



Research article

Research on digital diffusion of firms under the dual disturbance of carbon trading price volatility and yield uncertainty

Jinhan Yu¹, Licheng Sun^{1,*} and Xiaozhuang Jiang²

¹ School of Management, Jiangsu University, Zhenjiang, 212013, China

² School of Public Administration, Huaiyin Normal University, Huai'an, 223001, China

* **Correspondence:** Email: sunsee213@ujs.edu.cn.

Abstract: In this paper, we have explored the factors driving the diffusion of digital technology (DT) between firms in the context of carbon trading price volatility and yield uncertainty. First, we have constructed a game model containing traditional low-carbon firms and digital firms to explore the effects of carbon trading price volatility, yield uncertainty, and low-carbon competition on firms' optimal decision-making. Based on the model, a low-carbon DT diffusion model built on the Watts-Strogatz small-world network has further been constructed, and data on carbon trading prices and firm yield in reality were collected, using numerical simulation to explore the driving effect of each element on the diffusion of DT. It has been found: (i) The degree of firm rationality and the initial proportion of firms have a significant positive effect on the diffusion of DT, while the average node degree is rather negative for the diffusion of DT with a low degree of rationality. (ii) Improved DT capabilities and carbon trading price volatility, and increased yield uncertainty, are all effective incentives for firm-to-firm technology diffusion, which can improve the rate of diffusion. (iii) Growing low-carbon competition can have a hindering effect on the diffusion of DT, leading to lower diffusion rates. Based on this study, the influence of different factors on the diffusion of DT among firms has been revealed. Finally, some managerial insights derived from the findings can provide theoretical guidance for firms to achieve digital transformation in complex environments.

Keywords: carbon trading price volatility; yield uncertainty; digital diffusion; complex network; evolution game

Mathematics Subject Classification: 05C82, 91A22, 91A10

1. Introduction

Global climate change has contributed to a growing frequency of extreme weather, exerting widespread impacts on humanity and the natural environment. The international community has recognized the necessity of environmental sustainability, and many countries have taken action to reduce carbon emission in response to this global challenge. Carbon trading policy has become an important policy for countries to promote enterprises to achieve low-carbon development due to its flexibility and market-oriented characteristics [1,2]. In this context, digital technology (DT) has enhanced companies' innovation and operational efficiency by transforming production processes, business models, and value creation methods [3,4]. For instance, Baowu Steel Group has developed an AI large-scale model that uses data processing and cloud computing to improve efficiency in green manufacturing. Similarly, Midea's microwave oven factory in ShunDe has implemented interconnected equipment, digital applications, automation, smart logistics, and value-stream-driven upgrades, reducing product costs by 6% and carbon dioxide emission by 9.6%. These examples demonstrate that DT not only boosts production efficiency but also aligns with sustainability goals [5–7]. However, the true value of technology lies not in the technology itself but in its diffusion [8]. On one hand, the returns on DT investments become increasingly uncertain due to volatility in carbon prices and yield uncertainty. On the other hand, digital technologies exhibit significant external spillover effects. These factors collectively contribute to insufficient motivation for firms to invest in DT. Therefore, understanding how to achieve broad adoption of DT within firms, and examining the micro-level processes of technology adoption along with their macro-level diffusion effects, holds significant practical importance.

At present, scholars have mainly explored the contributors of DT diffusion from policy and market-driven perspectives, including government subsidies and consumer preferences [9,10]. However, the identification of the mechanisms that influence the internal and external uncertainties of firms is not clear enough. In practice, adoption of DT requires significant capital, which undoubtedly increases firms' financial pressure [11]. At the same time, the yield uncertainty in manufacturing, caused by equipment failures, raw material quality, and other uncontrollable factors, is often unavoidable. In addition, carbon trading price volatility leads to unregulated changes in firms' production costs and unsatisfactory returns on clean technology investments, forcing firms to flexibly adjust production volumes and reduce the amount of European Union Allowance (EUA) they need to purchase in order to maintain profitability [12,13]. For instance, in the second half of 2023, the Euro Area Manufacturing Purchasing Managers' Index (PMI) remained below the 50-point threshold for seven consecutive months, reflecting widespread weakness in industrial output and energy demand [14]. Meanwhile, the price of EUA has been declining steadily from its mid-year peak. During this period, RWE, a major German utility and key compliance buyer, announced the suspension of systematic carbon allowance purchases to reduce carbon costs amid weak demand. This aligns with the empirical findings of [15]: "industrial production is found to impact positively (negatively) the carbon market during periods of economic expansion (recession)." This confirms the link between macroeconomic activity, represented by industrial production, and carbon prices. Consequently, firms must factor carbon price uncertainty into production and emissions reduction decisions. This uncertainty compounds the inherent yield uncertainty in manufacturing, collectively increasing the complexity of firms' operational decision-making. In such an environment, firms gain greater motivation to mimic the behaviors and decisions of peer firms to maintain competitive parity or limit competition, thereby embarking on their DT journey [16,17].

The current global industrial system is faced with three major pressure: increasing carbon constraints, accelerating technology iteration, and intensifying market volatility. But at present, the research still focuses on the theoretical and empirical analyses of digital transformation, with a lack of exploration of the diffusion process of DT in enterprises. In practice, interactions between firms often exhibit several specific topological network features, such as small-world features, scale-free features, association structures, and hierarchical features. These complex network relationships serve as key diffusion channels for low-carbon technologies [18]. Therefore, this paper explores the impact of micro-level factors on the diffusion of macro low-carbon technologies using evolutionary game theory in the context of carbon trading price volatility and output uncertainty. We further integrate complex networks into our analytical framework by constructing an evolutionary complex-network game model of DT diffusion among firms. This model allows us to explore the mechanisms that drive the diffusion of digital transformation and to analyze the role of network characteristics and other relevant factors. This study aims to answer the following questions:

(1) How do carbon trading price volatility and yield uncertainty affect firms' decisions and the diffusion effects of digital technologies?

(2) How does variation in the intensity of low-carbon competition affect the effectiveness and rate of firms' DT diffusion?

