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How does the digital economy drive CO_2 reduction in China? Evidence from a novel decomposition model and scenario analysis

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Keywords: *digital economy; CO_2 emissions; GDI model; STIRPAT model; scenario forecasting*

Abstract

Research background: Increasing CO_2 emissions place considerable strain on environmental performance, whereas the digital economy, as a transformative economic paradigm, has been identified as an essential catalyst for mitigating environmental effects. However, the inherent limitations of conventional decomposition models have led previous decomposition analyses to overlook the driving effect of the digital economy on CO_2 emissions.
Purpose of the article: Examining the impacts of the digital economy within the framework of CO_2 emissions disaggregation and subsequently projecting the future pathways of CO_2 emissions. Ultimately, the research aims to offer scientific insights and recommendations for achieving low-carbon development through digital economic support.
Methods: The actual contribution of the digital economy to CO_2 emissions is assessed through a novel Generalized Divisia Index (GDI) model. Further, the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model is extended to project the CO_2 trajectories across distinct scenarios.
Findings & value added: The results unveil that the digital economy plays a weaker driving force in cutting CO_2 emissions. Carbon intensity and energy intensity within the digital economy show substantial potential to deliver CO_2 emission abatement, especially in the provinces of eastern and western regions. The carbon factor is manifested as the main accelerator of increasing CO_2 emissions. Under the low-CO_2 scenario, CO_2 emissions driven by the digital economy will meet the emission goals ahead of schedule, while reductions will suffer constraints in the baseline and high-CO_2 scenarios. The findings provide an empirical basis and scientific reference at the factor decomposition level for the digital economy to support CO_2 reduction.

Introduction

Global warming has been driven by greenhouse gases emissions, primarily CO_2, adversely affecting environmental performance (Doryń & Wawrzyniak, 2024). By 2023, global energy-related CO_2 emissions had risen to a staggering 37.4 billion tons, and the regulation of CO_2 emissions has emerged as a global imperative (IEA, 2024). Given this context, China has introduced the "3060" target to mitigate climate change, optimize energy structures, and promote high-quality economic growth. Striking the balance between economic expansion and emission reduction presents an urgent dilemma for China. As a transformative economic model, the digital economy has profoundly driven the reshaping of industrial structure and technological innovation, providing a new path for green development (Yu, 2025). The digital economy has made advanced significantly in China, even surpassing the secondary industry in its contribution to GDP in 2022 (CAICT, 2023). Consequently, the digital economy has been considered a pivotal engine for driving green development, particularly through its integration into the energy and environmental sectors.

Summarizing relevant research, the digital economy exerts multiple effects on CO_2 emissions evolution (as illustrated in Figure 1). First, the digital economy has facilitated technological upgrading, while the delivery of digitized information has expedited the innovation of green technologies (Zhang *et al.*, 2024; Zhou & Liu, 2024). New low-carbon technologies foster efficiency of energy usage and optimize the energy mix in production and transportation (Luo *et al.*, 2024; Zhou & Wang, 2024). Secondly, digital technology provides efficient information transmission and lower information collection costs, allowing enterprises to obtain new competitive advantages (Yang *et al.*, 2023). Additionally, the investment of digital products promotes industrial upgrading, which alleviates CO_2 emissions. Nevertheless, given the coal-dominated energy endowment of China, digital technologies cannot assist China in transitioning away from its energy-intensive structure in the short term (Bai *et al.*, 2024). Third, a rebound effect may occur in energy consumption, where the reduced cost of energy from digital technologies could lead to higher consumption, partially negating the emissions reductions from digitization (Lange *et al.*, 2020).

Although several researchers have attempted to evaluate how digital economic growth correlates with CO_2 emission changes by applying econometric methods, such methods exhibit significant limitations when dealing with nonlinear relationships, and the results are relatively complex to interpret (Niu *et al.*, 2024). In contrast, decomposition methods, represented by the Logarithmic Mean Divisia Index (LMDI), can study nonlinear relationships and offer greater intuitiveness, visualization, and interpretability in the study of CO_2 emission dynamics (Li *et al.*, 2023a). However, current decomposition analyses fail to quantify the actual contribution of the digital economy. It may be ascribed to traditional LMDI methods that can quantify the impact of a single absolute factor on CO_2 emissions, like GDP or energy (Shui *et al.*, 2024). Furthermore, although combining the STIRPAT model and LMDI has been proven effective in analyzing carbon peak pathways (Zhang *et al.*, 2023), there exists no research that combines the STIRPAT model with the GDI method. This gap hinders the further development of the GDI model.

In response to the identified research gaps, it is proposed to develop a novel GDI model, which is integrated with an enhanced STIRPAT framework to address the following doubts: (i) How might systematic decomposition methods capture the digital transformation's influence on CO_2 emissions? (ii) How can factors associated with the digital economy be effectively incorporated into the decomposition mechanism? (iii) What are the projected CO2 emission trends across various provinces in China, influenced by the digital economy? The contribution of this study is threefold: (i) This study introduces an innovative GDI model of CO_2 emission that can capture the effects of the digital economy, and other relevant indicators simultaneously. The new proposed model addressed the interdependencies present in the traditional LMDI model. (ii) Furthermore, an extended STIRPAT model is integrated with the GDI model to simulate the potential CO_2 evolution trends under the digital economy. The integration of these two methods fills a theoretical research gap and expands the analytical framework for CO_2 emission impact studies. (iii) The proposed models help to determine the elements that influence CO_2 emissions in practice, thereby offering a foundation for decision-making aimed at targeted CO_2 emission reduction within the rapidly evolving digital economy landscape.

Section 2 reviews the findings and methodology of the relevant studies. Section 3 details the modeling procedures for the novel GDI and STIRPAT models, including data sources. Section 4 provides descriptive statistical analyses of the various drivers and empirical results. The findings are evaluated and discussed in Section 5. The final section summarizes the research limitations, future perspectives, and policy implications. The research logic is illustrated in Figure 2.

Literature review

Relation of digital economy and CO_2 emissions

The commercialization of the Internet has driven the rapid emergence of the global digital economy since the 1990s (Rehman & Nunziante, 2023). In the 21st century, disruptive innovations in digital technologies have further accelerated economic digitalization, fostering industrial restructuring and business model innovation (Negi *et al.*, 2024). Given this, the rapid transformation of the digital economy has become a key driver of green socioeconomic development, attracting significant scholarly and institutional attention regarding its implications for energy utilization and CO_2 emissions (Owusu & Acheampong, 2025). For instance, through panel data analyses across various countries, Shahbaz *et al.* (2022) and Sultanova *et al.* (2022) have proven that the digital economy facilitates improvements in renewable energy and power generation structures, thereby contributing to CO_2 emission reductions. Kurniawan *et al.* (2023) highlighted that digitization of the waste recycling sector enables cost savings in urban waste management while enhancing CO_2 mitigation efficiency. Similarly, Wulf *et al.* (2024) found that digitalization has fostered the emergence of circular business models in the furniture industry, promoting resource recycling and CO_2 reduction. Additionally, Jalil *et al.* (2025) emphasized that green digital technologies support the efficiency of energy management and operations in the manufacturing sector, facilitating the effective decarbonization of green hydrogen systems.

