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Original scientific paper

Multi-Agent Collaborative R&D Strategies of General-Purpose Technologies: Commonality and Synergy Perspective

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Abstract: New round of emerging scientific and technological revolution mingled with industrial revolution has intensified the competition among countries for general-purpose technologies (GPTs), as they attempt to strengthen their strategic layout and seize decisive development opportunities. However, in reality, the collaborative R&D of GPTs by multiple subjects often fails, thereby leading to the low success rate of GPTs. To identify the influencing factors of multi-agent collaborative R&D GPTs, an evolutionary game model of multi-agent collaborative R&D based on types of GPTs and the degree of synergy among multiple agents was constructed in this study. The multi-agent collaborative R&D strategies under the two scenarios with and without government participation were then explored, and MATLAB numerical simulation was performed to compare the influence of different types of GPTs and the degree of synergy under government strategies and measures on multi-agent collaborative R&D strategies. Results show that: (1) in the R&D process of basic, pre-competitive and applied GPTs, the degree of synergy required for multi-agent cooperation gradually decreases, and the focus of synergy also changes along with types of technologies. (2) In the R&D process of basic GPTs, when the degree of synergy is higher than the critical value, the willingness of enterprises to conduct R&D decreases and then increases in a "U-shaped" trend as the willingness of universities and research institutes (UR) to conduct R&D increases. In the R&D process of pre-competitive GPTs, when the degree of synergy is lower than the critical value, the willingness of UR to conduct R&D increases and then decreases in an "inverted U" trend as the willingness of enterprises to conduct R&D decreases. In the R&D process of all three types of GPTs, government participation is particularly effective, and when the degree of synergy is much higher than the critical value, the willingness of enterprises to engage in R&D increases. (3) In the case of government participation, the proportion of subsidies, the strength of knowledge protection and the degree of synergy among multiple subjects are adjusted by the government in line with the importance of GPTs to act on precise policies. To some extent, conclusions provide theoretical basis and policy suggestions for industry-university-research collaborative R&Ds of GPTs and government measures.

Keywords: commonality degree; evolutionary game; general-purpose technologies; multi-agent collaborative R&D; synergy degree

1 INTRODUCTION

Looking back on previous industrial revolutions, developed countries, such as the United Kingdom, the United States, Germany, and Japan, have completed industrialization through engineering technology. At present, countries around the world are facing the fourth industrial revolution. The innovation and breakthroughs of key general-purpose technologies (GPTs), such as artificial intelligence, 5G, big data, and blockchain, can help these countries improve their independent innovation capabilities and complete their industrial transformation and upgrading [1]. Given their leading and supporting roles in driving innovation [2], GPTs can form leading advantages in some key technical fields, hence leading to their very important position across all countries.

Actually, GPTs, as pre-competitive general-purpose technologies, are characterized by high R&D costs, high uncertainty, high knowledge spillover, long investment cycles, multiple innovation subjects, and high requirements for collaboration among the participants [3, 4], hence preventing individual enterprises or research institutions from making individual breakthroughs in their R&D of GPTs given their tendency to encounter market, organizational, and diffusion failures [5, 6]. A collaborative R&D among industry, university, and research, communities as organized and mobilized by the government can bring into play the advantages of multi-agent complementary resources and shared benefits, reduce the R&D costs and risks for the participating individuals, and alleviate the R&D failure phenomenon to a certain extent [7]. Each type of GPTs has a unique set of characteristics, and the failure of the government to intervene properly can lead to the "government absence" or "government overreach" phenomenon [8]. To address these difficulties, the measures that the government can adopt to mitigate the negative impact of these characteristics on the decision-making behavior of participants for different types of GPTs must be identified, and the advantages of multi-agent collaborative R&D of GPTs should be expanded.

In this study, a commonality degree is employed to classify different types of GPTs, whereas a synergy degree is used to measure the degree of synergistic innovation among multiple agents. Considering the two cases with and without government participation, an evolutionary game model is constructed to identify the evolutionary stable strategies adopted by the government for the dynamic game among the participating subjects under the above cases, and a MATLAB numerical simulation is conducted to compare and analyze the effects of different types of GPTs, the degree of synergy under government strategies, and the changes in the collaborative R&D strategies of multiple agents as triggered by government measures to provide theoretical basis and policy recommendations for the collaborative R&D GPTs among multiple agents.

The rest of this study is organized as follows. Section 2 reviews the relevant literature on GPTs. Section 3 presents the construction and basic assumptions of the evolutionary model of the multi-agent dynamic game. Section 4 analyzes and discusses multi-agent collaborative R&D strategies. Section 5 concludes this study.

2 LITERATURE REVIEW

The concept of GPTs was introduced by Tassey, who classified technologies into basic, general-purpose, and proprietary technologies using the Technology Development Model and the Economic Growth Model of Technology [9]. Subsequently, GPTs have been defined by scholars from three perspectives, namely, stage of development, area of coverage, and scope of impact, and further subdivided these technologies using different criteria [10]. GPTs are located in the middle ground between government and profit-making organizations, such as enterprises; in other words, these technologies are placed at the front end of basic scientific research and the end of commercial applications, hence introducing both market and technological uncertainties; enterprises are therefore exposed to high risks and high discount rates in the R&D process, which would result in under-investment and market failure [11, 12]. Moreover, the property rights of GPTs, which are considered "quasi-public goods", are generally difficult to define, and enterprises do not have exclusive access to the results and benefits of GPTs [13]. GPTs also have strong externalities (sharing), which can reduce the motivation in the R&D process of GPTs. The technical characteristics of GPTs are also prone to failures in the R&D process, but their economic and social benefits are very large [14] as they can enhance the production efficiency of an entire industry through diffusion [15] and consequently promote industrial development and economic growth [16]. Therefore, in-depth research on the characteristics of GPTs presents great practical significance for the R&D of GPTs at this stage.

