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Evolutionary Dynamics in Data Trading with Risk Compensation

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Abstract: The fact that data can be privately possessed yet contain the attributes of public goods leads to the "Arrow's Information Paradox" in data trading. If left unchecked, supply-side deception about data quality and demand-side data leakage can seriously undermine the trust between suppliers and demanders. Inspired by the ideas of reputation and punishment, this paper combines a risk compensation mechanism, which is widely available in the financial sector, with data trading. Specifically, we propose a data trading model with risk compensation and study the evolutionary dynamics of the population using evolutionary game theory. We define λ as the demander's compensation share that the supplier has to bear for data quality cheating and η as the supplier's compensation share that the demander has to bear for data leakage. Through numerical solution and simulation, we analyze the evolutionary stable states of the population and find that the risk compensation mechanism in some data trading scenarios can limit the supply side from cheating on data quality or the demand side from leaking data. The results show that λ and η act asymmetrically, with λ being able to affect both supply-side and demand-side strategies, while η affects only the demand-side strategy. This work reveals chaos and asymmetry in data trading with risk compensation, and the proposed model and replication dynamic equations may have implications for future research.

Keywords: data trading; evolutionary dynamics; risk compensation

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1. Introduction

With the popularization and development of information technology, the speed of producing data and the efficiency of processing data are continuously improving [1–3]. The potential and value of data are highlighted in everyday life [4,5]. As one of the important ways to promote the release of data value, data trading is gaining more and more attention [6,7], and successful cases of data trading can be seen in many fields, such as in manufacturing [8], energy [9], and medical treatment [10].

However, data trading is different from the trading of other traditional products, and the contradiction between the private ownership of data and the public character of data leads to trust barriers between the supplier and demander in a data trading [11–13]. Specifically, like public goods that can be used by many people at the same time without wear and tear [14], the supplier in a digital trade can transact with multiple demanders without loss of data, and multiple demanders can use the product at the same time. So, the supplier cannot have sole ownership of the data by taking possession of it [15], and the demander cannot know about the data without jeopardizing its ownership, i.e., the

"Arrow's Information Paradox" [16,17]. Because of the "Arrow's Information Paradox", suppliers and demanders engage in a data trading game. They all pursue greater benefits at minimal cost [18,19], and the supplier can cheat on the quality of the data to obtain higher returns, while the demander may replicate and disseminate the data once they are acquired. So, suppliers and demanders face the risks of data leakage and data quality deception, respectively, and there are trust barriers between the two parties of the trading [20].

The unique characteristics of data mean that the trading mechanisms for traditional products are not applicable to data trading, and we need to design specialized mechanisms for data trading [7,21]. In response to the "Arrow's Information Paradox", many scholars have proposed technical solutions to address data leakage and data quality cheating in data trading, such as the data trading protocol exploiting blockchain [22], decentralized fair IoT data transactions via searchable proxy re-encryption [23], and fairness-aware federated unlearning for data trading [24]. However, the huge power consumption of blockchain technology [25] and the high computational complexity of the algorithms [26] make it difficult for these technologies to meet the real-time demands of data trading. These technologies still need to be improved in terms of energy consumption, cost, and computation [20,27]. On the other hand, the enactment of laws helps to ensure that data trading is carried out safely [28], but the long process of enacting laws makes it difficult to safeguard data trading at present. Overall, it seems that it is difficult to rely solely on technology or laws to ensure that data quality is not cheated and that data are not leaked in data trading. Additionally, it has been seen in many scenarios that the demander in a trading can perform a two-step trading [29–31]. When applying a two-step trading to data trading, if a demander is cheated about the data quality, then it is less costly because the demander has only traded a small portion of the data; if they are not cheated, then they can go on to complete the rest of the trade. But, two-step trading cannot limit the data leakage from the demander, which restricts data trading. Overall, it is necessary to design some mechanisms for data trading to combat the vicious behaviors of both suppliers and demanders so as to enhance their trust in each other and their confidence in trading [32,33].

Existing research on data trading mechanisms mainly focuses on technical solutions [20,21]. In contrast, this study hopes to introduce an innovative approach by combining the punishment mechanism in game theory with data trading. Drawing on existing research in evolutionary game theory, punishment [34] and reputation [35] have been shown to be effective in discouraging free-riding and other non-cooperative behaviors, both in the multi-player game PGG [36–39] and in the two-player game Prisoner's Dilemma [40–42]. However, there are unique challenges to implementing punishment and reputation mechanisms in data trading. These challenges include the inherent time lag in detecting undesirable behaviors and the subjectivity of the reputation assessment process [43]. To address these limitations, we apply the risk compensation mechanism, a concept that has worked well in the financial sector [44,45] in data trading. In data trading, we implement this concept by dynamically adjusting the trading price based on the behavioral preferences of suppliers and demanders. This adaptive pricing strategy mitigates potential losses due to specific behavioral preferences, thus creating a robust trading environment.

Compared to other trust-enhancing methods, the risk compensation mechanism has superior advantages in terms of both cost-effectiveness and operational efficiency. In contrast to centralized practices like third-party punishment or third-party reward, risk compensation mechanisms utilize information held by data trading platforms, including data quality feedback from demanders and post-transaction integrity assessments from suppliers, with no additional input required. Based on this information, the parameters of risk compensation can be automatically adjusted, reflecting the cost advantages of the

risk compensation mechanism. In terms of timeliness, those with compromised interests, whether suppliers or demanders, have the greatest incentive to provide feedback on this fact, thus ensuring that the risk compensation mechanism has access to timely and truthful behavioral information. The contract, as a legally binding instrument, safeguards the interests of both suppliers and demanders. However, its execution often requires a third party, especially in the event of a breach of contract requiring recourse to benefits. Taken together, the risk compensation mechanism promotes trust between the two trading parties and promotes fairness in data trading in a cost-effective and time-efficient manner.

An intuitive explanation of the risk compensation mechanism is to differentiate pricing based on the credits of trading parties, a practice that is common in the financial sector [46–48]. For example, in the personal credit business, financial institutions require lower interest rates for borrowers with better credit; conversely, they require higher interest rates for borrowers with poorer credit to compensate for the high probability of future delinquency. The risk compensation mechanism is particularly suitable for data trading scenarios for three main reasons. First, as the 'Arrow's Information Paradox' shows, the virtual nature of data poses a significant challenge to data assessment, which highlights the importance of assessing trading partners before entering into a trading. Second, in practice, the past trading behavior of the trading parties is recorded in the data trading platform. It is easy to evaluate the trading parties and calculate the risk compensation parameters based on such behavioral information, as subsequently indicated in our model. Finally, as a virtual asset trading infrastructure, the data trading platform monitors and guides transactions, making risk compensation not just a transaction outcome but potentially an intervention pathway to motivate the system to evolve in the desired direction. The risk compensation mechanism can help realize a win–win situation for all parties, which is what our proposed model tries to do.

While risk compensation works well in many scenarios [49–53], the effect of the risk compensation mechanism on data trading has yet to be investigated under the influence of the unique characters of data. Specifically, risk compensation is required for both suppliers' deception of data quality and demanders' leakage of data, and the evolutionary dynamics of the population under the combined effect of the two are difficult to predict. Moreover, the supplier and the demander have different ways of profiting from data trading, and the risk compensations for the two sides are asymmetric. Whether risk compensation can play a role in data trading and how to compensate for risks are questions that remain to be investigated. To answer the above questions, this paper proposes the data trading model with risk compensation. By establishing the replication dynamic equation, the evolutionary dynamics of the population and parameter sensitivity analysis are implemented through numerical solution and simulation analysis [54,55].

The rest of the paper is organized as follows. In Section 2, we develop the data trading model with risk compensation. In Section 3, we establish the replication dynamic equations and numerically analyze the evolutionary stable state of the population under different parameters. Section 4 simulates the evolutionary stable state of the population and the effect of parameters. Finally, we summarize and discuss the results in Section 5.

2. Data Trading Game with Risk Compensation

In our proposed data trading game model, there are two types of players: the supplier and the demander. In a single trading, both the supplier and the demander face multiple strategy choices. Before trading, the supplier has two alternative strategies with respect to data quality; either to cheat on data quality to obtain higher trading pricing, or to not cheat at all. The demander also needs to choose which way to complete the trading, i.e., one-time trading or two-step trading. In the case of a one-time trading, the supplier and the

demander trade all the data at once. In the case of a two-step trading, the supplier and the demander trade a portion of the data first, and if the demander is satisfied with the data quality, i.e., the supplier has not cheated on the data quality, then they trade the remaining data. After the trading, the demander also has two alternative strategies to proceed with for the obtained data, which are to leak the data to gain more revenue or not to leak it. In the data trading game described above, X denotes the proportion of suppliers who cheat on data quality, Y represents the proportion of demanders who leak data, and Z denotes the proportion of demanders who opt for a one-time trading.

In a data trading game, the supplier has a set of data with quantity $\alpha \in [0,1]$ and quality $\beta \in [0,1]$. When selling data, the supplier can deceive the demander and state that the data quality is β_m, $\beta_m > \beta$. The demander chooses whether or not to pay the cost W for a two-step trading. In a two-step trading, the demander first trades data of quantity $\theta\alpha$, $\theta \in (0,1)$. If they realize that they have been cheated, then the trading is terminated; otherwise, they proceed to trade the remaining data of quantity $(1-\theta)\alpha$. If there is no two-step trading, the demander buys the data in quantity α at once. Referring to other studies on data trading [56,57], the price P of a set of data is determined by both quantity $\hat{\alpha}$ and quality $\hat{\beta}$, and we let $P = g(\hat{\alpha}, \hat{\beta}) = (\hat{\alpha}\hat{\beta})^k$ in this paper, $k \in [0,1]$.