(3) How does the diffusion effect of digital technologies differ between firms across digital capabilities in response to carbon trading price volatility and yield uncertainty?

This research contributes to the literature in three aspects: First, traditional game models are difficult to solve in full consideration of uncertain changes in the real environment, whereas complex network theory considers that the interaction behavior between individuals has topological statistical characteristics. Therefore, this paper innovatively integrates the Stackelberg game model into the analytic framework of network evolutionary dynamics, which more accurately reflects the real-world scenario. Second, it quantifies the effect of DT on diffusion outcomes under carbon trading price volatility and yield uncertainty, providing theoretical support for the adoption of DT in firms. Third, this paper explores the mechanism and effect of carbon trading price volatility on digital diffusion in enterprises under low-carbon competition. Also it provides theoretical references and applications to promote the diffusion of DT in firms.

The main contents of this paper are as follows. Section 2 reviews the relevant literature. Section 3 establishes a Stackelberg game model between firms. In Section 4, a network model of complex networks is developed and the mechanism of network decision-making is set up. In Section 5, simulation experiments are conducted by collecting real data. Section 6 provides conclusions and managerial insights.

2. Literature review

In this section, we review the related literature from three aspects: operational decisions under carbon trading policy, yield uncertainty, and digital technology diffusion.

2.1. Operational decisions under the carbon trading policy

In recent years, carbon emissions have been recognized as an important factor influencing companies' decision-making due to emissions-related regulations. Among these regulations, non-

mandatory policy instruments (carbon trading policy and carbon tax policy) are favored by governments and businesses because of their flexibility compared to mandatory policy instruments. Moreover, carbon trading policy has been shown to be more profitable for companies than carbon taxes [19]. Current research has been conducted on carbon trading policy in operational management, including pricing decisions [20], production and remanufacturing decisions [21], carbon reduction decisions [22], and channel selection [23,24]. On this foundation, scholars have further combined carbon trading policy with the adoption of low-carbon technologies. Through evolutionary game theory and complex network evolutionary game theory, they have characterized the diffusion routes and steady-state strategies of low-carbon or green technologies under given quotas and carbon prices [25,26]. In these studies, a common assumption is that the emission price is fixed. However, under the carbon trading mechanism, carbon allowances can be used for trading as a general commodity to achieve resource complementarity between the trading parties. Therefore, the price of emissions is always fluctuating, threatening the development of carbon trading policy and the interests of firms as the main risk [27]. Moreover, carbon trading prices are more effective in controlling production and emissions than carbon allowances in the market [28]. While some other scholars have considered quality uncertainty [29], supply uncertainty, and demand uncertainty [30,31] under carbon trading policy, emissions price volatility and consequent yield uncertainty have often been neglected. Our study contributes to the existing research on this topic by introducing the volatility of the carbon trading price and exploring its impact on the adoption of digital technologies in the manufacturing industry in the context of yield uncertainty.

2.2. Yield uncertainty

Existing studies considering other uncertainties usually assume that yield is certain. But in practice, yield is often uncertain due to disturbances in raw material quality, equipment failures, and other uncontrollable factors, which can affect the firm's overall performance and strategic decisions [32]. Scholars have begun to pay attention to this phenomenon and to study the related issues. Several scholars have shown particular interest in studying firms' decision-making under yield uncertainty, finding that under yield uncertainty, firms tend to shift undesirable products to the low end of the markets to reduce their losses [33]. Under carbon trading policy, yield uncertainty has also been found to influence firms' financing preferences and ordering decisions [34]. This uncertainty has also been extended to other areas of supply chain firms' decision-making, including pricing decisions [35], emission reduction decisions [36,37], risk sharing [38], and remanufacturing [39]. Some other studies have focused on the coordination mechanisms supply chain under yield uncertainty [40–42], where scholars have further extended traditional contracts and designed a variety of composite contracts to positively impact supply chain performance [43–46]. In addition to this research, scholars have proposed a variety of solutions on how to deal with the negative effects of yield uncertainty. It has been found that cooperating with socially responsible suppliers [47], improving demand information updates [48], and multi-sourcing [49] can partly mitigate the negative impacts of yield uncertainty and reduce the risk of overproduction and underproduction. Additionally, a smaller portion of the research focuses on how firms can address the challenges they are faced with. For example, Paknejad [50] proposed optimizing the manufacturing process through yield enhancement programs, and Cao [51] proposed using data-driven machine learning algorithms to optimize orders with yield uncertainty, which can

significantly improve supply chain cost-savings and efficacy. The existing research reveals the impact of yield uncertainty and presents several insightful management implications. Based on this foundation, this paper links carbon price volatility to yield uncertainty, exploring the mechanism through which DT interventions impact firms' decision-making and the diffusion process of DT among firms.

2.3. Digital technology diffusion

Compared with traditional technology, DT's unique characteristics of autopoiesis, scalability, and openness make its diffusion process more complex and uncertain. To promote the digital upgrading of industries, scholars have actively studied the digital diffusion of firms from different perspectives. From the point of view of the attributes of DT, privacy and security as well as affordability are the main barriers to the adoption of DT for firms [52]. Besides, factors such as adoption costs [53,54], digital culture [55], and the peer pressures from trading partners [56] directly influence the rate of adoption of DT. In the study of the environmental driving mechanism of DT diffusion, the political-legal environment, technology environment, and the market environment form the external drivers of DT diffusion [57–59]. Therefore, governments provide financial support, tax incentives, and technical training to help firms overcome cost barriers to technology transformation and accelerate technology diffusion [60–63]. Meanwhile, in the context of digitalization and greening, carbon trading system and pilot policies for low-carbon cities show a dual driving effect. The former promotes the firms' adoption of DT through economic incentives [64], while the latter achieves the coupling of DT application and sustainable development goals through institutional innovation [65]. In addition, changes in the external environment of firms, especially environmental uncertainty and intensified competition in the industry, affect the tendency of firms to apply DT, and the adoption of DT can significantly improve the efficiency and competitiveness of firms [66]. Existing scholars have primarily focused on the impact of climate policies and macroeconomic uncertainty on firms' adoption of digital technologies. Some studies have found that uncertainty surrounding climate policies and oil prices can curb firms' willingness to adopt digital technologies by reducing their expectations and increasing the risk of investing in digital technologies [67]. Conversely, other studies indicate that climate policy uncertainty can motivate firms to view digital technologies as risk mitigation tools that enhance risk identification capabilities and operational resilience, thereby increasing digital adoption levels [68]. In research methodology, the complex network evolution game model can more effectively portray and analyze the strategic interaction and game evolution between the participating subjects during the diffusion process. Practically, firms often adjust their strategies by imitating or learning from similar firms [69]. This peer effect is fully reflected in complex network evolutionary game models. Moreover, this model breaks away from the assumptions of complete rationality and static equilibrium in traditional game models, thereby more accurately reflecting the dynamic process of technology diffusion. Furthermore, scholarly research on innovation diffusion [70] and new energy vehicle diffusion [71] indicates that complex network evolutionary game models possess unique advantages in characterizing strategy evolution and technology adoption.

