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Evolutionary Game Analysis of Data Resale Governance in Data Trading

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Abstract: Data trading is important for optimizing the allocation of data elements. However, data can be easily copied, disseminated, or resold, leading to disorderly development in the data trading market, and raising the issue of data governance. Data trading involves various participants, while existing research lacks an understanding of participant interactions and strategy adoption, as well as determination of optimal strategies for the participants. To address these gaps and provide insights for the governance of data trading platforms, this paper proposes an evolutionary game model for the governance of data trading involving three parties: data suppliers, demanders, and trading platforms. Our findings reveal that data trading platforms choosing to govern, data suppliers choosing to innovate positively, and data demanders choosing not to resell can be achieved under certain conditions. We also find that an increase in the price of data trading or the number of transactions can weaken the effectiveness of platform governance and make data trading more difficult to govern. Additionally, the incentives for data innovation provided by the trading platform can significantly promote data suppliers to innovate data positively. However, when these incentives are too high, the platform may weaken its level of governance or even move towards non-governance. Increasing penalties for data resale weakens data demanders' motivation to resell data, and a higher probability of data resale being reported lowers their motivation to do so. By examining the role of different participants in data trading, the model proposes ways to improve the efficiency and robustness of the data market while better protecting the interests of data traders.

Keywords: digital economy; data trading; data elements; platforms; governance; evolutionary game

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1. Introduction

The increasing involvement of digital technology in production and daily life is making the economic impact of data elements increasingly prominent [1–5]. Data is now a critical input for decision-making among countries, businesses, and individuals [6–8]. However, the generation and processing of data by different entities creates ownership differences [7], resulting in data silos [9,10]. Despite the absence of a clear solution regarding data rights, the need to open data channels between entities is indisputable due to the coexistence of high demand and supply of data. Creating the free flow of data elements through data exchange, sharing, or trading can improve allocation efficiency [11]. Many studies indicate that data exchange creates shared value among companies [12–14]. By using data resources to enhance business performance, companies can maintain their competitive edge and promote the rapid development of the digital economy [15]. Consequently, many firms are buying and selling data, leading to the emergence of data exchange networks [16].

Data trading involves matching data suppliers and demanders through market mechanisms (Figure 1). Data suppliers encapsulate the collected data and submit the data sets to the data market, while data demanders submit their demands, and the market matches them with available data sets for trading [17]. However, the risk of data being copied, retained, and resold by third parties during data sharing and trading poses a significant constraint to the development of data trading markets [18,19]. To facilitate effective data trading in big data markets, challenges such as ensuring data availability, protecting identity privacy, and ensuring fairness must be addressed [1,20]. Since digital products can be easily forged or copied, data trading faces a higher risk of loss and resale of data, for which there is currently no ideal solution.

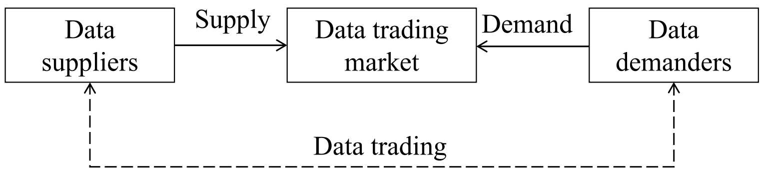

Figure 1. Market mechanisms for data trading.

Therefore, exploring protection options and risk prevention mechanisms for data trading is crucial to ensure stakeholders', particularly owners', legal rights and efficient allocation of data elements [6,21,22]. One of the main themes in the literature on data trading governance is the role of institutions and technologies in facilitating secure and fair data trade and mitigating moral hazards. At the institutional level, some studies suggest that data rights could balance the relationship between data circulation and the protection of personal rights in data trading [7,17]. Building a perfect data trading market could standardize the data trading process [23], reducing data resale, copying, and dissemination. At the technical level, studies are exploring the use of blockchain-based smart contracts [17] and optimized data encryption technology [21] to address data trading infringements.

However, there is a lack of research on how different participants in data trading interact with each other and what strategies they adopt in different scenarios. Data trading involves a complex interactive game process revolving around data trading and data rights [8]. Currently, very few studies use evolutionary games to explore the problem of games in data trading. Jing et al. [24] propose a differential game model to explore the coordination of data trade and government subsidies, investigate strategic interactions between data suppliers, data asset trading platforms, and governments, and provide optimal pricing and intervention strategies. Other related studies have focused on game problems in data formation, including data sharing [10,25], personal information protection [26], and big data discrimination [27].

Evolutionary games assume that humans are imperfectly rational and that participants face incomplete information conditions [28,29], reflecting the limited ideal situation in the actual game process and better reflecting the spontaneous evolutionary process of the strategies of different participants [30,31]. The stable evolutionary strategy (ESS) provides an optimal combination of strategies adopted by players when the game system reaches equilibrium, offering a quantitative framework for analyzing and determining the optimum strategies of different players.

To summarize, existing research on data trading lacks an understanding of participant interactions and strategy adoption, as well as determination of optimal strategies for players at equilibrium. To address these gaps, this paper proposes an evolutionary game model for governance of data trading involving three parties: data suppliers, demanders, and trading platforms. The aim is to explore the mechanisms of data innovation and resale behavior, as well as governance in data trading, and provide insights for the governance of data trading platforms. The novelty of the study lies in its use of an evolutionary game model to construct an integrated analytical framework that deepens the understanding of participant interaction and strategy adoption and helps to determine the optimal combination of strategies for players involved in data trading. Furthermore, by examining the role of different participants in data trading, the model proposes ways to improve the efficiency and robustness of the data market while better protecting the interests of data traders.

2. Model Design

2.1. Model Description

This paper focuses on the small data trading market. Cutting-edge technologies, such as cryptography and blockchain, have been employed to address the issues of data copying, distribution, and resale by those who demand it. While the application of these technologies is more beneficial for large data trading, the cost is too high and the benefit–cost ratio is too low to apply such technologies to small data trading. As a result, small data trading platforms have generally not adopted data resale circumvention technologies. Additionally, they often face the problem of non-compliant resale of data, which hinders the healthy and sustainable development of long-tail data transactions. Therefore, this paper aims to explore this issue in depth and find ways to optimize management and reduce non-compliance.

