

Research Article

Effect of Overconfidence on Product Diffusion in Online Social Networks: A Multiagent Simulation Based on Evolutionary Game and Overconfidence Theory

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The rapid development of online social media has significantly promoted product diffusion in online social networks (PDOSN). However, prior studies focusing on irrational behavior, such as overconfidence, in PDOSN are scarce. To investigate the effect of overconfidence on PDOSN, this study combined overconfidence and an evolutionary game to conduct a multiagent simulation on PDOSN. This combined method provided an effective reference to examine product diffusion in the context of irrational behavior. After careful consideration, this study identified three overconfidence scenarios, benefit, cost, and benefit and cost overconfidence, developed a multiagent simulation model for PDOSN using various overconfidence scenarios, and conducted a comparison with real-world cases to validate the model's feasibility. The findings indicated that adoption benefits and betrayal penalties had a positive effect on the results in all models, while adoption costs had the opposite effect. When benefit and cost overconfidence occurred simultaneously, benefit overconfidence offset the negative effect of cost overconfidence. Moderate connectivity, a large number of core nodes, and high reconnection probability fully promoted product diffusion. Benefit overconfidence and cost overconfidence had a significant impact on the results in different networks. As such, this study combined psychological theory with simulation methods, providing insights for future research on product diffusion.

1. Introduction

Recently, online social media such as LinkedIn, Instagram, and Facebook have developed rapidly, which has significantly promoted product diffusion in online social networks (PDOSN). PDOSN refers to the process by which products are bought by more consumers in online social networks over time [1] and involves consumers changing their opinions and making adaptive decisions based on information obtained from the entire consumer market and surrounding environment [2]. However, in complex situations, consumers are prone to irrational behaviors [3, 4]. Particularly, human decision-making is inevitably affected by emotions [5]. Irrational consumer behaviors affect purchase decisions in many situations, such as that described by the regret theory [6, 7]. Overconfidence is one of the most common irrational consumer behaviors [8]. Self-confidence

in judgment is an important human psychological behavior, which plays an important role in consumer decision-making. Therefore, it is necessary to combine *overconfidence theory* with consumer behavior to explore the impact of overconfidence on PDOSN.

Overconfidence theory is a new psychological theory that recently attracted significant attention from scholars, particularly in the field of decision-making [9–11]. Overconfidence, a common behavior, is rooted in the limited rationality of human decision-making. Moore and Healy proposed three categories of overconfidence: *overestimation*, which involves overestimating one's actual performance, *overplacement*, which refers to comparing others' overpositioning of one's own performance, and *overprecision*, which indicates overestimating one's own prediction accuracy for uncertain aspects [11]. Overconfidence can be applied to product diffusion in three main situations: benefit,

cost, and benefit and cost overconfidence. Benefit overconfidence indicates overconfidence regarding returns, with consumers believing that their purchasing behavior will bring higher returns. For instance, when Apple launches a new product, consumers often believe that buying the product would bring them higher returns. Cost overconfidence occurs when consumers' expected cost is higher or lower than the actual cost. For instance, although a wait time may be required after a new Apple product is released, consumers often ignore these waiting costs. Cost and benefit overconfidence indicates that consumers inaccurately estimate both the benefits and costs. To investigate the effect of overconfidence on PDOSN, this study posed the following research questions:

- (1) Considering the behavior of microindividuals and interaction of macrogroups, how does overconfidence affect consumer decision-making?
- (2) In different scenarios of overconfidence, how and to what extent does overconfidence impact consumer decision-making?
- (3) In different environmental networks, how does overconfidence impact consumer decision-making?

Traditional product diffusion models can be divided into three types: macrodiffusion, microdiffusion, and diffusion models based on complex system theory. The macroscopic diffusion model is mainly based on the Bass model [12]. As this model does not consider heterogeneity between consumers' repeat purchases and potential consumers, Haki et al. proposed a macroscopic diffusion model based on differential equations, which assumed that individuals are independent [13]. However, this model ignored the characteristics of the main body in the diffusion process. Therefore, Oren and Schwartz [14] proposed a new model from a microperspective. Meanwhile, many scholars have attempted to apply the complex system theory to product diffusion models. Schoder [15] used the master equation method to estimate the emergence of product diffusion patterns in the telecommunication service industry. Goldenberg et al. [16] used penetration models to study product diffusion. Goldenberg et al. [17] used cellular automata to analyze the spread of the products. However, existing studies have ignored the influence of individual irrationality (overconfidence) on the decision-making behavior in the process of product diffusion, leading to a decision-making bias, did not fully consider individual interactions underlying the macrogroup behavior, and failed to reveal the macrodiffusion resulting from individual interactions.

PDOSN is the result of interactions between individuals in online social networks. Consumers' buying behavior is affected by subtle changes in their perceptions, referred to as consumption reversal, which reduces result predictability [13]. Multiagent simulation has been widely used in the field of product diffusion [18]. As a bottom-up modeling method, it is suitable for studying the macroemergent phenomena caused by individual microinteractions [19] and provides new modeling and analysis perspectives for the dynamic evolutionary behavior of complex systems in social sciences [20].

However, it is relatively simple for describing individual interactions, and revealing the impact of microindividual psychological behavior (overconfidence) on macrodiffusion accurately is difficult. Evolutionary game theory effectively describes individual interactions in a group owing to its simplicity, efficiency, and strong analytical ability. Therefore, this study combined overconfidence and an evolutionary game to conduct a multiagent simulation study on the impact of overconfidence on PDOSN.

This study developed an evolutionary game model to describe the individual interactions by designing a learning algorithm that considered overconfidence. Three overconfidence scenarios were identified: benefit, cost, and benefit and cost overconfidence. Furthermore, a multiagent simulation model under different overconfidence scenarios was realized and validated. This study has the following implications. This study integrated multiagent simulation and evolutionary games, considering the impact of individual consumers on the entire macrogroup and constructed a product diffusion model in the consumer market. In addition, this study considered the influence of individual consumer preferences and self-cognition bias on decision-making behavior, incorporated overconfidence theory in consumer psychology, and studied product diffusion under three overconfidence scenarios.

The remainder of this paper is organized as follows. Section 2 reviews existing literature. Section 3 proposes a theoretical model that integrates overconfidence theory and an evolutionary game model and designs overconfidence scenarios. Section 4 develops a multiagent simulation model of PDOSN based on the theoretical model under different overconfidence scenarios and designs rules for simulation and network construction. Section 5 presents simulation experiments and results of different scenarios. Section 6 summarizes this study.

2. Literature Review

2.1. Product Diffusion in Online Social Networks. "Product diffusion" was first proposed by the American academic Frank Bass in his Bass model [21]. The Bass model states that product diffusion is a dynamic process in which few consumers initiate product adoption to more consumers in a certain period of time using mass media and word-of-mouth communication. The PDOSN theory reflects the law of consumer group behavior and promotes the development of market prediction, marketing strategy theory, and practice. However, this theory was proposed in the 1970s [21]. Science, technology, and business models have undergone profound changes since then and the PDOSN theory must keep pace with these changes. Successful diffusion is crucial for new product development and improves not only economic benefits but also the competitiveness of enterprises. Therefore, understanding the process of and factors affecting PDOSN has become increasingly important.

2.2. Product Diffusion in Online Social Networks Based on Game Theory. Game theory studies the direct interaction of the decision-maker's behavior and the equilibrium problem

of such type of decision [22]. The individual utility function studied in game theory is affected not only by the individual's own choice but also by others' choices. Therefore, an individual's best choice is the function of others' choices [23]. Market diffusion of a product involves many participants, such as customers, suppliers, middlemen, and competitors [24]. In game theory, each participant is a player, and each decision affects other participants. Players not only consider the decisions of other participants but also their reactions. Game theory studies how decisions are made taking into account the interests of all participants.

Game theory is simple, efficient, and analytical and is widely used to study the decision-making problems of various actors. Game theory has been utilized by scholars in many fields to explore and promote cooperation. Borge-Holthoefer et al. [25] constructed an evolutionary game model of community networks with dual preferences for social dilemmas and examined the influencing factors and mechanisms of cooperation emergence. Neville et al. [26] combined the snowdrift game model and proportional imitation strategy to analyze the influence of a scale-free network topology on the emergence of cooperation. Research shows that behaviors in social networks are largely based on dynamic public opinion evolutionary game models for decision-making analysis. Therefore, this study combined game theory with multiagent simulation based on Reinganum [27] who was the first to use game theory methods to investigate product diffusion. This study utilized a comprehensive consideration of self and neighbor's personality characteristics and learning the rules of historical information to describe the individual interaction process.

Previous literature failed to consider the individual interaction behind the macrogroup behavior or reveal macrodiffusion caused by individual interactions. However, consumers in online social networks are involved in a variety of complex interactions with multiple consumers. As consumers face various personalized scenarios, this study incorporated personalized scenarios into the multiagent simulation of PDOSN.

2.3. Product Diffusion in Online Social Networks Based on Personalized Recommendation Scenarios. Personalized product recommendation scenarios are based on deep mining of resource characteristics and user interests to predict the items that best match the target user in the current situation [28]. Product diffusion in a specific situation can also be called product diffusion based on personalized recommendations. According to Dey and Abowd, this "situation refers to all kinds of information describing the entity characteristics in a scene" [29]. On this basis, situations can be further divided into user, temporal, physical, computing, and social situations. Overconfidence, which is examined in this study, is a user situation. Yürür et al. [30] noted that the development of mobile Internet provides comprehensive and real-time situational information for the research on personalized recommendation. Whether situational factors can be introduced into online social network recommendation system largely determines

the quality of personalized recommendations. Shiraki et al. [31] demonstrated that different situational information elements, such as time, location, and weather, have different degrees of impact on the recommendation system. Therefore, for multidimensional situational recommendations, the impact of various situational elements on the recommendation results must be thoroughly examined. Stai et al. [32] designed, developed, and evaluated a framework composed of personalization, relevant feedback, and recommendation mechanism as the main method to create rich multimedia content according to user needs, preferences, and interests. Mallat et al. [33] revealed that, in some frequently changing environments, the user behavior mode of integrating situations can improve the ability to predict users to a certain extent, providing guidelines for integrating overconfidence scenarios into product diffusion in China.

Therefore, product diffusion research should consider online social network personalized recommendations that integrate situational information. This study introduced overconfidence scenarios into product diffusion model and discussed the new product diffusion mechanism in an overconfidence scenario by combining multiagent simulation and game theory.

2.4. Overconfidence Theory. Serrano and Iglesias found that overconfidence was an influencing factor of heuristics and bias (HB), affecting decision-makers' decisions [34]. Psychological experiments have revealed that people tend to believe that their judgments overestimate the probability of success and underestimate the role of luck, opportunity, and external forces. This cognitive bias is called "overconfidence." The *overconfidence theory* was first proposed by Griffin and Tversky [35]. Studies have shown that people tend to be overconfident when encountering difficult problems and less confident in the face of simple problems.

Overconfidence, which is a common cognitive bias in people's evaluations, was first observed in cognitive psychology research. Scholars have provided various definitions of overconfidence. Glaser and Weber [36] found that the literature on heuristics and biases has no precise definition of overconfidence. Misalignment, overly tight volatility estimations, and better-than-average effects may be considered overconfidence. Steen [37] used two new mechanisms for expanding overconfidence behavior, assuming that all people under these two mechanisms are Bayesian rational people that can openly disagree with their own beliefs, meaning that there are different priors. Moore and Healy [11] integrated three definitions of overconfidence in the research literature: *overestimation*, which refers to overestimating one's actual performance, *overplacement*, indicating comparing others' overpositioning of one's performance, and *overprecision*, which means overestimating one's prediction accuracy for uncertain aspects.