Due to their technical characteristics, GPTs require multi-agent cooperation in their R&D, and a collaborative innovation among industry, university, and research practitioners, as a cross-organizational cooperation model that links science and technology innovation with technology commercialization [17], has been highly valued by countries around the world for more than 30 years. This collaboration is highly conducive to improving the absorptive capacity of enterprises and promoting their learning and recreation of knowledge [18]. However, given the heterogeneity among subjects in the process of collaborative R&D, the motivation behind and behavioral goals of this form of cooperation often face conflicts [19], which influence the effectiveness of collaborative R&D. Various collaborative innovation mechanisms have been regulated by scholars to ensure the effective operation of collaborative innovation models. From the knowledge flow perspective, Shan et al. [20] conducted structural equation modeling to demonstrate that knowledge absorption is the dominant factor in enhancing the collaborative innovation capital among industry, university, and research. Meanwhile, reducing stickiness in the knowledge transfer among industry, university, and research can improve the efficiency of collaborative innovation as proven by Zhang and Wu [21] in their knowledge flow model. Harrison and Mouden [22] combined classical game models with simulation analysis to investigate the optimization of benefit distribution among participating parties. In his case study of collaborative R&D, Archetti [23] identified moral hazard as one of the main causes of inefficient collaboration. Some scholars have even explored the extent to which moral hazard affects collaborative innovation from the perspective of conflicting interests and negotiations that arise from tax systems and organizational cultural differences, among others.

GPTs, especially key GPTs, have always been the focus of competition among countries in science and technology; these countries are actively gathering the efforts of all parties through their governments and eliminate the possible failures in the R&D of GPTs through financial support, policy and institutional guidance, and establishment of GPTs innovation platforms, such as industry, university, and research cooperation bases and technology strategic alliances [24]. The government tends to provide direct funding to UR and indirect funding, such as R&D subsidies and incentives, to enterprises [25]. A large number of studies have also used empirical analysis and game models to confirm that the implementation of subsidies and incentives by the government can help increase the R&D investment of enterprises and promote collaborative R&D [26, 27]. The main aspects of policy and institutional guidance include the establishment of special programs, intellectual property regimes, and innovation funds for GPTs [28, 29]. Sawhney and Prandelli [30] emphasized the leading role of governments in the development of GPT platforms, which can facilitate the flow of knowledge among organizations and subsequently accelerate the development of GPTs [31].

However, the impact of government support on the R&D of GPTs remains uncertain. Most scholars agree that government support has a positive effect by increasing the R&D investment of enterprises and alleviating the financing constraints they face in the R&D process [32]. By contrast, other scholars argue that moderate government support has an inducing effect on enterprises R&D of GPTs, but excessive government support exerts a crowding-out effect on enterprises [33].

3 METHODOLOGY

3.1 Basic Assumptions

From the commonality and synergy perspectives, in consideration of those factors that influence the synergistic R&D of GPTs, evolutionary game models are constructed in this study to research the synergistic R&D strategies of multiple agents according to whether the government participates in R&D or not. The basic assumptions are as follows:

Assumption 1: Participating subjects. The collaborative R&D of GPTs involves enterprises, UR, and the government, which enterprises refer to large enterprises with a certain R&D foundation and strength that can facilitate the rapid commercialization of technologies. Accordingly, enterprises are mainly responsible for providing financial and material support to the UR, such as R&D funds and production and testing equipment. Meanwhile, the UR is mainly responsible for providing knowledge and scientific and technological human resources and bringing into play their advantages in basic research. The government mainly promotes the collaboration between industry, university, and research through subsidies, intellectual property protection systems, and other measures.

Assumption 2: R&D strategy. In the R&D of GPTs, enterprises mainly emphasize the commercial application side, whereas the UR mainly emphasizes the basic research side, thereby giving rise to potential conflicting goals between enterprises and UR. Therefore, this study assumes that the set of strategies for both enterprises and UR is {cooperation, non-cooperation}, whereas the set of strategies for the government is {participation, non-participation}. x denotes the probability that the UR will choose the "cooperation" strategy, y is the probability that the enterprises will choose the "cooperation" strategy, and $x, y \in [0, 1]$.

Assumption 3: Commonality degree. On the basis of technology evolution theory and the proximity of GPTs to basic science and commercial applications, GPTs are classified into three categories, namely, basic, pre-competitive, and applied GPTs, and the size of the commonality degree is exploited to portray these three types, where $e \in (0, 1)$ as shown in Fig. 1. A larger degree of commonality corresponds to basic GPTs, which are closer to the research end of basic science and have greater market and technology uncertainties, stronger externalities, quasi-public goods attributes, less benefits exclusive to the collaborative R&D of each participating subject, and greater R&D costs and risks.

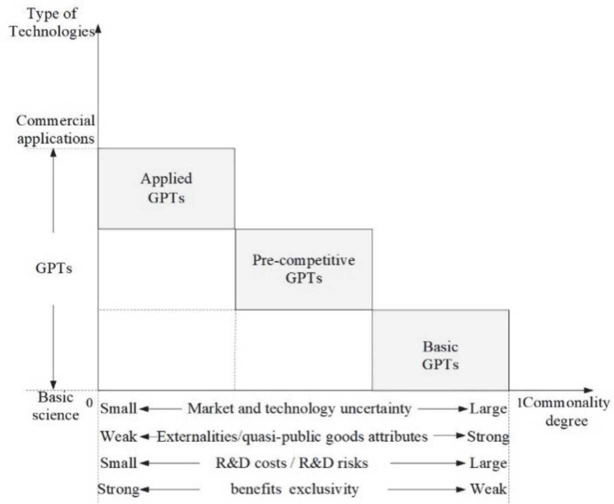

Figure 1 Classification of GPTs types (commonality degree)

Assumption 4: Synergy degree. The core of multi-agent collaborative innovation is knowledge synergy, which is accompanied by a flow of knowledge among multiple agents. In view of this knowledge flow, multi-agent knowledge collaborative behaviors are classified into knowledge sharing, knowledge transfer, and knowledge creation. In this study, the degree of collaborative innovation (i.e., synergy degree) refers to the degree of coordination of multi-agent knowledge collaborative behaviors as shown in Fig. 2. r denotes the degree of synergy between industry and UR without government participation, and $r+\Delta r$ denotes the degree of synergy with government participation, where Δr denotes the incremental degree of synergy, $r, r+\Delta r \in (0, 1)$.

