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Digital Transformation of Enterprises and Carbon Emission Reduction—Based on the Moderating Effect Test of Government Subsidies

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Abstract: *Confronting the global climate challenge, there is an imperative to reduce carbon emissions, which has emerged as a pivotal strategy in advancing the principles of sustainable development. However, within the current landscape of deep integration between digital transformation and the tangible economy, a notable gap exists in scholarly literature regarding the impact of digital transformation on enterprise carbon emissions and how government subsidies play a mechanistic role. Drawing on data from A-share listed companies spanning from 2007 to 2022, this study delves into the mechanisms through which digital transformation influences levels of enterprise carbon emissions. Empirical analyses reveal several key findings: firstly, digital transformation demonstrates a tangible capacity for reducing carbon emissions. Secondly, the efficacy of emission reduction stemming from enterprise digital transformation is particularly pronounced in the context of government subsidies, especially among enterprises benefiting from innovation-focused subsidies.*

Keywords: *Digital transformation; Carbon emission reduction; Government subsidies; Government innovation subsidy*

1. Introduction

Facing the formidable challenge posed by global climate change and striving towards the objective of environmental sustainability, the issue of carbon emissions assume a paramount position on the global environmental agenda, exerting profound influence on climate patterns, ecological equilibrium, and sustainable development. Given the significant role of enterprises as economic and social stakeholders, the carbon emissions directly impact greenhouse gas concentrations in the atmosphere, thereby exerting far-reaching consequences on the Earth's ecosystem. The stewardship of enterprise carbon emissions implicates considerations of social responsibility and sustainable development. By diminishing their carbon footprint, enterprises not only mitigate climate risks but also cultivate an environmentally-conscious corporate identity, thereby aligning with consumer and investor expectations regarding social responsibility (Hopwood, 2009). Carbon emission reduction serves as a manifestation of corporate social responsibility, capable of augmenting brand reputation and fostering consumer trust. Heightened environmental consciousness inclines consumers towards selecting environmentally-friendly products and services, often at premium prices (Nielsen, 2014), thereby bestowing market advantages onto enterprises. Furthermore, carbon emission reduction incentives innovation and technological advancement. Pursuing cleaner and more efficient production methods while enhancing resource utilization efficiency fosters green technology innovation within enterprises (Li et al., 2018), facilitating not only environmental burden alleviation but also a competitive edge in the market (Yin et al., 2020; Tu and Wu, 2021). Additionally, carbon emission reduction directly influences the investor decision-making processes. In light of these imperatives, devising strategies to curtail enterprise carbon emissions becomes an inescapable imperative for fostering the high-quality development of enterprises.

Propelled by cutting-edge digital technology, the global landscape is undergoing a transformative wave driven by scientific and technological revolution and innovation. In the digital era, enterprises increasingly recognize the indispensable nature of digital transformation. This paradigm shift entails the conversion of traditional business and operational modalities into digital, intelligent, and innovative forms, yielding profound and expansive impacts across a wide range of diverse sectors. Notably, the scale of China's digital economy has experienced rapid expansion in recent years, consistently ranking second place globally. According to the "China Digital Economy Development Research Report (2023)", China's digital economy surged to 50.2 trillion yuan in 2022, accounting for 41.5% of its GDP. It is imperative

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to underscore that digital transformation, as a potent catalyst for enterprise advancement, concurrently furnishes support for enterprises to curtail their carbon emissions. While extant research predominantly examines the economic value of digital transformation for enterprises, particularly its impact on financial performance, scant attention has been directed towards exploring its non-economic implications, such as their carbon emission levels. Hence, elucidating the nexus between digital transformation and enterprise carbon emission levels assumes significance in comprehensively understanding digital technology and enhancing corporate environmental responsibility.

2. Theoretical Analysis and Research Hypothesis

2.1 Digital transformation and carbon emission level of enterprises

The essence of digital transformation lies in enterprises or organizations undergoing comprehensive overhauls of their business processes, organizational structures, and value creation methodologies. This transformation is propelled by the adoption of advanced digital technology and innovative strategies, aimed at navigating the strategic transition required by the digital age. The overarching objectives of digital transformation encompass enhancing efficiency, fostering innovation capabilities, enriching customer experiences, adapting to market dynamics, and attaining sustainable competitive advantages (Annarelli et al., 2021).

