The driving effect of technological innovation on green development: dynamic efficiency spatial variation

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Received: 6 January 2022 / Accepted: 8 June 2022 / Published online: 4 July 2022
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Abstract
In order to further explore the internal transmission mechanism between technological innovation and green development in manufacturing industry under the background of obvious development characteristics in the new era, this paper constructed an integrated methodology system to evaluate the internal impact mechanism of technological innovation value chain efficiency on green development efficiency based on spatial perspective. First, the Network Slack-based model and Global Malmquist-Luenberger model are constructed to reveal the internal development law of technological innovation and green development of manufacturing industry. Secondly, the spatial Dubin model is employed to analyze the impact of current development characteristics and technological innovation on green development. The results show that innovation value chain efficiency is higher than technological innovation efficiency, and economic transformation efficiency is lower than that of technological innovation value chain. During the study period, the efficiency of technological innovation value chain in the four economic regions present fluctuant growth trend, and the eastern region has the highest value. The green development efficiency in the east, central, west, and northeast regions of manufacturing industry is higher than 1, and it shows an obvious spatial agglomeration effect. Besides, the efficiency of technological innovation, information and communication technology, urbanization, and the advanced industrial structure are all conducive to the improvement of green development in manufacturing industry. This paper studies the influence mechanism of technological innovation value chain efficiency on green development based on spatial perspective and puts forward relevant countermeasures and suggestions to effectively promote green development of manufacturing industry, providing relevant theoretical research for green and high-quality development.

Keywords  Technological innovation · Green development · Internal transmission mechanism · Spatial model

Introduction
Manufacturing industry is the pillar of national economy and the main battlefield of technological innovation. After more than 40 years of rapid development, China’s manufacturing industry has established a complete and independent manufacturing system, vigorously promoted the process of industrialization and modernization, and achieved remarkable achievements in economic construction. China became the world’s second largest economy in 2010. The report of the 19th Party Congress states that China’s economy has entered a new era. The development of China’s economy in the new era is characterized by rapid development to high-quality development. However, as most of China’s traditional manufacturing enterprises are still located in the professional processing and assembly links of the global value chain, most of these links are capital-intensive and have high emission intensity and thus fall into the low-end and high carbon lock, becoming the key to the problem of high energy consumption, high emissions, and high pollution. In order to achieve high-quality sustainable development and play a responsible role as a major power in the world, China’s government work report calls for strengthening pollution
prevention and control and speeding up efforts to develop a pattern of green development. Based on the development mode of traditional manufacturing industry and its position in national economy, the green development of manufacturing industry is an important way to achieve the high-quality development. Therefore, the development of China’s manufacturing industry is facing the double pressure of development requirements of The Times and environmental restrictions. Technological innovation is a sharp sword to solve the double dilemma of manufacturing industry, and the development of high-tech industry is an important way to promote innovation ability (Chen et al. 2022).

Compared to traditional manufacturing industry, high-tech industries are knowledge-intensive and technology-intensive industries (Yang and Zhu 2021). As the most active industry of technological innovation of the economic era, high-tech industries are highly valued by governments around the world, especially developed countries. After the financial crisis, developed countries implemented the re-industrialization policy to attract the return of high-end manufacturing industries, leading to profound changes in global manufacturing (Dong et al. 2020). They have formulated and implemented relevant strategic policies to vigorously promote the development of high-tech industries and seize the manufacturing high point of future industrial competition (Duan et al., 2021).

Technological innovation efficiency levels have a direct impact on the overall efficiency of China’s industry (Liu et al. 2020). Improving the efficiency of technological innovation to promote the green development ability is an important way to meet the challenges and improve the international competitiveness. Hence, due to the characteristics of the high-tech industry, it is not only the core of enhancing international competitiveness and technological innovation, but also the key to promote the green and high-quality development of China’s manufacturing industry (Wang et al. 2020). Therefore, in order to meet the severe challenge of international situation and the demand of high-quality development at home, improving the technological innovation ability of high-tech industry is an important way to cope with the double pressure.

Therefore, the contribution of this paper is as follows: First, a set of comprehensive evaluation model is constructed to analyze the internal transmission mechanism of the impact of technological innovation in high-tech industry on green development based on the development background of the new era. Second, in order to avoid single selection of technological innovation index and subjectivity, and complete evaluation of the efficiency of technological innovation in different stages, this paper builds a network evaluation model to evaluate the efficiency of technological innovation in high-tech industries. Third, the comprehensive environmental pollution index was incorporated into the evaluation model of green development efficiency, and the heterogeneity of green development efficiency is analyzed by region and development planning period. Fourth, the advanced industrial structure, urbanization, and information and communication development are included in the spatial evaluation system to analyze whether the new development characteristics and technological innovation will form a coupling and coordinated development ability to promote green development in the development environment of the new era.

The paper is organized as follows: the “Literature review” section presents the literature review; the “Methodology” section introduces the methodology; the “Data sources” section describes the data sources; the “Empirical analysis” section is the analysis of regional heterogeneity of technological innovation value chain and green development; and the conclusion and policy implication are summarized in the “Conclusion and policy recommendation” section.

Literature review

Technological innovation has strong social effect and is also the key to enhance national competitiveness (Liu and Dong 2021). Improvement of technological innovation efficiency is a vital way to improve technological innovation capabilities; hence, numerous studies have been performed to assess innovation activities. The evaluation of technological innovation efficiency involves different research perspectives, such as area, industry, and firm. In general, measuring the efficiency of technological innovation can be divided into two categories: black box and process-oriented measurement. Because the process-oriented research can provide more information than black box research, recent study has focused on process research. For instance, G. Carayannis et al. (2016) utilized the data of 23 European countries and their 185 corresponding regions and proposed a model that was based on DEA to evaluate the efficiency of innovation systems. Miao et al. (2021) constructed a two-stage SBM-DEA model to evaluate the green innovation efficiency, and the process of innovation efficiency is divided into two parts: technology development and achievement efficiency. Moreover, the tobit model is used to analyze the impact of input variable and influencing factors. Li et al. (2017) proposed a framework based on the combination of the dynamic DEA, meta-frontier analysis theory, and truncated regression model focusing on the efficiency of regional high-tech industries in China. Wang et al. (2020) from the industry research perspective evaluated high-tech industrial technological innovation industries based on the two-stage network DEA. Based on previous research and analysis, the research on technological innovation efficiency mainly focuses on technological innovation in high-tech industries and technological innovation efficiency in non-high-tech industries. At the method level, the two-stage DEA method is mainly used to measure efficiency. However, these studies mainly
focus on whether to open the black box of the intermediate production process and directly research the efficiency of the process-oriented but do not treat the innovation activities at different stages as a single research system. Combined with the actual situation of technological innovation activities in high-tech industry, it is of great significance to explore the different efficiency results caused by the complex structure of input-output in different stages of technological innovation in high-tech industry.

