technological innovation and progress in all industries (Sinton & Levine, 1994). For the firms in high-tech industries, it is possible to achieve more effective allocation of resources, accelerate the flow of innovation elements, improve the technological innovation efficiency, and promote productivity (Chambers et al., 2002; Cho & Pucik, 2005; Chen et al., 2019). For the firms in other industries, HTID facilitates them to acquire new knowledge, methods, technologies, and management systems through widespread adoption of modern production processes and equipment (Kemeny & Osman, 2018). Besides, HTID also stimulates the interaction of technology spillover across organizational units and external parties, especially among firms in high-tech industries and from the firms in higher-tech industries to those in lower-tech industries (Zhang et al., 2017).

All the technological innovations from HTID foster the improvement of energy efficiency by developing novel solutions for energy problems (Costa-Campi et al., 2015). Furthermore, high energy efficiency is the result of optimization in production, processes, and systems, which can be described as the technology progress (soft and hard technology) (Jaffe, 1986; Gerstlberger et al., 2014). More importantly, higher energy efficiency can be gained through the process of search-and-learn technological innovations (Broekel & Brenner, 2011), especially those referring to the processes of acquiring, purchasing, distributing, and using energy (Cagno et al., 2015). By acquiring and using dissimilar yet complementary new energy in various industries derived from technological innovation, critical insights for energy efficiency are generated (Hodson et al., 2018). In summary, energy efficiency can be increased due to the creation, accumulation, and spillover of technological innovation created by HTID. Accordingly, Hypothesis 2 is proposed as:

Hypothesis 2: Technological innovation plays a significant positive intermediary role in the effect of HTID on energy efficiency.

3.2.2 Industrial structure

Supported by HTID, industrial structure can be optimized in two ways. One way is related to industrial transformation, i.e., raising the share of high-tech industries in the economy (Kemeny & Osman, 2018). The other way refers to industrial upgrading, i.e., advancing technology in lower-end industries through diffusion, spillover, and integration of technology, information, knowledge, and resources (Apa et al., 2018). Tang et al. (2017) found that HTID has a certain influence on the optimization of industrial structure and the growth of industrial labor productivity in most countries. Liu et al. (2019) concluded that HTID drives total-factor productivity of medium and low technology industries through multiplier effect on related industries. Therefore, HTID is believed to have a positive influence on industrial restructuring (Wolf & Terrell, 2016).

Meanwhile, the industrial structure is confirmed as a decisive factor accused to huge discrepancies in energy efficiency among different industries. For example, Xiong et al. (2019) tested the impact of the industrial structure on provincial energy efficiency using a regression model. In fact, industrial transformation derived from the proportion increase of high-tech industries implies that high-tech and high-efficiency industries replace traditional high-pollution and energy-intensive industries (Tsai et al., 2009). Thus, along with the reduced energy consumption, energy efficiency can be improved (Borozan, 2018). Meanwhile, the industrial upgrading in traditional industries also adds higher value and promotes total factor productivity for the industries (Ameer & Othman, 2020), which in turn increase energy efficiency. Based on these, Hypothesis 3 is proposed as:

Hypothesis 3: Industrial structure plays a significant intermediary positive role in the effect of HTID on energy efficiency.

Taking all above into consideration, a conceptualized framework illustrating the key elements and research hypotheses are provided as illustrated in Figure 2.

4 Research methodology

4.1 Measurement of HTID and energy efficiency

There are generally two methods to measure HTID: evaluation index system and single index (Broekel, 2008). For the evaluation index system, scholars have proposed different measurement methods. Xiao & Du (2017) measured HTID based on comprehensive performance in terms of two aspects: efficiency of technology and economics. Yang et al. (2016) established four aspects for evaluation: production and operation, science and technology, employees, and fixed assets investment. Tang et al. (2017) considered three aspects of HTID: industrial scale, industrial innovation ability, and industrial benefit. Gui (2018) evaluated HTID based on fixed assets investment, R&D institutions, R&D activity, development and sales of new products, and production and operation situations of high-tech industries. For the single index, it is concluded that the indicators widely used in the existing literature tend to focus more on three characteristics of HTID. The first is scale, represented by the output of high-tech industry (Xu & Lin, 2018). The second is productivity, measured by the proportion of output (Fritsch & Slavtchev, 2011), main business income to gross domestic production (GDP) (Liu et al., 2019), total factor productivity (Chen et al., 2018b), or divesting technological progress from R&D capital (Chen et al., 2019). The third is industry agglomeration measuring the concentration level through an index, such as special agglomeration, diversified agglomeration, or market competition (Brenner, 2012); Cluster Quotient index (CQ) (Yum, 2019); or the location entropy (Chen et al., 2019).

In short, the evaluation index system and single index have their own pros and cons. However, considering HTID has large gaps in different aspects mentioned above among different regions in China, we decide to use more than one index for measuring HTID. Specifically, we consider scale, productivity, and agglomeration. They are respectively corresponding to the perspectives of scale, quality, and space (Ellison et al., 2010), which are the key components of high-tech industries with significant heterogeneity (Bieri, 2010). Besides, these perspectives also have important policy value expressing the different strategic orientations to balance for every government and its stakeholders. Thus, to measure HTID, three variables are applied in this study, as follows:

(1) HTID1 (scale): The ratio of main business income of high-tech industries to GDP[1], (Chen et al., 2018b).

1 Since 2008, China's high-tech industry yearbook has ceased publishing value-added data. Starting in 2012, the total output data was no longer published. Therefore, this study adopts main business income data from 1996 to 2016.

(2) HTID2 (productivity): The ratio of main business income to the average number of employees in high-tech industries (Gui, 2018).
(3) HTID3 (agglomeration): calculated as $LQ = (S_{ij}/S_j)/(S_i/S)$, where S_{ij} represents main business income of high-tech industry j in region i, S_i represents main business income of all industries in province i, S_j represents main business income of high-tech industry j in China; and S represents main business income of all industries in China (Drucker & Feser, 2012)[2].

The measurement of energy efficiency normally includes variables, such as energy intensity, energy productivity, total factor energy efficiency, etc. (Cagno et al., 2015; Borozan, 2018; Dunlop, 2019). Following most of the existing literature, energy productivity, expressed by GDP per unit of energy consumption, is used to measure energy efficiency (EE) in this study (Cagno et al., 2015; Bonilla-Camposab et al., 2020).

