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From digitalization to green transformation: empirical evidence from RCEP's industrial sectors

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Within the context of global industrial chain reconfiguration, the Regional Comprehensive Economic Partnership (RCEP) presents an array of collaborative opportunities for nations to foster industrial transformation. This study provides novel insights into the environmental implications of regional trade accords, focusing on the nexus between cross-border industrial integration, a hallmark of RCEP, and the advancement of green technologies within China's manufacturing sectors. Utilizing panel data from 11 RCEP member countries spanning 2011–2019, we employ the fixed effect, mediating effect, and moderating effect models to evaluate the impact of service industry digitalization. Our findings indicate that while the digitalization of services under the RCEP significantly propels the green technology development in China's manufacturing, this beneficial effect is dampened by increasingly rigid regulations governing digital services trade. The operational proficiency and innovative capacity of the manufacturing sector emerge as pivotal mediators in this dynamic. Conversely, the digitalization of service industries impedes the green transformation of technology-intensive manufacturing industries. Collectively, these insights elucidate the environmental repercussions of industrial digitization and affirm the environmental benefits of collaborative regional industrial chains.

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Introduction

The COVID-19 pandemic has significantly heightened the risks of global supply chain disruptions, prompting a re-evaluation of industrial strategies toward diversification, near-shoring, and localization. In this context, the Regional Comprehensive Economic Partnership (RCEP), which accounts for over one-third of the global economy, became operational on January 1, 2022, offering a timely framework for economic cooperation and resilience. According to the General Administration of Customs of China, the initial 11 months of 2022 saw trade between China and RCEP member countries reach 11.8 trillion CNY, which is 30.7% of China's total foreign trade, underscoring the pact's substantial impact on regional economic dynamics (Xiao and Xian 2020; Zhu et al. 2024). Trade-driven industrial cooperation can also introduce new technology and management expertise, which can elevate the status of the industrial value chain and advance technological advancement (Hayakawa et al. 2020). Green innovation, as a quasi-public good, has positive externalities on the environment in contrast to traditional innovation, which can reduce environmental damage and therefore do not belong to the one who invests in clean technology, doubling costs and weakening benefits, thereby inhibiting corporate investment in green innovation (Marchi 2012). Since the 13th China Five-Year Plan (FYP), maximizing resource utilization efficiency, reducing environmental effects, and fostering "green manufacturing" have all gained development importance. The high costs of green innovation can be reduced by international cooperation through increased technological infrastructure, more expertise, and increased foreign investment in R&D (Edler and Harald 2003). Businesses can use this as inspiration to produce green technologies more quickly and more affordably, thus advancing the greenization process (Wang and Cheng 2024).

Against the backdrop of climate change, the RCEP offers a critical juncture to explore innovative pathways for green development, a collective responsibility in the face of environmental challenges. This paper delves into the influence of service sector digitalization within the RCEP on the green transformation of China's manufacturing industry. Our research is particularly pertinent as it intersects the domains of digitalization, regional trade agreements, and sustainable development—emerging as pressing issues amidst the pursuit of industrial diversification and the imperative for green growth. This research intends to investigate two fresh topics: the presence of this influence and its operating mechanism. (1) Is it possible for China's manufacturing industry's green technological advancement to be impacted by the digital transformation of service industries in RCEP nations through frequent industry chain interactions? (2) What is the underlying mechanism for this? (3) What heterogeneity does the impact have? In an attempt to address the questions, this research uses panel data from 11 RCEP member countries between 2011 and 2019 to investigate whether service digitization may advance green technology in China's manufacturing sector. The objective is to support China's industrial transformation and offer empirical experience and policy recommendations to help China fully integrate into the Asia Pacific region, which is the world's largest economically active market.

Building on the existing body of knowledge, this paper makes distinct contributions that advance our understanding of the interplay between digitalization, regional trade agreements, and green technological progress. Unlike previous studies that have often focused on either the economic implications of digitalization or the environmental aspects of trade agreements in isolation, our research offers a holistic perspective by integrating these elements within the context of the RCEP. We provide novel empirical evidence that directly links the digitalization of service industries in RCEP countries to the green transformation of

China's manufacturing sector, a relationship that has been largely unexplored. Moreover, our methodological approach, which includes the application of the Slacks Base Measure (SBM) of Data Envelopment Analysis (DEA) to measure green technological progress bias, introduces a new level of sophistication in assessing environmental performance. Furthermore, our examination of the moderating effects of digital service trade barriers on this relationship fills a significant gap in the literature, highlighting the intricate dynamics between trade policy and environmental sustainability. In doing so, this paper not only enriches academic discourse but also offers practical insights for policymakers seeking to navigate the complex terrain of global trade, digital transformation, and environmental stewardship.

The remainder of this paper is structured as follows. Section "Literature review" is a literature review of relevant variables. Section "Theoretical analysis and hypotheses" is theoretical analysis and inference of research hypotheses. Section "Data, models, and variables" is the calculation and description of data and variables, as well as the setting of models. Section "Empirical results" is the empirical results and discussion. Section "Conclusions and discussion" is the conclusion and policy recommendations.

Literature review

This study is anchored in three distinct yet interrelated literature streams that explore the nexus between the environmental impacts of industrial integration, the role of digitalization in the manufacturing sector, and digital service trade barriers.

Environmental impacts of industrial integration. The first one discusses how industrial integration in the manufacturing and service sectors affects the environment. The discourse on the interplay between economic progress and environmental degradation has been a central theme in both policy and academic circles (Mahmood et al. 2024). The Environmental Kuznets Curve (EKC) theory continues to stimulate debate on the relationship between economic growth or technological advancement and environmental pollution levels within the digital economy era (Grossman and Krueger 1992; Ullah et al. 2024; Makarov and Alataş 2024). Numerous academics have discovered that new avenues for industrial green transformation will arise from the merger of the manufacturing and service sectors (Rosenberg 1963). Using data from 38 countries, Huang et al. (2022) demonstrated that input servitization significantly reduces the implicit carbon emissions in manufacturing export trade. Federica and Gonzales (2019) also used European manufacturing data to demonstrate that servitization can enhance sustainable management. In addition, the servitization of manufacturing can enhance resource utilization (Fishbein et al. 2000), company productivity (Zhang et al. 2024a), and even the efficiency of green innovation (Li et al. 2021). Furthermore, both input and output service-oriented manufacturing exhibit the benefits of lowering environmental pollution (Tang et al. 2022; Wang et al. 2023). From a management standpoint, Kohtamäki et al. (2023) contend that service-oriented manufacturing may effectively handle the conflict between manufacturing firms' profitability and sustainable development plans, creating a win-win scenario.

The impact of the digital economy on the green transformation. The second branch of literature is about the impact of the digital economy on the green transformation in manufacturing. Research at the enterprise level has established that digital transformation in manufacturing contributes to energy conservation and emission reduction, with green innovation emerging as a pivotal

Table 1 Literature review summary.

1. Environmental impacts of industrial integration	
Generalized environmental impacts of economic progress	Mahmood et al. (2024), Grossman and Krueger (1992), Ullah et al. (2024), Makarov and Alataş (2024)
Environmental benefits of service-oriented manufacturing	Rosenberg (1963), Fishbein et al. (2000), Federica et al. (2019), Li et al. (2021), Tang et al. (2022), Huang et al. (2022), Wang et al. (2023), Kohtamäki et al. (2023), Zhang et al. (2024a)
2. The impact of the digital economy on green transformation	
Double-edged sword of digitalization	Higon et al. (2017), Magazzino et al. (2021), Freitag et al. (2021), Zhang et al. (2022), Chatti and Majeed (2022), Evans and Mesagan (2022), Liu et al. (2023), Feng et al. (2024)
From digitalization to green transformation	Wang et al. (2023), Chen et al. (2024), Zhang et al. (2024b)
The measurement of green transformation: green technological progress bias	Hicks (1933), Wei et al. (2019), Ren and Zeng (2021), Ge et al. (2023), Qiu et al. (2023), Wang et al. (2024), Feng et al. (2024), Li and Cheng (2022), Yang et al. (2024), Zhang and Yang (2024)
3. Digital service trade barriers	
Positive for trade	Chen (2020)
Negative for trade	Ferracane et al. (2020), Qi and Qiang (2021), Zhou and Yao (2021)

channel (Wang et al. 2023; Chen et al. 2024). At the same time, the digital economy's capacity to form spatial networks in urban agglomerations, share innovative resources, and generate green innovation effects cannot be overlooked (Zhang et al. 2024b). However, the digitalization of manufacturing presents a double-edged sword; while it holds the potential for environmental benefits (Evans and Mesagan 2022), the high energy consumption of Information and Communication Technologies (ICT) (Higon et al. 2017; Magazzino et al. 2021), greenhouse gas emissions (Freitag et al. 2021; Zhang et al. 2022), and electronic waste pose significant environmental challenges (Liu et al. 2023). The debate on the net green effects of digitization is far from settled (Feng et al. 2024), with evidence suggesting varying impacts across developed and developing economies (Chatti and Majeed 2022).

