

## Article

# Better Earlier than Longer: First-Mover Advantage in Social Commerce Product Information Competition

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**Abstract:** Social commerce (SC) is a rapidly emerging branch of e-commerce. Effective information spread is the critical element in increasing the sales volume in this industry. However, few studies have explored the underlying mechanism and corresponding winning strategies from the perspective of information spread. This research fills the gap by using a simulation method. Combined with the Engel–Kollat–Blackwell (EKB) theory, we improved the Susceptible–Infected–Recovered (SIR) epidemic dissemination dynamic model to simulate the competitive information spread process on social commerce networks. Datasets collected from two of the biggest SC websites in China, Sina Weibo and Taobao, verified the accuracy of the proposed model. Parameter sensitivity analysis results indicated that releasing the product message earlier is more effective than increasing the spread duration for improving the performance of information diffusion so as to boost the sales volume. It was also shown that high discard probability destroys the sales volume caused by high purchase probability. Low discard probability can lead to a good sales volume eventually, even when the purchase probability is low. The results provide evidence for the First-Mover Advantage theory from the information spreading point of view. We come up with practical strategies for SC marketers based on the simulation results.

**Keywords:** social commerce; SC network; competitive information spread; sales volume; First-Mover Advantage

## 1. Introduction

Social commerce (SC) is an emerging form of e-commerce in which shopping and purchase transactions are facilitated via the social media environment [1]. The SC industry is expected to generate more than three billion US dollars in revenue worldwide in 2019 [2,3]. Effective product information spread is a crucial element for the success of SC. It is therefore critical that marketers understand the information spread process in SC networks [4].

The rate of information diffusion attenuates over time. In addition, the availability of new information in the network decreases the rate of diffusion of previously released information. The finiteness of consumers' attention limits their concentration on more than one piece of information at the same time [4], which implies competition for consumers' attention amongst product information sources [5]. Research shows that SC sellers who benefit the most are those who make the best use of the SC network to gain access to the network users [6]. Most firms have limited funds for marketing [7], especially in the SC area, where most sellers are individuals [6]. Li and Huang (2014) showed that social media can help small and medium businesses, as well as start-ups with limited marketing budgets, to improve profits [8].

Given the fierce competition between information providers (product marketers) and the often limited marketing budget, marketers need to develop strategies to optimize the effectiveness of information spread. The literature shows that effective information diffusion has a positive influence

on SC consumers' purchase intentions [9], due to enhancing consumers' feelings of trust [10,11] in cultural [12] and fashion [13], as well as agricultural [14–16], products. While some work has empirically examined what drives continued SC information spread behavior [17], there has been little study of social commerce competition [18,19]. Much remains to be understood about how to achieve effective product information diffusion. This work focuses on product information competition. We seek to understand what type of strategy is more effective for SC marketers for increasing the effectiveness of SC product information spread. We focus specifically on two strategies: early information release and extended duration information spread.

Prior studies have indicated that the First-Mover Advantage (FMA) [20] exists among traditional market and e-commerce platforms [21]. Our work shows that FMA also exists in the SC context. The sustainability of social commerce has caused widespread attention from both theoretical and practical perspectives [22]. We detect practical strategies to help marketers gain sustainable advantages among the fierce competition of the SC market. We introduce a mathematical method to simulate the information spread process in social commerce. Previously, researchers have adopted theories of epidemic diffusion to model information spread in social networks [23,24]. Because SC information spread occurs within an online social network made up of marketers and consumers [25,26] we adopt the same approach.

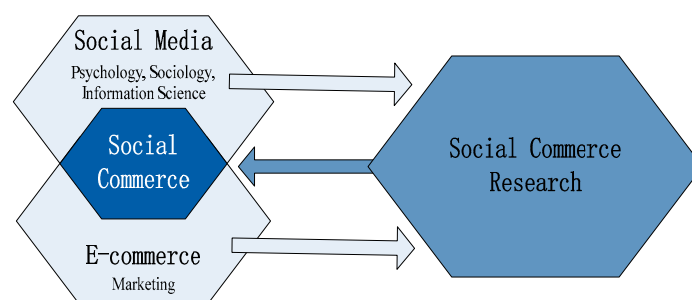
In a SC network, marketers release product information, consumers share purchase experiences, and both of these processes influence the sales volume [27,28]. We develop a model that reflects these features of information spread and consumer behaviors in SC by combining the Engel–Kollat–Blackwell (EKB) model, which is a classic theory in consumer behavior research, with the well-known epidemiological Susceptible–Infected–Recovered (SIR) model of disease diffusion. For practical reasons, the parameters in our model directly map onto the product features (purchase rate and discard rate), information release timing, and diffusion duration in the SC market. These features will enable marketers to utilize our model to directly develop effective strategies. Collecting real-world data SC websites also adds practical advantages to our methodology.

