How Does Carbon Emissions Trading System Affect Digital Transformation of Manufacturing Enterprises: Empirical Evidence from China

Abstract: This study develops a double machine learning model to empirically assess the influence of carbon emissions trading system (ETS) on the digital transformation of manufacturing enterprises (MDT) using panel data from Chinese A-share listed manufacturing enterprises. The empirical findings indicate a substantial positive impact of ETS on the MDT, a conclusion that remains robust across various tests. Furthermore, ETS is shown to enhance the MDT by enhancing energy efficiency and promoting green economic efficiency. Moreover, at the macro-regional level, the facilitating impact of ETS on the MDT is particularly pronounced in the pilot cities of Broadband China, cities along the Yangtze River Economic Belt and cities with moderate to low levels of green financial development. At the micro-enterprise level, the facilitating impact of ETS on the MDT is notably stronger in non-state-owned enterprises and in manufacturing enterprises at mature and declining stages. The study findings serve as a solid foundation for the formulation and enhancement of ETS, as well as the establishment and execution of incentives to drive the MDT in developing countries.

Keywords: Manufacturing enterprises, Digital transformation, Double machine learning model, Energy efficiency, Green economic efficiency

1. Introduction

The manufacturing industry serves as the cornerstone of the national real economy, the vital essence of the national economy, and a crucial sector in the development of a modernized industrial system (Liu et al., 2023). Motivated by technological advancements, shifts in energy paradigms, and alterations in market requirements, the manufacturing industry is intensifying its efforts towards intellectualization, digitalization, decarbonization, and servitization (Ching et al., 2022). For instance, Germany initiates early efforts in policy design, standardization, and digital education, completing a comprehensive strategic framework for the transformation and development of its manufacturing industry in the digital economy context (Ohlert et al., 2022). The United States has established a four-tier vertically integrated strategic framework—comprising law, innovation, manufacturing, and advanced manufacturing strategies—achieving a systematic design that spans from national-level strategic planning to the execution of advanced manufacturing initiatives (Brodeur et al., 2023). Japan has shifted its development focus from traditional manufacturing to upstream

areas such as advanced materials, parts, and technology development, as well as downstream areas like distribution and sales, completing the transition from manufacturing to smart manufacturing while adapting flexibly to global market changes (Tsukada et al., 2024). India has implemented the 'Make in India 1.0,' 'Make in India 2.0,' and 'Digital India' initiatives to actively promote the development of digital infrastructure, research and innovation in digital technologies, and enhance the integration of digital technology with manufacturing and other industries (Dubey et al., 2024; Dutta et al., 2020).

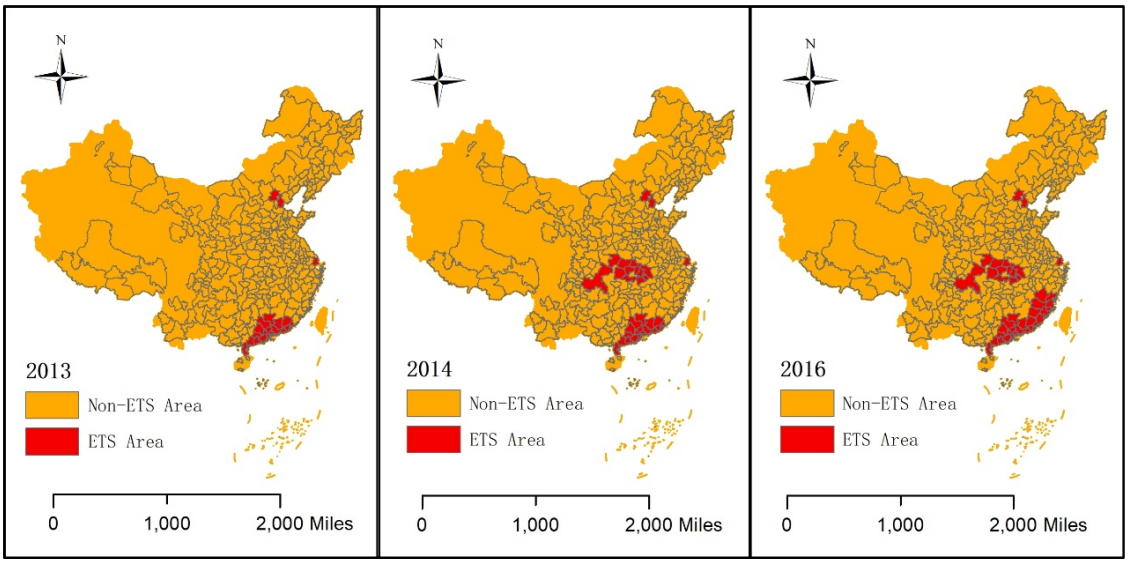
As an important engine of global economic growth, China has occupied the first place in the proportion of global manufacturing value-added for 14 consecutive years, and the proportion of global manufacturing value-added has already reached about 30% in 2023, which is a well-deserved “global manufacturing factory” The "Made in China 2025" initiative explicitly highlights the necessity to expedite the digital transformation of the manufacturing industry, drive the convergence of industrialization and informatization, and prioritize intelligent manufacturing. Digital transformation of manufacturing industry is the process of relying on digital technology, tools and platforms to drive industrial change, product, service and even management model innovation, thus improving business performance and shaping sustainable competitive advantage (Xu et al., 2023). Although the MDT has become the micro-foundation for the development of China's digital economy, the transformation process is still full of challenges. According to China's National Information Center, the digitalization penetration rate of China's manufacturing industry in 2021 is projected to be only 19.5%, significantly lower than the average level of 33% in developed countries. Meanwhile, Accenture's “2022 China Enterprise Digital Transformation Index Research Report” shows that only 25% of enterprises have successfully realized digital transformation, and only 17% of Chinese enterprises' digital inputs have been transformed into operational performance. How can manufacturing companies achieve high-quality digital transformation? This requires us to start the discussion with the drivers and influencers of MDT.

Established research findings have established that the MDT is an inherent consequence resulting from a convergence of internal and external determinants. Regarding internal factors, the adoption of advanced digital management technologies, strategic implementation of digital frameworks (Wang et al., 2023), and the presence of digitally astute leaders and teams collectively propel the progression of digital

metamorphosis within manufacturing organizations (AlNuaimi et al., 2022). In terms of external factors, the institutional environment (Wang and Shao, 2024), the social environment (Svarc et al., 2021) and the business environment (Llopis-Albert et al., 2021) are the main factors affecting the MDT. Additionally, existing studies have primarily employed empirical methods such as the fixed effects model (Sui et al., 2025), Tobit model (Zhang et al., 2023), difference-in-differences model (Zhang et al., 2023), and OLS regression (Xu et al., 2024) to explore the factors influencing the MDT, both within internal and external environments.

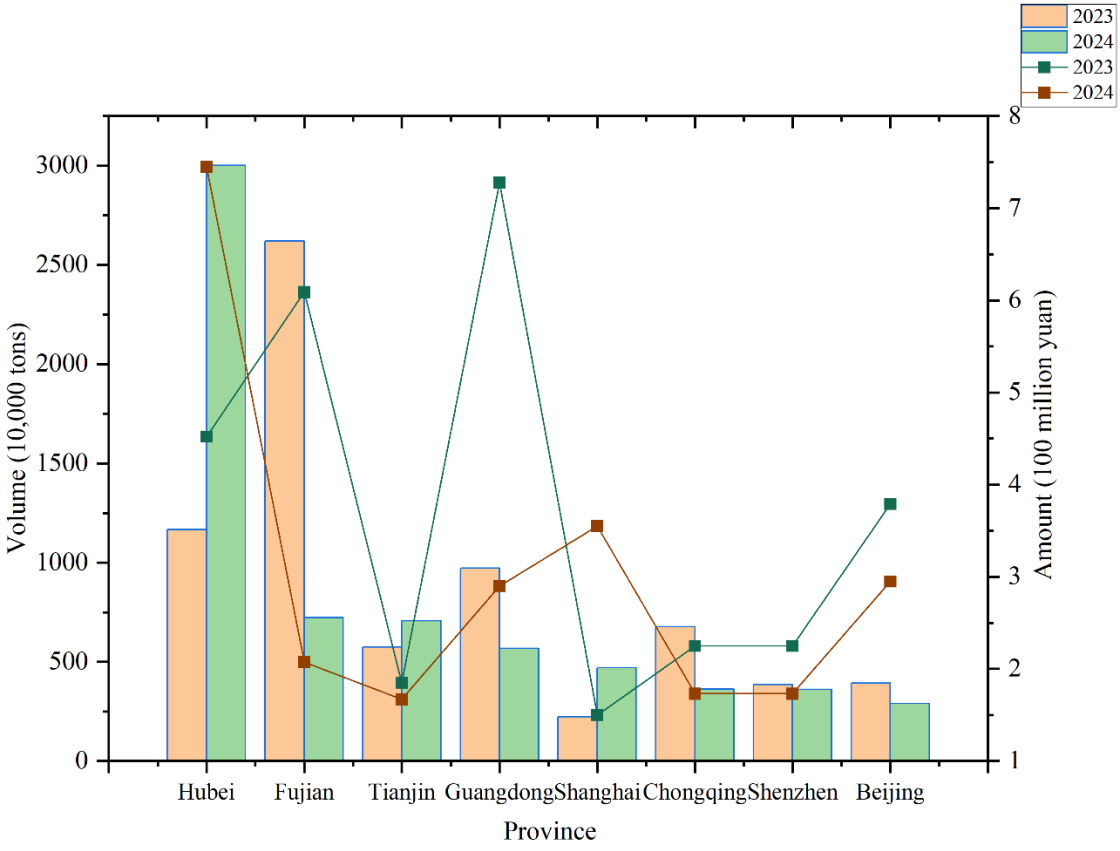
It is evident that while existing research has extensively investigated the drivers and influencers of digital transformation, notably limited studies have delved into the repercussions of external environmental policies, such as environmental regulations, on the MDT. MDT may be influenced by both internal and external factors; however, existing studies predominantly examine these influences from a linear perspective, generally overlooking potential non-linear effects (Alon et al., 2025). At present, the strengthening of ecological and environmental constraints has profoundly affected the development of manufacturing industry and the pattern of development. External environmental policies provide antecedent constraints for the formation of new competitive advantages resulting from digital transformation.