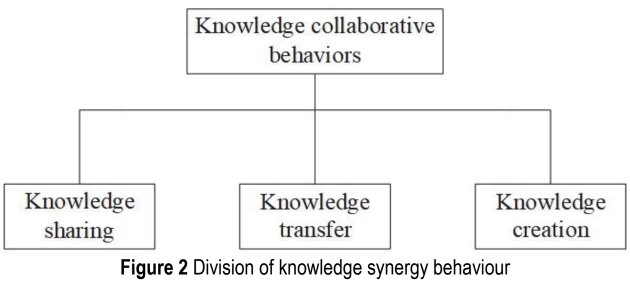

Figure 2 Division of knowledge synergy behaviour

Assumption 5: R&D benefits. R_1 and R_2 denote the obtainable benefits when the UR and enterprises choose not to cooperate, whereas $\Delta R (\Delta R > 0)$ denotes the ideal excess benefit that can be obtained when they cooperate. However, in the multi-agent collaborative R&D process, different types of GPTs with varying characteristics can have different impacts on R&D benefits, while the degree of synergy among the participants can change the impact on R&D benefits as a result. A composite form of commonality and synergy is then employed in this study to represent the impact of different types of GPTs on R&D benefits. Furthermore, to protect the research results in the R&D process, the participants will implement an IPR protection system, with ω denoting the level of knowledge protection, and $\Delta\omega$ denoting the incremental level of knowledge protection, giving $\omega, \omega+\Delta\omega \in (0, 1)$. As excess economic benefits are shared between the enterprise and UR, θ denotes the benefit distribution ratio, $\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega)\Delta R$ and $(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega)\Delta R$ denote the benefits that the UR and enterprises can obtain under the scenario where the government is not involved, $\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R$ and $(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R$ (where $\theta \in (0,1)$) denote the benefits they can obtain when the government is involved, respectively.

Assumption 6: R&D costs. In the case of no government participation, the R&D cost of the UR is $\lambda e^{\frac{1}{1-r}}(1+b)C$ and that of the enterprises is $(1-\lambda)e^{\frac{1}{1-r}}(1+b)C$. In the case of government participation, the R&D cost of the UR is $\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C$ and that of the enterprises is $(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C$, where λ denotes the share of the UR in the R&D cost and b denotes the cost factor of secondary development, $\lambda, b \in (0,1)$. The relationship among commonality degree, synergy degree, and R&D benefits and costs with constant knowledge protection strengths and secondary development cost factors is shown in Fig. 3.

Assumption 7: Penalties for breach of contract. The innovation behavior of the parties involved in the R&D of GPTs is bound by a cooperation agreement between the enterprise and the UR, with either party having to pay a penalty to the other party for breaching the cooperation agreement. K represents the amount of penalty for breach of contract, which is much smaller than the cost of R&D.

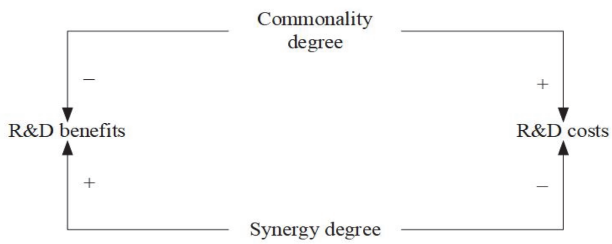

Figure 3 Relationship among commonality degree, synergy degree, and R&D benefits and costs

Assumption 8: Government subsidies. In the government participation scenario, to promote a collaborative R&D of GPTs between the industry and UR, the government provides R&D subsidies to these participants in the proportion of α, and $\alpha \in (0,1)$.

3.2 Evolutionary Game of Multi-Agent Collaborative R&D in the Absence of Government Participation

Based on the above basic assumptions, the multi-agent collaborative R&D evolutionary game payment matrix for the scenario without government participation can be obtained as shown in Tab. 1.

Based on this matrix, it follows that:

If the UR chooses cooperation, then the expected benefits will be:

$$E_{11}=y[R_1+\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C]+ \\ +(1-y)[R_1+K-\lambda e^{\frac{1}{1-r}}(1+b)C] \quad (1)$$

Table 1 Payment matrix of the multi-agent collaborative R&D evolutionary game without government participation

Strategy		Enterprises	
		Cooperation (y)	Non-cooperation$(1-y)$
Universities and research institutes	Cooperation (x)	$R_1+\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C$	$R_1+K-\lambda e^{\frac{1}{1-r}}(1+b)C$
		$R_2+(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C$	R_2-K
	Non-cooperation $(1-x)$	R_1-K	R_1
		$R_2+K-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C$	R_2

If the Ur chooses non-cooperation, then the expected benefits will be:

$$E_{12}=y(R_1-K)+(1-y)R_1 \quad (2)$$

The average expected benefits for the UR will be:

$$E_1=xE_{11}+(1-x)E_{12}= \\ =xy[R_1+\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C]+ \\ +x(1-y)[R_1+K-\lambda e^{\frac{1}{1-r}}(1+b)C]+ \\ +(1-x)y(R_1-K)+(1-x)(1-y)R_1 \quad (3)$$

The replication dynamics equation for the UR to choose cooperation is:

$$F(x)=\frac{dx}{dt}=x(1-x)[y\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C+K] \quad (4)$$

If the enterprises choose cooperation, then the expected benefits will be:

$$E_{21}=x[R_2+(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C]+ \\ +(1-x)[R_2+K-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C] \quad (5)$$

If the enterprises choose non-cooperation, then the expected benefits will be:

$$E_{22}=x(R_2-K)+(1-x)R_2 \quad (6)$$

The average expected benefits for the enterprises will be:

$$E_2=yE_{21}+(1-y)E_{22}=xy[R_2+(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R- \\ (1-\lambda)e^{\frac{1}{1-r}}(1+b)C]+(1-x)y[R_2+K-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C]+ \\ +x(1-y)(R_2-K)+(1-x)(1-y)R_2 \quad (7)$$

The replication dynamics equation for the enterprises to choose cooperation is:

$$F(y)=\frac{dy}{dt}=y(1-y)[x(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R- \\ -(1-\lambda)e^{\frac{1}{1-r}}(1+b)C+K] \quad (8)$$

Letting $F(x)=0$ and $F(y)=0$ yields 5 local equilibrium points: (0,0),(1,0),(0,1),(1,1),($\frac{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R}, \frac{\lambda e^{\frac{1}{1-r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R}$).