After purchasing the data, the demander processes the data to generate revenue. The value R created by data of quantity $\hat{\alpha}$ and quality $\hat{\beta}$ is obtained by extending the Cobb–Douglas production function. $R = {D_b}^{\varepsilon} a(\hat{\alpha}\hat{\beta})^{\zeta}$, where D_b is the buyer's data production capabilities, including production technology, digitization levels, employee data literacy, etc., a reflects the influence of other factors of production such as capital and labor, and $\varepsilon + \zeta > 1$ represents increasing return to scale for data. In addition, the demand side can leak the data to increase their revenue. The revenue from leaking data $p_l = (1+\gamma)P$, where $\gamma \in (-1, +\infty)$ reflects a range of factors other than the true price of the data.

We introduce risk compensation into the data trading game to restrain undesirable behavior from both suppliers and demanders.

For λ: λ is the demander' compensation share paid by the supplier to the demander due to the cheating on data quality by the supplier. Specifically, when the supplier has a behavioral preference to deceive the demander about data quality, such as deliberately exaggerating the size, granularity, and time span of the data, the price of the data P becomes $P' = (1-\lambda)P$ to compensate for the loss suffered by the demander, where $\lambda \in [0,1]$.

For η: η is the supplier's compensation share paid by the demander to the supplier due to the leaking of data by the demander. When the demander has a behavioral preference for leaking data, such as sharing acquired data with a third party or selling that data without authorization, the price of data P becomes $P' = (1+\eta)P$ to compensate the supplier for the loss due to the data leakage, where $\eta \in [0, +\infty)$.

As an example, for data with quantity α and quality β, if the supplier cheats on the quality of data and the demander leaks the data, the trading price of this set of data after risk compensation is $P = (1-\lambda)(1+\eta)(\alpha\beta_m)^k$.

The payoff matrix of the data trading game with risk compensation is shown in Table 1.

Table 1. Payoff matrix of the data trading game with risk compensation.

x	y	z	$P_s = (\alpha\,\beta_m)^k\,(1+\eta)\,(1-\lambda)$ $P_d = (\alpha\,\beta)^k\,(\gamma+1) + D_b{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta} + (\alpha\,\beta_m)^k\,(\eta+1)\,(\lambda-1)$
		$1-z$	$P_s = W + (1+\eta)\,(1-\lambda)\,(\alpha\,\beta_m\,\theta)^k$ $P_d = (\gamma+1)\,(\alpha\,\beta\,\theta)^k - W + D_b{}^{\varepsilon}\,a\,(\alpha\,\beta\,\theta)^{\zeta} + (\eta+1)\,(\lambda-1)\,(\alpha\,\beta_m\,\theta)^k$
	$1-y$	z	$P_s = (\alpha\,\beta_m)^k\,(1-\lambda)$ $P_d = (\alpha\,\beta_m)^k\,(\lambda-1) + D_b{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta}$
		$1-z$	$P_s = W + (1-\lambda)\,(\alpha\,\beta_m\,\theta)^k$ $P_d = (\lambda-1)\,(\alpha\,\beta_m\,\theta)^k - W + \mathrm{D_b}{}^{\varepsilon}\,a\,(\alpha\,\beta\,\theta)^{\zeta}$
$1-x$	y	z	$P_s = (\alpha\,\beta)^k\,(\eta+1)$ $P_d = (\alpha\,\beta)^k\,(\gamma+1) - (\alpha\,\beta)^k\,(\eta+1) + \mathrm{D_b}{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta}$
		$1-z$	$P_s = W + (\alpha\,\beta)^k\,(\eta+1)$ $P_d = (\alpha\,\beta)^k\,(\gamma+1) - (\alpha\,\beta)^k\,(\eta+1) - W + \mathrm{D_b}{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta}$
	$1-y$	z	$P_s = (\alpha\,\beta)^k$ $P_d = \mathrm{D_b}{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta} - (\alpha\,\beta)^k$
		$1-z$	$P_s = W + (\alpha\,\beta)^k$ $P_d = \mathrm{D_b}{}^{\varepsilon}\,a\,(\alpha\,\beta)^{\zeta} - (\alpha\,\beta)^k - W$

3. Equilibrium Analysis of the Digital Trading Evolutionary Game

3.1. Replication Dynamic Equation

Within the framework of evolutionary game theory, we systematically derive the revenues for various strategic interactions between suppliers and demanders. The revenue calculation follows a comprehensive approach: for each specific strategy adopted by a player, we compute its expected revenue by considering all possible strategy combinations of other participants. Mathematically, this involves the integration of probability distributions associated with strategy combinations and their corresponding revenues, conditional on the focal player's strategic choice.

We analyze two strategies for suppliers: cheating data quality and informing real data quality. The expected revenues for these strategies, denoted as U_x and U_{1-x}, respectively, are calculated by incorporating two other dimensions: (1) the implementation of two-step trading and (2) the potential risk of data leakage. The comprehensive evaluation of these factors yields the supplier's mean expected revenue, mathematically represented as $\bar{U_x}$.

$$\begin{aligned} U_x = {} & yz \times P_{s,xyz} + y(1-z) \times P_{s,xy(1-z)} \\ & + (1-y)z \times P_{s,x(1-y)z} + (1-y)(1-z) \times P_{s,x(1-y)(1-z)} \end{aligned} \tag{1}$$

$$\begin{aligned} U_{1-x} = {} & yz \times P_{s,(1-x)yz} + y(1-z) \times P_{s,(1-x)y(1-z)} \\ & + (1-y)z \times P_{s,(1-x)(1-y)z} + (1-y)(1-z) \times P_{s,(1-x)(1-y)(1-z)} \end{aligned} \tag{2}$$

$$\bar{U_x} = x \times U_x + (1-x) \times U_{1-x} \tag{3}$$

Similarly, we examine the strategic choices available to demanders, specifically focusing on leaking and not leaking data. The expected revenues associated with these two strategies, denoted as U_y and U_{1-y}, are derived through an assessment that incorporates two dimensions: (1) the implementation of two-step trading and (2) the occurrence of data quality cheating. The above analysis leads to the demander's mean expected revenue $\bar{U_y}$.

$$\begin{aligned} U_y = {} & xz \times P_{d,xyz} + x(1-z) \times P_{d,xy(1-z)} \\ & + (1-x)z \times P_{d,(1-x)yz} + (1-x)(1-z) \times P_{d,(1-x)y(1-z)} \end{aligned} \tag{4}$$

$$\begin{aligned} U_{1-y} = {} & xz \times P_{d,x(1-y)z} + x(1-z) \times P_{d,x(1-y)(1-z)} \\ & + (1-x)z \times P_{d,(1-x)(1-y)z} + (1-x)(1-z) \times P_{d,(1-x)(1-y)(1-z)} \end{aligned} \tag{5}$$

$$\bar{U}_y = y \times U_y + (1-y) \times U_{1-y} \tag{6}$$

We also investigated demanders' strategy choices between one-time and two-step trading. The expected revenues for these two strategies, denoted as U_z and U_{1-z}, were evaluated in terms of two dimensions: (1) the potential for data quality cheating and (2) the risk of data leakage. Based on the above analysis, the mean expected revenue, $\bar{U}_z$, was derived.

$$\begin{aligned} U_z = {} & xy \times P_{d,xyz} + x(1-y) \times P_{d,x(1-y)z} \\ & + (1-x)yz \times P_{d,(1-x)yz} + (1-x)(1-y) \times P_{d,(1-x)(1-y)z} \end{aligned} \tag{7}$$

$$\begin{aligned} U_{1-z} = {} & xy \times P_{d,xy(1-z)} + x(1-y) \times P_{d,x(1-y)(1-z)} \\ & + (1-x)y \times P_{d,(1-x)y(1-z)} + (1-x)(1-y) \times P_{d,(1-x)(1-y)(1-z)} \end{aligned} \tag{8}$$

$$\bar{U}_z = z \times U_z + (1-z) \times U_{1-z} \tag{9}$$

Combining the above average revenues, the replication dynamic equations for strategies x, y, and z are shown in Equations (10)–(12).

$$\begin{aligned} F_x = \tfrac{dx}{dt} &= x(U_x - \bar{U}_x) \\ &= x(1-x)(U_x - U_{1-x}) \\ &= x(x-1)(\eta\, y + 1)((\lambda + z - 1 - \lambda\, z)\,(\alpha\, \beta_m\, \theta)^k + (\alpha\, \beta)^k \\ &\quad + (\lambda\, z - z)\,(\alpha\, \beta_m)^k) \end{aligned} \tag{10}$$

$$\begin{aligned} F_y = \tfrac{dy}{dt} &= y(U_y - \bar{U}_y) \\ &= y(1-y)(U_y - U_{1-y}) \\ &= -y(y-1)((\alpha\, \beta)^k\,(\gamma - \eta - x + \eta\, x - \gamma\, x + x\, z + \gamma\, x\, z + 1) \\ &\quad - x\,(\gamma + 1)\,(z-1)\,(\alpha\, \beta\, \theta)^k - \eta\, x\,(\lambda - 1)\,(z-1)\,(\alpha\, \beta_m\, \theta)^k \\ &\quad + \eta\, x\, z\,(\alpha\, \beta_m)^k\,(\lambda - 1)) \end{aligned} \tag{11}$$

$$\begin{aligned} F_z = \tfrac{dz}{dt} &= z(U_z - \bar{U}_z) \\ &= z(1-z)(U_z - U_{1-z}) \\ &= -z(z-1)(W + x\, y\,(\alpha\, \beta)^k\,(\gamma + 1) + x\,(\alpha\, \beta_m)^k\,(\eta\, y + 1)\,(\lambda - 1) \\ &\quad + \mathrm{D_b}^{\varepsilon}\, a\, x\,(\alpha\, \beta)^{\zeta} - x\, y\,(\gamma + 1)\,(\alpha\, \beta\, \theta)^k \\ &\quad - x\,(\eta\, y + 1)\,(\lambda - 1)\,(\alpha\, \beta_m\, \theta)^k - \mathrm{D_b}^{\varepsilon}\, a\, x\,(\alpha\, \beta\, \theta)^{\zeta}) \end{aligned} \tag{12}$$

By solving the partial derivatives of F_x, F_y, and F_z, the 3×3 Jacobi matrix J can be obtained to analyze the evolutionary stable state of the data trading game. The value of each element in the Jacobi matrix J is shown in Table 2.

$$J = \begin{bmatrix} J_{11} & J_{12} & J_{13} \\ J_{21} & J_{22} & J_{23} \\ J_{31} & J_{32} & J_{33} \end{bmatrix} \tag{13}$$

Table 2. Jacobi matrix of the data trading game with risk compensation.