The digital economy has affected CO_2 evolution through various digital technological means (Balsalobre-Lorente & Shah, 2024). Based on Ullah *et al.* (2024), the application of digital instruments such as the Internet of Things (IoT) facilitates the energy transition in green economies. This includes implementing smart grid technologies, which enable users to track energy usage in real-time and make it easier to incorporate renewable energy sources into electrical systems. As a result, such advancements lessen dependency on fossil fuels and contribute to accomplishing sustainable development objectives. Does the application of digital technologies inevitably result in lower CO_2 emissions? The answer is negative. For example, from the standpoint of digital finance, Ali *et al.* (2023) and Khan *et al.* (2023) found that digital financial inclusion exhibits a significant positive correlation with CO_2 emissions. In contrast, Zaman *et al.* (2025) suggested that integrating climate change technology with green digital finance could redirect financial resources toward carbon reduction efforts, thereby enhancing the stability of decarbonization initiatives and promoting environmental sustainability. As for AI, Yin *et al.* (2023) pointed out that the development of AI-driven software leads to more efficient utilization of renewable energy, and that government support for renewable energy technologies is critical in this process. Furthermore, carbon prediction and carbon capture are rendered easier by the combination of big data processing and machine learning, which successfully lowers CO_2 emissions linked to human activities (Chauhan *et al.*, 2023). However, due to rebound effects and technical constraints, AI models, particularly in their early stages of application, consume substantial energy for training and inference, which raises CO_2 emissions (Delanoë *et al.*, 2023).

International evidence suggests significant disparities regarding the effects of the digital economy on CO_2 emissions, which provides valuable insights for assessing its impact under China's digital transformation context. Accelerated penetration of digitalization has enhanced economic efficiency and industrial structure (Zha *et al.*, 2022; Tan *et al.*, 2024). Nevertheless, due to the vast geographical area and fossil fuel-based energy structure, there exists a substantial heterogeneity in the performance of digitization in China. The transition and upgrading of digital production inevitably resulted in higher non-clean energy utilization and CO_2 emissions (Zhong *et al.*, 2022; Dong *et al.*, 2022). Moreover, the "rebound effect" of digital technologies can result in a simultaneous increase in energy efficiency and energy use (Wang *et al.*, 2022; Zhu & Lan, 2023). The pathways through which the digital economy drives CO_2 evolution are multifaceted, shaped by variations in economic development, digital technology applications, and resource endowments (Li & Wang, 2022). This complexity suggests that prior research relying on single-model approaches linking digital economic development and CO_2 emissions requires refinement. Additionally, research exploring the intricate connections between these two aspects at the indicator level requires supplementation. Conventional econometric methods employed in previous studies have struggled to accurately identify the primary factors of CO_2 emissions changes and quantify the contribution of factors associated with the digital economy to CO_2 changes. The factor decomposition approach offers a more sophisticated analytical framework by integrating pertinent variables into the decomposition mechanism of CO_2 changes, resolving these methodological constraints and offering a quantitative evaluation of each variable's contribution.

Decomposition and predicting the effects of the digital economy

Factor decomposition analysis has been extensively utilized to assess the specific contribution of correlated elements to target variables. Particularly in the study of CO_2 emission changes, Index Decomposition Analysis (IDA) is favored by scholars for its practicality for model construction and data processing (Jia *et al.*, 2023). Among them, LMDI avoids residuals and is easy to calculate, which has become a commonly used model for decomposing target variables such as CO_2 changes (Chen *et al.*, 2023). For example, Ni *et al.* (2024) revealed the remarkable correlation between China's CO_2 changes and the flourishing digital economy by applying the Kaya-

LMDI model. However, the LMDI method is limited by its reliance on the Kaya equation, which makes the decomposition results affected by factor selection and decomposition form, thereby reducing the scientific value of the findings (Wang & Balezentis, 2023). In contrast, the GDI model proposed by Vaninsky (2014) identifies intricate connections among relative and absolute factors, providing a more accurate technique for assessing CO_2 emissions changes. What's more, more influential factors are encompassed in the GDI model, which covers more absolute and relative factors and possesses higher practical application value (Sui *et al.*, 2024). Consequently, the GDI model is employed to evaluate the specific contribution of the relevant factors to CO_2 emissions.

Furthermore, the accurate prediction of CO_2 emission is essential (Chang *et al.*, 2023; Lu *et al.*, 2024). It assists the relevant sectors in identifying effective pathways for emission reductions and minimizes trial and error costs. Relevant studies combine decomposition analysis with forecasting methods, and such a composite of studies is conducive to revealing the impacts of the factors on the target variables (Li *et al.*, 2023b; Wang *et al.*, 2024). Given the influence of digital economy trends and associated policies, there arises a necessity to delineate the future evolution pathways of CO_2 emissions. The IPAT equation decomposes environmental pressure by examining factors such as population size, wealth, and technological advancement, which have been extensively applied in environmental research (Gan *et al.*, 2023). With the deepening of research, Dietz and Rosa (1994) introduced differential elasticity and error terms into the IPAT equation, establishing the STIRPAT model. This model possesses the advantage of expanding the measurement equations depending on the field of research, providing greater flexibility and application value (Wang & Zhu, 2023; Wei *et al.*, 2023). Moreover, the scenario analysis methods are applied in studies associated with CO_2 emission projections, which allow for a comprehensive assessment of possible states under different predetermined conditions. Therefore, the STIRPAT model has been extended from the digital economy perspective and combined with scenario analysis methods. It provides a scientific reference for analyzing the dynamics of CO_2 emissions driven by the digital economy.

Methods and data

A novel GDI model

The GDI decomposition method captures non-linear associations among factors, thereby compensating for the interdependence of variables in other decomposition models (Yan *et al.*, 2019a). This model offers a more precise and comprehensive approach to analyzing the actual contribution of factors associated with the digital economy to CO_2 emission changes. By synthesizing the dynamics of the digital economy, CO_2 evolving characteristics, and the theoretical structure of the GDI model, this study establishes a novel GDI model that connects the digital economy with energy and CO_2 emission within an indicator framework. Given the crucial effect of digitization on green development, the added value of the digital economy (*DV*) was calculated as one of the absolute factors. Energy systems produce the largest share of CO_2 emissions in the world, thereby energy consumption (*E*) is selected as another key absolute factor of CO_2 changes (Yan *et al.*, 2019b). Within the index decomposition framework, relative driving factors are constructed based on the target variables and the selected absolute factors. Specifically, CO_2 emissions per unit of absolute factor represents the carbon intensity of the factor, and energy consumption per unit of absolute factor denotes the energy intensity of the factor (Sui *et al.*, 2024). Combined with the analysis of Wang *et al.* (2021) for digital communication technologies affecting CO_2, the carbon intensity of digital economy (*DCI*), the energy intensity of digital economy (*DEI*), and the carbon intensity of energy consumption (carbon factor, *ECI*) are constructed as the relative factors for CO_2 emission evolutions. Table 1 shows the interpretation of each factor.