Pearce et al. (1989) proposed green development, which is characterized by “three lows” (low consumption, low emissions, and low pollution) and “three highs” (high efficiency, high benefit, and high sustainability) (Dong et al. 2021a, b). Therefore, improving the efficiency of green development is an important way to decouple economic growth from ecological and environmental degradation (Cheng 2020). Since then, the efficiency of green development has attracted the attention of politicians and scholars. There are two categories to measure the efficiency of green development. One is to construct a comprehensive evaluation index. However, the index selection and ranking of this method are relatively subjective, so this method is often not objective and accurate (Liu and Dong 2021; Dong et al. 2021a, b). The other is parametric stochastic frontier analysis (SFA) or non-parametric data envelopment analysis (DEA). The SFA approach has some excellent statistical properties, such as unbiased and consistent estimators (Aigner et al., 1977). However, the specific form of the production or cost function must be set in advance, leading to model misspecification biases (Wang et al. 2021). Moreover, it is only suitable for a single output; it does not solve the problem of multiple outputs, which is common in real-life production process (Huang et al. 2021). In view of the inadequacy of SFA method, DEA evaluation of green development efficiency has attracted more and more attention. Similarly, due to the radial problem, the traditional DEA method cannot solve the problem of undesirable output, which will lead to the neglect of the impact of environmental factors on efficiency, which will lead to biased measures and misleading policy recommendations (Pittman 1983). To address this concern, Chung et al. (1997) initially proposed the standard Malmquist-Luenberger productivity index (MLPI) to characterize the weak disposable relationship between undesirable and desirable outputs. Emrouznejad and Yang (2016) pointed out that DEA and MP index are the widely used mathematical techniques to address the relative efficiency and productivity of a group of homogenous decision-making units, such as industries or countries. However, in practical applications, especially those related to efficiency, wastes, pollutants, and carbon dioxide emissions tend to be unavoidable. Therefore, it is necessary to add undesirable output indicators into the actual efficiency assessment. Song et al. (2017) used the MLPI to measure green technology progress in large-scale thermoelectric enterprises in China. Lee (2021) employed the meta-frontier MLPI to measure the green development efficiency of Korean manufacturing firms. Fang et al. (2021) evaluated the green total factor productivity of China’s extractive industries through the MLPI and comprehensively analyzed the influencing factors. Zhu and He (2022) employed the MLPI to evaluate the environmental productivity of 48 iron and steel enterprises in China. However, although MLPI overcomes the constraints of environmental indicators, it cannot avoid possible linear programming constraints and other problems.

With the rise of a new round of technological revolution, technological innovation has received more and more attention, many scholars accepted that technological innovation could reduce energy intensity and carbon emissions without compromising global economic growth (Sun et al. 2021). In the actual operation, green development will not only be affected by the single factor of technological innovation, but also by the external changing development environment. In this regard, many scholars have carried out in-depth research on the influencing factors. Luo et al. (2021) employed bootstrap truncation regression to analyze the different impacts of innovation on eco-efficiency; results indicate that the invention patent and design patent have positive effects on China’s eco-efficiency, while the effect of foreign direct investment on eco-efficiency is different across different regions. Liu and Dong (2021) used the spatial econometric model to explore the relationship and the transmission mechanism between technological innovation and the green economy efficiency from the perspective of natural resources and urbanization. The result indicated that the intensive effect of technological innovation was significant and could considerably improve the green economic efficiency. Sun et al. (2021) used data from the OECD Triadic Patent Families database for 24 innovating countries between the years 1994 and 2013 to investigate the effect of technological innovation within certain countries on the energy efficiency performance of neighboring countries. The results indicated that there is a positive significance between knowledge spillover and country-specific energy efficiency performance.

To sum up, in terms of the selection of efficiency evaluation model, innovation activities at different stages are brought into the one research system based on the characteristics of technological innovation activities in high-tech industries. Considering the complexity of input-output structure of technological innovation activities at different stages, innovation activities in high-tech industries are gradually represented by digital and white box. The more complex Global Malmquist Luenberger Productivity Index is selected in this paper to decompose the green development efficiency to explore the internal variation mechanism of green development efficiency.
terms of the selection of influencing factors, many studies have confirmed that technological innovation has an impact on green development. However, in terms of the selection of technological innovation factors, most of them choose single factors such as technology spillover, patent, or R&D investment, and the research results may be biased due to single factors. Technological innovation efficiency is a comprehensive index to measure technological innovation ability, which can reflect the status quo of technological innovation ability. Analyzing the influence of technological innovation efficiency on green development is to comprehensively explore the influence mechanism of technological innovation on green development. However, there are few literatures analyzing the correlation between the two. In addition, China’s development pattern is changing rapidly, and it has entered the development stage of the new era. Whether changes in the external environment, such as the advanced industrial structure, urbanization, and information and communication technology, will affect China’s green development deserves further exploration. Based on this, in order to fill the research gap, this paper will take China’s high-tech industry as the research object to explore the comprehensive efficiency of technological innovation and green development and analyze the influence mechanism of the coupling of economic development characteristics and technological innovation on green development in the context of the new era.

**Methodology**

**Net Slack-based model**

The technology development stage is the process of transforming innovation resources into technological output, with knowledge and technology as the main output; the latter stage transforms the output of the technological research and development stage into economic benefits. Due to the different content and purpose of the input and output situation at each stage, if only the overall efficiency is considered, the evaluation effect will be general and unscientific. However, one of the shortcomings of the traditional DEA model is that it ignores intermediate products or link activities and cannot accurately evaluate the efficiency of each stage and the overall efficiency of the decision-making unit. Based on this, Tone and Tsutsui (2009) proposed a relaxation-based network DEA model, called Net Slack-Based Measure (NSBM), which can open the black box of the traditional DEA model and deal with intermediate products or link activities.

Suppose there are $n (j = 1, \ldots, n)$ decision-making units, each decision-making unit contains $K$ $(k = 1, \ldots, K)$ stages. $m_k$ and $r_k$ are the input and output of the $k$ stage, respectively. $(k, h)$ represents the link from stage $k$ to stage $h$ on the set $L$. The input resources of $DMU_j$ in stage $k$ are expressed as $\{ X_j^k \in R^{m_k}_+ \} (j = 1, \ldots, n; k = 1, \ldots, K)$. The output is expressed as $\{ Y_j^k \in R^{r_k}_+ \} (j = 1, \ldots, n; k = 1, \ldots, K)$. The intermediate link from stage $k$ to stage $h$ is expressed as $\{ Z_{j,k,h}^{(k,h)} \in R^{Z_{k,h}}_+ \} (j = 1, \ldots, n; (k, h) \in L)$, and $l_{(k,h)}$ represents the number of items linked $(k, h)$. The production possible set $p = \{ (X^k, Y^k, Z^{(k,h)}) \}$ is defined as:

$$X^k \geq \sum_{j=1}^{n} X^k_j \lambda^k_j (k = 1, \ldots, K),$$

$$Y^k \leq \sum_{j=1}^{n} Y^k_j \lambda^k_j (k = 1, \ldots, K),$$

$$Z_{j,k,h}^{(k,h)} = \sum_{j=1}^{n} Z_{j,k,h}^{(k,h)} \lambda^k_j (\forall (k, h)) (As \ the \ output \ of \ stage \ k),$$

$$Z_{j,k,b}^{(k,b)} = \sum_{j=1}^{n} Z_{j,k,b}^{(k,b)} \lambda^b_j (\forall (k, h)) (As \ an \ input \ to \ stage \ h),$$

$$\sum_{j=1}^{n} \lambda^k_j = 1 (\forall k), \lambda^k_j \geq 0 (\forall j, k)$$

where $\lambda^k \in R^n_+$ is the intensity vector of stage $K$. The above model assumes variable returns to scale and can study the technical efficiency and scale efficiency of production units. If the constraint $\sum_{j=1}^{n} \lambda^k_j = 1 (\forall k)$ is removed, the return to scale remains unchanged. $DMU_{\alpha} (\alpha = 1, \ldots, n)$ can be expressed as:

$$x^k_\alpha = X^k \lambda^k + s^- (k = 1, \ldots, K),$$

$$y^k_\alpha = Y^k \lambda^k + s^+ (k = 1, \ldots, K),$$

$$e \lambda^k = 1 (k = 1, \ldots, K),$$

$$\lambda^k \geq 0, s^- \geq 0, s^+ \geq 0, (\forall k)$$

where in Eq. (1), $x^k = (x^k_1, \ldots, x^k_n) \in R^{n \times m_k}$, $y^k = (y^k_1, \ldots, y^k_n) \in R^{n \times r_k}$, $s^- (s^+)$ is the input (output) slack vector.