The objectives of this work are (1) to explore the mechanism of competitive information spread on the SC network, and (2) to identify practical strategies for SC marketers. We start by describing the utility of applying an information diffusion analysis to the study of SC. We then develop a theoretical model to simulate information diffusion completion of competitive products in SC networks. We use data from two Chinese SC websites, Sina Weibo and Taobo, to validate our model. The sensitivity analysis results correspond with the well-known FMA marketing theory. We close with a discussion of theoretical implications and practical applications.

## 2. Theoretical Background and Hypotheses

### 2.1. Social Commerce

SC is a crucial evolution of e-commerce [29]. The SC domain covers four dimensions: e-commerce, social media, Web 2.0, and social activities [5]. Social commerce is an interdisciplinary field concerning network science, information technologies, consumer behavior theories, and marketing strategies [30]. The SC phenomenon is complex because it involves knowledge ranging from psychology theory, algorithm design, and sociology models, to marketing strategies. As Figure 1 illustrates, researchers from multiple disciplines—psychology [10], sociology [29], information science [4,18], and marketing in business—have contributed to the exploration of SC; the improvement of SC research, in turn, has provided theoretical explanations and practical strategies to aid success in the industry.



**Figure 1.** The interdisciplinary structure of social commerce.

Fazeli et al. (2017) used the Nash Equilibrium method to study the marketing strategy choices of two SC marketers in competitive relationships: (1) improving product quality, and (2) using concessions to attract consumers with a limited budget [31]. Social activity through Web 2.0 technology is a crucial point of social e-commerce, and its carrier is information diffusion [9]. Hajli and Sims (2015) [29] used empirical survey findings to argue that social information support has a positive effect on consumption intention. Data from Facebook revealed the influence of trust on purchase intention in SC, because it increases users' information seeking behavior [10]. Nevertheless, its internal mechanism—from the perspective of information diffusion—has not yet been determined. Research has depicted SC's underlying information diffusion mechanism [32]; however, it did not take the information competition into consideration, which is, in fact, a crucial phenomenon regarding the SC industry [5,22].

## 2.2. Information Diffusion in Social Commerce

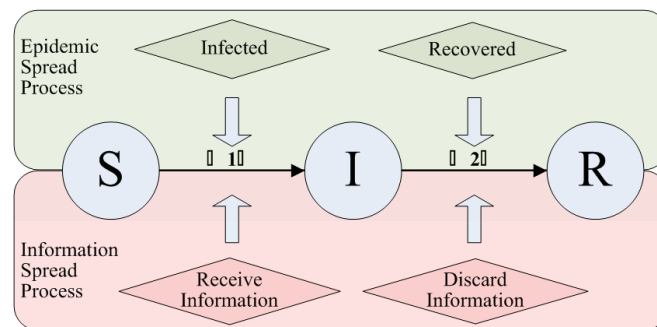
Traditional e-commerce has witnessed the importance of information spread, a critical element in improving sales, specifically in word of mouth and viral marketing strategies. As a branch of e-commerce, SC also relies heavily on the effectiveness of information diffusion to win out among fierce marketing competition. The SC framework design must consider the information dimension [33]. SC has evolved quickly in practice; nevertheless, researchers have not paid enough attention to SC from the perspective of the information science domain [34]. Existing research on information diffusion has two major branches [4], of which the first branch contains the Linear Threshold model [35], and the Independent Cascades model [36], which focus on the static social network structure underlying the diffusion process. This series of studies is limited to the challenges in depicting an entire social network structure and neighborhood details during spreading [4]. This method emphasizes the static network structure rather than the dynamic process which leads to the information competition outcome.