China is the first developing country in the world to control carbon emissions through a cap-and-trade system (Jiang et al., 2016). In recent years, China has promulgated and enforced a diverse array of command-and-control as well as market-driven environmental regulatory measures. Compared with the command-and-control environmental regulation, the ETS, as a major institutional innovation based on carbon pricing and starting with local pilots to realize the market incentives for carbon emission reduction, has been on line since 2013 (see Fig. 1), which can give full play to the role of market mechanism as an incentive to reduce the negative impact on the production behaviors of the manufacturing enterprises, and is more conducive to the promotion of the manufacturing industry to realize the transformation and upgrading of the industry, and at the same time, may also play a certain role in alleviating the financial pressure on the government (Chen et al., 2022). Positive results have been achieved in the ETS (See Fig.2). Therefore, studying how ETS influences the synergistic development of MDT and stable growth is of significant practical importance, taking into account the combined impact of internal and external factors on MDT.



Source: China Development and Reform Commission

Fig. 1. ETS Area



Source: Public disclosure of China's ETS markets

Fig. 2. Status of China's ETS Implementation

Our study provides incremental contributions in the following aspects. Initially, our study centers on elucidating the potential exogenous contribution of the ETS to the MDT. We delve into two conceivable impact mechanisms—energy efficiency and green economy efficiency—to unveil the theoretical nexus between the ETS and the MDT. Secondly, we effectively address the motivation behind the digital transformation of manufacturing enterprises, leveraging market-driven environmental regulations as a key incentive factor. Additionally, we make a theoretical contribution to the harmonious advancement of the digital economy and green economy. Lastly, we employ a novel double machine learning model to investigate the policy implications of the ETS. This innovative approach allows for the inclusion of a broader array of variables compared to conventional linear econometric models, enabling a precise evaluation of the ETS's influence on the MDT.

2. Theoretical analysis and research hypothesis

2.1 The Direct Impact of ETS on the MDT

We utilize institutional theory to examine the impact of ETS on MDT. Institutional theory posits that the institutional environment imposes coercive pressures on organizations, stemming from regulatory demands by government authorities, normative pressures associated with specialization, and mimetic pressures arising from the tendency to imitate those who are perceived as more legitimate or successful in their respective fields (Liu et al., 2024). The institutional foundation of ETS lies in the mandatory obligation for emission reduction compliance. The constraints imposed by carbon emission quotas increase production costs for enterprises and compress their profit margins (Lv and Bai, 2021). Consequently, this compels manufacturing firms to integrate advanced data technologies with manufacturing management, organizational operations, and research and innovation. Such integration aims to reduce search and matching costs, enhance the accuracy of market demand predictions, optimize production and inventory management, and replace low-skilled labor, thereby preventing resource wastage. Ultimately, these efforts contribute to improved efficiency in resource utilization and increased profitability (Wang and Li, 2024). Simultaneously, the ETS mandates that companies regularly disclose third-party-verified carbon emissions data, establishing a norm of 'data visibility.' This requirement compels manufacturing enterprises to implement foundational data collection systems and utilize AI algorithms to optimize production processes, thereby reducing carbon

emissions per unit of output to comply with carbon accounting requirements (Wang and Li, 2024). Furthermore, market orientation theory underscores the importance of firms closely monitoring market demand and competitive dynamics to inform their strategic decisions (Wang et al., 2025). In the face of significant competitive pressure, manufacturing firms will strive to align with the technological frontier of the industry by imitating and learning from the practices of leading firms within the sector (Tian et al., 2023). We therefore propose hypothesis H1:

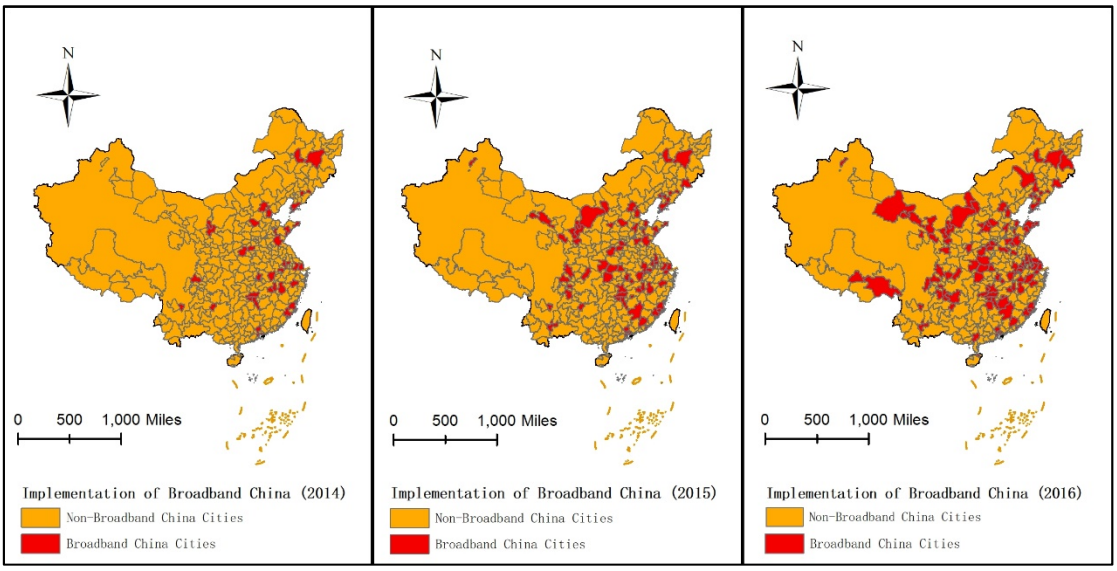
H1: ETS can facilitate MDT.

2.2 The heterogeneity effects of ETS for MDT

2.2.1. Regional dimensions

Zheng et al. (2024) shows that the information infrastructure represented by broadband network is an important engine to drive the manufacturing industry to realize high-quality development. China initiated the implementation of the Broadband China Strategy in 2014, as illustrated in Fig. 3. This strategy delineates broadband networks as pivotal strategic public infrastructure, expediting the establishment of a comprehensive next-generation national information infrastructure that is broadband, converged, secure, and omnipresent. Such infrastructure is envisioned to play an integral supportive role in economic advancement, societal service delivery, and enhancement of people's livelihood. The Broadband China Strategy establishes a fertile ground for the advancement of informatization within the designated implementation regions, enabling manufacturing enterprises to access cutting-edge core technologies and highly efficient machinery with greater ease (Zhang et al., 2022). Consequently, this initiative facilitates the overhaul of informatization practices within manufacturing firms and expedites the MDT process. Furthermore, the implementation of the Broadband China Strategy effectively facilitates manufacturing enterprises in leveraging digital services to access the positive externalities of technological advancement at a reduced cost, thereby effectively mitigating risks associated with the region's green transformation (Hong et al., 2023). This, in turn, enhances the efficacy of ETS in accentuating the impact of the MDT. This leads us to hypothesis H2a.

H2a: The facilitating effect of ETS on MDT is more obvious in regions where the Broadband China strategy has been implemented.

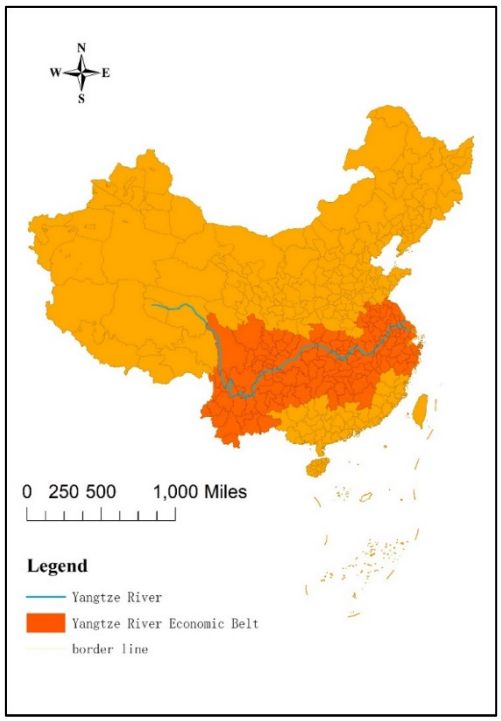


Source: China Development and Reform Commission

Fig.3. Implementation of Broadband China

The Yangtze River Economic Belt is known for its diverse economic, geographic and environmental characteristics, with more than 40% of China's population and economy, and is a key area for the development of China's advanced manufacturing, high-tech and service industries (Wang et al., 2024) (The distribution of China's Yangtze River Economic Belt is shown in Fig. 4). As a prominent regional development strategy in China, the development strategy of the Yangtze River Economic Belt consistently incorporates initiatives aimed at bolstering the core competitiveness of the manufacturing sector, fostering the growth and diversification of advanced manufacturing industries, and expediting the progress of strategic emerging industries and future-oriented sectors (Feng et al., 2024). This also creates a solid base for the MDT. Simultaneously, in contrast to other regions, the Yangtze River Economic Belt boasts prominent scientific research capabilities, a wealth of talent, and developmental advantages. The provinces and municipalities along this corridor exhibit tightly-knit economic relationships, showcasing robust digital technology innovation capacities and significant potential for digital and intellectual integration development (Feng et al., 2024). Consequently, the implementation of ETS can effectively drive the expansion of strategic industries within the Yangtze River Economic Belt, fostering the growth of burgeoning sectors and hastening the digitalization, networking, and intelligent transformation of the manufacturing industry. This leads us to hypothesis H2b.