Currently, there are various small data trading platforms in the market, which can be classified into three types. The first type is a professional community-based platform wherein data suppliers (individuals or organizations) upload data on the platform to sell at a price, and data demanders buy it according to their needs. Alternatively, data demanders can list their needs, and data suppliers can supply the required data accordingly. The second type consists of professional data agencies based on databases. These platforms are primarily established by professional data agencies that collect data by purchasing copyrights or other means and gather it into professional databases for sale to individuals or organizations. Direct users of the data can be individuals or enterprises. The third type is based on data collection and processing, established by specialized data organizations that possess professional data collection and processing skills. These platforms can collect a large amount of structured and unstructured data and provide customized services based on the users' requirements. These data trading platforms bring together a large number of long-tail supply and demand, making them an essential part of the data factor market.

This paper examines the data trading platform of the Economic Management Home Forum, a famous academic exchange forum for economic management in China. The platform allows data demanders and data providers to trade data through a data exchange center. The data transaction process involves the following steps: The seller publishes data information on the forum, such as data type, quantity, and quality. The seller sets the price based on the innovativeness of the data. The buyer pays for the data according to their needs and receives the data after payment. However, the platform faces the problem of data duplication and resale, where some people resell the data on the forum or other platforms for profit. The platform has taken some punitive measures to prevent this situation, such as warnings, fines, bans, and IP blocking. These measures include reviewing the data before publishing to avoid duplication, and penalizing the resellers who are reported by the data providers, such as by deleting their posts and withholding their forum coins and experience. The platform provides a good place for data trading, but it lacks mature technical support to eliminate data resale. It forms a multi-center governance data trading model through the game between the platform, the data suppliers, and the data demanders. This model can promote the orderly development of data transactions on the platform.

On all of the aforementioned data trading platforms, there exist varying degrees of data resale, which can be classified into two primary models. The first model is known as the intra-platform resale model (Figure 2a). In this model, the original data suppliers upload their data to the data trading platforms for sale, and the data demanders purchase the data for their use. Subsequently, data demanders continue to sell the data on the same platform at a low price. The second model is referred to as the inter-platform resale model (Figure 2b). In this model, the original data suppliers sell their data on one platform, and the data demanders acquire it for their use and subsequently resell it on other platforms.

When data resale becomes widespread on data trading platforms, the low price of resale can seriously impact the revenue of the original data suppliers, discouraging them from continuing to provide high-quality data.

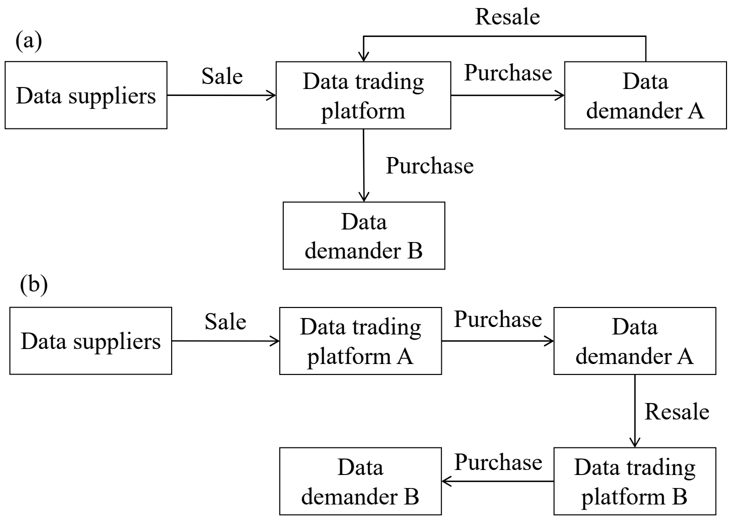

Figure 2. Data resale models in data trading. (**a**) Intra-platform resale model. (**b**) Inter-platform resale model.

Both intra- and inter-platform resale can have a detrimental effect on the healthy development of the data trading market. First, data infringement issues that arise from data resale can damage the reputation of data trading platforms, leading to a decline in the quality of data and innovation on these platforms. This, in turn, can reduce their market influence and profitability. To govern data resale, data trading platforms often take certain measures to restrict or penalize such practices. Secondly, data resale seriously infringes on the rights and interests of data suppliers' original data, discouraging them from providing high-quality and innovative data. Additionally, data suppliers may feel that they are not receiving an adequate benefit–cost ratio for their efforts, which may result in them avoiding the provision of data altogether. Third, resale data is a way for data demanders to benefit financially, either by selling it for their use or buying it solely to benefit from resale. However, there are significant risks associated with data resale, particularly in terms of governance by data trading platforms. Based on this, this article constructs an evolutionary game model between data trading platforms, data suppliers, and data demanders (Figure 3) to reveal the behavior of data resale and the interaction process among multiple entities in its governance.

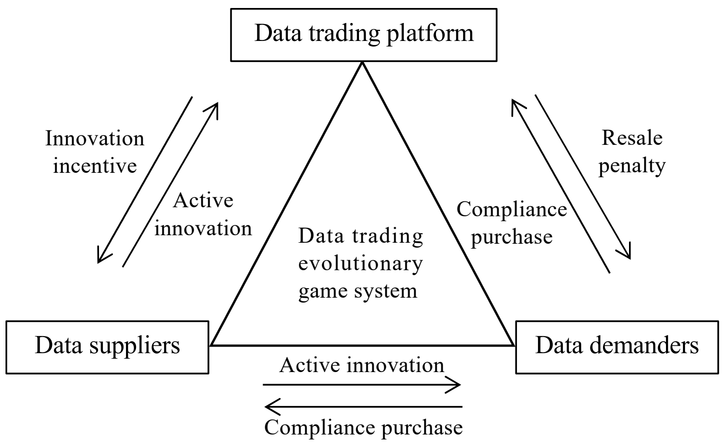

Figure 3. The evolutionary game of data resale governance in data trading.

2.2. Model Assumptions

This paper examines the game process involving data trading platforms, data suppliers, and data demanders in the model. We propose the following assumption based on the key factors that affect the data reproduction and dissemination behavior of these three parties in data trading (Table 1).

Table 1. Main parameters.