Firstly, enterprises' investment in research and development (R&D) of digital technology serves to elevate their level of green technology innovation, fostering modernized and environmentally sustainable production and manufacturing processes. This endeavor contributes to reductions in resource consumption and carbon emissions (Usman et al., 2021). Furthermore, digital transformation exerts a substantial influence on energy consumption by catalyzing technological innovation, expediting the accumulation of labor capital, and mitigating distortions in industrial structure (Xu et al., 2022). Notably, digital transformation facilitates telecommuting through Internet technology, thereby enhancing energy efficiency, optimizing economic structures (Alhassan and Adam, 2020), and curbing resource demands (Ren et al., 2021). For instance, it aids in reducing carbon emissions stemming from daily commuting and business travel.

Secondly, the pervasive influence of digitalization has revolutionized the production and operational paradigms of enterprises, prompting producers to realign industrial priorities, enhance efficiency in resource allocation, and optimize regional industrial structures (Kallal et al., 2021; Zheng and Wang, 2021). For instance, the adoption of intelligent manufacturing enables data-driven decision-making, streamlining production processes, minimizing energy-intensive steps, and consequently mitigating emissions. Likewise, optimization of supply chains results in shortened transportation distances, thereby reducing carbon emissions associated with logistics operations. Based on the above analysis, this paper posits hypothesis 1:

H1. Digital transformation can reduce the carbon emission level of enterprises.

2.2 Digital transformation, government subsidies and carbon emission level of enterprises

Innovative activities, such as the digital transformation of enterprises, often entail significant externalities, including price spillovers, knowledge spillovers, and the risk of imitation, which can potentially undermine the interests of enterprises and lead to market failures, necessitating government intervention (Dundas et al., 2010). Within the context of enterprise digital transformation's role in reducing carbon emissions, government subsidies assume a crucial role in promotion and guidance. Firstly, government subsidies exert a substantial incentive effect on enterprises' exploratory innovation performance, encouraging them to conduct innovative research and development in digital technology domains and augment R&D expenditure (Lee and Chen, 2010; Bronzini et al., 2014), thereby fostering the development of more environmentally friendly and efficient technologies and solutions (Beck et al., 2016). These technologies contribute to reducing energy consumption during the production process. Secondly, government subsidies alleviate enterprises' financing constraints, mitigating the risk associated with technological innovation and rendering enterprises more inclined to adopt new carbon emission reduction technologies. Digital transformation necessitates significant resource investments in equipment upgrades, training, and technology integration. When external investors receive the government subsidy signal, it enhances enterprises' ability to secure debt and equity financing, alleviates financing constraints, and diminishes financial pressures (Wang et al., 2022). This enables more enterprises to absorb these costs, thereby reducing carbon emissions. Thirdly, to forestall misappropriation of subsidy funds by

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enterprise management, the government intensifies supervision, conducts rigorous audits and oversight of subsidized enterprises, and mandates enterprises to disclose information on innovation activities to enhance financial transparency and information disclosure. This facilitates further standardization and guidance in the utilization of innovation funds by enterprises (Li et al., 2019).

While government subsidies can facilitate enterprise development to a certain extent, they also entail shortcomings and negative repercussions. Firstly, excessive government subsidies may engender market distortions and impede the normal functioning of market competition. This scenario can constrain economic development and undermine the efficiency of resource allocation within an imperfect market environment or institutional framework (Lazzarini, 2015). Government subsidies may inadvertently steer enterprises towards strategic innovation pursuits. For instance, deficiencies in local government company screening processes could result in resource misallocation, hinder market competition, and foster investment surges (Lin et al., 2011). Enterprises may prioritize obtaining subsidies rather than focusing on genuine innovation, leading to resource wastage and inefficient investment utilization, ultimately undermining long-term enterprise development. Secondly, government subsidies can have a crowding-out effect. Heightened demand for factors in R&D activities, spurred by government subsidies, can drive up factor prices, thereby inflating enterprises' R&D costs and diminishing their R&D expenditure (Leahy and Neary, 1997). Based on the foregoing analysis, this paper posits hypothesis 2:

H2a. The higher the government subsidy, the more the digital transformation of enterprises can reduce the carbon emission level of enterprises;

H2b. The higher the government innovative subsidy, the more the digital transformation of enterprises can reduce the carbon emission level of enterprises;

H2c. Non-innovative government subsidies and digital transformation of enterprises have no obvious effect on reducing the carbon emission level of enterprises.