Scholars used the principal-agent model to study retailer overconfidence on sales efforts and manufacturer's production price decision, comparing it with the retailer's complete rationality [38]. They found that retailer overconfidence increases the difference among marketing efforts,

manufacturer's optimal price and maximum profit, and the situation of completing rationality. The random demand of the market is manifested in two modes: additive and multiplicative decisions. Overconfident retailers should make optimal pricing and ordering decisions. This study addresses the influence of the retailer's overconfidence level on the maximum expected profit and optimal pricing and ordering decisions. Maximum expected profit is compared with the actual retailer's profit, and the retailer's overconfidence behavior reduces the expected profit.

Currently, overconfidence is widely used in research on management and enterprises. However, previous studies on product diffusion have not considered the impact of overconfidence on consumer behavior, resulting in decision-making bias. In product diffusion, the relationship between consumers and the diffusion market of products emerges from microlevel consumer behavior. Therefore, based on previous studies, this study introduced overconfidence into the consumer behavior model and combined it with product diffusion.

2.5. Multiagent Simulation. Multiagent systems (MASs) have been utilized in research on distributed artificial intelligence. MASs focus on coordinating the behavior of multiple agents in the system and aim to simulate human society, with the socioeconomic system being the most important applicable goal. Multiagent simulation technology has autonomous distribution and coordination as well as self-organization, learning, and reasoning abilities. Hence, it has a wide range of applications in social and economic systems.

In the field of diffusion, multiple agents have more applications. Jiang et al. [39] applied the MAS method to product diffusion, established a simulation model, and used the model to conduct simulation experiments on the dynamics of product diffusion. Berger [40] examined the impact of strategic portfolios on innovation diffusion and resource use by establishing a heterogeneous multiagent model considering the social and spatial interactions between agents and demonstrated that individual choices of farm residents in production, consumption, investment, and marketing were reflected in the recursive linear programming model. Berger's study revealed that multiagent spatial modeling could describe the innovation diffusion process and manage the use of resources.

Maienhofer and Finholt [41] established a multiagent simulation model and experimentally explored the optimal solution of innovation diffusion. By defining or changing the agent's goal, the simulation explained that the optimal quality changed significantly through the diffusion of the agent. The network emphasized the goal of a certain agent, and simulation explained why a good agent's goal could not be considered an opinion leader, indicating that choosing a good agent's goal could speed up diffusion. Neri [42] investigated the market interaction behavior under various specific information diffusion scenarios using a multiagent model and obtained better simulation results by using multiple evaluation agents and selecting different

information variables, such as the product advertising effect, consumers' memory space, and determining the communication between friends in market sharing.

Cebulla [43] used MAS technology to analyze the problem of knowledge diffusion supported by adaptability and situational attention. Multiple agents were used to establish meaningful communication with the external environment at the knowledge level, and a knowledge diffusion model for modeling the subadaptive process was proposed. Johnson et al. [44] used heterogeneous MAS to examine the West African cassava and explore new technology of geographic protective behavior. Oh et al. [45] used multiagent technology to establish a two-layer diffusion model and explore the unregulated state of the world's energy market.

These studies addressed the purchase and impact of consumers as agents, which help model the impact of consumers' overconfidence on product diffusion. This study simultaneously introduced game theory and the individual learning rule based on historical information into the model to describe and explore individual behavior and interaction. This integrated framework revealed a variety of modeling methods for complex group behavior generated from individual interaction.

An analysis of extant literature revealed the following shortcomings:

- (1) Previous literature did not examine the individual interaction behind the macrogroup behavior and failed to reveal the macrodiffusion caused by individual interaction. For instance, multiagent simulation is relatively intuitive, and accurately describing the consumer interaction behind the macrodiffusion is difficult.
- (2) Previous studies rarely considered the impact of individual irrationality (overconfidence) on consumer behavior, resulting in decision-making bias. Moreover, through consumer interaction, this individual bias can eventually emerge into macrodeviations of product diffusion model results.

As most previous studies examined product diffusion using MAS, this study also utilized this method. However, this method ignores the impact of consumer microinteraction on macrodiffusion. Therefore, this study introduced game theory to describe consumer individual interaction reasonably and applied game theory and multiagent simulation methods to product diffusion analyses. In addition, most studies are based on the assumption that consumers are completely rational, which is inconsistent with consumers in real life. Consumers have bounded rationality, and decision deviation may cause irrational behavior, such as overconfidence. Therefore, this study relaxed scholars' assumptions and considered the irrational behavior of consumer overconfidence. The model was in line with real product diffusion situations and more scientific than previous models. This study combined overconfidence and an evolutionary game to conduct a multiagent simulation for investigating the effect of overconfidence on PDOSN. Three overconfidence scenarios were identified: benefit, cost, and

benefit and cost overconfidence. In addition, this study developed a multiagent simulation model for PDOSN with these overconfidence scenarios.

3. Research Framework and Theoretical Model

3.1. Research Framework. PDOSN is the process by which a product is diffused in an online social network through interactions between consumers [14]. Consumers can be divided into two roles in this process: adopters and potential adopters [7]. When a piece of product information is transmitted in the market network, the adopter obtains the target information through other consumers in the network. Subsequently, the information is transmitted to the neighbor node. A potential adopter is a consumer who is either aware or unaware of the information but is not involved in its dissemination [46].

This study introduced the behavior theory into product diffusion research and analyzed the impact of overconfidence on PDOSN. The integrated framework included the overconfidence theory, the evolutionary game theory, and the multiagent simulation model [47]. Specifically, this study combined overconfidence with an evolutionary game to build a multiagent simulation model for PDOSN to reveal the impact of overconfidence. By designing a learning algorithm considering overconfidence, an evolutionary game model was established to describe the interaction between consumers. Three overconfidence scenarios were identified: benefit, cost, and benefit and cost overconfidence. Multiagent simulation models in these overconfidence scenarios were implemented and verified.

The study design is presented in Figure 1. The study included three stages. The first stage was the theoretical design based on the original model, with *overconfidence theory* and evolutionary games added to establish the utility function. Moreover, the interaction process between individuals was established by considering consumer preference, neighbor preference, and the realization of the surrounding environment. In the second stage, a multiagent simulation model was created, which involved initialization, main model design, and person class model design. In the third stage, simulation experiments, including utility, overconfidence, and network connection parameters, were conducted.

3.2. The Game-Theory-Based Model. In the process of PDOSN, individual consumers in online social networks demonstrate bounded rationality [14]. They consider the expected utility of their decision-making in the purchase and adjust their decision-making strategies based on their neighbors' strategies [47]. This is a process of continuous change and interactive learning. In this study, the evolutionary game model was used to reflect the process of individual decision-making, as shown in Figure 2. Three steps were combined to form the entire evolutionary game. First, the individual calculated expected utility based on own and neighbors' strategies. However, owing to the overconfidence of the individual, the estimation of the expected utility was

biased. Second, individuals imitated neighbor behavior through a learning algorithm. Finally, individuals combined the above two steps to judge and decide whether to adopt or reject their own behaviors. The experiment was conducted under the following assumptions: (1) individuals have bounded rationality, and the ultimate goal of the individual in decision-making is to maximize their own interests; (2) individuals only know their own and their neighbors' decision-making results, not all individuals in the market; and (3) individuals have overconfidence, which impacts individual decision-making.

During the entire product diffusion process, existing and potential consumers influence each other. In addition to their internal influences, PDOSN is affected by many external factors, such as consumers' perception of self-determination and the surrounding environment. Therefore, PDOSN can be represented by a game matrix, as shown in Table 1, which includes penalty parameters.

In Table 1, b represents the benefits of holding the adoption strategy and c represents the total cost of product diffusion. According to the previous assumption, buyers share the cost, n represents the total number of consumers, and x represents the proportion of consumers who purchase. Some consumers demonstrate free-riding behavior; that is, they do not buy the product but benefit from purchases made by others. d is the penalty of holding the rejection strategy (i.e., product income penalty), and $b - d > 0$ is defined here (i.e., $b > d$).

Generally, the dynamic replication method is used to detect evolutionary game equilibrium [48]. If x is the percentage of users who hold an adoption strategy in the network, the expected utility of the adoption of PDOSN can be expressed as

$$E_1 = x \left(b - \frac{c}{nx} \right) + \left(b - \frac{c}{nx} \right) (1 - x) = b - \frac{c}{nx}. \quad (1)$$

The expected utility of rejection can be expressed as

$$E_2 = x \left[b - \frac{d}{(n(1-x))} \right]. \quad (2)$$

The average expected utility of the group can be expressed as

$$E = xE_1 + (1 - x)E_2. \quad (3)$$

The game equilibrium equation can be expressed as

$$b - \frac{c}{nx} = x \left[b - \frac{d}{n(1-x)} \right]. \quad (4)$$

In the evolutionary game model, supposing that the consumer is a completely rational individual, the formula $B = b + \bar{X}$ was used to express the linear function of each individual's expected product diffusion benefit, where b is the benefit of individual adoption of PDOSN. In the model of PDOSN, $\bar{X} \sim N(0, \sigma^2)$, and \bar{X} were random disturbances. If X is the stabilized random disturbance and $X = \bar{X}/\sigma$, $X \sim N(0, 1)$ could be clearly obtained. Then, $B = b + \bar{X}$ could be extended to $B = b + \sigma X$, where $B \sim N(b, \sigma^2)$.

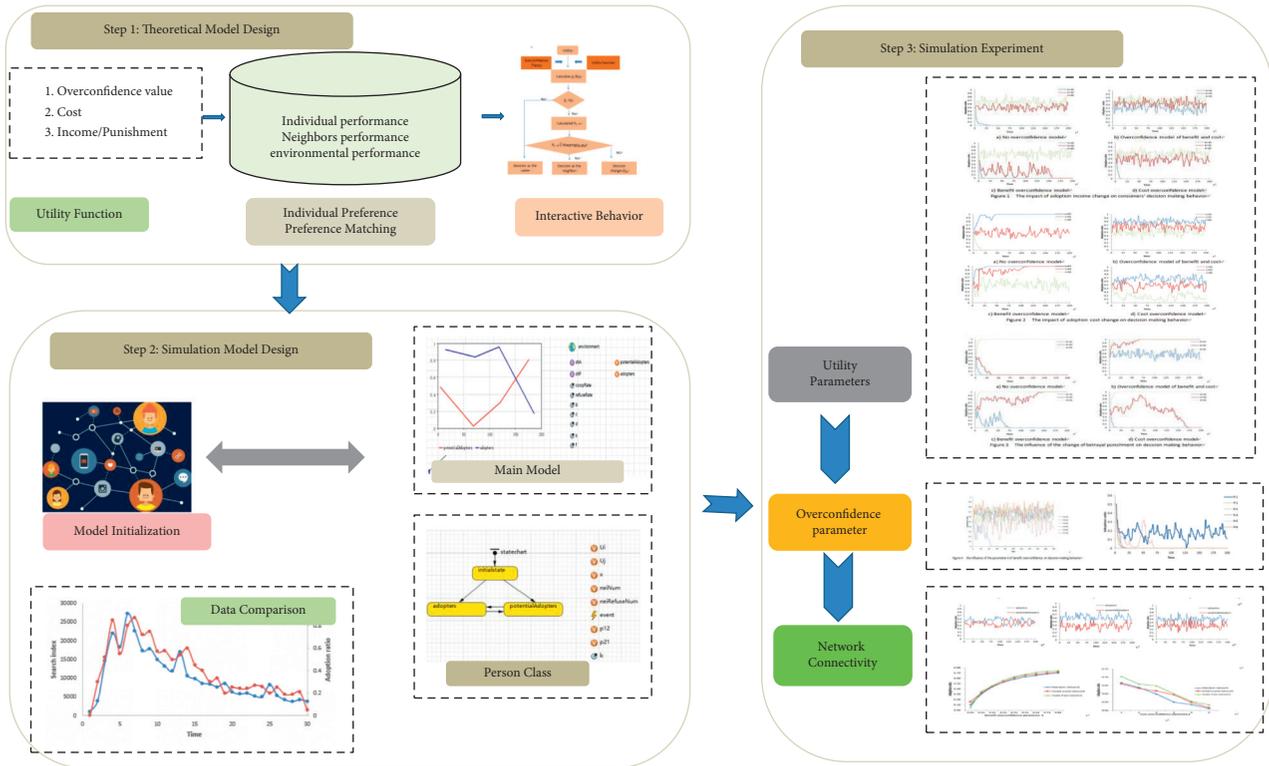


FIGURE 1: The research framework.