For the measurement of green transformation, this paper focuses on the green technological progress bias. Green total factor productivity (GTFP) has always been a core indicator for measuring green technological progress (Feng et al. 2024; Li and Cheng 2022), while this paper expands by selecting the decomposition term of it, which is biased technological progress. At the measurement level, the bias of technological progress itself is a decomposition term of GTFP, which expresses the contribution of inter group bias to GTFP. It conveys the inherent meaning of whether it can promote the bias of green technological progress and improve GTFP, making it a source of growth for GTFP. When the output change brought about by the input of a certain factor is greater than the input change of the factor itself, we believe that technological progress is biased toward that factor (Hicks 1933). Most research on biased technological progress is mainly limited to traditional factors such as capital and labor (Qiu et al. 2023; Wang et al. 2024). Faced with increasingly urgent environmental constraints, green technological progress bias can identify the sources of technological progress. Especially when technological progress leans toward energy conservation or reducing pollution emissions, it will promote environmental governance (Yang et al. 2024), achieve mutual benefit and win-win economic and environmental performance (Ren and Zeng 2021; Zhang and Yang 2024). For the influencing factors, existing literature is mainly limited to green finance (Ge et al. 2023) and factor substitution (Wei et al. 2019), seeing the related research is very scarce.

Digital service trade barriers. The third cluster focuses on digital service trade barriers. To deeply seek the economic impact of digitalization of service industries within the RCEP framework, digital service trade barriers are important influencing factor that we have to pay attention to. But research on digital service trade

barriers is very limited. Ferracane et al. (2020) argued that cross-border data flow regulation in developed countries has adverse effects on enterprises themselves, upstream and downstream enterprises, and even the industry. Based on Digital Service Trade Restriction Index (DSTRI) of the Organization for Economic Cooperation and Development (OECD), Qi and Qiang (2021) constructed a digital service trade restriction assessment framework and found that restrictive measures of bilateral trade countries have obstacles to service exports, which has also been validated using the Digital Trade Restrictions Index of European Centre for International Political Economy (ECIPE) by Zhou and Yao (2021). On the contrary, Chen (2020) found that the inclusion of the rule of "free flow of cross-border data" in regional trade agreements can promote smooth trade and have a positive impact on the development of digital trade. The above research indicates that there is still a blank space in the research on the impact of digital service trade regulation on industrial development.

In this literature review, we have traversed the expanse of scholarly work that touches on the realms of industrial integration, environmental impact, and the burgeoning field of digitalization within the manufacturing sector (see Table 1 for summary). Our paper builds upon this foundation by offering a multifaceted analysis that addresses a gap in the current literature: the specific impact of service industry digitalization on the green transformation of China's manufacturing sector within the RCEP framework. Unlike previous studies that have tended to consider the economic or environmental aspects in isolation, our research provides a comprehensive assessment that integrates these dimensions. We extend the conventional focus on capital and labor by introducing environmental factors into the measurement of green technological progress bias, thereby enriching the discourse on biased technological progress. Furthermore, our investigation into the role of digital service trade barriers as a moderator in the relationship between service industry digitalization and green technological progress introduces a novel perspective on the influence of trade policies on environmental outcomes. Collectively, these contributions not only enhance the theoretical understanding of the subject matter but also offer pragmatic insights for policymakers and industry leaders, positioning this study at the forefront of research at the intersection of digital economy, trade agreements, and sustainable development.

Theoretical analysis and hypotheses

In the industrial age, the service industry always participates in the process of production, providing added value for the

manufacturing industry. With the development of the times, the main functions undertaken by the service industry in advanced production systems have gradually shifted from finance to management and ultimately evolved into innovative design (Gu et al. 2006). It can be seen that the integration of services and manufacturing industries is it can improve their own level of digitalization and greening largely inseparable from information technology and data. Based on existing academic arguments, the integration of industries can absorb high-end and innovative factors, improve GTFP, and promote biased technological progress. And data, as a production factor with greater integration capabilities, may become a new source of added value for the industrial chain. We know that the emergence of an international networked production system has overcome physical distance and made the role of regional vertical division of labor increasingly prominent. As one of the sectors, by integrating digital elements and technologies, it can improve their own level of digitalization and greening while also potentially driving the improvement of production behavior in industries upstream and downstream of the industrial chain. How to achieve this ripple effect? First, the digital technology used by the upstream service sectors will overflow the downstream manufacturing sectors through cleaner intermediate goods and more intelligent services. On the one hand, the manufacturing sector directly uses green intermediate goods to reduce pollution emissions in production, and on the other hand, it helps green innovation by imitating and learning advanced technologies contained in intermediate goods. In addition, the digitalization of upstream service sectors has raised the threshold for downstream manufacturing. This matching effect has put forward higher requirements for potential collaborators, forcing downstream manufacturing to update and upgrade production technology, thereby improving the level of green transformation. We summarize this as a supply-driven forward linkage effect. If the digitalization of the service sector occurs downstream of the industrial chain, then the manufacturing sector that matches it is probably the leader in technological innovation in the industry so that it can provide with high-level intermediate goods. In addition, the demand preference of the downstream service sectors will promote healthy competition in the upstream sectors, ultimately promoting the green transformation of the manufacturing industry through backward-related demand pull (Dai and Yang 2022).

Hypothesis 1: The industrial linkage effect of digitalization of services has a positive promoting effect on green technological progress bias in the manufacturing industry.

Labor-intensive and capital-intensive sectors often play the role of imitators in the international division of industry chain. Through a large number of technological imitations, they can elevate production technology and promote their own technological progress. However, once developing countries attempt to enhance their value chain position by developing their production systems in industries with denser technological resources, simple imitation only has little effect, stimulating leading sectors to establish independent innovation capabilities. But, at this time, developed countries implement various means to hinder the above high-quality development in order to maintain their own industrial status, forcing developing countries to be intercepted at the low end of the value chain, resulting in “low-end locking” (Wang et al. 2014). Research has shown that China’s high-tech manufacturing industry is generally at a low-end level in the global value chain division of labor system, and it is difficult to achieve technological breakthroughs in the short term (Du et al. 2016). This state will have a negative impact on the strengthening of industrial linkages, as Wang (2022b) found. The embedding and upgrading of global value chains will actually have a restraining effect on TFP and technological progress of high-tech manufacturing.

Hypothesis 2: With the increase of technological complexity in the manufacturing sectors, stronger industry linkages will hinder the improvement of its green technological progress bias, resulting in industry heterogeneity.

Then we tried to analyze its impact mechanism. For one thing, driven by digital technologies such as the internet, innovation is gradually replacing efficiency as the main engine of overall economic development. First, the networking of service platforms has gradually made personalized needs of customers available, breaking the information barrier between customers and R&D personnel, opening up channels for consumers to join the R&D of enterprises, and achieving demand-oriented innovation. Also, the widespread application and upgrading iteration of high-tech can create innovation competition among enterprises, create a practical environment of “mass entrepreneurship and innovation,” and achieve supply-oriented innovation. As a result, the dual response and frequent interaction between the supply and demand sides have contributed to the continuous upgrading of industrial innovation capabilities, which are positively correlated with resource allocation efficiency, which in turn has an impact on GTFP in the long term.

For another, as the breadth and depth of industrial digitalization continue to expand, the characteristics of high fixed cost and low marginal cost of enterprise costs begin to emerge. High fixed costs mainly come from enterprise research and development expenses, while low marginal costs refer to the fact that finished products can be infinitely replicated at zero cost, greatly reducing the original production costs (Jing and Sun 2019). Moreover, since the digital economy can reduce the time and economic costs of searching for matches caused by information asymmetry between supply and demand, the problem of long inventory retention periods in enterprises has been addressed to some extent. Under these conditions, the high fixed costs of manufacturers are diluted, and large-scale economies are achieved with the further expansion of production scale (Zhao et al. 2021). Besides, digital technology also plays a significant role in modern enterprise management and control. Core technologies such as big data can help enterprises monitor and accurately calculate costs in modules such as cost prediction, accounting, control, evaluation, and feedback. Correspondingly, the operation and management of enterprises are more efficient, and valuable resources can be invested in value-added and green technology improvement processes, thereby improving GTFP and promoting high-level development of the manufacturing industry.

Hypothesis 3: Digitalization of services can promote green technological progress bias in the manufacturing industry through two mechanisms: improving the innovation capacity and operational level.

Many free trade agreements involve regulatory content for digital services trade, which will have a certain impact on it between countries, but the specific direction of the impact is not yet clear. From a positive perspective, the large-scale economy and positive externalities of digital trade can clearly create unimaginable appreciation space for enterprises, which may cause blind chaos among market speculators. At this time, appropriate trade rules and restrictive measures will help maintain market order, allowing countries to smoothly access foreign markets and effectively regulate the international benefits of industrial linkages. From a negative perspective, restrictive measures on digital service trade will increase the cost burden of service trade for enterprises and suppress industrial linkages. Strict regulation of digital service trade means that enterprises need to invest a lot of time and financial resources to coordinate and adapt to new policies and requirements (Nordäs 2016), hindering information sharing and collaborative operation among enterprises. Apart from that, digital service trade barriers will restrict the flow of

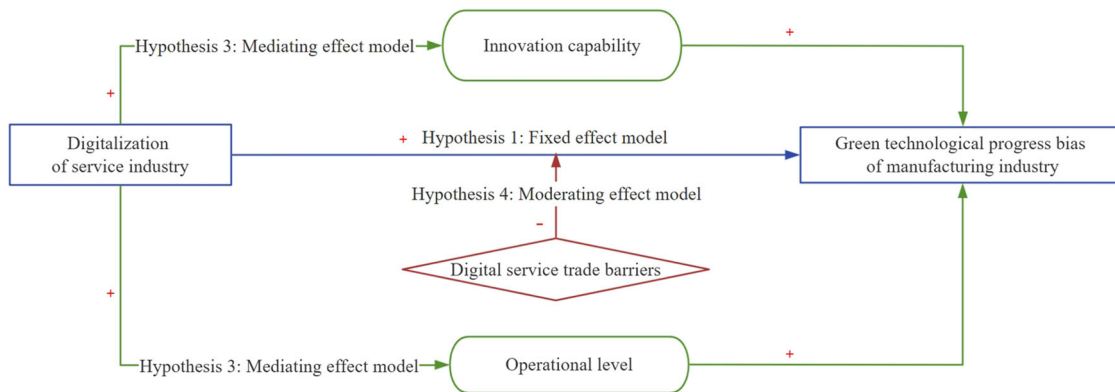


Fig. 1 Framework among variables. A process diagram and regression method used, with expected regression results represented by symbols.

data resources and technology transfer, increasing the import cost of digital services. The cumulative raise in trade costs caused by these restrictive measures has increased the difficulty of industry participation in global division of labor (Wei and Yi 2021), thus weakening the green effect of industrial linkages.

