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Research on the Evolutionary Mechanism of Government-Enterprise Collaboration in AI-Empowered Digital Transformation of the Manufacturing Industry

Fulei Shi [1] **,** ***Zisha Zhou*** [1] **,** ***Ying Zheng*** [2*]

[1] *School of Management and Engineering, Capital University of Economics and Business, Beijing 100070, China; shifulei@cueb.edu.cn (F.S.); 22025213039@cueb.edu.cn (Z.Z.)*

[2] *Accounting School, Capital University of Economics and Business, Beijing 100070, China*

ABSTRACT

Digital transformation can effectively enhance the core competitiveness of manufacturing enterprises. Artificial Intelligence (AI) technology is essential to promote the digital, networked, and intelligent development of enterprises. So, understanding how it influences enterprises' transformation decisions matters greatly for building a modern industrial system. In this paper, we build a government-enterprise evolutionary game model that brings in AI technology maturity as a moderating variable, and systematically analyzes the dynamic interaction mechanism between government incentive policies and manufacturing enterprises' digital transformation decisions. Through theoretical reasoning and numerical simulations, we uncover how AI maturity reshapes the cost-benefit structure of transformation. Our results show that AI technology maturity acts as a game-changing parameter. When maturity stays low, the system tends to be locked in an ineffective equilibrium where enterprises wait and see while the government lacks leverage. When AI technology maturity exceeds the critical threshold, enterprises' willingness to undergo independent transformation is significantly enhanced, and the government's strategy can accordingly shift from "strong incentives" to "routine guidance". Sensitivity analysis further reveals that enterprise transformation cost, benefit elasticity coefficient, waiting loss and transformation benefit are also critical to enterprises' digital transformation. This paper focuses on process manufacturing such as chemicals,

*CORRESPONDING AUTHOR:
Ying Zheng, Accounting School, Capital University of Economics and Business, Beijing 100070, China; Email: 32024040141@cueb.edu.cn

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pharmaceuticals and food processing. For these sectors, AI helps reduce production downtime, optimize supply chain coordination, improve product quality and boost productivity. Our findings help to understand the mechanism and effects of AI technology maturity on digital transformation, and provide a reliable basis for optimizing policy tools and effectively boosting the digital transformation of the manufacturing industry.

Keywords: AI Technology Maturity; Digital Transformation of Manufacturing Industry; Government-Enterprise Collaboration; Evolutionary Game

1. Introduction

At present, new-generation information technologies are developing rapidly. AI and other technologies are deeply integrated with manufacturing, accelerating factories' shift toward digitalization, networking and intelligence. On the one hand, increasingly mature AI technologies such as large models and industrial internet platforms can significantly reduce enterprises' transformation costs. On the other hand, AI empowerment across R&D, production and management can improve production efficiency and further increase transformation benefits. Therefore, under the current wave of artificial intelligence, studying the role of AI in promoting digital transformation of manufacturing is of great importance.

Many scholars hold the view that digital transformation serves as an important path to enhance the competitiveness and development quality of manufacturing enterprises. Wang et al. argue that digital transformation can significantly improve enterprise performance and operational efficiency [1]. Further research finds that digital transformation can also enhance total factor productivity and promote high-quality enterprise development [2]. From a long-term perspective, digital transformation helps strengthen sustainable competitiveness and improve the ability to cope with external risks [3]. Zhao et al. believe that digital transformation can alleviate financial distress and improve the financial situation of enterprises [4]. In an open economy, digital transformation can also increase the export technological sophistication of enterprises and enhance international competitiveness [5].

To find what drives digital transformation, scholars have launched comprehensive research from diverse research angles. From the internal perspective, dynamic capabilities, accumulated technical resources and human resource endowment directly decide how thoroughly enterprises can push forward digital upgrading [6]. Besides, leaders' cognitive vision, organizational flexibility and strategic orientation also greatly influence transformation choices [7]. From the external perspective, the business environment, industry competition and the level of industrial digitalization jointly shape enterprises' willingness to transform [8]. Other studies also prove that digital infrastructure, data availability and external technical support can strongly promote the progress of digital renovation [9]. Overall, the realization of enterprises' digital transformation relies on the joint effort of technological, organizational and environmental factors [10].

Among these influencing factors, policy incentives are a vital driving force to boost digital transformation progress. Financial subsidies can effectively ease corporate funding pressure, cut down potential transformation risks and improve enterprises' active participation enthusiasm [11]. Related academic findings verify that targeted fiscal aid and standardized policy guidance can quicken the pace of digital renovation and improve the overall digital construction level within the whole region [12]. Nevertheless, some research confirms that there exists an inverted U-shaped relationship between governmental intervention intensity and corporate innovative vitality. Excessively high subsidy support is likely to trigger abnormal incentive effects and even make enterprises form excessive reliance on policies [13]. Similarly, Zhang et al. find that while government subsidies can reduce manufacturers' transition costs and increase digital benefits, excessive subsidies can create financial burden on governments and may ultimately hinder the progress of digital transformation process [14]. Therefore, how to formulate reasonable, dynamically adjustable and highly practical policy measures has gradually turned into a key direction in current academic research.

