Honest or Dishonest? Promoting Integrity in Loot Box Games Through Evolutionary Game Theory

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***Abstract*—With the rapid advancement of free-to-play games featuring in-game payments, the loot box sales model challenges traditional fixed-price purchases by stimulating players' psychological desires. However, concerns have arisen among players regarding the transparency of loot box drop rates as claimed by game companies. Considering players' "partial information" and "bounded rationality" in-game, this study explores strategic interactions and evolutionary outcomes under various decision-making scenarios through a bipartite evolutionary game model, employing the replication dynamics approach. In contrast to conventional studies that examine market manipulation post hoc, evolutionary game theory enables a proactive examination of strategies to foster fairness within the loot box game market. The findings indicate that the dynamic between companies and players may ultimately converge to either a lose–lose or win–win scenario. Through simulation analysis, the impact of stakeholders' initial strategic ratios and critical parameters on the evolutionary trajectory is examined. It is observed that companies hold a dominant position in enhancing cooperation, whereas regulatory bodies can foster industry development through heightened regulation. This assertion is substantiated with real-world examples. The goal of this research is to advocate for integrity and transparency within the gaming industry, ensuring a fair environment for players.**

***Index Terms*—Drop rate, evolutionary game theory (EGT), loot box, market manipulation, video game.**

I. Introduction

With the global development of the Internet and continuous advancements in electronic devices, the diversity of online gaming platforms and genres has expanded significantly. This improvement in game quality has attracted a large audience across various gaming subgenres. Consequently, the global gaming market has witnessed rapid growth, with a steadily expanding market size. From the perspective of revenue models for game companies, games can be categorized into "pay-to-play" (P2P) and "free-to-play" (F2P) games [1]. P2P games require players to make a one-time purchase to access the complete game content, eliminating the need for additional transactions. Examples of P2P games include "The Legend of Zelda"[1] "Sekiro: Shadows Die Twice"[2] and "The Witcher 3."[3] F2P games, which can be downloaded and played for free, incorporate mechanisms for in-app purchases. In-app purchases enable players to acquire additional content using either virtual currency or real money. These in-app purchases, optional for players, can influence the game's progression, gameplay experience, or competitiveness. Examples of F2P games include "Hearthstone,"[4] "Arena of Valor,"[5] and "Genshin Impact."[6]

In recent years, the gaming market has witnessed a significant shift, with F2P games becoming increasingly mainstream, while the market share of P2P games has declined [2]. In 2020, the global mobile gaming market generated $76.5 billion in revenue from in-app purchases, representing 95% of the industry's total revenue [3]. Furthermore, numerous well-known gaming companies have explicitly shifted their focus toward the in-app purchase model. These trends signify a marked shift toward the popularity and profitability of F2P games, reflecting changes in consumer behavior and strategic directions of gaming companies.

Within F2P games, the concept of "loot box" has garnered increasing attention, contrasting with the sale of game items at fixed prices [4]. Loot boxes represent a game mechanism where players have a probabilistic chance of acquiring characters or special content upon opening them [5]. Each loot box carries a specific probability of yielding a reward, known as the "drop rate." Fig. 1 illustrates the business model underlying loot box games.

The drivers behind this trend are multifaceted. First, the loot box game model's design enhances profitability and sustainability. Compared to P2P games, F2P games enable players to continuously explore new characters and items through regular updates. Second, the randomness and unpredictability of the loot box system enhance player excitement and anticipation. The opportunity to obtain rare or coveted items induces a thrill and sense of achievement upon successful acquisition. Furthermore, loot boxes frequently incorporate social and competitive elements, encouraging players to display their collections of rare items. This cultivates a sense of community and motivates players to invest additional time and resources into the game, enhancing their status among peers [6].

[1]https://www.zelda.com/
[2]https://www.sekirothegame.com/
[3]https://www.thewitcher.com/us/en/witcher3
[4]https://hearthstone.blizzard.com
[5]https://www.arenaofvalor.com/
[6]https://genshin.hoyoverse.com/

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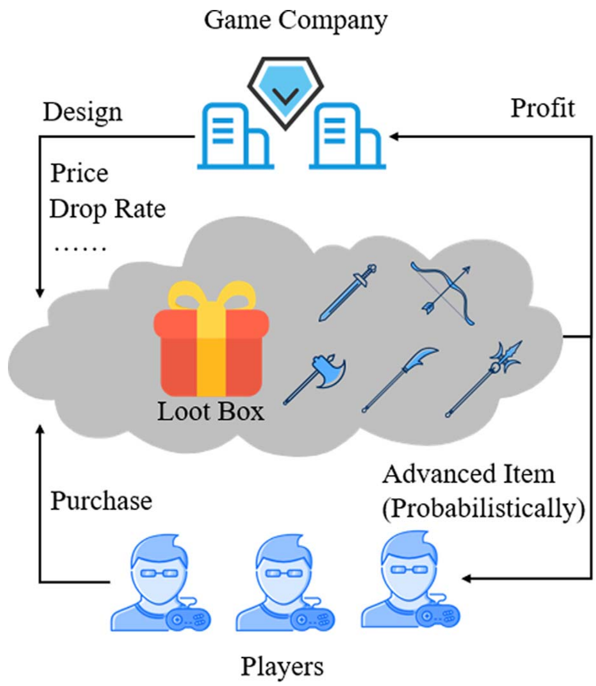

Fig. 1. Business model of loot box games.

However, in traditional loot box games, game companies control the rules and randomization algorithms, often leaving players without transparency or fairness assurances regarding the game's internal mechanisms. Consequently, game companies can manipulate players' chances of obtaining rare items by adjusting loot boxes' drop rates. Moreover, if a secondary market exists, companies might masquerade as individual players in the black market, selling rare items at inflated prices for substantial illicit gains. These potential gains have led players to question the honesty of game companies' claims. Obtaining illicit profits in this manner essentially constitutes market manipulation. Consequently, the honesty of loot boxes' drop rates has become a contentious and concerning issue [7].

This study employs evolutionary game theory (EGT) for an in-depth analysis of the honesty of loot boxes' drop rates. We consider game companies and players as stakeholders, analyzing their respective decision-making behaviors. Game companies are presented with two strategic options: honesty or dishonesty regarding loot boxes' drop rates, while players need to decide whether to purchase loot boxes. Our goal is to uncover the strategic interactions and evolutionary outcomes between game companies and players across varied decision-making scenarios. By developing a company-player evolutionary game model and payoff matrix, we simulate the strategy evolution process between companies and players. Through simulation analysis, we examine how the initial strategy ratios of stakeholders and critical parameters, such as loot boxes' price and advanced items' value, influence the evolution trajectory.

Previous research on loot boxes has predominantly focused on their pricing structures and the analysis of their association with gambling. Owing to the complexity of strategic decisions related to honesty and purchasing behavior across various scenarios, there is a lack of theoretical analysis on the honesty of loot drop rates in the existing literature. In the realm of market manipulation, traditional research predominantly centers on post hoc analyses of specific incidents. Our study employs EGT proactively to examine potential market manipulation tactics by gaming companies, aiming ultimately to enhance integrity and transparency within the gaming industry. To bridge this knowledge gap, our research contributes in the following dimensions.