Referring to the five-factor GDI modeling framework designed by Wang *et al.* (2023), this study incorporates the above-selected and constructed factors into the decomposition mechanism. The five-factor GDI model contains two absolute factors (X_1, X_3) and three relative factors (X_2, X_4, X_5). The target variable Z is expressed as a function of X_i (where i=1, 2, 3, 4, 5), as shown in equation (1) and (2).

$$Z = X_1 \cdot X_2 = X_3 \cdot X_4 \tag{1}$$

$$\begin{cases} X_2 = Z/X_1 \\ X_4 = Z/X_3 \\ X_5 = X_1/X_3 \end{cases} \tag{2}$$

Combining the above equations gives

$$\begin{cases}\varphi_1 = X_1 \cdot X_2 - X_3 \cdot X_4 \\ \varphi_2 = X_1 - X_3 \cdot X_5\end{cases}. \tag{3}$$

Then, the Jacobian matrix shown as equation (4) is obtained from the first-order partial derivatives of $\varphi = [\varphi_1, \varphi_2]$.

$$\phi_X = \begin{bmatrix} X_2 & X_1 & -X_4 & -X_3 & 0 \\ 1 & 0 & -X_5 & 0 & -X_3 \end{bmatrix}^T \tag{4}$$

Based on the GDI model, the variations of the target variable *C* are disaggregated into the summation of the contributions of the driving factors (ΔC_E, ΔC_{DV}, ΔC_{ECI}, ΔC_{DCI}, ΔC_{DEI}), as displayed in equation (5)–(6).

$$\Delta C[X|\phi] = \int \nabla C^T (I - \phi_X \phi_X^+) dX \tag{5}$$

$$\Delta C = \Delta C_E + \Delta C_{ECI} + \Delta C_{DV} + \Delta C_{DCI} + \Delta C_{DEI} \tag{6}$$

where $\phi_X^+ = (\phi_X^T \phi_X)^{-1} \phi_X^T$ and $\nabla C = (X_2, X_1, 0,0,0)^T$. The operation of the GDI model is accomplished through the R programming language.

An extended STIRPAT model

The STIRPAT model is capable of extending the model according to specific studies and has manifested as a randomized version of the IPAT equation (Zhou *et al.*, 2023a). Accordingly, based on the STIRPAT framework, this study introduces the potential CO_2 reduction factors of the digital economy derived from the decomposition results into the CO_2 emission prediction mechanism. Further, possible trends in the digital economy driving CO_2 emissions will be explored and analyzed. The standard form of the STIRPAT model exhibits the basic predictors that drive changes in environmental stress (*I*), including population (*P*), affluence (*A*), and technology (*T*). The expression can be represented as

$$I_t = \alpha_0 P_t^{\alpha_1} A_t^{\alpha_2} T_t^{\alpha_3} e \quad . \tag{7}$$

where α_0 represents the constant term. α_1, α_2, α_3 are exponential terms. *e* is the error term. For equation (7), take the logarithm on both sides:

$$ln\, I_t = ln\, \alpha_0 + \alpha_1\, ln\, P_t + \alpha_2\, ln\, A_t + \alpha_3\, ln\, T_t + \varepsilon_t. \quad (8)$$

Expanding on the STIRPAT model expressed in equation (8). Given the powerful abatement potential presented by DCI and DV in the decomposition mechanism of CO_2 change, these two factors are selected to replace the technology variable. In addition, considering that the strike of digital technologies on the industrial structure affects CO_2 emissions dramatically, the ratio of tertiary industry to GDP (IS) is selected as one of the predictors (Zhou *et al.*, 2023b). Accordingly, the extended STIRPAT model aiming at explaining the CO_2 emission volume as follows.

$$lnC_t = ln\alpha_0 + \alpha_1 lnP_t + \alpha_2 lnIS_t + \alpha_3 lnDV_t + \alpha_4 lnDCI_t + ln\varepsilon_t \quad (9)$$

Forecasting the possible paths of CO_2 emissions under diverse scenarios facilitate probing efficient digitalized energy-saving and carbon-reducing pathways. According to the economic and policy interventions, a combination of the extended STIRPAT model and the scenario forecasting method is adopted as a strategy in this paper. The setting scenarios include baseline (BCS), high-CO_2 (HCS), and low-CO_2 scenarios (LCS). Specifically, the BCS depicts a scenario that is consistent with the current trends in socio-economic growth and technological development. This scenario is realized by following current green development policies and measures. As one of the comparison scenarios, the HCS assumes that economic development will be constrained by reverse globalization. Both the digital economy and the abatement process in the HCS fall behind the other two scenarios, with lagging characteristics in both the upfront energy consumption and the later emission reduction. The LCS is another contrasting scenario in which people consciously address climate change and stimulate low-carbon technological innovation through digital channels. Based on this, energy utilization efficiency and industrial structure were upgraded promoted, and the process of saving energy and reducing CO_2 emissions has been accelerated.

Data sources

Given data availability and accuracy, this study takes a sample of 30 provinces in China. Since the input-output tables have provided a more detailed categorization of the industries associated with information technology since 2002, this paper sets 2002 as the starting year of the study. The data for measuring *DV* were sourced from provincial input-output tables, supplemented by the Economic Census Yearbook and Statistical Yearbook of China. Converting E to fuel consumption by standard coal coefficient, the data is available from the China Energy Statistical Yearbook. Referring to the CO_2 emission calculation methodology supplied by the Intergovernmental Panel on Climate Change (IPCC), *C* can be calculated via equation (10).

$$C_i^t = E_i^t \times V_i \times F_i \times O_i \times M \tag{10}$$

where E_i^t symbolizes the consumed volume from fuel *i* during year *t*, and V_i denotes the calorific index of the *i* fuel, and the data were collected from the China Energy Statistical Yearbook. F_i denotes the carbon content per calorific value and O_i indicates the CO_2 oxidation rate, and the relevant data originate from the IPCC. *M* denotes the conversion of carbon mass to CO_2 mass, typically with a value of 44/12.

The parameter settings in the prediction model (Eq. 9) are presented in Table 2. The projected average annual growth rates (AAGRs) of *P* are set according to Yu *et al.* (2023). The proportion of the tertiary sector will be affected by shifts in demographic trends and the expansion of digital technology (Liu & Li, 2024). It is expected that the growth rates of the primary and secondary sectors will decrease, while the tertiary sector is likely to experience growth (Huang *et al.*, 2023). In addition, advanced digital technologies will provide a robust impetus for the transition to a green economy. Consequently, the driving effect of increasing *DV* and decreasing *DCI* on CO_2 abatement will gradually strengthen. In conjunction with the *"14th Five-Year Plan" for the Development of the Digital Economy* and the *Digital China Development Report*, the projected AAGRs for *DV* and *DCI* have been determined.

Results

Dynamics of driving factors

Figure 3 shows the dynamic growth of the digital industry and its regional differences. From 2002 to 2020, the development of the digital economy exhibited an upward trend in all regions of China. Especially the eastern region, where *DV* has surged from 454.07 billion yuan to 304.92 billion yuan during 2002–2020. It is largely owed to the more advanced economic development and digital capacity of the eastern region. Although the mid-western region do not dominate the digital industry, their spatial structure share has increased from 2002 to 2020. In particular, the AAGR of *DV* in the western region reaches 15%, exceeding that of the eastern (11%) and northeastern (10%) regions. By contrast, both the eastern and northeastern regions saw a decrease in their share of spatial structure, from 74% and 10% in 2002 to 65% and 4% in 2020, respectively. This shift might benefit from the synergistic development strategy of arithmetic resources in China. In recent years, the data center has received synergistic development with the network, energy, arithmetic, data, and other elements.