Since approximately the early 2010s, a growing number of scholars have turned to evolutionary game theory to study government–enterprise interactions. Findings show that government incentives, transformation costs and expected returns all affect the evolving trend of the whole interactive system [15]. Under the multi-agent framework, the strategic game behaviors among local governments, core enterprises and small and medium-sized enterprises will further affect the synergy effect of transformation [16]. Other dynamic game studies point out that the government needs to flexibly adjust its supporting strategies according to the responses of enterprises, so as to reach a stable equilibrium in the long run [17]. By constructing a stochastic evolutionary game model involving core manufacturing enterprises, suppliers, and local government, Yi et al. also find that the dynamic incentive effect of the government is better than the static incentive [18], which reminds us to adjust policies on time. In addition, stochastic evolutionary games, differential games, and other methods have been applied to analyze strategy selection in transformation [19]. Through a tripartite evolutionary game model, Zhang et al. reveal the essential role of government support for high-quality SME development [20]. These studies provide important references for understanding government-enterprise collaboration mechanisms and the method is particularly relevant and suitable for our research because digital transformation involves bounded-rational actors. The government and enterprises cannot instantly optimize their strategies, rather, they adjust their behavior through trial, learning and observation of each other's behavior. Evolutionary game theory is based on the dynamic adjustment process, allowing us to model how the system evolves with AI technology maturity.

However, enterprises still face many difficulties in the process of transformation. For manufacturing businesses in particular, insufficient funds, talent shortages, high technical barriers and unclear practical paths all severely hold back their in-depth digital reform [21]. In addition, many enterprises can' t afford the huge expenditure brought by transformation due to insufficient resources. Under such circumstances, most of them choose to stand by and wait for opportunities, or merely conduct superficial transformation [22]. Such practical problems are especially obvious among small and medium-sized enterprises, which further cause evident gaps in digital reform progress across different regions and different types of enterprises [23]. For instance, Boonmee et al. confirm that financial constraints, workforce skill shortages and poor data quality are major obstacles to SME's AI adoption [24]. Moreover, during external crises, new technologies can either accelerate digital transformation or exacerbate the digital divide among SMEs [25].

Luckily, research has found that artificial intelligence, as a core new-generation technology, plays a key enabling role in digital transformation. This finding supports our model's assumption that AI technology maturity reduces transformation costs and increases benefits. As artificial intelligence grows increasingly mature in practical application, the overall expense of digital reform keeps going down, while the foreseeable economic benefits keep rising steadily. This change effectively strengthens the endogenous motivation of enterprises to take the initiative to transform [26], which inspires us to study at what level of AI maturity enterprises will spontaneously transform. Relevant studies also reveal that mature AI technology can help enterprises break through various development bottlenecks and finally accomplish in-depth digital and intelligent upgrading. This fully demonstrates the importance of enhancing the maturity of AI technology, and offers implications for policymakers seeking to promote sustainable entrepreneurship.

Although existing studies have achieved fruitful results, they still have limitations: (1) Most studies only focus on the overall impact of digital transformation without deeply analyzing how AI technology maturity reshapes transformation costs and benefits. (2) Most studies focus on static policy effects or individual enterprise decisions, without integrating government policy adjustment and enterprise transformation into a unified dynamic evolutionary framework, making it difficult to reveal their co-evolution laws with technological maturity.

The marginal contributions of this paper are as follows: (1) Based on policy optimization, this paper assumes that government policies adjust dynamically with AI technology maturity, and explores the impact of dynamic policies on digital transformation of small and medium-sized manufacturing enterprises, breaking through the limitation of static policy analysis and expanding the research perspective. (2) By introducing AI technology maturity into the evolutionary game model as a continuous moderating variable, this paper quantifies its asymmetric impact on transformation costs and benefits, providing a quantifiable theoretical basis for the adaptive evolution of policy tools. (3) By changing parameters, this paper simulates distinct evolutionary paths in different regions, demonstrates the ineffectiveness of "onesize-fits-all" policies, and provides a quantitative basis for regionally differentiated policies.

2. Materials and Methods

To investigate how AI technology maturity shapes the strategic interactions between local governments and manufacturing enterprises, we construct an evolutionary game model. Local governments and manufacturing enterprises are assumed to be bounded rational players, who dynamically adjust their strategies through trial and error and learning.

2.1. Model Assumptions

(1) Enterprises can choose "active transformation" or "passive waiting". Active transformation means that enterprises invest abundant capital, talent and other resources to carry out in-depth digital transformation with AI technology. Passive waiting means that enterprises continue traditional production modes or only carry out superficial informatization due to financial constraints and technical barriers. The cost incurred by enterprises for active transformation is C_e. It is assumed that all enterprises choosing active transformation will succeed and obtain benefits R_e after successful transformation. If enterprises choose passive waiting, they may face potential losses L. Regardless of whether enterprises transform or not, they receive a subsidy S when the government adopts the "strong incentives" strategy, and no subsidy when the government adopts "routine guidance".

(2) The government's strategy set includes "strong incentives" and "routine guidance". Strong incentives mean that the government fully promotes digital transformation of small and medium-sized manufacturing enterprises through high subsidies, tax reductions and preferential procurement. Routine guidance means that market forces play a greater role in digital transformation, and the government only provides basic public services. The cost incurred by the government for strong incentives is C_g. If enterprises transform actively, they will bring macro benefits R_g to the government, and the government can also obtain additional performance gains B. If the government fails to act effectively, it will face potential costs F, including losses from delayed industrial upgrading and diminished policy credibility.

(3) AI technology refers to advanced technologies with R&D bottlenecks, such as full-process digital twins, global intelligent scheduling and dynamic market prediction. Its maturity θ is a key moderating variable ranging from 0 to 1. A higher θ indicates more advanced comprehensive technology in algorithm maturity, data availability and computing cost, making AI easier to apply for small and medium-sized enterprises. α is the benefit elasticity coefficient: the larger α is, the stronger the amplification effect of AI on benefits. The smaller α is, the more AI mainly reduces costs with limited improvement in benefits.

The relevant variables in the above assumptions are explained in **Table 1**.

2.2. Payoff Matrix and Expected Returns

According to the model assumptions, the two-party game payoff matrix under the government's strong incentive and routine guidance strategies is shown in **Table 2**.

Table 1. Variable description.