Parameters	Description
C_g	Cost of governance of data trading platforms
D	Competitive pressure of data trading platforms if they choose not to govern
A	Innovative support for data suppliers from data trading platforms
W	Penalties for resale by data trading platforms to those who demand data
L	Reputational damage to data trading platforms caused by resale behavior
θ	Coefficient of revenue from each transaction
C_i	Data processing costs when data suppliers choose innovative strategies
P	Price of data general trading
Q	Quantity of data general trading
β	Degree of data innovation
m	Coefficient of gain from reselling data
α	Probability of being reported for supplying low-quality data
x	Probability of data trading platforms choosing to govern
y	Probability of data suppliers choosing to innovate positively
z	Probability of data demanders choosing to resale

Assumption 1. *This article focuses on small-scale data trading conducted through trading platforms. The primary objective of data trading platforms is to maintain transactional order and not interfere with the trading process. This study examines the governance mechanism of data resale behavior in the data trading system of "data trading platforms-data suppliers-data demanders" using an evolutionary game theory approach. The outcome of data resale governance is affected by the behavioral interaction between the three parties, each of which exhibits bounded rationality. Under conditions of information asymmetry, various actions are taken, and the decision-making process is stochastic.*

Assumption 2. *The set of strategies of data trading platforms against the resale behavior of the data is S_1 = {govern, do not govern}. To achieve platform revenue and a sustainable platform monopoly advantage, the platform may take certain governance measures with probability x. At this point, certain governance costs (C_g) must be paid, which generally include the cost of institution building, the cost of manpower, and the cost of technology needed to achieve an effective data exchange. If no governance measures are taken, huge competitive pressure can be felt in a fiercely competitive market (D). The data trading flow operated by the platform constitutes its revenue, assuming that the coefficient of revenue from each transaction is θ. To achieve a virtuous data trading cycle, the platform will incentivize data suppliers to actively supply original data (innovative data) and restrain data demanders from reselling data. The incentives given by the platform to data suppliers to supply original data include increasing data exposure through data quality scores, providing high price returns based on trading mechanisms, etc. Assume that the platform's innovation support is A. A also constitutes the cost of the platform. When the data resale behavior is reported by others, the platform will impose certain penalties on the data demanders, mainly including deducting its data resale proceeds, restricting its data trading rights, etc. Here, we mainly consider deducting part of the data resale proceeds (W) of the data demanders and attributing it to the data suppliers. When resale behavior on data trading platforms is more frequent, the platform must bear the reputation loss (L).*

Assumption 3. *The set of data suppliers' strategies is S_2 = {innovate positively, innovate negatively}. When data suppliers innovate positively, they can clean, process, and manipulate the data at their disposal to increase the value added by the data and to serve a more diverse and deeper* *market demand. The probability that data suppliers choose an innovative strategy is y when more data processing costs (C_i) are required and the degree of data innovation is β (β ≥ 1). Suppose that the general trading price of the data is P and the general trading quantity is Q; both the price and the sales volume are affected by its degree of innovation, and the benefit for the data suppliers is P-Q-β. When data suppliers supply high-quality data and have data resold by data demanders, data suppliers must report to data trading platforms; when data suppliers supply low-quality data, other users can report them, with the probability of reporting α.*

Assumption 4. *The data demanders strategy set is S_3 = {resale, do not resale}. Data demanders may sell the data they have purchased from data suppliers at a discount. When data demanders resell data, they can gain some revenue from resale after paying the cost of purchasing the data, but this may infringe on the rights of the data suppliers and affect the order of data trading on the platform. The probability that data demanders resell data is z, and the coefficient of gain from reselling data is m. When data is resold, if the data suppliers innovate positively, it will certainly be reported to the platform, and the data demanders will be punished for reselling data; if the data suppliers innovate negatively, it will not be reported to the platform, but the consumers of the data demanders' resold data may report the data based on data security and data rights considerations. The demanders' resale of data is likely to be reported based on data security and data rights.*

2.3. Payment Matrix

Based on these assumptions, we obtain the payment matrix of the three-party game (Table 2).

Table 2. Game payment matrix.

	Data Trading Platforms Choose to Govern (x)		**Data Trading Platforms Choose not to Govern ($1-x$)**	
	Data Suppliers Choose to Innovate Positively (y)	**Data Suppliers Choose to Innovate Negatively ($1-y$)**	**Data Suppliers Choose to Innovate Positively (y)**	**Data Suppliers Choose to Innovate Negatively ($1-y$)**
Data demanders choose to resell (z)	$\theta PQ\beta - A - C_g - L$ $PQ\beta - C_i + A + W$ $-PQ\beta + mPQ\beta - W$	$\theta PQ - C_g - L$ $PQ + \alpha W$ $-PQ + mPQ - \alpha W$	$\theta PQ\beta - L - D$ $PQ\beta - C_i$ $-PQ\beta + mPQ\beta$	$\theta PQ - L - D$ PQ $-PQ + mPQ$
Data demanders choose not to resell ($1-z$)	$\theta PQ\beta - A - C_g$ $PQ\beta - C_i + A$ $-PQ\beta$	$\theta PQ - C_g$ PQ $-PQ$	$\theta PQ\beta - D$ $PQ\beta - C_i$ $-PQ\beta$	$\theta PQ - D$ PQ $-PQ$

3. Model Analysis

3.1. Analysis of Replication Dynamics

Let the expected payoff of the digital platform choosing the governance strategy be E_{11}, the expected payoff of choosing the non-governance strategy be E_{12}, and the average payoff be $\overline{E}_1$; then, we have:

$$\begin{cases} E_{11} = (1-y)\big((1-z)\big(-C_g + PQ\theta\big) + z\big(-C_g - L + W\alpha + PQ\theta\big)\big) + \\ \qquad y\big((1-z)\big(-A - C_g + PQ\beta\theta\big) + z\big(-A - C_g - L + PQ\beta\theta\big)\big) \\ E_{12} = (1-y)((1-z)(-D + PQ\theta) + z(-D - L + PQ\theta)) + \\ \qquad y((1-z)(-D + PQ\beta\theta) + z(-D - L + PQ\beta\theta)) \\ \overline{E}_1 = xE_{11} + (1-x)E_{11} \end{cases} \tag{1}$$

According to the Malthusian dynamic equation, the replication dynamic equation for the choice of governance strategy for digital platforms is:

$$F(x) = \frac{dx}{dt} = x\big(E_{11} - \overline{E}_1\big) = (-1+x)x\big(C_g - D + Ay - Wz\alpha + Wyz\alpha\big) \tag{2}$$

Similarly, the replication dynamic equation for the choice of data suppliers and data demanders strategy can be obtained as:

$$F(y) = \frac{dy}{dt} = y\left(E_{21} - \overline{E}_2\right) = (-1+y)y(C_i - x(A+Wz) + P(Q - Q\beta)) \tag{3}$$

$$F(z) = \frac{dz}{dt} = z\left(E_{31} - \overline{E}_3\right) = (1-z)z(Wx(y(-1+\alpha) - \alpha) + mPQ(1 + y(-1+\beta))) \tag{4}$$

3.2. Stable Equilibrium Analysis

Combining Equations (2)–(4) yields a two-dimensional dynamical system (*I*), i.e.,

$$\begin{cases} F(x) = (-1+x)x\left(C_g - D + Ay - Wz\alpha + Wyz\alpha\right) \\ F(y) = (-1+y)y(C_i - x(A+Wz) + P(Q - Q\beta)) \\ F(z) = -(-1+z)z(Wx(y(-1+\alpha) - \alpha) + mPQ(1 + y(-1+\beta))) \end{cases} \tag{5}$$

Let $(F(x), F(y), F(z)) = \left(\frac{dx}{dt}, \frac{dy}{dt}, \frac{dz}{dt}\right) = (0,0,0)$. We can obtain E_1 (0, 0, 0), E_2 (1, 0, 0), E_3 (0, 1, 0), E_4 (0, 0, 1), E_5 (1, 1, 0), E_6 (1, 0, 1), E_7 (0, 1, 1), E_8 (1, 1, 1), E_9 (x^*, y^*, z^*). These equilibrium points are not necessarily stable strategies for ESS, so it is also important to discuss whether these stable points are stable strategies and the conditions under which they become stable strategies.