3. The Research Design

3.1 Selection of samples and variables

In this study, a sample comprising 412 listed companies in the China A-share market that disclosed carbon emission data from 2007 to 2022 was utilized. Dynamic mixed unbalanced panel data were assembled. Following the exclusion of ST, *ST, and data with significant missing values, a 1% tail reduction was implemented, leading to a final dataset comprising 2,103 valid samples. The selection of variables and data sources is delineated in the subsequent section.

3.1.1 The explained variable:

Following the methodology proposed by Chapple et al. (2013) for measuring carbon intensity, the carbon intensity is computed by dividing the carbon emissions of enterprises during the base period by their main income. Subsequently, the carbon intensity index is multiplied by the main income of listed companies to derive an approximate estimated carbon emission level index, denoted as Carbon_emi. Specifically, the carbon emission level index is calculated using the formula: (total energy consumption of enterprises × carbon dioxide conversion coefficient × carbon emission level index) divided by the main business income of enterprises. The energy consumption-related data is sourced from the annual reports of listed companies, while the main business income of enterprises is obtained from the CSMAR database.

3.1.2 Core explanatory variables

Drawing from existing research (Wen et al., 2022; Jiang et al., 2022; Chen and Hao, 2022; Liu et al., 2023), this study employs the text analysis method to formulate the digital transformation index of enterprises, with the annual reports of listed companies serving as the primary data source. The annual reports of listed companies comprise comprehensive financial and non-financial data, offering investors and stakeholders insights into the company's operations, financial status, and future prospects over the course of one year. The textual content in these reports holds significant value and provides deep insights into the company's operational characteristics and developmental trajectory. It aids in delineating the company's fundamental operational strategy, competitive advantage, and industry trends. It is helpful to describe the company's essential operation strategy, competitive advantage and industry trend. This study employs the natural logarithm of the total count of digital keywords plus 1 as the proxy index (DT) to gauge the extent of digital transformation. The specific process is as follows: First, this paper obtains

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national digital economy policy documents and development reports, such as “the 14th Five-Year Plan.”, “the development of the digital economy in the 14th Five-Year Plan period (2021-2025)”, “the development of green industrial in the 14th Five-Year Plan period (2021-2025)”, “the Special Action Plan for Digital Empowerment of Small and Medium-sized Enterprises” , and "Implementation Plan on Promoting the Action of ‘Using Data and Wisdom ’ to Cultivate New Economic Development" and "Report on the Trend of Digital Transformation in 2023", from the sorting of digital and digital transformation related characteristic library, form a digital term dictionary. Through the word segmentation process and manual screening in Python, the digital terms related to enterprises are finally determined, which constitute the dictionary of this paper. Subsequently, this study gathers and organizes the annual reports of all A-share listed companies on the Shanghai Stock Exchange and the Shenzhen Stock Exchange using Python crawler function. It then extracts the text content and management discussion and analysis section. Finally, using Python, the data pool created by extracting the text from the annual reports of listed companies is searched, matched, and tallied based on the characteristic words from the digital terminology dictionary. Subsequently, the word frequencies of key technical directions are categorized and compiled to generate the cumulative word frequency, thus establishing the index system for enterprise digital transformation. Due to the inherent "right-biased" nature of this data, logarithmic processing is conducted in this study. Specifically, after adding 1 to the frequency of occurrences of these terms in the annual report text, the natural logarithm is computed to serve as the proxy for the digital transformation index, denoted as DT.