For the link between two adjacent stages, there are two possible situations:

(a) “Free” link type

Linking activities are freely determined. When inputs and outputs are consistent, the number of links as intermediate outputs can be freely determined by the decision-making unit, which can maintain continuity between inputs and outputs at the same time:

$$Z_{j,k,h}^{(k,h)} \lambda^h = Z_{j,k,h}^{(k,h)} \lambda^k (\forall (k, h))$$
Among them
\[ Z^{(k,h)} = (z_1^{(k,h)}, \ldots, z_n^{(k,h)}) \in \mathbb{R}^{n}_{ik,h} \]

This situation can be used to judge whether the current link flow is suitable according to other decision units.

“Fixed” link type
\[ Z_o^{(k,h)} = Z^{(k,h)} x^h \] (\( \forall (k,h) \))

\[ Z_o^{(k,h)} = Z^{(k,h)} x^k \] (\( \forall (k,h) \))

In this case, the linking activity is constant (i.e., non-arbitrary), and the number of intermediate outputs is not controlled by the decision-making unit:

\[
\rho^i_o = \min_{x^i, y^i, z^i} \frac{\sum_{k=1}^n w_k^i 1 - \frac{x_k^i}{x_k^o}}{\sum_{h=1}^{n_2} x_h^o + \frac{x_k^i}{x_k^o}} \]

\[
z^{(k,h)} x^h = z^{(k,h)} x^k \] (\( \forall (k,h) \)),

\[ \lambda^k = 0, s^k - 0, s^k + \geq 0, (\forall k), \]

\[ x^k = x^k + s^k - (k = 1, \ldots, K), \]

\[ y^k = y^k + s^k - (k = 1, \ldots, K) \]

where \( \sum_{k=1}^n w_k^i = 1, w_k^i \geq 0(\forall k) \) and \( w_k^i \) is the relative weight of stage \( k \). Assuming that the optimal solution of the above model is \( (\lambda^k_1, s^k_1, s^k_2) \), the efficiency of \( k \)-stage efficiency is expressed as:

\[ \lambda^k = 1 - \frac{1 - \frac{m_j}{m_j^*} \frac{r_k}{r_j^*}}{1 + \frac{1 - \frac{m_j}{m_j^*} \frac{r_k}{r_j^*}}{1 + \frac{1 - \frac{m_j}{m_j^*} \frac{r_k}{r_j^*}}} (k = 1, 2, \ldots, K) \]

If and only if all sub-phases are valid, the DMU is overall valid. The invalid decision unit can be adjusted by the following formula:

\[
x_k^{(k,h)} = x_k^i - s^k - (k = 1, \ldots, K) \]

\[
y_k^{(k,h)} = y_k^i + s^k + (k = 1, \ldots, K) \]

\[
z^{(k,h)} = Z^{(k,h)} x^k \] (\( \forall (k,h) \))

**Global Malmquist-Luenberger**

Total factor productivity refers to the efficiency of production activities of a production unit in a certain period of time, and its essence is a comprehensive manifestation of the impact of technological progress on economic development (Fare et al. 1992). Therefore, total factor productivity is often used as an important indicator to measure the level of green development efficiency. However, the Malmquist index method does not have cyclic characteristics and cannot be compared across periods. Compared with the traditional Malmquist index model, the Global Malmquist-Luenberger (GML) index model overcomes the shortcomings of the traditional model. Therefore, this paper employs the GML model of the directional distance function: both expected output and undesired output are included in the evaluation system. Based on this, this article uses GML to evaluate green total factor productivity of manufacturing. The basic principle is: Assuming that each decision unit contains \( N \) input items \( x = (x_1, \ldots, x_n) \in \mathbb{R}^n_+ \), obtains \( M \) expected outputs \( y = (y_1, \ldots, y_m) \in \mathbb{R}^m_+ \), items of unexpected output \( b = (b_1, \ldots, b_n) \in \mathbb{R}^n_+ \). The set of production possibilities can be expressed as: \( P(x) = \{ (y, b)\} x \) could produce \( (y, b) \).

Suppose the directional vector is \( g = (g_x, g_b) \), among them \( g \in \mathbb{R}^M \times \mathbb{R}^n \). The directional distance function is
defined as:

\[
D(x, y, b, g_x, g_b) = \max \{ \beta | (y + g_x, b - g_b) \in P(x) \}
\]

This function shows that while the expected output increases, the undesired output decreases in the same proportion; \( \beta \) is the value of the directional distance function that tries to maximize the output \( y \) and minimize the pollutant \( b \). In this paper, the directional vector is set as \( g = (y, b) \), the corresponding directional distance function is expressed as \( D(x, y, b) \).

Oh (2010) defines and decomposes the GML index, and the current production possibility set is \( P(t+1) = \{ (y', b') | x' can produce (y', b'), t = 1, \ldots, T \} \), \( t^i = \{ P(t) \} \) is the global production possibility set, which means the union of all production feasible sets in the current period.

The GML index and its decomposition form are:

\[
GML^{t+1} (x', y', b', s^{t+1}, t^{t+1}) = \frac{1 + D^t(x', y', b')}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})} \]

\[
= \frac{1 + D^t(x', y', b')}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{1 + D^t(x', y', b')}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})} \]

\[
= EC^{t+1} \times TC^{t+1}
\]

In the formula, \( D^t(x, y, b) = \max \{ \beta | (y, b) \in P(t) \} \) is the global directional distance function, and the global production possibility set is \( P^G(t) ) \). \( EC^{t+1} \) and \( TC^{t+1} \) represent the efficiency change and technological change in the two periods, respectively. This paper further solves the four directional distance functions in the formula. Taking period \( t \) as an example, the directional distance function of the current period \( D^t(x', y', b') \) and the global directional distance function
on the current global production possibility set \(D^G(x', y', b')\), it is obtained by the following two linear programs:

\[
\begin{align*}
D'(x', y', b') &= \max \beta \\
\text{s.t.} \quad Y' z' &\geq (1 + \beta) y'_k \\
\quad B' z' &= (1 - \beta) b'_k \\
x' z' &\leq x'_k \\
z' &\geq 0 \\
D^G(x', y', b') &= \max \beta \\
\text{s.t.} \quad \sum_{f=1}^T Y^T z^T &\geq (1 + \beta) y'_k \\
\quad \sum_{f=1}^T B^T z^T &= (1 - \beta) b'_k \\
\quad \sum_{f=1}^T X^T z^T &\leq x'_k \\
z^T &\geq 0
\end{align*}
\]

(7)

(8)

The current direction distance function in \(t+1\) period \(D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})\) and the global direction distance function \(D^G(x^{t+1}, y^{t+1}, b^{t+1})\) can be obtained in the same way.

**Spatial autoregression**

Spatial econometrics is an emerging branch of economics, and its main research is to solve the problems of spatial interaction and spatial dependence structure in the regression model of cross-sectional data and panel data (Yang and Lee 2021). Compared with the traditional autoregression, the spatial autoregression makes up for the lack of the traditional panel model to describe the economic behavior to a certain extent. The spatial panel model combines the advantages of the traditional panel data model with the spatial econometric method, which not only considers the temporal and spatial characteristics but also incorporates the spatial effects into the research system, making the estimation results more effective. Common spatial panel data models include spatial lag model, spatial error model, and spatial Dubin model. Because the spatial Dubin model overcomes the common shortcomings of the spatial lag model and the spatial error model and integrates the spatial error model into the spatial lag model, both the spatial correlation of the dependent variable and the spatial correlation of the independent variables are considered. The spatial Dubin model is expressed as:

\[
y = \rho W y + \alpha r + X \beta + WX y + \epsilon \\
\epsilon \sim N(0, \sigma^2 I_n)
\]

(9)

\(W\)y is the spatial lag of the dependent variable, and WX is the spatial lag term of the independent variable. Without considering the lag term, the regression coefficient can reflect the influence of the independent variable on the dependent variable, and the spatial Dubin model can be represented by the following situation:

\[
(I_n - \rho W)y = X \beta + WX \theta + I_n a + \epsilon
\]