4.2 Control variables and mediating variables

The existing studies also suggest other factors that might have strong impacts on energy efficiency, such as foreign direct investment (Xu & Lin, 2018), energy structure (Li et al., 2019), urbanization (Xu & Lin, 2018), marketization degree (Yang et al., 2016), and energy price (Wu & Gao, 2019). Thus, a set of relevant control variables composing of these five is introduced.

(1) Foreign direct investment (FDI): Share of GDP. FDI brings advanced technology, equipment, and management experience for improving energy efficiency (Borozan, 2018). However, China is at the lower end of the global value chain, according to the "pollution paradise" theory. Thus, FDI may have a negative impact on energy efficiency.
(2) Energy consumption structure (ES): Proportion of coal consumption to total energy consumption. Different energy structures produce different energy mix efficiency. Coal accounts for more than 70% of energy consumption in China, but the coal utilization efficiency is generally low. Hence, an increase of coal consumption is expected to negatively influence energy efficiency (Borozan, 2018).
(3) Urbanization (Urb): Proportion of urban population to the total population. Urbanization is expected to have negative scale effect and positive technology effect on energy efficiency, with the total effect dependent on the net effects of the above two (Cheng et al., 2016).
(4) Marketization (Mar): Proportion of non-state economic fixed asset investment in the total social fixed asset investment. Marketization is one of the effective ways to allocate resources. The scarcity of resources will be reflected by the price level; foreign and private companies tend to be more energy efficient than state-owned companies. The improvement of marketization degree is conducive to improving resource allocation efficiency and energy utilization efficiency (Shao et al., 2011; Shao et al., 2019). Therefore, the influence of marketization on energy efficiency may be positive (Yang et al., 2016).
(5) Energy prices (EP): China's fuel and power price index. According to the substitution effect theory, it is assumed that all factors in economics have equal marginal productivity and rising energy prices can improve energy efficiency because of its positive elasticity coefficient on total energy consumption (Wu & Gao, 2019).

According to Hypotheses 2, 3, two mediating variables, i.e., technological innovation and industrial structure, need to be investigated, respectively, in order to further explore the underlying mechanisms. They are measured as follows.

(1) Technological innovation (TI): The number of authorized domestic patent applications (Malinauskaitea et al., 2019).
(2) Industrial structure (IS): The sum of added value of the secondary and tertiary industries per GDP (Yuan et al., 2012).

The information of all the variables is summarized in Table 1.

4.3 Model for examining the impact of HTID on energy efficiency

Existing studies have proved that strong spatial correlation exists in both HTID (Li et al., 2019) and energy efficiency (Shao et al., 2019). Therefore, the spatial panel model is considered for empirical research, incorporating the spatial lag of HTID and energy efficiency to control the spatial correlation. The commonly used spatial econometric models include spatial lag model, spatial error model, and spatial Durbin model. The spatial lag model is mainly used to detect whether dependent variables have spatial overflow effects between regions. The spatial error model is used to investigate the spatial effects of missing variables that are not included in the explanatory variables or unobservable random shocks (Cho & Pucik, 2005). Differently, the Spatial Dobbin Model proposed by Lesage and pace (2009) has the spatial lag term of both dependent and independent variables, which is more general form than spatial lag model and spatial error model. It reflects the spatial effect more comprehensively than the other two methods, hence being more objective and practical. Moreover, Spatial Dobbin Model integrates the spatial correlation of explained variables and explained variables into the model, which has more realistic explanatory power and can

2 From 1996 to 1998, there was no main business income of industrial enterprises, and the ratio of total industrial output value to main business income in 1999 was used for smoothing.

TABLE 1 Description and data resource of each variable.

Variable categories	Symbol and data resource	Meaning	Metrics and specifications	Unit
Explained variable	EE (1)	Energy productivity	Energy consumption per unit of GDP	Tons per 1,000 yuan
Primary explanatory variable	HTID1 (3)	High-tech industries development	Scale	percent
	HTID2 (3)		Productivity	10,000 yuan per people
	HTID3 (3)		Agglomeration	Ratio
Control variables	FDI (2)	Degree of openness	Foreign direct investment as a share of GDP	Percent
	ES (1)	Energy consumption structure	Coal consumption accounts for the proportion of total energy consumption	Percent
	Urb (2)	Urbanization	The proportion of urban population in the total population	Percent
	Mar (2)	Degree of marketization	1- The proportion of fixed assets investment in the state-owned economy in the total fixed assets investment	Percent
	EP (1)	Energy prices	China's fuel and power price index	Percent
Mediator variables	TI (2)	Technological innovation	Number of domestic patent applications authorized	Item
			The number of patent applications accepted	Item
	IS (2)	The industrial structure	The added value of the secondary and thirdary industries accounts for the proportion of GDP	Percent
			Thaier index	Ratio

Note: The number in () of column 2 means the data resource: (1) China energy statistical yearbook; (2) China statistical yearbook, 60 years of new China, and the statistical yearbook of 29 provinces; (3) China statistics yearbook on high technology industry.

consider the direct influence of explained variables by local variables and the indirect influence of explained variables and explained variables in other adjacent regions at the same time (Lesage and pace, 2008). Actually, in empirical studies, when spatial lag and spatial error exist at the same time, a spatial Durbin model is usually constructed for analysis (Cirillo et al., 2018). Therefore, this study adopts the spatial Durbin model for empirical testing. Additionally, considering the possible time-lag effect, the time-lag phase I of energy efficiency is introduced into the static space panel Durbin model to construct the dynamic space panel Durbin model as suggested by the existing studies, e.g., Shao et al. (2019), Feng & Wang (2019), Lee & Yu (2016), and Lv et al. (2019):

$$EE_{it} = \beta_0 + \beta_1 EE_{it-1} + \rho_1 \sum\nolimits_{i=1}^{n} \omega_{ij} EE_{jt} + \beta_2 HTID_{it}$$

$$+\rho_2 \sum\nolimits_{i=1}^{n} \omega_{ij} HTID_{jt} + \delta \sum X_{it} + \lambda \sum\nolimits_{i=1}^{n} \omega_{ij} X_{jt} + \mu_i + \varepsilon_{it} \qquad (1)$$

Where i represents the region i, t represents the year, EE is energy efficiency, EE_{it-1} represents the energy efficiency with a lag period. ω_{ij} is the element of the spatial weight matrix used to describe the spatial proximity relationship between regions. The most commonly used binary spatial weight matrix is adopted, i.e., when two regions are geographically adjacent, $\omega_{ij} = 1$, otherwise $\omega_{ij} = 0$. μ denotes the local fixed effect, and ε denotes the random disturbance term.