In summary, existing studies have explored the contributors of DT diffusion from different perspectives, revealing the key roles of factors like the technology's attributes, the policy environment, and firm management in driving the firms' adoption of DT. However, neither of the research studies related to the diffusion of digital technologies has considered the issue of carbon trading price volatility.

In practice, especially under the pressure of carbon emission regulations, the actual yield of low-carbon production is lower than the expected due to the quality of raw materials, process technology, and other factors. But few literatures have investigated the digital adoption process and mechanism of firms' emergence in social networks with carbon trading price volatility and yield uncertainty. Therefore, this paper, based on complex network evolutionary game theory, constructs a digital diffusion model for enterprises, and explores the impact of factors such as carbon trading price volatility and yield uncertainty on the macro-diffusion effects of DT. Table 1 summarizes the differences between the previous literature and this study.

Table 1. Literature comparison.

Literature	Focus point	Research methodology	Carbon trading	Digital technology	Yield uncertainty	Market competition
Peng et al. (2018)	Emission reduction decision	Stackelberg game model	√		√	
Wang et al. (2019)	Digital technology diffusion	Complex network evolutionary game		√		√
Zhao et al. (2021)	Optimal production decision	Nonlinear programming model	√		√	
Chen et al. (2024)	Manufacturers digital transformation	Duopoly model	√	√		
Zou et al. (2021)	Ordering decision	Stackelberg game model	√		√	
Chatterjee et al. (2023)	Organization flexibility and competition	Structural-equation modeling		√		√
Chen et al. (2025)	Digital technology decision	Evolutionary game model	√	√		√
Lin et al. (2024)	Resolve yield uncertainty	Stackelberg game model			√	√
Zhang et al. (2024)	Operation optimization	Complex network evolutionary game	√		√	
Cao et al. (2024)	Resolve yield uncertainty	Predictive machine learning		√	√	
This paper	Digital technology diffusion	Complex network evolutionary game model	√	√	√	√

3. Game modeling

3.1. Model assumptions

Consider a duopoly market in which there are two firms producing homogeneous substitutable products that generate unit carbon emissions of e . There is yield uncertainty in the production process of the products. To investigate the optimal decisions of firms' production and emission reduction under carbon trading price and yield uncertainty, the following assumptions are made:

Hypothesis 1 There exist two competitive low-carbon firms that aim to maximize profits. Facing carbon-price volatility and yield uncertainty, each firm may choose whether to adopt DT. Firms adopting DT are hereafter referred to as digital firms, while those not adopting DT are hereafter referred to as traditional low-carbon firms, denoted by D and L respectively.

Hypothesis 2 Under the emission cap-and-trade regulation, the government allocates free emission allowances to the firm, denoted by E_g . But if they over emission, firms must buy extra carbon allowances, and they can also sell their surplus. p_e is the carbon trading price, which is a random variable with $E(p_e) = p_0$ and $Var(p_e) = \sigma^2$, indicating the level of carbon trading price volatility.

Hypothesis 3 Due to carbon trading price volatility affecting firms production activities, we assume the correlation coefficient between carbon trading price p_e and firms' actual yields Q_i is $\rho \in (0,1)$, and then we have $\rho = \rho_{p_e Q_i} = -\rho_{p_e X}$ (see the Appendix). When $\rho \rightarrow 1$, this implies that carbon trading price volatility is associated with firm yield and significantly affects firm yield [15].

Hypothesis 4 Assume that the firm's inverse demand function is $P_i = a - Q_i + \eta_i - b\eta_j$, $i, j = D, L$, $i \neq j$, a is the maximum market price, and b is the low-carbon competition coefficient. The actual yield of the firm is $Q_i = q_i - (1 - d_i)X$, X is a random variable, $E(X) = 1$, $Var(X) = \sigma^2$, and changes in yield affect the selling price, reflecting the impact of yield uncertainty on the price of the product. $d \in (0,1)$ represents the digital capability of firm D , which indicates the firm's ability to use DT to collect, process, and analyze historical carbon trading price information, to make more accurate forecasts of the future trend of the carbon trading price, to achieve synergistic management of production and carbon assets through DT, and to reduce the variance of yield uncertainty.

Hypothesis 5 Product emission reduction effort is denoted by η , and the input cost of producing a low-carbon product is $\frac{g_i \eta_i^2}{2}$, where g_i is the low-carbon cost coefficient, and for simplicity of modelling let $g_D = g_L = g$ [72].

Hypothesis 6 If firm i adopts DT, in addition to variable abatement costs, there is a fixed investment cost F . If the firm only takes low-carbon technology to reduce emissions, there is no fixed investment cost F . Referring to reference [26], under the carbon trading mechanism, if the firm chooses DT, the firm's profit maximization model is established.