To overcome the limitation mentioned above, we employ the second branch—the non-graph-based approaches—which focus on the temporal dynamics of information diffusion; this overcomes the limitation of an unclear network structure and concentrates more on the change in the numbers of nodes in different information spread stages, and the outcome of diffusion. The Susceptible–Infected–Susceptible (SIS) and Susceptible–Infected–Recovered (SIR) epidemic models are two seminal representatives of this branch [37]. Epidemiology is widely applied in single [23,24] as well as multiple [4] information diffusion due to the similarity between epidemic spread and information diffusion processes. There are three states of nodes in an epidemic network—susceptible, infected, and recovered—which map to respective user states regarding the information spreading stages. A detailed introduction to epidemic models is provided in Section 2.3.

## 2.3. SIR Epidemic Model for Information Diffusion

The essential difference between the SIR and SIS models is whether the infected nodes can become immune to the epidemic after recovery. In the scenario of social media, due to limited attention [4] and interest loss, users tend to become “immune” to the information. In this case, SIR is more commonly used to simulate social network information diffusion [23,24].

As depicted in Figure 2, in the original SIR epidemic model, the dynamic process of epidemic spread maps onto that of information diffusion. In process (1), susceptible nodes become infected nodes through being informed by the message; this process could be seen as epidemic infection. For process (2), infected nodes become recovered nodes due to discarding the message, which could map to the process of recovering from the epidemic.



**Figure 2.** Original Susceptible-Infected-Recovered (SIR) epidemic model.

Due to the complexity of the social media network structure, there are more than three node states. Researchers modified the original model accordingly: authors focused on information diffusion under the influences of online community modularity and users' interest changing behaviors [24]. Authors introduced the "exposed" state to optimize the SIR model to simulate the information spread in Sina Weibo (a popular social media platform in China) [32].

#### 2.4. First-Mover (Dis) Advantage

The notion of FMA started from observations that first movers' performances tend to be better than those of later entrants [38]. The most common definition states that the FMA is the degree to which a pioneering firm can earn above-average profits [20]. FMA happens because early entrants may be able to pre-empt resources of various types. For this work, we apply the FMA theory in the SC environment; that is, the pioneer-released product information can occupy online users' attention resource first, so it attains better information spread effectiveness than a later product. Based on this logic, we had the following hypothesis:

**Hypothesis 1.** *Early information break-out timing has a positive influence on the information spread effectiveness.*

However, there is also evidence showing that FMA, per se, is not capable of sustaining a competitive advantage, but is part of a bigger picture. Data also show how an early entrant can be overcome by a late entrant; for example, a bank, offering the studied product amongst a variety of other services [39]. In this case, the superior product portfolio of the late entrant allows it to overcome the FMA of the early entrant. Following this stream of work, we suspected that the following hypothesis would be true:

**Hypothesis 2.** *Long information duration has a positive influence on the information spread effectiveness.*

Several studies have shown that pioneers have a long-lived market share advantage. As for the question of which factor has a stronger effect, we had the following hypothesis:

**Hypothesis 3.** *Early timing is more effective than a long duration in increasing the information spread effectiveness.*

### 3. Methodology and Data

An outline of our methodology is depicted in Figure 3. The core of the research model is the SIR model, which is a widely used epidemiology model for studying information spread in social networks (as mentioned in Section 2.3). We firstly proposed the research model by combining the SIR model with the EKB theory of consumer behavior to improve the original SIR model, making it more accurate in describing the phenomenon of the SC scenario. We then verified the proposed model with real data collected from the most popular Chinese SC websites. After that, we conducted a parameter sensitivity analysis of the proposed model to explore the key elements required to achieve success in SC business competition. We came up with strategies for SC marketers based on the results of the experiments.

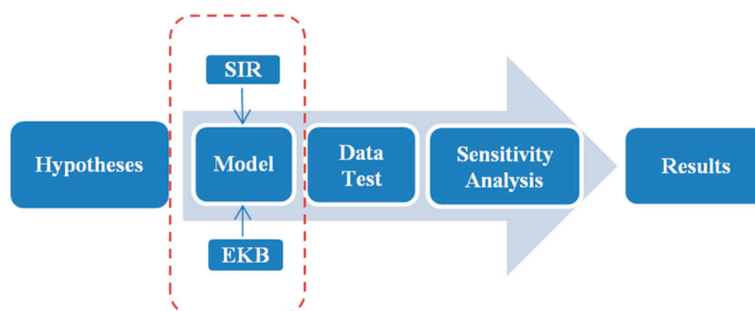


Figure 3. The methodology rationale.