4.4 Model for intermediary effect between HTID and energy efficiency

A mediating effect means that the explanatory variable has indirect influence on the explained variable through the intermediate variable. The widely used method to test the mediating effect is the step-by-step method proposed by Baron & Kenny (1986). In order to test the mediating effects of technological innovation and industrial structure suggested in Hypotheses 2, 3, we also follow the spatial econometric method (Shao et al., 2019). As illustrated in the equations and Figure 3 below, the steps are: 1) testing the regression coefficient c of the explanatory variable X to the explained variable Y; 2) testing the regression coefficient a of the explanatory variable X on the mediating variable M, and b of the mediating variable M on the explained variable Y, and if both a and b are significant, the indirect effect is significant; and 3) testing whether the regression coefficient c' of explanatory variable X to the explained variable Y is significant or not. An insignificant result indicates a complete mediating effect (i.e., only the mediating effect exists without a significant direct effect); and a significant result indicates that both the direct and the indirect effects are significant (Cincera, 1997; Shao et al., 2019).

$$Y = cX + e_1 \qquad (2)$$

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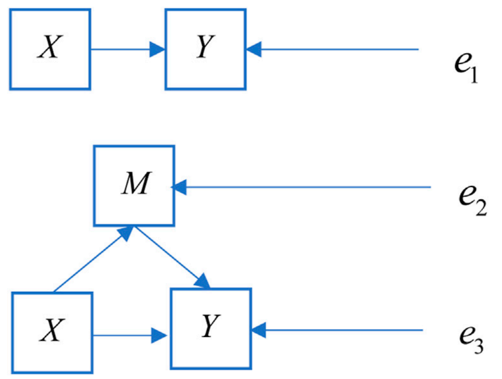

FIGURE 3
Schematic diagram of mediating effects test.

$$M = aX + e_2 \tag{3}$$

$$Y = c'X + bM + e_3 \tag{4}$$

According to Hypotheses 2, 3, technological innovation and industrial structure are the intermediary variable M, energy efficiency is explained variable Y, and HTID is explanatory variable X. The time lag and spatial lag item of the energy efficiency are the control variables, as well as FDI, ES, Urb, Mar, EP. Taking technological innovation and industrial structure as the mediating variable, respectively, the models for testing the mediating effects are set as follows:

$$TI_{it} = \gamma_0 + \gamma_1 TI_{it-1} + \theta_1 \sum\nolimits_{i=1}^{n} \varpi_{ij} TI_{jt} + \gamma_2 HTID_{it}$$
$$+ \theta_2 \sum\nolimits_{i=1}^{n} \varpi_{ij} HTID_{jt} \quad + \varsigma \sum X'_{it} + \theta_3 \sum\nolimits_{i=1}^{n} \varpi_{ij} X'_{jt} + \psi_i + \tau_{it} \tag{5}$$

$$EE_{it} = \alpha_0 + \alpha_1 EE_{it-1} + \pi_1 \sum\nolimits_{i=1}^{n} \omega_{ij} EE_{jt} + \alpha_2 HTID_{it}$$
$$+ \pi_2 \sum\nolimits_{i=1}^{n} \omega_{ij} HTID_{jt} \quad + \alpha_3 TI_{it} + \varphi \sum X'_{it} + \pi_3 \sum\nolimits_{i=1}^{n} \omega_{ij} X'_{jt} + v_i + \xi_{it} \tag{6}$$

$$IS_{it} = \gamma_0 + \gamma_1 IS_{it-1} + \theta_1 \sum\nolimits_{i=1}^{n} \varpi_{ij} IS_{jt} + \gamma_2 HTID_{it}$$
$$+ \theta_2 \sum\nolimits_{i=1}^{n} \varpi_{ij} HTID_{jt} \quad + \varsigma \sum X'_{it} + \theta_3 \sum\nolimits_{i=1}^{n} \varpi_{ij} X'_{jt} + \psi_i + \tau_{it} \tag{7}$$

$$EE_{it} = \alpha_0 + \alpha_1 EE_{it-1} + \pi_1 \sum\nolimits_{i=1}^{n} \omega_{ij} EE_{jt} + \alpha_2 HTID_{it}$$
$$+ \pi_2 \sum\nolimits_{i=1}^{n} \omega_{ij} HTID_{jt} \quad + \alpha_3 IS_{it} + \varphi \sum X'_{it} + \pi_3 \sum\nolimits_{i=1}^{n} \omega_{ij} X'_{jt} + v_i + \xi_{it} \tag{8}$$

Where TI and IS represent the technological innovation and industrial structure, respectively. TI_{it-1} and IS_{it-1} denote the technological innovation and industrial structure with lag period, respectively. Other variables are similar to Eq. 1. More specifically, Eqs 5, 7 can be viewed as the extension of Eq. 3, and Eqs 6, 8 can be viewed as the extension of Eq. 4 in the context of our study.

4.5 Sample data description

Based on the data availability and statistical caliber consistency, our sample includes 29 administrative regions (Tibet and Chongqing are eliminated due to missing data) at the provincial level in China (province, municipality directly under the central government, or autonomous regions) from 1996 to 2016. The data for total energy consumption, the proportion of coal consumption, China's fuel and power price index are from the "China Energy Statistical Yearbook" for the periods from 1996 to 2017. The data related to GDP, patent applications, main business income of industrial enterprises, FDI, urbanization, and industrial structure are from the "China Statistical Yearbook", "60 Years of New China," and the statistical yearbooks of 29 provinces for the periods from 1996 to 2017. Furthermore, according to the classification of China's high-tech industries yearbook, five major sectors (pharmaceutical, aerospace, electronics and communication equipment, computer and office equipment, and medical equipment industries) are selected for our study (Liu et al., 2019). The data for variables related to high-tech industries, such as the main business income and the average annual number of employees, are from the "China Statistics Yearbook on High Technology Industry" for the periods from 1996 to 2017. Value terms are adjusted to the price of 1996. In order to reduce the dispersion degree of sample data in empirical analysis and weaken multicollinearity and heteroscedasticity problems, the variable data (EE,HTID2,HTID3) in non-percentage units are logarithmic. Since the number of authorized domestic patent applications may be zero, technological innovation (TI) is also logarithmic. The statistical descriptions of variables can be seen in Table 2.