The stability of the equilibrium point of the evolutionary game system can be determined by the determinant $|J_1|$ and trace TrJ_1 of the Jacobi matrix J_1, which is:

$$J_1=\begin{Bmatrix} (1-2x)[y\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C+K] & x(1-x)\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R \\ y(1-y)(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R & (1-2y)[x(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C+K] \end{Bmatrix} \quad (9)$$

The values of determinant J_1 are:

$$|J_1|=(1-2x)[y\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-\lambda e^{\frac{1}{1-r}}(1+b)C+K]\cdot(1-2y)[x(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R-(1-\lambda)e^{\frac{1}{1-r}}(1+b)C+K]- \\ -x(1-x)\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R\cdot y(1-y)(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R \quad (10)$$

Table 2 Results of the stability analysis of the evolutionary game system in the absence of government participation

Equilibrium point	$\|J_1\|$	TrJ_1	Stability
O(0, 0)	+	−	*ESS*
A(1, 0)	+	+	Instability point
B(0, 1)	+	+	Instability point
C(1, 1)	+	−	*ESS*
$D\left(\dfrac{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R}, \dfrac{\lambda e^{\frac{1}{1-r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R}\right)$	−	0	Saddle point

The trace of J_1 is:

$$TrJ_1 = (1-2x)[y\theta(1-e)^{\frac{1}{r}}(1+\omega)\Delta R - \lambda e^{\frac{1}{1-r}}(1+b)C + K] + \\ +(1-2y)[x(1-\theta)(1-e)^{\frac{1}{r}}(1+\omega)\Delta R - (1-\lambda)e^{\frac{1}{1-r}}(1+b)C + K] \tag{11}$$

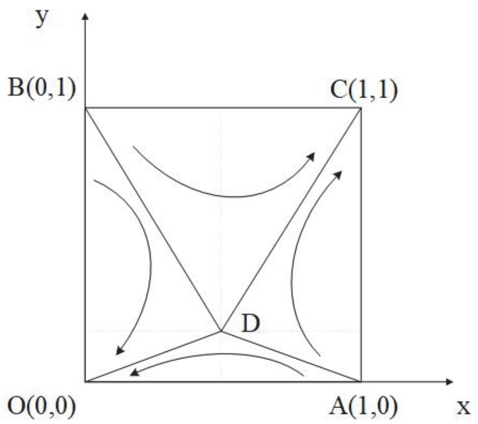

Figure 4 Evolutionary phase diagram in the absence of government participation

The stability of the equilibrium point is judged from the determinant and sign of the trace value of the local equilibrium point in the Jacobi matrix J_1, as shown in Tab. 2. The evolutionary phase diagram is shown in Fig. 4.

3.3 Evolutionary Game of Multi-Agent Collaborative R&D in the Context of Government Participation

Based on the above basic assumptions, the multi-agent collaborative R&D evolutionary game payment matrix for government participation is constructed, as shown in Tab. 3.

Similarly, the replication dynamic equation for the choice of cooperation between the UR and the enterprises can be derived as:

$$L(x) = \frac{\mathrm{d}x}{\mathrm{d}t} = x(1-x)[y\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R - \\ -(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C + K] \tag{12}$$

$$L(y) = \frac{\mathrm{d}y}{\mathrm{d}t} = y(1-y)[x(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R - \\ -(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C + K] \tag{13}$$

Table 3 Payment matrix of the multi-agent collaborative R&D evolutionary game in the case of government participation

Strategy		Enterprises: Cooperation (y)	Enterprises: Non-cooperation($1-y$)
Universities and research institutes	Cooperation (x)	$R_1+\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R-(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C$	$R_1+K-(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C$
		$R_2+(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R-(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C$	R_2-K
	Non-cooperation ($1-x$)	R_1-K	R_1
		$R_2+K-(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C$	R_2

Table 4 Results of the stability analysis of the evolutionary game system in the case of government participation

Equilibrium point	$\|J_2\|$	TrJ_2	Stability
O(0, 0)	+	−	*ESS*
A(1, 0)	+	+	Instability point
B(0, 1)	+	+	Instability point
C(1, 1)	+	−	*ESS*
$Q\left(\dfrac{(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}, \dfrac{(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}\right)$	−	0	Saddle point

Letting $F(x)=F(y)=0$ yields the 5 local equilibrium point: (0, 0), (1, 0), (0, 1), (1, 1), $\left(\frac{(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}, \frac{(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}\right)$.

Similar to above, the stability of the equilibrium point is judged based on the determinant and sign of the trace value of the local equilibrium point in the Jacobi matrix, as shown in Tab. 4.

The evolutionary phase diagram is shown in Fig. 5.

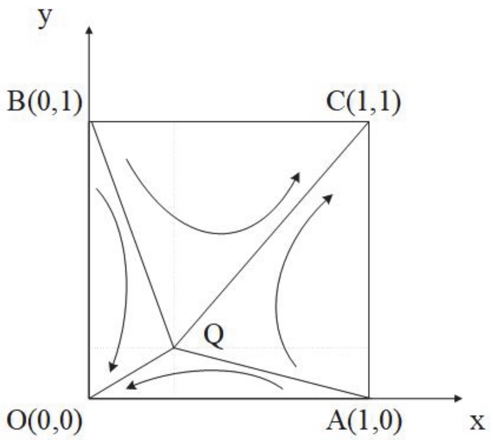

Figure 5 Evolutionary phase diagram for the government participation

4 RESULT ANALYSIS AND DISCUSSION

4.1 The Impact of Commonality and Synergy on Multi-Agent Collaborative R&D Strategies

Proposition 1: During the collaborative R&D process of GPTs, the willingness of multiple agents to collaborate on R&D decreases along with an increasing degree of commonality, and the negative impact of such degree is moderated by certain factors, such as degree of synergy, strength of knowledge protection, and breach of contract.