(10)

Among them

\[
S_r(W) = V(W)(I_2 \beta_r + W \theta_r), V(W)
\]

(11)

The matrix is expressed as:

\[
\begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_T \\
\end{bmatrix} = \sum_{i=1}^T \begin{bmatrix}
S_r(W)_{11} & S_r(W)_{12} & \ldots & S_r(W)_{1m} \\
S_r(W)_{21} & S_r(W)_{22} & \ldots & S_r(W)_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
S_r(W)_{tm} & S_r(W)_{t2} & \ldots & S_r(W)_{tm} \\
\end{bmatrix} \begin{bmatrix}
t_1 \\
t_2 \\
\vdots \\
t_m \\
\end{bmatrix} + V(W)u + V(W)\epsilon
\]

(12)

**Data sources**

**Innovation value chain**

**Technological innovation system (TIS)**

Due to the availability of data, this study mainly uses high-tech industry data from 2006 to 2015 as the research sample. Some data in Tibet, Qinghai, Xinjiang, and Inner Mongolia is not available, and the data of 27 provinces in China is finally used as the research object. In order to estimate the efficiency of the innovation value chain, this paper first employs the NSBM model to estimate the efficiency. When selecting indicators, the main consideration is whether the selected indicators could accurately reflect the problem to be studied in this paper. Therefore, according to the preliminary research of Zhang and Vigne (2021) and Li et al. (2021), the selection of indicators is divided into input indicators and output indicators. The investment indicators in the technological innovation stage are R&D activity personnel, R&D internal expenditure, and new product development expenditure. Output indicators are valid invention patents which could measure scientific and technological achievements.
Economic transformation system (ETS)

The economic transformation system in innovation value chain refers to the process in which high-tech enterprises transform their research and development (R&D) achievements (such as patents) into new products and realize commercialization. When companies obtain the achievement of the R&D stage, they need to transform the research results or introduce the required technologies in a targeted manner to realize the digestion and absorption of the innovation results. Therefore, when selecting indicators for estimating the conversion efficiency value of results, based on the former’s literature research and practical significance, the input indicators are effective invention patents, technical transformation funds, technical funds introduced, and technology digestion and absorption of funds. The output indicators are the sales revenue of new products and the export value of new products.

Due to the lag of the output of technological innovation achievements, the output indicators of the first stage and the second stage are 1 year behind (Zuo et al., 2022). The two-stage indicator selection for the efficiency of the innovation value chain is shown in Table 1.

Green development efficiency (GDE)

The key to the green transformation of the manufacturing industry is whether it can improve the green development efficiency, that is, whether it can achieve a balanced development of the environment and resources while improving the quality of manufacturing production. Under the background of increasingly fierce international technological competition and domestic demand of green transformation, improving the green development efficiency of high-tech industry can not only improve the international competitive advantage but also realize the internal demand of high-quality development at home. The selection index of labor input in the input index is the average number of employees in the high-tech industry. Financial investment indicators are internal R&D expenditures and new fixed assets. The expected output indicators are mainly business income and the number of patent applications. Due to the lack of data related to the environmental pollution index of high-tech industries, Han Jing’s (2012) data processing method is used for reference, and the comprehensive environmental pollution index of various places is used as an undesired output. The selection of indicators and specific data sources are shown in Table 2.

Environment variable

(1) Advanced industrial structure
Industrial structure optimization is an important way to promote the green and high-quality development of manufacturing industry (Zhu et al. 2019). The advanced industrial structure refers to the trend and process of continuously evolving the overall quality and efficiency of the industrial structure to a level of change through technological progress in accordance with the law of industrial structure evolution. In this paper, the indicators of advanced industrial structure are based on the indicator construction method of Fu (2010). First, take the proportion of advanced industrial structure are based on the indicator industrial structure evolution. In this paper, the indicators of technological progress in accordance with the law of the industrial structure to a level of change through continuously evolving the overall quality and efficiency of the industrial structure refers to the trend and process of manufacturing industry (Zhu et al. 2019). The advanced industrial structure is defined as the degree of informatization development in each province, and the vector $X_1 = (1, 0, 0)$, $X_2 = (0, 1, 0)$, and $X_3 = (0, 0, 1)$ arranged from low level to high level:

$$
\alpha_j = \arccos \left\{ \frac{\sum_{i=1}^{3} (x_{ij} \cdot x_{i,0})}{\left( \sum_{i=1}^{3} (x_{ij}^2)^{1/2} \cdot \sum_{i=1}^{3} (x_{i,0}^2)^{1/2} \right)^{1/2}} \right\} \quad (13)
$$



The advanced industrial structure is defined as $S$, and the calculation formula is as follows:

$$
S = \sum_{k=1}^{3} \sum_{j=1}^{4} \alpha_j \quad (14)
$$

The larger the $S$ value, the higher the level of industrial structure. The relevant data comes from the China Statistical Yearbook.

(2) **Information and communication technology**

With the in-depth development of networking, digitization, and intelligence, informatization represents the current advanced productivity. According to the National Informatization Development Strategy 2006–2020 released by the government, information and communication technology refers to the full use of information technology to develop resources and promote information exchange and knowledge sharing so as to improve the quality of economic growth and promote the transformation of economic and social development. Therefore, according to the characteristics of information and communication, it can improve the efficiency of industrial resource allocation and increase the added value of the industry in its development process and promote the transformation and upgrading of industrial enterprises (Zhu and Sun 2020). According to the existing literature research and the availability of data, this article uses the number of Internet users in each province to measure the degree of informatization development in each province. The data comes from the China Statistical Yearbook.

3) **Control variable**

GDP per capita is often used as an indicator of economic development in development economics and is one of the important macroeconomic indicators. In this article, per capita GDP is used as an indicator to measure the impact of economic development on the green transformation of manufacturing.

The Central Committee of the Communist Party of China proposed in the decision of the Third Plenary Session of the 18th Central Committee to make the market play a decisive role in the allocation of resources. In addition, in recent years, the supply-side structural reform has been further proposed to improve resource allocation and increase economic efficiency. Therefore, under the call of the government and the promotion of policies, market-oriented reform has become the most important task of China’s economy at present, and it is also an important factor in improving total factor productivity. This paper attempts to explore the impact of market-oriented development on the green development of manufacturing.

Enterprise competitiveness refers to the comprehensive ability of an enterprise to realize its own value on the basis...
of creating value for customers through its own capabilities and comprehensive utilization of internal resources and external resources (Tu and Wu 2020). In this study, corporate competitiveness uses the number of companies in high-tech industries as an indicator to explore the impact of corporate competitiveness on the green transformation of manufacturing.

Since the reform and opening up, with the acceleration of industrialization, the process of urbanization has accelerated. Urbanization is not only a process of industrial and population agglomeration, continuous economic and social development, but also a process of massive energy consumption and high concentration of carbon emissions. Besides, urbanization has beneficially promoted the transformation and upgrading of the industrial structure and is a powerful driving force (Chen et al. 2021). Therefore, it is of great significance to explore the impact of urbanization on green development. Hence, this paper explores the impact of the development of urbanization on the green development of manufacturing. The data comes from the China Statistical Yearbook.

Outward foreign direct investment (OFDI), especially technology sourcing OFDI, is not only a channel for developing countries to acquire advanced technology, but also an important way and mean to overcome trade barriers from developed countries and break through the bottleneck of their own technology to enter the global high-end value chain (Zhao et al. 2020). Since the Chinese government actively promoted the construction of the Belt and Road in 2013, OFDI’s impact on China’s innovation efficiency has attracted much attention. Therefore, exploring the impact of OFDI on the efficiency of green innovation has important practical significance. The data comes from the China Foreign Direct Investment Bulletin.