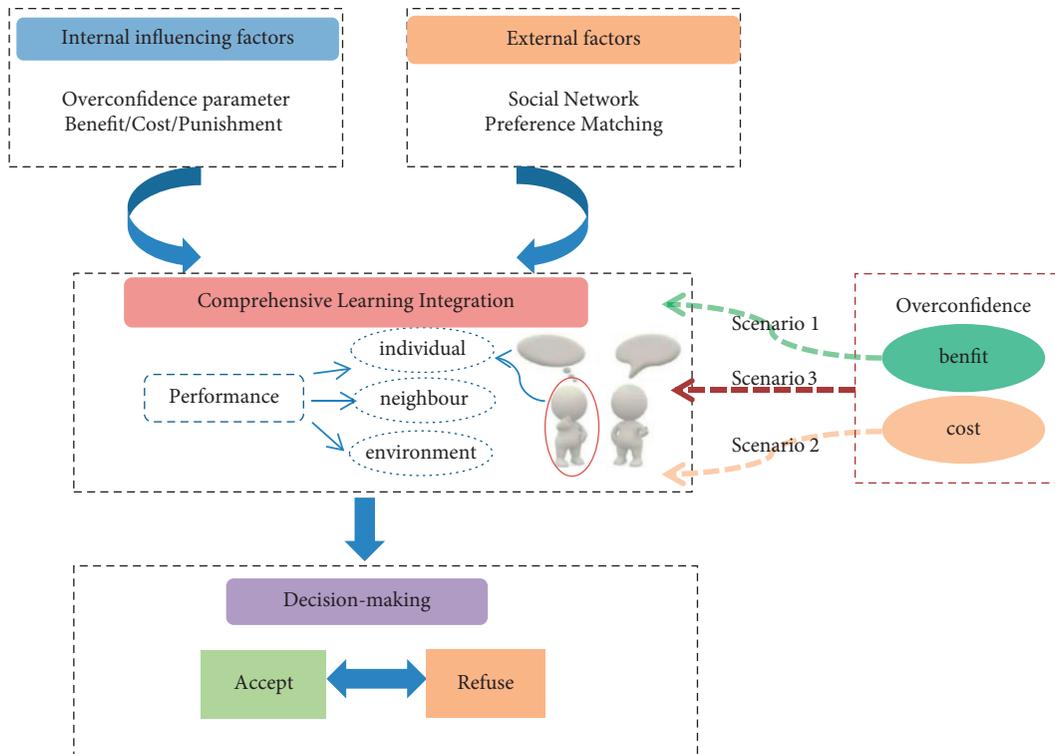


FIGURE 2: Conceptual model of individual decision-making behavior.

TABLE 1: Interactive behavioral game payoff matrix with penalty parameters.

| Player 1 | Player 2 | |
|-----------|------------------------------|------------------------------|
| | Adoption | Rejection |
| Adoption | $b - c/(nx), b - c/(nx)$ | $b - c/(nx), b - d/n(1 - x)$ |
| Rejection | $b - d/n(1 - x), b - c/(nx)$ | 0, 0 |

Considering the above random disturbance, the expected utility of adoption can be expressed as

$$U_i = x \left(B - \frac{c}{nx} \right) + \left(B - \frac{c}{nx} \right) (1 - x) = b + \sigma X - \frac{c}{nx} \quad (5)$$

Similarly, the expected utility of rejection can be expressed as

$$\begin{aligned} U_j &= x \left[B - \frac{d}{n(1-x)} \right] \\ &= x \left[b + \sigma X - \frac{d}{n(1-x)} \right]. \end{aligned} \quad (6)$$

In this case, the equilibrium point of the game equation is difficult to obtain. Therefore, multiagent simulation must be adopted to model the product diffusion process, and the game equations are used to reflect the behavior rules of agents.

This product diffusion model based on game theory was the basis for this study. This study added *overconfidence theory* to the existing model, as described below, to examine the influence of consumer overconfidence on product diffusion.

3.3. Evolutionary Model of Product Diffusion considering Overconfidence. Product diffusion emerges from the microlevel interaction between individual consumers [3]. Consumer behaviors in complex situations often incline to irrationality [3, 4]. For instance, individual consumer decision-making behavior may be affected by overconfidence [47]. Therefore, this study considered the impact of consumer overconfidence on PDOSN and comprehensively examined three scenarios: benefit, cost, and benefit and cost overconfidence [11].

Scenario 1. Benefit overconfidence. The forms of overconfidence include overestimation and overprecision [11]. The former overestimates decision-making ability and success probability and believes that their decision-making can bring better results. The latter means that consumers think their judgment ability is higher than the actual level and believe that they have the ability to control the fluctuation range of variables. Based on the above perspective, this study considered that estimation of the expected mean and variance of overconfident individuals is biased. Assuming that the expected return is u_0 , while the actual return is u , $u_0 > u$. In addition, overconfident individuals overestimate their predictive ability, resulting in a smaller estimated return variance than actual return variance. Assuming that return variance is σ_0^2 and actual return variance is σ^2 , $\sigma_0^2 < \sigma^2$.

Assuming that individuals have the same degree of overconfidence, k is defined as the impact of individual overconfidence on expected returns in information dissemination, $k \in [0, 1]$, and k is directly proportional to the degree of overconfidence.

Patterson Hann [49] found that, before purchasing a product, consumers conduct an all-round evaluation of its benefits and believe that their own decision-making will produce good results. This is a classic benefit overconfidence scenario. There are two aspects of consumers' overconfidence in benefits: they overestimate the benefits of the product and underestimate the range of benefits. Therefore, we use B_0 to represent the overestimated and overprecise expected return of the overconfident, where $B_0 = (1+k)b + (1-k)\sigma X_0$ and $X_0 \sim N(0, 1)$, $B_0 \sim N((1+k)b, (1-k)^2\sigma^2)$.

Considering the benefit overconfidence, the expected utility of adoption can be extended from formula (5) to

$$\begin{aligned} U_i &= x \left(B_0 - \frac{c}{nx} \right) + \left(B_0 - \frac{c}{nx} \right) (1 - x) \\ &= [(1+k)b + (1-k)\sigma X_0] - \frac{c}{nx}. \end{aligned} \quad (7)$$

Similarly, the expected utility of rejection can be extended from formula (6) to

$$U_j = x \left[B_0 - \frac{d}{n(1-x)} \right] = x \left[(1+k)b + (1-k)\sigma X_0 - \frac{d}{n(1-x)} \right]. \quad (8)$$

Scenario 2. Cost overconfidence. Moore and Healy argued that overconfident consumers believe that their judgment ability is higher than the actual level and that they have the ability to control the fluctuation range of variables, resulting in overly high expectations regarding their choices [11]. If the expected cost of consumers is represented by c_0 and the actual cost is c , the level of cost overconfidence is $f = c_0 - c$; that is, consumers have an estimated bias for the expected effect of the product, resulting in an overestimation, and f represents the level of cost overconfidence. Overconfidence is assumed to be proportional to the individual's perceived cost. That is, as f increases, consumer's perceived cost increases over actual cost.

Considering cost overconfidence, the expected utility of adoption can be extended from formula (5) to

$$U_i = x \left(B - \frac{c_0}{nx} \right) + \left(B - \frac{c_0}{nx} \right) (1 - x) = b + \sigma X - \frac{c+f}{nx}. \quad (9)$$

Similarly, the expected utility of rejection can be extended from formula (6) to

$$U_j = x \left[B - \frac{d}{n(1-x)} \right] = x \left(b + \sigma X - \frac{d}{n(1-x)} \right). \quad (10)$$

For instance, in the diffusion process of Internet products, consumer costs for social products, such as Facebook, Twitter, Tumblr, and other platforms, and content products, such as YouTube, Pinterest, and Snapchat, are small. However, transportation and time costs are not considered. This is the case with cost overconfidence.

Scenario 3. Benefit and cost overconfidence. Overconfident individuals overestimate their ability to obtain benefits, exaggerate the size of the benefit, and believe that the level of return is higher than it really is. Overconfidence can be expressed as an overestimation of both benefits and costs. In this scenario, the benefit is $B_0 = (1+k)b + (1-k)\sigma X_0$ and the cost is $c_0 = c + f$. The benefit and cost overconfidence formula is substituted into formula (5), and the resulting formula (11) yields a cost and benefit overconfidence scenario.

The expected utility of adoption can be extended from formula (5) to

$$\begin{aligned} U_i &= x \left(B_0 - \frac{c_0}{nx} \right) + \left(B_0 - \frac{c_0}{nx} \right) (1-x) \\ &= [(1+k)b + (1-k)\sigma X_0] - \frac{c+f}{nx}. \end{aligned} \quad (11)$$

Similarly, the expected utility of rejection can be extended from formula (6) to

$$U_j = x \left[B_0 - \frac{d}{n(1-x)} \right] = x \left[(1+k)b + (1-k)\sigma X_0 - \frac{d}{n(1-x)} \right]. \quad (12)$$

For instance, with product diffusion, consumers buy Internet products, such as financial products and stock funds [47]. They are overconfident in the benefit generated by the purchase behavior and cost. This causes them to enter the market for purchase and investment blindly and they incur losses due to the double overconfidence of benefit and cost.

4. The Computational Model

The multiagent model can be used to model the group behavior of complex systems [39]. In the present multiagent model, an agent was used to represent a consumer in online social networks, and a multiagent model was built to simulate the behavior of consumers in the process of PDOSN.

4.1. The Game Learning Algorithm for Users in the Product Diffusion. In online social networks, individuals can only understand their own and their neighbors' behavior decisions, not those of everyone. Therefore, the decision of agents at time t in the model is affected by the decision of neighbors at the next time point. That is, consumers imitate another player with the highest income. In the model, individuals learn the

random process from the neighbor with the highest income, as shown in the following formula [48]:

$$P(i \rightarrow j) = \frac{1}{1 + e^{U_i - U_{jmax}/k}}. \quad (13)$$

The flow chart of individual learning behavior is shown in Figure 3, where U_i is the expected utility of an individual, while U_{jmax} is the largest expected utility of neighborhoods that have a straight linking with an individual at time t , and k is the information noise. When k is very large (very noisy), around impending ∞ , P nears 1/2, which is comparable to the result of coin tossing. On the contrary, when k is very small, the values of P are close to 1, indicating that the individual would imitate the neighborhood.