Symbol	Meaning and Explanation
R_g	Macro benefits obtained by the government when enterprises successfully transform
C_g	Policy cost of the government implementing the "Strong Incentive" strategy
B	Extra performance gains for the government when enterprises transform actively and the government provides strong incentives ($B > 0$)
F	Potential cost of government inaction
R_e	Basic benefits of enterprises after successful transformation
C_e	Basic cost of enterprises carrying out "Active Transformation"
θ	AI technology maturity ($0 \leq \theta \leq 1$)
α	Benefit elasticity coefficient ($\alpha > 0$)
S	Subsidy received by enterprises under government "Strong Incentive" ($S > 0$); no subsidy under "Routine Guidance"
L	Potential loss if enterprises choose "Passive Waiting"

Table 2. Payoff matrix.

Government Strategy		Strong Incentive (y)	Routine Guidance (1 - y)
Enterprises Strategy	Active transformation (x)	$R_e(1+\alpha\theta)-C_e(1-\theta)+S$ R_g+B-C_g	$R_e(1+\alpha\theta)-C_e(1-\theta)$ R_g
	Passive waiting ($1-x$)	$S-L$ $-C_g$	$-L$ $-F$

Assuming the probability of enterprises choosing active transformation is x, then the probability of choosing passive waiting is $1-x$; The probability of the government choosing strong incentives is y, and the probability of choosing routine guidance is $1-y$, with $0 \leq \{x, y\} \leq 1$. When enterprises choose active transformation and passive waiting, respectively, the expected returns are shown in Equations (1) and (2):

$$U_{11} = R_e\ (1+\alpha\theta) - C_e\ (1-\theta) + yS \tag{1}$$

$$U_{12} = yS - L \tag{2}$$

Based on Equations (1) and (2), the replicator dynamic equation for enterprises' active transformation strategy is shown in Equation (3):

$$F_{(x)} = x(1-x)(U_{11} - U_{12}) \tag{3}$$

When the government chooses to incentivize strongly or guide routinely, the expected benefits are shown in Equations (4) and (5):

$$U_{21} = x(R_g + B) - C_g \tag{4}$$

$$U_{22} = x(R_g + F) - F \tag{5}$$

The replication dynamic equation of the government when choosing strong incentives is shown in Equation (6):

$$F_{(y)} = y(1-y)(U_{21} - U_{22}) \tag{6}$$

2.3. Simulation Setup

We use Python to further simulate the strategy selection process of enterprises and the government. The initial probability for enterprises to choose active transformation strategy and the government to choose strong incentive strategy were set to $[x, y] = [0.4, 0.5]$. Parameter values for different scenarios are specified in Section 3.2 where each simulation result is presented.

3. Results

3.1. System Stability Analysis

By combining the replication dynamic equations of enterprises and the government, the three-dimensional replication dynamic system equation of the evolutionary game model can be obtained:

$$\begin{cases} F_{(x)} = \dfrac{dx}{dt} = x(1-x)[R_e(1+\alpha\theta) - C_e(1-\theta) + L] \\ F_{(y)} = \dfrac{dy}{dt} = y(1-y)[x(B-F) - C_g + F] \end{cases} \tag{7}$$

To obtain the equilibrium point of this system, let $\begin{cases} F_{(x)} = 0 \\ F_{(y)} = 0 \end{cases}$, it is easy to know that there are 4 pure strategy equilibrium points in the defined domain $\Omega = \{0 \leq x \leq 1, 0 \leq y \leq 1\}$, namely: $M_1(0,0)$, $M_2(0,1)$, $M_3(1,0)$ and $M_4(1,1)$. Define the net transformation benefit parameter $A = R_e(1+\alpha\theta) - C_e(1-\theta) + L$. From $F_{(x)}$, when $A > 0$, $dx/dt > 0$ and enterprises tend to choose active transformation. When $A < 0$, $dx/dt < 0$ and enterprises tend to choose passive waiting. It can be seen that AI technology maturity θ, by affecting the value of parameter A, becomes a key factor changing the system's evolutionary path.

According to the system stability discrimination method[27,28], the local stability of the equilibrium point of the dynamic system can be determined by the corresponding eigenvalues of its Jacobian matrix. If all eigenvalues of the matrix are negative real numbers, then (x_0, y_0) is called the asymptotic stable equilibrium point of the dynamic system.

The Jacobian matrix corresponding to the dynamic system can be expressed as:

$$J = \begin{bmatrix} (1-2x)[R_e(1+\alpha\theta) - C_e(1-\theta) + L] & 0 \\ y(1-y)(B-F) & (1-2y)[x(B-F) - C_g + F] \end{bmatrix} \tag{8}$$

From the above analysis, the system may have four pure strategy equilibrium points. We first discuss the condition that the system satisfies asymptotic stability at $M_1(0,0)$, where the Jacobian matrix is as follows:

$$J_{M_1} = \begin{bmatrix} R_e(1+\alpha\theta) - C_e(1-\theta) + L & 0 \\ 0 & -C_g + F \end{bmatrix} \tag{9}$$

When $A < 0$ and $F < C_g$, all eigenvalues of J_{M_1} are negative, and $M_1 = (0,0)$ is the unique Evolutionary Stable Strategy (ESS). In this scenario, the net transformation benefit is negative, meaning the benefits of active transformation cannot cover the costs. Meanwhile, the government's potential cost of inaction is less than the incentive cost, so the government lacks motivation to incentivize enterprises. Thus, enterprises tend to wait passively and the government tends to provide routine guidance, locking the system in an ineffective "double-low equilibrium". To avoid this ineffective state, measures can be taken in two aspects: first, improve AI technology maturity through R&D subsidies and demonstration projects to increase enterprises' net transformation benefit. Second, increase the government's inaction cost through assessment and accountability mechanisms to make it higher than the incentive cost.