Hypothesis 4: The deepening of restrictive measures on digital service trade will play a moderating role in the impact path of industrial linkages on the green transformation of the manufacturing industry, depending on the sum of positive and negative impacts. All hypotheses are presented in Fig. 1.

Data, models, and variables

Data sources. This paper uses three sets of data. First, to measure the independent variable digitalization of services, we use Asian Development Bank Multi Region Input–Output Table (ADB-MRIO) with wide coverage and high update frequency to select relevant data from 11 countries or regions, including China, Japan, South Korea, Indonesia, Malaysia, the Philippines, Thailand, Singapore, Brunei, Laos, and Vietnam, from 2011 to 2019, to study the industrial interconnection and interaction within the RCEP region. For the selection of sectors, referring to the practices of Xi et al. (2015) and Guo and Xu (2015), C23–C30 (inland transport; water transport; air transport; other supporting and auxiliary transportation activities; post and telecommunications; financial intermediation; real estate activities; renting and other business activities) are identified as service sectors, C3–C16 (agriculture, hunting, forestry, and fishing; mining and quarrying; food, beverages, and tobacco; textiles and textile products; leather, leather products, and footwear; wood and products of wood and cork; pulp, paper, paper products, printing, and publishing; coke, refined petroleum, and nuclear fuel; chemicals and chemical products; rubber and plastics; other nonmetallic minerals; basic metals and fabricated metal; machinery, nec; electrical and optical equipment) is identified as the manufacturing sectors, while C14 and C27 are selected as the digital sectors (He 2021; Zhang and Yu 2021).

The second set of data is from the China Statistical Yearbook, which includes the China Science and Technology Statistical Yearbook, China Industrial Statistical Yearbook, China Environmental Statistical Yearbook, and China Energy Statistical Yearbook. After collecting the raw data, we compare and match the manufacturing industry classification in the China Statistical Yearbook with the ADB-MRIO industry classification. So that the dependent variable, mediator variable, and control variable can be calculated. Also, in terms of measuring restrictive measures in digital services trade, the DSTRI released by the OECD from 2014 to 2019 is used. This index scores the restrictive measures implemented by various economies in digital services trade, with

a final score range of 0–1, and the closer the value is to 1, the higher the degree of restriction.

Model and variable definition

Model settings. Drawing on the inspiration from the research of Li et al. (2018), this paper uses the green technological progress bias in various manufacturing sectors in China as the dependent variables and digitalization of services in other RCEP member countries as the independent variables to test Hypothesis 1. Common panel data models include fixed effect model and random effects models. The fixed effect model assumes that the intercept of each individual is fixed, meaning that the differences between individuals are fixed and do not change over time. This allows the model to focus on analyzing the impact of internal changes on the dependent variable, which is currently one of the most common empirical methods in the benchmark regression in applied economics research. In order to achieve more precise empirical design, we adopted the Hausman test in the selection of the random effects model and fixed effect model. After testing, *P* value of <0.01 rejected the null hypothesis, indicating that individual effects are related to the independent variable, and the fixed effect model should be chosen. The following regression equations are constructed:

$$OBTC_{kt} = \alpha_0 + \alpha_1 Dig_{kt}^{Forward} + \sum_j \alpha_j Control_{kt} + \epsilon_{kt} \quad (1)$$

$$IBTC_{kt} = \alpha_0 + \alpha_1 Dig_{kt}^{Forward} + \sum_j \alpha_j Control_{kt} + \epsilon_{kt} \quad (2)$$

$$BIAS_{kt} = \alpha_0 + \alpha_1 Dig_{kt}^{Forward} + \sum_j \alpha_j Control_{kt} + \epsilon_{kt} \quad (3)$$

In Eqs. (1)–(3), $Dig_{kt}^{Forward}$ the forward linkage effect is used to test the impact of digitalization of service in RCEP countries on the green transformation of China’s downstream manufacturing industry *k* in year *t*. Then change it to $Dig_{kt}^{Backward}$, a backward linkage effect used to test the impact of digitalization of services in RCEP countries on the green transformation of China’s upstream manufacturing industry. $IBTC_{kt}$ and $OBTC_{kt}$, respectively, represents input biased toward technological changes and output biased toward technological changes. For the bias of output technological progress, this paper sets it as a dummy variable. If the output technological progress of manufacturing industry *k* in China tends to reduce pollution, then $BIAS_{kt} = 1$; on the contrary, if the output technological progress tends to promote generate more pollution, $BIAS_{kt} = 0$. $Control_{kt}$ represents the set of control variables that may have an impact, which will be explained in detail later. ϵ_{kt} denotes the random error.

Digitalization of services. The input–output method was originally developed by economists Leontief (1936) and Ghosh (1958). It is

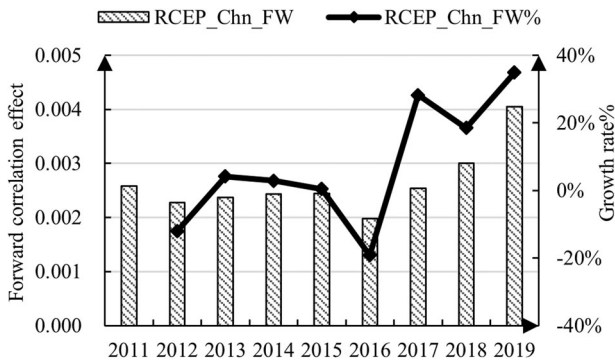


Fig. 2 Forward linkage and growth rate of digitalization of service industry in RCEP countries on China's manufacturing industry (the independent variable). This figure shows the demand for downstream manufacturing in the upstream service industry has been increasing year by year, and the growth rate is also accelerating.

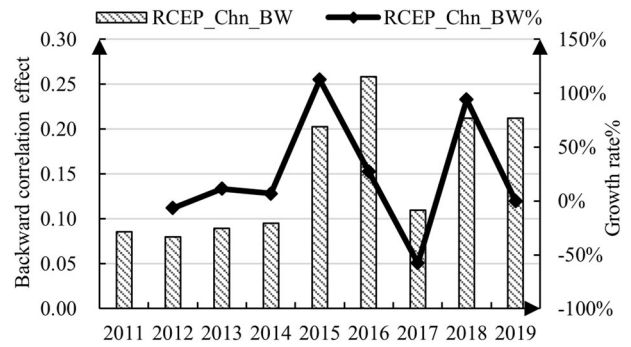


Fig. 3 Backward linkage and growth rate of digitalization of service industry in RCEP countries on China's manufacturing industry (the independent variable). This figure not only reflects the growth trend, but also demonstrates that the backward linkage is numerically stronger than the forward linkage, combined with Fig. 2.

proposed that using a matrix form input–output table to describe the input sources and usage directions of production activities in various sectors of the national economy during a certain period of time, which can better reveal the quantitative relationship of interdependence and mutual constraints among various sectors (industries) of the national economy. These days the input–output method is widely used in the measurement of industrial digitization (Autor and Salomons 2018), we calculate the complete consumption coefficient (DC_{dj}^c) to reflect the digitalization level of service industry by the software of R:

$$DC_{dj}^c = a_{dj} + \sum_{m=1}^N a_{dm} a_{mj} + \sum_{l=1}^N \sum_{m=1}^N a_{dl} a_{lm} a_{mj} + \dots \quad (4)$$

Equation (4) represents the direct consumption of digital sector d by service sector j , the first indirect consumption of digital sector d by service sector j through sector m , the second indirect consumption of digital sector d by service sector j through sectors m and l , and so on.

To measure more accurately, referring to the approach of Wang (2022a), the internet penetration rate of country a in year t $internet_{at}$ from the World Bank database is used to multiply with DC_{dj}^c to attach it to the level of digital economy development in the country:

$$Digital_{ajt} = \sum_d DC_{dj}^c \cdot internet_{at} \quad (5)$$

Subsequently, by using the multi-regional input–output method to calculate industry linkage, the service industry is linked to China's manufacturing industry. At this point, the composition of the independent variables has been completed:

$$Dig_{kt}^{forward} = \sum_{j,\alpha} g_{\alpha jkt} \times Digital_{ajt} \quad (6)$$

$$Dig_{kt}^{backward} = \sum_{j,\alpha} b_{\alpha jkt} \times Digital_{ajt} \quad (7)$$

In Eq. (6), $g_{\alpha jkt}$ comes from the Ghosh inverse matrix, which reflects the degree of the upstream services industry j of country a invests in the downstream manufacturing industry k in year t , namely, the forward linkage effect, reflecting supply driven in Fig. 2. In Eq. (7), $b_{\alpha jkt}$ is derived from the Leontief inverse matrix, which reflects the demand of downstream service industry j in country a for manufacturing industry k in year t , namely, the backward linkage effect, reflecting demand pull in Fig. 3.