Empirical analysis

Results of innovation value chain efficiency

The innovation efficiency of high-tech industries is an important manifestation of a country or region’s scientific and technological R&D strength and economic competitiveness. Improving the efficiency of technological innovation is the key to enhancing international competitiveness and promoting green and high-quality development. High-tech industry innovation process includes multi-input, multi-output, and multi-link process, which is called the technological innovation value chain according to Schumpeter’s innovation theory. The technological innovation value chain includes the technological innovation system and the economic transformation system. Increasing R&D investment can improve R&D efficiency to a certain extent, but the presentation of high-tech achievements is in addition to investment links, but also production and product links (Zhang et al. 2019). In this paper, the research purpose is to explore the overall efficiency and segmented efficiency of the technological innovation value chain of high-tech industries and to fully understand the technological innovation capabilities of China’s high-tech industries from time and region. Therefore, this paper firstly uses the NSBM model to evaluate the technological innovation value chain and segmentation efficiency of the high-tech industry based on the relevant data of China’s high-tech industry from 2006 to 2015. The technological innovation value chain of each province and its segmented efficiency results are shown in Table 3.

As can be seen from the results, regional heterogeneity exists in efficiency at different stages. As a whole, the efficiency of technological innovation and the innovation process is on the rise. Specifically, as shown in Table 3, during the study period, the overall efficiency of the technological innovation value chain is 0.547, and the technological innovation efficiency and economic transformation efficiency is 0.529 and 0.489, respectively. The mean value of technological innovation value chain efficiency (IVCE) is 0.547, and 13 provinces had higher value chain efficiency than the mean value. Among them, Beijing has the highest efficiency of technology innovation value chain of high-tech industries, with a value of 0.977. The efficiency of technological innovation system (TISE) is 0.529, with the highest value of 0.954 in Beijing among all provinces. The mean efficiency of economic transformation system (ETSE) is 0.489, among which 13 provinces had higher efficiency than the mean, and the highest efficiency is Beijing. Besides, the IVCE, TISE, and ETSE of Beijing, Tianjin, Shanghai, Jiangsu, Shandong, Guangdong, Guizhou, and Yunnan are all above the average. These regions are highly innovative and transformational. In the context of the coordinated development of Beijing-Tianjin-Hebei, the three efficiency values of Beijing are particularly prominent, and the high-tech industries are in a state of agglomeration and development. Tianjin and Shanghai are municipalities directly under the Central Government of China. Relying on government policies and geographical advantages, high-tech industries have prominent technological innovation capabilities and economic transformation advantages. Guangdong, Shandong, and Jiangsu are coastal cities in the eastern region, occupying favorable geographical locations and frequent foreign trade. Moreover, these provinces have developed economies, strong strengths, rapid development of high-tech industries, and relatively large R&D investment. Therefore, the efficiency value of the technological innovation value chain in these regions is higher than the national average. With the policy support of the Western Development Strategy, the overall efficiency,
technological innovation efficiency, and economic transformation efficiency of the technological innovation value chain in Guizhou and Yunnan are all higher than the national average.

Figure 1 presents the changes of efficiency of the innovation value chain efficiency during the study period. As shown in the figure, from 2006 to 2015, the IVCE relatively obviously changes. It is obvious from the illustration that efficiency declined significantly from 2008 to 2010, possibly due to the impact of the financial crisis. From the regional point of view, the efficiency of technological innovation chain in the central, west, and northeast regions and the east region has increased significantly, while that of the northeast has decreased. In fact, during different periods of development, development methods and development policies will have a great impact on IVCE, TISE, and ETSE. Therefore, this paper further analyzes the efficiency of the technological innovation chain of high-tech industries from the perspective of time and region. According to the national economic development plan, combined with the research interval, the time is divided into two stages: the 11th Five-Year Plan (FYP) period and the 12th FYP. According to the administrative division of the People’s Republic of China, the study area is divided into four major economic administrative areas, namely the eastern region, the central region, the western region, and the northeast region. The efficiency of the high-tech industry technological innovation value chain at various development stages and region is shown in Table 6.

As shown in Table 4, the IVCE, TISE, and ETSE of the high-tech industries in the four regions during the period of 12th FYP are all higher than that during the period of 11th FYP. From the regional point of view, the efficiency of technological innovation chain at various development stages and region is shown in Table 6.
Fig. 1 IVCE trend changes in different regions

| Table 4 Regional differences in the efficiency of innovation value chains |
|---------------------------------|-----------------|-----------------|-----------------|
|                                  | 11th FYP (2006–2010) |                  | 12th FYP (2011–2015) |
|                                  | IVCE  | TISE  | ETSE  | IVCE  | TISE  | ETSE  |
| East                             | 0.573 | 0.586 | 0.570 | 0.747 | 0.808 | 0.766 |
| Central                          | 0.363 | 0.402 | 0.277 | 0.530 | 0.692 | 0.554 |
| West                             | 0.396 | 0.491 | 0.391 | 0.639 | 0.735 | 0.570 |
| Northeast                        | 0.235 | 0.494 | 0.216 | 0.584 | 0.477 | 0.602 |

region has gradually narrowed. The development focus of the eastern economic zone is the simultaneous transformation of traditional industries and existing technologies and the active improvement of the industrial structure, the transformation from traditional energy-intensive heavy industry manufacturing to knowledge and technology-intensive industries, and the active development of emerging industries. From the geographical analysis, the eastern region belongs to the coastal economic belt. The Yangtze River Delta, the Pearl River Delta, and the Shandong Peninsula are all agglomerations of economic open areas, with convenient transportation, a developed commodity economy, and agglomeration of foreign-funded industries, resulting in technology spillover effects. Analyzing from the perspective of policy development strategy, the state first proposed the strategy of the eastern coastal area. Therefore, combined with the advantages of geographical location, industrial foundation, and government policy support, the eastern region has a solid economic foundation and is the most economically developed region among the four regions. With the development of economic transformation and the deepening of the industrial structure contradictions dominated by heavy industries in the northeast, the State Council has proposed a strategy for revitalizing the northeast and implemented a series of preferential policies for the revitalization of the northeast. As shown by the empirical results, the efficiency of the technological innovation value chain in Northeast China during the period of 12th FYP has been improved overall compared to the period of 11th FYP. Moreover, during the 12th FYP period, the economic transformation efficiency of the northeast region is second only to the eastern region. Under the guidance of the national development strategy, the efficiency of the technological innovation value chain, the efficiency of technological research and development, and the efficiency of economic transformation in the central and western regions during the 12th FYP period have been greatly improved.
FYP period, the efficiency value of the technological innovation value chain of high-tech industries in the western region is higher than that in the central region. During the 12th FYP period, the efficiency of the technological innovation value chain and the efficiency of technological research and development in the western region are higher than those in the central region.

Results of green development efficiency

On the strength of high-tech industry, prioritizing the development of high-tech industries has important strategic significance for improving social and economic benefits and international competitiveness. Green total factor productivity is the key indicators to evaluate the green development efficiency. Global Malmquist-Luenberger index model is constructed to measure the green development efficiency (GDE) of China’s 27 provinces from 2006 to 2015 and further deconstructs the technological changes (TC) and efficiency change (EC) of the high-tech industry; the results are presented in Table 5.

As shown in Table 5, the average value of the green development efficiency (GDE), technological change (TC), and efficiency change (EC) of the high-tech industry are all greater than 1, indicating that China’s high-tech industry’s technological innovation capabilities have been continuously improved, resources have been effectively allocated and utilized, and considerable technological development and progress have been made. The average production of TC in Tianjin, Hebei, Heilongjiang, and Fujian is lower than the frontier, and the average production of Hainan Province is lower than the frontier.

Due to the heterogeneity of regional development, the development of high-tech industries has become unbalanced. Based on the empirical results, this paper will analyze the development trend of GDE of high-tech industries in the four major economic regions.