Similarly, we discuss the condition that the system satisfies asymptotic stability at $M_2(0,1)$. When $A < 0$ and $F > C_g$, all eigenvalues of J_{M_2} are negative, and $M_2 = (0,1)$ is the unique ESS. In this scenario, the net transformation benefit remains negative, and the high inaction cost forces the government to adopt strong incentives. However, due to the lack of endogenous economic motivation, enterprises still tend to wait passively despite strong government incentives. To reverse this situation, the key is to improve AI technology maturity to turn the net transformation benefit from negative to positive. Simply increasing government incentives without improving technology maturity will lead to inefficient use of fiscal funds and diminishing policy effects.

Third, we discuss the condition that the system satisfies asymptotic stability at $M_3(1,0)$. When $A > 0$ and $B < C_g$, all eigenvalues of J_{M_3} are negative, and $M_3 = (1,0)$ is the unique ESS. In this scenario, high AI maturity brings positive net transformation benefits, giving enterprises endogenous motivation for digital transformation. However, the government's extra performance gains from incentives are less than the incentive cost, making incentives economically inefficient. Therefore, enterprises spontaneously choose active transformation while the government chooses routine guidance, forming a healthy market-driven state.

Finally, we discuss the condition that the system satisfies asymptotic stability at $M_4(1,1)$. When $A > 0$ and $B > C_g$, all eigenvalues of J_{M_4} are negative, and $M_4 = (1,1)$ is the unique ESS. At this time, enterprises have positive net transformation benefits, and the government's incentive benefits exceed costs. Enterprises transform actively and the government provides strong incentives, forming a virtuous circle of government-enterprise collaboration. This scenario is an ideal state after technological maturity. In this state, the government should follow the trend, shift from strong incentives to routine guidance, focus on public services and market environment improvement, and let market mechanisms play a decisive role in resource allocation.

The results of the discussion above are shown in **Table 3**.

Table 3. Local stability analysis of system equilibrium points.

Equilibrium	Eigenvalue Symbol	Stability
$M_1(0,0)$	When $A < 0$ and $F < C_g$, all negative values	Asymptotic stable point
$M_2(0,1)$	When $A < 0$ and $F > C_g$, all negative values	Asymptotic stable point
$M_3(1,0)$	When $A > 0$ and $B < C_g$, all negative values	Asymptotic stable point
$M_4(1,1)$	When $A > 0$ and $B > C_g$, all negative values	Asymptotic stable point

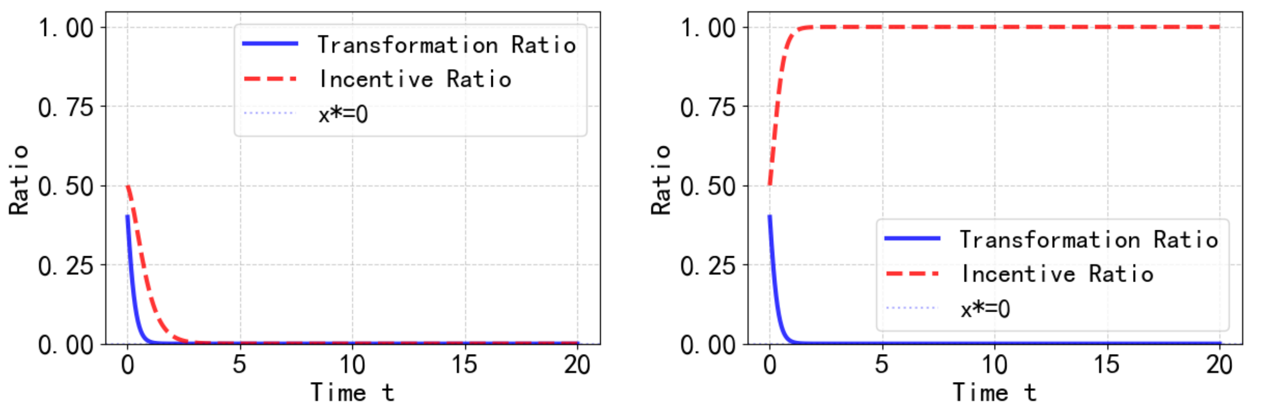
From the above scenarios, AI technology maturity θ is the key variable driving the system from policy dependence to endogenous drive. Define the critical technology maturity $\theta^* = (C_e - R_e - L)/(\alpha R_e + C_e)$. When $\theta < \theta^*$, $A < 0$ and the system is in the policy-driven stage. Policies should focus on R&D support, pilot demonstrations and infrastructure investment to improve AI maturity. When $\theta > \theta^*$, $A > 0$ and the system is in the endogenous-driven stage. Policies can shift to optimizing market environment, formulating standards and cultivating talents.

3.2. Simulation Analysis

3.2.1. Developed Regions

We divide AI technology maturity into three levels: low, medium, and relatively high. Based on this, we set two scenarios by adjusting the relationship between the government's potential inaction cost F and the policy cost C_g of implementing a "strong incentive" strategy: routine guidance and strong government incentives. When $F < C_g$, the government faces low pressure to provide strong incentives, corresponding to the "routine guidance" scenario. When $F > C_g$, the government faces high pressure to provide strong incentives, corresponding to the "strong incentives" scenario.

From **Figure 1**, we can see that when AI maturity is low, the trajectories converge to $(0, 0)$ or $(0, 1)$. The government eventually chooses either routine guidance or strong incentives based on the pressure of potential costs, while enterprises consistently choose passive waiting. This indicates that, regardless of government efforts, the benefits of transformation remain far lower than the benefits of maintaining the status quo. Government subsidies have no effect on enterprises' willingness to transform, and the system is locked in a state where policy-driven efforts are weak and endogenous motivation cannot be formed.