H2b: The facilitating effect of ETS on the MDT is more obvious in areas along the Yangtze River Economic Belt.



Source: China Development and Reform Commission

Fig.4. Cities along the Yangtze River Economic Belt

The essence of green finance is to realize the effective allocation of financial resources under the constraints of environmental governance, with green credit as the main support method (Yi et al., 2023). In regions characterized by a limited presence of green finance, financial institutions continue to allocate significant volumes of non-green capital, thereby exacerbating issues of "greenwashing" in corporate investment and financing. This phenomenon hampers the attainment of the environmentally sustainable and low-carbon objectives central to the mandate of green finance (Lan et al., 2023). In regions characterized by a robust presence of green finance, the inherent environmental regulatory features of green finance subject manufacturing enterprises to not only the penalties and enforcement measures of government environmental regulations but also the dual pressures arising from financing constraints and increased financing costs associated with green finance. As a result, the intended promotional impact of the ETS on MDT is impeded. Therefore, the “weak Porter hypothesis”, i.e., that appropriate green finance development enables ETS to exert a catalytic effect on the MDT, is only likely to be valid in regions with moderate levels of green finance (Fabrizi et al., 2024). This leads us to hypothesis H2c.

H2c: The facilitating effect of ETS on the MDT is more obvious in regions with a moderate level of green finance development.

2.2.2. Enterprise dimensions

Subsequently, we posit potential heterogeneity among enterprises in the nexus of ETS and MDT. In contrast to managers in non-state-owned enterprises, those directing state-owned manufacturing enterprises exhibit a preference for a risk-averse developmental approach geared towards short-term gains and performance enhancement (Zhang et al., 2023). This makes state-owned manufacturing enterprises relatively insensitive to ETS in carrying out digital transformation. Conversely, non-state-owned enterprises exhibit a pronounced financial imperative and proclivity for innovation, coupled with a heightened requirement to secure a sustainable competitive edge through digital innovation endeavors, rendering them more attuned to the implications of the ETS. This leads us to hypothesis H3a.

H3a: The facilitating effect of ETS on the MDT is more obvious in non-state-owned manufacturing enterprises.

The life cycle theory posits that enterprises in varying stages of development exhibit substantial disparities in their digital technology infrastructure, capital raising capabilities, and readiness to undergo transformative processes (Tamym et al., 2023), which may affect the ETS-MDT relationship. In particular, the inadequate financial backing for manufacturing enterprises in the growth phase of development exacerbates the costs associated with trial-and-error in embarking on digital transformation initiatives, potentially impeding the transformative impact of the ETS on MDT. In mature manufacturing enterprises, ample financial reserves and robust management systems enhance management's propensity to partake in digital innovation endeavors (Fan et al., 2022), with the objective of securing novel market breakthroughs through the proactive pursuit of first-mover advantages stemming from digital transformation initiatives. For enterprises in recession, the implementation of ETS eases their financing constraints, allowing external investors to increase their confidence in their investments, and increasing their willingness and ability to devote resources to digitization projects. This leads us to hypothesis H3b.

H3b: The facilitating effect of ETS on the MDT is more obvious in maturing and declining manufacturing enterprises.

2.3 Mediation analysis of ETS-MDT

Lastly, we conduct a comprehensive examination of the potential mechanisms

through which the ETS influences MDT. The implementation of the ETS provides a commodity attribute for carbon emissions, leading to an optimal allocation of resources and factors. Through the "price-signal" mechanism, the ETS effectively distinguishes the competitive advantage of enterprises employing advanced abatement technologies with low pollution levels, while concurrently highlighting the competitive disadvantage of enterprises exhibiting lower productivity coupled with high pollution and emissions. This process facilitates the transition of the societal production mode from extensive to intensive, fostering overall green technological advancement within society. Consequently, it promotes the enhancement of energy utilization efficiency (Song et al., 2023). The enhancement of energy utilization efficiency typically coincides with a transition process from conventional energy sources to intelligent energy systems and emerging renewable energy technologies. In light of the Chinese government's concerted efforts to introduce incentives such as research and development (R&D) subsidies, tax exemptions, and purchase subsidies to support the advancement of new energy vehicles in recent years, there has been a notable alleviation of financial constraints faced by manufacturing enterprises (Lv et al., 2020). This strategic initiative has spurred these enterprises to leverage contemporary digital technologies to assist the demand side in attaining objectives related to energy conservation, consumption reduction, and the transition towards environmentally sustainable and low-carbon practices. This leads us to hypothesis H4a.

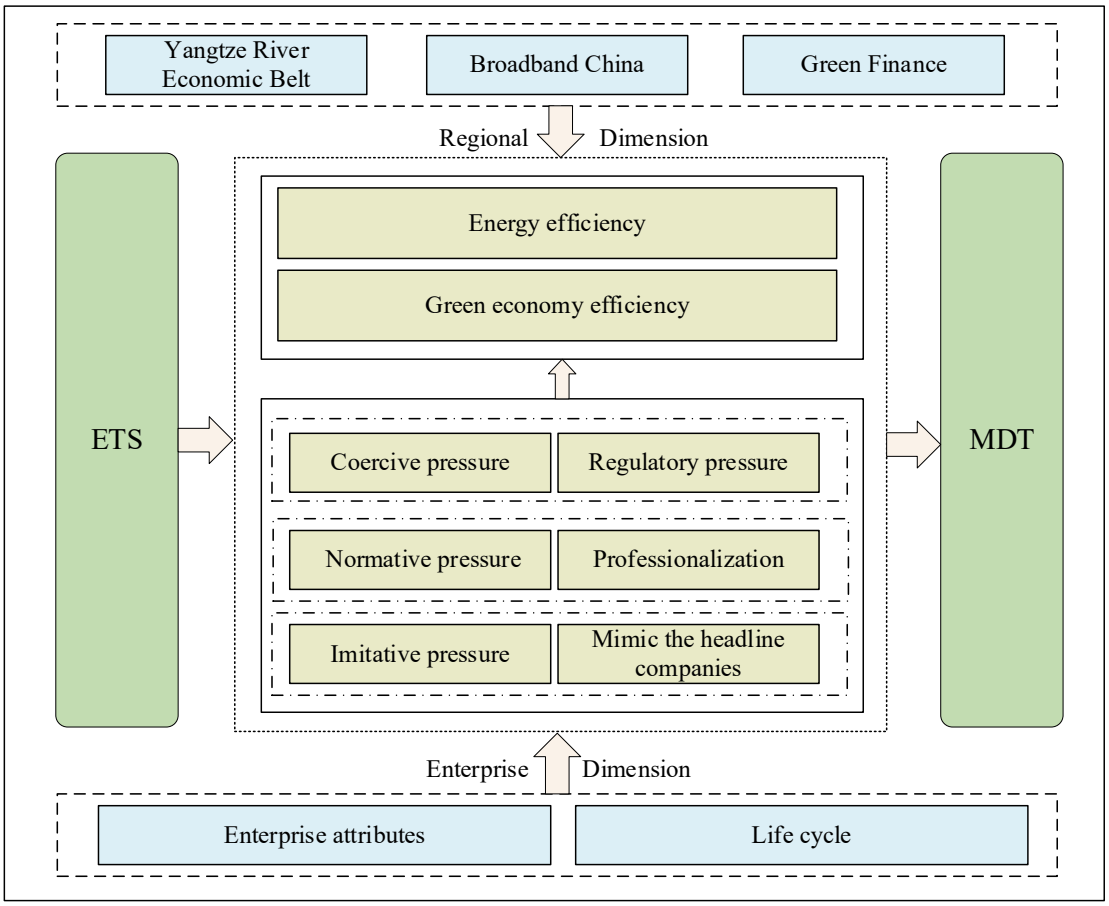
H4a: The implementation of ETS can promote the MDT by enhancing energy efficiency.

Beyond the ETS-Energy Use Efficiency-MDT mechanism, we believe that ETS may facilitate MDT by enhancing green economic efficiency. The ETS represents a governmental environmental policy that operates within a market framework. Through the allocation of carbon emission quotas within the carbon market and the direct imposition of carbon emission reduction targets on enterprises, the ETS positions businesses as central actors in carbon reduction efforts. This approach serves to consolidate corporate responsibility, compelling key industries to effectively manage and control carbon emissions. While reducing carbon at low cost, ETS also promotes the innovation of climate investment and financing tools, providing basic support and financial support for investment and financing of low-carbon, zero-carbon, and carbon-negative technologies (Lv and Bai, 2021), which in turn enhances the efficiency of the green economy. According to firm competition theory, enhanced efficiency within the

green economy not only boosts the potential of the green consumption market but also triggers an "innovation compensation" effect. This effect incentivizes manufacturing firms to adopt advanced digital technologies to amplify productivity gains through green innovation incentives, efficiency enhancements, and resource reallocations (Rubashkina et al., 2015). This leads us to hypothesis H4b.

H4b: The implementation of ETS can promote the MDT by enhancing green economic efficiency.

Fig. 5 shows the framework of the study



Source: author's own production

Fig.5. Research framework

3. Methodology and data

3.1 Variable selection

3.1.1. Dependent variable: MDT.

For publicly listed companies in the manufacturing industry, the information disclosed in their annual reports from preceding years serves as a reliable indicator of the company's business strategy, competitive strengths, industry trends, and signifies the focal areas of corporate attention and resource allocation. Therefore, we adopt the

research method of Wang et al. (2023) and Zhao et al. (2023) and compile a digital transformation feature word data pool based on enterprise experience and national policy reports. First, using Python crawler technology, we employ text analysis methods to segment the Management Discussion and Analysis (MD&A) sections of annual reports from pairs of manufacturing companies. We then perform word frequency statistics and summation on the text. The MD&A section is crucial for reflecting the strategic direction of listed companies and has been widely utilized in the literature as a measure of strategic direction. Second, we use a dictionary related to digital transformation to extract keywords concerning the digital transformation direction from the MD&A sections (see Table S1 for the list of keywords). Finally, we add 1 to the total word frequency of digital-related keywords in the annual reports and take the natural logarithm to quantify the firms' digital transformation. The annual reports used in this analysis are sourced from publicly available reports of listed companies, verified by third-party organizations, ensuring objectivity in the selection of digital-related keywords (Hu et al., 2023; Li et al., 2023). This approach offers advantages such as accessibility and broad coverage.