1) Unlike most existing studies focusing on post hoc analyses of market manipulations, our study proactively models the decisions and payoff of game companies and players.
2) For the first time, we use EGT to address the issue of dishonest drop rates in loot box games, analyzing strategy interactions and evolutionary outcomes under diverse decision-making scenarios.
3) Through simulation analysis, we verify the results and elucidate the dynamic evolution of participants' strategies. Concurrently, we conduct a sensitivity analysis of critical parameters to demonstrate how to steer the evolutionary game toward a more stable equilibrium.

The structure of this article is organized as follows. Section II reviews the relevant literature. Section III details the evolutionary game strategies of game companies and players and analyzes the outcomes of the model. Section IV presents simulations and sensitivity analyses of pertinent parameters. Section V concludes the article and suggests directions for future research.

II. Related Work

A. Loot Box

"Loot boxes" in video games offer randomized rewards, acquired either through in-game activities such as defeating enemies and completing quests, or by purchase with real-world money [8]. Particularly, loot boxes purchased with real money, directly contributing to game companies' profits, have become a focal point of discussion in both industry and academia. Yifan Jiao investigates the transparency of in-game item sales, finding that when game providers endogenously set virtual goods prices, transparency is ineffective. Instead, adopting an "opaque selling" strategy, where information about an opponent's skill level is concealed from players, is deemed optimal [9]. Ningyuan Chen delves into optimizing loot box pricing and design for revenue maximization, examining whether boxes should drop duplicate items. Findings indicate that despite traditional boxes yielding duplicates, the expected purchase volume mirrors that of a unique box strategy, albeit at a significantly lower optimal price [10]. Yu Jiang explores optimal strategies for players and game companies in decentralized network loot box games, revealing that companies employing prospect theory (PT) modeling should favor a conservative pricing approach to enhance their utility [11].

Numerous studies have investigated the association between loot boxes and gambling behaviors. These investigations highlight that the random nature and reward mechanisms of loot boxes exhibit gambling characteristics, potentially inducing gambling addictionlike behaviors among players [12], [13]. Additionally, research indicates that teenage players' engagement with loot boxes can foster unhealthy spending habits and elevate the risk of developing gambling addiction [14], [15].

In conclusion, the "loot box" mechanism for virtual item purchases has garnered significant attention within both the gaming industry and academic circles. However, research addressing the issue of dishonest drop rates from a theoretical perspective remains absent. Game theory is effectively applied to analyze conflict coordination and interaction among stakeholders with divergent objectives. The game-theoretic solution enables stakeholders to maximize benefits and identify the most advantageous strategies by anticipating the actions of others.

B. EGT

Classic static game theory assumes absolute rationality and complete information among stakeholders, often diverging from real-world scenarios. EGT enhances traditional game theory by incorporating incomplete information, bounded rationality and treating strategy selection as a dynamic process. A foundational work in EGT is Robert Axelrod's "The evolution of cooperation" [16]. Axelrod demonstrates the emergence and persistence of cooperative strategies in evolving populations using the iterated prisoner's dilemma game. He shows, via computer simulations and tournament-style competitions, that simple strategies emphasizing reciprocity and cooperation could outperform complex self-interested ones. Another significant contribution is John Maynard Smith's concept of evolutionary stable strategies (ESSs), which are strategies that, once established in a population, are resilient against invasion by alternatives [17]. Moreover, the application of EGT extends beyond biological systems. In economics, it is used to study market dynamics, the emergence of stable equilibria, and the impact of trading strategies [18], [19], [20]. In sociology, it analyzes social norms, cultural evolution, and social network dynamics [21], [22], [23]. In engineering, it addresses issues such as partial offloading in fog computing and mining pool selection in blockchain [24], [25], [26].

In evaluating various analytical approaches, we considered traditional game theory [27], metaheuristic algorithms [28], [29], and auction theory methodologies [30]. However, given our study's specific objectives and requirements, EGT emerged as the most suitable methodology. EGT addresses the challenges of complete information and absolute rationality that traditional static games assume, aligning with our research problem.

1) Incomplete information: Players are uncertain about the game company's honesty in loot box transactions, and companies are unaware of players' purchasing intentions regarding loot boxes.
2) Bounded rationality: While game companies may prioritize profit maximization, players' decisions to purchase loot boxes are influenced by factors such as gambler psychology and sunk costs, preventing absolute rationality.
3) Dynamic gameplay: The frequent purchase of loot boxes by players and the game companies' adjustments to drop rates based on these purchases exemplify the dynamic nature of the game, as opposed to static.

C. Market Manipulation

Generating illegal profits via dishonest loot box drop rates constitutes a form of market manipulation. Despite limited research on market manipulation within the loot box game market, significant investigations have been conducted in other areas, such as the stock market. Talis Putnins outlines multiple forms of market manipulation, ranging from classical schemes such as pump and dump, bear raids, and painting the tape, to more recent tactics such as spoofing, layering, pinging, and quote stuffing [31]. Akram offers a comprehensive review of global research on stock market manipulations spanning four decades. The analysis reveals that most research in this field is event based, concentrating on insider trading and pump-and-dump schemes. Additionally, the article highlights the growing significance of technology-based manipulations, indicating an expanding research area in utilizing technology to comprehend market behaviors and manipulations [32]. Peter Fratrič investigates Bitcoin market manipulation through agent-based models. This method provides a more comprehensive understanding of fraudulent traders' roles in the Bitcoin market. It develops a data-driven model focused on the causal impact of fraudulent behavior on Bitcoin prices, introducing a novel perspective to the economic analysis of market manipulations. [33]. Regarding information manipulation in the NFT market, Hongzhou Chen examines the linkage between social media accounts and Ethereum addresses, analyzing the NFT market's microstructure using Goblintown.wtf as a case study. He argues that joining NFT online communities likely consumes investors' limited attention, complicating their ability to make rational investment decisions [34].

These studies reveal several recurring themes. First, a significant emphasis is placed on event-based analysis, especially concerning financial crises. Second, technology's role in market manipulations is expanding, serving as both a mechanism for manipulation and a method for its detection and analysis. Third, manipulation methods vary widely, from traditional insider trading to complex schemes enabled by technological progress. Notably, our research diverges from the predominant focus on postevent analysis found in previous studies. Instead, we introduce a novel theoretical model to explore the dynamics between game companies and players. This model facilitates the investigation of potential manipulative behaviors and suggests measures to mitigate market manipulation risks. This proactive approach, employing theoretical models to preemptively address issues rather than reacting postfactum, represents our pioneering contribution.