The firm's profit function is:

$$\pi_D = P_D Q_D - p_e [e(1 - \eta_D)Q_D - E_g] - \frac{g\eta_D^2}{2} - F \quad (1)$$

$$\pi_L = P_L Q_L - p_e [e(1 - \eta_L)Q_L - E_g] - \frac{g\eta_L^2}{2} \quad (2)$$

Since firm yield uncertainty affects decision-making and hence profits, the expected profit is used to represent the firm's profit, based on the previous assumptions about the random variable X . The firm's expected revenue is known as:

$$\begin{aligned}
E(\pi_D) &= p_0 E_g + a[q_D - (1 - d)] - e\{p_0[q_D - (1 - d)] + \rho(1 - d)\sigma\sigma_e\} \\
&\quad - \left[(q_D - (1 - d))^2 + \sigma^2(1 - d)^2 \right] - b[q_D - (1 - d)]\eta_L + [q_D - (1 - d)]\eta_D \\
&\quad + e\{p_0[q_D - (1 - d)] + \rho(1 - d)\sigma\sigma_e\}\eta_D - \frac{g\eta_D^2}{2} - F
\end{aligned} \tag{3}$$

$$\begin{aligned}
E(\pi_L) &= p_0 E_g + a(q_L - 1) - e[p_0(q_L - 1) + \rho\sigma\sigma_e] - [(q_L - 1)^2 + \sigma^2] \\
&\quad - b(q_L - 1)\eta_D + (q_L - 1)\eta_L + e[p_0(q_L - 1) + \rho\sigma\sigma_e]\eta_L - \frac{g\eta_L^2}{2}
\end{aligned} \tag{4}$$

The optimal decision variables are obtained by solving the derivation:

$$q_D = \frac{bg(BY + 2e\rho\sigma\sigma_e) - b^2(-1 + d)YH + A[2dg - g(2 + a - ep_0) + YH] - dYH}{(bY)^2 - (-A)^2} \tag{5}$$

$$\eta_D = \frac{BY(bY - A) + 2e[bY + (-1 + d)A]\rho\sigma\sigma_e}{(bY - A)(bY + A)} \tag{6}$$

$$q_L = \frac{bk[BY - 2(-1 + d)e\rho\sigma\sigma_e] + b^2YH + A[-g(2 + a - ep_0) + YH]}{(bY)^2 - (-A)^2} \tag{7}$$

$$\eta_L = \frac{BY(bY - A) + 2e[-A - b(-1 + d)Y]\rho\sigma\sigma_e}{(bY - A)(bY + A)} \tag{8}$$

where $B = (a - ep_0)$, $A = 2g - (1 + ep_0)^2$, $H = 1 + e(p_0 - \rho\sigma\sigma_e)$, $Y = 1 + ep_0$.

3.2. Model analysis

Proposition 1 In the model of the oligopoly game, 1. is for the digital firm M_A , $\frac{\partial q_D}{\partial b} < 0$, $\frac{\partial \eta_D}{\partial b} < 0$; $\frac{\partial q_L}{\partial b} < 0$, $\frac{\partial \eta_L}{\partial b} < 0$. 2. Is for the traditional firm M_B , when $0 < d < \frac{(bY - A)^2}{(bY)^2 + (-A)^2} = d_2$, and we have $\frac{\partial q_L}{\partial b} < 0$, $\frac{\partial \eta_L}{\partial b} < 0$, and $\frac{\partial q_D}{\partial b} > 0$, $\frac{\partial \eta_D}{\partial b} > 0$ at $d_2 < d < 1$. The proofs are given in the Appendix.

Proposition 1 shows that: 1. In the context of carbon trading price volatility and yield uncertainty, although DT can more accurately help firm M_D to predict carbon trading price volatility and optimize production decisions. But with the intensification of low-carbon competition, M_D experiences a decline in product prices and yield, leading to a reduction in profits. This weakens its motivation to reduce emissions, and the reduction rate is subsequently decreased.

2. For M_L , a traditional firm that does not adopt DT, it faces the same yield uncertainty, and thus similarly tends to adopt the strategy of M_D , choosing to reduce yield and emission reductions to avoid the risk. However, when firm A has a high level of DT capability ($d_2 < d < 1$), firm B observes that firm M_D uses DT to accurately predict market changes and optimize production and abatement decisions. It will maintain its market share by increasing its production and abatement efforts.

Proposition 2 In the model of the oligopoly game: 1. For digital firm M_D , when $0 < d_D < 1 + \frac{bY}{-A} = d_1$, we have $\frac{\partial q_D}{\partial \sigma} > 0$, $\frac{\partial q_D}{\partial \sigma_e} > 0$, $\frac{\partial \eta_D}{\partial \sigma} > 0$, $\frac{\partial \eta_D}{\partial \sigma_e} > 0$. When $d_1 < d < 1$, we have $\frac{\partial q_D}{\partial \sigma} < 0$, $\frac{\partial q_D}{\partial \sigma_e} < 0$, $\frac{\partial \eta_D}{\partial \sigma} < 0$, $\frac{\partial \eta_D}{\partial \sigma_e} < 0$. 2. For traditional firm M_L , $\frac{\partial q_L}{\partial \sigma} > 0$, $\frac{\partial q_L}{\partial \sigma_e} > 0$, $\frac{\partial \eta_L}{\partial \sigma} > 0$, $\frac{\partial \eta_L}{\partial \sigma_e} > 0$, regardless of the DT capacity of the M_D . The proof is given in the Appendix.

Proposition 2 shows that: 1. At $0 < d < d_1$, when digitization capacity is low, the effects of yield uncertainty are difficult to eliminate. To maintain market share in a complex competitive environment, yield must be increased to secure market demand. This also leads to the increase of carbon allowances required by firm M_D . Reducing the disturbance to the total cost caused by carbon trading price volatility can only be achieved by increasing the rate of emission reduction and finding a balance between costs and benefits. At $d_1 < d < 1$, firm M_D has a higher degree of DT available for a one-time investment and can help reduce losses from yield uncertainty, preferring to invest in DT over costly low-carbon technology. It also reduces the carbon allowances by reducing yield to avoid the impact of carbon trading price volatility on the firm's profit. Therefore, carbon trading price volatility and yield uncertainty negatively affect the yield and reduction rate of firm M_D . 2. For traditional firm M_L that does not adopt DT, when carbon trading price volatility and yield uncertainty increase, to maintain low-carbon competitiveness in the market and reduce carbon costs, firm M_L will continue to make low-carbon inputs and increase its yield to maintain revenues with thin profits and high sales. Therefore, carbon trading price volatility and yield uncertainty positively affect yield and reduction rates of firm M_L .