$J_{11} = \frac{dF_x}{dx}$	$J_{11} = (2x-1)(\eta y+1)\left((\alpha\beta)^k - (\lambda-1)\left((z-1)(\alpha\beta_m\theta)^k - z(\alpha\beta_m)^k\right)\right)$
$J_{12} = \frac{dF_x}{dy}$	$J_{12} = \eta x(x-1)\left((\alpha\beta)^k - (\lambda-1)\left((z-1)(\alpha\beta_m\theta)^k - z(\alpha\beta_m)^k\right)\right)$
$J_{13} = \frac{dF_x}{dz}$	$J_{13} = -x(x-1)(\alpha\beta_m)^k\left(\theta^k-1\right)(\eta y+1)(\lambda-1)$
$J_{21} = \frac{dF_y}{dx}$	$J_{21} = -y(y-1)(\eta\left((\alpha\beta)^k - (\lambda-1)\left((z-1)(\alpha\beta_m\theta)^k - z(\alpha\beta_m)^k\right)\right)$ $+(\gamma+1)(z-1)(\alpha\beta)^k\left(1-\theta^k\right))$
$J_{22} = \frac{dF_y}{dy}$	$J_{22} = -(2y-1)(x(\eta\left((\alpha\beta)^k - (\lambda-1)\left((z-1)(\alpha\beta_m\theta)^k - z(\alpha\beta_m)^k\right)\right)$ $+(\gamma+1)(z-1)(\alpha\beta)^k\left(1-\theta^k\right)) + (\alpha\beta)^k(\gamma-\eta+1))$
$J_{23} = \frac{dF_y}{dz}$	$J_{23} = -xy(y-1)\left(1-\theta^k\right)\left((\gamma+1)(\alpha\beta)^k + \eta(\lambda-1)(\alpha\beta_m)^k\right)$
$J_{31} = \frac{dF_z}{dx}$	$J_{31} = z(z-1)(y(\gamma+1)(\alpha\beta)^k\left(\theta^k-1\right) + (\eta y+1)(\lambda-1)(\alpha\beta_m)^k\left(\theta^k-1\right)$ $+\mathrm{D_b}^{\varepsilon} a(\alpha\beta)^{\zeta}\left(\theta^{\zeta}-1\right))$
$J_{32} = \frac{dF_z}{dy}$	$J_{32} = -xz(z-1)\left(1-\theta^k\right)\left((\gamma+1)(\alpha\beta)^k + \eta(\lambda-1)(\alpha\beta_m)^k\right)$
$J_{33} = \frac{dF_z}{dz}$	$J_{33} = -(2z-1)(W + xy(\alpha\beta)^k(\gamma+1)\left(1-\theta^k\right)$ $+x\left(1-\theta^k\right)(\alpha\beta_m)^k(\eta y+1)(\lambda-1) + x\,\mathrm{D_b}^{\varepsilon} a(\alpha\beta)^{\zeta}\left(1-\theta^{\zeta}\right))$

3.2. Stability Analysis of Evolution Strategies

By solving the system of Equation (14), we obtain 10 possible equilibrium points $E_{1\sim10}$, where eight of these points $E_{1\sim8}$ are vertices in a three-dimensional space consisting of x, y, and z, and two of which $E_{9,10}$ lie in the planes at $y = 0$ and $y = 1$, respectively. Each possible equilibrium point is brought into the Jacobi matrix, and by analyzing the eigenvalues of this matrix, we can conclude whether the possible equilibrium points are evolutionary stable or not.

$$\begin{cases} F_x &= 0 \\ F_y &= 0 \\ F_z &= 0 \end{cases} \tag{14}$$

In order to clearly analyze the conditions under which each point becomes an equilibrium point, we define the eigenvalue expressions as symbols, such that

$$A = \left((\lambda-1)(\alpha\beta_m\theta)^k + (\alpha\beta)^k\right)$$
$$B = \left((\gamma+1)(\alpha\beta)^k + \eta(\lambda-1)(\alpha\beta_m)^k\right)$$
$$C = W - (\lambda-1)(\alpha\beta_m)^k\left(\theta^k-1\right) - \mathrm{D_b}^{\varepsilon} a(\alpha\beta)^{\zeta}\left(\theta^{\zeta}-1\right)$$
$$D = \left((\alpha\beta)^k + (\lambda-1)(\alpha\beta_m)^k\right)$$
$$E = \left(W + (\lambda-1)(\alpha\beta_m)^k\left(1-\theta^k\right) + \mathrm{D_b}^{\varepsilon} a(\alpha\beta)^{\zeta}\left(1-\theta^{\zeta}\right)\right)$$
$$+\left(1-\theta^k\right)\left((\alpha\beta)^k(\gamma+1) + \eta(\lambda-1)(\alpha\beta_m)^k\right)$$
$$F = W\left(1-\theta^k\right)(\gamma+1)(\alpha\beta)^k\left((\alpha\beta)^k + (\alpha\beta_m)^k(\lambda-1)\right) +$$
$$\left(\theta^k-1\right)(\alpha\beta_m)^k(\alpha\beta)^k(\lambda-1)(\gamma-\eta+1)\left((\alpha\beta_m)^k(\lambda-1)\left(\theta^k-1\right) + \left(\theta^{\zeta}-1\right)\mathrm{D_b}^{\varepsilon} a(\alpha\beta)^{\zeta}\right)$$

Table 3 analyzes the conditions under which $E_{1\sim8}$ become equilibrium points.

For $E_2(1,0,0)$, E_2 is ESS under the condition $A \le 0 \wedge B \le 0 \wedge C \le 0$. $A \le 0$ implies that the trading price of a one-time trading when the data quality is true is no greater than the price of a two-step trading when the data quality is false. $B \le 0$ means that the gain from leaking data is not higher than the resulting loss in the case of a one-time trading, and the data quality is false. And $C \le 0$ suggests that a two-step trading is more profitable than a one-time trading for the demander in the case of being cheated. In the

case $A \leq 0 \wedge B \leq 0 \wedge C \leq 0$, suppliers cheat on data quality, while demanders trade in two steps and do not leak data, which is an evolutionary stable state. Taking $E_7(0,1,1)$ as an example, E_7 is ESS when $D \geq 0$. $D \geq 0$ means that the trading price for informing about the actual data quality in a one-time trading is greater than the trading price for deceiving about the data quality. In this case, all suppliers choose to disclose the real data quality, while all demanders choose to leak the data and pursue a one-time data trading. When $D < 0$, that is, when the trading price for cheating data quality in a one-time trading is greater, E_7 is a saddle point. Similar to the examples of E_2 and E_7 above, we can reason about the equilibrium conditions for each possible equilibrium point by analyzing the realistic meaning of their eigenvalues in Table 4.

Table 3. Possible equilibrium points $E_{1\sim8}$ and their eigenvalues.

Point	Eigenvalue1	Eigenvalue2	Eigenvalue3
$E_1(0,0,0)$	W	$-\left((\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k\right)$	$(\alpha\beta)^k(\gamma-\eta+1)$
$E_2(1,0,0)$	$(\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k$	$(\gamma+1)(\alpha\beta\theta)^k+\eta(\lambda-1)(\alpha\beta_m\theta)^k$	$W-(\lambda-1)(\alpha\beta_m)^k\left(\theta^k-1\right)-\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}\left(\theta^{\zeta}-1\right)$
$E_3(0,1,0)$	W	$-(\alpha\beta)^k(\gamma-\eta+1)$	$-(\eta+1)\left((\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k\right)$
$E_4(0,0,1)$	$-W$	$-\left((\alpha\beta)^k+(\lambda-1)(\alpha\beta_m)^k\right)$	$(\alpha\beta)^k(\gamma-\eta+1)$
$E_5(1,1,0)$	$(\eta+1)\left((\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k\right)$	$-(\gamma+1)(\alpha\beta\theta)^k-\eta(\lambda-1)(\alpha\beta_m\theta)^k$	$W+(\lambda-1)(\alpha\beta_m)^k\left(1-\theta^k\right)+\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}\left(1-\theta^{\zeta}\right)+\left(1-\theta^k\right)\left((\alpha\beta)^k(\gamma+1)+\eta(\lambda-1)(\alpha\beta_m)^k\right)$
$E_6(1,0,1)$	$(\alpha\beta)^k+(\lambda-1)(\alpha\beta_m)^k$	$(\gamma+1)(\alpha\beta)^k+\eta(\lambda-1)(\alpha\beta_m)^k$	$-W-\left(1-\theta^k\right)(\alpha\beta_m)^k(\lambda-1)-\left(1-\theta^{\zeta}\right)\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}$
$E_7(0,1,1)$	$-W$	$-(\alpha\beta)^k(\gamma-\eta+1)$	$-(\eta+1)\left((\alpha\beta)^k+(\lambda-1)(\alpha\beta_m)^k\right)$
$E_8(1,1,1)$	$(\eta+1)\left((\alpha\beta)^k+(\lambda-1)(\alpha\beta_m)^k\right)$	$-(\alpha\beta)^k(\gamma+1)-\eta(\alpha\beta_m)^k(\lambda-1)$	$-W-(\lambda-1)(\alpha\beta_m)^k\left(1-\theta^k\right)-\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}\left(1-\theta^{\zeta}\right)-\left(1-\theta^k\right)\left((\alpha\beta)^k(\gamma+1)+\eta(\lambda-1)(\alpha\beta_m)^k\right)$

Table 4. Stability of $E_{1\sim8}$.