3.1.3 Adjusting variables

Following the research approach outlined by Guo (2018), this paper employs the following methods to formulate proxy variables for government innovation subsidies: Listed companies disclose government subsidy information in the "details of government subsidies" section under "non-operating income" in their annual report financial statement notes. Given the absence of a standardized disclosure format, this study employs a "keyword search" method to identify project names within the government subsidy details, thereby categorizing them as innovation subsidies. Subsequently, the total annual innovation subsidies for each listed company are calculated through summation, along with the total non-innovation subsidies obtained by summing subsidies not categorized as innovation subsidies.Keyword-terms constitute a dictionary for screening innovation subsidies. Using word separation and manual screening in Python, these terms identified in the financial statement notes of the annual report are categorized as innovation subsidies. Following the addition of 1 to the current year's innovation subsidies, the natural logarithm is applied to derive the government innovation subsidy index for enterprises, denoted as Ino__Subs. Similarly, after adding 1 to the non-innovation subsidies, the natural logarithm is utilized to calculate the government non-innovation subsidy index, denoted as NonIno__Subs. The combination of innovation subsidies and non-innovation subsidies yields the government subsidy index for enterprises, represented as Subs = Ino__Subs + NonIno__Subs.

3.1.4 Control variables

Drawing from established literature in the field of carbon emissions (Wang et al., 2023; Xing et al., 2023), and recognizing that enterprise behavior may influence their carbon emissions, the following enterprise-level control variables are included. The enterprise size (Size) represents the logarithm of total assets at the end of the period; Leverage ratio (Lev) signifies the ratio of total liabilities to total assets at the period's end; Growth rate (Growth) denotes the growth rate of total operating income. The rate of earnings on shareholders' equity (Roa) indicates the ratio of net profit to total assets at the end of the period; Tobin's Q (TBQ) represents the ratio of market value (the market value of an enterprise's stock) to replacement cost (the market value of total assets or replacement cost); Asset turnover rate (ATO) denotes the ratio of sales revenue to average total assets; Employee size (Employee) corresponds to the natural logarithm of the number of employees; Director size (Board) reflects the natural logarithm of the number of directors, and management share (Mngshare) represents the proportion of management shares, including directors. To enhance the robustness of the empirical analysis results, this study additionally incorporates year and individual fixed effects as controls.

3.2 Model setting

3.2.1 Benchmark regression model

$$Carbon\_emi_{it} = \alpha + \beta DT_{it} + \theta Controls_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{1}$$

Following hypothesis 1, this study establishes a benchmark regression model (Model 1) to investigate the impact of enterprise digital transformation and its subsidiary indicators on enterprise carbon emission

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levels. Within this framework, the parameters in Model 1 capture the overall effect of digital transformation on enterprise carbon emission levels. A significant negative coefficient indicates a detrimental impact of digital transformation on enterprise carbon emission levels.

3.2.2 Moderating effect test model

To test hypothesis 2, this study introduces government subsidy variables and interactive terms based on the benchmark regression model.

$$Carbon\_emi_{it} = \alpha + \beta_1 DT_{it} + \beta_2 Subs_{it} + \beta_3 Subs_{it} \times DT_{it} + \theta Controls_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$Carbon\_emi_{it} = \alpha + \beta_1 DT_{it} + \beta_2 Ino_{it} + \beta_3 Ino_{it} \times DT_{it} + \theta Controls_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$Carbon\_emi_{it} = \alpha + \beta_1 DT_{it} + \beta_2 NotIno_{it} + \beta_3 NotIno_{it} \times DT_{it} + \theta Controls_{it} + \lambda_i + \lambda_t + \varepsilon_{it} (4)$$

Model (2) represents a regression equation with government subsidy as the adjustment variable, where represents the government subsidy, and represents the interaction between government subsidy and enterprise digital transformation. If the parameters of core explanatory variables and interaction terms are significant, the adjustment effect is significant. Model (3) is a regression equation with government innovation subsidy as the adjustment variable. Here, represents the government innovation subsidy, and represents the interaction term between government subsidy and enterprise digital transformation. If the parameters of the interaction terms are significant, the adjustment effect is significant. Model (4) is a regression equation with government non-innovation subsidy as the adjustment variable. In this equation, represents the government non-innovation subsidy, and represents the interaction between government subsidy and enterprise digital transformation. If the parameters of the interaction terms are significant, the adjustment effect is significant.