First, the asymptotic stability of the above eight equilibrium points is further discerned by the local stability of the Jacobi matrix [32,33]. The Jacobi matrices of the game equations are obtained by taking the first-order partial derivatives of $F(x)$, $F(y)$, and $F(z)$ concerning x, y, and z, respectively:

$$J = \begin{bmatrix} F_x(x) & F_y(x) & F_z(x) \\ F_y(y) & F_y(y) & F_y(y) \\ F_z(z) & F_z(z) & F_z(z) \end{bmatrix} \tag{6}$$

According to Lyaplov stability theory, a Jacobi matrix is asymptotically stable when all its eigenvalues $\lambda < 0$; it is unstable when all its eigenvalues $\lambda > 0$; and the equilibrium point is the saddle point when the Jacobi matrix has positive and negative eigenvalues λ [32]. The asymptotic stability analysis of the equilibrium point is shown in Table 3. E_2 (0, 0, 1), E_4 (1, 0, 0), E_5 (1, 1, 0), E_6 (1, 0, 1), E_7 (0, 1, 1), and E_8 (1, 1, 1) have asymptotic evolutionary stability when the following conditions are satisfied:

Table 3. Asymptotic stability analysis of local equilibrium points.

Equilibrium Point	Eigenvalue	Results
(0, 0, 0)	$\lambda_1 = -C_g + D$; $\lambda_2 = -C_i - P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q$	When $-C_g + D > 0$ and $C_i\,(-1 + P\,Q\,\beta) > 0$, it is an unstable point, otherwise a saddle point
(0, 0, 1)	$\lambda_1 = -C_g + D + W\,\alpha$; $\lambda_2 = -C_i - P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q$	When $-C_g + D + W\,\alpha < 0$ and $-C_i - P\,(Q - Q\,\beta) < 0$, it is a stable point, otherwise a saddle point or unstable point
(0, 1, 0)	$\lambda_1 = -A - C_g + D$; $\lambda_2 = C_i + P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q\,\beta$	When $-A - C_g + D > 0$ and $C_i + P\,(Q - Q\,\beta) > 0$, it is an unstable point, otherwise a saddle point
(1, 0, 0)	$\lambda_1 = C_g - D$; $\lambda_2 = A - C_i - P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q - W\,\alpha$	When $C_g - D < 0$, $A - C_i - P\,(Q - Q\,\beta) < 0$ and $m\,P\,Q - W\,\alpha < 0$, it is a stable point, otherwise a saddle point or unstable point
(1, 1, 0)	$\lambda_1 = A + C_g - D$; $\lambda_2 = -A + C_i + P\,(Q - Q\,\beta)$; $\lambda_3 = -W + m\,P\,Q\,\beta$	When $A + C_g - D < 0$, $-A + C_i + P\,(Q - Q\,\beta) < 0$ and $-W + m\,P\,Q\,\beta < 0$, it is a stable point, otherwise a saddle point or unstable point
(1, 0, 1)	$\lambda_1 = C_g - D - W\,\alpha$; $\lambda_2 = A - C_i + W - P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q + W\,\alpha$	When $C_g - D - W\,\alpha < 0$, $A - C_i + W - P\,(Q - Q\,\beta) < 0$ and $m\,P\,Q + W\,\alpha < 0$, it is a stable point, otherwise a saddle point or unstable point
(0, 1, 1)	$\lambda_1 = -A - C_g + D$; $\lambda_2 = C_i + P\,(Q - Q\,\beta)$; $\lambda_3 = m\,P\,Q\,\beta$	When $-A - C_g + D < 0$ and $C_i + P\,(Q - Q\,\beta) < 0$, it is a stable point, otherwise a saddle point or unstable point
(1, 1, 1)	$\lambda_1 = A + C_g - D$; $\lambda_2 = -A + C_i - W + P\,(Q - Q\,\beta)$; $\lambda_3 = W\,m\,P\,Q\,\beta$	When $A + C_g - D < 0$, $-A + C_i - W + P\,(Q - Q\,\beta) < 0$ and $W\,m\,P\,Q\,\beta < 0$, it is a stable point, otherwise a saddle point or unstable point

Scenario 1. E_2 (0, 0, 1) is a stable evolutionary equilibrium strategy when $-C_g + D + W\ \alpha < 0$ and $-C_i - P\ (Q - Q\ \beta) < 0$. An example of this might be something that arises in the early days when data regulations and standards are not well established or enforced. The platform may have a high governance cost due to the lack of trust and transparency among the data providers and demanders. The data providers may have a high innovation cost due to the lack of infrastructure and skills to produce high-quality data. The data demanders may have a low penalty for resale data due to the lack of legal consequences or ethical awareness. This was common in the past decade, when data trading was less mature than today, and some small and unprofessional Chinese data trading platforms witnessed frequent data resale. This could result in a low-quality and inefficient data market that does not benefit any of the parties involved.

Scenario 2. E_4 (1, 0, 0) is a stable evolutionary equilibrium strategy when $C_g - D < 0$, $A - C_i - P\ (Q - Q\ \beta) < 0$ and $m\ P\ Q - W\ \alpha < 0$. An example of this situation could be a data trading platform that operates in a highly regulated industry such as healthcare or finance, where the data quality and security standards are very high. The platform may have a low governance cost due to the compliance with the existing regulations and the trust among the data providers and demanders. The data providers may have a high innovation cost due to the complexity and sensitivity of the data they produce. The data demanders may have a high penalty for resale data due to the legal and ethical implications of violating the data privacy and security rules. This could result in a well-regulated but less innovative data market.