*3.1.2 Independent variable: treat*post*

China's National Development and Reform Commission (NDRC) has opened ETS in Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing and Fujian since 2013. We designate the geographical area where the carbon emissions trading market is established as the treatment dummy variable, denoted as *treat* and the period when the carbon emissions trading market commences operation as the post-treatment dummy variable, denoted as *post*. Furthermore, we define the interaction term *treat*post*, which takes a value of 1 if the carbon emissions trading market is officially launched in the corresponding region and 0 otherwise.

3.1.3 Control variables

The double machine learning approach we employ effectively addresses scenarios with high-dimensional control variables through the utilization of its regularization algorithm. Hence, in order to enhance the precision of estimating the impact of ETS on manufacturing digital transformation, we refer to the research conducted by Li et al. (2022), Wang et al. (2023), Zhao et al. (2023), Zhong et al. (2023), and the work by Zhuo and Chen (2023). We leverage their insights to delineate the city and firm dimensions, respectively, encompassing factors that may influence the digital transformation within the manufacturing industry, as detailed in Table 1.

Table 1

Descriptive statistics

Variable classification	Variables	Vriable measurement	Obs	Mean	Std. dev.	Min	Max
Enterprise level	Total assets	/	10,920	22.14	1.239	17.04	27.54
	Age of business	/	10,920	22.46	5.033	12	46
	Shareholding checks and balances	/	10,920	2.213	3.047	-2.07	126.9
	Ssset-liability ratio	/	10,920	0.428	0.308	0.7	133.9
	Book-to-market ratio	/	10,920	0.352	0.477	0	1
	Institutional investor shareholding	/	10,920	0.392	0.227	0	1.514
	Proportion of independent directors	/	10,920	0.373	0.055	0.181	0.8
	Tobin's Q	/	10,920	2.297	0.703	0	3.433
	Profit from main Business as a percentage	/	10,920	4.648	124.1	-6092	10194
Urban level	Financial development	Balance of loans from financial institutions at the end of the year	10,920	15500	18700	91203	81000
	Economic development	Real GDP	10,920	69800	69100	13688	30300
	Industrial structure	Ratio of tertiary industry to total industry	10,920	50.36	12.45	10.15	83.87
	Human capital	Expenditure on education	10,920	18449	26545	10067	11400
	Openness level	Number of foreign-invested enterprises above designated size/number of industrial enterprises above designated size	10,920	0.112	0.091	-0.01	0.436
	Technological level	Expenditures on science and technology	10,920	76036	12233	753	55498
	Infrastructure development	Investment in urban environmental infrastructure completed for the yea	10,920	304.6	1230.	-0.18	10471

335 *3.1.4. Mechanism variables*

336 In order to corroborate whether the mechanisms of hypotheses H4a and H4b are
337 valid, we selected the following mechanism variables for mechanism testing.

338 (1) Energy efficiency (*Eff*): in order to test hypothesis H4a, drawing on the research
339 results of Guo and Liu (2022), we used *Eq.1* to measure to get the urban energy
340 utilization efficiency. Where *Energy* denotes the three energy resources used by each
341 city, fuel oil (tons), natural gas (10,000 m^3) and electricity (kWh), which are multiplied
342 by their respective discounted standard coal coefficients (see Table 2), and finally
343 summed to obtain the total amount of energy consumed. *GDP* indicates the real GDP
344 of each city for the calendar year (in billions of dollars).

345 $$Eff = \frac{Energy}{GDP} \tag{1}$$

346 **Table 2**

347 Standard coal coefficients

Energy	Coefficients	Unit
Fuel oil	1.7143	tons of standard coal/ton
Natural gas	13.3	Tons of standard coal per 10,000 m^3
Electricity	1.229	Tons of standard coal per 10,000 kWh

348 (2) Green economic efficiency (*gee*): To examine hypothesis H4b, building upon
349 the work of Ji et al. (2022), we integrate land and energy constraints into our analysis.
350 Employing the non-expected output super-efficiency SBM model, we calculate the
351 green economic efficiency of the city. This metric serves to capture the impact of
352 resource and environmental limitations on the prevailing economic development
353 trajectory. The specific process is described in *Eq. 2* and *Eq. 3*.

354 $$min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{x_i}{x_{ik}}}{\frac{1}{s_1+s_2}\left(\sum_{o=1}^{s_1}\frac{\bar{y}_o}{y_{ok}}+\sum_{u=1}^{s_2}\frac{\bar{z}_u}{z_{uk}}\right)} \tag{2}$$

355 $$s.t.\begin{cases} \bar{x}_i = \bar{x}_{i0} + s^-, i = 1,2,\dots m \\ \bar{y}_o = \bar{y}_{ok} - s, o = 1,2,\dots s_1 \\ \bar{z}_u = \bar{z}_{uk} + s, o = 1,2,\dots s_2 \\ \bar{x} \geq x_0, 0 \leq \bar{y}_o \leq y_k, \bar{z}_u \geq z_k, \bar{z}_u \geq 0 \\ \bar{x} \geq \sum_{j=1,j\neq 0}^{n} x_j * \lambda_j \\ \bar{y}_o \leq \sum_{j=1,j\neq 0}^{n} y_{oj} * \lambda_j \\ \bar{z}_u \geq \sum_{j=1,j\neq 0}^{n} Z_{oj} * \lambda_j \\ 0 \leq \lambda_j \end{cases} \tag{3}$$

Eq.2 is the objective function and *Eq. 3* is the qualification. Where *n* is the number of decision making units (DMUs) and *m* is the number of input variables. s_1 and s_2 represent desired and non-desired outputs, respectively. *x, y & z* are the elements in the input, desired output and undesired output matrices, respectively, and λ is the weight vector. The selection and measurement of input indicators, desired outputs and non-desired outputs are shown in Table 3.

Table 3

Description of input-output indicators

Primary indicator	Secondary indicator	Measurement method
Input indicators	Capital Inputs	Fixed capital stock
	Energy Inputs	Total energy consumption
	Labor Inputs	Employment
desired outputs	Economic Output	Real GDP
Non-desired outputs	Industrial Waste	Industrial sulfur dioxide emissions
		Industrial soot emissions
		Industrial wastewater emissions

3.2 Model specification

In constructing models for assessing the effects of ETS implementation, most of the established studies have used traditional linear models such as difference in differences and propensity score matching methods for empirical testing, which inevitably leads to limitations such as unpredictability of nonlinear relationships and non-isolation of multicollinearity (Lv and Bai, 2021; Zhang et al., 2022). Hence, we draw on the research methodology of Chernozhukov et al. (2018) to construct a double machine learning model to accurately identify the relationship between MDT and ETS. This approach relaxes the linearity assumption governing the relationships among individual variables, thereby accommodating potential nonlinear and interactive associations among them. Furthermore, it facilitates the concurrent inclusion of high-dimensional control variables, enhancing the accuracy of estimating causal relationships. We construct our model as follows:

$$MDT = \beta_0 ETS + g(X) + U, E[U|X, ETS] = 0 \quad (4)$$

$$ETS = h(X) + V, E[V|X] = 0 \quad (5)$$

Eq.4 and *Eq.5* are the double machine learning models we constructed. Where *MDT* is the explanatory variable in this paper and denotes MDT. *ETS* is the core explanatory variable of the paper and denotes ETS. *X* is the set of high-dimensional control variables, and *U* and *V* are perturbation terms. β_0 is the treatment effect we are interested in, and from *Eq.4* and *Eq.5*, the control variable vector *X* affects the *MDT*

and *ETS* through the function *g(X)* and the function *h(X)*, respectively.

Next, we estimate $\hat{g}(X) = E[MDT|X]$ using *Eq.4* to further estimate the treatment effect $\widehat{\beta_0}$, and the treatment process is described in *Eq.6*:

$$ETS - \hat{g}(X) = \beta_0 MDT + U, E[U|X, ETS] = 0 \quad (6)$$

To obtain unbiased estimates of the disposition coefficients, we further remove the effect of *X* on the *MDT* to eliminate the estimation bias of $\hat{g}(X)$. We orthogonalize the *MDT* to obtain the orthogonal regression quantity $\hat{V} = MDT - \hat{h}(X)$. Combining *Eq.6*, we obtain the *Eq.7* for $\widehat{\beta_0}$.

$$\widehat{\beta_0} = (\frac{1}{n}\sum_i \hat{V}_i MDT_i)^{-1} \frac{1}{n}\sum_i \hat{V}_i (ETS_i - \hat{h}(X_i)) \quad (7)$$

Eq.7 can also be approximated as *Eq.8*:

$$\sqrt{n}(\widehat{\beta_0} - \beta_0) = [\mathrm{E}(V^2)]^{-1} \frac{1}{\sqrt{n}}\sum_i V_i U_i + \left[\mathrm{E}(V^2)]^{-1} \frac{1}{\sqrt{n}}\sum_i [\,\hat{g}(X_i) - g(X_i)\right] \left[\hat{h}(X_i) - \mathrm{h}(X_i)\right] \quad (8)$$

$$[E(V^2)]^{-1} \frac{1}{\sqrt{n}}\sum_i V_i U_i \sim N(0, \sum) \quad (9)$$

In the case of satisfying *Eq.9*, $\left[E(V^2)]^{-1} \frac{1}{\sqrt{n}}\sum_i [\,\hat{g}(X_i) - g(X_i)\right] \left[\hat{h}(X_i) - h(X_i)\right]$ has an upper limit of $\sqrt{n}n^{-(\gamma_1+\gamma_2)}$, γ_1 and γ_2 denote the rate of convergence of $\hat{g}(X_i)$ to $g(X_i)$ and $\hat{h}(X_i)$ to $h(X_i)$, respectively, and can converge to zero. With the help of *Eq.8*, we are able to obtain unbiased estimates of the disposition coefficients (i.e., the coefficients of the *ETS* on the *MDT*).