4.2. Validation of the Multiagent Simulation Model. An agent-based simulation model is difficult to verify, as it involves many parameters and assumptions [24]. Therefore, this study conducted internal verification, cross model effectiveness, and actual case verification to test the feasibility of the simulation model. Internal verification (Figure 4) was to check the influence of the basic parameters (b , c) on the product diffusion through the control variable method and judge whether it conformed to the ideal scenario.

Therefore, this study used two extreme cases to test the simulated system and the "extreme" parameter setting to provide the expected results. For instance, in Figure 4(a), if the adoption benefit was very large ($b = 1000$), the PDOSN adoption rate remained extremely high (e.g., close to 1) over time. This was consistent with the actual case. As per Figure 4(b), the adoption rate of PDOSN increased when the cost of adoption decreased ($c = 0, 100, \text{ and } 1000$), which was consistent with the expectation that the cost of adoption hindered PDOSN.

Cross-model validity and real-case validation (Figure 5) was conducted by comparing the present model, the Bass model, and real-world case data. To verify the simulation model's effectiveness further, the simulation results were compared with the actual information dissemination case data. Baidu Index (<http://index.baidu.com>), a search data analysis platform that provides various types of data and contains behavior data of Chinese Internet users, such as search quantity and time data of a certain term, was used. Based on the platform, with "clove doctor," which is a Chinese Internet health application, as the keyword, this study obtained the diffusion level of medical and health Internet products over a period of 30 days (1/20/2020–2/18/2020).

In Figure 5, the main ordinate axis is the Baidu search index, which represents Internet users' attention to keyword searches and continuous change. Taking the search volume and keywords of Internet users in Baidu as the statistical object, this paper scientifically analyzes and calculates the weighted search frequency of each keyword in Baidu network search. The secondary ordinate is the simulation data, which is the adoption rate of Internet products and the diffusion rate of products. Figure 4 shows that the fluctuation trend of the simulation results is consistent with the actual results, which indicates that the simulation model can reflect the real world.

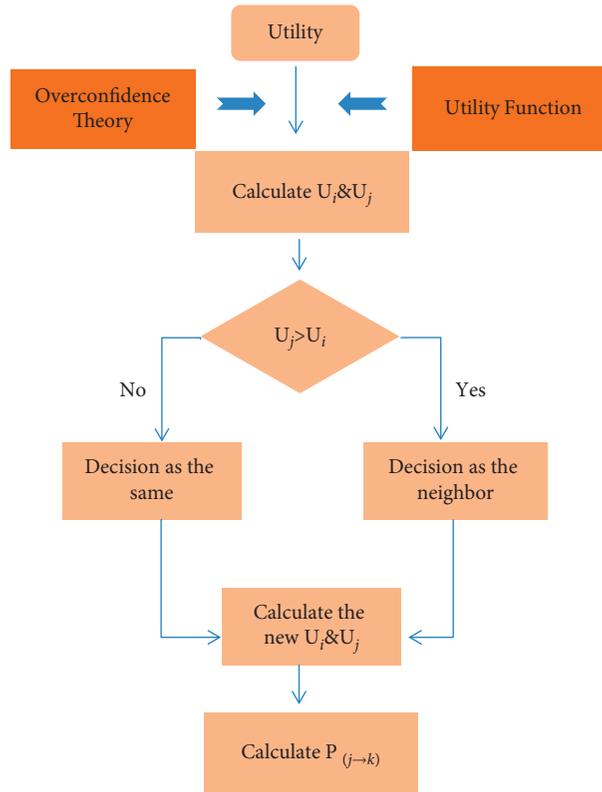


FIGURE 3: Flow chart of individual learning behavior.

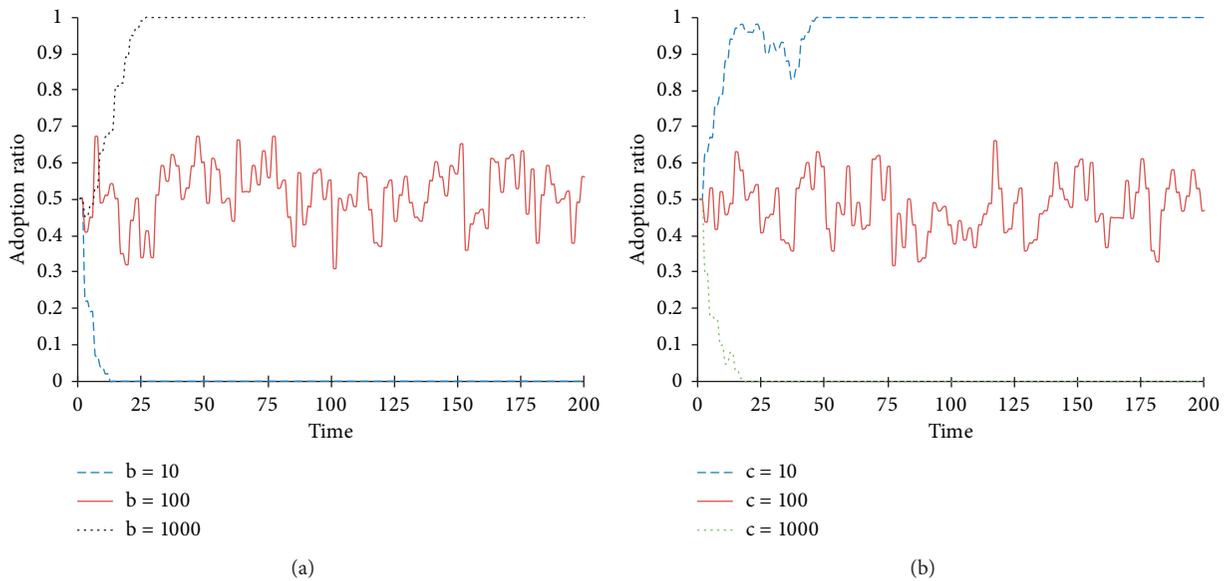


FIGURE 4: Internal validation indicating simulation model conformance with the conceptual model.

5. Computational-Experimental System and Virtual Experiment

This study designed a multiagent simulation model and conducted various numerical experiments in different scenarios to simulate the process of PDOSN. The simulation and experiments were implemented using AnyLogic 6.4.1.

5.1. Main Model and Person Class Design. The setup of the main model is shown in Figure 6; *people class* represented the user collection and the environment represented the environment where the user was located. The term *adopters* referred to adopters and *potentialAdopters* indicated rejecters. As shown in Figure 5, the numbers of adopters and rejections were stored in *dtA* and *dtP*, respectively. The

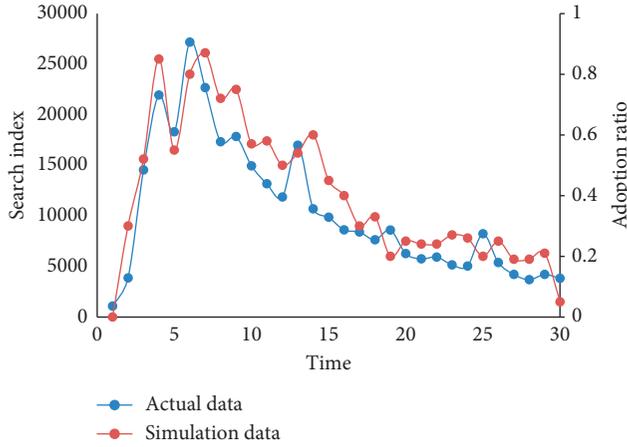


FIGURE 5: Comparison of simulated environment and real market results.

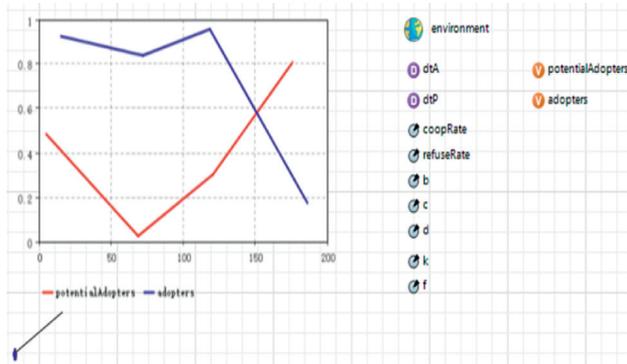


FIGURE 6: Main model.

adoption rate was represented by *coopRate*, and the rejection rate was represented by *refuseRate*.

As shown in Figure 7, in the setting of the person class, the decisions of consumers and neighbors were represented by U_i and U_j , respectively, the adoption rate and total number of neighbors were represented by x and $neiNum$, respectively, and the total number of neighbors rejected was represented by $neiRefuseNum$. In the process of consumer decision-making, $p12$ represented the state change from adoption to rejection, and $p21$ represented the state change from rejection to adoption. In the main model, a broken line diagram shows the results of model operation, in which the horizontal axis is the model operation cycle, a total of 200 cycles, the vertical axis is the adoption proportion, the blue line represents the change of adoption proportion, and the red line represents the change of rejection proportion. Most of the results in this study are represented similarly.

5.2. Influence of Product Utility Parameters on Product Diffusion

5.2.1. Influence of Adoption Benefit on Product Diffusion.

This study compared the results of no overconfidence, benefit and cost overconfidence, benefit overconfidence, and cost overconfidence models to reveal the influence of

adoption benefit (Figure 8). The results demonstrated that adoption ratio increased with the adoption benefit b , which was consistent with previous studies [48]. However, the results indicated that the effect of adoption benefit on adoption ratio was most significant in the benefit overconfidence model, indicating that businesses could use consumers' overconfidence in adoption benefit to promote product diffusion more effectively. Typical examples include TikTok and Uber, which increase adoption rates by issuing coupons, points, and prizes when launching their products.

5.2.2. Influence of Adoption Cost on Product Diffusion.

Adoption cost was set at 30, 35, and 40 for no overconfidence, benefit and cost overconfidence, benefit overconfidence, and cost overconfidence models (Figure 9). The experimental results demonstrated that the adoption proportion decreased with the increase of the adoption cost in all models, with the greatest decrease in the no overconfidence model. This indicated that the adoption cost had a negative effect on the adoption ratio in each model, particularly in no overconfidence. In practice, the time cost or money cost can be reduced through page simplification, personalized recommendations, product promotion, and group buying activities to stimulate consumers' adoption for product diffusion.

5.2.3. Influence of Betrayal Punishment on Product Diffusion.

The betrayal punishment was set as 15, 20, and 25. The results for the four models indicated that increasing betrayal penalty steered the consumer group to reach a stable state more quickly (Figure 10). This positive effect of betrayal punishment on adoption ratio could be explained by the fact that punishment can restrict people's behavior. Accordingly, penalty measures could be utilized by government departments and other institutions to regulate market behavior and strengthen consumers' adoption intention.

5.3. Influence of Overconfidence on Product Diffusion

5.3.1. Influence of Benefit Overconfidence on Product Diffusion.

A random network was set in the benefit overconfidence model and other parameters remain unchanged; that is, $b = 40$, $c = 40$, and $d = 15$. As shown in Figure 11, increasing the benefit overconfidence parameter k reduced the adoption ratio fluctuation of consumers in the market. Volatility fluctuation demonstrated that consumers' overconfidence affected the stability of product diffusion.

The dominant strategy changed from rejection to "tit for tat" to adoption, indicating the positive effect of overconfidence on the adoption ratio. This study further conducted a t -test to examine the significance of the effect (Table 2). A p value less than 0.05 indicated significant differences between the samples of each group, suggesting that benefit overconfidence significantly impacted product diffusion. Therefore, consumers' benefit overconfidence could be increased through marketing means to promote product diffusion.