Green technological progress bias. The traditional GTFP is an indicator for the efficiency of output brought by unit input and measuring sustainable economic growth. In the calculation using the DEA method, the Malmquist–Luenberger (ML) can be

obtained by introducing a distance function. The ML productivity index can be decomposed into neutral technological progress, input-biased technological progress, and output-biased technological progress (Färe et al. 1995; Acemoglu 2007). At present, research on biased technological progress is very rare. This paper uses it as a proxy variable for green transformation.

The main methods for measuring the green technological progress bias are Stochastic Frontier Analysis (SFA) and DEA. Due to the fact that the method does not require parameter models and can handle situations with multiple inputs and outputs, it is widely used now. Most of the related studies start with Färe et al.'s (1995) pioneering research, using the DEA Malmquist index to analyze total factor productivity in traditional DEA models, the measurement of the degree of inefficiency only includes the proportional reduction (increase) of all inputs (outputs), ignoring the measurement errors caused by variable looseness and radial problems, resulting in inaccurate measurement results. To improve this issue and objectively reflect the actual situation of each element, Fukuyama and Weber (2009) proposed a non-radial and non-directional SBM directional distance function based on chi variables, which has the following basic form:

$$D_V^-(x^{t,k}, y^{t,k}, b^{t,k}, g^x, g^y, g^b) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{g_n^x} + \frac{1}{M+1} (\sum_{m=1}^M \frac{s_m^y}{g_m^y} + \sum_{i=1}^I \frac{s_i^b}{g_i^b})}{2} \quad (8)$$

$$s.t. \begin{cases} \sum_{k=1}^K z_k^t x_{kn}^t + s_n^x = x_{kn}^t, \forall n \\ \sum_{k=1}^K z_k^t y_{km}^t - s_m^y = y_{km}^t, \forall m \\ \sum_{k=1}^K z_k^t b_{ki}^t + s_i^b = b_{ki}^t, \forall i \\ \sum_{k=1}^K z_k = 1; z_k \geq 0; s_n^x \geq 0; s_m^y \geq 0; s_i^b \geq 0 \end{cases} \quad (9)$$

In Eqs. (8) and (9), $x^{t,k}, y^{t,k}, b^{t,k}$ represent the input, expected output, and unexpected output vectors of province k during period t . g^x, g^y, g^b represent the direction vectors of input reduction, expected output increase, and unexpected output decrease, respectively. The relaxation vectors corresponding to s_n^x, s_m^y , and s_i^b represent the excess (redundancy) of input and unexpected output and the deficiency of expected output.

Further constructing the ML index based on the directional distance function of SBM, the ML productivity index from t to

Table 2 Description statistics of variables.

Type	Variables	Observations	Mean	Standard deviation	Min.	Max.
Dependent variables	BIAS	112	0.464	0.501	0	1
	OBTC	112	0.988	0.0784	0.773	1.295
	IBTC	112	1.013	0.0586	0.821	1.307
Independent variables	Dig ^{forward}	112	0.264	0.185	0.0335	0.930
	Dig ^{backward}	112	0.158	0.315	0.00650	2.376
Mediating variables	inno	112	0.321	0.229	0.0687	1.019
	cost	112	0.880	0.0525	0.699	0.934
Moderating variable	DSTRI	84	2.629	0.0305	2.59228	2.689
Control variables	open	112	5.929	12.06	0.380	56.05
	kl	112	10.72	8.390	0.385	37.82
	es	112	0.472	0.495	0.0104	2.475
	cap	112	-0.0415	0.184	-0.783	0.406

$t + 1$ is:

$$ML = \sqrt{\frac{D^t(x^{t+1}, y^{t+1}, b^{t+1}; g)}{D^t(x^t, y^t, b^t; g)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)}{D^{t+1}(x^t, y^t, b^t; g)}} \quad (10)$$

And because $ML = EFFCH \times TECH$, ML can be decomposed into:

$$ML = \frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)}{D^t(x^t, y^t, b^t; g)} \times \sqrt{\frac{D^t(x^t, y^t, b^t; g)}{D^{t+1}(x^t, y^t, b^t; g)} \times \frac{D^t(x^{t+1}, y^{t+1}, b^{t+1}; g)}{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g)}} \quad (11)$$

To investigate whether technological progress tends toward desirable or undesirable outputs, $TECH$ is further decomposed into three parts: $MATC$, $IBTC$, and $OBTC$ (using software of $MAXDEA$):

$$MATC = \frac{D_0^1(y_g^t, y_b^t, x^t)}{D_0^{t+1}(y_g^t, y_b^t, x^t)} \quad (12)$$

$$IBTC = \sqrt{\frac{D_0^{t+1}(y_g^t, y_b^t, x^t)}{D_0^t(y_g^t, y_b^t, x^t)}} \times \sqrt{\frac{D_0^t(y_g^t, y_b^t, x^{t+1})}{D_0^{t+1}(y_g^t, y_b^t, x^{t+1})}} \quad (13)$$

$$OBTC = \sqrt{\frac{D_0^t(y_g^{t+1}, y_b^{t+1}, x^{t+1})}{D_0^{t+1}(y_g^{t+1}, y_b^{t+1}, x^{t+1})}} \times \sqrt{\frac{D_0^{t+1}(y_g^t, y_b^t, x^{t+1})}{D_0^t(y_g^t, y_b^t, x^{t+1})}} \quad (14)$$

In Eqs. (12)–(14), $MATC$ is the scale change index of technological progress, $IBTC$ is input-biased technological progress, and $OBTC$ is output-biased technological progress. Due to the fact that $OBTC$ itself cannot reflect the bias of biased technological progress between desirable and undesirable outputs, we refer to the research of Weber and Domazlicky (1999) and Li et al. (2018) to calculate the bias index within the output factor group as π_{YB} :

$$\pi_{YB} = \left(\frac{Y^{t+1}}{B^{t+1}} \Big/ \frac{Y^t}{B^t} - 1 \right) \times (OBTC - 1) \quad (15)$$

$\frac{Y^{t+1}}{B^{t+1}} \Big/ \frac{Y^t}{B^t}$ is the ratio of the marginal substitution rate of output between desirable output Y and undesirable output B . If $\pi_{YB} > 0$, it indicates that technological progress tends to produce more undesirable pollution while reducing desirable profit. This indicates that the output bias of technological progress is environmentally deterioration, setting $BIAS = 0$. $\pi_{YB} < 0$ indicates environmentally friendly, setting $BIAS = 1$.

Control variables. In addition to the core independent variables, a series of control variables that may affect the regression results will also be considered. Based on existing research, this paper selects the following control variables: (1) energy structure (es) is the proportion of coal consumption in the industry to the total energy consumption, indirectly reflecting the industry’s level of reducing energy consumption and pollutant emissions (Ding et al. 2020). (2) Endowment structure (kl) is the ratio of sector capital stock to the number of employees. (3) Openness ($open$) is the proportion of industry export delivery value to industrial added value. (4) Capital change rate (cap) is the change rate of industry capital stock (Yuan and Xie 2015).

Mediating variables. (1) Innovation Capability ($inno$) is the proportion of internal R&D expenditure to the industrial added value of industrial enterprises above industry scale. (2) Operation level ($cost$) is the cost-expense ratio of industrial enterprises above the industry scale. The cost-expense ratio is equal to the main business cost plus management expenses compared to the main business revenue (Zhao et al. 2021).

Moderating variable. According to Ferracane et al. (2020) and Qi and Qiang (2021), we use $DSTRI$ as the moderating variable, to further analyze the impact of digital service trade barriers on the main effects in various countries.

The description statistics of variables are shown in Table 2.

Empirical results

Benchmark regression results. First of all, the model is subjected to benchmark regression, and Table 3 reports the regression results of Models 1–6. From Models 1, 4, and 5, it can be seen that a unit change in the digitalization level of the service industry in RCEP member countries has led to a significant increase of coefficients of 0.0803 and 0.0754 in the green technology progress of China’s manufacturing industry. This indicates that both upstream and downstream service industries in the industrial chain have a marked impact on the manufacturing industry, thus verifying Hypothesis 1. However, the insignificance of Model 2 demonstrates the digitalization of services mainly affects the output bias of green technological progress in manufacturing, that is, the proportion of pollution emissions and economic benefits in improving technology development. As for which side is the proportion biased toward? Models 3 and 6 measure the impact of digitalization in service industries on the types of green technological progress in manufacturing. The coefficients show that compared to the demand of downstream service industries when the upstream service industry increases its input in manufacturing, green technology progress is more likely to transition from an environmentally deteriorating type to an environmentally

Table 3 Benchmark regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OBTC	IBTC	BIAS	OBTC	IBTC	BIAS
$Dig^{forward}$	0.0803*** (0.0302)	-0.110 (0.0863)	1.147** (0.436)			
$Dig^{backward}$				0.0754*** (0.0219)	0.0179* (0.00882)	0.207** (0.101)
es	-0.0558 (0.0366)	0.0696 (0.0459)	-0.0770 (0.420)	0.0874** (0.0382)	0.0768* (0.0430)	0.197 (0.265)
kl	0.00324 (0.00245)	-0.0141** (0.00598)	-0.00646 (0.0224)	-0.00813 (0.00705)	-0.0132** (0.00565)	-0.0238* (0.0132)
open	-0.00194*** (0.000477)	0.00663** (0.00258)	-0.0220*** (0.00526)	-0.00626*** (0.00150)	0.00423 (0.00286)	-0.0106** (0.00416)
cap	0.0407 (0.0356)	0.197** (0.0828)	0.453** (0.199)	0.0655* (0.0342)	0.181* (0.0853)	0.121 (0.337)
Constant	0.972*** (0.0136)	1.093*** (0.0653)	0.417* (0.201)	1.062*** (0.0708)	1.067*** (0.0630)	0.669*** (0.197)
Observations	112	112	112	112	112	112
R ²	0.083	0.220	0.173	0.101	0.219	0.441

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

Table 4 Robustness testing of replacement variables.