From a provincial level, Guangdong and Jiangsu exhibit stronger strengths in digital industry development, while Ningxia, Xinjiang, and Gansu are relatively weaker. Provinces with higher digital economy development growth rates than their regional AAGR include Jiangsu, Jiangxi, Shanxi, Anhui, Chongqing, Guizhou, and Jilin. Provinces with digital economy development growth rates higher than their regional AAGR include Jiangsu, Jiangxi, Shanxi, Anhui, Chongqing, Guizhou, and Jilin. In contrast, Zhejiang, Hunan, Gansu, Xinjiang, and Heilongjiang show a lower digital economy development momentum than their regional AAGRs. The dynamic evolution of the digital economy exhibits distinct regional disparities. Accordingly, the relevant sectors should emphasize guiding the scale and intensive development of data centers, as well as promoting the efficient complementarity and synergy of regional arithmetic power.

Figure 4(a) illustrates the trends in absolute factors (*E* and *DV*). It can be observed that the growth trends of *E* and *DV* performed consistently during 2002-2010. Nevertheless, *DV* has demonstrated a powerful growth momentum since 2010, with an AAGR of 11.97% from 2002 to 2020. The innovation and application of digital technologies has yielded notable achievements, and various industries are moving forward with robust momentum in their digital transformation. Despite the obvious moderation in the growth rate of *E* from 2011, its AAGR remains at a high level (6.78%). Obviously, the energy efficiency of China has been upgraded, but the energy structure transformation requires further strengthening.

Figure 4(b) demonstrates the trends of the relative factors (*ECI*, *DCI*, *DEI*). Specifically, the general trend of *ECI* performs relatively stable. It suggests that the structural transformation of energy usage performs inadequately and that the most prominent source of CO_2 emissions stays with the energy system. Both *DCI* and *DEI* exhibited marked decreases with similar magnitudes (AAGRs of -4.67% and -4.64% respectively). It implies that digital technologies can boost energy efficiency, although improving the energy mix brings high CO_2 emissions. On this basis, to accomplish an efficient digital energy-saving and carbon-reducing process, digital low-carbon technological innovation should be promoted positively. Enhancing the utilization efficiency of renewable energy in light of the existing energy endowment is an essential issue for enterprises and relevant departments.

Decomposition results

National decomposition results

According to the GDI model constructed above, CO_2 changes are decomposed over successive years. This decomposition logic reveals the variation in the driving capacity of each factor (see Figure 5). The growth rate of *C* declined dramatically in 2011. This may be due to the fact that China accelerated its industrial and energy restructuring, which resulted in the consumption of fossil energy and energy-related CO_2 emissions. Specifically, *ECI* and *E* exhibit high promoting effects, with annual average contributions of 4.56% and 0.85%, respectively, over the 2011-2020 period.

Relative factors relevant to the digital economy exhibit greater potential for mitigating CO_2 emissions. The average annual contribution of *DCI* is -3.58%, suggesting that digital transformation serves an important role in minimizing CO_2 emissions. Nevertheless, the carbon reduction power that *DEI* has exhibited in successive years was unremarkable, with an average annual contribution of only -0.22% after 2011. It can be concluded that the core technologies for digital energy saving need to be further explored, which requires endeavors to promote the energy efficiency of the digital industry. Moreover, the average annual contribution of *DV* to mitigate CO_2 emissions (-1.21%) exceeds that of *DEI* during 2011–2020, despite the driving effect of *DV* showing positive in certain years. There exists a compelling need to enhance resource utilization through ICT measures to assist enterprises in improving quality, increasing efficiency, and reducing consumption and emissions.

According to the above decomposition analysis for consecutive years, it is revealed that the factors exhibited varying contributions in different time intervals. Figure 6(a) presents the stage decomposition results at the national level. Both *DCI* and *DEI* exhibit the ability to reduce CO_2 emissions at all stages. Particularly in the 2010-2015 period, these two factors account for the primary share of decreasing CO_2 emissions. The subsequent phase (2015-2020) shows a weakened contribution to reducing emissions, which is mainly attributed to the decreasing rate of CO_2 emissions. Moreover, the CO2 emissions increased by *E* and *ECI* exhibit a phased weakening trend, which proves that digitalization displays excellent energy-saving and carbon-reducing effects. Therefore, the convergence of digital industries has promoted the efficiency and structure of energy.

The stage decomposition results for the four regions can be compared and analyzed from Figs. 6(b)-(e). The direct driving effect on CO_2 change exhibited by *DV* is insignificant in all four regions. Obviously, the digital economy provides indirect abatement of CO_2 emissions primarily through channels such as digital technology. Although the abatement capacity of *DCI* and *DEI* in the mid-west lagged behind that of other regions during 2002-2005, they overtook in the following three five-year cycles. The revolution in digital technology has facilitated energy efficiency in energy-rich regions, largely avoiding additional CO_2 emissions. The energy structure effect demonstrates better optimization in the eastern region, as evidenced by the significant downward trend in CO_2 contributed by *ECI*.

Provincial decomposition results

Given that resource endowment and digital economy development exhibit significant regional variability, the contributing effects of factors across the 30 provinces are quantified in this section. According to the analysis in the above section, the growing rate of CO_2 emissions changed dramatically in the year 2011, therefore, the CO_2 emission changes are decomposed for the stages of 2002–2010 and 2010–2020 respectively. As shown in Figure 7(a), CO_2 maintains a high growth rate during 2022-2010. The effect of *E* and *ECI* in raising CO_2 emissions is evident, especially in Shanxi, Inner Mongolia, and Guizhou, which possess better energy endowments. Even though *DV* and *DEI* exhibited the ability to reduce CO_2 in most provinces, the abatement power is feeble. In contrast, *DCI* exerts a pivotal force towards mitigating CO_2 emissions in most provinces, especially in Jiangxi (-43.03%) and Chongqing (-48.17%). Social production during the period 2002–2010 was dominated by the large consumption of fossil fuels, and technologies for clean energy utilization were not well developed. It is evident that this emerging economic situation has not been exploited efficiently in the past constrained by digital technology and digital dividends.

With the popularization and deployment of ICT and other digital technologies, the social benefits of the digital economy have been manifested. As illustrated in Figure 7(b), the influence of *E* and *ECI* in stimulating CO_2 has decreased over 2010–2020. The ability to reduce CO_2 in *DV* has enhanced, especially in Beijing (-11.27%). Furthermore, the mitigating effect of *DEI* on CO_2 emissions was manifested, with Beijing (-13.67%) and Chongqing (-14.29%) being the most prominent. Meanwhile, *DCI* exerts the most prominent carbon reduction effect in all provinces except Xinjiang. It can be noted that the energy-saving and CO_2-reducing effect promoted by the digital economy is evident in more provinces, and this effect is spreading across the entire country. This may be attributed to the full consideration of factors such as regional development, environmental governance and protection by the relevant departments, as well as their focus on strengthening regional collaboration and deepening the application of data resources in various industries.

Forecasting results

National forecasting results

According to the current state of China's economic and digital technology, different prediction scenarios are designed to portray the possible evolution path of CO_2 emissions. Figure 8 presents the forecast results of national CO_2 emissions under each scenario. The black line (under BCS) indicates the trend of potential CO_2 change without additional economic interventions and energy-saving low-carbon policies. The factors will follow past population structure and economic development inertia to drive CO_2 changes. Under this scenario, CO_2 emissions will probably keep growing until 2030, and the emissions are expected to reach 13.07 Gt by 2030.The potential AAGR of CO_2 under this scenario reaches -7.15% between 2021 and 2060. Further, the other two scenarios (LCS and HCS) are developed by increasing or decreasing the intensity of digital economy development based on BCS.