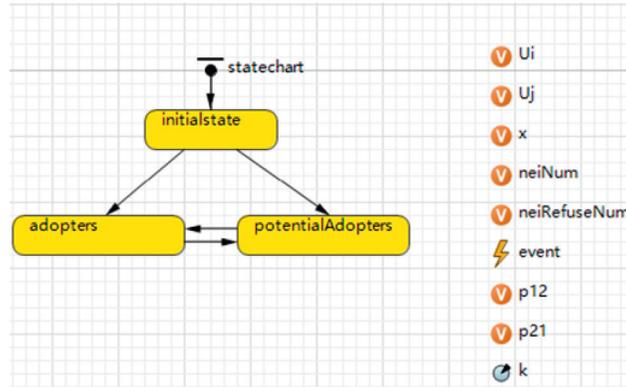


FIGURE 7: Person class description.

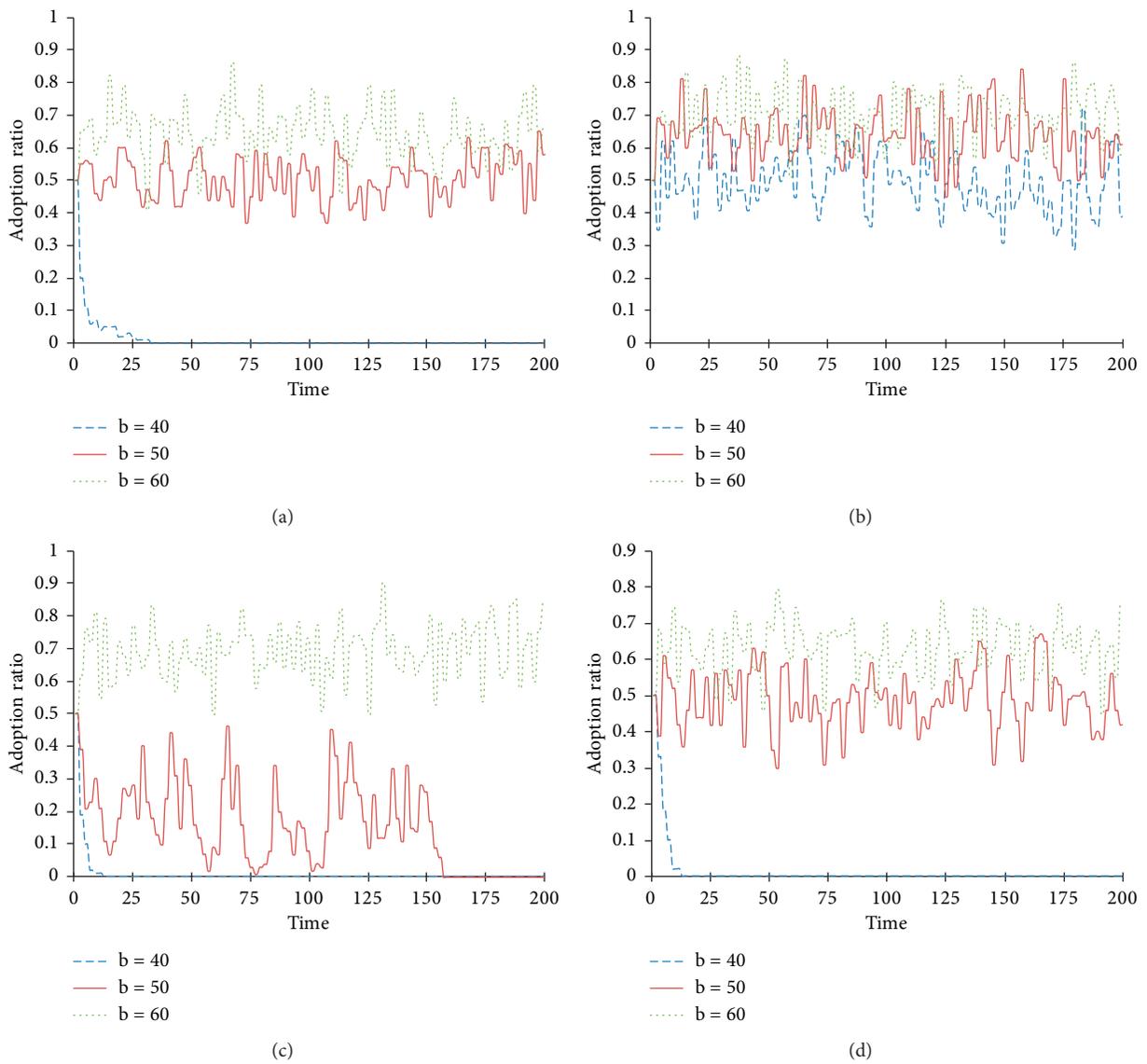


FIGURE 8: Impact of adoption benefit on product diffusion. (a) No overconfidence model. (b) Benefit and cost overconfidence model. (c) Benefit overconfidence model. (d) Cost overconfidence model.

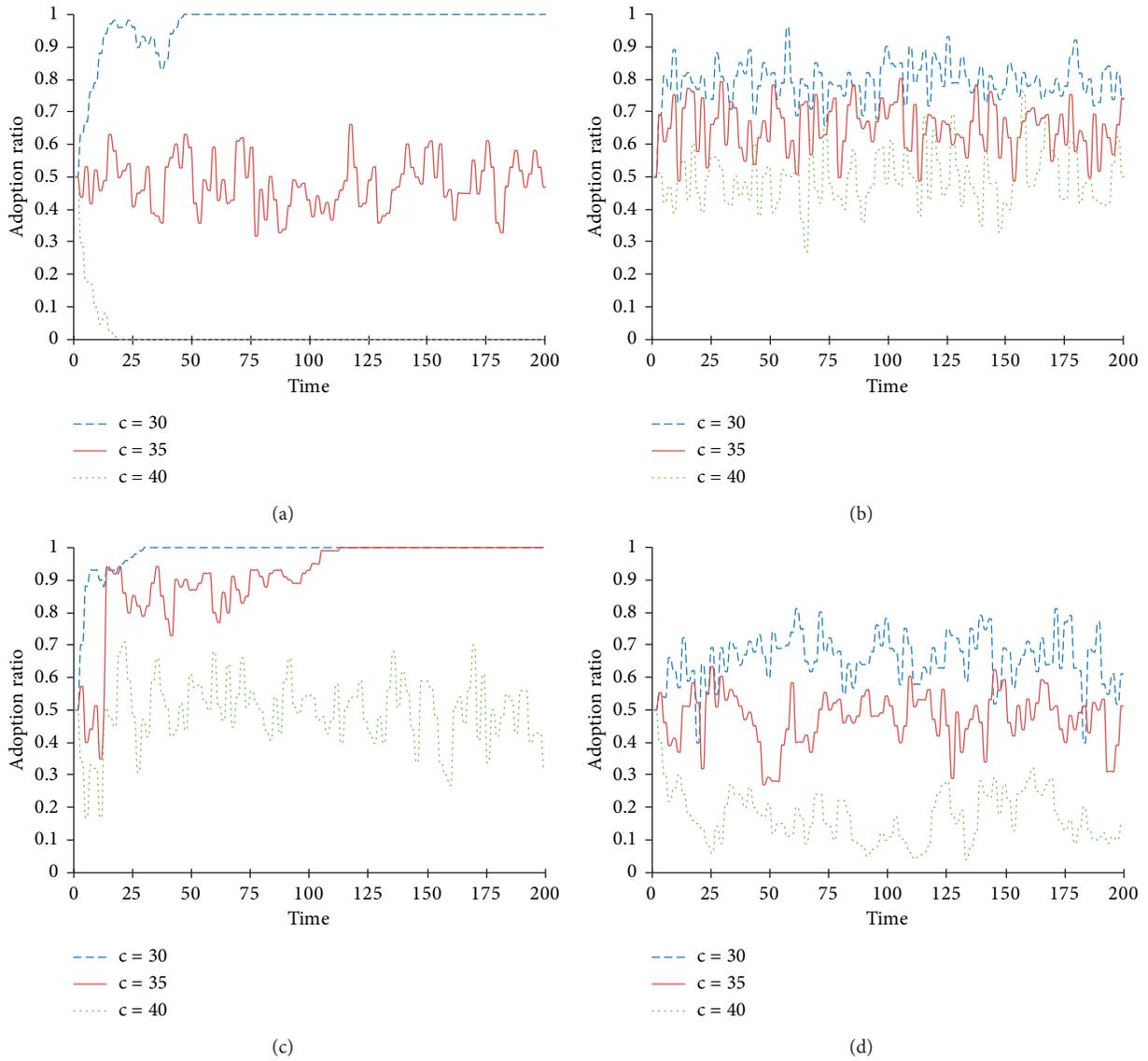


FIGURE 9: Impact of adoption cost on product diffusion. (a) No overconfidence model. (b) Benefit and cost overconfidence model. (c) Benefit overconfidence model. (d) Cost overconfidence model.

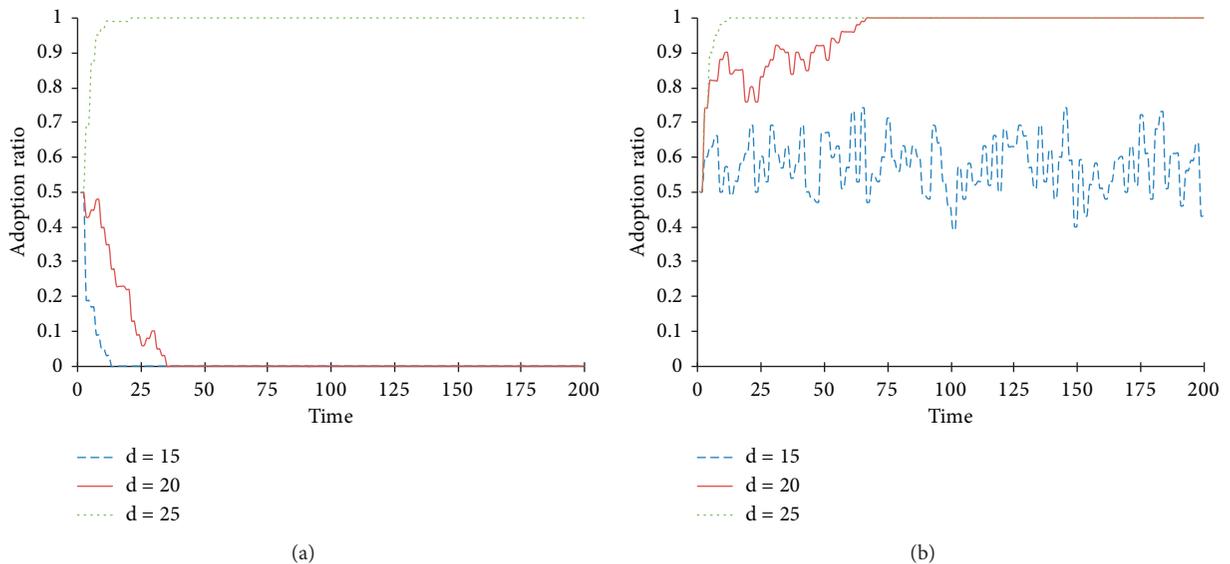


FIGURE 10: Continued.