Proposition 3: A further comparison of the optimal decisions for the two firms results in: $q_D - q_L < 0$, $\eta_D - \eta_L < 0$. The proofs are given in the Appendix.

Proposition 3 shows that the optimal yield and emission reduction efforts of digital firms are both lower than those of traditional low-carbon firms. For digital firms, digital capabilities mitigate the impact of carbon price volatility and yield uncertainty to some extent. Moreover, lower yield decisions mean fewer carbon allowances are required, leading to reduced carbon costs even without increasing emission reductions. Thus, digital firms can maximize profits at lower yields and moderate emission reduction rates. Conversely, traditional low-carbon firms, lacking digital support, must reduce their demand for carbon allowances by increasing emission reduction rates to mitigate the impact of carbon price volatility. They also need to increase planned yield to address yield uncertainty. Consequently, they achieve higher production and greater emission reductions.

4. Complex network modeling

The complex network evolution game mainly contains three parts: a game model, network structure, and evolution rules. First, firms will make a choice between investing in technology (M_D) and only investing in low-carbon technology (M_L) strategies according to their actual situation and the context of carbon trading price volatility, gaining the benefits from it. When embedded in networks, the profits from firm-to-firm game models depend not only on market factors but also on network structure and evolutionary rules. Moreover, the characteristics of complex networks dictate that the evolutionary process cannot be expressed analytically. In the following evolutionary process, firms compare strategy benefits based on a specific network structure and according to evolutionary rules up to a steady state. Therefore, this paper takes firms as nodes, constructs a complex network model with a low-carbon competitive relationship network of firms, and realizes the diffusion of DT among nodes based on the comparative benefit of updating rules.

4.1. Network structure

In manufacturing firms, it is common for firms to shape close industrial clusters or supply chain networks, where there is close cooperation and interaction between firms. Examples include the electronics manufacturing cluster in the Pearl River Delta region of China, the Detroit vehicle manufacturing center in the United States, and the textile manufacturing cluster in northern Italy. These firm clusters facilitate information transfer, resource sharing, and collaborative innovation, promoting the efficient operation of the entire manufacturing ecosystem. In perspective, this paper analyzes the game of DT diffusion among low-carbon firms using the WS small-world network as a carrier.

4.2. Evolution rules

Considering the reality of firms' decision-making with irrational factors, this paper adopts the Femi rule to portray firms' updating strategies. In each round of the game, firms can only learn from each other by continuously playing and comparing their returns with their neighbors for strategy updating, which eventually evolves into stable strategy choices. It means that firm i randomly chooses a neighbor j for profit comparison, and if the neighbor's return in the current round is higher than its own, it will update its strategy in the next round by copying its neighbor's behavior with a probability. The specific expression is as follows [73]:

$$P(s_i \leftarrow s_j) = \frac{1}{1 + \exp\left(\frac{\pi_i - \pi_j}{k}\right)} \quad (9)$$

Here k is the degree of limited rationality, and the degree of its value reflects the degree of rationality and uncertainty in the firm's strategy learning process. It represents the possibility of members to make irrational game decisions. As k increases, individuals are less rational, and when $k \rightarrow \infty$, members are completely irrational and transformed into random copying rules. $\pi_i - \pi_j$ is the average profit difference between the two firms, and the larger its distance, the lower the probability $P(s_i \leftarrow s_j)$ that firm i copies firm j 's strategy.

5. Numerical modeling and simulation analysis

In this section, based on the aforementioned game model and small-world network algorithm, initial parameter values are set for numerical simulation to analyze the patterns of firms' low-carbon competition, DT maturity, carbon trading price volatility, and yield uncertainty on firms' profits and diffusion. Based on existing studies on evolutionary games in complex networks, let the average node degree $m = 5$, the probability of random reconnection $p = 0.3$, and the total number of nodes N in the network be set to 400. Referring to the Digital Transformation Index Study of Chinese Firms in 2023 launched by Accenture and the National Industrial Information Security Development Research Centre, 37% of Chinese firms carried out digitization and automation of single-function departments in 2023, so this paper sets the initial proportion of firms adopting DT at $\gamma = 0.3$. Referencing studies by Faccio et al. [74] and Zhao et al. [75], China formally launched its national carbon market in July 2021, establishing a unified national carbon pricing system. Therefore, the carbon price was derived from the monthly data samples of China's Carbon Emissions Trading Market between July 2021 and

August 2024, calculating the average and standard deviation. The monthly average trading price was approximately 64.57 yuan/t, with a standard deviation of 14.63. So we set $p_0 = 64.6$ and $\sigma_e = 14.63$. In recent years, vehicle firms have faced increased uncertainty in their production activities as a result of epidemics, chip shortages, continued increases in raw material prices, and international political and economic factors. Therefore, in this paper, we refer to the production data of the vehicle industry in the China Statistical Yearbook from 2013 to 2023 to portray the production uncertainty, and set $\sigma = 2.14$. The initialization of the relevant parameters is shown in Table 2.

Table 2. Parameter settings.

Parameters	m	p	N	γ	k	p_0	σ_e	σ
Assign a value	5	0.3	400	0.3	0.2	64.6	14.63	2.14
Parameters	F	d	a	b	ρ	g	Eg	e
Assign a value	4	0.5	20	0.5	0.5	150	8	0.1

5.1. Diffusion rates of firms' DT in different network environments

Since the inter-firm game model is embedded in a network, the benefits of the game are not only related to market factors, but also affected by the network structure and evolutionary rules. Therefore, we performed the following exploration.