3.3 Data sources

The primary dataset utilized in this study comprises two main components: ETS and MDT. The ETS is derived from public information on the official website of the National Development and Reform Commission of China (https://www.ndrc.gov.cn/), while the data pertaining to the MDT is extracted from the annual reports of the selected enterprises in our sample. Furthermore, the city-level control variables and mechanism variables employed in the empirical analysis are sourced from the China Statistical Yearbook and the China Urban Statistical Yearbook. The firm-level control variables are extracted from the CSMAR database and the Wind database. Restricted by the availability of data and in order to guarantee the authenticity of the data as much as possible, we set the sample range from 2011 to 2020 and exclude the samples of ST, *ST, PT companies and the samples of missing values, and finally get 1092 listed companies with a total of 10,920 initial observations.

4. Results and discussions

4.1 Benchmark regression results

To test hypothesis H1, a double machine learning model is constructed, employing the random forest algorithm for regression prediction. It is worth noting that the sample split ratio was set to 1:4. Following Zhao et al. (2024), the random forest model comprises 1,000 trees—a number determined through preliminary analysis to optimally balance computational efficiency and model accuracy. To mitigate estimation bias caused by potential overfitting in machine learning algorithms, this study employs K-fold cross-validation to enhance the robustness of the estimation, and the regression outcomes are presented in Table 4. It can be found that the coefficients on *ETS* are all significantly positive at least at the 5% level, regardless of whether we control for individual firm fixed effects, year fixed effects, or city fixed effects, which suggests that our empirical results corroborate Hypothesis H1, that is, the implementation of the ETS promotes the MDT.

Table 4

Benchmark regression results

	(1)	(2)	(3)	(4)	(5)
	MDT	MDT	MDT	MDT	MDT
ETS	0.0442***	0.0274***	0.0434***	0.0261***	0.0228**
	(4.02)	(3.18)	(3.79)	(2.90)	(2.16)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual effect	No	Yes	No	Yes	Yes
Year effect	No	No	Yes	Yes	Yes
City effect	No	No	No	No	Yes
_cons	-0.0071***	0.0075***	-0.0076***	0.00810***	0.0073***
	(-4.53)	(9.32)	(-4.80)	(9.90)	(9.02)
N	10920	10920	10920	10920	10920

Note: t statistics in parentheses, ** p < 0.05, *** p < 0.01

Our study shares similarities with the research conducted by Zhao et al. (2023), as both studies confirm the supportive function of environmental regulations in driving MDT. However, it is important to note that Zhao et al. (2023) adopt a stringent constraint perspective centered on command-and-control environmental regulations to assess the influence of low-carbon city pilots on the MDT. Their study underscores environmental regulations as external pressures that prompt manufacturing enterprises to adopt a passive "end-of-the-pipe" strategy in implementing digital transformation initiatives. Chen and Fan (2025), on the other hand, reach similar conclusions primarily using the DID model, tested on Chinese A-share listed firms. This phenomenon is further substantiated by stakeholder theory, which posits that companies engage in digital transformation not solely to maximize revenues but also to fulfill their

environmental responsibilities, particularly in terms of pollution prevention.

In contrast to Zhao et al. (2023), we highlight that ETS possesses both "incentive" and "constraint" attributes, and can serve to offset the environmental costs incurred by regulated enterprises. It is crucial to emphasize that ETS not only imposes constraints but also provides incentives, thereby aiding in the mitigation of environmental expenses for regulated entities. Specifically, the ETS provides incentives for manufacturing enterprises to adopt more advanced digital collection, production, detection and early warning technologies to dynamically control their own energy consumption and pollutant emissions through the effective transmission of the “price-signal” mechanism. Specifically, through the effective transmission of the “price-signal” mechanism, the ETS provides incentives for manufacturing enterprises to dynamically control their own energy consumption and pollutant emissions by adopting more advanced digital collection, production, detection and early warning technologies (Stallkamp and Schotter, 2021), with the aim of reducing the consumption of resources in the industrial chain in order to offset the increase in unproductive inputs and obtain additional income from emission reductions. On the other hand, we differentiate our approach from Chen and Fan's (2025) findings by incorporating a broader set of control variables, both internal and external to the firms, and assessing the impact of ETS on MDT from a nonlinear perspective using a double machine learning model. Our results extend their conclusion, demonstrating that the relationship between ETS and MDT is not only linear but also exhibits nonlinear effects.

4.2 Robustness tests

4,2,1. Reinventing Machine Learning Models

The double machine learning model could introduce bias in the setup, potentially influencing the regression outcomes. To ensure the robustness of our empirical findings, we perform a robustness analysis by adjusting the sample split ratio and substituting the machine learning algorithm. First, we set the sample split ratio to 1:5 and regress it again, and the regression results are shown in column (1) of Table 5. We find that the coefficient of *ETS* is significantly positive at the 1% level, which indicates that the empirical results remain robust after resetting the sample split ratio again. Furthermore, we substitute the random forest algorithm previously employed with the neural network utilizing the gradient boosting algorithm and re-run the regression analysis. The outcomes are presented in columns (2) and (3) of Table 5. Notably, the coefficients associated with *ETS* remain significantly positive at the 1% level even after this

algorithmic transition, reaffirming the robustness of our empirical findings.

4.2.2. Consideration of other policies during the sample period

The degree of external openness is intricately connected to the MDT, whereby regions exhibiting high levels of external openness witness the inflow of high-quality FDI, thereby fostering technological spillovers that drive the digital transformation and enhancement of enterprises (Nambisan et al., 2019). Therefore, we need to exclude pilot free trade zones (test ports) policies that may interfere with the ETS-MDT relationship during the concurrent period. Moreover, beyond the ETS, the low-carbon city pilot policy may also influence MDT during the sample period. To account for this, we re-estimate the baseline regressions by incorporating dummy variables for the pilot free trade zone and low-carbon city pilot policies. The results, presented in columns (4) and (5) of Table 5, show that the coefficient of ETS remains significantly positive at least at the 5% level, confirming the robustness of our findings after controlling for additional policy influences.

4.2.3. Consideration of outliers

The inclusion of numerous control variables in our model may introduce bias into the regression results, particularly in the presence of a significant number of data outliers. To achieve this, we apply a 1% shrinkage to the control variables and conduct a regression analysis based on the treated samples. The outcomes of this test are presented in column (6) of Table 5. It can be found that the coefficient of *ETS* remains significantly positive after removing the effect of outliers. This indicates that our results remain robust.

4.2.4. Placebo tests

To mitigate the potential impact of random factors in the estimation process, placebo tests were conducted by shifting the ETS implementation time to construct counterfactual scenarios. Assuming ETS was implemented one and two years earlier, if the direction and significance of the treatment coefficients remain consistent with the baseline results, it may suggest the influence of other confounding factors. Conversely, differing results would support the conclusion that ETS has a genuine positive effect on MDT. The results of the placebo test are presented in columns (7) and (8) of Table 5, where the ETS coefficients are found to be statistically insignificant, indicating the robustness of our conclusions.

Table 5

Robustness tests

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

	MDT	MDT	MDT	MDT	MDT	MDT	MDT	MDT
ETS	0.0272***	0.6104***	0.0573***	0.0431**	0.0465***	0.0198*	0.0163	0.0116
	(2.76)	(78.40)	(78.40)	(2.38)	(3.64)	(1.95)	(1.52)	(0.65)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.0072***	4.1e+03***	0.0012	0.0081***	-0.0079***	0.0074***	0.0065***	0.0055***
	(8.84)	(22.78)	(0.86)	(8.57)	(-5.00)	(9.05)	(7.84)	(6.39)
N	10920	10920	10920	10920	10920	10920	10920	10920

Note: t statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01

5. Further analysis and discussions

5.1 Heterogeneity analysis

5.1.1. Regional heterogeneity

To examine hypothesis H2a, the sample is segmented into subsamples of non-Broadband China pilot cities and Broadband China pilot cities based on the Broadband China pilot program. Subsequent regression analyses are conducted, and the outcomes are displayed in columns (1) - (2) of Table 6. The sub-sample of non-Broadband China pilot cities includes 354 manufacturing enterprises, while the sub-sample of Broadband China pilot cities includes 738. It can be found that the coefficient of *ETS* is positive but not significant in the non-Broadband China pilot city subsample. In contrast, in the broadband China pilot city subsample, the coefficient of *ETS* is significantly positive at the 10% level. This indicates that the promotion effect of the ETS on the MDT is more significant in the broadband China pilot city subsample, and hypothesis H2a is verified. This phenomenon can be attributed to the primary objective of Broadband China city initiatives, which focus on expediting information infrastructure development and leveraging information consumption to stimulate industrial growth. This approach fosters interregional and interdisciplinary knowledge exchanges, facilitating the integration of information technology throughout the entirety of product production management within manufacturing enterprises (Wang et al., 2022). By establishing extensive connections among individuals, machinery, and processes in production management, this strategy elevates the interconnectedness and intelligence levels of systems and equipment. Therefore, it provides valuable technical support for the facilitating effect of ETS on the MDT.