3.3 Descriptive statistics

Table 1 presents the descriptive statistics of all variables selected in this paper. The standard deviation of Carbon_emi is 3.212, and the range between the maximum and minimum values is 21.85, suggesting considerable variation in carbon emission levels among different enterprises.

Table 1: Descriptive statistics

variable	N	mean	sd	min	max
Carbon_emi	2,103	11.150	3.212	1.936	23.786
DT	2,103	1.381	1.332	0	6.140
Size	2,103	24.209	2.130	19.732	31.191
Lev	2,103	0.546	0.210	0.0561	1.135
Roa	2,103	0.045	0.056	-0.556	0.295
Growth	2,103	0.156	0.313	-0.56	2.756
TBQ	2,103	1.731	1.520	0.711	18.167
ATO	2,103	0.628	0.480	0.0141	4.755
Employyee	2,103	9.190	1.477	3.367	13.189
Boaed	2,103	2.249	0.256	1.609	2.944
Mngshare	2,103	4.208	11.907	0	61.927
Subs	2,103	21.610	8.011	7.601	41.461
Ino	2,103	5.131	7.224	0	21.372
NotIno	2,103	16.479	2.385	7.601	23.115

4. Empirical Analysis

4.1 Benchmark regression

Table 2 presents the benchmark regression results of econometric model (1). Overall, the results indicate that the estimation parameters of digital transformation on the carbon emission level of enterprises are significantly negative, regardless of whether individual and time-fixed effects are controlled. For instance, in the fourth column, the estimated parameter of digital transformation is negative and significant at the 5% level. This suggests that a 1% increase in the degree of digital transformation will lead to a reduction in the carbon emission level of enterprises by 0.032%. Hence, hypothesis 1, which posits that digital transformation reduces the carbon emission level of enterprises, is

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essentially confirmed in this paper.

Table 2: Benchmark Regression Results

	(1)	(2)	(3)	(4)
DT	-0.036** (0.014)	-0.032*** (0.008)	-0.018 (0.015)	-0.032** (0.015)
Size	0.286*** (0.068)	0.563*** (0.067)	0.871*** (0.090)	0.563*** (0.112)
Lev	-1.993*** (0.431)	-0.658** (0.265)	-1.036*** (0.374)	-0.658* (0.382)
Roa	-3.919*** (1.248)	-0.306 (0.477)	-0.808 (0.542)	-0.306 (0.584)
Growth	-0.002 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
TBQ	-0.139*** (0.041)	0.004 (0.019)	0.001 (0.015)	0.004 (0.016)
ATO	1.225*** (0.146)	0.775*** (0.103)	0.854*** (0.153)	0.775*** (0.140)
Employyee	0.893*** (0.076)	0.209*** (0.062)	0.114 (0.101)	0.209* (0.112)
Board	-0.717*** (0.270)	0.324* (0.183)	0.006 (0.373)	0.324 (0.373)
Mngshare	-0.009 (0.005)	-0.000 (0.005)	-0.002 (0.004)	-0.000 (0.004)
Cons	-1.341 (1.098)	-5.579*** (1.222)	-10.780*** (1.818)	-5.579*** (2.120)
Year	NO	YES	NO	YES
Firm	NO	NO	YES	YES
N	2103	2103	2103	2103
adj. R^2	0.307	0.241	0.226	0.241

The regression results of the control variables largely align with expectations. For instance, in the fourth column, the influence of enterprise scale on the carbon emission level of enterprises is significantly positive, with a coefficient of 0.563%. Conversely, the asset-liability ratio of enterprises exhibits a negative impact on carbon emissions, with every 1% increase in the ratio leading to a 0.658% decrease in carbon emissions. Moreover, the asset turnover rate has a significantly positive effect on carbon emissions, with a 1% increase associated with a 0.775% increase in emissions. Additionally, employee size shows a significant positive impact on carbon emissions, with a 1% increase leading to a 0.209% rise in emissions. Although the effect of board size on emissions is not significant, the positive estimated parameter value suggests a potential positive influence of board expansion on emissions. Notably, at a significance level of 1%, the asset turnover rate exhibits the most substantial influence on carbon emissions, followed by enterprise scale.