5.1.1. Impact of the initial proportion

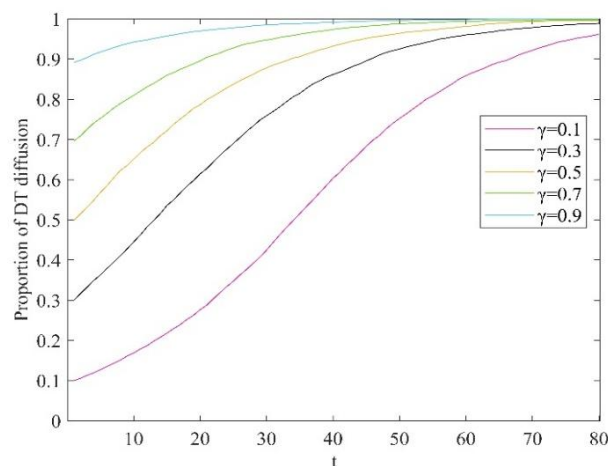


Figure 1. The impact of initial proportion on the diffusion of DT in firms.

In order to examine the impact of the initial state digital firm's proportion on the diffusion of DT, the initial proportion γ is simulated by taking different values, and the results are shown in Figure 1. At an initial ratio of $\gamma = 0.1$, the diffusion rate progresses slowly and eventually reaches 96%. From $\gamma = 0.3$, the diffusion proportion increases more rapidly with increasing time than at $\gamma = 0.1$. From $\gamma = 0.5$, the initial proportion rises rapidly with time and approaches 100% as the diffusion proportion increases. It can be seen that the higher the initial level of firm digitalization, the faster the diffusion of DT occurs, and the easier it is to reach a state of saturation.

5.1.2. Impact of the degree of rationality and average node degree

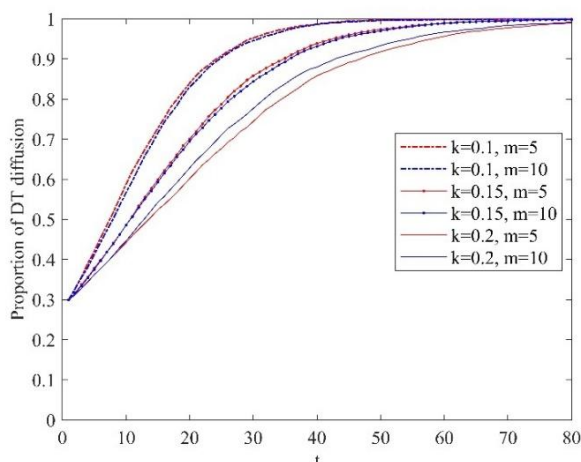


Figure 2. The impact of rationality and average node degree on the diffusion of DT in firms.

To examine the effect of Fermi-Dirac rule parameter changes on the conclusions, numerical simulations are respectively carried out according to $k = 0.1, 0.15, 0.2$, and the average node degree $m = 5, 10$. As shown in Figure 2, the higher the degree of rationality of a firm, the faster the rate of DT diffusion. This is mainly because firms with a high degree of rationality pay more attention to long-term strategic planning, and can recognize that DT is a key factor in the competitiveness of future firms in a low-carbon competitive environment. This not only reduces the impact of yield uncertainty in the present, but also helps firms to predict future carbon trading price trends to gain an advantage in low-carbon competition. However, at lower levels of rationality ($k = 0.1, 0.15$), the rate of DT diffusion accelerates as the average node degree increases. At higher degrees of rationality ($k = 0.2$), the opposite happens. This is because a higher average node degree means that firms are more connected to each other, and knowledge transmission and technology exchange are more frequent. Lower rationality firms are more likely to copy the behavior of high benefit firms in their neighborhood. Higher rationality firms, more concerned with their own competitive advantage and long-term strategy, adopt a more rational and cautious application of DT, thus the more nodes, the slower the diffusion rate.

5.2. Analysis of factors influencing the diffusion of DT in the firms

5.2.1. The impact of DT capabilities on technology diffusion

Digital capability represents the ability of a firm to collect, process, and analyze historical carbon trading price information using DT. The higher the digital capability, the more accurate the prediction of the future trend of the carbon trading price, and the better the ability to convert carbon trading price information into effective information, creating more profit value for the firm. Its effect on the diffusion of digital DT among firms is shown in Figure 3. For firms, there is a critical value between $[0.5, 0.6]$ for firm digital capability on DT diffusion. When the digital capability is greater than the critical value, the rate of DT diffusion accelerates with the growth of digital capability, and when it is lower than the critical value, DT diffusion is not achieved. The reason is that when digitization capacity is low, its ability to collect, process, and analyze historical carbon trading price information is limited.

The less-effective information available through DT makes it difficult to protect against the negative impact of carbon trading price volatility and yield uncertainty on profits in competitive markets. But as firms' digitization capacity increases, the returns of firms that make digital investments grow, and firms that only make low-carbon investments choose to invest in DT. After comparing their returns, DT is able to achieve diffusion among the community.

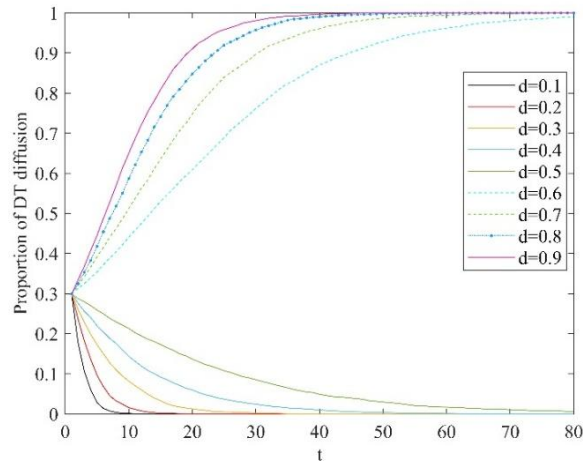


Figure 3. The impact of digital capabilities on the diffusion of DT in firms.