As shown in Table 2, the observations number is 609 from 29 provinces during the period from 1996 to 2016. The mean of EE is 1.4912, less than its Std. dev., and the gap between its Max and Min is large, as well as HTID2 (Productivity) and HTID3 (Agglomeration). The scale of HTID of China in the sample period is in the range between 53.8519 and 0.2266, with the average being 10.1982.

5 Results

Before the parameter estimation of the spatial panel model, the spatial correlation test is conducted for the residual error of the ordinary least squares (OLS) estimation. The results show that the explained variables of the equation have significant spatial correlation, making it necessary to apply the spatial panel model for research. Considering the correlation of time and space and the possible endogeneity of the explained variables, the dynamic spatial Durbin model is estimated using the generalized method of moments (GMM), which allows some independent variables to be endogenous and thus makes it a better estimation method for the possible endogeneity of the explained variables. For comparative analysis, the estimation

TABLE 2 Statistical description of variables.

Variable	Observations	Mean	Std. dev.	Max	Min
EE	609	1.4912	0.5350	5.3026	−2.1882
HTID1 (Scale)	609	10.1982	11.4255	53.8519	0.2266
HTID2 (Productivity)	609	28.1796	0.9444	219.3788	2.0610
HTID3 (Agglomeration)	609	5.7454	1.1216	53.8499	−4.4128
FDI	609	59.2465	14.9453	87.4551	13.1201
ES	609	61.5384	16.1643	95.5645	8.6326
Urb	609	46.3843	16.9879	89.6000	16.7746
TI	609	4095.7290	1.7151	269952.15	43.0000
IS	609	86.0637	7.6642	102.1287	63.5549
Mar	609	59.0898	15.2812	87.9504	15.5759
EP	609	191.3956	87.2614	744.7856	98.2376

TABLE 3 Impact of HTID on energy efficiency.

	Durbin model for static space panel (FGLS)			Durbin model of dynamic space panel (FE)			Durbin model of dynamic space panel (GMM)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.EE				0.8712*** (0.0190)	0.8704*** (0.0189)	0.8693*** (0.0195)	0.9659*** (0.0081)	0.9684*** (0.0082)	0.9566*** (0.0094)
HTID1	0.0141*** (0.0017)			0.0002 (0.0006)			0.0006** (0.0003)		
HTID2	0.3433*** (0.0236)			0.0237*** (0.0100)			0.0129** (0.0056)		
HTID3		0.2076*** (0.0167)			0.0005 (0.0078)			0.0192*** (0.0042)	
FDI	−0.0036 (0.0029)	−0.0056** (0.0027)	−0.0022 (0.0027)	0.0002 (0.0007)	0.0002 (0.0007)	0.0002 (0.0007)	−0.0001 (0.0008)	0.0000 (0.0008)	0.0000 (0.0007)
ES	−0.0009 (0.0013)	−0.0019* (0.0011)	−0.0005 (0.0012)	−0.0005** (0.0002)	−0.0006** (0.0002)	−0.0005** (0.0002)	−0.0006** (0.0003)	−0.0006** (0.0003)	−0.0006** (0.0003)
Urb	0.0047*** (0.0012)	0.0031*** (0.0011)	0.0051*** (0.0011)	−0.0002 (0.0003)	−0.0002 (0.0003)	−0.0002 (0.0003)	0.0004** (0.0002)	0.0004 (0.0002)	0.0004* (0.0003)
Mar	0.0047 (0.0029)	0.0064** (0.0026)	0.0037 (0.0027)	−0.0002 (0.0006)	−0.0001 (0.0006)	−0.0001 (0.0006)	−0.0003 (0.0007)	−0.0003 (0.0007)	−0.0004 (0.0006)
EP	−0.0000 (0.0002)	−0.0002 (0.0002)	−0.0000 (0.0002)	−0.0000 (0.0000)	−0.0001 (0.0000)	−0.0001 (0.0000)	−0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
ω.EE	−0.1260*** (0.0190)	−0.0730*** (0.0164)	−0.1294*** (0.0173)	−0.0120*** (0.0056)	−0.0123** (0.0056)	−0.0123** (0.0056)	−0.0028 (0.0029)	0.0003 (0.0025)	0.0006 (0.0027)
ω.HTID1	0.0031*** (0.0009)			−0.000 (0.0003)			−0.0004*** (0.0001)		
ω.HTID2	0.0022 (0.0110)			−0.0678 (0.0636)			−0.0066*** (0.0022)		
ω.HTID3		0.0230*** (0.0085)			0.0018 (0.0036)			−0.0007 (0.0015)	
R^2			0.9596	0.9600	0.9596	0.9888	0.9888	0.9889	

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

results of the dynamic spatial Durbin model fixed effect (FE) and static spatial panel Durbin model feasible generalized least square method (FGLS) are also reported. Especially, the latter, which reduces intra-group heteroscedasticity and autocorrelation, is used for comparative analysis of the static panel model.

5.1 Test of hypothesis 1: Impact of HTID on energy efficiency

Table 3 provides the estimation results regarding the impact of HTID on energy efficiency. In this table, columns (1), (4), and (7) are the regression results with HTID1 (the scale of HTID) as the explanatory variable; columns (2), (5), and (8) refer to the regression results with HTID2 (the productivity of HTID) as explanatory variable; and columns (3), (6), and (9) show the regression results with HTID3 (the agglomeration of HTID) as the explanatory variable.

According to the estimated results of columns (7), (8), and (9) in Table 3, the impacts of scale (HTID1), productivity (HTID2), and agglomeration (HTID3) of HTID on energy efficiency are positive. Nevertheless, HTID3 has a more significant effect at 1% with a higher coefficient, showing that the agglomeration of HTID is likely to outperform the scale and productivity on increasing energy efficiency. In other words, Hypothesis 1 is confirmed that HTID can significantly improve energy efficiency in terms of scale, productivity and agglomeration.

Furthermore, comparing the impacts of three aspects of local HTID on energy efficiency, the scale and productivity of HTID in neighborhoods (i.e., $\omega\cdot$ HTID1 and $\omega\cdot$ HTID2) could significantly decrease local energy efficiency. The possible reason is that available resources for HTID are limited, and resource occupation by high-tech industries in neighborhoods would be detrimental to local HTID, thus inhibiting the increase of energy efficiency. According to the Durbin model for static space panel (FGLS), all three perspectives (HTID1, HTID2, HTID3) have the statistically significant positive effect at 1%. The scale and agglomeration of HTID in neighborhoods (i.e., $\omega\cdot$ HTID1 and $\omega\cdot$ HTID3) can have a positive impact on local energy efficiency, meaning that HTID has a significantly positive spatial spillover effect through scale and agglomeration, while the productivity is not significant, which may be due to its own spatial characteristics.