Scenario 3. E_5 (1, 1, 0) is a stable evolutionary equilibrium strategy when $A + C_g - D < 0$, $-A + C_i + P\ (Q - Q\ \beta) < 0$ and $-W + m\ P\ Q\ \beta < 0$. An example of this situation could be a data trading platform that operates in a highly innovative industry such as scientific research, where the data quality and value are very high. The platform may have a low cost of governance and innovation incentive for data providers due to the alignment with the industry standards and customer expectations. The data providers may have a high gain from innovation and data trading due to the differentiation and demand for their data. The data demanders may have a high penalty for resale data due to the platform rules and the competitive advantage of their data. This could result in a high-quality and efficient data market that incentivizes data providers to innovate and data demanders to use data in compliance with the regulations.

Scenario 4. E_6 (1, 0, 1) is a stable evolutionary equilibrium strategy when $C_g - D - W\ \alpha < 0$, $A - C_i + W - P\ (Q - Q\ \beta) < 0$ and $m\ P\ Q + W\ \alpha < 0$. An example of this situation could be a data trading platform that operates in a highly competitive and dynamic industry such as social media or entertainment, where the data quality and value are very low. The platform may have a low governance cost due to the lack of regulation and standardization in the industry. The data providers may have a high innovation cost due to fast-changing customer preferences and behaviors. The data demanders may have high benefit from reselling data due to the high demand and low supply of data in the market. This could result in a low-quality and chaotic data market that does not incentivize data providers to innovate or data trading platforms to govern.

Scenario 5. E_7 (0, 1, 1) is a stable evolutionary equilibrium strategy when $-A - C_g + D < 0$ and $C_i + P\ (Q - Q\ \beta) < 0$. An example of this situation could be a data trading platform that operates in a highly unregulated and fragmented industry, where the data quality and value are very diverse. The platform may have a high cost of governance and innovation incentive for data providers due to the lack of industry standards and customer feedback. The data providers may have a low innovation cost due to the availability and accessibility of data sources. The data demanders may have a high benefit from reselling data due to the lack of governance by the platform and the high demand and low supply of data in the market. This could result in a diverse but chaotic data market that incentivizes data providers to innovate and data demanders to resell. This equilibrium is generally not sustainable.

Scenario 6. E_8 (1, 1, 1) is a stable evolutionary equilibrium strategy when $A + C_g - D < 0$, $-A + C_i - W + P\ (Q - Q\ \beta) < 0$ and $W\ m\ P\ Q\ \beta < 0$. An example of this situation could be a data trading platform that operates in a highly collaborative and creative industry, where the data quality and value are very subjective. The platform may have a high cost of governance and innovation incentive for data providers due to the diversity and complexity of the data they produce. The data providers may have a high gain from innovation incentives, compensation for data being resold and data trading due to the recognition and reward for their data. The data demanders may have a high benefit from reselling data due to the lack of governance by the platform and the high demand and low supply of data in the market. This could result in a diverse and dynamic data market that incentivizes data providers to innovate but cannot effectively regulate the resale behavior of data demanders.

4. Numerical Simulation

In reference to the relevant research [34,35], the correctness of the analysis was further tested through a numerical simulation to reveal the stability of the equilibrium strategy of the evolutionary game with different factors influencing the elements and to seek insights into the governance of data resale behavior in data trading. Considering that (1, 1, 0) is the ideal equilibrium state when the data trading platforms govern, the data suppliers innovate positively and the data demanders do not sell data, the conditions that must be satisfied are $A + C_g - D < 0$, $-A + C_i + P\,(Q - Q\,\beta) < 0$ and $-W + m\,P\,Q\,\beta < 0$. Based on this set of parameters, $C_g = 1$, $D = 3$, $A = 1$, $W = 2$, $C_i = 1$, $P = 1$, $Q = 1$, $\beta = 2$, $m = 0.5$, $\alpha = 0.5$, $x = 0.5$, $y = 0.5$, $z = 0.5$, and the simulation period was set at 10.

4.1. Influence of Data Price and Volume Trading on the Evolutionary Game System

Figure 4 shows that the probability of data trading platforms choosing a governance strategy decreases, while the probability of data suppliers choosing an innovative strategy and data demanders choosing a resale strategy increases, as the price or the number of trades of data trading increases. The price (P) and the quantity (Q) of data trading affect the payment of the three parties indirectly through the game system, as they determine the amount of data trading. Data trading platforms can obtain revenue from any data trading amount, regardless of their strategy. The higher the price and quantity of data trading, the higher the benefit ($P\,Q$) and the incentive for data suppliers to choose the data innovation strategy. Data demanders buy data for utility, but they can also profit from reselling data. The higher the value of data trading, the higher the resale revenue ($m\,P\,Q$). This implies that more data trading may lead to more frequency and circulation of data resale, which may reduce the effectiveness of platform governance and increase t.he difficulty of regulating data trading.

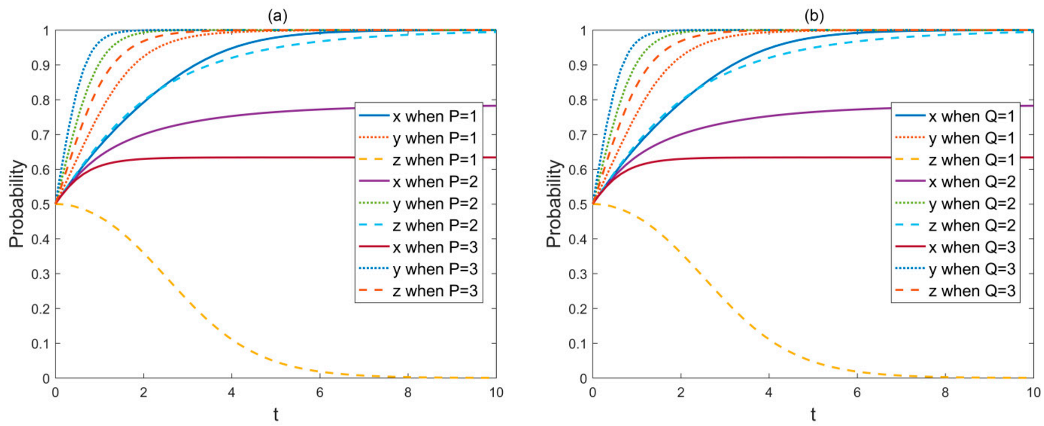

Figure 4. Influence of data trading price and quantity parameters on the evolutionary game system. (**a**) Influence of data trading price. (**b**) Influence of data trading quantity.