Proof: By taking the evolutionary phase diagram in the absence of government participationas an example for analysis, let the area of OBDA be S_1.

$$S_1=\frac{1}{2}\left[\frac{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C-K}{(1-\theta)\left(1-e\right)^{\frac{1}{r}}(1+\omega)\Delta R}+\frac{\lambda e^{\frac{1}{1-r}}(1+b)C-K}{\theta\left(1-e\right)^{\frac{1}{r}}(1+\omega)\Delta R}\right]$$

$$\frac{\partial S_1}{\partial e}=\frac{\{e^{\frac{1}{1-r}}[(1-r)e+(1-e)r][(1-\theta)\lambda+(1-\lambda)\theta]C-e(1-r)K\}}{2\theta er(1-r)(1-\theta)(1-e)^{1+\frac{1}{r}}(1+\omega)\Delta R}$$

Given that $K<\min\{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C,\lambda e^{\frac{1}{1-r}}(1+b)C\}$, $(1-\theta)\lambda+(1-\lambda)\theta$ is between λ and $1-\lambda$, then $\frac{[(1-r)e+(1-e)r][(1-\theta)\lambda+(1-\lambda)\theta]}{(1-r)e}>\min\{\lambda,1-\lambda\}$, and finally $\frac{\partial S_1}{\partial e}>0$. Similarly, let $\frac{\partial S_1}{\partial r}$ be the partial derivative of K, ω, and C, which gives $\frac{\partial S_1/\partial e}{\partial K}<0$, $\frac{\partial S_1/\partial e}{\partial \omega}<0$, and $\frac{\partial S_1/\partial e}{\partial C}>0$. The proof of Proposition 1 is complete.

The willingness of multiple agents to collaborate on R&D, as suggested by Proposition 1, is negatively correlated with the degree of commonality, which means that breach of contract and strength of knowledge protection will mitigate the negative impact of degree of commonality, R&D costs will aggravate the negative impact of degree of commonality, and degree of synergy has a moderating effect. In other words, when GPTs are close to the basic science research end, the participating subjects need to take the corresponding measures, such as improving their knowledge protection strengths, to mitigate the negative impact of technical characteristics and take advantage of collaborative innovation to reduce R&D costs.

Proposition 2: The degree of synergy has a positive reinforcing effect on the willingness of multiple agents to collaborate in the R&D of GPTs, but the reinforcing effect diminishes along with increasing degree of commonality.

Proof:

$$\frac{\partial S_1}{\partial r}=\frac{\frac{\{[(1-\theta)\lambda+(1-\lambda)\theta]e^{\frac{1}{1-r}}C-K\}\ln(1-e)}{r^2}+\frac{[(1-\theta)\lambda+(1-\lambda)\theta]e^{\frac{1}{1-r}}C\ln e}{(1-r)^2}}{2\theta(1-\theta)\left(1-e\right)^{\frac{1}{r}}(1+\omega)\Delta R}$$

As $K<\min\{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C,\lambda e^{\frac{1}{1-r}}(1+b)C\}$, $(1-\theta)\lambda+(1-\lambda)\theta$ is between λ and $1-\lambda$, $0<1-e,e<1$, and $\ln(1-e),\ln e<0$, so $\frac{\partial S_1}{\partial r}<0$. Then let $\frac{\partial S_1}{\partial r}$ be the partial derivative of e, which gives $\frac{\partial S_1/\partial r}{\partial e}<0$. The proof of Proposition 2 is complete.

According to Proposition 2, the area of S_1 decreases while that of S_2 increases along with an increasing degree of synergy, which would further strengthen the positive influence of the synergy effect and increase the possibility of the evolutionary result tending to (1, 1). Meanwhile, the degree of commonality has a reverse inhibitory influence on the synergy effect. In other words, the participating subjects need to pay attention to GPT types to encourage the R&D participants to choose active cooperation while improving the efficiency of collaborative innovation and take targeted measures to reduce the negative effects of the commonality degree.

4.2 The Impact of Government Measures on Multi-Agent Collaborative R&D Strategies

Proposition 3: In the case of government participation, the willingness of multiple agents to collaborate on R&D is positively correlated with the increment in synergy degree Δr, the proportion of R&D cost subsidy α, and the increment in knowledge protection strengths $\Delta\omega$. In other words, government participation is more conducive to the R&D of GPTs.

Proof: Taking the evolutionary phase diagram for government participation as an example, let the area of OBQA be S_3.

$$S_3=\frac{1}{2}\left[\frac{(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}+\frac{(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}\right]$$

$$S_1-S_3=\frac{1}{2}\left[\frac{(1-\lambda)e^{\frac{1}{1-r}}(1+b)C-K}{(1-\theta)\left(1-e\right)^{\frac{1}{r}}(1+\omega)\Delta R}-\frac{(1-\alpha)(1-\lambda)e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{(1-\theta)(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}+\frac{\lambda e^{\frac{1}{1-r}}(1+b)C-K}{\theta\left(1-e\right)^{\frac{1}{r}}(1+\omega)\Delta R}-\frac{(1-\alpha)\lambda e^{\frac{1}{1-r-\Delta r}}(1+b)C-K}{\theta(1-e)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}\right]>0$$

$$\frac{\partial S_3}{\partial\alpha}=-\frac{[(1-\theta)\lambda+(1-\lambda)\theta]e^{\frac{1}{1-r-\Delta r}}(1+b)C}{2\theta(1-\theta)\left(1-e\right)^{\frac{1}{r+\Delta r}}(1+\omega+\Delta\omega)\Delta R}<0.$$

Similarly, let S_3 be the partial derivative of Δr and $\Delta\omega$, which gives $\frac{\partial S_3}{\partial\Delta r}<0$ and $\frac{\partial S_3}{\partial\Delta\omega}<0$. The proof of Proposition 3 is complete.

According to Proposition 3, the addition of Δr, α, and $\Delta\omega$ is conducive to increasing the willingness of multiple agents to collaborate on R&D, and the government plays an important role in the R&D of GPTs. In other words, when choosing an R&D model for GPTs, a model in which enterprises and UR are the main innovation subjects and where the innovation is both market-driven and government-led should be preferred.