#### 3.1. An Improved SIR Model for Competitive Information Diffusion

The original SIR model has three nodes states. To precisely simulate the information spread among social network users we adapted it by combining it with the EKB model, which is a classic one of consumer behavior theory, also commonly used in SC research [40]. As Figure 4 shows, according to the four stages of consumption in the EKB model, we classified all nodes into four categories in order to describe the mechanisms of social commerce competition, as follows:

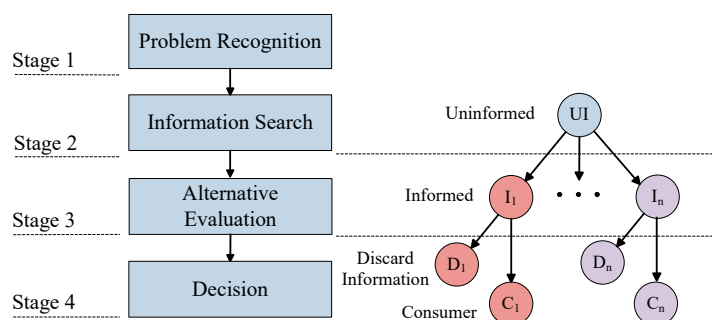


Figure 4. Adapted Engel–Kollat–Blackwell (EKB) model of consumer behaviors in social commerce. Adapted from Engel et al. [41].

**Uninformed (UI):** A node that has not received the information and has a chance of receiving the information. This state stands for the nodes in stage one, Problem Recognition, and stage two, Information Search, where nodes have the requirement of consumption and are choosing between multiple types of product information.

**Informed (I):** A node that has received the information but has not purchased it yet; it has the ability to spread the information. This state stands for the nodes in stage three, Alternative Evaluation, where nodes choose one particular piece of product information.

**Customer (C):** A node that decides to purchase after receiving the information and has the ability to spread the information. This state stands for one kind of node in stage four, Decision, where the node decides to purchase after evaluating the particular piece of information chosen in stage three.

Discard ( $D$ ): A node that has received the information but decides not to purchase it, and instead, discards the information. It does not have the ability to spread the information. This state stands for the other kind of node in stage four, Decision, where the node decides to discard the information after evaluating it, rather than purchasing it.

We could abstract the mechanism of competitive information diffusion in social commerce as shown Figure 5. Let  $UI(t)$ ,  $I(t)$ ,  $D(t)$ , and  $C(t)$ , separately denote the numbers of the  $UI$ ,  $I$ ,  $D$ , and  $C$  nodes at time  $t$ . Let  $I_i(t)$  denote the number of  $I$  nodes holding message  $i$ . The information spread process only occurs along the links from  $I$  to  $UI$ . That is, information can only be spread from node  $I$  to node  $UI$ . As shown in Figure 5,  $I$  nodes may become  $C$  nodes or  $D$  nodes; we suppose that nodes in the state of  $C$  and  $D$  will no longer change state anymore, and due to the limitation of each node's attention, once it is infected by one particular piece of product information, it cannot be informed by another piece of information in the same consumption round.

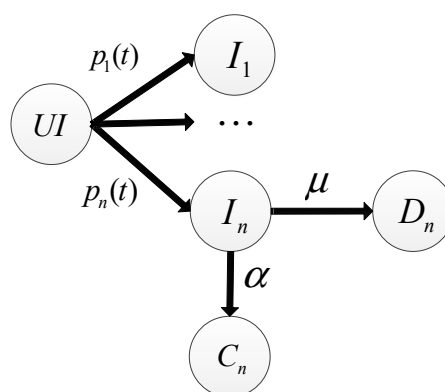


Figure 5. Diffusion of information from multiple sources in a social commerce network.

In Figure 5,  $p_i(t)$  represents the attractiveness function of the product information  $i$ , which represents the probability of  $UI$  nodes becoming infected with the product information  $i$  by  $I_i$  or  $C_i$  nodes. We describe the constituents of  $p_i(t)$  in Equation (1):

$$p_i(t) = L_i * e^{-\frac{(t-\rho_i)^2}{2\sigma_i^2}}, \quad t \geq 0, \quad \rho_i > 0, \quad \sigma_i > 0, \quad 0 \leq L_i \leq 1. \quad (1)$$

In Equation (1),  $L$  represents the maximum attractiveness of information during the whole propagation process, which we define as the attractiveness degree of the information.