Point	ESS Condition	Saddle Point Condition	Unstable Point Condition
E_1	$--$	$A \geq 0$	$A < 0$
E_2	$A \leq 0 \wedge B \leq 0 \wedge C \leq 0$	$(A \leq 0 \vee B \leq 0 \vee C \leq 0) \wedge \neg(A \leq 0 \wedge B \leq 0 \wedge C \leq 0)$	$A > 0 \wedge B > 0 \wedge C > 0$
E_3	$--$	all conditions	$--$
E_4	$--$	all conditions	$--$
E_5	$A \leq 0 \wedge B \geq 0 \wedge E \leq 0$	$(A \leq 0 \vee B \geq 0 \vee E \leq 0) \wedge \neg(A \leq 0 \wedge B \geq 0 \wedge E \leq 0)$	$A > 0 \wedge B < 0 \wedge E > 0$
E_6	$D \leq 0 \wedge B \leq 0 \wedge C \geq 0$	$(D \leq 0 \vee B \leq 0 \vee C \geq 0) \wedge \neg(D \leq 0 \wedge B \leq 0 \wedge C \geq 0)$	$D > 0 \wedge B > 0 \wedge C < 0$
E_7	$D \geq 0$	$D < 0$	$--$
E_8	$D \leq 0 \wedge B \geq 0 \wedge E \geq 0$	$(D \leq 0 \vee B \geq 0 \vee E \geq 0) \wedge \neg(D \leq 0 \wedge B \geq 0 \wedge E \geq 0)$	$D > 0 \wedge B < 0 \wedge E < 0$

It is worth pointing out that, according to Table 4, the possible equilibrium points E_1 and E_4, which simultaneously satisfy the supply-side no-cheating data quality and the demand-side no-leakage data, cannot be the ESS of the data trading scenarios. This means that by adjusting the risk compensation parameters λ and η, the data trading scenario can only maintain a dynamic balance between the supplier not cheating on data quality and the demander not leaking data, which leaves the data trading system in a chaotic state.

$$\left(\frac{W}{(\lambda-1)(\alpha\beta_m)^k\left(\theta^k-1\right)+\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}\left(\theta^{\zeta}-1\right)},0,\frac{(\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k}{(\lambda-1)(\alpha\beta_m)^k\left(\theta^k-1\right)}\right) \tag{15}$$

$$\left(-\frac{W}{\left((\lambda-1)(\alpha\beta_m)^k\left(1-\theta^k\right)+\mathrm{D_b}^{\varepsilon}a(\alpha\beta)^{\zeta}\left(1-\theta^{\zeta}\right)\right)+\left(1-\theta^k\right)\left((\alpha\beta)^k(\gamma+1)+\eta(\lambda-1)(\alpha\beta_m)^k\right)},1,\frac{(\lambda-1)(\alpha\beta_m\theta)^k+(\alpha\beta)^k}{(\alpha\beta_m)^k\left(\theta^k-1\right)(\lambda-1)}\right) \tag{16}$$

In addition to the eight possible equilibrium points mentioned above, there are E_9 and E_{10}, as shown in Equations (15) and (16), respectively. However, solving for the eigenvalues of E_9 and E_{10} is less workable, and we analyzed the equilibrium conditions for E_9 and E_{10} by com-

puting the determinant *det* and trace *tr* of the corresponding Jacobian matrix. *det* is the product of all the eigenvalues of the matrix, and *tr* is equal to the sum of the eigenvalues of the matrix. By analyzing the sign of the product and summation of three eigenvalues, we can infer the combination of the signs for the eigenvalues. Let $F = W\left(1-\theta^k\right)(\gamma+1)(\alpha\beta)^k\left((\alpha\beta)^k+(\alpha\beta_m)^k(\lambda-1)\right)+(\theta^k-1)(\alpha\beta_m)^k(\alpha\beta)^k(\lambda-1)(\gamma-\eta+1)\left((\alpha\beta_m)^k(\lambda-1)(\theta^k-1)+(\theta^\zeta-1)\mathrm{D_b}^\varepsilon a(\alpha\beta)^\zeta\right)$. E_9 exists when $C \le 0 \wedge D \le 0$. When $F \le 0$, $det_9 \le 0$ and $tr_9 \le 0$, and then E_9 is a saddle point or ESS. When $(F > 0) \wedge (C = 0 \vee D = 0)$, $det_9 = 0$ and $tr_9 > 0$, then E_9 is a saddle point. When $F > 0 \wedge C \neq 0 \wedge D \neq 0$, $det_9 > 0$ and $tr_9 > 0$, then E_9 is a saddle point or an unstable point. E_{10} exists when $D \le 0 \wedge E \le 0$. When $D < 0 \wedge E < 0$, $det_{10} > 0$, and $tr_{10} > 0$, E_{10} is a saddle point or unstable point. When $D \neq 0 \wedge E = 0$, $det_{10} = 0$, and $tr_{10} > 0$, E_{10} is a saddle point. When $D = 0$, $det_{10} = 0$, and $tr_{10} = 0$, E_{10} is a saddle point or ESS. According to Equations (15) and (16), E_9 and E_{10} are both trade-offs between cheating data quality and two-step trading in the case of no data leakage and data leakage, respectively. So, compared to $E_{1\sim8}$ where strategies have a share of 0 or 1, the conditions for E_9 and E_{10} to become ESS are more demanding.

In summary, the evolutionary equilibrium points and their conditions in data trading with a risk compensation mechanism are shown in Table 5.

Table 5. Evolutionary equilibrium points and their conditions.

Condition	ESS	Strategy
$A \le 0 \wedge B \le 0 \wedge C \le 0$	E_2	The suppliers cheat on data quality, and the demanders do not leak the data and pursue two-step trading.
$A \le 0 \wedge B \ge 0 \wedge E \le 0$	E_5	The suppliers cheat on data quality, and the demanders leak the data and pursue two-step trading.
$D \le 0 \wedge B \le 0 \wedge C \ge 0$	E_6	The suppliers cheat on data quality, and the demanders do not leak the data and pursue one-time trading.
$D \ge 0$	E_7	The suppliers do not cheat on data quality, the demanders leak the data and pursue one-time trading.
$D \le 0 \wedge B \ge 0 \wedge E \ge 0$	E_8	The suppliers cheat on data quality, and the demanders leak the data and pursue one-time trading.
$C \le 0 \wedge D \le 0 \wedge F \le 0$, $det_9 \le 0$ and $tr_9 \le 0$	E_9(saddle point or ESS)	The demanders do not leak the data, and there is a trade-off between data quality cheating and two-step trading.
$E \le 0 \wedge D = 0$, $det_{10} = 0$ and $tr_{10} = 0$	E_{10}(saddle point or ESS)	The demanders leak the data, and there is a trade-off between data quality cheating and two-step trading.

4. Simulation Analysis of the Digital Trading Evolutionary Game

4.1. Simulation Analysis of Stability Strategy

We simulated the evolution of the data trading game in Matlab (latest v. 2024R) software to verify the accuracy of the above numerical solution results and to visualize the evolutionary path of the population. Specifically, we analyzed the evolutionary paths and results of suppliers and demanders in different data trading scenarios, i.e., setting the parameter values of the data trading model according to the eigenvalues. By comparing the numerical analysis results and simulation results in different scenarios, we verified and demonstrated the population's evolution dynamics.

Scenario 1: In order to have $A < 0, B < 0, C < 0, D < 0, E < 0, F < 0$, let $\alpha = 0.8$, $\beta = 0.1$, $k = 0.8$, $a = 0.9$, $D_b = 0.8$, $\varepsilon = 0.9$, $\zeta = 0.9$, $\beta_m = 0.9$, $\gamma = 0.1$, $\theta = 0.5$, $\lambda = 0.1$, $\eta = 0.5$, $W = 0.2$. Depending on the parameter values, in this scenario, cheating the data quality can improve the quality from $\beta = 0.1$ to $\beta_m = 0.9$, and the risk compensation of cheating is not much ($\lambda = 0.1$), which means that the suppliers are likely to adopt strategy x. For the demanders, the profit from leaking data is not much ($\gamma = 0.1$) but the risk compensation is large ($\eta = 0.5$), so data leaking is not a cost-effective option. In addition, the cost of two-step trading is very low ($W = 0.2$) but effective ($\theta = 0.5$). As a result, the demanders are likely to choose not to leak data and to conduct two-step tradings.