5.2.2. The impact of carbon trading price volatility on technology diffusion

Figure 4 illustrates the impact of carbon trading price volatility on the diffusion of DT between firms. The diffusion rate is 0% at $\sigma_e < 24.63$, and the diffusion of DT among firms changes only when $\sigma_e > 24.63$, reaching 100%. At this point, the evolution of the system also starts to accelerate with the increase of σ_e . This is because the carbon trading price can be used as a market signal—its volatility will directly affect firms' production and low-carbon decisions. It can also be seen from Table 3 that traditional firms have higher yield and emission reduction rates, and when carbon trading price volatility is small ($\sigma_e < 24.63$), they have no demand for DT as they can reduce carbon trading costs through emission reduction inputs and gain more product benefits from low-carbon competition than the expected benefits from digitized firms. However, as carbon trading price volatility increases, traditional low-carbon firms are unable to accurately adjust yield uncertainty and reduction rates in a timely manner, resulting in higher carbon costs and compressed profit margins. In contrast, digital firms are better able to predict carbon trading price trends through DT, relieving cost pressures caused by carbon trading price volatility, and have higher expected benefits than traditional low-carbon firms. Therefore, traditional low-carbon firms are beginning to adopt DT, and the greater the carbon trading price volatility, the wider the gap between the two firms' returns, thus accelerating the speed of evolution.

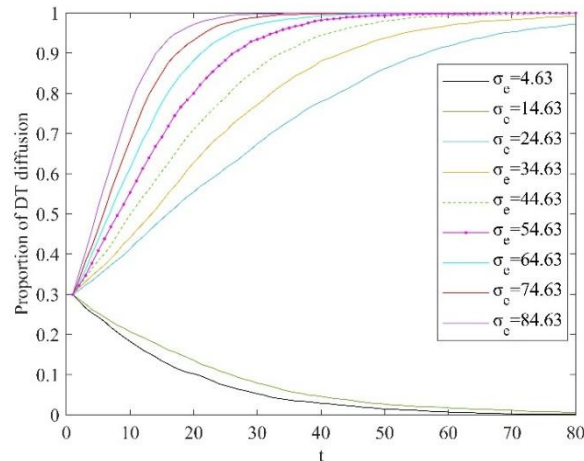


Figure 4. The impact of carbon trading price volatility on the diffusion of DT in firms.

Table 3. The impact of carbon price volatility on firms' decision-making.

σ_e	q_D	q_L	η_D	η_L	$E(\pi_D)$	$E(\pi_L)$
4.63	8.69	9.20*	0.409	0.411*	566.08	566.51*
14.63	8.71	9.23*	0.413	0.420*	565.73	565.87*
24.63	8.72	9.26*	0.418	0.429*	565.39*	565.24
34.63	8.73	9.30*	0.422	0.437*	565.04*	564.61
44.63	8.75	9.33*	0.426	0.446*	564.70*	564.00
54.63	8.76	9.36*	0.430	0.455*	564.35*	563.39
64.63	8.78	9.39*	0.435	0.463*	564.01*	562.79
74.63	8.79	9.42*	0.439	0.472*	563.68*	562.21
84.63	8.80	9.45*	0.443	0.481*	563.34*	561.63

Note: * represents the firm with the higher yield, emission reduction rate, and profit among the two firms.

5.2.3. The impact of yield uncertainty on technology diffusion

From Figure 5, it can be shown that the DT diffusion rate is 0 when $\sigma < 2.34$; when $\sigma \geq 2.34$, the DT diffusion rate reaches 100% in the steady state, and as σ increases, the system reaches stability gradually. The above phenomenon occurs mainly due to the following reasons: On the one hand, firms need to invest a substantial amount of capital, time, and labor costs to introduce DT, and in a relatively stable production environment ($\sigma < 2.34$), the input-output ratio of DT is poor, so the diffusion of DT lacks incentives. On the other hand, it can also be seen from Table 4 that although digitized firms temporarily lag behind traditional low-carbon firms in terms of yield and emissions reduction, however, by capturing the carbon trading price trend more accurately to optimize production decisions and better planning the investment in emission reduction, the reduced carbon cost can offset part of the loss caused by yield uncertainty, and profits are less affected. In contrast, as yield uncertainty increases, the negative impact on profits of over-or underproduction is directly reflected in the earnings of traditional low-carbon firms, and this negative impact increases as yield uncertainty increases. Therefore, traditional low-carbon firms choose to adopt DT after comparing the benefits, which promotes the diffusion of DT between firms.

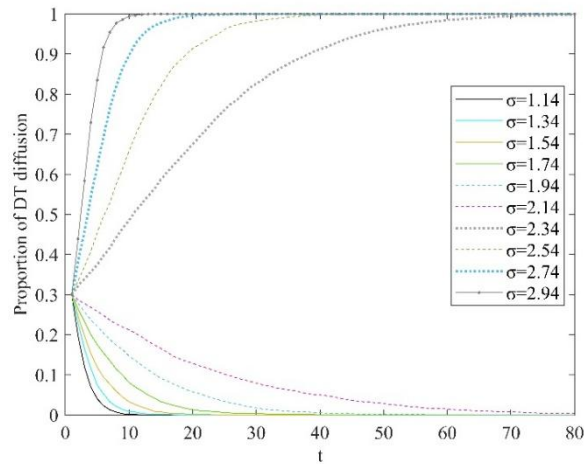


Figure 5. The impact of yield uncertainty on the diffusion of DT in firms.

Table 4. The impact of yield uncertainty on business decision-making.

σ	q_D	q_L	η_D	η_L	$E(\pi_D)$	$E(\pi_L)$
1.14	8.698	9.211*	0.4105	0.414*	566.79	569.59*
1.34	8.699	9.216*	0.4111	0.415*	566.62	569.00*
1.54	8.701	9.220*	0.4116	0.416*	566.43	568.34*
1.74	8.703	9.224*	0.4122	0.418*	566.22	567.60*
1.94	8.705	9.229*	0.4128	0.419*	565.99	566.77*
2.14	8.707	9.233*	0.4134	0.420*	565.73	565.87*
2.34	8.709	9.237*	0.4140	0.421*	565.46*	564.89
2.54	8.711	9.241*	0.4145	0.422*	565.17*	563.82
2.74	8.713	9.246*	0.4151	0.423*	564.86*	562.68
2.94	8.714	9.250*	0.4157	0.425*	564.53*	561.46

Note: * represents the firm with the higher yield, emission reduction rate, and profit among the two firms.