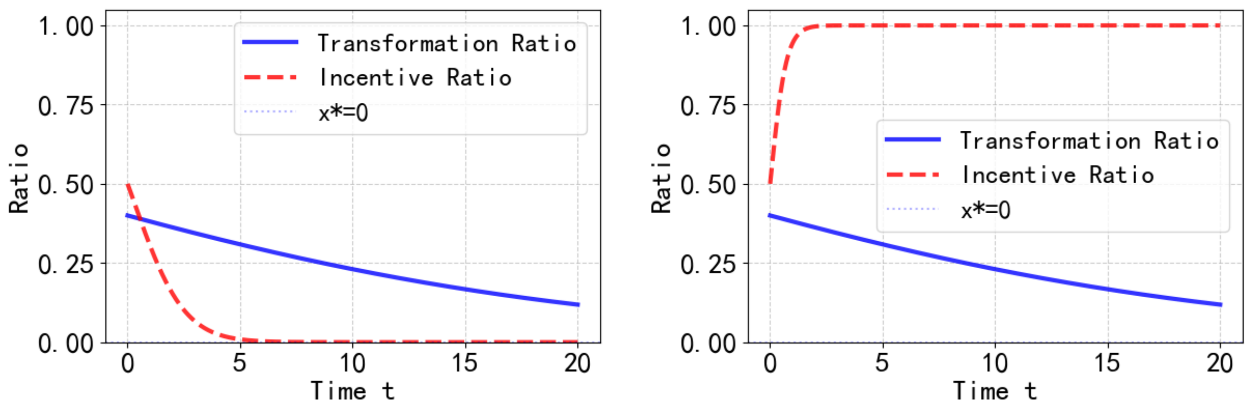


(a) **(b)**

Figure 1. Evolutionary game under low AI technology maturity. (**a**) Routine guidance with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 4, C_g = 6, \theta = 0.3$; (**b**) Strong incentives with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 10, C_g = 6, \theta = 0.3$.

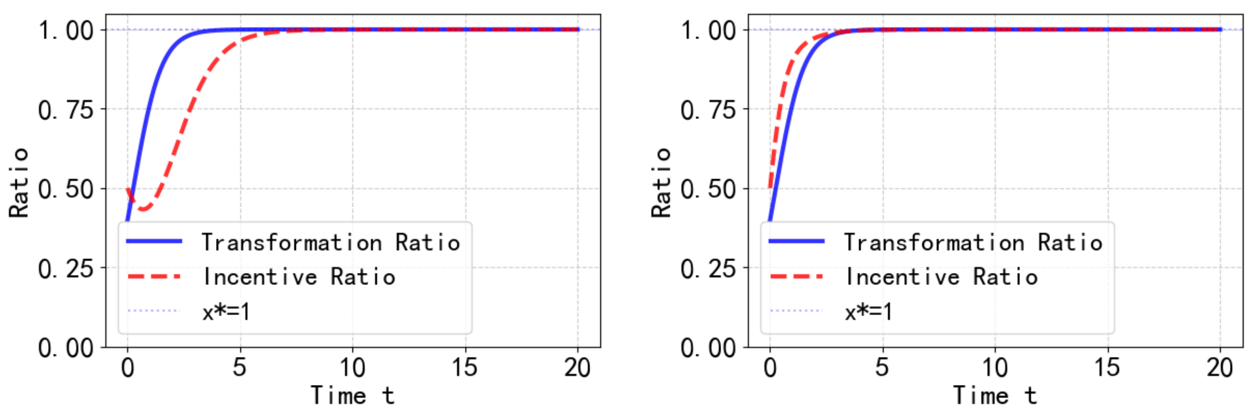
From **Figure 2**, we can see that when AI maturity is medium, the trajectories still end up at either $(0, 0)$ or $(0, 1)$. In this situation, enterprises still tend to wait passively. However, due to the modest gains from transformation starting to add up, the drop in enterprises' willingness to act becomes much slower. This slowdown occurs because the net transformation benefit parameter $A = R_e(1 + \alpha\theta) - C_e(1 - \theta) + L$ is gradually approaching zero from a negative value. As A approaches zero, the potential loss from waiting and the gains from transformation begin to offset the transformation cost. Consequently, some enterprises begin to embrace the development of AI technology, conduct pilot projects or make small-scale investments. However, based on consideration of risks, most enterprises still decide to wait until A becomes positive before making a full-scale transformation. At this stage, the government's policies are extremely crucial. Since government subsidies S cannot directly affect A, therefore, providing more subsidies will not have a fundamental impact on the outcome. So, governments should invest in AI infrastructure like computing centers and open datasets to further reduce transformation cost C_e, or improve firms' AI absorption capacity through formal training.

From **Figure 3a**, we can see that under the routine guidance scenario, the enterprise transformation ratio quickly converges from an initial value of 0.4 to 1. This shows that at high AI maturity, the net benefit of transformation turns positive, forming endogenous driving force without the need for strong government intervention. The government incentive ratio shows a pattern of "initial slight decline followed by a rapid rise". A possible reason is that the government initially adopts a wait-and-see attitude due to unclear enterprise willingness to transform. As the transformation trend becomes apparent, the government adjusts its strategy accordingly and eventually chooses strong incentives, forming positive coordination with enterprise behavior. From **Figure 3b**, we can see that under the strong incentives scenario, the enterprise transformation ratio also converges rapidly to 1 and the government has no wait-and-see phase; the incentive ratio directly converges from 0.5 to 1, with a faster-rising curve. This indicates that under high accountability pressure, the government directly responds to the enterprise transformation trend.



(a) **(b)**

Figure 2. Evolutionary game under medium AI technology maturity. (**a**) Routine guidance with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 4, C_g = 6, \theta = 0.52$; (**b**) Strong incentives with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 10, C_g = 6, \theta = 0.52$.