Under LCS, more information platforms and digital industries are exploding, while economic development shifts digitally to a greater extent. As the blue line suggests the possible trend of CO_2 emissions, CO_2 under LCS will grow at a faster rate until 2025 compared to BCS, with emissions estimated to be 13.18 Gt by 2025. It takes a certain time for energy-efficient low-carbon technologies to transition from digital upgrading to mature applications. After a transition to a low rate of CO_2 mitigation during 2025-2030, CO_2 emissions under LCS decline rapidly, driven by mature digital low-carbon technologies. With a projected AAGR of -8.67% for CO_2 emissions over 2021-2060, LCS outperforms the BCS scenario in terms of mitigating emissions after 2030. In contrast, under the HCS (illustrated by the red line) the initial restricted economic development trend results in lower CO_2 emissions than the BCS. However, with the penetration of the global digital transformation momentum, the thick economic development makes its CO_2 emissions surpass the other two scenarios after 2034. The delayed digital transformation and application fail to minimize CO_2 emissions, with an AAGR of -6.21%. It suggests that the building of digital infrastructure should be expedited at this stage, and the cross-fertilization of digitized green technologies into multiple industries requires to be fostered.

Provincial forecasting results

Portraying the potential tendencies of provincial CO_2 emissions contributes to revealing the regional characteristics of digital carbon abatement. Figure 9 summarizes the future CO_2 emission evolution paths of the 30 provinces under the three scenarios. From the projections, it can be noticed that more provinces trade lower CO_2 emissions for slower socioeconomic development under the HCS. Under BCS, the CO_2 reduction efficiency of Beijing, Tianjin, Jiangsu, and Hainan in the eastern region lags behind the historical stage. There exists greater room for upgrading the implementation of the current economic development and low-carbon transition measures. Digitization eliminates geographic constraints, reduces the cost of knowledge search and management, and facilitates technological innovation efficiency, thereby reducing CO_2 emissions. In the LCS where digital technologies are effectively employed, the CO_2 abatement process will advance faster in most provinces. In particular, the eastern region (Hebei, Zhejiang), the central region (Anhui, Shanxi, Fujian), and the western region (Guangxi, Yunnan, Shaanxi) possess more strengths in mitigating CO_2 emissions under this scenario.

Discussion

The study applied a factor decomposition mechanism to identify and quantify the contribution of the digital economy to CO_2 emissions, which in turn outlines the future evolution of CO_2 emissions driven by digitalization under different scenarios. Dogan *et al.* (2025) and Rani *et al.* (2025) utilized econometric methods to investigate the causal relations of digital economic transformation, clean energy utilization, and CO_2 emissions in BRICS countries. On the other hand, Vu and Hartley (2022) and Ni *et al.* (2024) applied index decomposition techniques to demonstrate the productivity benefits of digital transformation and reveal key drivers of CO_2 emissions in data centers. This study integrates factor decomposition with econometric techniques and designs a GDI factor decomposition model that incorporates digital economy and energy indicators. This model pinpoints the primary forces behind or obstacles to CO_2 reduction by accurately estimating the rate at which each component contributes to changes in CO_2 emissions, providing more intuitive policy recommendations.

Consistent with prior findings, the decomposition results revealed that *E* and *ECI* were positively correlated with CO_2 changes. As noted by Horvey *et al.* (2024), accelerating the efficient transition to clean energy and enhancing its utilization efficiency are essential prerequisites for environmental sustainability. Nonetheless, the green transformation of the energy structure cannot be achieved overnight; it necessitates continuous innovation in digital technologies to improve energy efficiency (Lee & Yan, 2024). According to Shahbaz *et al.* (2022) and Ullah *et al.* (2024), digital transformation assists in adopting cleaner energy sources and optimizing the energy structure, thereby lowering CO_2 emissions. Nevertheless, the factor decomposition analysis in this study reveals that, at the current stage, the mitigating effects of *DV* and *DEI* on CO_2 emissions remain insignificant. Similarly, Ozturk and Ullah (2022) believe that the inclusivity of green digital finance should be improved, as digital inclusive finance has driven economic growth while also bringing higher CO_2 emissions.

In addition, several studies have examined the regional heterogeneity in the effects of the digital economy. Razzaq *et al.* (2023) investigated the role of digital finance and green technological innovation in promoting green growth in diverse areas. The effects of the digital economy on CO_2 emissions vary depending on regional resource dependency (Hwang & Venter, 2025). Therefore, in addition to conducting a national-level decomposition, this study further performs regional and provincial factor decompositions. The eastern region demonstrates superior performance in energy mix effects, with a significant downward trend in the CO_2 emissions contributed by *ECI*. *DCI* and *DEI* exhibit better effects in reducing emissions in the midwest, indicating that the digital technology revolution has effectively improved energy efficiency in resource-rich areas while mitigating additional CO_2 emissions. The eastern region of China benefits from a well-established big data infrastructure and mature digital industries, whereas the midwestern region possesses comparative advantages in energy resources. The empirical findings of this study at the regional level align with the conclusions of Hwang and Venter (2025). Accordingly, policymakers should fully account for regional disparities and collaboratively allocate technological, financial, and human resources to enhance energy efficiency and reduce CO_2 emissions effectively.

Furthermore, considering China's socio-economic realities, this study incorporates three perspectives (baseline, high-carbon, and low-carbon) when forecasting CO_2 emissions, aligning with the scenario settings of Chen *et al.* (2023) and Shi *et al.* (2023). The difference lies in the screening of key elements associated with the digital economy, enabling the construction of a novel STIRPAT model to predict future CO_2 emission changes. Driven by the digital economy, a new wave of the information technology revolution is emerging, profoundly reshaping production and lifestyles (Mukalayi & Inglesi-Lotz, 2023). Consistent with the empirical findings of Balsalobre-Lorente and Shah (2024), CO_2 reduction is most pronounced when the digital economy fosters renewable energy consumption, drives green technological innovation, and supports digital green transformation across industries. This effect is most evident in most provinces in the eastern and central regions, including Hebei, Zhejiang, and Anhui. Given that digital technology provides a critical impetus to carbon mitigation, efforts should be made to expedite the digital transformation of carbon trading markets and leverage digital platforms to promote the green transition of household consumption.

Specifically, this study also provides a preliminary assessment of the CO_2 reduction effects of digital transformation across provinces, depending on the current status of China's digital industry and the potential pathways of CO_2 emissions. As depicted in Figure 10, for most of the provinces in the eastern region, despite the wider distribution of data centers bringing in more energy consumption, the region has achieved energy efficiency and avoided additional CO_2 emissions with the assistance of fast-developing digital technologies. Consequently, except for Hebei, Shandong and Zhejiang, which require further digital emission reduction efforts, the other eastern provinces have to maintain their current digital economy development efforts. In contrast, the western region possesses ample resources, particularly clean energy, which provides a potential for developing data hubs and taking over the arithmetic demand from the east. Driven by the future big data industry, most provinces across the western region will largely realize the digitalization of economic development and strengthen digital emission reduction. In addition, Liaoning, Shanxi, Fujian and Jiangxi also require high-speed data transmission networks to promote efficient complementarity and synergy of digital energy-saving technologies.