For the control variables, the effects of urbanization (Urb) and technological innovation on energy efficiency are significantly positive, perhaps due to the advance technology and increased electricity consumption efficiency with advanced electricity consumption facilities in cities along with urbanization (Xu & Lin, 2018). The impact of energy consumption structure (ES) on energy efficiency is significantly negative, indicating that the increase in coal consumption proportion can have a negative impact on energy efficiency. Reducing the proportion of coal in the energy mix is necessary and has been in progress in China for more than 20 years. The influences of openness (FDI), marketization (Mar), and energy prices (EP) on energy efficiency are uncertain (showing different effects in every regression result of Table 3), but these are not the main factors examined in this study.

5.2 Test of hypothesis 2: The mediating effect of technological innovation

The GMM dynamic spatial Durbin model is applied to estimate the mediating effect. According to the mediating effect test model, the mediating effect of technological innovation on the relationship between HTID and energy efficiency is empirically tested by following Eqs 1, 5, 6. Specifically, the test examines whether the coefficients of the impact of HTID on technological innovation in Eqs 5, 6 are statistically significant. When both are significant, technological innovation has a mediating effect between HTID and energy efficiency. In Table 4, columns (1) and (2) report the results while considering the scale of HTID; columns (3) and (4) refer to the productivity of HTID, and columns (5) and (6) show the agglomeration of HTID.

In Table 4, columns (1), (3), and (5) inspect the impact of HTID on the intermediary variable (technological innovation, TI). Scale of HTID is shown to have no significant influence on technological innovation, while productivity and agglomeration of HTID has statistically positive effects at last 10% level. Column (2) in Table 4 demonstrates that although the influence of technological innovation on energy efficiency is significantly positive, technological innovation has no mediating effect between the scale of HTID (HTID1) and energy efficiency. This is further confirmed by the Sobel test (Mackinnon et al., 2002). Moreover, given the results in Table 3 showing that the effects of HTID on energy efficiency are significantly positive, columns (4) and (6) in Table 4 indicate the full mediating effect of technological innovation on the relationship between productivity of HTID (HTID2) and energy efficiency, and partial mediating effect on the relationship between agglomeration of HTID (HTID3) and energy efficiency. In other words, the productivity of HTID can facilitate the increase of energy efficiency fully through technological innovation, and agglomeration impact partly through technological innovation. Therefore, Hypothesis 2 is partially supported.

5.3 Test of hypothesis 3: The mediating effect of industrial structure

The mediating effect of industrial structure on the relationship between HTID and energy efficiency is empirically tested by following Eqs 1, 7, 8. The results are shown in Table 5, indicating whether industrial structure plays an intermediary role in the effect of HTID on energy efficiency. Again, in Table 5, columns (1) and (2) report the results considering the scale of HTID; columns (3) and (4) refer to the productivity of HTID, and columns (5) and (6) indicate the agglomeration of HTID.

In Table 5, columns (1), (3), and (5) show that the influences of scale and agglomeration of HTID on industrial structure are significantly positive at the 10% level, while productivity of HTID is negative and not significant. Columns (2) and (6) in Table 5 show that the influences of scale and agglomeration of HTID on energy efficiency are significantly at 10% level. Thus, in addition to the results in Table 3 showing that the effects of HTID on energy efficiency are

TABLE 4 Intermediary effect test of technological innovation.

	(1)	(2)	(3)	(4)	(5)	(6)
	TI	EE	TI	EE	TI	EE
L.EE		0.9854*** (0.0070)		0.9875*** (0.0068)		0.9724*** (0.0083)
L.TI	0.9745*** (0.0099)		0.9692*** (0.0102)		0.9713*** (0.0102)	
TI		0.0125*** (0.0035)		0.0115*** (0.0035)		0.0112*** (0.0034)
HTID1	0.0015 (0.0011)	0.0007 (0.0018)				
HTID2			0.0292* (0.0163)	0.0035 (0.0058)		
HTID3					0.0268** (0.0126)	0.0150*** (0.0041)
FDI	−0.0011 (0.0022)	−0.0023 (0.0003)	−0.0012 (0.0022)	0.0001 (0.0008)	−0.0010 (0.0022)	0.0002 (0.0008)
ES	0.0007 (0.0009)	−0.0006** (0.0003)	0.0007 (0.0009)	−0.0006** (0.0002)	0.0006 (0.0009)	−0.0006** (0.0003)
Urb	−0.0006 (0.0007)	−0.0005** (0.0002)	−0.0008 (0.0007)	−0.0005** (0.0002)	−0.0004 (0.0007)	−0.0005* (0.0003)
Mar	0.0025 (0.0020)	−0.0005 (0.0007)	0.0026 (0.0021)	−0.0005 (0.0007)	0.0023 (0.0021)	−0.0006 (0.0007)
EP	−0.0004*** (0.0001)	0.00004 (0.00003)	−0.0003*** (0.0001)	0.0004*** (0.0001)	−0.0003*** (0.0001)	0.0004* (0.0002)
ω.EE		0.0065*** (0.0025)		0.0057*** (0.0022)		0.0020*** (0.0024)
ω.HTID1	−0.0010** (0.0004)	0.0004*** (0.0001)				
ω.HTID2			−0.0116* (0.0064)	0.0050*** (0.0019)		
ω.HTID3					−0.0045 (0.0043)	−0.0000 (0.0015)
ω.TI	0.0116*** (0.0025)		0.0117*** (0.0029)		0.0100*** (0.0025)	
R^2	0.9889	0.9884	0.9889	0.9883	0.9888	0.9885

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

TABLE 5 Intermediary effect test of industrial structure.