(a) **(b)**

Figure 3. Evolutionary game under relatively high AI technology maturity. (**a**) Routine guidance with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 4, C_g = 6, \theta = 0.6$; (**b**) Strong incentives with parameters $R_e = 5, C_e = 18, L = 2, \alpha = 0.6, B = 7, F = 10, C_g = 6, \theta = 0.6$.

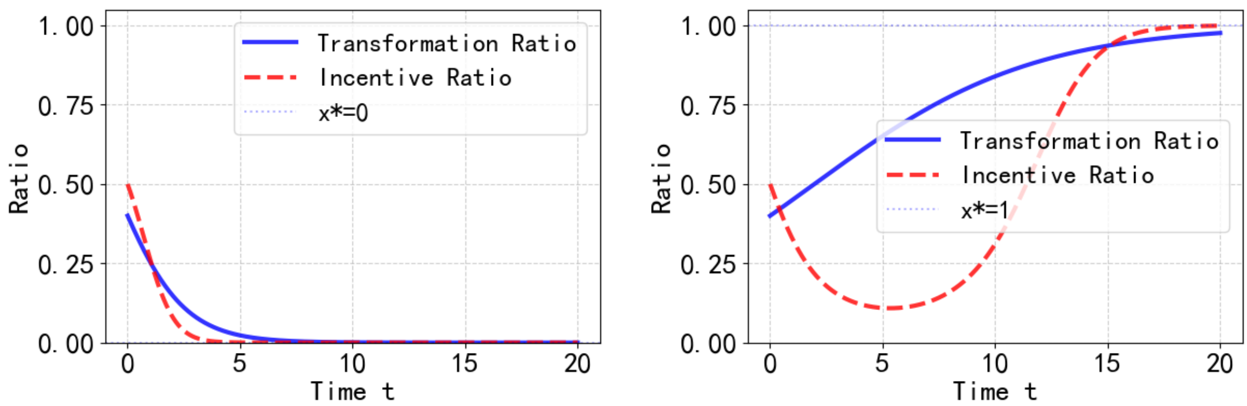
A comparison of the two scenarios shows that when AI maturity exceeds the critical threshold, the endogenous motivation for enterprise transformation is sufficiently strong. External policy pressure is no longer a key constraint on government behavior, and the government can smoothly transition from “strong incentives” to “routine guidance”, achieving a virtuous cycle of government-enterprise coordination.

3.2.2. Underdeveloped Regions

Compared with developed regions, underdeveloped regions lack digital infrastructure such as computing centers and have low public data openness, which greatly reduces AI application effects. Thus, enterprises face higher basic costs for active transformation. Meanwhile, underdeveloped regions have low AI technology conversion efficiency and insufficient local market demand, so AI has a weaker amplification effect on manufacturing benefits and enterprises gain lower basic benefits after successful transformation.

From the simulation results of developed regions, government incentive intensity is not the main factor affecting digital transformation. When AI maturity exceeds the critical threshold, enterprises transform spontaneously even under routine government guidance. In addition, due to the low fiscal self-sufficiency rate, weak corporate profitability and high expenditure on public services in underdeveloped regions, there is a huge funding gap in these areas and it is not realistic for the government to provide strong incentives for them in the long term. Therefore, we only conduct numerical simulation under routine government guidance, and we believe the results can alleviate the government's financial pressure and have practical significance.

From **Figure 4**, we can see that when $\theta = 0.7$, the system trajectory converges to $(0, 0)$, and enterprises finally tend to wait passively; when $\theta = 0.74$, the trajectory converges to $(1, 1)$, and most enterprises choose active transformation, forming endogenous drive. Compared with developed regions, it can be seen that underdeveloped regions have a higher critical value of AI maturity. This means that simply raising AI maturity in underdeveloped regions to the level of developed regions has little effect on local manufacturing enterprises' willingness to transform. Therefore, for underdeveloped regions, governments should formulate differentiated policies and invest more resources to improve AI technology maturity.



(a) **(b)**

Figure 4. Evolutionary game under government routine guidance. (**a**) Low AI Technology Maturity with parameters $R_e = 3, C_e = 21, L = 2, \alpha = 0.3, B = 7, F = 4, C_g = 6, \theta = 0.7$; (**b**) Relatively High AI Technology Maturity with parameters $R_e = 3, C_e = 21, L = 2, \alpha = 0.3, B = 7, F = 4, C_g = 6, \theta = 0.74$.

3.2.3. Sensitivity Analysis

Since the critical threshold of AI technology maturity is higher in underdeveloped regions, requiring a greater technological breakthrough to achieve transformation, we conduct the sensitivity analysis based on the benchmark of underdeveloped regions.

(1) Sensitivity to Transformation Cost C_e

Taking the parameters of underdeveloped regions ($\theta = 0.74$, $R_e = 3$, $\alpha = 0.3$, $L = 2$) as the reference, we conduct the sensitivity analysis of C_e, and the results are shown in **Figure 5a**.

Taking representative curves as examples, when $C_e = 21.0$, the enterprise transformation ratio shows a monotonically increasing trend, converging to 1. As C_e increases, the rising speed of the curve gradually slows down. When $C_e = 21.8$, the curve approaches a horizontal trend, with the transformation ratio showing a declining tendency. When $C_e = 22.0$, the curve becomes monotonically decreasing, and the enterprise transformation ratio continuously declines over time, converging to 0. As C_e further increases, the declining speed of the curve gradually accelerates.

The above phenomena indicate the existence of a critical cost threshold. When C_e is below this threshold, transformation is economically feasible, and enterprises can achieve positive returns through sustained transformation. When C_e is above this threshold, the transformation cost exceeds what enterprises can bear, making transformation difficult even with high AI technology maturity. Therefore, reducing transformation costs is a fundamental prerequisite for promoting digital transformation in underdeveloped regions.