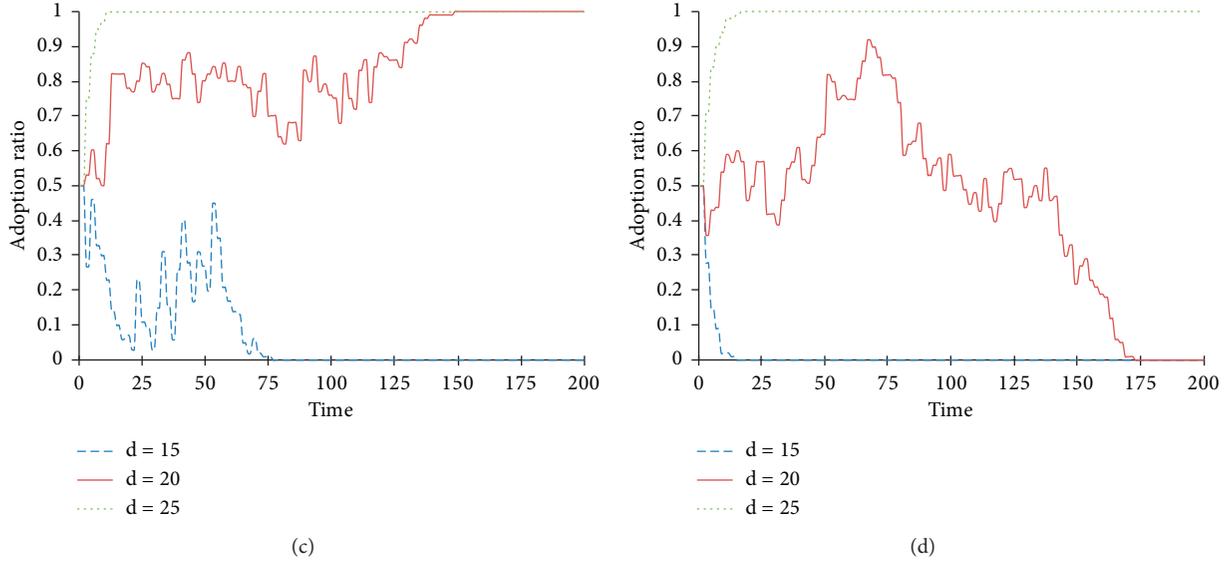


FIGURE 10: Influence of betrayal punishment on product diffusion. (a) No overconfidence model. (b) Benefit and cost overconfidence model. (c) Benefit overconfidence model. (d) Cost overconfidence model.

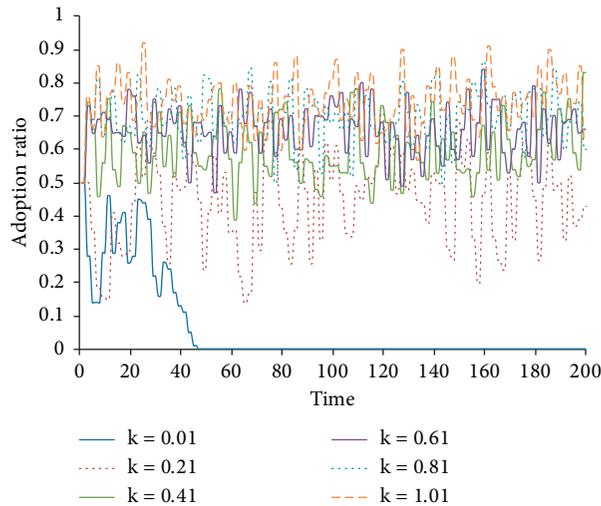


FIGURE 11: Influence of benefit overconfidence on product diffusion.

TABLE 2: The sample t -test results.

| | The first group | | The second group | | The third group | |
|---------------|-----------------|----------|------------------|----------|-----------------|----------|
| | $k=0.01$ | $k=0.21$ | $k=0.41$ | $k=0.61$ | $k=0.81$ | $k=1.01$ |
| Average | 0.0606 | 0.4447 | 0.5966 | 0.6583 | 0.6963 | 0.7412 |
| Variance | 0.016548 | 0.018883 | 0.008449 | 0.006036 | 0.006608 | 0.006555 |
| df | 396 | | 387 | | 398 | |
| t stat | -28.8578 | | -7.25005 | | -5.53443 | |
| $P(T \leq t)$ | $1E-99$ | | $1.14E-12$ | | $2.84E-08$ | |
| t -value | 1.648711 | | 1.648801 | | 1.648691 | |

5.3.2. Influence of Cost Overconfidence on Product Diffusion.

This study varied the overconfidence parameter f from 1 to 6 with the increment of 1 to observe the effect of cost overconfidence on product diffusion. The results (Figure 12) demonstrated that adoption ratio decreased with cost overconfidence, indicating a negative effect of

overconfidence on product diffusion. In addition, the results revealed that the volatility of adoption ratio became smaller with the increase of overconfidence, indicating that overconfidence could increase the stability of product diffusion.

This study conducted a t -test to examine the significance of the effect (Table 3). The p value was less than 0.05 in the

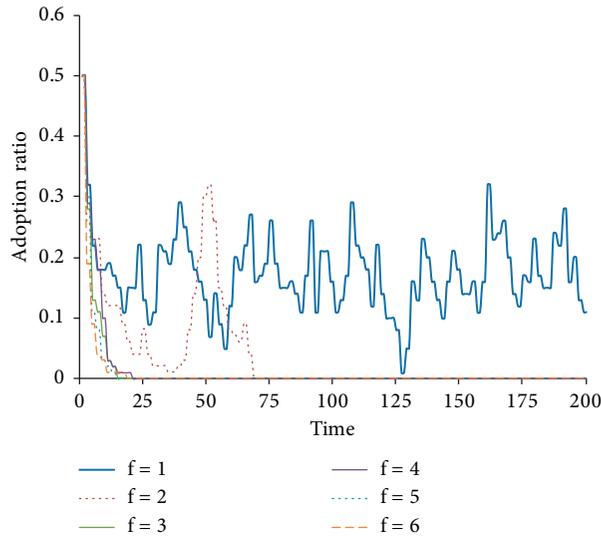


FIGURE 12: Influence of cost overconfidence on product diffusion behavior.

TABLE 3: The *t*-test results of samples.

| | The first group | | The second group | | The third group | |
|----------------------------------|-----------------|-------------|------------------|-------------|-----------------|-------------|
| | <i>f</i> =1 | <i>f</i> =2 | <i>f</i> =3 | <i>f</i> =4 | <i>f</i> =5 | <i>f</i> =6 |
| Average | 0.1745 | 0.041 | 0.0114 | 0.0138 | 0.0105 | 0.0089 |
| Variance | 0.004437 | 0.007304 | 0.003524 | 0.00414 | 0.003506 | 0.002906 |
| df | 376 | | 395 | | 395 | |
| <i>t</i> stat | 17.42424 | | -0.3877 | | 0.282565 | |
| <i>P</i> (<i>T</i> ≤ <i>t</i>) | 1.44E-50 | | 0.349222 | | 0.388829 | |
| <i>t</i> -value | 1.648916 | | 1.64872 | | 1.64872 | |

first group of samples (*f*=1, 2) but more than 0.05 in the second (*f*=3, 4) and third groups (*f*=5, 6), indicating that the effect of cost overconfidence was only significant at its low level.

5.3.3. Influence of Benefit and Cost Overconfidence on Product Diffusion. The results revealed that different overconfidence scenarios (Figure 13) had different converging speeds in reaching the equilibrium. Cost overconfidence accelerated the diffusion speed in reaching equilibrium.

In addition, cost overconfidence had a negative impact on consumer adoption, while benefit overconfidence had a positive effect. The effect of benefit and cost overconfidence was between the two. Therefore, improving consumers' benefit overconfidence and reducing cost overconfidence were conducive to product diffusion.

5.4. Influence of Different Network Structures under Overconfidence

5.4.1. Influence of Complex Network Structure Parameters

(1) Influence of Network Connectivity. The impact of network connectivity (*l*=1, 3, 5) on product diffusion was examined. The results (Figure 14) indicated that, with an

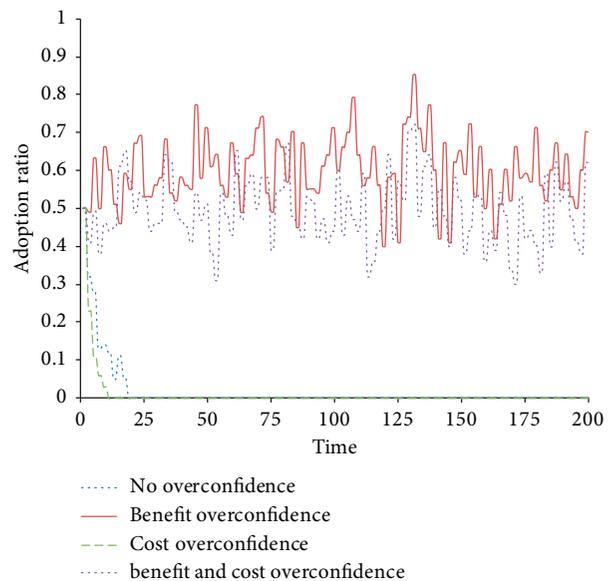


FIGURE 13: Effect of different scenario models on product diffusion.

increase in network connectivity, the adoption ratio increased and subsequently decreased. In other words, appropriate network connectivity effectively promoted product diffusion. Therefore, when conducting product

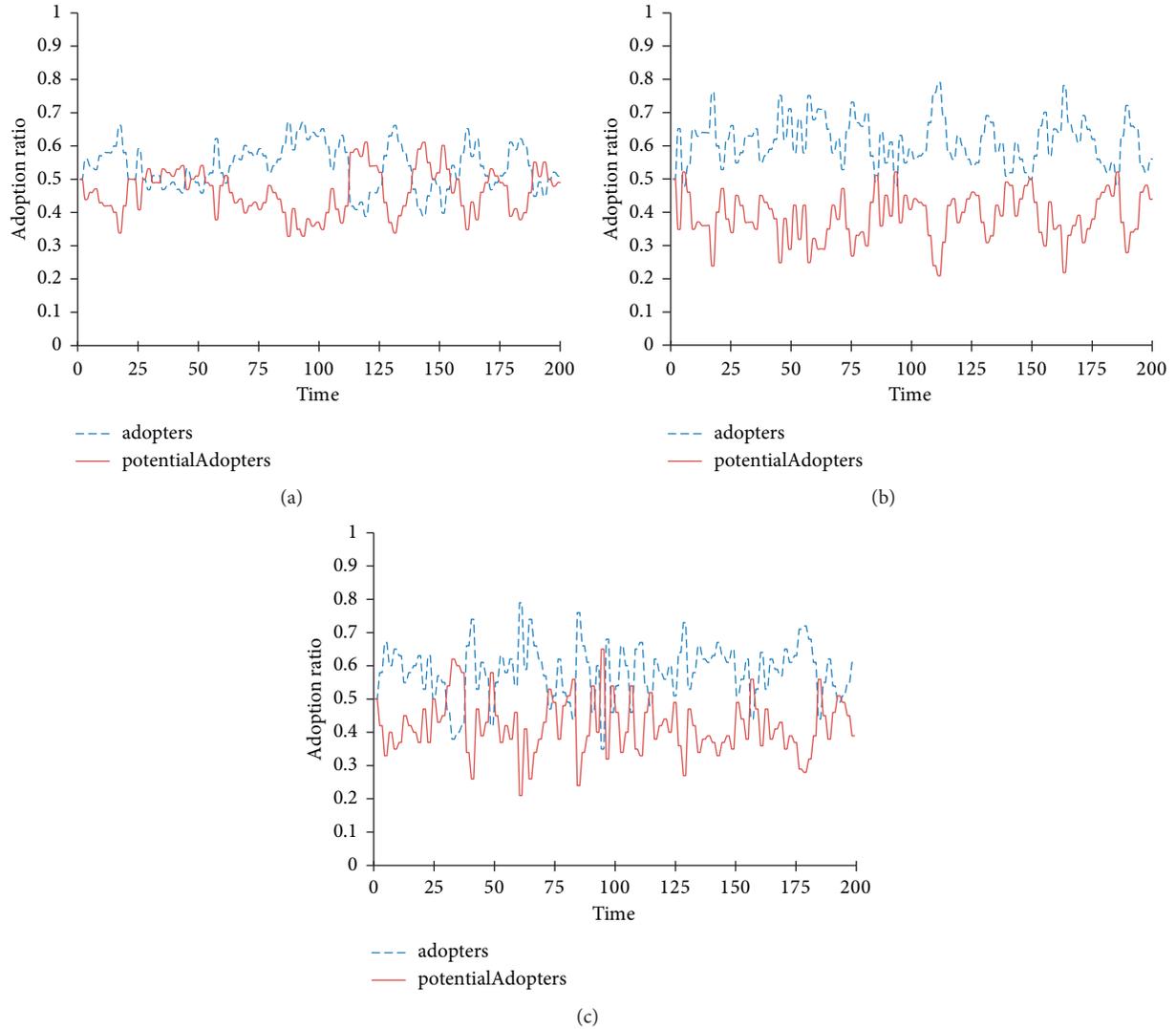


FIGURE 14: Effect of l on product diffusion. (a) $l=1$, (b) $l=3$, and (c) $l=5$.

diffusion, enterprises could leverage the network connectivity between online users to promote product diffusion.