The paths and results of the population evolution in Scenario 1 are shown in Figure 1. Figure 1a illustrates the evolutionary path of the population starting from any point in the three-dimensional space consisting of the three strategies of x, y, and z. On the one hand, the evolutionary results of all points are E_2, indicating that E_2 is the evolutionary stable state in Scenario 1, which is consistent with the results of the numerical analysis. On the other hand, the evolutionary paths of points with different initial positions are different, and the pathway points include E_5, E_6, etc., which are saddle points in the numerical analysis. Specifically, as demonstrated in Figure 1b, we fix four starting points to observe their evolutionary paths, which are $(0.1, 0.9, 0.9)$, $(0.1, 0.1, 0.9)$, $(0.1, 0.1, 0.1)$, and $(0.1, 0.9, 0.1)$. The starting points 1, 2, and 4 evolve to E_2 via E_8, E_6 and E_5, respectively, while starting point 3 evolves directly to E_2. The results in Section 3.2 show that E_2 is the ESS and E_{3-8} are saddle points in Scenario 1, so the results presented in Figure 1 are consistent with the numerical analysis.

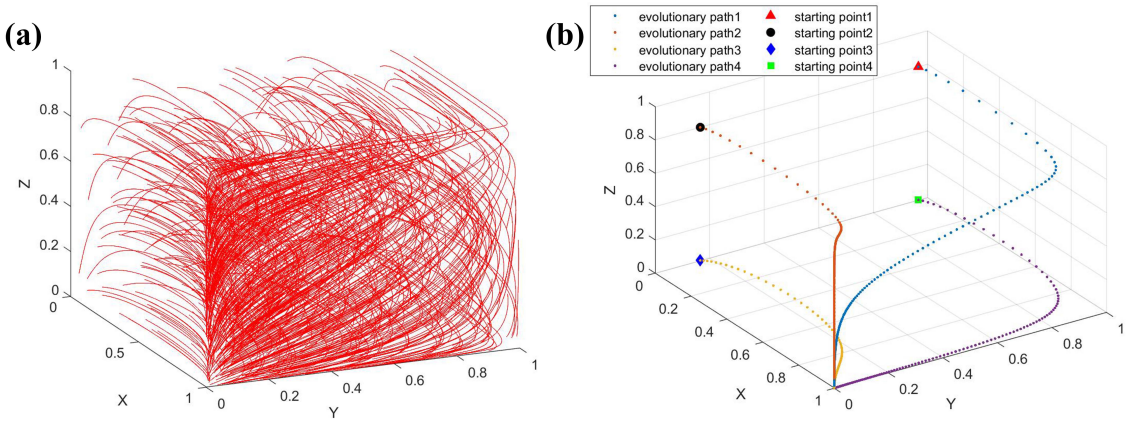

Figure 1. Evolutionary paths and results in Scenario 1. (**a**) presents global evolutionary paths originating from any initial point within the three-dimensional space, and (**b**) demonstrates four characteristic evolutionary paths emerging from selected starting points.

Taken together, in Scenario 1, the trading price for a one-time trading with true data quality does not exceed the price of a two-step trading with fake data quality. Additionally, the demander's potential gain from data leakage is outweighed by the resulting loss in cases where a one-time trading involves fake data quality. Furthermore, a two-step trading is more profitable for the demander when faced with data quality deception. As a result, suppliers trading data in Scenario 1 would eventually evolve to cheat on data quality, while the demanders would avoid leaking data and opt for a two-step trading in order to avoid losses.

Scenario 2: In order to have $A > 0, B > 0, C > 0, D > 0, E > 0, F > 0$, let $\alpha = 0.8$, $\beta = 0.2$, $k = 0.3$, $a = 1$, $D_b = 1$, $\varepsilon = 0.7$, $\zeta = 0.9$, $\beta_m = 0.9$, $\gamma = 0.8$, $\theta = 0.5$, $\lambda = 0.6$, $\eta = 0.1$, $W = 0.1$. The suppliers can improve the data quality by $\beta_m - \beta = 0.7$ by cheating the quality. However, unlike Scenario 1, the risk compensation for cheating the data quality in Scenario 2 is very high, with $\lambda = 0.6$. So, cheating the data quality is not a reasonable choice for suppliers. Given that $\gamma = 0.8$, demanders can be highly profitable by leaking data, and $\eta = 0.1$ implies that the risk compensation for leaking data is small, so it is logical for demanders to choose data leaking to generate more revenue. Also, $W = 0.1$ and $\theta = 0.5$ make the two-step trading a low-risk option for demanders. Depending on the parameter values, the strategy combination $(0, 1, 1)$ is more dominant in Scenario 2.

Figure 2 illustrates the simulation results for Scenario 2, where the populations at each starting point in Figure 2a eventually evolve to $E_7(0, 1, 1)$, which is consistent with our analysis above. In Figure 2b, we choose four representative starting points to observe their

different evolutionary paths. Figure 2 illustrates the simulation results for Scenario 2, where the populations at each starting point in Figure 2a eventually evolve to $E_7(0, 1, 1)$, which is consistent with our analysis above. In Figure 2b, we choose four representative starting points to observe their different evolutionary paths, which are $(0.5, 0.1, 0.1)$, $(0.5, 0.01, 0.5)$, $(0.9, 0.5, 0.1)$, and $(0.9, 0.5, 0.9)$. The four populations with different strategies' proportions all pass through the vertices of the three-dimensional space and finally reach E_7. The evolutionary paths indicate that E_7 is the evolutionary stable state in Scenario 2, while the other vertices in three-dimensional space are saddle points, and these results are in line with the numerical analysis in Section 3.2.

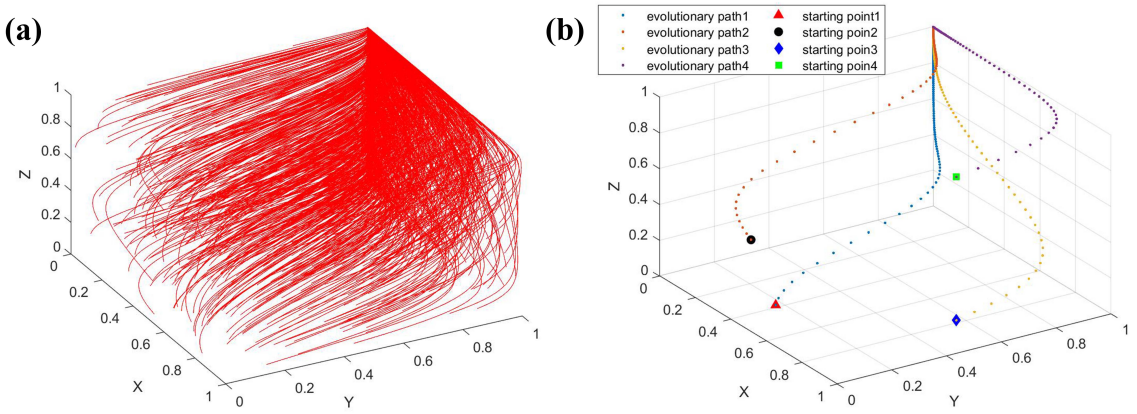

Figure 2. Evolutionary paths and results in Scenario 2. (**a**) shows the evolutionary paths of the population from any initial point in the three-dimensional space, and (**b**) displays four representative evolutionary paths from fixed starting points.

In Scenario 2, for a one-time trading, the trading price when suppliers disclose the true data quality exceeds the price when the data quality is not true. Consequently, all suppliers in this scenario ultimately choose to reveal the actual data quality, while all demanders opt to disclose the data and engage in one-time transactions.

To summarize the above, E_2 and E_7 are the evolutionary steady states of the populations in Scenarios 1 and 2, respectively. Similarly to these two, scenarios where E_5, E_6, and E_8 are evolutionary stable states can all be presented and analyzed by the above process, which will not be repeated here. Through the simulation analysis of the digital trading game with risk compensation, we analyzed the evolutionary processes and results of the populations in data trading scenarios with different characteristics, and we found that there is at most one evolutionary stable state in each data trading scenario. The simulation analysis results are consistent with the numerical solution results, which verifies the correctness of the numerical solution in Section 3.2.

4.2. Simulation Analysis of Parameters

We focused on Scenario 1 and performed a sensitivity analysis of parameters λ and η in order to answer the question of how to set the risk compensation parameters in this part. We discovered different evolutionary stable states in data trading scenarios with different characteristics through the numerical solution in Section 3.2 and the simulation analysis in Section 4. For practical applications, it is more critical to set parameters of risk compensation that can influence the evolutionary path of the population.

(1) Risk compensation parameter for cheating data quality λ

Whether a supplier cheats on data quality depends on whether they will make more profit. So, in addition to the risk compensation parameter for cheating data quality λ, both β and β_m affect the supplier's strategy choice. In Scenario 1, where $\beta = 0.1$ and $\beta_m = 0.9$,

the supplier's profitability from cheating on data quality is high. Under this premise, when λ is small, suppliers would definitely cheat for profit. Only when λ is very large are suppliers likely to refrain from cheating, considering that the risk compensation for cheating is significant.

We examine the evolution of population at $\lambda = 0.1$, $\lambda = 0.5$, and $\lambda = 1$ under the parameter settings of Scenario 1, as shown in Figure 3. As λ goes from 0.1 to 0.5 to 1 in Figure 3a–c, the evolutionary stable state of the population changes from $(1,0,0)$ to $(1,0,1)$ to $(0,0,1)$. When $\lambda = 0.1$, suppliers choose to cheat because of the large profits. As λ becomes larger, suppliers cheat at decreasing profits. When $\lambda = 1$, all suppliers stop cheating. The demanders change their strategy along with the supplier's strategy. Regardless of how λ changes, demanders leak data to gain more revenue. And as the supplier's profits decrease, demander's tradings evolve from one-time tradings to two-step tradings.