4.3 Simulation Analysis

To intuitively analyze and compare the influencing factors of multi-agent collaborative R&D willingness, MATLAB is used to simulate the game process. Assume that the parameters are as follows: $x=0.35$, $y=0.55$, $\theta=0.45$, $\lambda=0.3$, $e=0.4$, $r=0.4$, $\Delta r=0.05$, $R_1=180$, $R_2=300$, $\Delta R=500$, $C=300$, $\omega=0.25$, $\Delta\omega=0.1$, $b=0.3$, $K=10$, $\alpha=0.2$.

4.3.1 Basic GPTs (Commonality Degree $e\to 1$): The Impact of Synergy on Multi-Agent R&D Strategies

Fig. 6 shows that a large degree of commonality corresponds to a high critical value of synergy. However, in the case of government participation, the critical value of synergy is relatively low (0.5 to 0.6). When the degree of synergy exceeds the critical value, the willingness of enterprises to conduct R&D initially decreases and then increases along with the willingness of researchers in a "U-shaped" trend. Eventually, both parties agree to cooperate with the equilibrium point of the system tending to be (1, 1). In the case of government participation, as the degree of synergy increases, the willingness of enterprises to conduct R&D gradually exceeds that of the UR. At this time, GPTs are closer to basic scientific research, which means that the technology route and application market are in the early stage of generation, and enterprises cannot easily judge the market value and application prospect of GPTs. Therefore, the participants in the R&D are bound to communicate and exchange knowledge on the scientific principles, process reliability, economic feasibility, and other issues associated with basic GPTs through knowledge sharing. Afterward, these participants engage in knowledge transfer to transform and integrate different levels and forms of knowledge elements and then engage in knowledge creation. All of these processes have high requirements on the degree of synergy. Specifically, when the degree of synergy is below the critical value, enterprises, as financial and material investors, face not only uncertainty in the technology, market, and benefits of GPTs but also high R&D costs. As their willingness to engage in R&D and the amount of their capital investment gradually decrease, these enterprises eventually choose not to cooperate, which would force the UR to follow suit. Conversely, when the degree of synergy exceeds the critical value, the willingness of academic and researcher parties, as the main suppliers of basic GPTs, gradually increases along with the production of innovative results. Meanwhile, enterprises show a small decline in their R&D willingness given that the externalities and quasi-public goods of GPTs are stronger at this point, and the R&D results can easily spillover to a certain or multiple industries. Therefore, the non-participating subjects can benefit from the R&D results by "freeriding" or at a lower cost. The profitability and reliability of GPTs are highlighted when the innovation results are transformed from "0 to 1" by UR, and the willingness of enterprises to conduct R&D gradually increases, thus showing a general "U-shaped" trend of decrease followed by increase.

4.3.2 Pre-Competitive GPTs: Impact of Synergy on Multi-Agent R&D Strategies

As clearly revealed in Fig. 7, pre-competitive GPTs require less synergy than basic GPTs. When the degree of synergy is lower than the critical value, the willingness of the UR increases and then decreases along with that of enterprises, showing an "inverted U" trend. Eventually, both the UR and enterprises choose not to cooperate, and the equilibrium point of the system tends to (0, 0). Meanwhile, when the degree of synergy exceeds the critical value, the enterprises and UR show similar trends in their willingness to engage in R&D. In the case of government participation, increasing the degree of synergy will make the R&D willingness of enterprises gradually higher than that of UR. This phenomenon can be ascribed to the fact that the technical route of pre-competitive GPTs is relatively mature compared with that of basic GPTs, and the amount of subsequent secondary development is within the range of enterprises' technical capacity. Therefore, the focus of synergy between enterprises and UR is on knowledge transfer and knowledge creation. However, when the degree of synergy is below the critical value, certain barriers to knowledge transfer can be observed among the participating subjects, and the mobility of tacit knowledge from the UR to the enterprises is weakened. With the financial support from the government, the financial investment of enterprises, and their advantages at the basic research end, the UR can complete the R&D and innovation at the front end of GPTs in universities, national laboratories, and other venues. Due to the existence of barriers, enterprises cannot easily assimilate and digest their existing knowledge with their innovation capacity and transform such knowledge into real productivity, thereby eventually forcing the scientific and technological achievements to remain in the laboratory stage and triggering an "inverted U" trend of an initial increase and then decrease in the R&D willingness of the UR. When the degree of synergy exceeds the critical value, given that pre-competitive GPTs are in the middle of basic research and commercial application stages, both the externality of technology and the risk of R&D results spillover are reduced. GPTs also have certain application prospects and face technical barriers (i.e., the research results of GPTs are not easily accessible to interested subjects who are not involved in R&D), and the participating enterprises can transform GPTs into proprietary technologies through subsequent secondary development and accumulate market revenue accordingly. In other words, as the synergies increase, the R&D willingness of enterprises increases at a faster rate as the benefits for the participating subjects continue to increase.

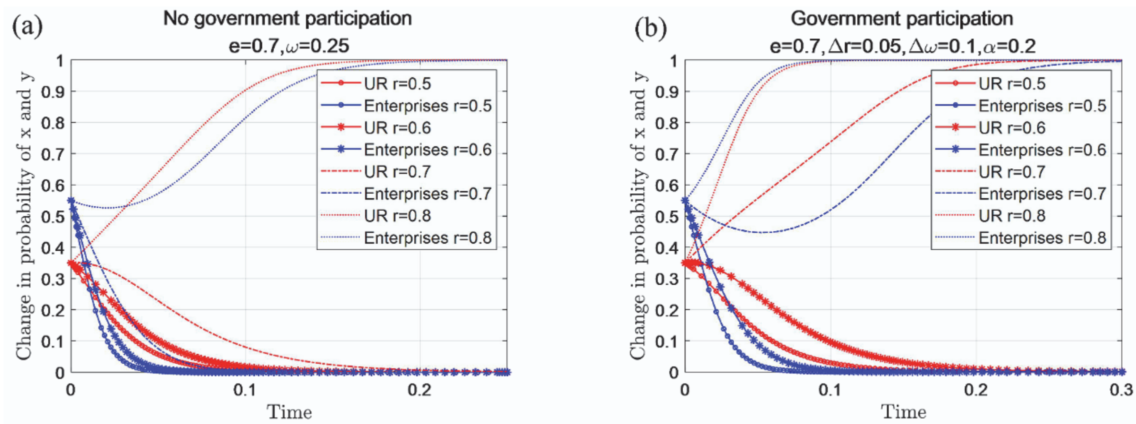

Figure 6 Evolutionary results of the multi-agent collaborative R&D strategies ($e = 0.7$)