(2) *Influence of Large Nodes.* The impact of large nodes ($m=1, 2, 3$) on product diffusion was examined. As shown in Figure 15, the adoption ratio gradually increased with increase in m , indicating that larger nodes were associated with higher product diffusion level. This is likely because large nodes, such as online celebrity, opinion leader, and Big V, increased social interactions on social media, thus promoting product diffusion. In the emerging “live streaming economy,” businesses could leverage influencer marketing with KOL (Key Opinion Leader) and KOC (Key Opinion Consumer). In addition, the effect of these influencers could be enhanced through emerging IT technologies, such as 5G and VR.

(3) *Influence of Reconnection Probability.* The effect of reconnection probability ($p=0.01, 0.55, 0.95$) on product

diffusion was examined. As shown in Figure 16, the results indicated that adoption ratio increased, while its volatility decreased with the increase of reconnection probability, indicating that reconnection probability promoted product diffusion and increased its stability. In practice, enterprises could launch various activities, such as sharing discount and group purchase discount, to stimulate more contacts among consumers to promote product diffusion. This issue could be exemplified by Facebook’s “Meet New Friends” function, which allows Facebook users to connect with strangers.

5.4.2. Influence of Overconfidence on Product Diffusion in Different Networks

(1) *Influence of the Benefit Overconfidence on Product Diffusion under Different Networks.* The impact of benefit overconfidence (k) on adoption ratio in different network structures was examined (Figure 17). In all three networks,

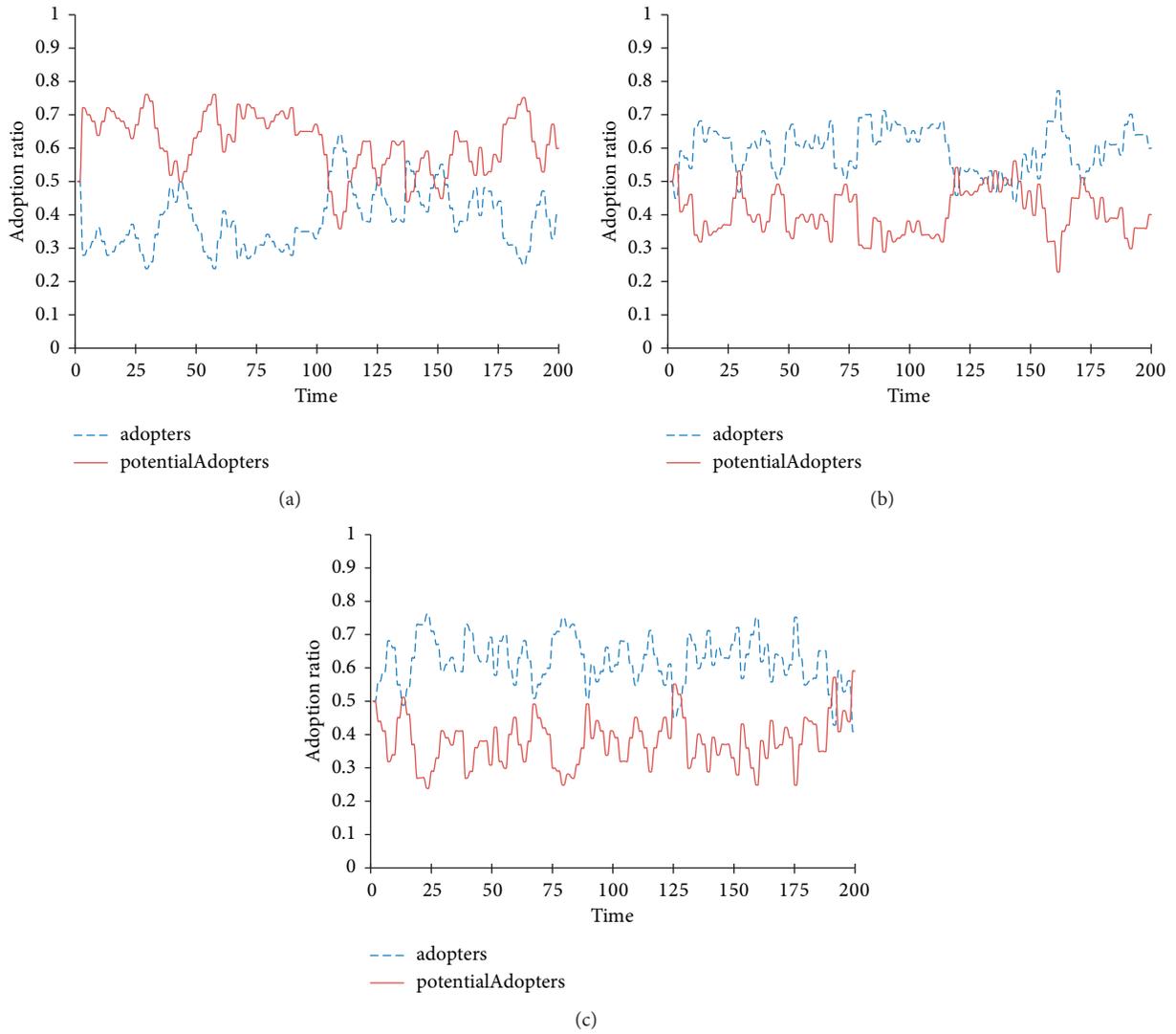


FIGURE 15: Effect of m on product diffusion. (a) $m = 1$, (b) $m = 2$, and (c) $m = 3$.

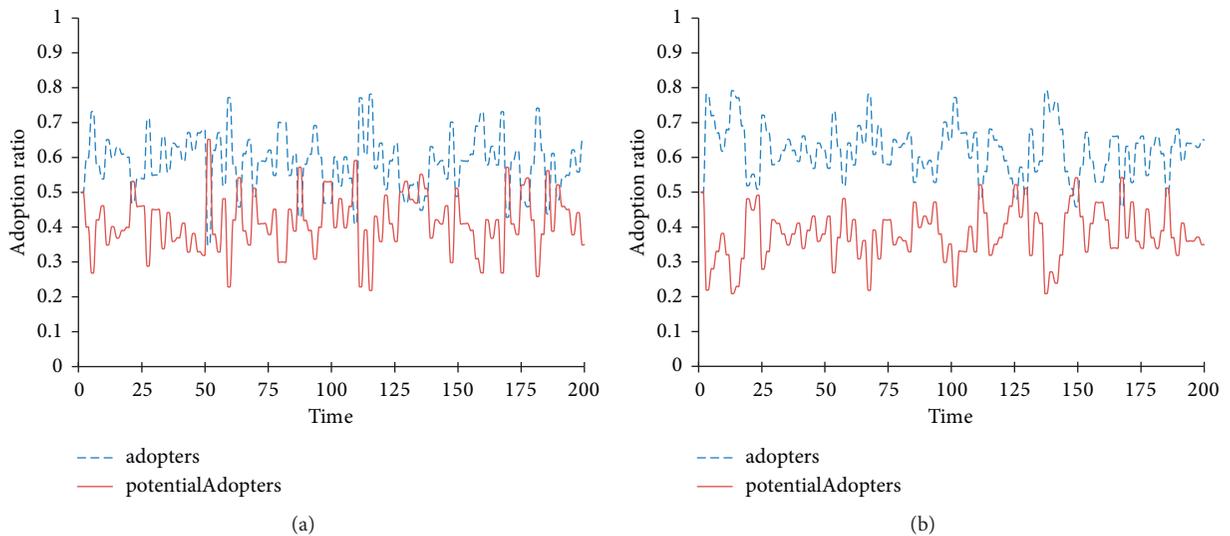


FIGURE 16: Continued.

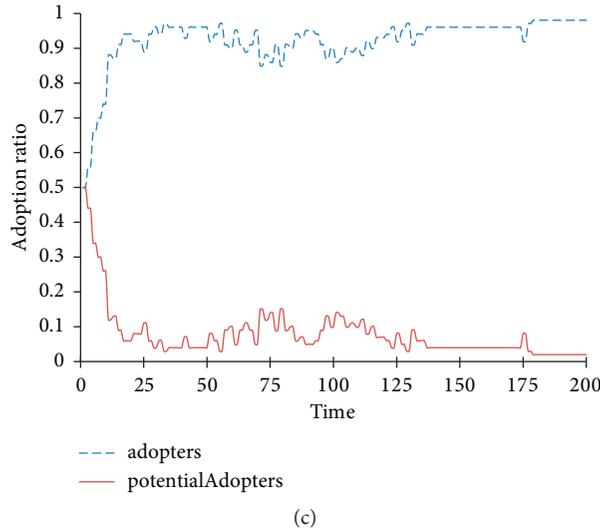


FIGURE 16: Effect of p on product diffusion. (a) $p = 0.01$, (b) $p = 0.55$, and (c) $p = 0.95$.

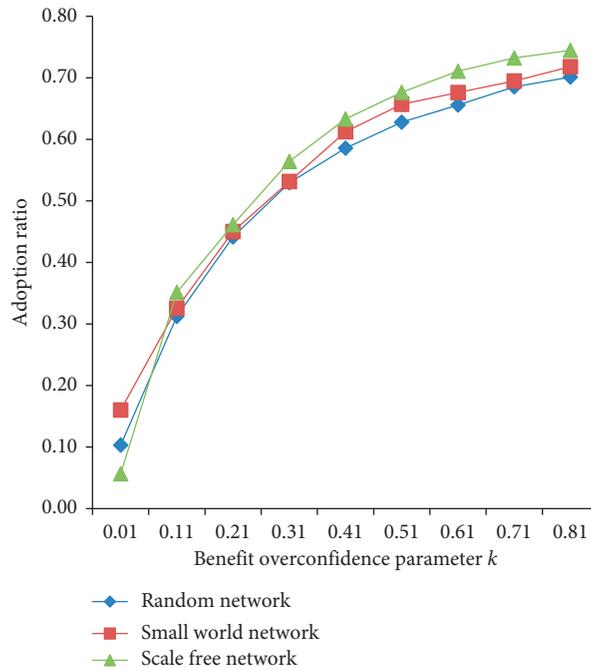


FIGURE 17: Effect of benefit overconfidence on product diffusion under different networks.

the adoption rate increased with benefit overconfidence, indicating that benefit overconfidence positively affected product diffusion. In addition, in order to check the significance of the effect, this study conducted a pairwise test (t -test) on the sample data of different network structures. As shown in Table 4, the p values of the three groups of samples were less than 0.05, indicating significant differences between the samples of each group. Therefore, the positive effect of benefit overconfidence was significant in different network structures.