$\rho$  represents the time when the information is the most attractive. We define  $\rho$  as the information boom time. In other words, the attractiveness of the product information is the greatest at time  $\rho$ . In the social commerce scenario,  $\rho$  is related to the product information release time.

$\sigma$  is the variance of attractiveness. We define  $\sigma$  as the information prosperity index. The bigger  $\sigma$  is, the longer information prosperity will be. That is to say, when  $\sigma$  is large, attractiveness is small in the initial propagation process, and then increases quickly, after which it will decrease slowly as time goes by. On the contrary, when  $\sigma$  is small, attractiveness is low in the initial propagation process, and will then increase slowly, and decrease quickly as time goes by. In the social commerce scenario,  $\sigma$  reflects the product information diffusion duration.

In Figure 5,  $\alpha$  and  $\mu$  reflect the probability parameter of  $I$  nodes becoming  $C$  nodes, and of  $I$  nodes becoming  $D$  nodes, respectively. We describe the specific computing method in Section 3.2. When it comes to the SC environment,  $\alpha$  reflects the probability of users purchasing the product, while  $\mu$  reflects the probability of users discarding the product information.

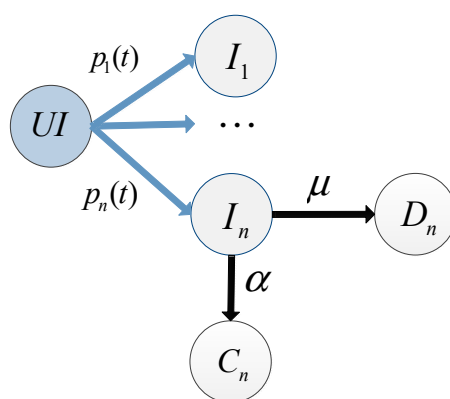
### 3.2. Mathematical Analysis

In this section, we provide the mathematical derivation of the proposed model. Firstly, explanations for all the symbols, parameters, and variables are given in Table 1.

**Table 1.** Explanations of symbols and variables.

Symbol	Explanation		
$UI$	A node that has not received the information; it has the chance to receive the information		
$I$	A node that has received the information but has not purchased yet; it has the ability to spread the information		
$C$	A node that purchases only once after receiving the information; it has the ability to spread the information		
$D$	A node that has received the information and discards it after that		
$UI(t)$	Number of $UI$ nodes at time $t$		
$I(t)$	Number of $I$ nodes at time $t$		
$C(t)$	Number of $C$ nodes at time $t$		
$D(t)$	Number of $D$ nodes at time $t$		
$V(t)$	Number of the nodes that have been informed ( $C&D$ ) at time $t$		
$\varphi_{ij}(t, t + \Delta t)$	The indicator that $UI$ node $j$ receives information $i$ in time interval $[t, t + \Delta t]$		
$\delta_{ik}(t, t + \Delta t)$	The indicator that $I$ node $k$ purchases product $i$ in time interval $[t, t + \Delta t]$		
$v_{ik}(t, t + \Delta t)$	The indicator that $I$ node $k$ discards information $i$ in time interval $[t, t + \Delta t]$		
Variable	Explanation	Parameter	Explanation
$N$	Number of all nodes	$L$	Information attractiveness degree
$M$	Amount of product information	$\rho$	Information breakout time
$T$	Maximum message lifetime	$\sigma$	Information diffusion duration
$i$	A particular piece of product information	$\lambda$	Exponential parameter of the nodes' contact rate
$j$	An $I$ state node	$\alpha$	Exponential parameter of the purchase rate
$k$	A $UI$ state node	$\mu$	Exponential parameter of discard rate

In this section, we describe the numbers of each kind of node separately. First of all, as the blue part shows in Figure 6, for the number of  $UI$  nodes, note that one node can receive at most one message in the propagation process. Interested nodes may receive message from  $I$  nodes carrying message  $i$ .