Variables	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	OBTC	IBTC	BIAS	OBTC	IBTC	BIAS
$Dig^{forward}_t$	0.0706** (0.0341)	0.0152 (0.0273)	1.134** (0.430)			
$Dig^{backward}_t$				0.154* (0.0805)	0.0913* (0.0502)	0.521** (0.215)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.993*** (0.0144)	1.016*** (0.00983)	0.419* (0.201)	0.992*** (0.0121)	1.022*** (0.00870)	0.533*** (0.0285)
Observations	112	112	112	112	112	112
R ²	0.097	0.055	0.173	0.078	0.370	0.124

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

friendly type. This explains that new green technologies are progressing in increasing profits and reducing pollution at this time.

In terms of controlling variables, the impact of energy structure (es) on the green technological progress bias is significantly positive, while factor endowment (kl) has a restraining effect. There are two characteristics in the improvement of green technology progress of inputs: first, it relies on the consumption of fossil fuels, etc., and second, labor factors still serve as a remarkable source of technological progress, which may be related to the demographic dividend of China’s labor market (Su et al. 2017). Meanwhile, openness (open) has a notable inhibitory effect on output bias, while it has a promoting effect on input bias. This may be attributed to the double-edged sword of trade. As openness increases, developing countries will attract developed countries to relocate pollution-intensive enterprises to their own countries by lowering their own environmental regulatory standards, which is not conducive to China’s environmental improvement. Simultaneously, opening trade will bring more technology and capital, which is beneficial for the progress of green technology. The impact of the capital change rate (cap) on technological progress is positive, indicating that capital deepening contributes to the realization of green transformation in the manufacturing industry.

Robustness and endogenous tests. To verify the reliability of benchmark regression, the following robustness tests will be conducted. The first is the robustness test of replacement variables. This paper adopts a method based on complete dependency (DR_{dj}^c) replaces the complete consumption coefficient (DC_{dj}^c) to calculate the degree of digitalization in the service industry ($Dig_{kt}^{forward}$, $Dig_{kt}^{backward}$) to replace the core independent variable:

$$DR_{dj}^c = \sum_d \left(DC_{dj} / \sum_{k=1}^N DC_{kj} \right) \tag{16}$$

As in the “Data, models, and variables” section, DC_{dj} is the complete consumption coefficient in Eq. (16). The regression results are shown in Table 4. It can be seen that after changing the index measurement method, the core conclusion of this paper is still robust.

Then, we will perform a 2.5% tail off on the independent variable to eliminate the influence of outliers. The results are shown in Table 5, and it can be seen that the results are basically the same as the benchmark regression, thereby confirming the robustness of the results.

Although the above regression results confirm the hypothesis in this paper, there may be endogeneity issues of missing variables and reverse causality, resulting in biased and inconsistent estimation results. To alleviate this problem, the lagged

Table 5 Robustness testing after winsorizing.

Variables	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
	OBTC	IBTC	BIAS	OBTC	IBTC	BIAS
$Dig^{forward}$	0.0807*** (0.0305)	0.0147 (0.0392)	1.141*** (0.306)			
$Dig^{backward}$				0.0705** (0.0334)	0.0196* (0.0116)	0.179 (0.217)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.972*** (0.0137)	1.014*** (0.0120)	0.419*** (0.0945)	0.994*** (0.0141)	1.012*** (0.0110)	0.610*** (0.0912)
Observations	112	112	112	112	112	112
R ²	0.083	0.014	0.173	0.099	0.141	0.070

The standard errors of the regression coefficients are shown in parentheses. **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

Table 6 Endogenous test results.

Variables	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
	OBTC	IBTC	BIAS	OBTC	IBTC	BIAS
$Dig^{forward}$	0.106*** (0.0368)	0.0293 (0.0263)	1.309*** (0.304)			
$Dig^{backward}$				0.0678*** (0.0202)	0.0270* (0.0164)	0.197*** (0.0507)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM	18.340	18.340	18.340	6.728	6.728	6.728
Cragg-Donald Wald F	214.818	214.818	214.818	196.896	196.896	196.896
Observations	98	98	98	98	98	98
R ²	0.096	0.009	0.168	0.094	0.374	0.756

The standard errors of the regression coefficients are shown in parentheses. **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

instrumental variable method is adopted. The lagged independent variable has a direct impact on the current period and is not related to the error perturbation term of the current period, thus meeting the basic requirements for selecting instrumental variables. Through the tests of unrecognizable and weak instrumental variables, it was found that the regression results in Table 6 reject the assumption that all independent variables are exogenous variables and satisfy the hypothesis conditions. Therefore, this paper uses the two-stage least squares (2SLS) method for instrumental variable regression. It can be found that the impact of industrial linkage on the green technological progress bias is significantly positive, consistent with the benchmark regression results, proving that the conclusion of this paper is still valid.

Heterogeneity test. On the basis of a full sample, this paper draws on the classification and merging method of Qu and Zhao (2022), and further divides the manufacturing industry into three categories based on factor intensity: labor (C3-C6), capital (C7-C12), and technology-intensive (C13-C15). We explore the heterogeneity of the impact of digitalization of services on different types of manufacturing industries, and serve as a robustness test for subsample regression. And based on the insignificant impact of IBTC mentioned above, it will be excluded in subsequent tests.

It is not difficult to see from Tables 7–8 that labor-intensive and capital-intensive manufacturing industries exhibit certain commonalities, say digitalization of services is beneficial for the green technology bias of these industries. Similar to the benchmark regression, the coefficients of the forward linkage effect are larger (0.499 > 0.371, 0.788 > 0.455, 0.0872 > 0.0856, 0.154 > 0.109), once again indicating the role of manufacturing input in sericitization. This phenomenon gives us two inspirations. One is that as a

developing country, China mainly exports labor-intensive or technologically mature products with low-cost advantages, benefiting industries that produce such products. Another is that for industries with medium to low-end technological content, the embedding of modern service elements such as digital information services can bring about technological spillovers, while helping to green production and supporting the green transformation of manufacturing easily. The opposite phenomenon can be seen in Models 27, 30, 33, and 36. In technology-intensive manufacturing, the digitalization of services has a significantly negative impact on green technology output bias, which confirms that the impact exhibits heterogeneity due to the level of division, consistent with Hypothesis 2. Possible reasons are as follows. Undoubtedly, the service-oriented input and output of manufacturing can promote production specialization and market division of labor. However, technology-intensive industries have relatively mature technologies and are highly embedded in regional industrial chains and value chains. These industries have gradually completed the initial stage of technological progress, attempting to seek functional and chain upgrades with regional industrial chains. At this point, it is likely to touch upon the interests of multinational corporations in developed countries, who are considering their own stage and designing products with higher technology, quality, and other excellent performance to suppress and control such industries. Therefore, developing countries will be captured by developed countries at the low end, which was originally a theory in the value chain and is also applicable in industrial chain analysis (Li et al. 2020). This will force Chinese companies to lose the space for progress and development capabilities.

Mechanism test. Regarding mechanism analysis, there are currently two main approaches in the academic community: first,

Table 7 Heterogeneity test results of BIAS.

Variables	BIAS					
	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30
	Labor	Capital	Technology	Labor	Capital	Technology
<i>Dig^{forward}</i>	0.499* (0.204)	0.788* (0.346)	-2.655* (0.803)			
<i>Dig^{backward}</i>				0.371*** (0.0381)	0.455** (0.143)	-0.949* (0.315)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.225 (0.661)	0.313 (1.595)	0.787 (0.462)	0.334 (0.566)	-0.288 (1.272)	-0.151 (0.401)
Observations	32	48	24	32	48	24
R ²	0.082	0.170	0.407	0.019	0.084	0.531

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

Table 8 Heterogeneity test results of OBTC.

Variables	OBTC					
	Model 31	Model 32	Model 33	Model 34	Model 35	Model 36
	Labor	Capital	Technology	Labor	Capital	Technology
<i>Dig^{forward}</i>	0.0872** (0.0226)	0.154 (0.205)	-0.253** (0.0947)			
<i>Dig^{backward}</i>				0.0856*** (0.00798)	0.109*** (0.0215)	-0.0247 (0.0184)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.916*** (0.0866)	0.895*** (0.212)	1.036*** (0.0545)	0.929*** (0.0306)	1.038*** (0.205)	1.049*** (0.0488)
Observations	48	48	24	48	48	24
R ²	0.278	0.144	0.611	0.113	0.068	0.647

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

theoretical derivation, which refers to the efforts we made in Hypothesis 3 described in the section “Theoretical analysis and hypotheses.” Second, empirical testing, involves using regression models to examine whether the independent variable has an impact on the mediator variable and whether the mediator variable has an impact on the dependent variable. This paper has confirmed that digitalization of the service industry in RCEP countries can enhance the progress of green technology in China’s manufacturing industry. We also explained the mechanism of innovation capability and operational level from a theoretical perspective in Hypothesis 3 described in the section “Theoretical analysis and hypotheses,” but it has not been empirically proven.

Table 9 presents the results of the mediation effect test for green technology progress types (BIAS). Models 38 and 41 are the regression results of the mediating variable on the independent variable, both significant at the 1% level. The digitalization of service industries can indeed enhance innovation capabilities and improve operational levels, thereby helping green technology environmentally friendly. Models 39 and 42 represent the regression results that include all variables. The coefficients are also significant, reflecting the coexistence of direct and indirect effects of digitalization in service industries. The above results of innovation capability and operational level have passed the Sobel Z-value test.