As shown in Fig. 2, during the study period of 2006–2015, the GDE of high-tech industries in the eastern region developed steadily. From 2010 to 2012, the GDE is lower than the production frontier. The east region is dominated by coastal cities with frequent overseas trade. The global financial crisis in 2008 has impacted the economic development of China and the development of international trade. Due to the lag of technology development and transformation, the technology development and the technology spillover effect brought by foreign trade during this period were all affected, which also had an impact on the development of China’s high-tech industry. The GDE, TC and EC of the provinces and cities in the eastern region are relatively stable, which are all higher than or at the forefront of production. The development of GDE of high-tech industries in the central, west, and northeast regions showed a fluctuating growth trend. The central provinces of Henan, Jiangxi, Shanxi, and Hunan had relatively high GDE between 2006 and 2015. With the exception of Hainan and Yunnan provinces of the west region, GDE is higher than the production frontier. With the support of the west development policy and the implementation of various preferential policies, the west region has developed rapidly and the unbalanced regional development has gradually improved.

As shown in Table 6, during the 11th FYP period, the green total factor productivity, efficiency changes, and technological changes in the eastern region are higher than the production frontiers and are developing steadily. The green total factor productivity of the central, western, and northeastern regions is all higher than the production frontier, and the green total factor productivity of the western region is the highest. During the 12th FYP period, the green total factor productivity of the eastern, central, western, and

### Table 5 The evolution trend of manufacturing green development efficiency

| DMU     | GDE | TC  | EC  |
|---------|-----|-----|-----|
| Beijing | 1.091 | 1.091 | 1.000 |
| Tianjin | 1.003 | 0.985 | 1.021 |
| Hebei   | 1.040 | 0.990 | 1.056 |
| Shanxi  | 1.218 | 1.096 | 1.206 |
| Liaoning| 1.064 | 1.025 | 1.047 |
| Jilin   | 1.161 | 1.053 | 1.210 |
| Heilongjiang | 1.045 | 0.983 | 1.077 |
| Shanghai| 1.044 | 1.044 | 1.000 |
| Jiangsu | 1.089 | 1.089 | 1.000 |
| Zhejiang| 1.060 | 1.045 | 1.129 |
| Anhui   | 1.227 | 1.038 | 1.208 |
| Fujian  | 1.001 | 0.989 | 1.018 |
| Jiangxi | 1.149 | 1.018 | 1.134 |
| Shandong | 1.110 | 1.063 | 1.070 |
| Henan   | 1.148 | 1.029 | 1.174 |
| Hubei   | 1.067 | 1.045 | 1.038 |
| Hunan   | 1.114 | 1.031 | 1.269 |
| Guangdong| 1.034 | 1.034 | 1.000 |
| Guangxi | 1.155 | 1.036 | 1.134 |
| Hainan  | 1.036 | 1.043 | 0.995 |
| Chongqing| 1.195 | 1.046 | 1.161 |
| Sichuan | 1.176 | 1.013 | 1.134 |
| Guizhou | 1.093 | 1.102 | 1.181 |
| Yunnan  | 1.067 | 1.042 | 1.051 |
| Shanxi  | 1.078 | 1.064 | 1.044 |
| Gansu   | 1.122 | 1.079 | 1.210 |
| Ningxia | 1.230 | 1.046 | 1.194 |
| Average | 1.104 | 1.041 | 1.102 |
northeastern regions is higher than the production frontier, and technological development has made continuous progress.

Descriptive statistics and spatial correlation analysis

Descriptive statistics

In order to observe the data characteristics of the variables used in the research more intuitively, firstly, the variables are statistically described. The statistical results are shown in Table 7.

Before empirical research, it is necessary to conduct unit root tests on variables to avoid false regression and ensure the credibility of empirical results. Therefore, the unit root test in this paper adopts LLC test and IPS test, respectively. The results are shown in Table 8.

According to the results, green development efficiency (gde), information and communication technology (lnict), market-oriented (lnmk), GDP per capita (lngdp), outward foreign direct investment (lnofdi), technological innovation system efficiency (lnetse), economic transformation system efficiency (lnetse), firm competition (lnfc), and urbanization (lnur) have all passed the stationarity test at a confidence level of 1%, and advanced industrial structure (lnais) is a first-order stationary sequence at a confidence level of 1%.

Table 6  Regional differences in the dynamic efficiency of high-tech manufacturing during different development strategies

|          | 11th FYP (2006–2010) | 12th FYP (2011–2015) |
|----------|----------------------|----------------------|
|          | GDE | EC   | TC   | GDE  | EC   | TC   |
| East     | 1.085 | 1.028 | 1.075 | 1.023 | 1.029 | 1.006 |
| Central  | 1.222 | 1.288 | 1.050 | 1.096 | 1.037 | 1.074 |
| West     | 1.154 | 1.092 | 1.155 | 1.128 | 1.125 | 1.021 |
| Northeast| 1.152 | 1.083 | 1.144 | 1.038 | 1.083 | 0.968 |
Spatial correlation analysis

Based on the characteristics of the spatial measurement model, before employing the spatial measurement model, it is necessary to use the Moran I index to test the spatial correlation of the research variables to determine whether the research variables have spatial correlation. The Moran I index and statistical values of the green development efficiency of China’s high-tech industry from 2006 to 2015 are obtained, as shown in Table 9.

As shown in Table 9, the Moran I value of China’s green development efficiency is positive during 2006–2015, among them, the year of 2006, 2008, 2010, 2013, and 2015 are significant at the level of 10%. The year of 2007, 2009, 2012, and 2014 are significant at the level of 5%. And the year of 2011 is significant at the level of 1%. The result indicates that green development efficiency of China’s high-tech industry will be affected by neighboring region and tend to be concentrated in space. This paper will further use Moran’s I scatterplot to observe the spatial agglomeration characteristics of China’s high-tech industries. The results are shown in Fig. 3.

As shown in Fig. 3, the local Moran I index of green development efficiency presents a trend of clustering. The first quadrant represents the high-high agglomeration quadrant, indicating that the green development efficiency has a high spatial linkage effect in space. The surrounding provinces have a good diffusion effect. The third quadrant represents the low-low agglomeration quadrant, which shows the opposite development trend from the first quadrant. The second and fourth quadrants are low-high quadrants and high-low quadrants, respectively, indicating that the spatial linkage is not strong and the regional development differences are large. According to the results, it can be found that the first and third quadrants contain most of the provinces, showing a high-high or low-low agglomeration feature. Therefore, the spatial model is suitable for this study.

### Table 7 Descriptive statistical characteristics of variables

| Variable | Definition                        | Mean   | Min    | Max    | std    |
|----------|-----------------------------------|--------|--------|--------|--------|
| gde      | Green development efficiency      | 1.066  | 0.530  | 1.990  | 0.185  |
| mk       | Market-oriented                   | 6.602  | 3.380  | 10.920 | 1.635  |
| ais      | Advanced industrial structure     | 6.561  | 5.914  | 7.600  | 0.312  |
| ofdi     | Outward foreign direct investment | 54.508 | 0.012  | 909.404| 121.320|
| ict      | Information and communication technology | 36.334 | 3.779  | 77.776 | 17.667 |
| gdp      | GDP per capita                    | 39,289.236 | 4105.000 | 164,045.000 | 24,306.516 |
| tise     | Technological innovation efficiency | 0.625  | 0.006  | 1.00   | 0.265  |
| etse     | Economic transformation efficiency | 0.543  | 0.007  | 1.000  | 0.277  |
| fc       | Firm competition                  | 948.179| 14.000 | 6570.000| 1271.726|
| ur       | Urbanization                      | 0.535  | 0.275  | 0.896  | 0.143  |