Conclusions

The disruptive growth of the digital economy has stimulated significant reforms in industrial structures and business models, affecting energy systems and driving the evolution of CO_2 emissions. Exploring the relations of the digital economy on CO_2 emissions and leveraging digital technologies to facilitate energy conservation and carbon reduction has become a key issue in current research. However, the digital economy, as a critical factor, has not been explored within the decomposition mechanisms of CO_2 emission changes. This study fills this gap by upgrading the GDI model, which minimizes residual interference and accommodates a broader range of absolute factors, which enables accurate quantification of digital economy indicators within the decomposition framework of CO_2 emission changes. This approach enables the study to pinpoint the primary factors driving CO_2 emission evolution in terms of the digital economy. Furthermore, an extended STIRPAT model was constructed to simulate the potential trends of CO_2 emissions driven by digital economy development under different scenarios.

Results of factor decomposition indicate that *E* and *ECI* exert a positive driving effect in the historical evolution of CO_2 emissions, and this effect exhibits a weakening trend. Although *DV* makes an insignificant contribution to mitigating CO_2 emissions, its alleviation capacity shows an increasing trend. *DCI* provides the strongest driving force for CO_2 reduction, with most provinces in the eastern and western regions performing more prominently. *DEI* exhibits considerable potential for CO_2 abatement, especially in Beijing, Tianjin, Chongqing, and Sichuan. Furthermore, the forecast results demonstrate that under the LCS with enhanced digital economic development and digital energy saving, the whole country and provinces will be able to achieve effective reductions in CO_2 emissions and contribute to the early completion of the "dual-carbon" target. In terms of provincial prediction, Beijing, Henan and Chongqing stand out in terms of their ability for digital emission control. Provinces such as Shandong, Inner Mongolia and Shaanxi, on the other hand, require further consideration of the potential of digitization in their carbon abatement policies

The integration and development of high energy-consuming industries with advanced digital technologies should be fostered to promote the low-carbon transformation in enterprise production and management. Digital platforms such as energy management systems ought to be upgraded to foster the quick penetration of digital energy efficiency and digital low-carbon technologies into energy-intensive sectors. For example, this system provides real-time monitoring of enterprise production to analysis of energy consumption. In turn, it is imperative to combine the digital management platform organically with information technology tools (such as artificial intelligence) in order to adopt intelligent control measures, optimize energy utilization strategies, and achieve efficient management and comprehensive utilization of energy.

A regional synergetic mechanism of "digitalization-energy-CO_2" should be established. In contrast to decentralized efforts, regions are expected to develop joint action frameworks to maximize regional advantages and energy efficiency. For instance, building a regional carbon reduction sharing platform to realize the accumulation of regional carbon factor (energy structure) data, support carbon disclosure and carbon footprint digitization, as well as promote the upgrading of carbon management and carbon trading models. Each region should collaborate to foster the digital transformation of low-carbon technologies, achieve high-quality trading and utilization of energy, and assist the national energy-saving and carbon-reducing strategy with a regional Internet model for emission reduction.

This study extended the factor decomposition system for CO_2 emission and provided support and a decision-making basis for related sectors to develop specific digital energy saving and digital carbon reduction policies. The study features certain limitations. Given that this study focuses on China, it covers digital economic production, digital economic exchange, and digital circulation when calculating the indicators, that can effectively measure its digital economy development. However, the definition and classification of the digital economy vary across different countries and regions. Therefore, when studying other countries, it should not be limited to the measurements in this study. Yin *et al.* (2023) and Zaman *et al.* (2025) focus on micro-level aspects such as AI software and digital finance. This study focused on the macro level, aiming to incorporate digital economy indicators into the factor decomposition system and offering a novel perspective on CO_2 reduction driven by the digital economy. As such, it cannot provide specific guidance for energy-saving and carbon-reduction strategies related to segmented digital technologies. This study used scenario analysis with diverse scenarios for assessing the potential dynamics in the CO_2 emission.

As the digital economy permeates various aspects of the economic system, future studies could introduce additional absolute factors into the decomposition mechanism, such as industrial structure and investment, to examine the synergistic impacts of the digital economy with other systems on CO_2 evolutions. Subsequent studies can further refine the indicator set by concentrating on specific digital economy sectors, such as AI and big data analytics. It can reveal the differentiated impacts of specific digital technologies on CO_2 emissions from a micro perspective. Future research may also seek to forecast the underlying variables using quantitative approaches and perform the decomposition analysis based on the forecast results. Also, the accuracy of such forecasts may be ensured by embarking on ex-post forecasting.

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Compliance with ethical standards

This article does not contain any studies with human participants or animals performed by the authors. Extracting and inspecting publicly accessible files (scholarly sources) as evidence, before the research began no institutional ethics approval was required.

Data availability statement

All data generated or analyzed are included in the published article. The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation. The raw anonymized data can be provided by emailing the primary author.

Author contributions

All listed authors have made a substantial, direct and intellectual contribution to the work, and approved it for publication. The authors take full responsibility for the accuracy and the integrity of the source analysis.

Conflict of interest statement

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

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Annex

Table 1. The definitions of five factors

Symbols	Calculation	Meaning	Unit
Z=C	-	CO_2 emissions	Mt CO_2
X_1=E	-	Energy consumption	Mtce
X_2=ECI	C/E	Carbon factor	Mt CO_2/Mtce
X_3=DV	-	Digital economy added value	Billion CNY
X_4=DCI	C/DV	Carbon intensity of digital economy	Mt CO_2/CNY
X_5=DEI	E/DV	Energy intensity of digital economy	Mtce/CNY

Table 2. Parameter settings in different scenarios (%)

Parameter	Scenario	Periods							
		2020-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050	2050-2055	2055-2060
AAGRs of *P*	LCS	-0.08	-0.08	-0.37	-0.37	-0.66	-0.66	-0.95	-0.95
	BCS	0.02	0.02	-0.30	-0.30	-0.58	-0.58	-0.80	-0.80
	HCS	0.10	0.10	-0.22	-0.22	-0.45	-0.45	-0.65	-0.65
Share of tertiary sector, *IS*	LCS	62.40	62.40	66.5	66.50	70.30	70.30	73.60	73.60
	BCS	62.40	62.40	66.5	66.50	69.80	69.80	73.00	73.00
	HCS	60.10	60.10	63.7	63.70	67.00	67.00	70.30	70.30
AAGRs of *DV*	LCS	6.25	6.25	3.34	3.34	1.86	1.86	0.76	0.76
	BCS	5.34	5.34	3.29	3.29	1.65	1.65	0.55	0.55
	HCS	4.69	4.69	2.22	2.22	0.72	0.72	0.11	0.11
AAGRs of *DCI*	LCS	-3.90	-6.00	-8.00	-10.00	-12.00	-14.00	-16.00	-18.00
	BCS	-3.90	-4.40	-6.00	-8.00	-10.00	-12.00	-14.00	-16.00
	HCS	-3.90	-4.00	-4.00	-6.00	-8.00	-10.00	-12.00	-14.00

Figure 1. Possible pathways for the digital economy to drive change in CO_2 emission