In Table 10, for OBTC, the results are somewhat different. In Model 45, the regression coefficient of inno on OBTC is significant, while the effect of digitalization of services (*Dig^{forward}*) on OBTC is no longer significant. This reflects that there is only a mediating effect in the path of the digitalization of

services affecting green technology progress through innovation level. In Model 48, even though digitalization of services can significantly affect operational levels (see Model 47), it does not constitute the final channel that affects OBTC, and the mediating effect is not obvious.

Moderating test. The moderating effect in empirical research is specifically manifested as the moderating variable affecting the magnitude of the independent variable’s impact on the dependent variable. In data analysis, it generally exists in the form of cross terms that alter the coefficient of influence of independent variables. To examine the moderating effect of restrictive measures on digital service trade, this paper introduces a cross-term between DSTRI and the independent variable for testing.

In the moderation effect test (see Table 11), the interaction coefficient is the focus of our attention. In Models 49–51, the interaction coefficient is significantly negative in the tests of OBTC and BIAS. Indicating that digital service trade barriers can weaken the green impact of upstream service industries on downstream manufacturing industries. The cross-border data flow restriction policy, as an important part of the digital service trade barrier, covers restrictive measures such as data localization requirements. These measures hinder the flow of data elements from upstream service industries to downstream manufacturing industries along the industrial chain. In Models 52–54, the interaction coefficient is positive but only significant at the 10% level, showing that positive regulation helps the service industry to play a role. One possible explanation is that the backward

Table 9 Mechanism test results of BIAS.

Variable	Model 37 BIAS	Model 38 INNO	Model 39 BIAS	Model 40 BIAS	Model 41 COST	Model 42 BIAS
<i>Dig^{forward}</i>	1.147** (0.436)	0.241*** (0.0807)	0.807** (0.372)	1.147** (0.436)	0.122*** (0.0305)	0.868*** (0.322)
<i>inno</i>			1.411** (0.426)			
<i>cost</i>						2.287** (0.955)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.417* (0.201)	143.6** (70.08)	0.366*** (0.101)	0.417* (0.201)	0.866*** (0.00941)	-1.563* (0.832)
Sobel Z			2.616***			2.054**
Observations	112	112	112	112	112	112
R ²	0.173	0.726	0.207	0.173	0.250	0.216

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

Table 10 Mechanism test results of OBTC.

Variable	Model 43 OBTC	Model 44 INNO	Model 45 OBTC	Model 46 OBTC	Model 47 COST	Model 48 OBTC
<i>Dig^{forward}</i>	0.0803*** (0.0302)	0.241*** (0.0490)	0.0568 (0.0361)	0.0803*** (0.0302)	0.122*** (0.0305)	0.0572 (0.0349)
<i>inno</i>			0.122* (0.0645)			
<i>cost</i>						0.187 (0.128)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Sobel Z			1.812*			1.236
Constant	0.972*** (0.0136)	0.179*** (0.0243)	0.955*** (0.0161)	0.972*** (0.0136)	0.866*** (0.00941)	0.809*** (0.108)
Observations	112	112	112	112	112	112
R ²	0.083	0.726	0.089	0.083	0.250	0.094

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

Table 11 Moderating test results.

Variables	Model 49 OBTC	Model 50 IBTC	Model 51 BIAS	Model 52 OBTC	Model 53 IBTC	Model 54 BIAS
<i>Dig^{forward}</i>	0.114** (0.0452)	0.0374* (0.0224)	1.810*** (0.0263)			
<i>Dig^{forward}</i> × DSTRI	-1.040* (0.499)	-0.473 (0.449)	-13.79** (6.000)			
<i>Dig^{backward}</i>				0.0845*** (0.0189)	0.0192 (0.0235)	0.176 (0.161)
<i>Dig^{backward}</i> × DSTRI				0.871* (0.410)	0.403* (0.218)	6.764* (3.889)
DSTRI	-0.0262 (0.255)	-0.0204 (0.213)	-3.147* (1.836)	0.201 (0.401)	-0.500* (0.254)	-0.753 (1.812)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.036 (0.664)	1.059* (0.556)	8.601* (4.800)	0.536 (1.206)	2.564*** (0.754)	2.322 (4.767)
Observations	84	84	84	84	84	84
R ²	0.077	0.018	0.276	0.127	0.130	0.164

The standard errors of the regression coefficients are shown in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% confidence levels, respectively.

linkage effect itself is a demand pull from downstream service to upstream manufacturing, with the initiative held in the hands of the service. Therefore, the restrictive measures in countries where the service industry is located will not impede their own demand from upstream manufacturing, but rather play a beneficial role in moderate regulation. The above conclusion confirms Hypothesis 4.

Conclusions and discussion

Conclusions. This study set out to explore the implications of the digitalization of the service sector within the RCEP on the green transformation of China’s manufacturing industry. Our findings yield several key conclusions that contribute to both academic and policy discourses.

First, we find that the digitalization of the service sector in RCEP countries significantly promotes the green technological progress of China's manufacturing industry. Theoretically, prior research has only shown that technical innovation (Wen et al. 2023) and the digitization of the service sector can propel the auxiliary manufacturing sector up the value chain (Bian and Fan 2024). Our study shows how the digitization of the service sector affects green development, underscoring the potential of regional trade agreements to foster environmental sustainability through digital innovation, aligning with the growing global emphasis on green development.

Furthermore, the overall function of green technology in the production process is to raise the efficiency of end-of-pipe emissions or to optimize the exploitation of energy factors. The choice of technology in these two areas can be reflected in this paper's measurement of green technology bias. We found advanced green technologies can increase economic benefits and reduce pollution, aiming to improve the efficiency of end-of-pipe discharge. This finding differs from and adds to the body of knowledge already available on green technologies that increase the effectiveness of using renewable energy sources (Murshed 2021). In addition, heterogeneity tests indicate that manufacturing industries that require a lot of manpower and capital seem to profit more. Digitalization of the service sector has a restraining effect on green technology in technology-intensive manufacturing industries. This could be an indication that other countries have suppressed technological upgrading in these industries to maintain their monopoly positions, which would explain the low-end lock-in phenomenon observed in value chain research (Li et al. 2020). A defensive stance is nevertheless evident in the high-end manufacturing sectors of many nations, even in the context of regional cooperation. This insight suggests that the path to green transformation may vary across industries, with policy considerations needing to account for these differences. Mechanism test shows innovation capability is more crucial than operational level, emphasizing that businesses must continue to depend on independent research and development in order to overcome the challenge of green manufacturing. This finding emphasizes the importance of fostering innovation and efficiency in the manufacturing sector to achieve greener outcomes.

Lastly, we fear that growing trade obstacles pertaining to digital services may sabotage the benefits of regional trade. Many trade obstacles have evolved as a result of governments waiting to see what benefits developing trade, like digital trade, will bring and hoping to safeguard their own data resources in the early stages. This will negatively affect industrial integration. Empirical evidence demonstrates that our concerns are not unfounded. This inhibitory effect arises in the supply of services to manufacturing, the service-oriented investment in manufacturing (Yu and Yao 2024), indicating the need for balanced trade policies that support both digitalization and environmental goals.

Theoretical implications. The research methodology and content pertaining to the current industrial chain, the digital economy, and green development are further enhanced by this study. First, the industry linkages variable in this paper can connect the technological and economic links between the two sides of the industry through an input-output table, which is a significant improvement over the single indicator established in current industry chain research, such as the servitization of manufacturing inputs (Tang et al. 2022) or the digitization of industry chains (Lin and Teng 2023). The practicality and scientificity of measurements are further demonstrated by the growing industrial interdependence within RCEP region (Fig. 2), offering a fresh approach to cross-border industrial chain study. Second, present

research on digital services trade barriers is primarily textual (Ferencz and Gonzales 2019; Yu and Yao 2024), while significant empirical research has only recently surfaced. This paper uses DSTRI data to broaden the research area of digital service trade barriers, emphasizing the importance of the manufacturing industry. Third, the academic community has long researched the growth source of GTFP, while current research decomposes GTFP into only three intrinsic indices (Feng et al. 2024; Li and Cheng 2022). On this foundation, this paper deconstructs and proposes a new research avenue for investigating the inherent driving force of greenization.

Policy implications. The conclusions of this paper can offer specific plans and inspirations for policymakers regarding industrial green transformation.

First, within the context of RCEP regional coordinated growth, countries in the region should actively implement digital economy governance norms to ensure the smooth development of industries. This paper emphasizes the significance of moderately regulating digital service trade, as excessive regulation may harm the interests of various countries. Consequently, governments should reach international agreements to enhance cooperation in digital economy governance. For instance, they should comply with international standards on key topics such as data security protection and data asset management. Additionally, China and other countries should fully utilize the RCEP international cooperation platform and the leading role of the United Nations. They should support domestic and foreign research institutes, universities, and enterprises to jointly establish digital economy research and development centers, accelerate the narrowing of the digital divide between countries, and promote digital technology in RCEP countries through international forums, conferences, and other means to boost the global economy.

Second, from a national perspective, this paper validates that the green transformation of the manufacturing industries in surrounding countries can benefit from the digitalization of the service economy. Therefore, the orderly development of digital trade can contribute to improving the efficiency of digital transformation in the service sector. Specifically, countries should expedite the creation of open platforms for trade in services, increase the export of digital goods and technologies, establish distinctive export bases for services, and enable more developing countries to gain from the boom in digital economic development. Moreover, free trade zones should construct a management structure characterized by the digital economy, openness in the service industry, and technological innovation. They should seize the opportunity presented by the expansion of the national service industry's comprehensive demonstration zone for opening up and the pilot program for creative development of service trade to drive the digital transformation of the service industry.