**Figure 6.** The change in the number of uninformed ( $UI$ ) nodes.

Given a minor time interval  $\Delta t$ , we can determine the change in the number of  $UI$  nodes as follows:

$$UI(t + \Delta t) = UI(t) - \sum_{i \in [1, M]} \sum_{j \in \{UI(t)\}} \varphi_{ij}(t, t + \Delta t). \quad (2)$$



In Equation (2), the symbol  $\varphi_{ij}(t, t + \Delta t)$  denotes whether the  $UI$  node,  $j$ , receives information,  $I$ , and changes to  $I$  state in time interval  $[t, t + \Delta t]$ . We have  $\varphi_{ij}(t, t + \Delta t) = 1$  when the event happens; otherwise,  $\varphi_{ij}(t, t + \Delta t) = 0$

$$P(\varphi_{ij}(t, t + \Delta t) = 1) = 1 - \left(1 - (1 - e^{-\lambda \Delta t})p_i(t)\right)^{I_i(t) + C_i(t)}. \quad (3)$$

By combining Equations (1)–(3), we have the following equation:

$$\begin{aligned} \lim_{\Delta t \rightarrow 0} \frac{E(UI(t + \Delta t)) - E(UI(t))}{\Delta t} &= - \lim_{\Delta t \rightarrow 0} \frac{E(UI(t))E\left(1 - \prod_{i=1}^M \left(1 - (1 - e^{-\lambda \Delta t})p_i(t)\right)^{I_i(t) + C_i(t)}\right)}{\Delta t} \\ \Rightarrow E(\dot{UI}(t)) &= -\lambda E(UI(t)) \sum_{i=1}^M (E(I_i(t)) + E(C_i(t)))p_i(t). \end{aligned} \quad (4)$$

As the blue part shows in Figure 7, for  $I$  nodes, on the one hand, the  $UI$  nodes can receive the information and change into  $I$  nodes; on the other hand,  $I$  nodes can discard messages and become  $D$  nodes. They can also purchase and change their state to  $C$ .

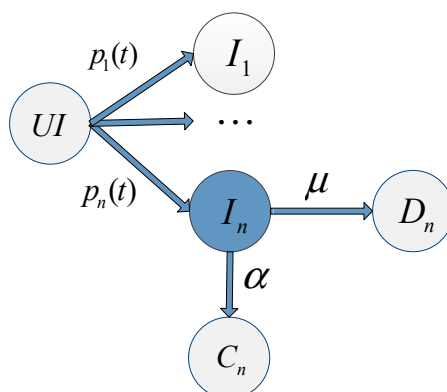


Figure 7. The change in the number of informed ( $I$ ) nodes.

Given a time interval  $\Delta t$ , we can determine the change in the number of  $I$  nodes holding message  $i$  as follows:

$$I_i(t + \Delta t) = I_i(t) - \sum_{\substack{j \in \{UI(t)\} \\ i \in [1, M]}} \varphi_{ij}(t, t + \Delta t) - \sum_{k \in \{I_i(t)\}} \delta_{ik}(t, t + \Delta t) - \sum_{k \in \{I_i(t)\}} v_{ik}(t, t + \Delta t). \quad (5)$$

The symbol  $\delta_{ik}(t, t + \Delta t)$  represents the event of whether the  $I$  node  $k$  holding message  $i$  changes to  $D$  state in time interval  $[t, t + \Delta t]$ . We have  $\delta_{ik}(t, t + \Delta t) = 1$  when the event happens; otherwise, we have  $\delta_{ik}(t, t + \Delta t) = 0$ .  $I$  nodes discard messages following a Poisson distribution with the parameter  $\mu$  [23]. We can obtain,

$$P(\delta_{ik}(t, t + \Delta t) = 1) = 1 - e^{-\mu \Delta t}. \quad (6)$$

The symbol  $v_{ik}(t, t + \Delta t)$  denotes the event of whether in time interval  $[t, t + \Delta t]$ , the  $I$  node  $k$  holding message  $i$  purchases the commodity and becomes a  $C$  node. We have  $v_{ik}(t, t + \Delta t) = 1$  when the event happens; otherwise, we have  $v_{ik}(t, t + \Delta t) = 0$ . The purchase behavior of  $I$  nodes follows a Poisson distribution with the parameter  $\alpha$  [23]. We can obtain,