III. Evolutionary Game Analysis

A. Problem Description

In loot box games, player experience originates from the inherent enjoyment of gameplay. Furthermore, the option to purchase loot boxes further influences players' overall utility

TABLE I
PAYOFF MATRIX

		Company	
		Honest (x)	Dishonest ($1-x$)
Players	Purchase (y)	R_1+P+aW, $R_2+VK_1+(1-a)W-P$	R_1+P+R_3, R_2+VK_2-P
	Not purchase ($1-y$)	R_1-D, R_2	R_1, R_2

in the game. The utility of acquiring loot boxes is linked to factors such as their price, the perceived value of advanced in-game items, and the drop rate. These critical parameters, controlled by the game company, strategically shape player experiences. Conversely, the game company's utility is closely tied to its profits, derived from loot box revenues, advertising, and player donations. Game companies face a critical decision regarding the honesty of loot box drop rates. If the actual drop rate is set lower than advertised, it could lead to increased profits for the game company. However, this strategy poses significant risks. If players discern the exploitation of this illicit revenue source, it could irreparably harm their trust and perception of the company's integrity. This adverse sentiment may result in reluctance or refusal to purchase loot boxes, leading to lost legitimate income that could have been earned through honest practices. This delicate balance highlights the complex considerations and tradeoffs between short-term gains and long-term player engagement. Achieving the right balance is crucial for maintaining a harmonious relationship between game companies and players, and for promoting an ethical gaming environment.

B. Hypothesis

H1. Both the game company and players exhibit bounded rationality and possess incomplete information. Game companies cannot predict players' loot box purchases, and players are uncertain about the honesty of loot box drop rates.

H2. The game company and players learn from each other, continuously refining their strategies through error correction, given the initial difficulty in selecting the optimal strategy for maximum benefit.

H3. The game company employs two strategies: "honest" and "dishonest," with probabilities $x(0 \leq x \leq 1)$ and $1-x$.

H4. Game players also employ two strategies: "purchase" and "not purchase," with probabilities $y(0 \leq y \leq 1)$ and $1-y$.

C. Evolutionary Game Model

Following the outlined problem description and identified conflicts between game companies and players, we define the game model's relevant parameters. R_1 represents the game company's income excluding loot boxes, encompassing advertising revenue and player donations, among others. A large R_1 indicates diversified profit avenues beyond loot boxes for the game company, whereas a smaller R_1 suggests a greater reliance on loot box revenue. R_2 denotes the player's base utility from gameplay, which is the enjoyment derived from the game itself, excluding loot boxes. P is the price of a loot box as determined by the game company. For model simplicity, we assume loot boxes either yield a single advanced item or none. V represents the value of the advanced item obtained through a loot box purchase. K_1 is the probability of acquiring items from loot boxes under honest conditions, while K_2 represents the probability in dishonest conditions ($K_1 \geq K_2$). When the game company adopts the "honesty" strategy and players choose the "purchase" option, loot boxes are sold at a fair price. This strategy allows the game company to not only earn revenue from loot boxes but also enhance user base, popularity, and reputation. Consequently, user utility increases alongside the game's reputation and user base. As a result, this cooperation generates a synergistic benefit value W, with additional utility distributed based on the distribution ratio a $(0 \leq a \leq 1)$. If the game company opts for "honesty" but players do not purchase, the company incurs a utility loss D, reflecting the industry confidence loss due to overlooking honest practices. Choosing "dishonesty" while players purchase allows the game company to gain additional profits in the secondary market beyond loot box sales, notably through prop scalping. The additional revenue from dishonesty is denoted as R_3. If the game company opts for "dishonesty" and players do not purchase, the company's utility reverts to R_1, and player utility remains at R_2, derived from the game itself. The parameters' definitions and the payoff matrix for the game company and players are detailed in Tables II and I, respectively.

TABLE II
SYMBOLS AND MEANINGS

Symbol	Meaning
R_1	Regular utility of the game company
R_2	Regular utility of game players
R_3	Extra income from dishonest behavior
P	Loot box price
V	Value of the advanced item
K_1	Honest drop rate
K_2	Dishonest drop rate
D	Utility loss of honest companies due to neglect
W	Synergy benefit generated from cooperation
a	Distribution ratio of synergy benefit

D. System Stability Analysis

Based on the payoff matrix, the expected payoff for the game company if it chooses the "honest" strategy is formulated as follows:

$$\begin{aligned} E_{c1} &= y(R_1+P+aW)+(1-y)(R_1-D) \\ &= yP+ayW+R_1-D+yD. \end{aligned} \tag{1}$$

TABLE III
LEP ANALYSIS

LEP	det J	tr J
A(0,0)	$D(P-VK_2)$	VK_2-P-D
B(0,1)	$(aW-R_3)(P-VK_2)$	$aW-R_3+P-VK_2$
C(1,0)	$D[VK_1+(1-a)W-P]$	$D+VK_1+(1-a)W-P$
D(1,1)	$(aW-R_3)[VK_1+(1-a)W-P]$	$R_3-aW+P-(1-a)W-VK_1$
E(x^*,y^*)	$\frac{D(VK_2-P)(aW-R_3)[VK_1+(1-a)W-P])}{(aW+D-R_3)[VK_1-VK_2+(1-a)W]}$	0

If the game company chooses the "dishonest" strategy, the expected payoff of the game company is formulated as follows:

$$\begin{aligned} E_{c2} &= y(R_1+P+R_3)+(1-y)R_1 \\ &= yP+yR_3+R_1. \end{aligned} \tag{2}$$

Therefore, the average payoff for the game company is formulated as follows:

$$\begin{aligned} \overline{E_c} &= xE_{c1}+(1-x)E_{c2} \\ &= axyW-xD+xyD+yP+yR_3+R_1-xyR_3. \end{aligned} \tag{3}$$

Similarly, the expected payoff for game players if they choose the "purchase" strategy is formulated as follows:

$$\begin{aligned} E_{p1} &= x(R_2+VK_1+(1-a)W-P) \\ &\quad +(1-x)(R_2+VK_2-P) \\ &= xVK_1-xVK_2+(1-a)xW+R_2+VK_2-P. \end{aligned} \tag{4}$$

The expected payoff for game players if they choose the "not purchase" strategy is formulated as follows:

$$E_{p2} = xR_2+(1-x)R_2 = R_2. \tag{5}$$

Therefore, the average payoff of the game players is formulated as follows:

$$\begin{aligned} \overline{E_p} &= yE_{p1}+(1-y)E_{p2} \\ &= xyVK_1-xyVK_2+(1-a)xyW+yVK_2-yP+R_2. \end{aligned} \tag{6}$$

Subsequently, the replication dynamics equation representing the game company's "honest" strategy is presented as follows:

$$\begin{aligned} F(x) &= \frac{dx}{dt} = x(E_{c1}-\overline{E_c}) \\ &= x(1-x)(E_{c1}-E_{c2}) \\ &= x(1-x)[(aW+D-R_3)y-D]. \end{aligned} \tag{7}$$

The replication dynamics equation for players' "purchase" strategy is as follows:

$$\begin{aligned} F(y) &= \frac{dy}{dt} = y(E_{p1}-\overline{E_p}) \\ &= y(1-y)(E_{p1}-E_{p2}) \\ &= y(1-y)\{[VK_1-VK_2+(1-a)W]x+VK_2-P\}. \end{aligned} \tag{8}$$

The replicated dynamical system is constructed by combining (7) and (8). The local equilibrium point (LEP) can be obtained by making the above two equations equal to zero. Thus, the five LEPs appear as follows: (0,0), (0,1), (1,0), (1,1), and (x^*,y^*)

$$x^* = \frac{P-VK_2}{VK_1-VK_2+(1-a)W} \tag{9}$$

$$y^* = \frac{D}{aW+D-R_3}. \tag{10}$$

At the same time, the LEPs obtained above are not necessarily an ESS, and the stability of the LEP can be determined by the Jacobian matrix J of the system as shown in (11) at the bottom of the page [35].