	(1)	(2)	(3)	(4)	(5)	(6)
	IS	EE	IS	EE	IS	EE
L.EE		0.9734*** (0.0066)		0.9708*** (0.0066)		0.9682*** (0.0068)
L.IS	0.9540*** (0.0092)		0.9655*** (0.0082)		0.9579*** (0.0092)	
IS		−0.0013* (0.0007)		−0.0006 (0.0007)		−0.0018** (0.0008)
HTID1	0.0090* (0.0050)	0.0003** (0.0001)				
HTID2			−0.0940 (0.0803)	0.0020 (0.0052)		
HTID3					0.1050* (0.0468)	0.0075** (0.0034)
FDI	0.0052 (0.0098)	0.0000 (0.0008)	0.0080 (0.0098)	0.0001 (0.0007)	0.0075 (0.0098)	0.0002 (0.0007)
ES	−0.0030 (0.0043)	−0.0005* (0.0003)	−0.0014 (0.0044)	−0.0004 (0.0007)	−0.0026 (0.0042)	−0.0004* (0.0003)
Urb	0.0073** (0.0034)	0.0004 (0.0014)	0.0076** (0.0037)	0.0003* (0.0002)	0.0075** (0.0033)	0.0003 (0.0002)
Mar	0.0026 (0.0089)	−0.0003 (0.0006)	0.0031 (0.0089)	−0.0004 (0.0006)	0.0015 (0.0090)	−0.0004 (0.0006)
EP	−0.0003 (0.0005)	0.0004*** (0.0000)	−0.0006*** (0.0000)	−0.0000 (0.0000)	−0.0005 (0.0005)	0.0004*** (0.0000)
ω.EE		0.0067** (0.0026)		−0.0028 (0.0021)		0.0012 (0.0023)
ω.HTID1	0.0037* (0.0020)	−0.0004** (0.0001)				
ω.HTID2			−0.0984***(0.0292)	−0.0019** (0.0009)		
ω.HTID3					0.0667*** (0.0232)	0.0012 (0.0014)
ω.IS	0.0058** (0.0022)		0.0052** (0.0020)		0.0076** (0.0022)	
R^2	0.9859	0.9885	0.9860	0.9887	0.9861	0.9886

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

significantly positive, industrial structure has a partial negative mediating effect between the scale and agglomeration of HTID (HTID1 and HTID3) and energy efficiency. Meanwhile, columns (3) and (4) in Table 5 demonstrate that the influence of industrial structure and productivity of HTID on energy efficiency is not significant, which is further confirmed by the Sobel test (Mackinnon et al., 2002). This further demonstrates that industrial structure has no mediating effect between the productivity of HTID (HTID2) and energy efficiency. Therefore, Hypothesis 3 is also partially supported.

5.4 Robustness test

Although the above study shows that HTID can significantly improve energy efficiency, there are different measurements for energy efficiency and the mediating variables, which might affect the robustness of the results. Therefore, we further evaluate our results by changing the measurement of energy efficiency and the mediating variables. We use the total-factor energy efficiency based on the SFA model to measure energy efficiency (Zou et al., 2019); Theil index (Gan et al., 2011) to represent the industrial structure (replacing the proportion of the added value of the secondary and tertiary industries in GDP), and the number of accepted patent applications (Yuan et al., 2012) to represent technological innovation (replacing the number of authorized patent applications). As noted previously, only the optimal GMM estimation is used. Table 6 reports the basic regression results of the robustness test according to the above considerations. The effect of HTID on energy efficiency is significantly positive, which are consistent with results in Table 3.

Tables 7, 8 show further investigations of the mediating effects of technological innovation and industrial structure by using the new measures.

In Table 7, columns (2), (4), and (6) show that technological innovation has a positive impact on energy efficiency, but only productivity and agglomeration of HTID have significantly positive influences on technological innovation as shown in columns (1), (3), and (5). In addition to the results shown in Table 6, we can get the same conclusion i.e., complete mediating effect of technological innovation between productivity of HTID (HTID2) and energy efficiency, while partial mediating effect between agglomeration of HTID (HTID3) and energy efficiency.

In Table 8, columns (2), (4), and (6) illustrate that the impact of industrial structure on energy efficiency is negative, while only the influences of scale and agglomeration of HTID (HTID1 and HTID3) on industrial structure and energy efficiency are significantly positive. In addition to the results shown in Table 6, we can achieve the same conclusion, i.e., industrial structure has a partial negative mediating effect between the scale and agglomeration of HTID and energy efficiency, meaning that expansion of HTID scale and agglomeration negatively influences energy efficiency through industrial structure.

TABLE 6 Robust test of the impact of HTID on energy efficiency.

	(1)	(2)	(3)
L.EE	0.9127***(0.0064)	0.9272***(0.0066)	0.9111***(0.0064)
HTID1	0.0032***(0.0002)		
HTID2		0.0087**(0.0032)	
HTID3			0.0122***(0.0002)
FDI	0.0002 (0.0006)	0.0002 (0.0006)	0.0002 (0.0006)
ES	−0.0008**(0.0001)	−0.0006**(0.0002)	−0.0012***(0.0002)
Urb	0.0013**(0.0003)	0.0005***(0.0002)	0.0004**(0.0002)
Mar	−0.0008 (0.0006)	−-0.0008 (0.0006)	−0.0008 (0.0006)
EP	0.0001***(0.0000)	0.0002**(0.0000)	0.0001***(0.0000)
ω.EE	−0.0012 (0.0019)	−0.0025 (0.0019)	−0.0015 (0.0022)
ω.HTID1	−0.0012**(0.0001)		
ω.HTID2		−0.0007***(0.0003)	
ω.HTID3			−0.0002 (0.0012)
R^2	0.9878	0.9878	0.9880

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

6 Discussion

The impact of HTID on energy efficiency and its underlying mechanisms derived from our empirical analysis are shown in Figure 4. It is illustrated that, on the one hand, the scale, productivity and agglomeration of HTID all have significant positive effects on energy efficiency. On the other hand, the scale of HTID also has an indirect negative impact through industrial structure; the productivity of HTID has an indirect positive impact on energy efficiency through technological innovation; the agglomeration of HTID has an indirect positive impact through technological innovation and an indirect negative impact through industrial structure. These results will be further discussed below.

First, HTID has a significant impact on energy efficiency, which is important for the climate change. In other words, our findings enrich the existing knowledge by suggesting that the scale, productivity and agglomeration of HTID all could improve the total-factor energy efficiency and increase energy efficiency.

Second, the scale of HTID leads to not only a direct increase of energy efficiency and but also an indirect reduction of energy efficiency through industrial structure. This conclusion conflicts with the expected results and previous studies, e.g., Kemeny & Osman (2018) and Ameer & Othman (2020). In combination with China's national conditions, the potential explanation might be that like the traditional industries, HTID in China still remains the extensive growth mode and depends on the economies of scale to improve energy efficiency (Li et al., 2017). In other words, HTID in China still focuses on the low-end expansion now, rather than upgrading. Hence, the optimization of industrial structure in China stimulated by

TABLE 7 Robust test of the intermediary effect of technological innovation.