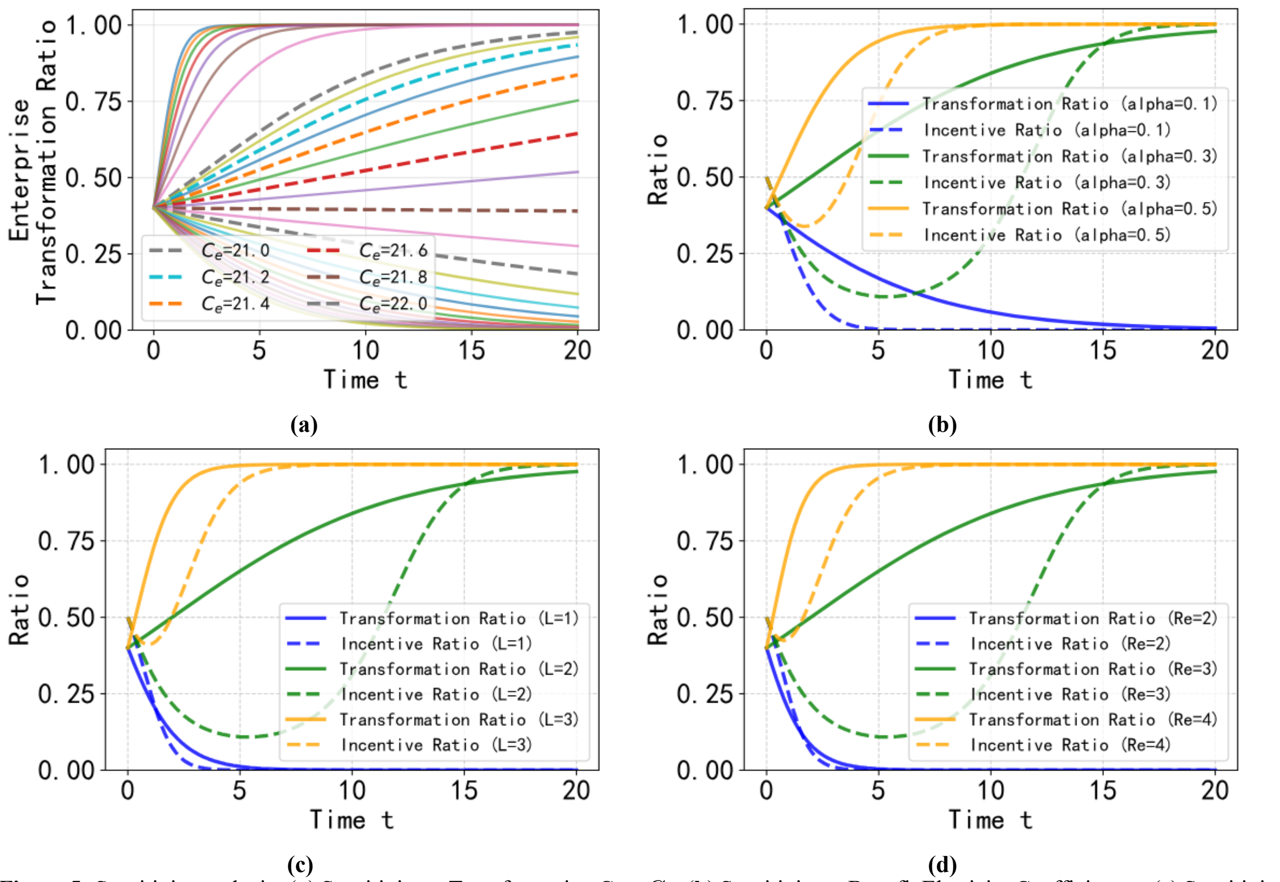


Figure 5. Sensitivity analysis. (**a**) Sensitivity to Transformation Cost C_e; (**b**) Sensitivity to Benefit Elasticity Coefficient α; (**c**) Sensitivity to Waiting Loss L; (**d**) Sensitivity to Transformation Benefit R_e.

(2) Sensitivity to Benefit Elasticity Coefficient *α*

Taking the parameters ($\theta = 0.74$, $C_e = 21$, $R_e = 3$, $L = 2$) as the reference, the sensitivity analysis of α is conducted, and the results are shown in **Figure 5b**.

When $\alpha = 0.1$, the enterprise transformation ratio continuously declines from its initial value of 0.4 to 0, resulting in transformation failure. When $\alpha = 0.3$, the enterprise transformation ratio steadily increases and converges to 1. As α further increases, the rising speed of the transformation ratio gradually accelerates.

This result indicates that α has a critical threshold. When α is below this threshold, the amplification effect of AI technology on returns is insufficient. Even with high technology maturity, enterprises find it difficult to obtain adequate economic returns and thus choose to maintain the status quo. When α exceeds this threshold, the technological returns are fully released, and enterprises' willingness to transform significantly strengthens. Therefore, simply improving AI technology maturity without enhancing enterprises' ability to absorb and transform technology may still lead to transformation failure.

(3) Sensitivity to Waiting Loss *L*

From **Figure 5c**, we can see that the waiting loss L also has a critical threshold. When L is below this threshold, the loss from not transforming is relatively small, and waiting becomes the dominant strategy. When L exceeds this threshold, market competition pressure, customer churn risk, and other factors force enterprises to actively transform. Therefore, the government can indirectly increase the potential loss of not transforming by intensifying market competition, raising industry standards, and promoting the upgrading of customer demand, thereby forcing enterprises to proactively undergo digital transformation.