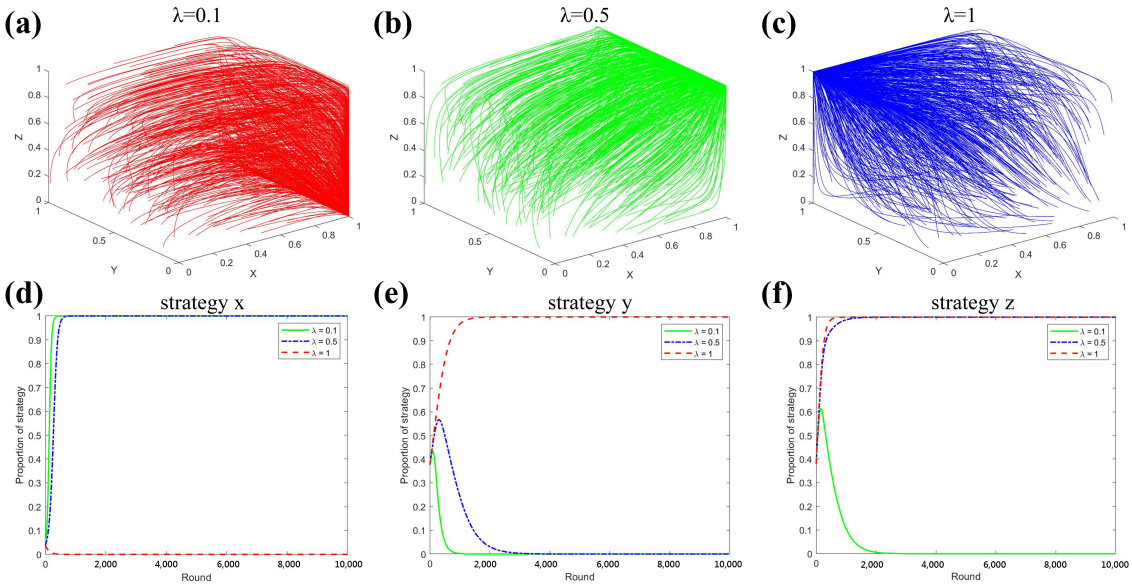

Figure 3. Simulation analysis of parameter λ. (**a**–**c**) show how the evolutionary paths of the populations change when λ = 0.1, 0.5, and 1.0, while (**d**–**f**) illustrate the corresponding strategy shares within the populations under these same parameter conditions.

In addition, we fixed the initial strategy proportions of the population to $(0.038, 0.375, 0.378)$ and observed the changes in the strategies' proportions due to the variation in λ. As shown in Figure 3d–f, with a larger λ, the proportions of x, y, and z decrease, increase, and increase, respectively. Although the value of λ directly affects the supplier's revenues, in a tightly interconnected system, the demander's revenues are also affected and their strategies change together. The change in suppliers' strategies is not linear, and while they all cheat at $\lambda = 0$, they have chosen not to cheat at both $\lambda = 0.5$ and $\lambda = 1$, so adjustments to the value of λ need to be slow.

In summary, adjusting the value of λ in a specific data trading scenario can indeed change the evolutionary direction of the population, even if the data quality can be improved a lot through cheating. It is possible to constrain suppliers from cheating on data quality by increasing λ. However, both suppliers' and demanders' strategies vary non-linearly, so adjustments to λ should be small.

(2) Risk compensation parameter for leaking data η

In the absence of risk compensation, data leakage is certain to be profitable for the demanders. In the data trading model with risk compensation, demanders need to consider both the risk compensation parameter for leaking data η and the profit parameter of leaking

data γ when deciding whether or not to leak the data. In Scenario 1, $\gamma = 0.1$, which means that the gain from leaking the data is very limited. Then, only if the value of η is very small shall the demander gain more by leaking the data.

Figure 4 illustrates how the evolutionary paths (in Figure 4a–c) and strategy shares (in Figure 4d–f) of the population change when η is 0.1, 0.5, and 1. Unlike λ, the three values of η do not result in three evolutionary stable states for the population. When $\eta = 0.1$, $(1, 1, 0)$ is ESS for the population, while $(1, 0, 0)$ is ESS at both $\eta = 0.5$ and $\eta = 1$. It is worth noting that the variation in η only triggers a change in the demander's choice of strategy y, while x and z are unaffected. It is possible that this phenomenon is caused by the small value of γ. So, we further verified the situation when $\gamma = 0.5$ and $\gamma = 0.9$ and found that this phenomenon persists. Combining Figures 3 and 4 shows that although both λ and η are risk compensation parameters, their effects are asymmetric, with λ leading to a full change in the population's choices of x, y, and z, while η leads to a change in only a single dimension of strategy y.

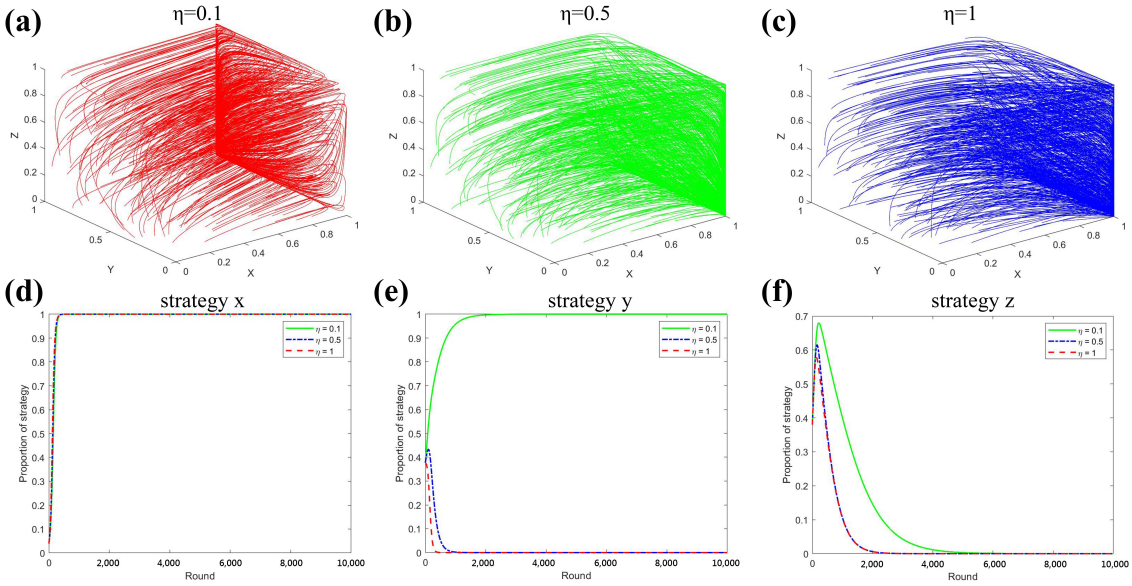

Figure 4. Simulation analysis of parameter η. (**a**–**c**) demonstrate the variation of evolutionary paths when η = 0.1, 0.5, and 1.0, while (**d**–**f**) present the corresponding strategy shares under these identical parameter conditions.

Like Figure 3, the randomly generated initial point $(0.038, 0.375, 0.378)$ is again used in Figure 4 to observe the change in the shares of the three strategies. As in Figure 4a–c, the increase in η in Figure 3d leads to a sudden change in the share of strategy y from 1 to 0. Meanwhile, the trajectories of the three lines in Figure 4d are identical, indicating that the supplier's choice of strategy x is not affected in any way by the change in η. For strategy z, all three curves rise, then fall, and finally drop to 0, suggesting that changes in η have no effect on the share of strategy z when the evolution of the population is stable. The different peaks of these three curves reflect the role of η in the evolution of the population. Although the population tries to choose one-time tradings, it is ultimately invaded by two-step tradings.

Taken together, the risk compensation parameters λ and η act asymmetrically in that parameter λ can affect the choice of strategies x, y, and z simultaneously and parameter η affects the choice of strategy y only. Intuitively, λ represents the compensation share paid by the supplier to the demander as a result of the supplier's cheating on data quality. Since the supplier's only strategic choice is whether or not to cheat on data quality, adjusting λ will directly, and necessarily, affect the supplier's revenue, so adjusting λ would influence

the supplier's strategic choice. The demander's decision and revenue depend on the supplier's actions. Consequently, adjusting λ can indirectly influence the strategic choices made by the demander. In contrast, η represents the compensation share paid by the demander to the supplier as a result of the demander's data leakage. The demander possesses greater strategic flexibility compared to the supplier, as the demander can not only decide whether to leak data but can also enhance revenue by choosing between one-time or two-step trading. So, a potential scenario is that the demander can maintain their revenue independent of η by coordinating its two strategies: whether to leak data and whether to engage in a two-step trading. This coordination prevents η from indirectly impacting the supplier. Thus, while η directly influences the data leakage behavior of the demander, it may have no bearing on the strategy of the supplier. This asymmetric working model provides us with the means to target and guide the strategies of both suppliers and demanders in data trading. Adjusting the value of η helps us to guide the demand-side strategy, changing the value of λ changes the strategy of both supply and demand, and adjusting λ and then η affects the strategy of the supply side.

5. Conclusions

The fact that data can be privately possessed yet have the attributes of a public good leads to the "Arrow's Information Paradox" in data trading. If left unchecked, supply-side deception about data quality and demand-side leakage of data can seriously undermine the trust between suppliers and demanders. Many scholars have proposed information technology-based trading frameworks to facilitate data trading, but new technologies often take a long time to mature and be adopted. While the classical mechanisms of reputation and punishment in evolutionary game theory work well, it is very hard to obtain accurate behavioral information in a timely manner in data trading, leading to difficulties in applying both. Inspired by the ideas of reputation and punishment, this paper combines a risk compensation mechanism, which is widely available in the financial sector, with data trading. The risk compensation mechanism compensates individuals for the risks they may face by adjusting the trading price, e.g., due to a supplier's preference to cheat on the data quality, the trading price of the data is lowered to compensate the demander for the risk of being cheated. Our experimental results find that the risk compensation mechanism cannot help data trading completely escape from the "Arrow's Information Paradox". However, by adjusting the risk compensation parameters, the data trading scenario can maintain the dynamic balance between the supplier not cheating the data quality and the demander not leaking the data, which reflects the chaos of the data trading scenario.