5.2.4. The impact of low-carbon competitive intensity on technology diffusion

Figure 6 shows the effect of low-carbon competition on the rate of DT diffusion between firms, which are all at 0% and decrease faster as low-carbon competition is fierce. This is due to the fact that the competitive pressure on firms gradually increases as a result of increased low-carbon competition. On the one hand, the capacity of DT to address yield uncertainty and carbon trading price volatility is limited, squeezing firms out of funding for low-carbon inputs, and is not sufficient to attract firms to invest in DT. On the other hand, intensified low-carbon competition has led to simultaneous declines in product prices and yield, further reducing overall firms' profits. As shown in Table 5, compared to digitized firms, traditional low-carbon firms achieve higher emission reduction rates and yield, thus benefiting more from increased low-carbon competition. This also confirms the conclusion in Proposition 1. The shift in profits has made enterprises more eager to enhance R&D for emission reduction, leading them to prioritize allocating limited resources to emission reduction technologies over DT. This ultimately prevents digital technologies from developing sustainable profit advantages during their evolution, resulting in their abandonment.

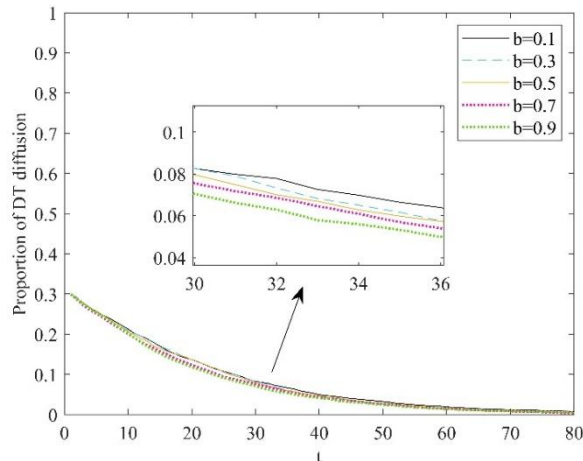


Figure 6. The impact of the intensity of low-carbon competition on the diffusion of DT in firms.

Table 5. The impact of low-carbon competition on firms' decision-making.

b	q_D	q_L	η_D	η_L	$E(\pi_D)$	$E(\pi_L)$
0.1	8.81	9.33*	0.418	0.425*	567.12	567.23*
0.3	8.76	9.28*	0.416	0.422*	566.42	566.55*
0.5	8.71	9.23*	0.413	0.420*	565.73	565.87*
0.7	8.66	9.18*	0.411	0.417*	565.06	565.21*
0.9	8.61	9.13*	0.408	0.415*	564.40	564.55*

Note: * represents the firm with the higher yield, emission reduction rate, and profit among the two firms.

6. Conclusions and managerial insights

This paper constructs a complex network model considering firms' yield uncertainty in the context of carbon trading price volatility. It solves and analyzes the game process of low-carbon firms' yield and emission reduction decisions at the micro level, and further explores the diffusion mechanism, evolution rules, and evolution process of DT among low-carbon firms on the complex network from a dynamic perspective. Based on simulation experiments, the effect of variables on diffusion efficiency is further analyzed.

The principal conclusions and management insights are below:

(1) In different network environments, higher degrees of firm rationality and the proportion of initial firm digitization lead to a faster rate of DT diffusion. But increasing the average node degree leads to faster DT diffusion when the firm's degree of rationality is low, while the opposite is possible when the degree of rationality is high. Therefore, it is necessary to improve the initial adoption rate of DT through policy incentives and industry advocacy to accelerate the rate of technology diffusion. Moreover, the DT diffusion strategy should be flexibly adjusted according to the network environment and the degree of rationality of the firms. In traditional manufacturing agglomerations (e.g., steel, textile, and traditional machining), the technology spread between firms can be accelerated by increasing the linkages with upstream and downstream partners and technology suppliers. In high-tech industrial parks (e.g., semiconductors and new energy), the emphasis has shifted toward supporting "small-scale networks," establishing technology patent pools and innovation alliances to curb resource wastage caused by free-riding.

(2) The promotion in digitization capacity has a significant incentive effect on the diffusion of DT between firms, and the rate of diffusion of DT between firms increases significantly with carbon trading price volatility and firm yield uncertainty, which is because a firm's ability to collect and process information is limited by DT. Firms need to invest more in digital infrastructure and professionals to break through existing DT capabilities, effectively respond to market volatility and uncertainty, optimize their decision-making processes, and reduce operational risks. In addition, by actively participating in digital collaboration and knowledge-sharing within the industry, firms can strengthen links between them and accelerate the diffusion of DT between firms.

(3) Yield uncertainty and carbon price volatility have significant threshold effects and accelerating impacts on the diffusion of digital technologies. When uncertainty and volatility are low, traditional low-carbon firms can maintain their competitive edge through emissions reduction alone, lacking motivation to adopt DT. However, when the critical threshold is higher, digital firms maintain their advantage through digital technologies, prompting traditional firms to shift to DT adoption and enabling technological diffusion. Thus, market uncertainty and volatility are both triggers for digital diffusion and key drivers accelerating its spread. Policy-makers can use the carbon pricing mechanism's signaling effect to guide firms in increasing digital investments. By adding financial subsidies, tax incentives, and technology-sharing platforms, they can relieve firms' financial and capability limitations during digital transformation, lower barriers to digital adoption, and build a favorable competitive environment. This approach will further advance digital and low-carbon transformation and development.

(4) Low-carbon competition is also an important factor hindering the diffusion of DT, and when low-carbon competition becomes fierce, the rate of DT diffusion decreases. Although it is important to gain a low-carbon competitive advantage in the market, excessive focus may crowd out resources for digital transformation, leading to a "prisoner's dilemma" situation for firms and hindering the diffusion of DT. At the same time, the government can introduce relevant policies to encourage collaborative innovation and the sharing of resources among firms, achieving a win-win situation in terms of low-carbon goals and digital transformation.

Author contributions

Jinhan Yu: Writing—original draft, Formal analysis, Validation, Visualization; Licheng Sun: Methodology, Supervision; Xiaozhuang Jiang: Writing—review and editing.

Use of Generative-AI tools declaration

AI tools used: ChatGPT (OpenAI, version [GPT-4]).

Purpose of use: language refinement.

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Conflict of interest

The authors declare that they have no conflicts of interest relevant to this study.

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