In the pursuit of testing hypothesis H2b, the sample is bifurcated into two distinct

subsamples based on their affiliation with cities along the Yangtze River Economic Belt. Subsequent regression analyses are conducted, and the findings are illustrated in columns (3)-(4) of Table 6. The subsample of cities along the Yangtze River Economic Belt includes 575 manufacturing enterprises, while the subsample of cities not along the Belt includes 517.It can be found that the coefficient of *ETS* is not significant in the subsample of cities along the non-Yangtze River Economic Belt, while it is significantly positive at the 5% level in the subsample of cities along the Yangtze River Economic Belt. This indicates that the promotion effect of ETS on the MDT is more significant in the subsample of cities along the Yangtze River Economic Belt, and hypothesis H2b is verified. China's emphasis on scientific and technological innovation within the Yangtze River Economic Belt development strategy has facilitated the conversion of the region's scientific research and talent strengths into developmental assets (Sun and Li, 2022). This strategic focus aims to advance ecological environmental protection and integrated economic and social development, laying a robust foundation for MDT initiatives. Simultaneously, the development strategy of the Yangtze River Economic Belt facilitates the effective resource allocation within the region and bolsters the intra-regional market competition mechanism. Leveraging the market selection effect, inefficient manufacturing enterprises in the Yangtze River Economic Belt area are compelled to exit the intra-regional market, thereby enabling efficient manufacturing firms to achieve economies of scale more readily (Yang and Zhou, 2023). This environment is conducive for enhancing the market incentive attribute of ETS to drive the advancement of MDT.

Table 6

Regional heterogeneity regression results

	(1) MDT	(2) MDT	(3) MDT	(4) MDT	(5) MDT	(6) MDT	(67 MDT
ETS	0.0200	0.0284*	0.0285**	0.0551	0.0138	0.0497**	0.0300
	(1.55)	(1.75)	(2.16)	(1.54)	(0.77)	(2.23)	(1.47)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.0026**	0.0079***	0.0053***	0.0052***	0.0054***	0.0093***	0.0166***
	(2.36)	(7.46)	(4.51)	(4.73)	(4.40)	(5.59)	(7.97)
N	3540	7380	5750	5170	3560	3590	3760

Number of enterprises	354	738	575	517	356	360	376

Note: t statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01

To examine the construction of H2c, we draw on the research methodology of Yi et al. (2023) to measure the level of green finance and divide it into three sub-samples of low, medium, and high to re-register, and the results are shown in columns (5)-(7) of Table 6. The three sub-samples of manufacturing enterprises with low, medium, and high green finance levels include 356, 360, and 376 enterprises, respectively. It can be found that the coefficient of *ETS* is significantly positive at the 5% level in the medium green finance subsample, while it is not significant in the remaining two subsamples. This indicates that the promotional effect of ETS on the MDT is more significant in the medium green finance development subsample and hypothesis H2c is verified. Our findings reaffirm the findings of (Saintpaul, 1992). The substantial financial investment required by the MDT to address elevated sunk capital costs and associated business risks during the transition phase poses a challenge. This scenario hampers the ability of ETS to catalyze the development of the MDT, particularly in regions with limited green finance availability. In regions with elevated levels of green finance, stringent environmental regulations and heightened government oversight are common. Consequently, manufacturing firms face pressure to escalate unproductive expenditures, leading to a crowding out effect on productive investments. This dynamic diminishes firms' competitiveness and impedes the progress of MDT.

5.1.2. Enterprise heterogeneity

To test hypothesis H3a, manufacturing enterprises are segmented into sub-samples based on state ownership status. Subsequently, these sub-samples, comprising state-owned and non-state-owned enterprises, are subjected to regression analysis. The outcomes of this analysis are presented in columns (1)-(2) of Table 7. Of these, 408 state-owned manufacturing enterprises and 684 non-state-owned manufacturing enterprises were involved. It can be found that the coefficient of *ETS* is positive but not significant in the sub-sample of state-owned enterprises. Whereas in the non-state-owned enterprises subsample, the coefficient of *ETS* is significantly positive at the 1% level. This suggests that the facilitating effect of ETS on the MDT is more significant in the non-state-owned enterprises subsample, and hypothesis H3a is verified.

There are discrepancies between our results and the findings of some established studies (Du et al., 2023; Javeed et al., 2024). Why did state-owned enterprises, as important participants in energy efficiency and emission reduction efforts, not profit

from the incentive effect of the ETS? This phenomenon can be attributed to the close relationship between state-owned Enterprises and the government, facilitating their access to state subsidies. Nonetheless, a significant portion of these subsidies is directed towards energy-saving facility upgrades, resulting in instances of "subsidy cheating" where energy-saving equipment or process enhancements are implemented without actual utilization. This practice diminishes the efficacy of ETS in promoting emission reductions. Conversely, Chinese state-owned enterprises leverage their institutional advantages to secure substantial market shares, potentially leading to a lack of intrinsic drive and motivation for engaging in long-term, high-risk digital transformations. In contrast, non-state-owned enterprises exhibit greater responsiveness to policy trends and societal needs, displaying a heightened eagerness for the MDT to swiftly establish a competitive edge within the dynamic market landscape.

To examine hypothesis H3b, we adopt the methodology outlined in the study by Lai et al. (2012). Following the life cycle theory, the sample is partitioned into three sub-samples representing growth, maturity, and decline stages. Subsequently, regression analysis is conducted on these sub-samples, with the outcomes detailed in columns (3)-(5) of Table 7. Of these, 275, 295, and 522 manufacturing firms were involved in the growth, maturity, and decline phases, respectively. It can be found that the coefficients of *ETS* are significantly positive at least at the 5% level in the maturity and decline subsamples, except for the growth period subsample, which suggests that the promotional effect of ETS on the MDT is more significant in the maturity and decline subsamples, and hypothesis H3b is verified.

Table 7

Enterprise heterogeneity regression results

	(1)	(2)	(3)	(4)	(5)
	MDT	MDT	MDT	MDT	MDT
ETS	0.0100	0.0537***	0.0131	0.0234**	0.0405**
	(0.60)	(3.69)	(0.60)	(2.19)	(2.40)
Control variables	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes
City effect	Yes	Yes	Yes	Yes	Yes
_cons	0.00477***	0.00828***	0.00279*	0.00353**	0.000761
	(4.45)	(7.32)	(2.21)	(2.84)	(0.57)
N	4080	6840	2750	2950	5220
Number of enterprises	408	684	275	295	522

Note: t statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01

Systems theory suggests that as the life cycle shifts from one stage to another, the system of elements that determine enterprise performance will be reconfigured (Karniouchina et al., 2013). During the growth stage, manufacturing enterprises undergo significant adjustments in their production infrastructure, technology mix, and equipment utilization, with ample room for adaptation. Given the limited internal resources at this juncture and a primary focus on profit generation, the emphasis on digital transformation remains restrained. Consequently, the impact of ETS on the MDT is not distinctly pronounced, aligning with findings from prior research such as that of Hu et al. (2023). In mature manufacturing enterprises, factors such as corporate market reputation, profitability, and market share exhibit greater stability, bolstering their resilience against external disruptions. Consequently, these enterprises can adeptly transition from the external influences of ETS to internal drivers, facilitating a smoother integration of enterprise-wide digital transformation initiatives. In contrast to manufacturing enterprises in the growth and maturity phases, those in the decline phase encounter a myriad of challenges including dwindling market share, escalating competitive pressures, outdated products or services, constrained cash flows, and inflexible organizational frameworks. When presented with external opportunities stemming from ETS adoption, these enterprises tend to navigate the digital transformation journey by fostering transparent environments of shared interests and value alignment with stakeholders. This approach, in turn, enhances the innovation ecosystem's resilience in confronting crises to a certain degree.

5.2 Mechanism tests

We examine the mechanism of ETS-promoted MDT conduction based on lasso regression by drawing on double machine learning causal mediated effects analysis, and the results are shown in Table 8. In Row 1 of Table 8, the outcomes of the energy efficiency mechanism test are displayed. The analysis reveals that the indirect impact of energy efficiency is notably positive, reaching statistical significance at least at the 10% level for both the disposal and control groups. This suggests that the enhancements in energy efficiency resulting from the adoption of ETS play a substantial role in advancing the MDT. As a result, hypothesis H4a is verified.

Our findings reaffirm the robustness of the conclusions drawn by Song et al. (2023) and introduce a novel research perspective to existing literature. While prior studies by Deng et al. (2024) and Wang and Wang (2024) have demonstrated that MDT can

enhance energy efficiency, our research reveals a reciprocal relationship: energy efficiency can also serve as an incentive for the advancement of MDT. Hence, China and other developing nations should consider developing an energy regulatory framework tailored to the interconnected requirements of the carbon trading market and energy policies. This framework should integrate the carbon market with conventional and renewable energy pricing mechanisms, thereby offering robust institutional support for enhancing energy efficiency. By effectively channeling the policy impacts of the ETS towards the MDT, such an approach can optimize the transmission of policy effects while fostering improved energy efficiency.

Table 8

Mechanism test results

	(1) Total effect	(2) Disposal group direct effect	(3) Control group direct effect	(4) Disposal Group Indirect Effect	(5) Control Group Indirect Effect
Energy efficiency	0.040***	0.040***	0.038***	0.002*	0.000*
Green economic efficiency	0.062***	0.058***	0.053***	0.009*	0.005*

Note: t statistics in parentheses, * $p < 0.1$, *** $p < 0.01$

In Row 2 of Table 8, the outcomes of the green economic efficiency mechanism test are displayed. The analysis reveals that the indirect impact of green economic efficiency is notably positive, reaching statistical significance at least at the 10% level for both the disposal and control groups. This suggests that the enhancements in green economic efficiency resulting from the adoption of ETS play a substantial role in advancing the MDT. As a result, hypothesis H4b is verified. Our conclusions are consistent with Wang and He (2022). Green economic efficiency can realize a shift in economic growth from crude to intensive. Hence, China and other developing nations should allocate increased financial resources towards the enforcement of ETS and other environmental regulatory measures. Enhancing infrastructure and policy support within industrial clusters is essential to foster a conducive environment for the advancement of green economic efficiency. By creating a supportive policy ecosystem, these regions can attract foreign investments, talent, data, technology, and other essential resources, thereby leveraging both internal and external synergies to cultivate new drivers for the MDT.