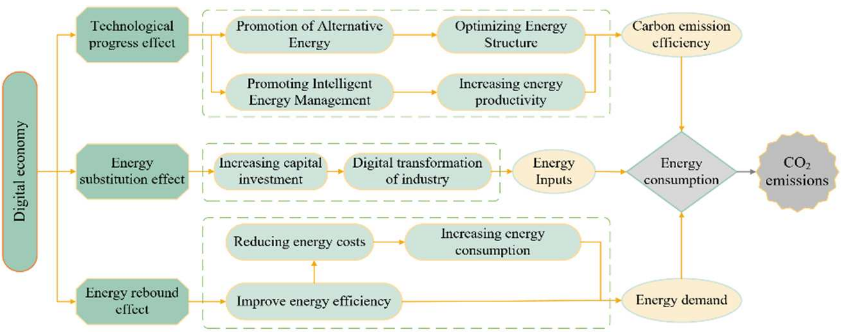

Figure 2. Research framework

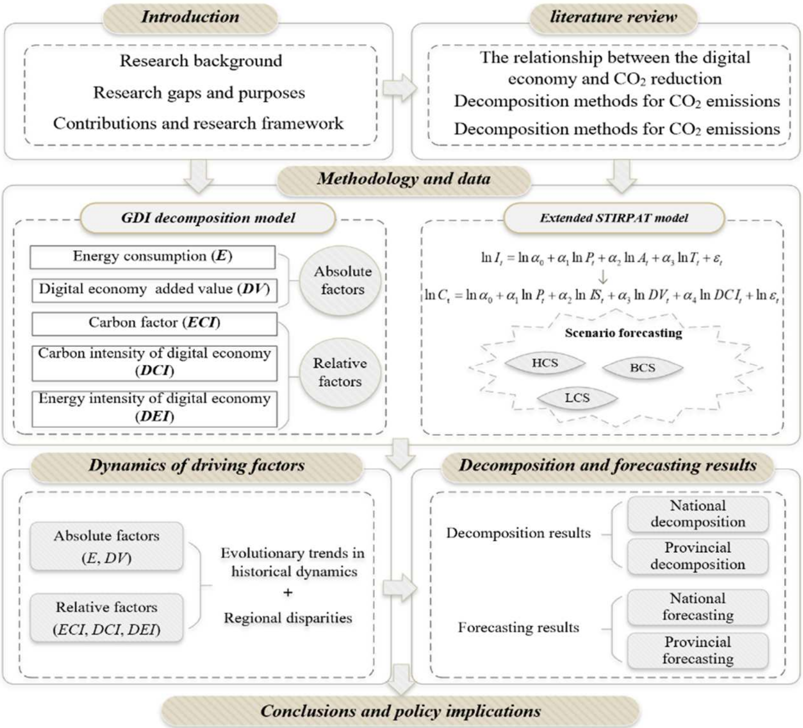

Figure 3. The dynamics and regional disparities of the digital economy, 2002–2020