According to Friedman [36], when the LEP of the replicated dynamical system satisfies the conditions det $J>0$ and tr $J<0$, the equilibrium point represents the ESS. The results of det J and tr J for each LEP are shown in Table III.

We have the following inferences and assumptions to simplify the analysis: 1) $VK_1-VK_2+(1-a)W>0$. Since $K_1>K_2$ and $0\leq a\leq 1$, it infers that $VK_1-VK_2+(1-a)W>0$. 2) $P-VK_2>0$. Since K_2 represents the dishonest drop rate, a profit-maximizing game company will set K_2 to be less than the value of the premium item divided by the loot box price P/V. Therefore, $K_2<P/V$, which implies $P-VK_2>0$. In other words, $VK_2-P<0$. 3) $aW+D-R_3>0$. The purpose of our research is to promote the healthy development of the loot box game industry. Therefore, in the long run, in a benign and orderly game environment, game companies can gain synergistic benefits through cooperation with players. The benefits coupled with what honest game companies suffer from being neglected must be greater than the profit it brings through fraud. Even though dishonesty may bring additional income to the game company in the short term, players will lose confidence in the game company in the long run. Therefore, $aW+D-R_3>0$.

Then, let us discuss the signs of $aW-R_3$ and $VK_1+(1-a)W-P$. $aW-R_3$ represents the comparison between the synergy brought by honest management to game companies and the additional income brought by dishonest management. $VK_1+(1-a)W-P$ represents the synergy effect of the cooperation to the player plus the expected revenue of the item minus the loot box price.

$$J = \begin{bmatrix} (1-2x)[(aW+D-R_3)y-D] & x(1-x)(aW+D-R_3) \\ y(1-y)[VK_1-VK_2+(1-a)W] & (1-2y)[(VK_1-VK_2+(1-a)W)x+VK_2-P] \end{bmatrix}. \tag{11}$$

TABLE IV
EVOLUTIONARY STABILITY STATE UNDER VARIOUS CASES

LEP	det J	tr J	State
Case 1: $aW < R_3$ **and** $VK_1 + (1-a)W < P$			
A(0, 0)	+	–	ESS
B(0, 1)	–	Uncertain	Saddle Point
C(1, 0)	–	Uncertain	Saddle Point
D(1, 1)	+	+	Unstable
E(x^*, y^*)	–	0	Saddle Point
Case 2: $aW < R_3$ **and** $VK_1 + (1-a)W > P$			
A(0, 0)	+	–	ESS
B(0, 1)	–	Uncertain	Saddle Point
C(1, 0)	+	+	Unstable
D(1, 1)	–	Uncertain	Saddle Point
E(x^*, y^*)	+	0	Saddle Point
Case 3: $aW > R_3$ **and** $VK_1 + (1-a)W < P$			
A(0, 0)	+	–	ESS
B(0, 1)	+	+	Unstable
C(1, 0)	–	Uncertain	Saddle Point
D(1, 1)	–	Uncertain	Saddle Point
E(x^*, y^*)	+	0	Saddle Point
Case 4: $aW > R_3$ **and** $VK_1 + (1-a)W > P$			
A(0, 0)	+	–	ESS
B(0, 1)	+	+	Unstable
C(1, 0)	+	+	Unstable
D(1, 1)	+	–	ESS
E(x^*, y^*)	–	0	Saddle Point

Therefore, as shown in Table IV, there are four evolutionary states that need to be analyzed, and we denote the area ABCD as the mixed strategy space of this evolutionary game.

1) Case 1 ($aW < R_3$ and $VK_1 + (1-a)W < P$): As shown in Table IV, point $A(0, 0)$ is the ESS of the system, that is, {dishonest, not purchase}, and the evolution path is shown in Fig. 2(a). In this case, it suggests that for game companies, even when operating honestly and facilitating loot box purchases, the profit increase does not match the illicit gains from dishonest practices, leading companies to opt for dishonesty. For players, when the cost of loot boxes significantly exceeds the anticipated value of the items obtained, they are dissuaded from making purchases.
2) Case 2 ($aW < R_3$ and $VK_1 + (1-a)W > P$): As shown in Table IV, point $A(0,\ 0)$ is the ESS of the system, that is, {dishonest, not purchase}, and the evolution path is shown in Fig. 2(a). In this case, it indicates that for game companies, operating honestly and selling loot boxes might not yield profits as high as those generated from dishonest behavior. Consequently, when a game company opts for dishonesty, the price of loot boxes, even if set below the value implied by the declared drop rate VK_1 may exceed the value calculated using the actual dishonest drop rate VK_2, deterring player purchases.

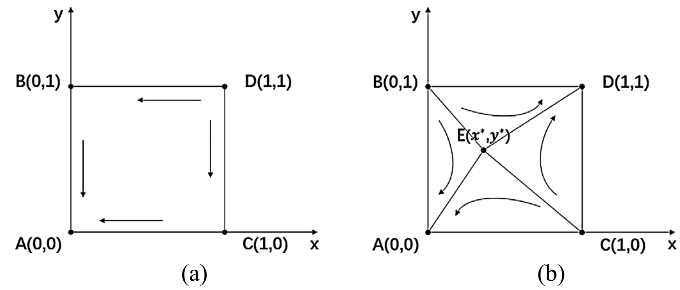

Fig. 2. Replicated dynamic diagrams. (a) Case 1,2,3; (b) Case 4.

3) Case 3 ($aW > R_3$ and $VK_1 + (1-a)W < P$): As shown in Table IV, point $A(0, 0)$ is the ESS of the system, that is, {dishonest, not purchase}, and the evolution path is shown in Fig. 2(a). In this case, while the profits from dishonest behavior fall short of the synergistic benefits generated from cooperation between the two parties, the price of loot boxes for players significantly exceeds not only their expected returns from obtaining items but also their anticipated benefits from the items plus the synergistic gains of cooperation. Consequently, this discourages players from making purchases, rendering the honest operation of game companies ineffectual.
4) Case 4 ($aW > R_3$ and $VK_1 + (1-a)W > P$): As shown in Table IV, point $A(0,\ 0)$ and point $D(1,\ 1)$ are both ESSs of the system, namely {dishonest, not purchase} and {honest, purchase}, and the evolution path is shown in Fig. 2(b). In this case, game companies' revenue from illicit activities falls below the synergistic benefits of cooperation, and players find the cost of purchasing a loot box to be less than the combined value of items obtained and the synergistic benefits from such cooperation. As shown in Fig. 2(b), the final ESS is determined not only just by the saddle point $(x,\ y)$ but also by the initial strategy ratio chosen by stakeholders. Specifically, the system converges to {dishonest, not purchase} if the player's initial state falls within the $ABEC$ region; conversely, it shifts to {honest, purchase} if within the $BDCE$ region.