Based on evolutionary game theory, we analyze the evolutionary dynamics of the population by numerical solution and simulation. We identify 10 possible equilibrium points, but there is at most one evolutionary stable state in each of the featured data trading scenarios, and the other possible equilibrium points are saddle points in most cases. Sensitivity analyses of the parameters show that the risk compensation parameters for deceptive data quality and data leakage have an asymmetric effect on the choice of population strategies. The risk compensation parameter for cheating data quality has the ability to change the proportions of all strategies, whereas the risk compensation parameter for data leakage only has an impact on the choice of whether or not to leak data. Being application-oriented, this asymmetry allows us to target the suppliers and demanders separately and guide them in adapting their strategies.

The risk compensation mechanism we propose can be applied to real-world data trading scenarios where suppliers and demanders are visible and ratable to each other in a data trading platform on the World Wide Web. And it is suitable for the trading parties and the data trading platform to implement the mechanism. Specifically, the realization

of the risk compensation mechanism requires the identification of undesirable behaviors, the determination of behavioral preferences, the determination of risk compensation parameters, and the implementation of risk compensation. Undesirable behaviors refer to cheating data quality and leaking data, and the identification of undesirable behaviors can be performed by the data trading platform after the transaction, or by both parties through the transaction scoring for each other after the transaction. The identification of behavioral preferences is usually performed by the platform, e.g., a supplier with a 20% frequency of cheating data quality in past transactions is identified as having a preference for cheating data quality. After this, all those with undesirable behavioral preferences will be risk-compensated according to the established λ and η in subsequent transactions. Data trading platforms can also adjust λ and η to facilitate data trading based on the findings in Sections 3 and 4.

According to the implementation of the risk compensation mechanism above, the mechanism penalizes the person who performs the undesirable behavior, regardless of whether the undesirable behavior is identified by the trading parties or by the platform. The bounded rationality of individuals in game theory leads to the emergence of behaviors such as opportunism and free-riding [58]. However, the risk compensation mechanism means that none of these behaviors can enhance the individual's returns in the long run, and that they can even harm the individual's returns. In other words, the risk compensation mechanism can avoid hindering group cooperation due to the Arrow's Information Paradox in data trading scenarios.

In practice, policymakers or data trading platforms need to conduct qualitative analyses using information about the trading environment to categorize different types of data trading. Subsequently, they can determine appropriate risk compensation parameters for specific data trading scenarios based on simulation results. For instance, if the benefits of data quality cheating are high while the benefits of data leakage are low, this data trading scenario is the same as Scenario 1 described in Section 4.1. In such cases, based on the simulation results, since η primarily influences data leakage behavior, policymakers and data trading platforms can first keep η to 0.1 or lower values to suppress the data leakage behavior. Then, λ can be incrementally reduced from a higher initial value (e.g., 0.9) and adjusted dynamically based on the real-time percentage of data quality cheating until an optimal regulatory outcome is achieved. Coordinating the values of λ and η in various data trading scenarios is a key direction for future research, based on the results of this study.

From our study, there are three main potential research directions oriented towards practical applications. The first is extending group performance analysis from static ESS to dynamic evolutionary processes. This entails quantifying ESS evolutionary paths, including steady-state convergence time and fluctuations in population performance. This research direction can provide a basis for the regulation of evolutionary process, since stabilizing the population performance in an acceptable interval is a practical approach. The second is finding a way to steer population performance. As stated earlier, this means proposing a way to dynamically adjust λ and η to facilitate data trading while minimizing data quality cheating and data leakage. To achieve this, it is necessary to propose objective functions that combine costs and benefits, and then extend the solution of ESS in this paper to the solution of discrete dynamic optimization problems. Finally, the applicability of the risk compensation mechanism can be enhanced. In practical data trading, datasets exhibit significant heterogeneity across multiple dimensions, including accessibility (public vs. private), exclusivity (exclusive vs. non-exclusive), and aggregation level (individual vs. group data). Consequently, the risk compensation mechanism needs to be adapted to accommodate these different data characteristics.

Our findings imply that it is entirely possible for data trading platforms to achieve better results in market governance. To achieve this goal, first, platforms need to establish a reliable feedback mechanism (e.g., rating/message systems) between suppliers and demanders. Based on this information, platforms can update behavioral preferences in real time, which in turn makes preference-based risk compensation an easily accessible management measure for platforms. Second, based on our results, platforms can autonomously set the values of risk compensation parameters, e.g., uniform parameters based on global information or differentiated parameters for individuals, thus guiding population evolution toward desired outcomes. To ensure reasonable risk compensation parameters, the platform needs to identify the characteristics of the data transaction scenario, such as potential gains from data deception and leakage. Considering the great variation in data resources, a feasible approach for platforms is to summarize some typical trading patterns based on data characteristics and then to map each trading pattern to different values of risk compensation parameters. Moving forward, our research will focus on developing practical implementations of the risk compensation mechanism for data trading, aiming to provide industry practitioners with actionable guidelines and tools to facilitate real-world data trading.

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References

1. Hallaji, E.; Razavi-Far, R.; Saif, M.; Wang, B.; Yang, Q. Decentralized Federated Learning: A Survey on Security and Privacy. *IEEE Trans. Big Data* **2024**, *10*, 194–213. [CrossRef]
2. Dang, T.D.; Hoang, D.; Nguyen, D.N. Trust-Based Scheduling Framework for Big Data Processing with MapReduce. *IEEE Trans. Serv. Comput.* **2022**, *15*, 279–293. [CrossRef]
3. Yang, L.; Liao, Y.; Cheng, X.; Xia, M.; Xie, G. Efficient Edge Data Management Framework for IIoT via Prediction-Based Data Reduction. *IEEE Trans. Parallel Distrib. Syst.* **2023**, *34*, 3309–3322. [CrossRef]
4. González, A.B.R.; Burrieza-Galán, J.; Díaz, J.J.V.; de Castro, I.P.; Wilby, M.R.; Cantú-Ros, O.G. Using App Usage Data From Mobile Devices to Improve Activity-Based Travel Demand Models. *IEEE Trans. Big Data* **2024**, *10*, 633–643. [CrossRef]
5. Basole, R.C.; Park, H.; Seuss, C.D. Complex business ecosystem intelligence using AI-powered visual analytics. *Decis. Support Syst.* **2024**, *178*, 114133. [CrossRef]
6. An, B.; Xiao, M.; Liu, A.; Xu, Y.; Zhang, X.; Li, Q. Secure Crowdsensed Data Trading Based on Blockchain. *IEEE Trans. Mob. Comput.* **2023**, *22*, 1763–1778. [CrossRef]
7. Zhang, X.; Li, X.; Miao, Y.; Luo, X.; Wang, Y.; Ma, S.; Weng, J. A Data Trading Scheme With Efficient Data Usage Control for Industrial IoT. *IEEE Trans. Ind. Inform.* **2022**, *18*, 4456–4465. [CrossRef]
8. Cheng, J.; Mahinder Singh, H.S.; Zhang, Y.C.; Wang, S.Y. The impact of business intelligence, big data analytics capability, and green knowledge management on sustainability performance. *J. Clean. Prod.* **2023**, *429*, 139410. [CrossRef]
9. Shin, S.J.; Um, J. Deploying data analytics models in asset administration shells: Energy prediction in manufacturing. *Eng. Appl. Artif. Intell.* **2024**, *138*, 109269. [CrossRef]
10. Marichamy, V.S.; Natarajan, V. Blockchain based Securing Medical Records in Big Data Analytics. *Data Knowl. Eng.* **2023**, *144*, 102122. [CrossRef]
11. Jones, C.I.; Tonetti, C. Nonrivalry and the Economics of Data. *Am. Econ. Rev.* **2020**, *110*, 2819–2858. [CrossRef]
12. Yang, J.; Yang, D.; Cheng, J. The non-rivalry of data, directed technical change and the environment: A theoretical study incorporating data as a production factor. *Econ. Anal. Policy* **2024**, *82*, 417–448. [CrossRef]