	(1)	(2)	(3)	(4)	(5)	(6)
	TI	**EE**	**TI**	**EE**	**TI**	**EE**
L.EE		0.9905*** (0.0066)		0.9940*** (0.0067)		0.9792*** (0.0071)
L.TI	0.5170*** (0.0325)		0.5722*** (0.0292)		0.5637*** (0.0295)	
TI		0.0045** (0.0020)		0.0046** (0.0020)		0.0038* (0.0020)
HTID1	0.0008 (0.0060)	−0.0004 (0.0002)				
HTID2			0.0638* (0.0431)	0.0037 (0.0052)		
HTID3					0.1207** (0.0589)	0.0127*** (0.0030)
FDI	−0.0266** (0.0127)	−0.0000 (0.0006)	−0.0314** (0.0126)	0.0000 (0.0006)	−0.0306** (0.0127)	−0.0000 (0.0006)
ES	0.0013 (0.0034)	0.0002 (0.0002)	0.0018 (0.0036)	0.0003 (0.0002)	0.0015 (0.0035)	0.0002 (0.0002)
Urb	0.0097** (0.0041)	0.0004** (0.0002)	0.0079* (0.0042)	0.0006*** (0.0002)	0.0067* (0.0038)	0.0002 (0.0002)
Mar	0.0262** (0.0118)	−0.0006 (0.0005)	0.0309** (0.0120)	−0.0006 (0.0005)	0.0292** (0.0119)	−0.0007 (0.0005)
EP	0.0003 (0.0006)	0.0001*** (0.0000)	0.0004 (0.0006)	0.0001** (0.0000)	0.0005 (0.0006)	0.0001*** (0.0000)
ω.EE		0.0003 (0.0020)		0.0016 (0.0020)		0.0008 (0.0022)
ω.HTID1	0.0015 (0.0020)			0.0007*** (0.0003)		
ω.HTID2		0.0000 (0.0001)			0.0006 (0.0021)	
ω.HTID3			0.0007 (0.0025)			−0.0001 (0.0012)
ω.TI	0.0124*** (0.0036)		0.0029 (0.0105)		−0.0198 (0.0202)	
R^2	0.4989	0.9876	0.4890	0.9876	0.4923	0.9879

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

TABLE 8 Intermediate effect test of industrial structure (Theil index).

	(1)	(2)	(3)	(4)	(5)	(6)
	IS	**EE**	**IS**	**EE**	**IS**	**EE**
L.EE		0.9894*** (0.0065)		0.9929*** (0.0065)		0.9788*** (0.0071)
L.IS	0.3318** (0.0357)		0.3312*** (0.0351)		0.3297*** (0.0352)	
IS		−0.0372*** (0.0076)		−0.0138 (0.0174)		−0.0140** (0.0047)
HTID1	0.0014** (0.0006)	0.0006** (0.0002)				
HTID2			−0.0068 (0.0077)	0.0048 (0.0051)		
HTID3					0.0066** (0.0025)	0.0138*** (0.0031)
FDI	0.0002 (0.0016)	0.0002 (0.0006)	0.0001 (0.0016)	0.0002 (0.00063)	0.0002 (0.0016)	0.0001 (0.0006)
ES	0.0000 (0.0003)	0.0002 (0.0002)	0.0001 (0.0003)	0.0002 (0.0002)	0.0000 (0.0003)	0.0002 (0.0002)
Urb	0.0006 (0.0004)	0.0003 (0.0002)	0.0002 (0.0004)	0.0005*** (0.0002)	0.0002 (0.0003)	0.0001 (0.0002)
Mar	0.0004 (0.0015)	−0.0008 (0.0006)	0.0005 (0.0015)	−0.0008 (0.0006)	0.0003 (0.0015)	−0.0008 (0.0006)
EP	−0.0001** (0.0001)	0.0001 (0.0000)	−0.0001** (0.0001)	0.0001** (0.0000)	−0.0001** (0.0001)	0.0001*** (0.0000)
ω.EE		0.0013 (0.0019)		0.0025 (0.0019)		0.0015 (0.0000)
ω.HTID1	0.0001 (0.0002)	0.0000*** (0.0000)				
ω.HTID2			0.0002 (0.0009)	0.0007** (0.0003)		
ω.HTID3					−0.0006 (0.0018)	−0.0002 (0.0012)
ω.IS	0.0835*** (0.0002)		0.0831*** (0.0078)		0.0829*** (0.0078)	
R^2	0.3776	0.9878	0.3784	0.9878	0.3787	0.9880

Note: *significant at 10%; **significant at 5%; ***significant at 1%; L. means lag phase one.

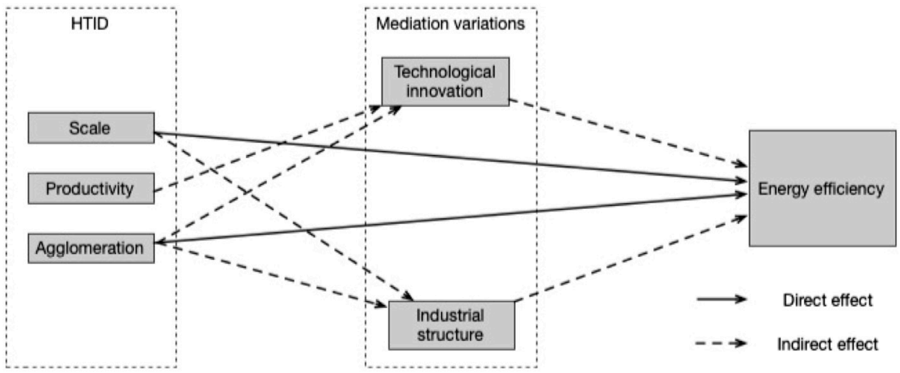

FIGURE 4
The impact of HTID on energy efficiency and its underlying mechanisms.

HTID emphasizes scale exploration and centers more on addressing the output growth of HTID (Tang et al., 2017; Chen et al., 2018b; Malinauskaitea et al., 2019). Therefore, the scale of HTID has failed to achieve the expected positive effect on energy efficiency through promoting synchronous growth and upgrading industrial structure.