IV. SIMULATION ANALYSIS

A. System Simulation Analysis

We use Python to simulate the dynamic evolution trajectory of the evolution system to verify the accuracy of the model results and make the dynamic evolution trends more clear and vivid. The multiple lines with different colors represent different trajectories of strategy evolution over time. Each line tracks changes in the initial strategy ratios of both the game company and players. Parameter settings for different scenarios are detailed as follows.

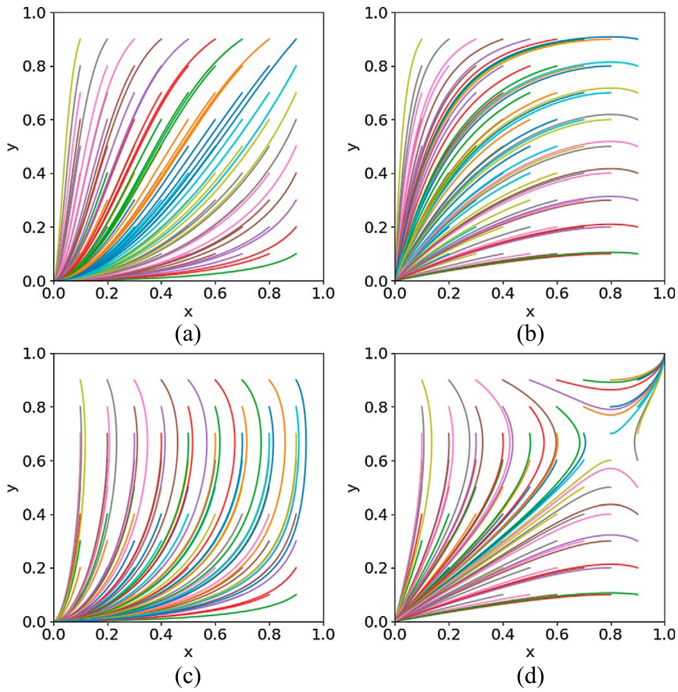

Fig. 3. Dynamic evolutionary paths. (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4.

In case 1, $R_1 = 5$, $R_2 = 5$, $R_3 = 8$, $P = 8$, $V = 10$, $K_1 = 0.2$, $K_2 = 0.1$, $D = 4$, $W = 10$, $a = 0.6$, the dynamic evolution trajectory is shown in Fig. 3(a).

In case 2, $R_1 = 5$, $R_2 = 5$, $R_3 = 8$, $P = 5$, $V = 10$, $K_1 = 0.2$, $K_2 = 0.1$, $D = 4$, $W = 10$, $a = 0.6$, the dynamic evolution trajectory is shown in Fig. 3(b).

In case 3, $R_1 = 5$, $R_2 = 5$, $R_3 = 4$, $P = 8$, $V = 10$, $K_1 = 0.2$, $K_2 = 0.1$, $D = 4$, $W = 10$, $a = 0.6$, the dynamic evolution trajectory is shown in Fig. 3(c).

In case 4, $R_1 = 5$, $R_2 = 5$, $R_3 = 4$, $P = 5$, $V = 10$, $K_1 = 0.2$, $K_2 = 0.1$, $D = 4$, $W = 10$, $a = 0.6$, the dynamic evolution trajectory is shown in Fig. 3(d).

1) Case 1: The evolution trajectory will eventually tend to ESS $A(0, 0)$, which is consistent with the model analysis.
2) Case 2: The evolution trajectory will eventually tend to ESS $A(0, 0)$, which is consistent with the model analysis.
3) Case 3: The evolution trajectory will eventually tend to ESS $A(0, 0)$, which is consistent with the model analysis.
4) Case 4: The evolution trajectory will eventually tend to ESS $A(0, 0)$ and $D(1, 1)$ according to the position of the starting point, which is consistent with the model analysis.

B. System Sensitivity Analysis

It can be seen from the above analysis that the evolutionary game systems under cases 1, 2, and 3 all have only one ESS. Under case 4, the ESSs will be {dishonest, not purchase} and perfect {honest, purchase}. Due to the position of the saddle point (x, y) and the respective initial selection probabilities of the stakeholders, the system will eventually evolve in different directions. Therefore, it is very meaningful to study the factors that affect the evolution path of the system.

TABLE V
CORRELATION OF PARAMETERS AND THE PROBABILITY

Parameters	$P\uparrow$	$R_3\uparrow$	$K_1\uparrow$	$W\uparrow$
S_{ABEC}	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$

As shown in Fig. 2(b), the area of the quadrilateral $ABEC$ represents the probability that the final ESS is {dishonest, not purchase}, and the area of the quadrilateral $BDCE$ represents the probability that the final ESS is {honest, purchase}. The abscissa x is the proportion of game companies who initially choose {honest}, and the ordinate y is the proportion of game players who initially choose purchase. After having the horizontal and vertical coordinates, we have the position of the initial point. $A(0, 0)$ will be ESS if the initial state is in the region $ABEC$. Similarly, $D(1, 1)$ will be ESS if the initial state is in region $BDCE$. To increase the probability that the system tends to {honest, purchase}, the position of point E should converge to the direction of point A to reduce the area of $ABEC$. The calculation formula is as follows:

$$S_{ABEC} = \frac{1}{2}\left(S_{ABE} + S_{ACE}\right) = \frac{1}{2}\left(x^* + y^*\right) = \frac{1}{2}\left(\frac{P - VK_2}{VK_1 - VK_2 + (1-a)W} + \frac{D}{aW + D - R_3}\right). \quad (12)$$

Equation (12) reveals that S_{ABEC} is determined by the values of x^* and y^*, and its variation is attributed to the variation of eight parameters P, V, K_1, K_2, a, W, D, and R_3. It is easy to deduce that $(\partial S_{ABEC}/\partial P) > 0$, $(\partial S_{ABEC}/\partial R_3) > 0$, $(\partial S_{ABEC}/\partial K_1) < 0$, and $(\partial S_{ABEC}/\partial W) < 0$. So P and R_3 are positively correlated with S_{ABEC}, K_1 and W are negatively correlated with S_{ABEC}. The influence of related parameters on the probability is presented in Table V. However, the influence of the remaining parameters on the S_{ABEC} is uncertain. Therefore, for analytical purposes, it is beneficial to employ numerical simulations to explore how initial percentage changes in participant choices and changes in various parameters affect the evolutionary trajectory in case 4.