4.2. Influence of the Behavioral Parameters of the Data Trading Platforms on the Evolutionary Game System

The main factors that influence the behavior of data trading platforms are the cost of governance, the competitive pressures not to govern, and the incentives and penalties for data traders. This paragraph focuses on the first two factors. Figure 5 illustrates that the higher the cost (C_g) of governance for data trading platforms, the lower their motivation to govern. This means that they will offer fewer incentives for data innovation and impose fewer penalties for data resale, which will discourage data suppliers from innovating and encourage data demanders from the resale, resulting in data trading governance failure. On the other hand, the competitive pressure (D) on data trading platforms not to govern, which stems from the risk of losing market share to other platforms, will increase their motivation to govern. This means that they will offer more incentives for data innovation and impose more penalties for data resale, which will encourage data suppliers to innovate and discourage data demanders from the resale, leading to data trading governance success. These two behavioral parameters suggest that data trading platforms need to consider their governance costs and optimize their institutional facilities and cost control to achieve effective data resale governance when the market competition is high.

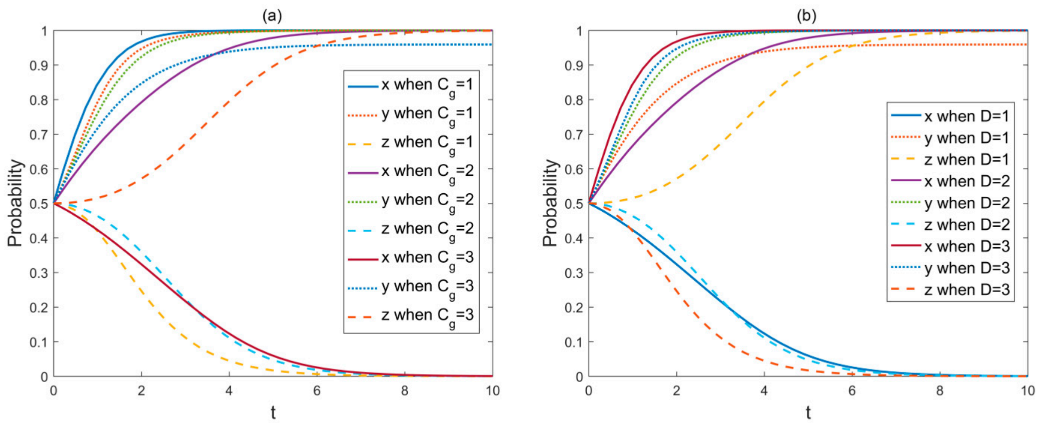

Figure 5. Influence of data trading platforms behavior parameters on the evolutionary gaming system. (**a**) Influence of the cost of governance for data trading platforms. (**b**) Influence of the competitive pressure on data trading platforms not to govern.

4.3. Influence of Data Supplier Behavior Parameters on the Evolutionary Game System

The behavior of data suppliers depends mainly on three parameters: the cost of data innovation, the degree of data innovation, and the reward for data innovation. The first two are internal factors and the last one is external.

Figure 6 shows that the data innovation incentive (A) from data trading platforms can significantly increase the motivation of data suppliers to innovate, but it can also increase the cost of governance for data trading platforms. If the incentive is too high, data trading platforms may reduce their governance level or even stop governing, and data demanders may increase their resale behavior under lower constraints. This may decrease the motivation of data suppliers to innovate again, which indicates that the effect of incentives from data trading platforms is uncertain. The higher the cost (C_i) of innovation for data suppliers, the lower their motivation to innovate; the higher the motivation of data trading platforms to govern for sustainable competitive advantage; the higher the risk of the data trading market shrinking; and the higher the motivation of data demanders to choose resale strategy despite the penalty constraint. The higher the degree of data innovation (β) for data suppliers, the higher their motivation to choose an innovative data strategy; the lower the motivation of data trading platforms to govern; and the higher the revenue and motivation of data demanders to resell data.

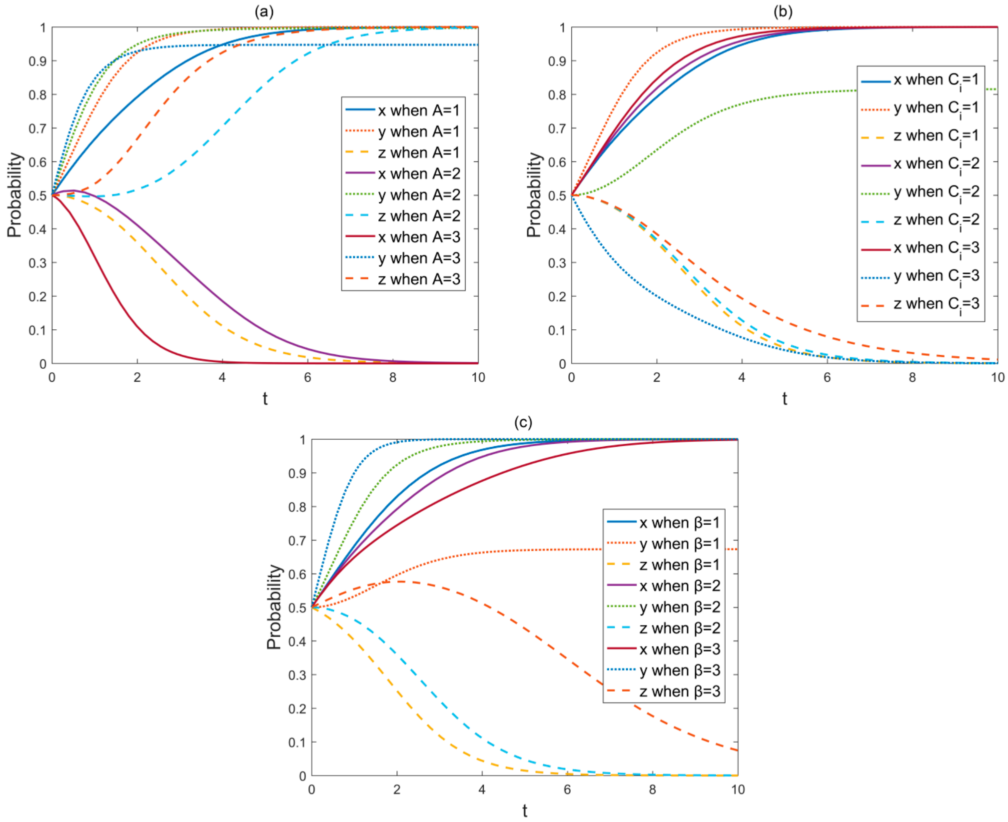

Figure 6. Influence of data suppliers behavior parameters on the evolutionary game system. (**a**) Influence of the data innovation incentive from data trading platforms. (**b**) Influence of the cost of innovation for data suppliers. (**c**) Influence of the degree of data innovation for data suppliers.