Third, the productivity of HTID promotes energy efficiency through technological innovation as expected. Somehow, this is also implied in Chen et al. (2019) and Cho & Pucik (2005), but it is beyond our expectation that this mediating effect is complete. Nevertheless, such unexpected result can be explained by applying the theory of competition strategy and technological innovation (Gerstlberger et al., 2014). According to this theory, some advanced industries may stimulate innovation in other industries through input-output linkages (Isaksson et al., 2016). As mentioned above, high-tech industries are normally knowledge- and technology-intensive, with the key elements as intellectual resources rather than fixed assets (Alegre et al., 2013). Therefore, their direct effect on improving energy efficiency might be limited. However, high-tech industries can promote productivity through continuous technological progress and enhance the technical level in all industries due to technology spillover and diffusion (Tang et al., 2017). Accordingly, the marginal productivity increases accused to widespread adoption of modern production technology and equipment (Sinton & Levine, 1994). In other words, technological innovation stimulates the adoption of different but complementary new energy in various industries, so as to improve energy efficiency (Hodson et al., 2018). Therefore, the productivity of HTID has a positive indirect influence on energy efficiency completely through technological innovation, and such indirect influence is complete.

Finally, the agglomeration of HTID not only significantly promotes energy efficiency directly and indirectly through technological innovation, but it also has a negative impact through industrial structure. Such conflicting effects can be further understood by applying industrial cluster theory (Drucker & Feser, 2012; Delgado et al., 2014). According to this theory, industrial agglomeration is beneficial to promote technological innovation in high-tech industries (Yang et al., 2016). On the one hand, due to “external economies,” the agglomeration of HTID benefits enterprises through shared labor pools, specialist suppliers, and public infrastructure (Kemeny & Osman, 2018), especially for knowledge companies that rely on face-to-face contact, social networks, and tacit knowledge exchange (Asheim et al., 2011). The resulting technological innovation reduces energy consumption and greenhouse gas emissions to a certain extent (Cieslik & Ghodsi, 2015). However, on the other hand, we found that agglomeration of HTID indirectly inhibits energy efficiency through industrial structure, which is inconsistent with our expectations and the conclusion of Tsai et al. (2009) and Borozan (2018). In line with the spatial characteristics of high-tech industrial agglomeration, the possible explanation is that the level of energy efficiency mainly depends on technological progress (Fisher-Vanden et al., 2004). During the sample investigation period, Chinese technological level and the degree of HTID’ agglomeration are relatively low, the economies of scale of energy consumption have not yet formed, making it difficult for agglomeration to play a significant role in promoting energy efficiency through its positive externalities such as technology spillovers. Furthermore, the “closure” characteristic of high-tech industry agglomeration hinders its access to external knowledge and leads to the phenomenon of “free riding” (Yang et al., 2021). Finally, the increase of HTID’s agglomeration in some regions has accelerated outputs, which boost energy consumption, and thereby inhibit energy efficiency. Thus, the net influence is positive between the positive one from technological innovation and negative one from industrial structure.

7 Conclusions and policy recommendations

Along with global warming and energy resources exhausting, energy efficiency has become one of the main aspects of national policy strategies, where HTID is expected to play an increasingly important role. However, it remains unclear how HTID impacts on energy efficiency as well as the mechanisms behind. In order to address these two gaps, this study proposes two research questions related to the impact of HTID on energy efficiency and the mediating effects of technological innovation and industrial structure. Taking China as research context and applying the dynamic panel Durbin model and the intermediary effect model, it further examines three hypotheses regarding the impact of HTID on energy efficiency and the mediating effects of technological innovation and industrial structure. In doing so, this study makes two-fold theoretical contributions. On the one hand, it contributes on the existing body of scientific knowledge by expounding the relationship between scale, productivity, and agglomeration of HTID and energy efficiency. More specifically, our analysis confirms that HTID has a significant positive impact on energy efficiency from three aspects of scale, productivity, and agglomeration of HTID, among which, agglomeration has the greatest influence on energy efficiency. On the other hand, it further deepens the understanding on such relationship by revealing two underlying mechanisms behind, i.e., through promoting technological innovation, the productivity and agglomeration of HTID can either completely or partially improve energy efficiency, while through reorganizing industrial structure the scale and agglomeration of HTID can hinder energy efficiency to a certain level.

Corresponding to the findings above, the following policy recommendations can be proposed. First, actions should be taken to develop high-tech industries. Especially, the productivity and spatial agglomeration of high-tech industries should receive more attention than scale expansion for improving energy efficiency, and further for achieving the sustainable economics. Second, in the current development stage of China, promoting technological innovation is critical for higher energy efficiency, which further helps to achieve climate change goal. Thus, technological innovation should be set as the goal of strengthening industrial productivity and agglomeration. Finally, the scale enlargement and agglomeration of HTID currently decrease energy efficiency due to industrial structure, indicating that HTID is in the low-end expansion stage. Hence, efforts should be made to promote the transformation and upgrading of industrial structure, in order to increase energy efficiency.

This research has certain limitations, which present opportunities for future research. First, the development level of high-tech industries in different regions of China is uneven. The eastern region of China has great superiority in HTID based on the high quality of human resources and the abundant presence of investment capital. The rich supply of natural resources in the central and western regions makes them locked in a low value-added position in the industrial chain (Dong et al., 2016). Therefore, regional heterogeneity should be considered in the future to gain an in-depth understanding of the relationship between HTID and energy efficiency. Second, the measurement of the high-tech industry scale only reflects output growth. As the scale level inhibits energy efficiency through industrial structure, different orientation strategies of HTID should be considered in the future. Third, in addition to technological innovation and industrial structure, it is also meaningful to investigate whether economic growth has an intermediary impact between HTID and energy efficiency. We hope future research will address these issues.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

There are six authors for this paper. Their contributions are listed below: YZ: Conceptualization; Funding acquisition; Project administration; Resources; Roles/Writing—original draft; Writing—review and editing. MH: Subsequent revision of manuscript; Addition of literature review and graphics; Writing—review and editing. WX: Data curation; Formal analysis; Software; Validation; Visualization; Roles/Writing—original draft. LL: Formal analysis; Software; Validation; Visualization; Roles/Writing—original draft. YL: Software; Validation; Visualization; Writing—review and editing. JG: Writing—review and editing. YC: Conceptualization; Investigation; Methodology; Project administration; Supervision; Validation; Writing—review and editing.

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Conflict of interest

JG was employed by UNEP Copenhagen Climate Centre.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.962627/full#supplementary-material

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