### Table 8 Unit root test

| LLC     | IPS    |
|---------|--------|
| Lnnde   | −14.923*** | −25.827*** |
| Lnict   | −11.135*** | −54.515*** |
| Lnmk    | −27.744*** | −18.676*** |
| Lngdp   | −12.522*** | −27.422*** |
| Lnofdi  | −10.447*** | −3.724***  |
| Lnais   | −8.058***  | −0.346     |
| d.Lnais | −19.857*** | −8.472***  |
| LnIsse  | −42.045*** | −13.341*** |
| Lnrtse  | −52.205*** | −15.401*** |
| Lnfc    | −12.350*** | −11.236*** |
| Lnur    | −1.100***  | −9.941***  |

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels

### Table 9 Global Moran’s I index of green development efficiency

| Year | Moran’s I | Z    |
|------|-----------|------|
| 2006 | 0.073*    | 0.946|
| 2007 | 0.205**   | 1.341|
| 2008 | 0.037*    | 0.611|
| 2009 | 0.190**   | 1.193|
| 2010 | 0.070*    | 0.258|
| 2011 | 0.311***  | 2.256|
| 2012 | 0.168**   | 1.173|
| 2013 | 0.111*    | 0.583|
| 2014 | 0.229**   | 1.526|
| 2015 | 0.063*    | 0.790|

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels
Test results and discussion

Spatial model selection

In model selection, the model with a significant LM test result is preferred. If the statistical results of the two models are both significant, the comparison is made according to the robust R-LM. When the LM (lag) statistic is significant, the spatial lag model is more suitable. When the LM (err) statistic is more significant, the spatial error model is better. Therefore, panel models without spatial factors are used for regression first.

Results are shown in Table 10: pooled OLS, time fixed effect, spatial fixed effect, and spatial and time fixed effect

| Variable | Pooled OLS | Spatial fixed | Time fixed | Spatial and time fixed |
|----------|------------|---------------|------------|-----------------------|
| Lnmk     | 0.0552**   | −0.004*       | 0.038***   | 0.010*                |
|          | (0.0790)   | (0.028)       | (0.020)    | (0.030)               |
| Lngdp    | 0.06035**  | 0.028*        | −0.003*    | 0.020*                |
|          | (0.0294)   | (0.054)       | (0.046)    | (0.054)               |
| Lneff    | −0.0297*** | −0.126***     | −0.052**   | −0.072***             |
|          | (0.0106)   | (0.060)       | (0.050)    | (0.058)               |
| Lnce     | 0.0098**   | 0.025*        | −0.027*    | −0.004*               |
|          | (0.0176)   | (0.086)       | (0.059)    | (0.084)               |
| Lnofdi   | −0.0137**  | −0.012**      | −0.015**   | −0.006*               |
|          | (0.0079)   | (0.013)       | (0.010)    | (0.013)               |
| Lnfc     | 0.0055**   | −0.009*       | 0.009*     | 0.093***              |
|          | (0.0110)   | (0.067)       | (0.018)    | (0.072)               |
| Lnur     | −0.1318*** | −0.306*       | −0.114*    | −1.256***             |
|          | (0.0654)   | (0.958)       | (0.277)    | (0.972)               |
| Lnnet    | −0.0531**  | −0.007***     | −0.004***  | −0.006***             |
|          | (0.0348)   | (0.003)       | (0.002)    | (0.003)               |
| Lnis     | −0.5887**  | 0.009*        | −0.038*    | 0.068*                |
|          | (0.3506)   | (0.197)       | (0.103)    | (0.214)               |
| _cons    | 0.9436**   |               |            |                       |
|          | (0.8361)   |              |            |                       |

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels
model are selected for regression, respectively. The LM test results showed that there are spatial autocorrelation and spatial error terms in each model. In addition, the spatial Hausman test is needed to further test the choice of the random effect model and the fixed effect model. As shown in Table 11, according to the test results, the $P$ value is 0.003, and the null hypothesis is rejected at the 5% significance level. The fixed effect model is more suitable in this paper.

Besides, whether the spatial Dubin model can be chosen as the applied research model in this paper remains to be further determined. Because the spatial lag model is flexible, only considering the significance level is not rigorous enough. Therefore, the LR test is employed in this paper to test whether the SDM model will degenerate into an SLM model or an SEM model. The results are shown in Table 12.

There are two null hypotheses for the LR test: the first is to test whether SDM will degenerate into SLM, and the second is whether SDM will degenerate into SEM. The statistical results of the test are shown in Table 12. The spatial Durbin model is more suitable in this research.

### Spatial effect analysis

Due to the close links between regional developments, the green development is not only affected by the region, but also by neighboring regions. According to the test results of Moran's I index, the spatial agglomeration effect is obvious. Therefore, the spatial Dubin model is used to analyze the spatial linkage effect of the green development efficiency.

The regression results of the spatial Dubin model are shown in Table 13. The coefficient of local market-oriented is positive; for every 1% increase in market-oriented, green development capacity will increase by 0.345%, which indicates that the development of local market-oriented is conducive to the improvement of green development efficiency. However, there is a negative relationship between the market-oriented of neighboring regions and the green development efficiency, indicating that the improvement of the marketization index of neighboring regions is not beneficial to the green development efficiency. The influence coefficient of GDP on the green development of manufacturing industry is 0.878, and the spatial influence coefficient is 0.281, which indicates that GDP per capita could promote the improvement of green development efficiency and the economic growth will also promote the improvement of green development efficiency in neighboring regions. Technological innovation activities on the value chain of technological innovation have different effects on the green development efficiency of manufacturing industry. As it turns out, the relationship between local and adjacent TISE and green development efficiency is positive. Every 1% increase in TISE will increase the green development efficiency by 0.064 and drive the green development efficiency of neighboring areas to increase by 0.023%. However, the relationship between ETSE and green development efficiency is negative both locally and in the neighborhood. That is probably because the higher the efficiency of economic transformation in surrounding areas, the higher the conversion rate of innovation achievements, the more new products produced, and the first to seize the market. Therefore, it is not conducive to the sales and development of local products, thereby affecting the improvement of green development efficiency. OFDI in local and neighboring regions are conducive to the improvement of green development efficiency. And local OFDI has a higher

### Table 11 Spatial Hausman test results

| Hypothesis       | Chi-sq | $P$    |
|------------------|--------|--------|
| Spatial Hausman test | 129.01 | 0.0032 |

### Table 12 LR test statistical results

| Hypothesis | Whether SDM will degenerate into SLM | Whether SDM will degenerate into SEM |
|------------|-------------------------------------|-------------------------------------|
| LR test    | 39.88                               | 29.67                               |
| $P$        | 0.000                               | 0.001                               |

### Table 13 Regression estimated values of spatial Dubin model

| Variables | Coe | Variables | Coe |
|-----------|-----|-----------|-----|
| mk        | 0.354* | W*mk      | −0.320** |
|           | (0.189) |           | (0.230) |
| gdp       | 0.878* | W*gdp     | 0.281*** |
|           | (0.298) |           | (0.486) |
| tise      | 0.064** | W*tise    | 0.023 |
|           | (0.426) |           | (0.702) |
| etse      | −0.036* | W*etse    | −0.033 |
|           | (0.582) |           | (0.117) |
| ofdi      | 0.113** | W*ofdi    | 0.064* |
|           | (0.083) |           | (0.222) |
| fc        | 0.762** | W*fc      | −0.071* |
|           | (0.164) |           | (0.222) |
| ur        | −0.319** | W*ur      | −0.207** |
|           | (0.214) |           | (0.337) |
| ict       | 0.035*** | W*ict     | −0.060* |
|           | (0.015) |           | (0.210) |
| ais       | 0.395** | W*ais     | 0.618* |
|           | (0.319) |           | (0.151) |
| _cons     | 0.702** |           |       |
|           | (1.704) |           |       |

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels.
impact on green development efficiency than neighboring regions. Urbanization in local and its surrounding areas is not conducive to the improvement of green development efficiency. The main possible reason is the unbalanced development of urbanization. The influence of firm competition and information and communication on green development efficiency is positive in local and negative in neighboring. In the new era of development, information is currently the most advanced productive force. When the degree of local information and communication is higher, the high integration of informatization and industrialization will improve the competitiveness. The advanced industrial structure is conducive to the improvement of local green development efficiency and in adjacent region also has an obvious driving effect on the increase of local green development. In order to better analyze the spatial correlation between explanatory variables and green development efficiency, they are further decomposed. As shown in Table 14, results of the total effect, direct effect, and indirect effect are presented.