1) Initial Ratios of Strategies: First, we discuss the impact of the game company and game players' initial behavioral strategy choice ratios on ESS. The original policy ratios for x and y are set as (0.6, 0.6) (0.7, 0.7) (0.8, 0.8), and (0.9, 0.9), respectively. The simulation results are shown in Fig. 4. It can be clearly seen that the selection of different initial ratios makes the evolution system have different evolution directions. The simulation results show that when the initial ratios of the game company choosing {honest} strategy and the player choosing purchase strategy are both 0.6 and 0.7, the ESS is {dishonest, not purchase}, as shown in Fig. 4(a) and 4(b). However, when these initial ratios rise to 0.8 and 0.9, the ESS will be {honest, purchase}, as shown in Fig. 4(c) and 4(d). This proves that the initial state of both sides of the game will directly affect the final

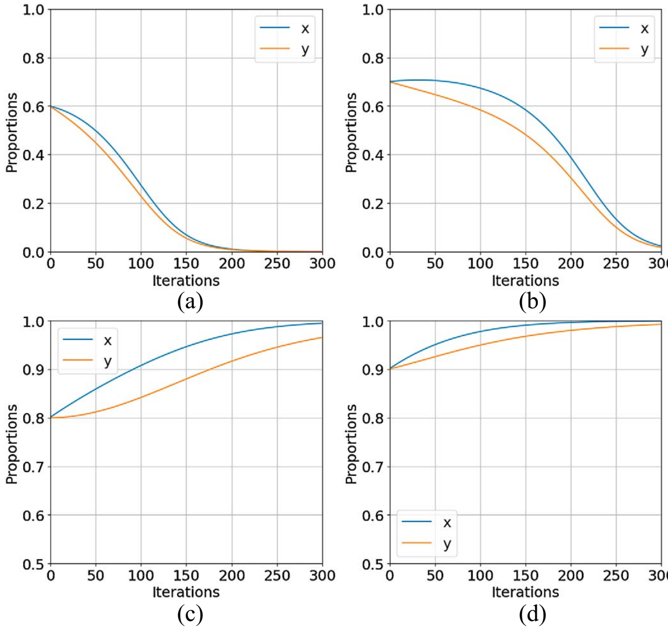

Fig. 4. Dynamic evolutionary paths under various initial ratios. (a) Initial ratios (0.6, 0.6). (b) Initial ratios (0.7, 0.7). (c) Initial ratios (0.8, 0.8). (d) Initial ratios (0.9, 0.9).

ESS. Therefore, it is helpful to adjust the price of loot boxes and other factors to increase the possibility of game companies initially choosing {honest} strategy and players initially choosing {purchase} strategy, which has leading significance for the optimization of the game environment.

2) Critical Parameters Related to Loot Boxes: This section studies the sensitivity of the participants to the parameters in case 4, namely loot box price (P), value of the advanced item (V), honest drop rate (K_1), dishonest drop rate (K_2), distribution ratio of synergy benefit (a), synergy benefit generated from cooperation (W), utility loss of honest companies due to neglect (D), and extra income from company's dishonest behavior (R_3). We assume that when modeling the sensitivity of one parameter, the values of the other parameters are held constant in case 4, with the stakeholder's initial choice ratios being 0.5 and 0.5, respectively.

1) Fig. 5 illustrates stakeholders' sensitivity to the loot box price (P) by setting P to 1, 2, 3, 4, 5. For higher loot box prices ($P = 3, 4, 5$), the ESS will be {dishonest, not purchase}, and the larger the P value is, the faster the system evolves. This aligns with the observation that consumers' willingness to purchase decreases as prices increase, assuming the item's value remains constant. When P is lowered to 2, the ESS will evolve into {honest, purchase}, with players' evolution pace outstripping that of companies. Additionally, a lower P value correlates with faster system evolution, suggesting that game companies can incentivize loot box purchases by lowering prices. This indicates that while higher loot box prices may increase per-unit revenue for companies, reducing prices appropriately can boost player purchases, creating a virtuous cycle that supports the development of the industry.

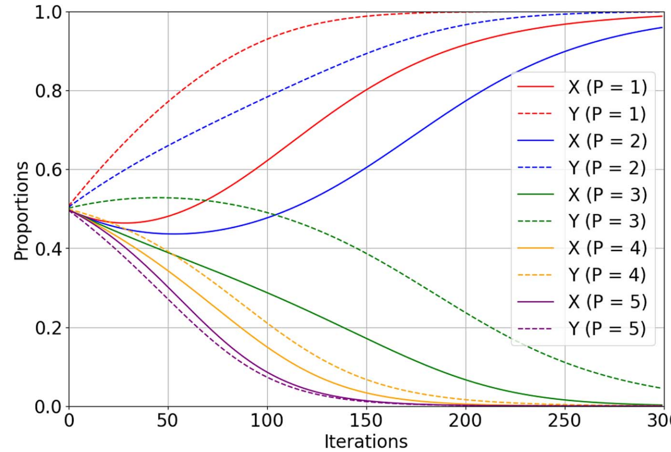

Fig. 5. Sensitivity of loot box price.

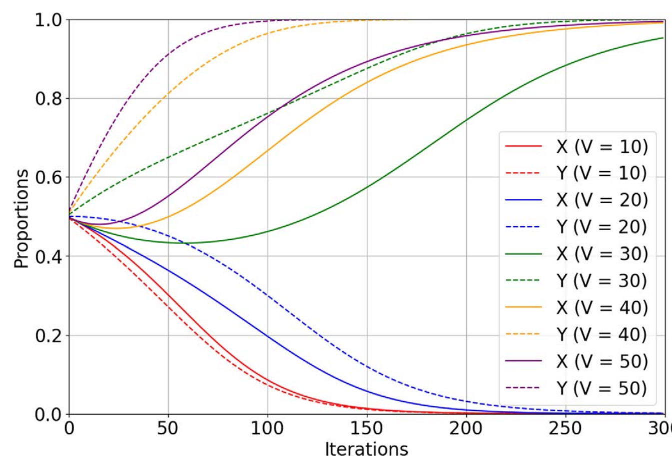

Fig. 6. Sensitivity of value of the advanced item.

2) Fig. 6 illustrates stakeholders' sensitivity to the value of the advanced item (V) by setting V to 10, 20, 30, 40, 50. When the value of advanced items is relatively low ($V = 10, 20$), the ESS will tend to {dishonest, not purchase}. As the value of advanced items decreases, the system evolves more rapidly. When V increases to 30 and above, the ESS shifts to {honest, purchase}, with players' evolution outpacing that of companies. This indicates increased player willingness to purchase loot boxes as the item value within them rises. Consequently, game companies can motivate loot box purchases by enhancing the value of contained items. Additionally, given the unique nature of video games where the marginal cost of loot box items is nearly zero, game companies must carefully balance item rarity and value to achieve sustained high returns.