6. Conclusions and limitations

Our main conclusions include: (1) ETS is effective in facilitating the MDT, and this conclusion remains valid after a series of robustness tests. (2) The facilitation effect

of ETS on MDT has significant regional heterogeneity and enterprise heterogeneity. At the macro level, the impact of ETS on the MDT is notably pronounced in the pilot regions of Broadband China, areas along the Yangtze River Economic Belt, and regions demonstrating a moderate level of green finance development. On a micro level, the influence of ETS on the MDT is particularly conspicuous within non-State-Owned Enterprises (non-SOEs) and manufacturing enterprises beyond the growth stage. (3) ETS facilitates the advancement of MDT through two primary mechanisms: enhancing energy efficiency and promoting green economic efficiency.

Our findings demonstrate the positive policy effects of ETS on micro agents. Currently, developed regions such as the United States, European Union, Japan, and South Korea, as well as developing countries like India and Mexico, have implemented or are in the process of implementing ETS frameworks. Evidence from China's experience offers valuable insights for improving ETS systems in these countries. Our findings suggest that in implementing ETS, quota allocation strategies and enterprise entry thresholds should be tailored to the specific economic conditions, regional characteristics, and industry profiles. Additionally, financial instruments such as carbon taxes should be complemented with subsidies or tax incentives to encourage the participation of non-state-owned and small- to medium-sized enterprises, thereby promoting broader engagement in carbon trading and preventing market monopolization. On the other hand, promoting MDT should incorporate both government leadership and market regulation, adopt differentiated strategies, and integrate environmental protection throughout the entire industrial value chain. This approach supports the development of a green digital ecosystem and fosters the synergistic advancement of digital and green transformation.

While our findings offer valuable insights that may guide the transition of the manufacturing industry and foster high-quality economic development in developing nations, it is important to acknowledge the presence of certain limitations. Our analysis, while innovative in its exploration of the drivers of MDT from an exogenous standpoint, was constrained by factors such as data availability, necessitating an examination of the endogenous drivers of MDT. Notably, the investigation of green innovation was regrettably overlooked. Nevertheless, we maintain the belief that our findings can offer valuable insights to developing countries, aiding them in achieving a mutually beneficial scenario of low-carbon development alongside high-quality economic growth.

Declaration of competing interest

The authors declare there is no conflict interest.

Data availability

Data will be made available on request.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

The authors would like to thank funding support from National Natural Science Foundation of China (72374150).

References

[1] AlNuaimi, B.K., Singh, S.K., Ren, S., Budhwar, P., Vorobyev, D., 2022. Mastering digital transformation: The nexus between leadership, agility, and digital strategy. J. Bus. Res. 145, 636–648. https://doi.org/10.1016/j.jbusres.2022.03.038

[2] Alon, I., Bretas, V.P.G., Galetti, J.R.B., Gotz, M., Jankowska, B., 2025. Determinants of human-machine interaction technology usage: An automated machine learning approach. TECHNOVATION 143, 103230. https://doi.org/10.1016/j.technovation.2025.103230

[3] Brodeur, J., Deschamps, I., Pellerin, R., 2023. Organizational changes approaches to facilitate the management of Industry 4.0 transformation in manufacturing SMEs. J. Manuf. Technol. Manag. 34, 1098–1119. https://doi.org/10.1108/JMTM-10-2022-0359

[4] Chen, L., Liu, S., Liu, X., Wang, J., 2022. The Carbon Emissions Trading Scheme and Corporate Environmental Investments: A Quasi-natural Experiment from China. Emerg. Mark. FINANCE TRADE 58, 2670–2681. https://doi.org/10.1080/1540496X.2021.2009338

[5] Chen, S., Fan, Q., 2025. Can market-based environmental regulation promote corporate intelligent transformation: Evidence from the carbon emission trading system. FINANCE Res. Lett. 76, 106950. https://doi.org/10.1016/j.frl.2025.106950

[6] Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., Robins, J., 2018. Double/debiased machine learning for treatment and structural parameters. Econom. J. 21, C1–C68. https://doi.org/10.1111/ectj.12097

[7] Ching, N.T., Ghobakhloo, M., Iranmanesh, M., Maroufkhani, P., Asadi, S., 2022. Industry 4.0 applications for sustainable manufacturing: A systematic literature review and a roadmap to sustainable development. J. Clean. Prod. 334, 130133. https://doi.org/10.1016/j.jclepro.2021.130133

[8] Deng, F., Cai, L., Ma, X., 2024. Does digital transformation restrict the carbon emission intensity of enterprises? Evidence from listed manufacturing enterprises in China. Nat. Resour. FORUM 48, 364–384. https://doi.org/10.1111/1477-8947.12381

[9] Du, H., Zhang, Y., Evans, O.-M., Chen, W., 2023. Will emission trading promote enterprise diversification? Evidence from China. Environ. Sci. Pollut. Res. 30, 79194–79214. https://doi.org/10.1007/s11356-023-28115-6

[10] Dubey, R., Bryde, D.J., Blome, C., Dwivedi, Y.K., Childe, S.J., Foropon, C., 2024. Alliances

and digital transformation are crucial for benefiting from dynamic supply chain capabilities during times of crisis: A multi-method study. Int. J. Prod. Econ. 269, 109166. https://doi.org/10.1016/j.ijpe.2024.109166

[11] Dutta, G., Kumar, R., Sindhwani, R., Singh, R.K., 2020. Digital transformation priorities of India's discrete manufacturing SMEs - a conceptual study in perspective of Industry 4.0. Compet. Rev. 30, 289–314. https://doi.org/10.1108/CR-03-2019-0031

[12] Fabrizi, A., Gentile, M., Guarini, G., Meliciani, V., 2024. The impact of environmental regulation on innovation and international competitiveness. J. Evol. Econ. 34, 169–204. https://doi.org/10.1007/s00191-024-00852-y

[13] Fan, Y., Dai, C., Huang, S., Hu, P., Wang, X., Yan, M., 2022. A life-cycle digital-twin collaboration framework based on the industrial internet identification and resolution. Int. J. Adv. Manuf. Technol. 123, 2883–2911. https://doi.org/10.1007/s00170-022-10269-1

[14] Feng, Y., Sun, M., Pan, Y., Zhang, C., 2024. Fostering inclusive green growth in China: Identifying the impact of the regional integration strategy of Yangtze River Economic Belt. J. Environ. Manage. 358, 120952. https://doi.org/10.1016/j.jenvman.2024.120952

[15] Guo, W., Liu, X., 2022. Market fragmentation of energy resource prices and green total factor energy efficiency in China. Resour. POLICY 76, 102580. https://doi.org/10.1016/j.resourpol.2022.102580

[16] Hong, J., Shi, F., Zheng, Y., 2023. Does network infrastructure construction reduce energy intensity? Based on the ?Broadband China? strategy. Technol. Forecast. Soc. CHANGE 190, 122437. https://doi.org/10.1016/j.techfore.2023.122437

[17] Hu, Y., Che, D., Wu, F., Chang, X., 2023. Corporate maturity mismatch and enterprise digital transformation: Evidence from China. FINANCE Res. Lett. 53, 103677. https://doi.org/10.1016/j.frl.2023.103677

[18] Javeed, S.A., Latief, R., Cai, X., San Ong, T., 2024. Digital finance and corporate green investment: A perspective from institutional investors and environmental regulations. J. Clean. Prod. 446, 141367. https://doi.org/10.1016/j.jclepro.2024.141367

[19] Ji, J., Xie, Z., Li, C., Ji, F., 2022. The influence of the manufacturing agglomeration heterogeneity on the green economic efficiency in China. Electron. Commer. Res. https://doi.org/10.1007/s10660-022-09641-w

[20] Jiang, J., Ye, B., Ma, X., Miao, L., 2016. Controlling GHG emissions from the transportation sector through an ETS: institutional arrangements in Shenzhen, China. Clim. POLICY 16, 353–371. https://doi.org/10.1080/14693062.2014.1003526

[21] Karniouchina, E.V., Carson, S.J., Short, J.C., Ketchen, D.J., 2013. Extending the firm vs. industry debate: Does industry life cycle stage matter? Strateg. Manag. J. 34, 1010–1018. https://doi.org/10.1002/smj.2042

[22] Lai, K., Wong, C.W.Y., Cheng, T.C.E., 2012. Ecological modernisation of Chinese export manufacturing via green logistics management and its regional implications. Technol. Forecast. Soc. CHANGE 79, 766–770. https://doi.org/10.1016/j.techfore.2011.10.004

[23] Lan, J., Wei, Y., Guo, J., Li, Q., Liu, Z., 2023. The effect of green finance on industrial pollution emissions: Evidence from China. Resour. POLICY 80, 103156. https://doi.org/10.1016/j.resourpol.2022.103156

[24] Li, C., Long, G., Li, S., 2023. Research on measurement and disequilibrium of manufacturing digital transformation: Based on the text mining data of A-share listed companies. DATA Sci.