As the results show, the direct effect, indirect effect, and total effect of the improvement of efficiency in two stages of technological innovation value chain and green development efficiency are all positive. This shows that technological innovation is an important tool to promote the green and high-quality development of manufacturing industry. In addition, the advanced industrial structure and the development of information and communication technology can improve the efficiency of green development. However, from the results, the development of urbanization is not conducive to the improvement of green total factor productivity in the local and surrounding areas. Although the growth of China’s urbanization rate has shifted from a traditional urbanization growth model to a new urbanization development model focusing on improving quality, Zheng et al. (2018) pointed out that China’s urbanization development still has certain status of disorder development and unbalanced development. The direct effect and total effect of market-oriented and firm competition can promote the green development of manufacturing industry, but the relationship between indirect effect and green development is negative. Market-oriented is beneficial to stimulating market vitality and enhancing enterprise competitiveness. Hence, market-oriented is conducive to stimulating local enterprises to improve green development capacity. The spillover effect of GDP can promote green development. Besides, OFDI helped the green development efficiency to improve.

### Conclusion and policy recommendation

#### Conclusion

Based on the data from 2006 to 2015, this paper evaluates the efficiency of innovation value chain and green development in high-tech industry and further analyzes the spatial linkage effect of green development in manufacturing industry. And the following main conclusions are drawn:

First, the efficiency of technological innovation is higher than the efficiency of economic transformation, and the dilemma of high input and low output still exists. From a regional perspective, the efficiency of the technological innovation value chain in the east is significantly higher than that in the central, west, and northeast. Compared with the 11th FYP period, the gap between the efficiency of the high-tech industry innovation value chain in the northeast, central, and west during the 12th FYP period and the east has gradually narrowed.

Second, the Global Malmquist-Luenberger index analyzes the evolution trend and regional heterogeneity of green development efficiency. The results turn out that the average value of green development efficiency, technological change, and efficiency change is greater than 1. From the perspective of regional research, the green development efficiency of high-tech industries in the east developed steadily; in the northeast, central, and west, the development of green development efficiency showed a fluctuating growth trend.

Third, the spatial agglomeration effect is significant, indicating that the green development of the manufacturing industry has an obvious spatial linkage effect. Technological innovation efficiency, advanced industrial structure, information and communication technology, GDP, OFDI, and enterprise competition have a positive impact on green development efficiency, while economic transformation efficiency and urbanization have negative impacts on green development efficiency.

### Table 14 Direct effects and spatial linkage effects of spatial Dubin model

|       | Direct  | Indirect | Total   |
|-------|---------|----------|---------|
| mk    | 0.367** | −0.340** | 0.271*  |
|       | (0.202) | (0.241)  | (0.107) |
| gdp   | 0.803** | 0.244*** | 0.108***|
|       | (0.300) | (0.414)  | (0.538) |
| tise  | 0.059** | 0.019*   | 0.040*  |
|       | (0.041) | (0.068)  | (0.061) |
| etse  | 0.036*  | 0.009*** | 0.035*  |
|       | (0.056) | (0.103)  | (0.113) |
| ofdi  | 0.104** | 0.060*   | −0.049  |
|       | (0.082) | (0.204)  | (0.240) |
| fc    | 0.702*  | −0.045   | 0.206   |
|       | (0.163) | (0.021)  | (0.109) |
| ur    | −0.319**| −0.184*  | −0.503***|
|       | (0.214) | (0.344)  | (0.216) |
| ict   | 0.031***| 0.003    | 0.038***|
|       | (0.017) | (0.022)  | (0.019) |
| ais   | 0.240** | 0.070*   | 0.072*  |
|       | (0.086) | (0.156)  | (0.196) |
Policy recommendation

Based on the results of empirical research, this paper proposes the following policy recommendations:

First of all, establish and improve the trading platform of scientific and technological achievements, so that intellectual property rights can be implemented and the efficiency of transformation could be improved. The empirical results show that the problems of high input and low output in high-tech industries still exist. Therefore, combined with the development characteristics of China’s new era, to build a unified market and stimulate market vitality improve the ability of green development of the market. And, relevant departments should strengthen the integration of industries, universities, and research institutes and improve public research and development platforms. On the one hand, they should enhance the improvement of technological innovation capacity. On the other hand, they should strengthen the implementation of technological innovation results and improve the transformation capacity.

Second, deepen the supply-side structural reform and promote the advanced industrial structure. Based on the relevant development experience of the industrial economic development process of developed countries, the advanced industrial structure is the key to achieving economic transformation. The constraints of China’s transformation from a manufacturing country to a manufacturing power are still obvious. Whether it is the external challenge of re-industrialization in developed countries or the need for high-quality development of China’s internal economy, it is imperative to promote advanced manufacturing industry structure. An important way for the green transformation of manufacturing is the integrated development of information technology and manufacturing. China should continue to deepen supply-side structural reforms, further improve the level of intelligent manufacturing in manufacturing, consolidate the foundation for the integrated development of manufacturing and informatization, and promote advanced industrial structure. Construct a moderately balanced spatial layout of new urbanization, strengthen spatial governance capabilities, promote the coordinated and balanced development of informatization and marketization among regions, and build a new path to industrialization with Chinese characteristics.

Third, deepen international cooperation and promote the formation of a new pattern of full opening. In the process of advancing the high-quality development of the manufacturing industry, the innovation-driven system is a collection of multiple innovation methods. The introduction and transformation of overseas technology will help support and deepen the integration of China’s manufacturing industry and the Internet. In the international development environment where international trade protection is on the rise, China should continue to promote and deepen the development of the Belt and Road and establish mutually beneficial and friendly partnerships with countries along the route. Make good use of the unimpeded trade brought about by the Belt and Road initiative, actively promote the development of international trade and optimize the industrial chain, as well as accelerate the promotion of its position in the global value chain. Actively promote the “going out” of the entire chain of the integration of manufacturing and information technology, promote new products and services, expand overseas markets, and enhance China’s international influence. Through the bringing in of foreign companies, using the resource benefits brought about by technology spillovers, understanding and learning international advanced management and business models, and promoting high-quality economic development.

Research limitations

Based on the development characteristics of the new era, this paper discusses the spatial impact of technological innovation capability on the green development of manufacturing industry from a new perspective of technological innovation value chain, but there are still shortcomings. Although the investment in technological innovation has a positive effect on the green transformation of the manufacturing industry, whether there are thresholds or mediating effects for investment in technological innovation. High-tech industries are divided into six categories. Based on the heterogeneity of industry development, the development characteristics of high-tech industry have not been explored in detail. This will be the direction that needs to be explored in future research.

Acknowledgements The authors are also grateful to the editor and anonymous reviewers for their careful review and insightful comments.

Author contribution Manli Cheng: conceptualization, data curation, analysis, and writing. Zongguo Wen: writing, review, and supervision. Shanlin Yang: review and supervision.

Funding This research received financial support from the National Science Fund for Distinguished Young Scholars of China (71825006).

Data availability Datasets used and analyzed during the current study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate This research did not involve human participants, human data, or human tissues. This study was based on the published materials.

Consent for publication This research does not contain any individual person’s data in the form of individual details, images, or videos. This work is based on the published literature.
Competing interests The authors declare no competing interests.

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