The horizontal axis is the overconfidence parameter, the vertical axis is the adoption ratio, the blue line represents the PDOSN in the random network, the red line represents the

PDOSN in the small-world network, and the green line represents the PDOSN in the scale-free network.

(2) *Influence of the Cost Overconfidence on Product Diffusion under Different Networks.* The impact of cost overconfidence (f) on adoption ratio in different network structures was examined. As shown in Figure 18, in three network structures, the adoption rate decreased with increase in cost overconfidence, indicating the negative effect of cost overconfidence on adoption rate. To verify the significance of the effect further, this study conducted a pairwise test (t -test) on the sample data. The results (Table 5) demonstrated that p values of the three groups of samples were less than 0.05,

TABLE 4: The t -test results of samples.

| | Random network | | Small-world network | | Scale-free network | |
|--------------------|----------------|------------|---------------------|------------|--------------------|------------|
| | $k = 0.01$ | $k = 0.51$ | $k = 0.01$ | $k = 0.51$ | $k = 0.01$ | $k = 0.51$ |
| Average | 0.1032 | 0.628 | 0.16 | 0.657 | 0.0566 | 0.6765 |
| Variance | 0.021425 | 0.005799 | 0.029403 | 0.006015 | 0.012316 | 0.00505 |
| df | 299 | | 277 | | 339 | |
| t stat | -44.9815 | | -37.3473 | | -66.5252 | |
| p ($T \leq t$) | $2E - 135$ | | $2E - 110$ | | $6.2E - 197$ | |
| t -value | 1.649966 | | 1.650373 | | 1.649361 | |

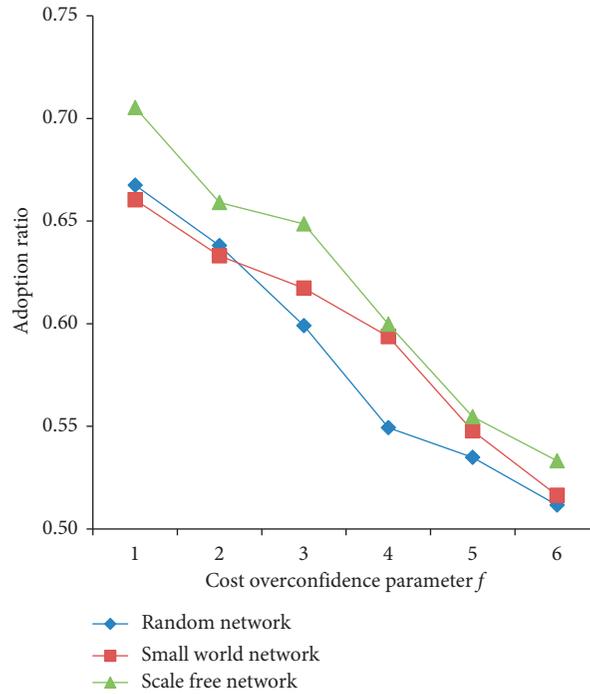


FIGURE 18: Effect of cost overconfidence on product diffusion under different networks.

TABLE 5: The t -test results of samples.

| | Random network | | Small-world network | | Scale -free network | |
|--------------------|-----------------|-------------|---------------------|-------------|---------------------|-------------|
| | $f = 1$ | $f = 3$ | $f = 1$ | $f = 3$ | $f = 1$ | $f = 3$ |
| Average | 0.6675 | 0.599 | 0.6603 | 0.6173 | 0.7053 | 0.6486 |
| Variance | 0.006034925 | 0.009194975 | 0.006565739 | 0.005485136 | 0.006841116 | 0.007059337 |
| df | 382 | | 395 | | 398 | |
| t stat | 7.849772144 | | 5.53954601 | | 6.801169389 | |
| P ($T \leq t$) | $2.12164E - 14$ | | $2.77316E - 08$ | | $1.90881E - 11$ | |
| t -value | 1.648852302 | | 1.648720389 | | 1.648691174 | |

indicating significant differences among the samples of each group. Therefore, cost overconfidence had a significant negative impact on product diffusion regardless of network structures.

6. Computational Complexity to Determine the Optimal Solution

The proposed framework can be used to determine the optimal solution to deal with the product diffusion problem in different scenarios. For instance, we set $b = 40$, $c = 40$, and $d = 15$, as well as the initial adoption ratio x to

vary from 0% to 100% (in steps of 10%). The simulation results are shown in Figure 19. With the above parameters and continuous increase of the initial adoption proportion p , the change trend of the adopter proportion was found to increase and subsequently decrease, and the curve of the adopter proportion showed an obvious peak. Under these parameter settings, the optimal initial adoption ratio $x^* = 50\%$. Similarly, the optimal solution to deal with the product diffusion problem in other scenarios can be determined.

We further provided the computational complexity and its theoretical analysis in order to determine the optimal

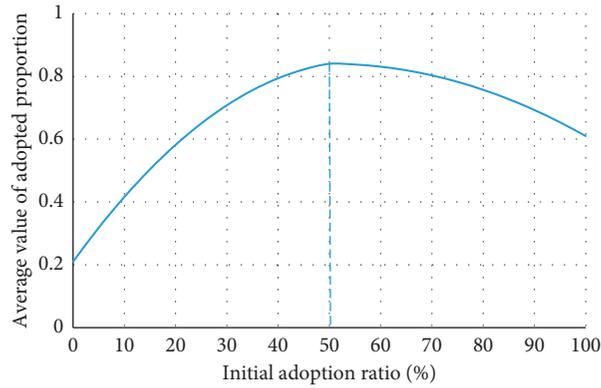


FIGURE 19: Optimal solution analysis.

solution to deal with the product diffusion problem. To compare the computational complexity of the models in different networks with the traditional Bass model, this study mainly selected two important indicators of space occupation and running speed for research and comparison. As shown in Table 6, the space occupations of random network, small-world network, and scale-free network were 44 kb, 48 kb, and 43.1 kb, respectively, smaller than that of the Bass model (1.3 M). The running speeds of the three networks were also higher than that of the Bass model. Obviously, the complexity of this PDOSN model is significantly less than that of the traditional Bass model, indicating that it has more advantages. Therefore, the operating efficiency of this proposed framework was revealed to be better than the traditional one.

7. Discussions, Implications, and Future Research

7.1. Conclusions. In a bid to resonate with the recent call for introducing behavioral theory into the research on product diffusion and robustly and rigorously discover and analyze the effect of overconfidence on PDOSN, a sequential simulation approach subsuming the overconfidence theory, evolutionary game, and multiagent simulation model was proposed in this study. This study combined overconfidence and an evolutionary game to conduct a multiagent simulation on the impact of overconfidence on PDOSN. An evolutionary game model was built and a learning algorithm that considered overconfidence was designed to describe the interactions between consumers. Three overconfidence scenarios were identified: benefit, cost, and benefit and cost overconfidence. Finally, a multiagent simulation model in different overconfidence scenarios was realized and validated. The conclusions are as follows:

- (1) Adoption benefits and betrayal penalties have a positive effect on the results in all the models, while adoption costs were found to have an opposite effect.
- (2) When benefit and cost overconfidence occur simultaneously, benefit overconfidence offsets the negative effect of cost overconfidence.

- (3) Moderate connectivity, a large number of core nodes, and high reconnection probability fully promote product diffusion.
- (4) In different network structures, benefit overconfidence and cost overconfidence significantly impact the results.

7.2. Contributions to Theory. The behavioral and psychological perspective (overconfidence effect) provided an unprecedented new perspective for the study of product diffusion. This study was the first to add overconfidence to the research on product diffusion. This study examined product diffusion in three overconfidence scenarios, which may help broaden the research field of product diffusion. This study provided a further theoretical foundation for the integration of other behavior theories into the new product diffusion model.

In addition, this study contributed to the theory of product diffusion from the macrolevel and microlevel. This study integrated multiagent simulation and evolutionary game to examine product diffusion caused by consumer interaction. It increased the research on product diffusion at the microlevel and compensated for the unity of macro-research on product diffusion.

Furthermore, this study revealed a variety of modeling methods of complex group behavior generated from individual interaction. Overconfidence theory was used to identify potential individual level mechanisms and served as the microbasis of the multiagent simulation model. This multiagent method provided a basic framework for the combination of simulation method and behavior as well as psychology theory to test dynamic group behavior.

7.3. Practical Implications. These results can increase consumers' benefit overconfidence, reduce their cost overconfidence, and help build the brand for new products. Companies could introduce consumers to product characteristics and benefits in detail. This would increase overconfidence in consumer decision-making. In addition, companies could educate consumers on products through product manuals and provide on-site repair and installation services, which would reduce consumers' overconfidence in

TABLE 6: Computational complexity comparison.

| | Model | Space occupation | Running speed (sec) |
|------------------------------------|---------------------|------------------|---------------------|
| PDOSN models in different networks | Random network | 44 kb | 1.9 |
| | Small-world Network | 48 kb | 1.9 |
| | Scale-free network | 43.1 kb | 1.9 |
| Traditional model | Bass model | 1.3 M | 2.3 |

decision-making costs and effectively promote new product diffusion. Companies could increase their advertising efforts or promote word-of-mouth publicity with the help of celebrities to create brand effects for new products. When consumers are overconfident about the benefits of purchasing decisions, they desire to buy, increasing the possibility of final transactions.

The results suggested prioritizing the connections between individuals who renew the product diffusion market. The results indicated that only moderate connectivity fully promoted product diffusion and maximized the diffusion effect of new products. Low connectivity promoted the group decision-making and vice versa greater fluctuations. The greater the number of core nodes was, the greater the probability of reconnection was, and the easier it was for new products to spread. Therefore, when companies diffuse new products, they must conduct macrocontrol on the market. Different regional markets require different strategies to promote product diffusion. For instance, in a market with many loyal users, existing users could invite new users and be rewarded. For new regional markets, controlling the degree of contact between the spread of new products and local celebrities is necessary. Alternatively, organizations could send invitations to promote products. Celebrities could establish relationships with consumers, thereby controlling the stability and efficiency of the spread of new products.

In different network structures, the product diffusion strategies formulated by the enterprises are different. This study demonstrated that, in different network structures, benefit and cost overconfidence parameters had a significant impact on consumer decision-making behavior. Therefore, whether in small-world, scale-free, or random networks, companies should focus on the impact of benefit and cost overconfidence on consumer decision-making. However, relevant strategies need to consider consumers' benefit overconfidence and cost overconfidence to ensure that the diffusion of new products achieves the best results.

7.4. Limitations and Future Research. As overconfidence is a relatively new psychological theory, it merits further examination. This study provided a reference for the combination of psychological theory and computer simulation, helped deepen consumers' understanding of new product diffusion, and provided support for new product marketing decisions. However, this study has some limitations. Consumer decision-making is affected by personal preferences, and embedding preference factors into evolutionary game simulation model requires further investigation. In addition, future studies should test the rationality and robustness of

parameter settings in the simulation system, particularly by combining multiple actual scenarios.

Data Availability

Data are available from the authors upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgments

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