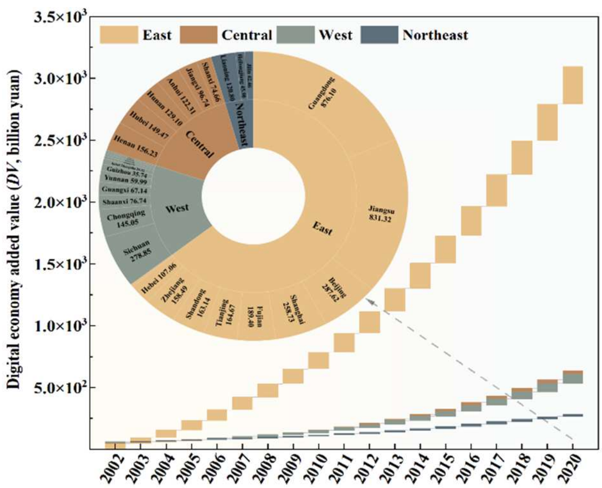

Figure 4. The trend of absolute and relative factors, 2002–2020

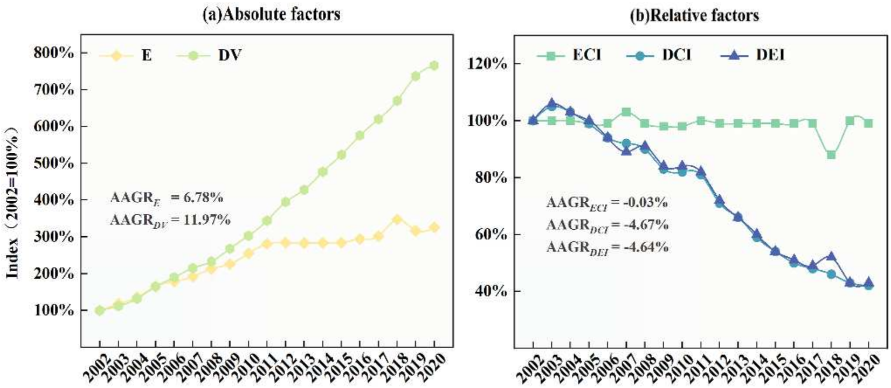

Figure 5. Decomposition results of CO_2 changes in successive years

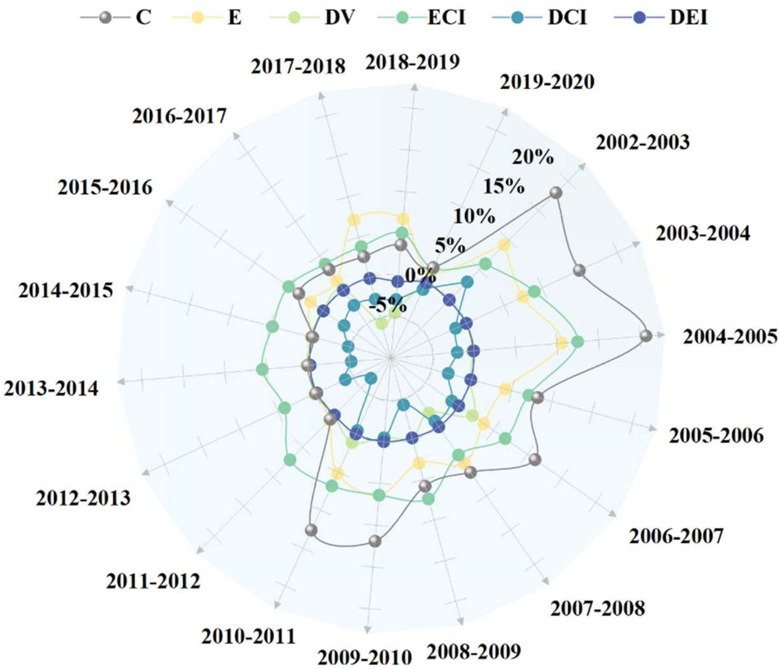

Figure 6. The decomposition results for the whole country and four regions

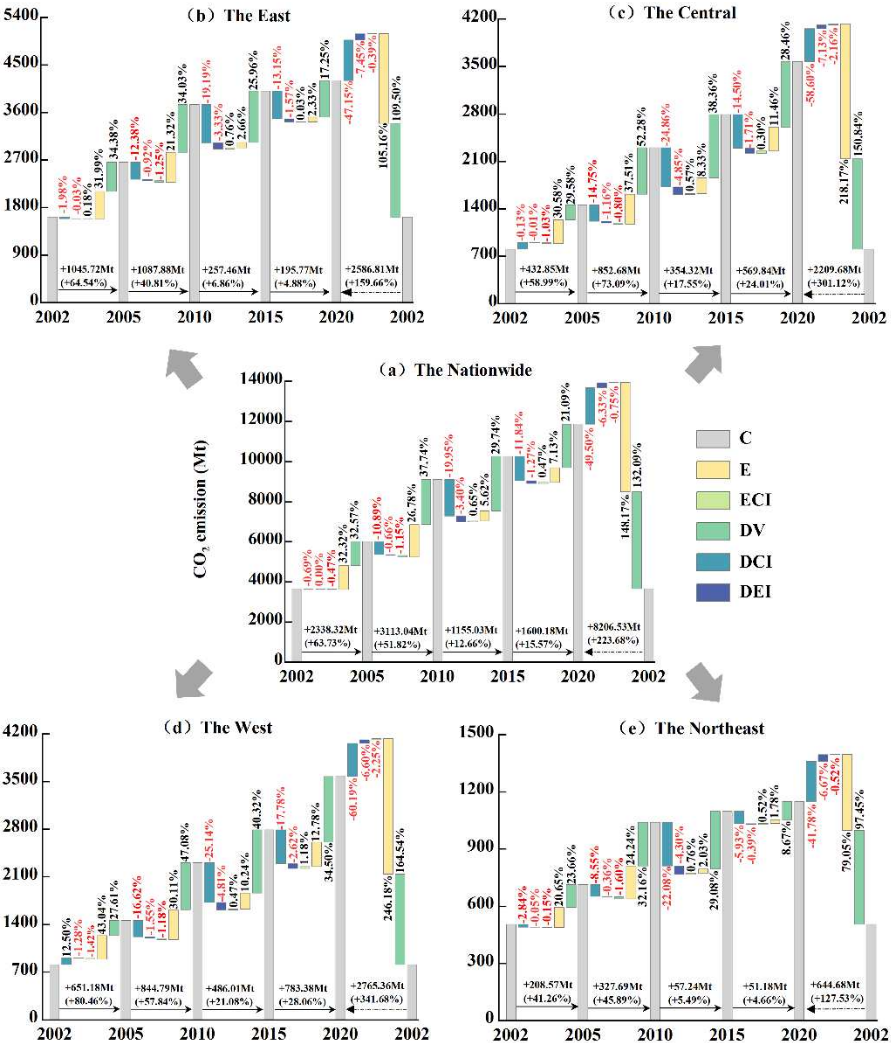

Figure 7. Decomposition of changes in CO_2 emission in 30 provinces

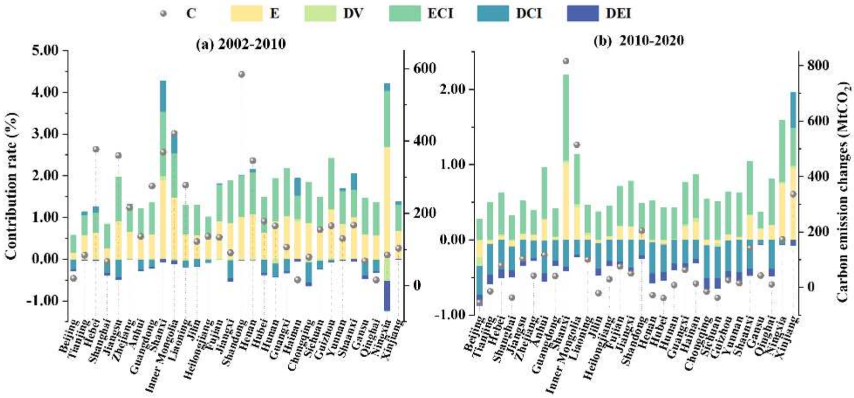

Figure 8. Potential pathways for CO_2 emission at the national level

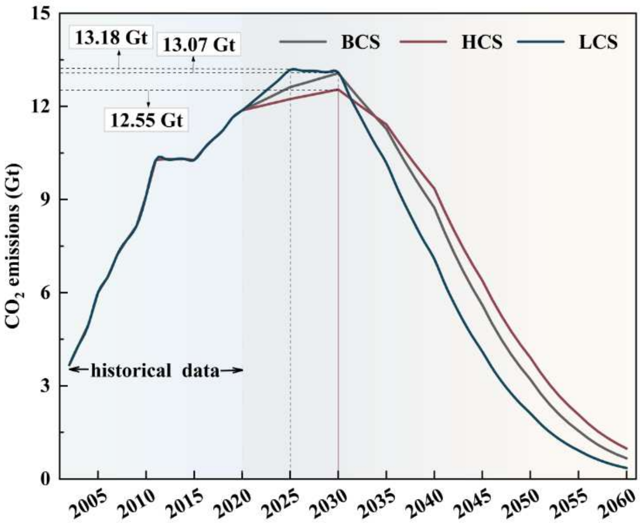

Figure 9. Potential pathways for CO_2 at the provincial level

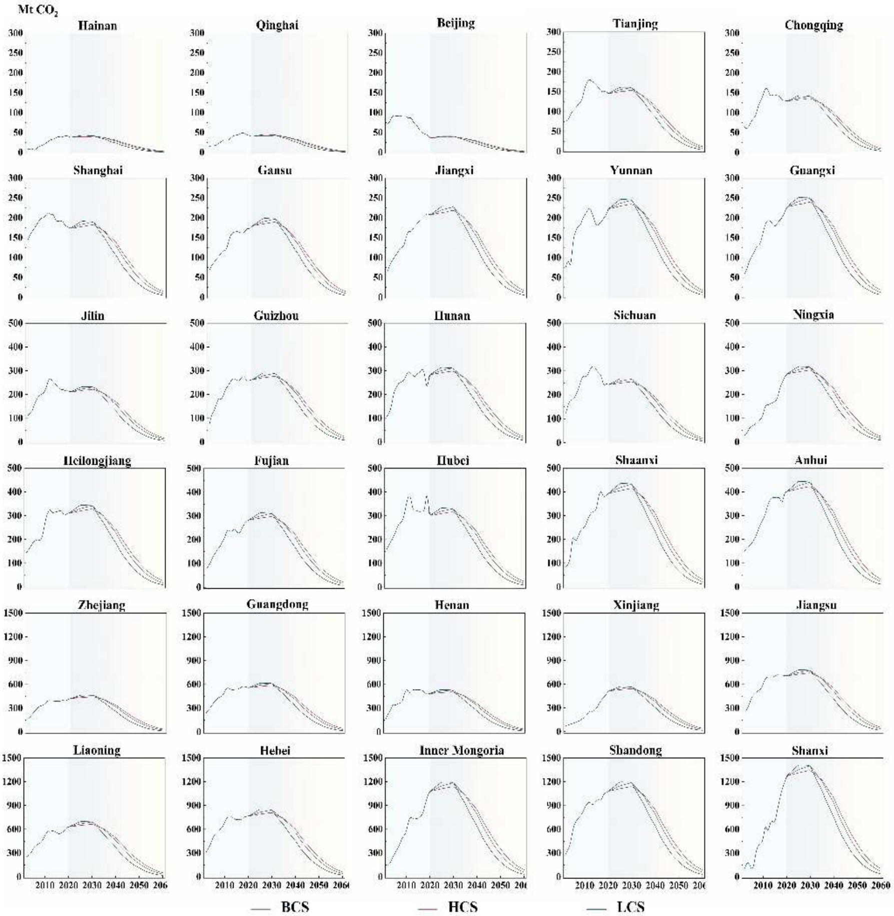

Figure 10. The directions on strengthening the digitization to achieve emission reductions

	Eastern	Central	Western	Northeastern
Strengthen	Hebei, Zhejiang, Shandong	Anhui, Shanxi, Fujian, Jiangxi	Inner Mongolia, Guangxi, Yunnan, Shaanxi, Gansu, Ningxia, Xinjiang	Liaoning
Maintain	Beijing, Tianjin, Shanghai, Jiangsu, Guangdong, Hainan	Henan, Hubei, Hunan	Chongqing, Sichuan, Guizhou, Qinghai	Jilin, Heilongjiang