4.2 Moderating effect analysis

Table 3 presents the regression results after introducing the Moderating effect of government subsidies. In column (3), for instance, the estimation coefficient of digital transformation is -0.028, significant at the 5% level, indicating that the role of digital transformation in reducing the carbon emission level of enterprises remains significant under the regulatory effect of government subsidies. Furthermore, the coefficient of the interaction term DT×Sub is significantly negative, indicating a positive regulatory effect of government subsidies on the relationship between the performance of digital transformation and the carbon emission level of enterprises. This confirms the establishment of hypothesis 2a, suggesting that the larger the scale of government subsidy, the stronger the role of digital transformation in reducing the carbon emission level of enterprises. This may be attributed to the high-speed development stage of enterprise digital transformation in China. Combining this with Chinese enterprise practices, entities with substantial government subsidies exhibit enhanced business capabilities and a stronger sense of social responsibility, making them more inclined to actively reduce carbon emissions. Consequently, enterprises are more likely to integrate digital transformation into their daily business activities, leading to lower carbon emissions in areas with high government subsidies.

Upon further analysis, government subsidies received by enterprises are categorized into innovative

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and non-innovative subsidies. Column (1) presents the regression results after introducing the regulatory effect of government innovative subsidies. The estimation coefficient of digital transformation is -0.027, significant at the 5% level, indicating that the role of digital transformation in reducing the carbon emission level of enterprises remains significant under the regulatory effect of government innovative subsidies. In column (2), the regression results introduce the adjustment effect of government non-innovative subsidies. The estimation coefficient of digital transformation is -0.041. Comparing the interaction terms introduced by the two regulatory variables, the coefficient of the interaction term DT×Ino is significantly negative, suggesting a positive regulatory effect of government innovative subsidies on the relationship between the performance of digital transformation and the carbon emission level of enterprises. Conversely, the coefficient of the interaction term DT×NotIno is positive and not significant, indicating that government non-innovative subsidies have no positive regulatory effect on the relationship between the performance of digital transformation and the carbon emission level of enterprises. This confirms the establishment of hypotheses 2b and 2c, indicating that the larger the scale of government innovative subsidies, the stronger the role of digital transformation in reducing the carbon emission level of enterprises. However, the effect of non-innovative subsidies on carbon emission reduction in enterprise digital transformation is not evident.

Table 3: Impact of government subsidies

	(1) Carbon_emi	(2) Carbon_emi	(3) Carbon_emi
DT	-0.027** (0.015)	-0.041* (0.022)	-0.028** (0.015)
Ino_ Subs	-0.001 (0.006)	-	-
DT×Ino	-0.004** (0.002)	-	-
NotIno	-	0.001 (0.008)	-
DT×NotIno	-	0.001 (0.001)	-
Subs	-	-	-0.004 (0.003)
DT× Subs	-	-	-0.003** (0.001)
Controls	YES	YES	YES
Firm	YES	YES	YES
Year	YES	YES	YES
Cons	-3.862** (1.653)	-3.861** (1.670)	-3.883** (1.687)
N	2017	2017	2017
adj. R^2	0.407	0.412	0.414

5. Main conclusions and policy suggestions

Currently, the world is transitioning into the era of the digital economy. Leading the digital age, digital transformation is no longer an option for companies but a necessity (Ahmadova et al., 2022). This study, based on data from China A-share listed manufacturing companies spanning from 2007 to 2020, revealed that digital transformation significantly decreased the carbon emission levels of enterprises. Subsequent research reveals that the decrease in carbon emission levels is further amplified following adjustments to government subsidies in digital transformation, particularly after these subsidies are categorized as innovative subsidies. This underscores the pivotal role of government innovative subsidies in reducing carbon emissions of enterprises. Conversely, non-innovative subsidies did not exhibit a discernible regulatory effect.

In the era of digital economy, both the government and enterprises must strive to accelerate the digital development of enterprises. For enterprises, they should speed up digital transformation, deepen technological innovation and build the cornerstone of sustainable development. Both the digital transformation and low-carbon transformation of enterprises need continuous investment in innovation resources. Enterprises should increase investment in innovation to ensure the rational and efficient

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allocation of resource elements in the business process, so as to further stimulate the vitality of sustainable development and tap the potential of sustainable growth.

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