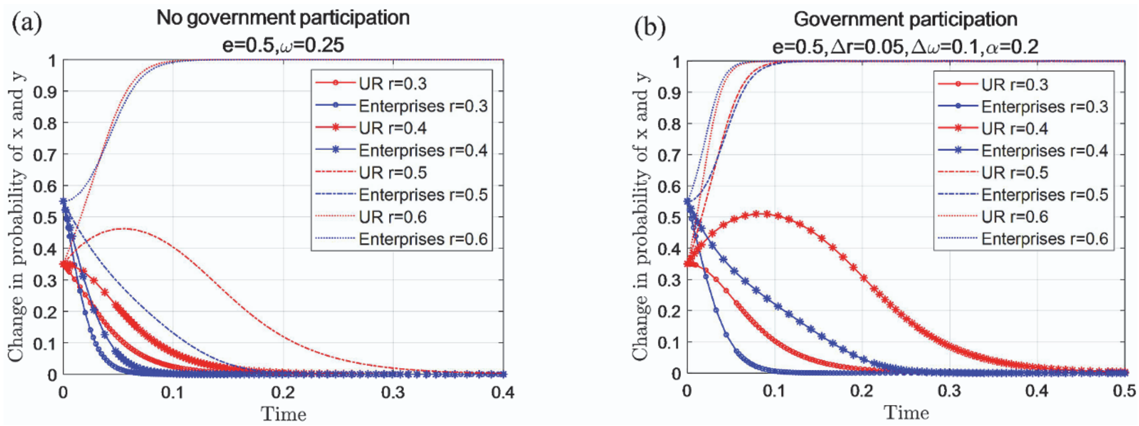

Figure 7 Evolutionary results of the multi-agent collaborative R&D strategies ($e = 0.5$)

4.3.3 Applied GPTs (Commonality Degree $e \to 0$): Impact of Synergy on Multi-Agent R&D Strategies

As shown in Fig. 8, applied GPTs require the lowest degree of synergy between industry and UR among the three types of GPTs, and government participation is highly conducive to promoting collaborative R&D GPTs. When the degree of synergy exceeds the critical value, increasing the degree of synergy will lead to the enterprises' R&D willingness to gradually exceed that of the UR, and the final evolutionary strategy of both subjects converges to (1, 1). This phenomenon can be ascribed to the fact that applied GPTs are closer to commercial applications and require very little secondary development work, hence allowing the participating parties to easily reach a consensus on their target recognition and technical completion standards. In addition, enterprises can combine GPTs and proprietary technologies well with their professional application backgrounds in collaboration with UR to achieve knowledge creation, hence requiring less degree of synergy. Given the platform attributes of GPTs, as the market value of applied GPTs comes to the fore, those enterprises that are not involved in R&D will imitate and apply these technologies, thereby driving the proliferation of applied GPTs within the industry. When the degree of synergy exceeds the critical value, the participating enterprises need to invest less capital and bear less risk to commercialize and diffuse applied GPTs. As the degree of synergy increases, the benefits available to enterprises increase, and the increase in their willingness to conduct R&D gradually accelerates. In the case of government participation, the government can mitigate the risk of applied GPTs results spillover by strengthening the protection of intellectual property rights and other institutions, thereby safeguarding the economic interests of the participating subjects and increasing their R&D incentives.

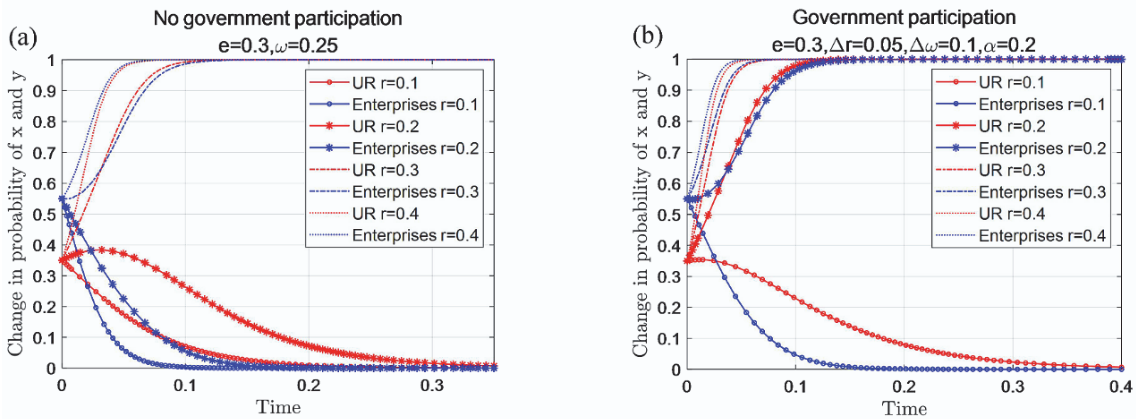

Figure 8 Evolutionary results of the multi-agent collaborative R&D strategies ($e = 0.3$)

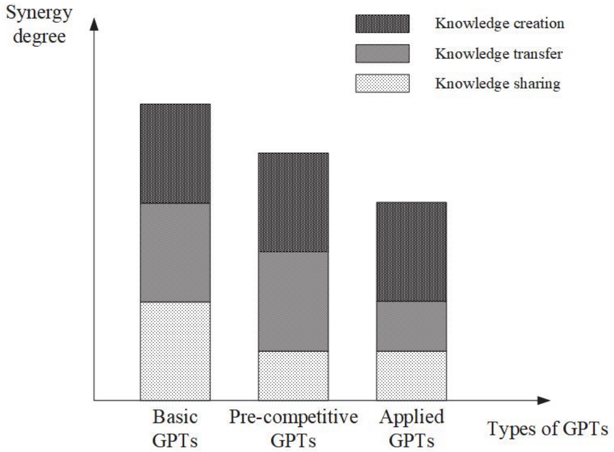

Figure 9 Comparison of the degree of synergy among multiple agents under different types of GPTs

In sum, in the face of basic, pre-competitive, and applied GPTs, the degree of synergy to be achieved by multi-agent cooperation gradually decreases, and the requirements for knowledge sharing, knowledge transfer, and knowledge creation change accordingly as shown in Fig. 9.