Third, from an industrial perspective, the empirical findings of this paper indicate that innovative capabilities and operational levels are crucial for the green transformation of the manufacturing sector, and the government should intervene accordingly. Policies should allocate specific tax funds to support the development of green technology. Increasing R&D subsidies will be the most effective incentive tool. On the one hand, it is necessary to raise the consumption tax on highly polluting fossil fuels, provide subsidies for the use of clean energy, and offer tax incentives for green products. Corporate R&D initiatives and government R&D subsidies will work in tandem if the assessment and feedback of these subsidies create a positive feedback loop. More precisely, enterprises themselves should conduct cutting-edge low-carbon industrial research and implement low- and

zero-carbon industrial process reengineering initiatives. They should focus on researching fundamental elements, procedures, essential materials, and revolutionary low-carbon technologies for decarbonization and carbon reduction. A batch of key core technologies such as efficient energy storage, energy electronics, hydrogen energy, carbon capture, utilization, and storage, as well as the resource utilization of carbon dioxide under mild conditions need to be applied. The progress of carbon reduction technology in one link of a manufacturer can predict the advancement of the entire industry or even on a larger scale.

Limitations and future directions. Although this paper has made some contributions in both theoretical and practical aspects, there are still some limitations. Based on the research results that the digitalization of the service industry does not have a significant impact on the input bias of green technology in the manufacturing industry, this paper does not continue to conduct relevant tests on energy-biased technological progress in the input factors. Further research can be explored.

In addition, this paper has found heterogeneity in the impact of digitalization on green technologies in technology-intensive industry samples, namely, the inhibitory effect of service industry digitalization on these industries. Does this phenomenon come from threshold? Is this caused by the effect before or after crossing the threshold? These are all questions worth considering in future research.

Data availability

The data used in this paper were obtained from the ADB-MRIO and China Statistical Yearbook. The website is available at <https://kidb.adb.org/globalization> and <https://data.cnki.net/>, respectively. Due to the involvement of data licensing in the latter database, if validation is required, data will be made available on request.

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References

- Acemoglu D (2007) Equilibrium bias of technology. *Econometrica* 75(5):1371–1409. <https://doi.org/10.2139/ssrn.861424>
- Autor D, Salomons AF (2018) Is automation labor-displacing? Productivity growth, employment, and the labor share. *Brookings Pap Econ Act* 2018:1–87. <https://doi.org/10.3386/w24871>
- Bian R, Fan Z (2024) Digitalization of services, innovation and manufacturing GVC upstreamness. *Technol Soc* 78(1):102660. <https://doi.org/10.1016/j.techsoc.2024.102660>
- Chatti W, Majeed MT (2022) Information communication technology (ICT), smart urbanization, and environmental quality: evidence from a panel of developing and developed economies. *J Clean Prod* 366:132925. <https://doi.org/10.1016/j.jclepro.2022.132925>
- Chen H (2020) Can the signing of “Free Flow of Cross Border Data” effectively promote digital trade: an empirical study based on OECD service trade data. *Int Econ Trade Explor* 10:4–21. <https://doi.org/10.13687/j.cnki.gjijmts.2020.10.001>
- Chen J, Guo Z, Lei Z (2024) Research on the mechanisms of the digital transformation of manufacturing enterprises for carbon emissions reduction. *J Clean Prod* 449:141817. <https://doi.org/10.1016/j.jclepro.2024.141817>
- Dai X, Yang S (2022) Digital empowerment, sources of digital investment, and green transformation of manufacturing industry. *China Ind Econ* 9:83–101
- Ding L, Yang Y, Zheng H et al. (2020) A study on the heterogeneity and influencing factors of inter provincial green technology progress in China: based on a new Malmquist Luenberger multidimensional decomposition index. *China Popul Resour Environ* 30(09):84–92
- Du C, Feng J, Li Y (2016) Empirical analysis of low-end lock-in and breakthrough paths in China’s high-tech manufacturing industry. *J China Univ Geosci* 4:114–124. <https://doi.org/10.16493/j.cnki.42-1627/c.2016.04.014>
- Eidler L, Harald H (2003) Toxicokinetic modeling for environmental health problems. *Environmetrics* 14(2):193–202. <https://doi.org/10.1002/env.576>

- Evans O, Mesagan EP (2022) ICT-trade and pollution in Africa: Do governance and regulation matter? *J Policy Model* 44:511–531. <https://doi.org/10.1016/j.jpolmod.2022.06.003>
- Färe R, Grifell-Tatjé E, Grosskopf S, Lovell CA (1995) Biased technical change and the Malmquist productivity index. *Scand J Econ* 99:119–127. <https://doi.org/10.1111/1467-9442.00051>
- Federica D, Antonio C, Silvio BM (2019) Servitization and sustainability actions. Evidence from European manufacturing companies. *J. Environ. Manag* 234:367–378. <https://doi.org/10.1016/j.jenvman.2019.01.004>
- Feng C, Ye X, Li J et al. (2024) How does artificial intelligence affect the transformation of China’s green economic growth? An analysis from internal-structure perspective. *J Environ Manag* 834:155306. <https://doi.org/10.1016/j.jenvman.2023.119923>
- Ferencz J, Gonzales F (2019) Barriers to trade in digitally enabled services in the G20. *OECD Trade Policy Papers* 232. <https://doi.org/10.1787/264c4c02-en>
- Ferracane MF, Kren J, Marel E (2020) Do data policy restrictions impact the productivity performance of firms and industries? *Rev Int Econ* 28(3):676–722. <https://doi.org/10.2139/ssrn.3384004>
- Fishbein B, McGarry LS, Dillon PS (2000) *Leasing: a step toward producer responsibility*. INFORM, NY
- Freitag C, Berners-Lee M, Widdicks K et al. (2021) The climate impact of ICT: a review of estimates, trends and regulations. <https://doi.org/10.1016/j.patter.2021.100340>
- Fukuyama H, Weber WL (2009) A directional slacks-based measure of technical inefficiency. *Socio-Econ. Plan. Sci* 43(4):274–287. <https://doi.org/10.1016/j.seps.2008.12.001>
- Ge P, Liu T, Huang X (2023) The effects and drivers of green financial reform in promoting environmentally-biased technological progress. *J Environ Manag* 339:117915. <https://doi.org/10.1016/j.jenvman.2023.117915>
- Ghosh A (1958) Input-output approach in an allocation system. *Economica* 25(97):58–64
- Grossman GM, Krueger AB (1992) Environmental impacts of a North American free trade agreement. *CEPR Discussion Papers* 8(2):223–250. 10.3386/w3914
- Gu N, Bi D, Ren W (2006) Interactive development between services and manufacturing industry: a literature review. *Economist* 6:35–41
- Guo J, Xu Y (2015) Urbanization distortion and service industry lagging: mechanism and empirical research. *Financ Res* 12:118–128. <https://doi.org/10.16538/j.cnki.jfe.2015.12.011>
- Hayakawa K, Laksanapanyakul N, Matsuura T (2020) Do regional trade agreements really help global value chains develop? Evidence from Thailand. *J Jpn Int Econ* 58:101092. <https://doi.org/10.2139/ssrn.1668575>
- He W (2021) Research on digital transformation and the climbing effect of China’s manufacturing global value chain. *Stat Decis Mak* 10:97–101. <https://doi.org/10.13546/j.cnki.tjjc.2021.10.21>
- Hicks JR (1933) The theory of wages. <https://doi.org/10.2307/2224288>
- Higon A, Gholami D et al. (2017) ICT and environmental sustainability: a global perspective. *Telemat Inform* 34(2017):85–95. <https://doi.org/10.1016/j.tele.2017.01.001>
- Huang Y, Zhang Y, Xiang Y et al. (2022) Has servitization reduced the embodied carbon emissions of manufacturing export trade? Evidence from 38 countries. *Environ. Technol. Innov* 28:102950. <https://doi.org/10.1016/j.eti.2022.102950>
- Jing W, Sun B (2019) Digital economy promotes high quality economic development: a theoretical analysis framework. *Economist* 2:66–73. <https://doi.org/10.16158/j.cnki.51-1312/f.2019.02-008>
- Kohtamäki M, Bhandari KR, Rabetino R, Ranta M (2023) Sustainable servitization in product manufacturing companies: the relationship between firm’s sustainability emphasis and profitability and the moderating role of servitization. *Technovation* 129:102907. <https://doi.org/10.1016/j.technovation.2023.102907>
- Leontief W (1936) Quantitative input and output relations in the economic systems of the United States. *Rev Econ Stat* 18(3):105–125
- Li J, Chi J, Wu H (2018) Measurement and analysis of industrial green technological progress bias based on water resources Chinese population. *Resour Environ* 10:131–142
- Li L, Tian C, Xu J (2021) The impact of service-oriented manufacturing on regional green innovation efficiency. *J Cent China Norm Univ* 5:862–875. <https://doi.org/10.19603/j.cnki.1000-1190.2021.05.018>
- Li S, Cheng K (2022) Do large cities have a productivity advantage in China? From the perspective of green total factor productivity growth. *J Clean Prod* 379(6):134801. <https://doi.org/10.1016/j.jclepro.2022.134801>
- Li Y, Sun H, Huang J, Huang Q (2020) Low-end lock-in of Chinese equipment manufacturing industry and the global value chain. *Sustainability* 12(7):1–25. <https://doi.org/10.3390/su12072981>
- Lin B, Teng Y (2023) Digital revolution: Does industrial chain digitalization lead the energy-saving wave? *Sustain Energy Technol Assess* 60:103516. <https://doi.org/10.1016/j.seta.2023.103516>
- Liu K, Tan Q, Yu J et al. (2023) A global perspective on e-waste recycling. *Circ Econ* 2(1):100028. <https://doi.org/10.1016/j.ccc.2023.100028>