13. Goldfarb, A.; Tucker, C. Digital Economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
14. Veldkamp, L.; Chung, C. Data and the Aggregate Economy. *J. Econ. Lit.* **2024**, *62*, 458–84. [CrossRef]
15. Varian, H.R. Artificial Intelligence, Economics, and Industrial Organization. *Ewing Marion Kauffman Found. Res. Pap. Ser.* **2018**.
16. Arrow, K.J. The Economic Implications of Learning by Doing. *Rev. Econ. Stud.* **1962**, *29*, 155–173. [CrossRef]
17. Piazza, M.; Pedicini, M. What Arrow's Information Paradox Says (to Philosophers). In *On the Cognitive, Ethical, and Scientific Dimensions of Artificial Intelligence: Themes from IACAP 2016*; Berkich, D., d'Alfonso, M.V., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 83–94.
18. Li, C.; He, A.; Wen, Y.; Liu, G.; Chronopoulos, A.T. Optimal Trading Mechanism Based on Differential Privacy Protection and Stackelberg Game in Big Data Market. *IEEE Trans. Serv. Comput.* **2023**, *16*, 3550–3563. [CrossRef]
19. Seo, E.; Kim, H.; Krishnamachari, B.; Elmroth, E. An ICN-Based Data Marketplace Model Based on a Game Theoretic Approach Using Quality-Data Discovery and Profit Optimization. *IEEE Trans. Cloud Comput.* **2023**, *11*, 2110–2126. [CrossRef]
20. Chen, F.; Zhang, H.; Xiang, T.; Liu, J.K. A Two-Stage Approach for Fair Data Trading Based on Blockchain. *IEEE Trans. Inf. Forensics Secur.* **2024**, *19*, 9835–9849. [CrossRef]
21. Zhang, S.; Wang, R.; Wang, H.; Deng, Z.; Yang, Z.; Wu, D. Bilateral Task-Driven Privacy-Preserving Data Acquisition for Crowdsensed Data Trading. *IEEE Internet Things J.* **2024**, *11*, 9766–9780. [CrossRef]
22. Abla, P.; Li, T.; He, D.; Huang, H.; Yu, S.; Zhang, Y. Fair and Privacy-Preserved Data Trading Protocol by Exploiting Blockchain. *IEEE Trans. Inf. Forensics Secur.* **2024**, *19*, 9012–9025. [CrossRef]
23. Lu, X.; Zhang, Z.; Zhou, T.; Niu, T.; Li, M.; Guan, Z.; Ma, T.; Zhu, L. Decentralized Fair IoT Data Trading via Searchable Proxy Re-Encryption. *IEEE Internet Things J.* **2024**, *11*, 19485–19499. [CrossRef]
24. Su, W.; Wang, P.; Wang, Z.; Muhammad, A.; Tao, T.; Tong, X.; Zhang, Q. F2UL: Fairness-Aware Federated Unlearning for Data Trading. *IEEE Trans. Mob. Comput.* **2024**, *23*, 13539–13555. [CrossRef]
25. Vranken, H. Sustainability of bitcoin and blockchains. *Curr. Opin. Environ. Sustain.* **2017**, *28*, 1–9. [CrossRef]
26. Zhang, K.; Long, J.; Wang, X.; Dai, H.N.; Liang, K.; Imran, M. Lightweight Searchable Encryption Protocol for Industrial Internet of Things. *IEEE Trans. Ind. Inform.* **2021**, *17*, 4248–4259. [CrossRef]
27. Zhang, M.; Li, X.; Miao, Y.; Luo, B.; Xu, W.; Ren, Y.; Deng, R.H. Privacy-Preserved Data Disturbance and Truthfulness Verification for Data Trading. *IEEE Trans. Inf. Forensics Secur.* **2024**, *19*, 5545–5560. [CrossRef]
28. Tang, M.; Jiang, L.; Mao, Y.; Cao, L. Does the depth of digital trade rules promote bilateral value chain cooperation? *Int. Rev. Financ. Anal.* **2025**, *99*, 103952. [CrossRef]
29. Wu, C.; Chen, X.; Hua, H.; Yu, K.; Gan, L.; Wang, B. Optimal energy sharing for renewable portfolio standard and carbon cap-and-trade scheme: A two-step energy trading approach. *Int. J. Electr. Power Energy Syst.* **2024**, *162*, 110334. [CrossRef]
30. Wang, L.; Ren, X.; Ma, Y.; Liu, Z.; Dong, W.; Ni, L. Optimal low-carbon scheduling of integrated energy systems considering stepped carbon trading and source-load side resources. *Energy Rep.* **2024**, *12*, 3145–3154. [CrossRef]
31. Zeng, Z.; Ma, C.; Chang, X. Multi-step reward ensemble methods for adaptive stock trading. *Expert Syst. Appl.* **2023**, *230*, 120547. [CrossRef]
32. Li, J.; Li, J.; Wang, X.; Qin, R.; Yuan, Y.; Wang, F.Y. Multi-Blockchain Based Data Trading Markets With Novel Pricing Mechanisms. *IEEE/CAA J. Autom. Sin.* **2023**, *10*, 2222–2232. [CrossRef]
33. Cai, H.; Yang, Y.; Fan, W.; Xiao, F.; Zhu, Y. Towards Correlated Data Trading for High-Dimensional Private Data. *IEEE Trans. Parallel Distrib. Syst.* **2023**, *34*, 1047–1059. [CrossRef]
34. Fehr, E.; Gchter, S. Altruistic punishment in humans. *Nature* **2002**, *415*, 137–140. [CrossRef] [PubMed]
35. Milinski, M.; Semmann, D.; Krambeck, H.J. Reputation helps solve the 'tragedy of the commons'. *Nature* **2002**, *415*, 424–426. [CrossRef] [PubMed]
36. Liu, J.; Zhang, Q.; Tang, R. Fostering cooperative evolution through probabilistic punishment and environmental feedback in public goods game. *Chaos Solitons Fractals* **2024**, *189*, 115693. [CrossRef]
37. Ding, R.; Wang, X.; Zhao, J.; Gu, C. Effects of punishment driven by inequity aversion on promoting cooperation in public goods games. *Chaos Solitons Fractals* **2025**, *190*, 115778. [CrossRef]
38. Gao, S.; Suo, J.; Li, N. Cooperation under endogenous punishment in the spatial public goods game. *Appl. Math. Comput.* **2025**, *489*, 129156. [CrossRef]
39. Zou, K.; Huang, C. Incorporating reputation into reinforcement learning can promote cooperation on hypergraphs. *Chaos Solitons Fractals* **2024**, *186*, 115203. [CrossRef]
40. Song, Q.; Cao, Z.; Tao, R.; Jiang, W.; Liu, C.; Liu, J. Conditional neutral punishment promotes cooperation in the spatial prisoner's dilemma game. *Appl. Math. Comput.* **2020**, *368*, 124798. [CrossRef]
41. Nie, J.; Wang, J.; Niu, H.; Xia, C. Impact of multi-step punishment on the spatial prisoner's dilemma game. *Phys. Lett. A* **2022**, *446*, 128274. [CrossRef]
42. Ma, J.; Zhao, H. Cooperation dynamics of reputation-based manhattan distance social circle in spatial prisoner's dilemma game in evolutionary game theory. *Chaos Solitons Fractals* **2024**, *189*, 115688. [CrossRef]

43. Hu, Q.; Jin, T.; Jiang, Y.; Liu, X. Reputation incentives with public supervision promote cooperation in evolutionary games. *Appl. Math. Comput.* **2024**, *466*, 128445. [CrossRef]
44. Yan, X.; Jia, Z.; Zhang, B. Evaluating the risk compensation of HIV/AIDS prevention measures. *Lancet Infect. Dis.* **2022**, *22*, 447–448. [CrossRef] [PubMed]
45. Kang, C.M.; Kim, D. Risk management transparency and compensation. *J. Corp. Financ.* **2022**, *75*, 102245. [CrossRef]
46. Herring, R.J.; Vankudre, P. Growth Opportunities and Risk-Taking by Financial Intermediaries. *J. Financ.* **1987**, *42*, 583–599. [CrossRef]
47. John, K. Market Resolution and Valuation in Incomplete Markets. *J. Financ. Quant. Anal.* **1984**, *19*, 29–44. [CrossRef]
48. Iachan, F.S.; Silva, D.; Zi, C. Under-diversification and idiosyncratic risk externalities. *J. Financ. Econ.* **2022**, *143*, 1227–1250. [CrossRef]
49. Khirirat, S.; Magnússon, S.; Johansson, M. Compressed Gradient Methods With Hessian-Aided Error Compensation. *IEEE Trans. Signal Process.* **2021**, *69*, 998–1011. [CrossRef]
50. Erkan-Barlow, A.; Nguyen, T. Cybersecurity and executive compensation: Can inside debt-induced risk aversion improve cyber risk management effectiveness? *Int. Rev. Financ. Anal.* **2024**, *93*, 103173. [CrossRef]
51. Luo, L.; He, W.; Hu, H. Government subsidy policies for guarantee financing: Risk compensation vs. fee reduction. *Eur. J. Oper. Res.* **2024**, *314*, 747–759. [CrossRef]
52. Lin, Y.E.; Jiang, X.T.; Yu, B.; Lam, K.S. Compensation peer crash risks and corporate own investments: New evidences from U.S. stock markets. *Int. Rev. Financ. Anal.* **2023**, *89*, 102774. [CrossRef]
53. Mili, K.; Bengana, I.; Ouassaf, S.; Kabdi, M. Testing the co-integration relationship between auto insurance premiums and risk compensation amount. *Comput. Hum. Behav. Rep.* **2024**, *13*, 100377. [CrossRef]
54. Xue, X.; Yu, X.; Zhou, D.; Wang, X.; Bi, C.; Wang, S.; Wang, F.Y. Computational Experiments for Complex Social Systems:Integrated Design of Experiment System. *IEEE/CAA J. Autom. Sin.* **2024**, *11*, 1175–1189. [CrossRef]
55. Xue, X.; Li, G.; Zhou, D.; Zhang, Y.; Zhang, L.; Zhao, Y.; Feng, Z.; Cui, L.; Zhou, Z.; Sun, X. Research Roadmap of Service Ecosystems: A Crowd Intelligence Perspective. *Int. J. Crowd Sci.* **2022**, *6*, 195–222. [CrossRef]
56. Tang, X.; Lan, T.; Zhong, H.; Li, D.; Miao, Q. An evolutionary game model for indirect data sharing in manufacturing big data consortium. *Expert Syst. Appl.* **2024**, *255*, 124807. [CrossRef]
57. Liu, Z.; Huang, B.; Li, Y.; Sun, Q.; Pedersen, T.B.; Gao, D.W. Pricing Game and Blockchain for Electricity Data Trading in Low-Carbon Smart Energy Systems. *IEEE Trans. Ind. Inform.* **2024**, *20*, 6446–6456. [CrossRef]
58. Tsintsaris, D.; Tsompanoglou, M.; Ioannidis, E. Dynamics of Social Influence and Knowledge in Networks: Sociophysics Models and Applications in Social Trading, Behavioral Finance and Business. *Mathematics* **2024**, *12*, 1141. [CrossRef]

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