4.3.4 The Impact of Government Action on Multi-Agent Collaborative R&D Strategies

The above discussion clearly shows that government participation is highly conducive to a multi-agent collaborative R&D of GPTs. This section then takes basic GPTs as an example and examines the impact of the proportion of subsidies, incremental knowledge protection, and incremental synergy on multi-agent collaborative R&D strategies under the case of government participation.

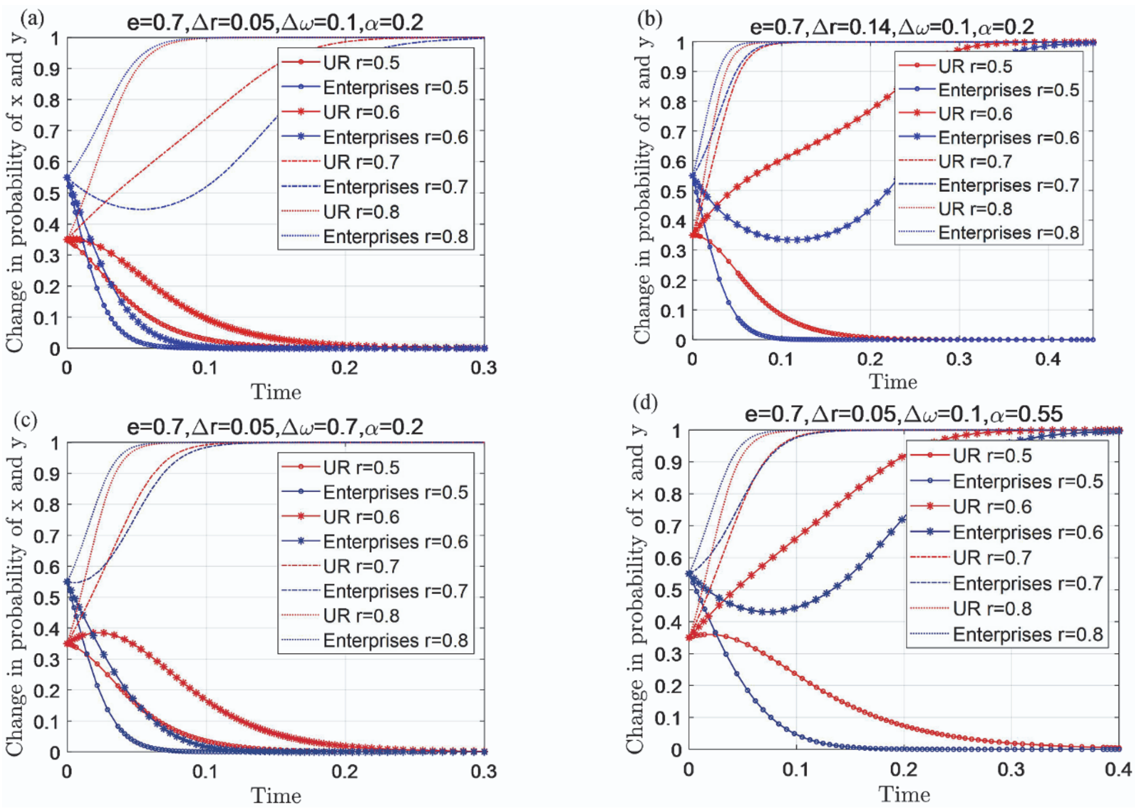

Figure 10 Evolutionary results of the multi-agent collaborative R&D strategy (α , Δr , $\Delta\omega$)

5 CONCLUSIONS

From the perspectives of commonality and synergy, an evolutionary game model for analyzing the stability of multi-agent collaborative R&D strategies is constructed in this study while considering the cases with and without government participation. A MATLAB numerical simulation is also conducted to determine the influence of commonality and synergy on multi-agent collaborative R&D strategies under different government strategies. Combined with the previous analysis, the following conclusions can be drawn:

(1) In the R&D process of basic, pre-competitive, and applied GPTs, the degree of synergy to be achieved by multi-agent collaboration gradually decreases, whereas the focus on knowledge sharing, knowledge transfer, and knowledge creation changes along with the types of technologies.

(2) In the R&D process of basic GPTs, when the degree of synergy exceeds the critical value, the R&D willingness of enterprises decreases and then increases in a "U-shaped" trend. In the R&D process of pre-competitive GPTs, when the degree of synergy is below the critical value, the R&D willingness of UR increases and then decreases in an "inverted U" trend. In the R&D process of all three types of GPTs, when the degree of synergy is much higher than the critical value, the R&D willingness of enterprises is always higher than that of UR.

(3) In the R&D process of all three types of GPTs, government participation is highly conducive to the synergistic R&D of GPTs involving multiple subjects. In the case of government participation, increasing the proportion of subsidies, incremental knowledge protection strengths, and incremental synergy degree can increase the willingness of multiple agents to engage in R&D. Such willingness is highly sensitive to changes in the proportion of subsidies and incremental synergy degree.

An evolutionary game model and MATLAB numerical simulations are exploited in this study to draw important conclusions related to the collaborative R&D of GPTs, but certain limitations need to be noted. For example, not all relevant subjects of interest and influencing factors are included in the analysis. Future scholars may consider further refining and combining the proposed evolutionary game model with quantitative analysis to verify the influencing factors of multi-agent collaborative R&D strategies.

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