- Magazzino C, Porrini D, Fusco G, Schneider N (2021) Investigating the link among ICT, electricity consumption, air pollution, and economic growth in EU countries. *Energy Sources B: Econ, Plan, Policy* 16:976–998. <https://doi.org/10.1080/15567249.2020.1868622>
- Mahmood H, Meraj G, Hassan MS, Furqan M (2024) Bioenergy expansion and economic sustainability from environment-energy-food security nexus: a review. *Int J Sustain Dev Plan* 19(8):2813–2823. <https://doi.org/10.18280/ijstdp.190801>
- Makarov I, Alataş S (2024) Production- and consumption-based emissions in carbon exporters and importers: a large panel data analysis for the EKC hypothesis. *Appl Energy* 363:123063. <https://doi.org/10.1016/j.apenergy.2024.123063>
- Marchi V (2012) Environmental innovation and R&D cooperation: empirical evidence from Spanish manufacturing firms. *Res Policy* 41(3):614–623. <https://doi.org/10.1016/j.respol.2011.10.002>
- Murshed M (2021) Can regional trade integration facilitate renewable energy transition to ensure energy sustainability in South Asia. *Energy Rep* 7:808–821. <https://doi.org/10.1016/j.egyr.2021.01.038>
- Nordäs HK (2016) Services trade restrictiveness index (STRI): the trade effect of regulatory differences. *OECD Trade Policy Papers*. <https://doi.org/10.1787/5JLZ9Z022PLP-EN>
- Qi J, Qiang H (2021) Has the restriction measures on digital service trade affected service exports empirical analysis based on the digital service industry. *World Econ Res* 9:37–52. <https://doi.org/10.13516/j.cnki.wes.2021.09.004>
- Qiu Y, Han W, Zeng D (2023) Impact of biased technological progress on the total factor productivity of China's manufacturing industry: the driver of sustainable economic growth. *J Clean Prod* 409:137269. <https://doi.org/10.1016/j.jclepro.2023.137269>
- Qu Y, Zhao X (2022) Analysis of regional cascade upgrading and evolution path of China's manufacturing industry - based on changes in regional industrial agglomeration level and its impact on total factor productivity. *Ind Econ Rev* 2:37–58. <https://doi.org/10.19313/j.cnki.cn10-1223/f.2022.02-001>
- Ren W, Zeng Q (2021) Is the green technological progress bias of mariculture suitable for its factor endowment?—Empirical results from 10 coastal provinces and cities in China. *Mar Policy* 124:104338. <https://doi.org/10.1016/j.marpol.2020.104338>
- Rosenberg N (1963) Technological change in the machine tool industry, 1840–1910. *J Econ Hist* 23:414–443. <https://doi.org/10.1017/S0022050700109155>
- Su H, Zheng L, Mou Y (2017) Factor endowment and upgrading of China's manufacturing industry: analysis based on WIOD and China industrial enterprise database. *Manag World* 4:70–79. <https://doi.org/10.19744/j.cnki.11-1235/f.2017.04.007>
- Tang Y, Zhu S, Luo Y, Duan W (2022) Input servitization, global value chain, and carbon mitigation: an input-output perspective of global manufacturing industry. *Econ Model* 117:106069. <https://doi.org/10.1016/j.econmod.2022.106069>
- Ullah A, Dogan M et al. (2024) The impact of digitalization, technological and financial innovation on environmental quality in OECD countries: investigation of N-shaped EKC hypothesis *Technol Soc* 77:102484. <https://doi.org/10.1016/j.techsoc.2024.102484>
- Wang D, Yu Z, Liu H et al. (2024) Impact of capital and labour based technological progress on carbon productivity. *J Clean Prod* 467:142827. <https://doi.org/10.1016/j.jclepro.2024.142827>
- Wang H (2022a) The impact of digital economy development level on import and export trade and trade efficiency: based on data analysis of Jiangsu and RCEP agreement countries. *Mod Manag Sci* 3:145–153
- Wang J (2022b) Global value chain embedding status and digital transformation development of Chinese listed enterprises. *Ind Econ Res* 6:101–113+142. <https://doi.org/10.13269/j.cnki.ier.2022.06.006>
- Wang J, Wang W, Wu H et al. (2023) Exploring the effects of manufacturing servitization on enterprise energy conservation and emissions reduction moderated by digital transformation. *Energy Econ* 122:106706
- Wang L, Cheng Z (2024) Impact of the Belt and Road Initiative on enterprise green transformation. *J Clean Prod* 468:143043. <https://doi.org/10.1016/j.jclepro.2024.143043>
- Wang Y, Lin H, Lv C (2014) The technological progress effect of global value chain embedding: an empirical study from industrial panel data in China. *China's Ind Econ* 9:65–77. <https://doi.org/10.19581/j.cnki.ciejournal.2014.09.005>
- Weber WL, Domazlicky BR (1999) Total factor productivity growth in manufacturing: a regional approach using linear programming. *Reg Sci Urban Econ* 29:105–122. [https://doi.org/10.1016/S0166-0462\(98\)00013-1](https://doi.org/10.1016/S0166-0462(98)00013-1)
- Wei L, Yi Z (2021) How does the heterogeneity of digital service regulation affect China's relative division of labor position—empirical research based on DSTRI database. *Chinese Soft Sci* (S1):365–375
- Wei Z, Han B, Han L et al. (2019) Factor substitution, diversified sources on biased technological progress and decomposition of energy intensity in China's high-tech industry. *J Clean Prod* 231:87–97. <https://doi.org/10.1016/j.jclepro.2019.05.223>
- Wen H, Chen W, Zhou F (2023) Does digital service trade boost technological innovation?: International evidence. *Socio-Econ Plan Sci* 88:101647. <https://doi.org/10.1016/j.seps.2023.101647>
- Xi Q, Chen X, Li G (2015) Research on the model selection of service industry in Chinese cities - guided by the improvement of industrial efficiency. *China's Ind Econ* (02):18–30. <https://doi.org/10.19581/j.cnki.ciejournal.2015.02.003>
- Xiao W, Xian G (2020) The development history of RCEP: stake games among various parties and China's strategic choices. *Int Econ Coop* (02):12–25
- Yang B, Wang H, Zhao L et al. (2024) How does carbon biased technological progress promote carbon haze collaborative governance? Evidence from Chinese cities. *Environ Res* 257:119312. <https://doi.org/10.1016/j.envres.2024.119312>
- Yu H, Yao L (2024) The impact of digital trade regulation on the manufacturing position in the GVC. *Econ Model* 135:106712. <https://doi.org/10.1016/j.econmod.2024.106712>
- Yuan Y, Xie R (2015) FDI, environmental regulation, and growth of green total factor productivity in Chinese industry: an empirical study based on the Luenberger index. *Int Trade Issues* (08):84–93. <https://doi.org/10.13510/j.cnki.jit.2015.08.009>
- Zhang C, Khan I, Dagar V et al. (2022) Environmental impact of information and communication technology: unveiling the role of education in developing countries. *Technol Forecast Soc Change* 178:121570. <https://doi.org/10.1016/j.techfore.2022.121570>
- Zhang C, Yang S (2024) The synergy effect of energy security and carbon-haze collaborative management: from the perspective of biased technological progress. *Environ Res* 252:118741. <https://doi.org/10.1016/j.envres.2024.118741>
- Zhang F, Yin X, Zhang H et al. (2024a) Does environmental regulation enhance servitization in aspirant markets? Evidence from China's manufacturing sector. *Technovation* 131:102952. <https://doi.org/10.1016/j.technovation.2024.102952>
- Zhang Q, Yu J (2021) Digitalization of manufacturing investment and high end leap in the global value chain: a re-examination based on differences in input sources. *Financ Res* (09):93–107. <https://doi.org/10.16538/j.cnki.jfe.20210616.203>
- Zhang X, Wu X, Zhou W et al. (2024b) Research on the green innovation effect of digital economy network - empirical evidence from the manufacturing industry in the Yangtze River Delta. *Environ Technol Innov* 34:103595. <https://doi.org/10.1016/j.eti.2024.103595>
- Zhao C, Wang W, Li X (2021) How digital transformation affects total factor productivity of enterprises. *Financ Trade Econ* (07):114–129. <https://doi.org/10.19795/j.cnki.cn11-1166/f.20210705.001>
- Zhou N, Yao T (2021) Empirical study on the impact of restrictive measures on cross-border data flow on the technological complexity of digital trade exports. *J Guangdong Univ Financ Econ* 36(02):4–15
- Zhu N, Wang Y, Yang S et al. (2024) Structure characteristics and formation mechanism of the RCEP manufacturing trade network: an ERGM analysis. *Phys A Stat Mech Appl* 635:129488. <https://doi.org/10.1016/j.physa.2023.129488>

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Author contributions

LW: conceptualization, methodology, formal analysis, investigation, writing—original draft, reviewing and editing, supervision, funding acquisition. XW: conceptualization, methodology, validation, data curation, writing—original draft, supervision. YF: formal analysis, investigation, writing—original draft, visualization. GH: formal analysis, investigation, writing—original draft, visualization.

Competing interests

The authors declare no competing interests.

Ethical approval

This paper does not contain any studies with human participants performed by any of the authors.

Additional information

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