3) Fig. 7 illustrates stakeholders' sensitivity to the honest drop rate (K_1) by setting K_1 to 0.1, 0.3, 0.5, 0.7, 0.9. When the honest drop rate is extremely high ($K_1 = 0.9$), the ESS will tend to {honest, purchase}. However, game companies typically maintain low loot box drop rates

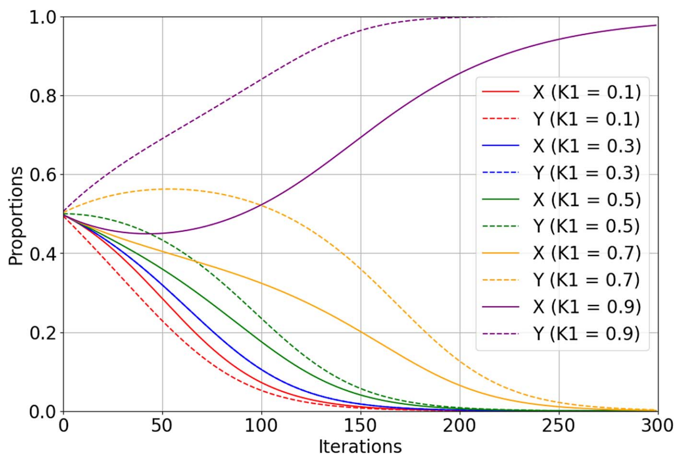

Fig. 7. Sensitivity of honest drop rate.

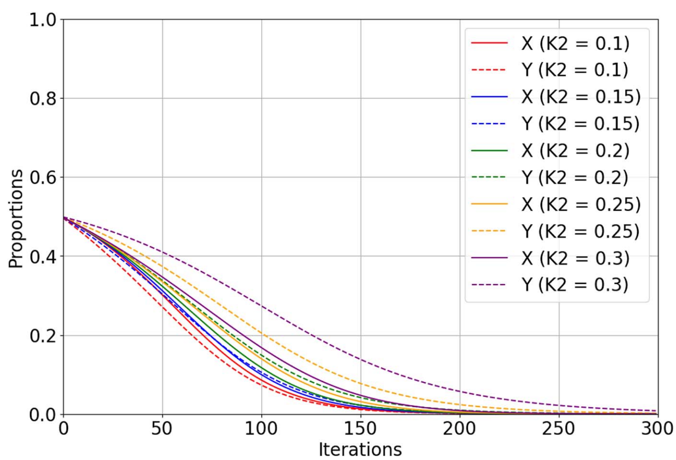

Fig. 8. Sensitivity of dishonest drop rate.

to preserve the scarcity of advanced items. As in other cases in the experiment ($K_1 = 0.1, 0.3, 0.5, 0.7$), the ESS will tend to {dishonest, not purchase} and the evolution speed will accelerate as K_1 decreases. This indicates that a lower actual loot box drop rate reduces players' willingness to purchase. Consequently, game companies must carefully calibrate drop rates. A too low rate can result in player complaints and dissatisfaction, ultimately deterring loot box purchases. Conversely, a high rate diminishes the scarcity and thus the value of high-level items, as their worth is intrinsically linked to rarity—if every player possesses high-level items, their perceived value declines.

4) Fig. 8 illustrates stakeholders' sensitivity to the dishonest drop rate (K_2) by setting K_2 to 0.1, 0.15, 0.2, 0.25, 0.3. Both the company and players will develop in the direction of {dishonest, not purchase}, and the evolution speed will accelerate as K_2 decreases. This indicates that, with other factors constant, increased levels of company dishonesty correlate with decreased player willingness to purchase. This outcome emphasizes the critical value

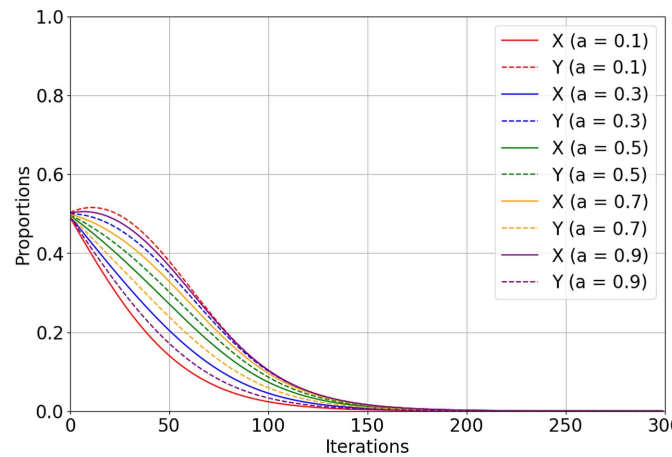

Fig. 9. Sensitivity of distribution ratio of synergy benefit.

players place on game companies' honesty and integrity. As dishonesty intensifies, players' concerns about the company's trustworthiness and ethics grow, ultimately influencing their purchasing decisions. Therefore, it is crucial for game developers to maintain a reputation for honesty and fairness to foster positive relationships with players and ensure long-term industry success.

5) Fig. 9 illustrates stakeholders' sensitivity to the distribution ratio of synergy benefit (a) by setting a to 0.1, 0.3, 0.5, 0.7, 0.9. Both the company and the player will develop in the direction of {dishonest, not purchase}. As a decreases, the company's evolution accelerates, while the player's evolution decelerates. This trend offers a crucial insight: adjusting the distribution ratio of synergy benefits (a) influences the evolution pace for both the company and players, though not their evolutionary direction. Consequently, this analysis highlights a key principle for fostering an equitable and prosperous gaming ecosystem. It becomes clear that achieving a fair and prosperous gaming environment requires more than adjusting resource distribution; it demands a comprehensive approach aimed at expanding the overall benefit.

6) Fig. 10 illustrates stakeholders' sensitivity to the synergy benefit generated from cooperation (W) by setting W to $10, 15, 20, 25, 30$. When the synergy is low ($W = 10, 15$), ESS will tend to {dishonest, not purchase}. When the synergistic benefit is high ($W = 20, 25, 30$), the ESS will tend to {honest, purchase}. When cooperation inclination decreases, players evolve faster than the company. This indicates that players adapt more quickly to changes, demonstrating a higher "escape velocity" in their strategic responses compared to the company. Conversely, with increased cooperation, the company's evolution speed surpasses that of the players. This differential adaptation rate highlights the company's increased sensitivity to higher synergistic benefits. Moreover, enhancing the total rewards for cooperation can further promote collaboration.