(4) Sensitivity to Transformation Benefit *R_e*

Figure 5d shows that transformation benefit R_e also has a critical threshold effect. When R_e is below the critical value, the direct economic returns from digital transformation are insufficient to cover the transformation costs, and enterprises choose passive waiting. When R_e exceeds the critical value, enterprises actively transform. Thus, only when enterprises can obtain sufficient economic returns from transformation will the transformation be sustainable. Therefore, the government should increase the actual returns of enterprises after digital transformation and enhance the economic attractiveness of transformation by exploring market demand, optimizing industrial supporting facilities, and promoting supply chain coordination.

Based on the above analysis, the digital transformation of underdeveloped regions cannot rely solely on improving AI technology maturity. The government should adopt multiple measures to form a combined approach of reducing costs, enhancing capabilities, increasing pressure and creating returns. Only when costs are affordable, capabilities keep pace, pressure is sufficient, and returns are guaranteed will enterprises truly shift from "passive waiting" to "active transformation".

4. Conclusions

In the context of the accelerated development of AI, we construct a two-population evolutionary game model between enterprises and the government and simulate the behavior strategy game and learning process of them. By defining the critical value θ^* of AI technology maturity, we divide AI technology maturity into low, medium and relatively high levels. Finally, we use Python software to simulate further and analyze the impact of AI technology maturity on the system evolution process. We think these findings merit further discussion:

1. Our results show that AI technology maturity is a "threshold condition" for digital transformation. When AI technology maturity θ is below the critical value θ^*, the net transformation benefit of enterprises is negative. Regardless of whether the government adopts strong incentives or routine guidance, enterprises tend to choose "passive waiting", and the system faces a dilemma of weak policy-driven incentives and insufficient endogenous motivation. This result matches with Chen's research [13], which pointed out an inverted U-shaped relationship between government intervention and enterprise innovation. In other words, additional subsidies will yield diminishing returns when the actual AI technology maturity is below the threshold. Instead, when θ exceeds the critical value, the net transformation benefit turns from negative to positive. It means that even without government subsidies, enterprises will spontaneously transform due to higher expected returns, forming an "endogenous driving force". Based on this result, we think policy efforts are better directed at raising AI maturity rather than at subsidizing reluctant enterprises before AI reaches a certain maturity level.
2. The threshold value of AI technology maturity presents obvious regional differences. The critical threshold of developed regions is approximately 0.52. By contrast, restricted by imperfect digital infrastructure, low technical conversion efficiency and inadequate market demand, the critical threshold in underdeveloped areas reaches around 0.73. We think this finding resonates with the technology-organization-environment framework discussed by Xu [9], which means the effect of policies is closely related to the regional environment and comprehensive development level. So, merely lifting the local AI technology maturity to match the standard of developed areas can hardly effectively stimulate the digital transformation intention of local enterprises.
3. Successful digital transformation cannot merely rely on enhancing the maturity of AI technology. According to the results of sensitivity analysis, apart from AI technology maturity, we discover that enterprise transformation cost, benefit elasticity coefficient, waiting loss and transformation benefit all possess critical threshold characteristics. These core parameters affect the net benefit gained by enterprises, and further exert indirect influences on the evolutionary trend between government and enterprises. As Kovič et al. [21] noted, manufacturing firms face multiple practical obstacles including insufficient funds, talent shortages and high technical barriers. If we just address only one of these while ignoring others, we' re unlikely to succeed. So, we suggest that local governments formulate diversified and comprehensive strategies because single-type policy regulation is far from enough to drive system

optimization.

Based on the above findings, we propose the following policy recommendations:

1. Governments should roll out targeted development plans, focus on tackling core technologies and cultivating high-end professional talents, so as to steadily elevate the overall social maturity level of AI technology.
2. Along with the gradual upgrading process of AI technology maturity, local governments need to adjust and optimize existing policy instruments in a dynamic manner. For instance, policy focus should gradually shift from relying on high financial subsidies to offset high transformation costs, toward establishing a standardized and equitable market operation environment.
3. For developed and underdeveloped regions, governments should implement differentiated policies, tilting resources and policy priorities toward underdeveloped regions, and focusing on improving their AI technology maturity and related supporting capabilities. Especially for underdeveloped regions, we suggest that the government build a regional public computing power platform and promote industry data sharing at the same time to lower the threshold for enterprises to use AI. Besides, the government can screen several leading enterprises with the willingness to transform and focus on assisting them in their digital transformation. After the successful pilot, refine its transformation model and promote it throughout the industry, thereby allaying the concerns of other enterprises. We also suggest that the government provide AI-driven foreign trade process services for enterprises, including multilingual AI translation, compliance risk early warning, cross-border logistics optimization and so on, to promote the connection between local industries and global supply chains and enhance international competitiveness.

To be honest, our model also has some limitations. Firstly, our model assumes all actively transforming enterprises can achieve success, but this is not always the case in reality. Secondly, our model didn’ t take third parties like technology suppliers into consideration. However, the actual situation will be more complex than the model we have set. Thirdly, we didn’ t distinguish the heterogeneous characteristics across different manufacturing sub-industries. The promoting effect of AI on the digital transformation of different industries varies, and various industries differ significantly in AI application scenarios, transformation cost structures and technology absorption cycles. The parameter settings of our model fail to fully reflect this industry heterogeneity. Future research should extend the current framework to disaggregate manufacturing into sector-specific subgroups to capture heterogeneous transformation pathways.

Author Contributions

Conceptualization, F.S. and Y.Z.; methodology, F.S. and Y.Z.; software, Z.Z. and Y.Z.; formal analysis, F.S., Z.Z. and Y.Z.; resources, F.S.; data curation, Y.Z.; writing—original draft preparation, F.S. and Y.Z.; writing—review and editing, F.S., Z.Z. and Y.Z.; supervision, F.S. and Z.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely for language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were critically reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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