4.4. Influence of Data Demanders Behavior Parameters on the Evolutionary Game System

The behavior of data demanders is affected by both internal and external factors. An internal factor is the benefit coefficient (m) of resale data, and two external factors are the data resale penalty from data trading platforms and the probability of data resale being reported.

Figure 7 illustrates that the higher the benefit coefficient of resale data, the higher the motivation of data demanders to choose resale strategy; the higher the motivation of data suppliers to choose innovation strategy; and the lower the motivation of data trading platforms to choose governance strategy. The higher the data resale penalty (W) from data trading platforms, the lower the motivation of data demanders to resell data; the higher the motivation of data trading platforms to govern, as they can partially collect the penalty and compensate for their loss caused by data resale; and the higher the motivation of data suppliers to innovate. The higher the probability (α) of data resale being reported, the lower the motivation of data demanders to resale data; the lower the motivation of data suppliers to innovate; and the higher the motivation of data trading platforms to govern.

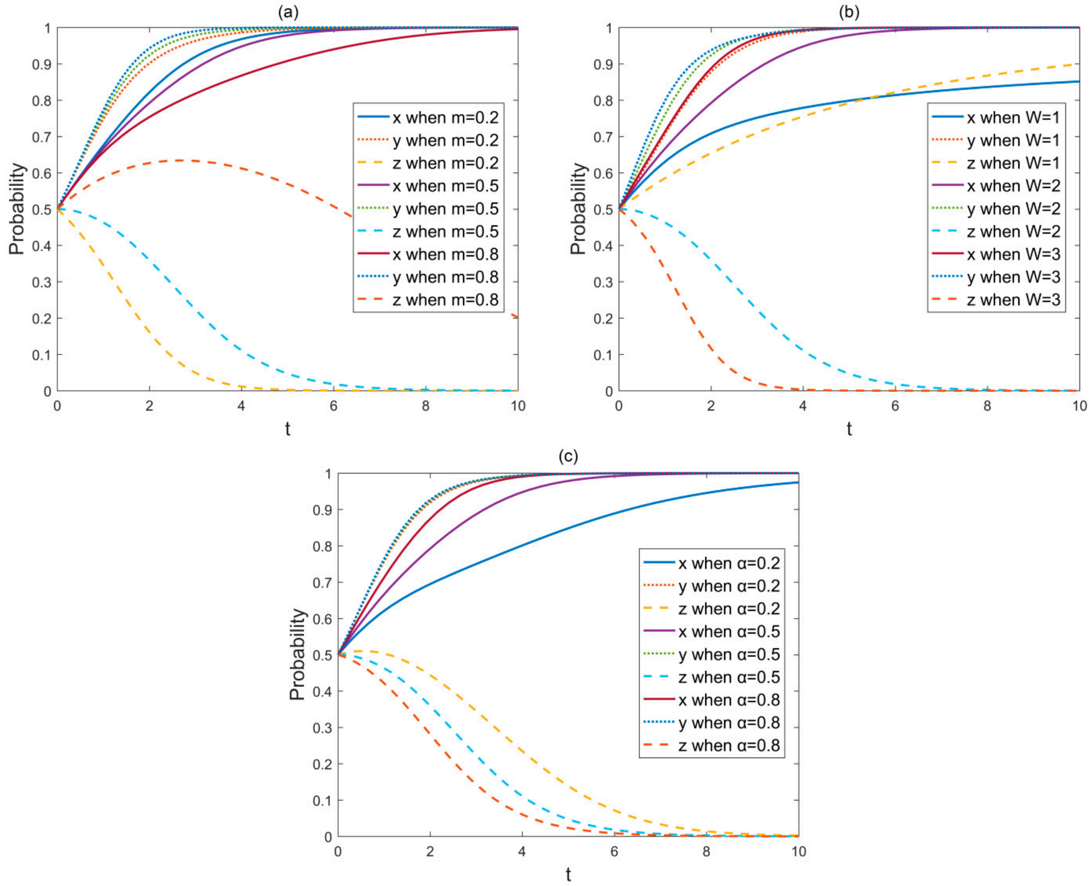

Figure 7. Influence of data request behavior parameters on the evolutionary game system. (**a**) Influence of the benefit coefficient of resale data. (**b**) Influence of the data resale penalty from data trading platforms. (**c**) Influence of the probability of data resale being reported.

5. Discussion

The digital economy has entered a new era driven by innovative data resources, and data has become a significant factor in economic and social development. Promoting the market for data elements and their flow is necessary for economic growth and innovation [6–8]. The platform trading model has become an essential approach to facilitate the effective flow of data and maximize its value, while governance through platforms is an efficient way to secure data and promote its free circulation [11,36]. Generally, in addition to data buyers and sellers, the data trading market comprises third-party platforms, data subjects, and professional technical service suppliers [15,23,24,36]. After determining the data price, it still requires an orderly operation in the context of mutual games among all participants in the data market. As the contribution to the distribution of data values is often uneven, quantifying the overall and individual returns fairly and reasonably, and developing a dynamic adaptation and stable price operation mechanism are crucial to establishing a data factor market system [22,37,38].

Despite the introduction of data laws, regulations, and standards in recent years in the US, the EU, Asia, and other countries or regions, such as the California Consumer Privacy Act, the General Data Protection Regulations in Europe, and the Data Security Law in China, the boundaries of data ownership remain unclear [22,23]. This is due to the nature of data, which can be shared and controlled by multiple entities simultaneously, making it difficult for data subjects to establish their rights or prevent others from accessing it [22]. It has been argued that sharing data creates a win-win situation, as data can be reproduced at a low cost without degradation and can generate new economic value. However, without effective means to establish and protect data rights, the transfer of access to data can pose challenges for all parties involved [39,40].

The predominant belief is that data resale violates the rights of the original seller [22,41,42], and those involved in data trading may only use the data rather than resell them. Similarly to intellectual property rights in film, television, and music, downloading works for private distribution after watching them on platforms such as YouTube is not permitted. This is because data lack competitiveness and exclusivity, allowing easy and widespread copying and distribution once resold, making it challenging to control and manage [22,43,44]. To mitigate this issue, ownership of the data could remain with the provider, while the right to use the data could be licensed to the user, promoting shared value through the circulation of the data usage right.