7) Fig. 11 illustrates stakeholders' sensitivity to the utility loss of honest companies due to neglect (D) by setting

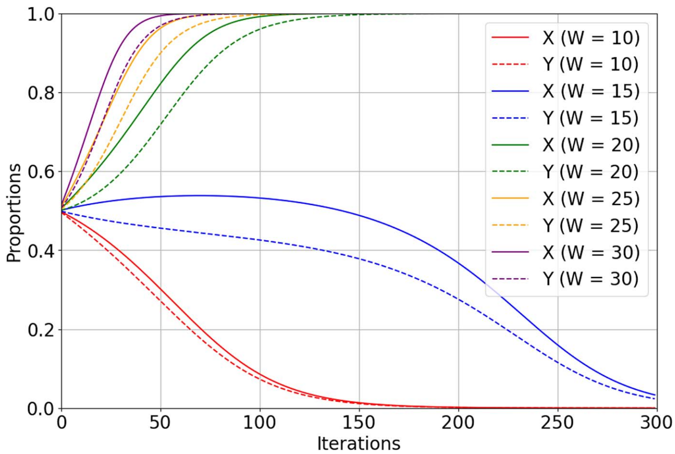

Fig. 10. Sensitivity of synergy benefit generated from cooperation.

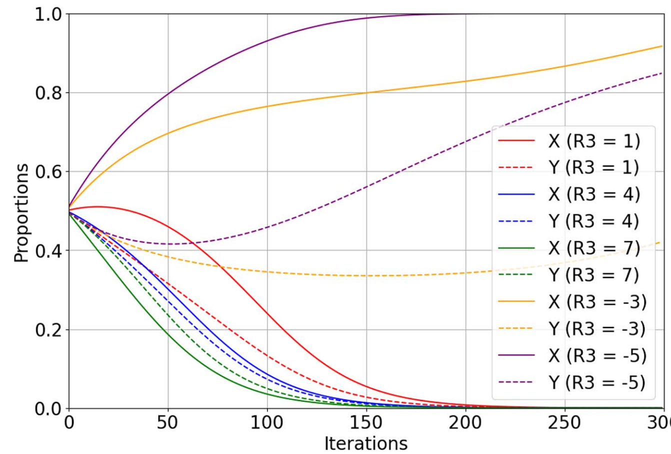

Fig. 12. Sensitivity of extra income from company's dishonest behavior.

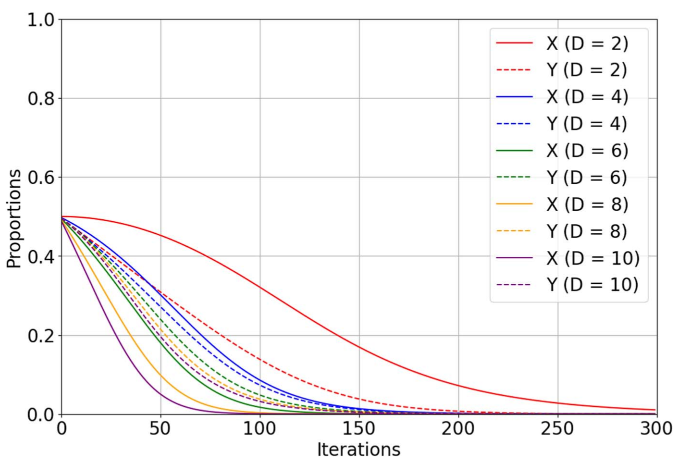

Fig. 11. Sensitivity of utility loss of honest companies due to neglect.

D to 2, 4, 6, 8, 10, the ESS will evolve toward {dishonest, not purchase}, and as D becomes larger, the system evolves faster. This finding highlights a critical dynamic: the magnitude of losses incurred by honest companies due to neglect directly influences the industry's overall disposition. As D increases, the pace of industry evolution accelerates, propelling the ecosystem toward a more dishonest orientation. This suggests a worrying feedback loop where increased neglect of honest companies fosters the rapid spread of dishonest practices within the industry. Consequently, industry associations can counter the trend toward dishonesty by compensating honest companies for their utility loss due to neglect. This strategic intervention can mitigate losses for honest companies and serve as a catalyst for positive industry-wide development.

8) Fig. 12 illustrates stakeholders' sensitivity to the extra income from company's dishonest behavior (R_3) by setting R_3 as 1, 4, 7, –3, –5. When $R_3 > 0$, ESS will evolve toward {dishonest, not purchase}, and as R_3 gets bigger, the system evolves faster. This indicates that the greater the additional income from dishonest behavior, the more likely game companies are to engage in such conduct. A unique experiment in this simulation involved setting R_3 to negative values. When $R_3 < 0$, ESS will evolve toward {honest, purchase}, and the smaller R_3 is, the faster the evolution speed. This demonstrates that proactive measures to curb illegal gains from dishonest behaviors can help associations rectify the gaming environment. These interventions aim to reduce the allure of extra income from dishonesty and promote a culture of integrity and ethics within the industry.

C. Simulation Results Discussion

The simulation analysis clearly demonstrates the pivotal role of game companies in fostering cooperation between themselves and players in loot box games. When game companies focus exclusively on short-term gains, seek illicit profits, and manipulate parameters to exploit players, the ESS invariably shifts toward {dishonest, not purchase}. This scenario results in a lose–lose situation for both game companies and players. Conversely, honest game companies can dynamically adjust variables such as the loot box price, advanced item value. Offering players reasonable returns early on allows these ethical companies to enhance player engagement and cultivate a culture of loot box purchasing. This symbiotic relationship ultimately results in a win–win scenario for both parties.

External oversight by game industry associations serves a dual purpose. Commending honest and penalizing dishonest game companies, associations bolster responsible behavior and transparency. These actions create a ripple effect, fostering an environment where both companies and players can thrive harmoniously. Various global examples highlight efforts to regulate and penalize unfair loot box practices in the gaming industry. Taiwan and South Korea mandate disclosure of odds for obtaining rewards in loot boxes. Italy and the Netherlands also enforce this, considering nondisclosure of loot box odds as misleading under EU consumer protection law [37]. On 3 January 2024, the Korea Fair Trade Commission fined Nexon 11.6 billion won for unfairly altering drop rates in "MapleStory" and "Bubble Fighter." In the United States, Senator Josh Hawley proposed

"The Protecting Children from Abusive Games Act" to protect minors from manipulative designs such as loot boxes and pay-to-win mechanisms. These examples showcase a global trend toward regulating video game loot boxes, from age ratings and odds disclosures to gambling law bans. These measures address concerns over the exploitative and gamblinglike nature of loot boxes, particularly in games targeting young players.

V. Conclusion

This study introduced a two-party evolutionary game model involving game companies and players within the context of loot box games. Utilizing the replication dynamics method, we analyzed the evolutionary game model and identified the ESS. We then simulated the strategy evolution process between the company and players under various decision-making scenarios. Through simulation analysis, the impact of stakeholders' initial strategy ratios and critical parameters on the evolutionary trajectory was examined. Subsequently, recommendations for optimizing the loot box game environment were proposed. The ultimate goal is to foster integrity and transparency in the gaming industry, ensuring a fair and equitable environment for players.

While our focus has been on direct player revenue, we have established a foundation for more complex future research. These initial simplifications, crucial for our analysis, set the stage for future model expansions to incorporate varied revenue sources, including advertising, and multiparty interactions. Furthermore, the transparency inherent in blockchain technology prevents game companies from being dishonest about loot box drop rates. Thus, comparing nonblockchain and blockchain games to understand their transformation motivations constitutes our next research focus.

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