FINANCE Econ. 3, 30–54. https://doi.org/10.3934/DSFE.2023003
[25] Li, R., Rao, J., Wan, L., 2022. The digital economy, enterprise digital transformation, and enterprise innovation. Manag. Decis. Econ. 43, 2875–2886. https://doi.org/10.1002/mde.3569
[26] Liu, G., Liu, J., Gao, P., Yu, J., Pu, Z., 2024. Understanding mechanisms of digital transformation in state-owned enterprises in China: An institutional perspective. Technol. Forecast. Soc. CHANGE 202, 123288. https://doi.org/10.1016/j.techfore.2024.123288
[27] Liu, S., Lu, Y., Shen, X., Bao, J., 2023. A digital thread-driven distributed collaboration mechanism between digital twin manufacturing units. J. Manuf. Syst. 68, 145–159. https://doi.org/10.1016/j.jmsy.2023.02.014
[28] Llopis-Albert, C., Rubio, F., Valero, F., 2021. Impact of digital transformation on the automotive industry. Technol. Forecast. Soc. CHANGE 162, 120343. https://doi.org/10.1016/j.techfore.2020.120343
[29] Lv, M., Bai, M., 2021. Evaluation of China's carbon emission trading policy from corporate innovation. FINANCE Res. Lett. 39, 101565. https://doi.org/10.1016/j.frl.2020.101565
[30] Lv, Y., Chen, W., Cheng, J., 2020. Effects of urbanization on energy efficiency in China: New evidence from short run and long run efficiency models. ENERGY POLICY 147, 111858. https://doi.org/10.1016/j.enpol.2020.111858
[31] Miao, Z., 2022. Industry 4.0: technology spillover impact on digital manufacturing industry. J. Enterp. Inf. Manag. 35, 1251–1266. https://doi.org/10.1108/JEIM-02-2021-0113
[32] Nambisan, S., Wright, M., Feldman, M., 2019. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Res. POLICY 48, 103773. https://doi.org/10.1016/j.respol.2019.03.018
[33] Ohlert, C., Giering, O., Kirchner, S., 2022. Who is leading the digital transformation? Understanding the adoption of digital technologies in Germany. NEW Technol. WORK Employ. 37, 445–468. https://doi.org/10.1111/ntwe.12244
[34] Rubashkina, Y., Galeotti, M., Verdolini, E., 2015. Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. ENERGY POLICY 83, 288–300. https://doi.org/10.1016/j.enpol.2015.02.014
[35] Saintpaul, G., 1992. Technological Choice, Financial-Markets and Economic-Development. Eur. Econ. Rev. 36, 763–781. https://doi.org/10.1016/0014-2921(92)90056-3
[36] Song, M., Zheng, H., Shen, Z., 2023. Whether the carbon emissions trading system improves energy efficiency-Empirical testing based on China?s provincial panel data. ENERGY 275, 127465. https://doi.org/10.1016/j.energy.2023.127465
[37] Stallkamp, M., Schotter, A.P.J., 2021. Platforms without borders? The international strategies of digital platform firms. Glob. STRATEGY J. 11, 58–80. https://doi.org/10.1002/gsj.1336
[38] Sui, X., Hu, H., Wang, R., 2025. The impact of digital transformation on the servitization transformation of manufacturing firms. Res. Int. Bus. FINANCE 73, 102588. https://doi.org/10.1016/j.ribaf.2024.102588
[39] Sun, S., Li, X., 2022. Productive services agglomeration, financial development and regional innovation efficiency in the Yangtze River Economic Zone. FINANCE Res. Lett. 50. https://doi.org/10.1016/j.frl.2022.103221
[40] Tamym, L., Benyoucef, L., Moh, A.N.S., El Ouadghiri, M.D., 2023. Big Data Analytics-based life cycle sustainability assessment for sustainable manufacturing enterprises evaluation. J. BIG DATA 10, 170. https://doi.org/10.1186/s40537-023-00848-8

[41] Tian, M., Chen, Y., Tian, G., Huang, W., Hu, C., 2023. The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. Int. J. Prod. Econ. 262, 108929. https://doi.org/10.1016/j.ijpe.2023.108929

[42] Tsukada, O., Ibusuki, U., Kuchii, S., de Almeida, A.T. de S.B., 2024. Is lean manufacturing maturity a prerequisite for industry 4.0? Survey of SMEs in Japan and Brazil. Int. J. LEAN SIX SIGMA 15, 1102–1126. https://doi.org/10.1108/IJLSS-08-2023-0149

[43] Wang, D., Shao, X., 2024. Research on the impact of digital transformation on the production efficiency of manufacturing enterprises: Institution-based analysis of the threshold effect. Int. Rev. Econ. FINANCE 91, 883–897. https://doi.org/10.1016/j.iref.2024.01.046

[44] Wang, H., Jiao, S., Bu, K., Wang, Yebin, Wang, Yaxian, 2023. Digital transformation and manufacturing companies' ESG responsibility performance. FINANCE Res. Lett. 58, 104370. https://doi.org/10.1016/j.frl.2023.104370

[45] Wang, J., Liu, Y., Wang, W., Wu, H., 2023. How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. J. Clean. Prod. 406, 136954. https://doi.org/10.1016/j.jclepro.2023.136954

[46] Wang, Jie, Wang, Jun, 2024. "Booster" or "Obstacle": Can digital transformation improve energy efficiency? Firm-level evidence from China. Energy 296, 131101. https://doi.org/10.1016/j.energy.2024.131101

[47] Wang, Q., Hu, A., Tian, Z., 2022. Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. ENERGY Econ. 115, 106346. https://doi.org/10.1016/j.eneco.2022.106346

[48] Wang, S., Li, J., 2024. How carbon emission trading mechanism and supply chain digitization affect manufacturing enterprises' competitiveness? Evidence from China. J. Clean. Prod. 452, 142164. https://doi.org/10.1016/j.jclepro.2024.142164

[49] Wang, S., Xu, J., Zhang, W., 2024. Evaluation and analysis of carbon neutralization capacity in the Yangtze River Economic Belt: Based on time weighted-rough set and unascertained model. Ecol. Indic. 160, 111911. https://doi.org/10.1016/j.ecolind.2024.111911

[50] Wang, Y., He, L., 2022. Can China?s carbon emissions trading scheme promote balanced green development? A consideration of efficiency and fairness. J. Clean. Prod. 367, 132916. https://doi.org/10.1016/j.jclepro.2022.132916

[51] Wang, Z., You, J., Li, T., Zhang, Y., 2025. The era of digital trade: Exploring new mechanisms and threshold effects for green upgrading of manufacturing companies. J. Environ. Manage. 373, 123433. https://doi.org/10.1016/j.jenvman.2024.123433

[52] Xu, J., Yu, Y., Zhang, M., Zhang, J.Z., 2023. Impacts of digital transformation on eco-innovation and sustainable performance: Evidence from Chinese manufacturing companies. J. Clean. Prod. 393, 136278. https://doi.org/10.1016/j.jclepro.2023.136278

[53] Xu, L., Zhou, Y., Chen, L., 2024. Digital Transformation and Breakthrough Innovation in Chinese Manufacturing Firms: Based on Ability-Motivation-Opportunity (AMO) Framework of Human Capital. SAGE OPEN 14, 21582440241264348. https://doi.org/10.1177/21582440241264348

[54] Yang, T., Zhou, K., 2023. Green development evaluation of China's Yangtze River Economic Belt based on hierarchical clustering and composite ecosystem index system. Environ. Dev. Sustain. https://doi.org/10.1007/s10668-023-03524-2

[55] Yi, H., Hao, L., Liu, A., Zhang, Z., 2023. Green finance development and resource efficiency:

A financial structure perspective. Resour. POLICY 85, 104068. https://doi.org/10.1016/j.resourpol.2023.104068

[56] Zhang, L., Tao, Y., Nie, C., 2022. Does broadband infrastructure boost firm productivity? Evidence from a quasi-natural experiment in China. FINANCE Res. Lett. 48, 102886. https://doi.org/10.1016/j.frl.2022.102886

[57] Zhang, S., 2023. The impact of digital transformation on ESG performance and the moderation of mixed-ownership reform: The evidence from Chinese state-owned enterprises. Corp. Soc. Responsib. Environ. Manag. https://doi.org/10.1002/csr.2656

[58] Zhang, W., Li, G., Guo, F., 2022. Does carbon emissions trading promote green technology innovation in China? Appl. ENERGY 315, 119012. https://doi.org/10.1016/j.apenergy.2022.119012

[59] Zhang, W., Xu, N., Li, C., Cui, X., Zhang, H., Chen, W., 2023. Impact of digital input on enterprise green productivity: Micro evidence from the Chinese manufacturing industry. J. Clean. Prod. 414, 137272. https://doi.org/10.1016/j.jclepro.2023.137272

[60] Zhao, S., Zhang, L., An, H., Peng, L., Zhou, H., Hu, F., 2023. Has China's low-carbon strategy pushed forward the digital transformation of manufacturing enterprises? Evidence from the low-carbon city pilot policy. Environ. IMPACT Assess. Rev. 102, 107184. https://doi.org/10.1016/j.eiar.2023.107184

[61] Zhao, X., Ke, X., Jiang, S., You, X., 2024. Exploring the dynamics of urban energy efficiency in China: A double machine learning analysis of green finance influence. Environ. Technol. Innov. 35, 103653. https://doi.org/10.1016/j.eti.2024.103653

[62] Zhao, Y., Xu, H., Liu, G., Zhou, Y., Wang, Y., 2023. Can digital transformation improve the quality of enterprise innovation in China? Eur. J. Innov. Manag. https://doi.org/10.1108/EJIM-05-2023-0358

[63] Zheng, Y., Yao, S., Fu, F., 2024. Digital economy, industrial agglomeration and high-quality development. Appl. Econ. Lett. https://doi.org/10.1080/13504851.2023.2301471

[64] Zhong, S., Peng, L., Li, J., Li, G., Ma, C., 2023. Digital finance and the two-dimensional logic of industrial green transformation: Evidence from green transformation of efficiency and structure. J. Clean. Prod. 406, 137078. https://doi.org/10.1016/j.jclepro.2023.137078

[65] Zhuo, C., Chen, J., 2023. Can digital transformation overcome the enterprise innovation dilemma: Effect, mechanism and effective boundary. Technol. Forecast. Soc. CHANGE 190, 122378. https://doi.org/10.1016/j.techfore.2023.122378