This paper examines the risks of data practices in small trading markets, in which third parties copy, retain, and resale data. An evolutionary game model is constructed that comprises data suppliers, demanders, and trading platforms to investigate innovation, resale behavior, and governance in data trading. The analysis indicates that the resale of data by demanders suppresses innovation incentives for suppliers and depletes the data trading market. To govern such behavior, trading platforms implement measures to restrict or penalize data resale. Model analysis shows that innovation rewards for data suppliers by trading platforms increase innovation incentives, while penalties for data resale by demanders reduce such behavior. Of course, these processes vary depending on the stage of data trading development and the market environment. A robust data trading market can be established as the data trading system improves and the market matures.

To develop an effective data trading market, we put forward some possible policy recommendations and their potential implementation: (1) Establishing data as a legal asset that can be owned, traded, and protected by law. This would require defining the rights and obligations of data suppliers, demanders, and trading platforms, as well as setting up a registration system for data ownership and circulation. (2) Promoting the development of a data element market that allows for the exchange of various types of data (such as personal information, location, behavior, preferences, etc.) among different parties. This would require issuing guiding documents to clarify the objectives and principles of data element allocation and governance, as well as encouraging pilot testing and innovation. (3) Enhancing the oversight and coordination of data trading by the government and relevant authorities. This would require establishing a top-level governance framework for data trading, setting up standards and rules for data quality, security, and privacy, as well as monitoring and enforcing compliance. (4) Improving the transparency and efficiency of data trading by using technical means such as blockchain and multiparty secure computing. This would enable tracing data element circulation, verifying data authenticity and integrity, and reducing transaction costs. (5) Encouraging the participation and education of retail investors in the data trading market. This would require providing accessible and reliable information on data products and services, raising awareness of the risks and opportunities of data trading, and fostering financial literacy and competence.

6. Implications

In this paper, an evolutionary game model is constructed to discuss the behavior of data resale and its governance mechanism. The main marginal contribution of this paper is to advance the theoretical knowledge of data trading governance by applying an evolutionary game model to analyze the behavior and choices of data suppliers, demanders, and trading platforms. The model identifies the factors and scenarios that lead to stable equilibrium strategies for different parties and provides suggestions for enhancing the orderliness and sustainability of the data market. The paper also investigates the impact of data innovation and resale behavior on data trading and how they are affected by various parameters such as data cost, value, innovation degree, and resale penalty. It deepens the comprehension of data trading processes and offers a numerical tool for evaluating and optimizing the strategies of data traders.

However, this study has some limitations that offer opportunities for further research. It mainly considered the interests of three stakeholders in data trading: data trading platforms, data suppliers, and data demanders. However, data resale behavior in the data trading process is also affected by other players or factors that we did not take into account, such as government governance agencies and intermediary structures. Future research could adopt a more comprehensive and holistic approach to analyze the roles and impacts of these factors on data trading dynamics and outcomes. For example, a multi-agent simulation model could be developed to capture the interactions and feedback among different actors and scenarios in data trading markets.

This paper focuses on small-scale data trading platforms that do not adopt advanced technologies such as cryptography and blockchain to prevent data resale. These technologies can enable data encryption, verification, and traceability, which can reduce the information asymmetry and moral hazard problems in data trading. They can also facilitate the creation of smart contracts, decentralized autonomous organizations and token economies, which can change the incentives and behaviors of data sellers and buyers. Future research could extend the model to incorporate the effects of these technologies on data trading governance and compare the results with the current model. Such a comparison could help to evaluate the advantages and disadvantages of different governance approaches and technologies for data trading, as well as to identify the optimal design and configuration of data trading platforms.

Furthermore, this paper primarily focuses on the game-theoretical aspects of data resale governance in data trading, without delving into the ethical implications of applying evolutionary game analysis in this context. As technology becomes increasingly intertwined with society, it is indeed worth studying how the behavior and interactions of socio-technical actors in data trading are influenced by moral values, norms, and principles. A study that adopts a systems approach to investigate the roles of socio-technical actors within complex adaptive systems is indeed worth considering [45,46]. The literature recognizes that socio-technical actors are not isolated or rational agents, but rather embedded and adaptive agents that co-evolve with their environment and with each other. Future research could benefit from integrating this literature with the game-theoretical framework presented in this paper, to provide a more comprehensive and nuanced understanding of data trading governance.

7. Conclusions

As technology advances and data become increasingly vital to society, their impact on the economy is becoming more evident. Data trading has gained the attention of both government and market actors as a means of optimizing data element allocation. However, due to the ease of forgery and copying of digital products, disorderly data trading has become a significant issue. Thus, establishing an effective data governance mechanism is crucial in reducing the speculative behavior of data resale, protecting data suppliers' rights and interests, and improving the efficiency of data element market allocation. To address this, this paper constructs an evolutionary game model comprising three parties—data trading platforms, data suppliers, and data demanders—and assesses the influence of various governance strategies on the stability of the evolutionary game system within data trading platforms. The central findings are as follows:

(1) When certain conditions are met, E_2 (0, 0, 1), E_4 (1, 0, 0), E_5 (1, 1, 0), E_6 (1, 0, 1), E_7 (0, 1, 1), and E_8 (1, 1, 1) have progressive stability, where E_5 (1, 1, 0) is a stable equilibrium strategy that can satisfy the effective governance of data trading platforms and can lead to data trading platforms choosing to govern, data suppliers choosing to innovate positively, and data demanders choosing not to resale.

(2) The higher the price and amount of data trading, the lower the probability that the data trading platforms will choose to govern, and the greater the probability that the data suppliers will choose a positive innovative strategy, while the probability that

the data demanders will choose a resale strategy increases. The higher the price and the number of data transactions, the more difficult it is to govern data transactions.

(3) The higher the cost of governance on data trading platforms, the lower the incentive to govern, the lower the incentive for data suppliers to innovate, and the higher the incentive for data demanders to resell. The greater the competitive pressure on data trading platforms not to govern, the greater the incentive to govern, the greater the incentive for data suppliers to innovate and the lower the incentive for data demanders to resale.

(4) The data innovation incentives of data trading platforms can significantly promote the motivation of data suppliers to innovate data positively; when the incentives are too high, data trading platforms will weaken their level of governance or even move towards non-governance; in addition, the greater the cost of innovative data for data suppliers, the lower their motivation to innovate data; the greater the level of data innovation for data suppliers, the higher their motivation to choose innovative data strategies.

(5) The higher the payoff factor for data demanders to resell data, the greater their incentive to choose a resale strategy; and the greater the incentive for data suppliers to innovate data positively, the weaker the incentive for data trading platforms to govern it. The greater the data resale penalty on the data trading platforms, the weaker the incentive for data demanders to resell data; the greater the probability of data resale being reported, the less incentive for data demanders to resale data.

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