$$P(v_{ik}(t, t + \Delta t) = 1) = 1 - e^{-\alpha \Delta t}. \quad (7)$$



By combining Equations (5)–(7) we have,

$$\begin{aligned} & \lim_{\Delta t \rightarrow 0} \frac{E(I_i(t+\Delta t) - E(I_i(t)))}{\Delta t} = \\ & \lim_{\Delta t \rightarrow 0} \frac{E(UI(t)E(1 - (1 - (1 - e^{-\lambda \Delta t})p_i(t))^{I_i(t) + C_i(t)}))}{\Delta t} - \lim_{\Delta t \rightarrow 0} \frac{E(I_i(t)E(1 - e^{-\mu \Delta t}))}{\Delta t} - \lim_{\Delta t \rightarrow 0} \frac{E(I_i(t)E(1 - e^{-\alpha \Delta t}))}{\Delta t} \\ & \Rightarrow E(\dot{I}_i(t)) = \lambda E(UI(t))(E(I_i(t)) + E(C_i(t)))p_i(t) - (\mu + \alpha)E(I_i(t)). \end{aligned} \quad (8)$$

As the blue part in Figure 8 shows,  $I$  nodes may purchase and change state to  $C$ ;  $I$  nodes may also discard messages and change state to  $D$ .

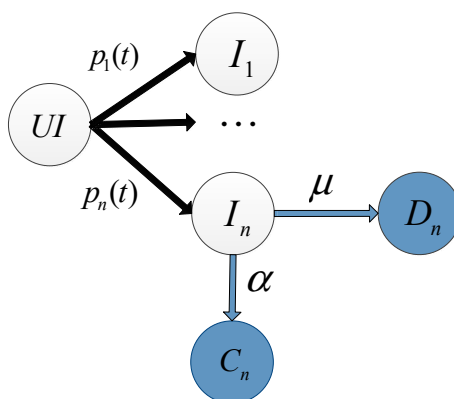


Figure 8. The change in the number of  $C$  and  $D$  nodes.

Similar to Equations (2) and (5), we have,

$$C_i(t + \Delta t) = C_i(t) + \sum_{k \in \{I_n(t)\}} v_{ik}(t, t + \Delta t), \quad (9)$$

$$D_i(t + \Delta t) = D_i(t) + \sum_{k \in \{I_n(t)\}} \delta_{ik}(t, t + \Delta t). \quad (10)$$

$v_{ik}(t, t + \Delta t)$  and  $\delta_{ik}(t, t + \Delta t)$ , which were described previously, respectively represent whether the  $I$  node  $i$  becomes a  $C$  node in time interval  $[t, t + \Delta t]$ , and whether the  $I$  node  $i$  becomes a  $D$  node in time interval  $[t, t + \Delta t]$ . Similar to Equations (4) and (8), we can obtain,

$$E(\dot{C}_i(t)) = \alpha E(I_i(t)), \quad (11)$$

$$E(\dot{D}_i(t)) = \mu E(I_i(t)). \quad (12)$$

Now we have four ordinary differential equation (ODE) equations: Equations (4), (8), (11), and (12). There are four variables in all, and given the initial value, we can obtain the values of the variables at any time.

### 3.3. Data Collection and Parameter Setting

Researchers have widely applied Social Networks Services (SNS) data sources to the social sciences. Saura et al. (2019) explored a financial brand image by using both the traditional approach and sentiment analysis. Findings indicated that big data-based digital methodology is as effective as, but more efficient than, the traditional method [42]. We used the Web crawler tool Octoparse software (Shenzhen vision information technology co. LTD, Shenzhen, China) to collect data from the Sina Weibo and Taobao websites, China's most popular social commerce platforms, to validate the proposed information diffusion model. Sina Weibo, established in 2009, is the most popular social media site in China. Sina Weibo has 462 million monthly active users in 2019 and is also known as "Chinese Twitter".

Taobao was founded by the Alibaba group in May 2003. It is the most popular online retail platform in China, with nearly 500 million registered users, and over 60 million regular visitors every day, with almost 48,000 goods sold every minute. We chose these two websites because they are the most influential websites in their respective domains. Social commerce is the combination of social media and e-commerce. Therefore, the combination of these two websites is the most significant representative of SC. Researchers have explored the effects of social media on consumers' purchase decisions by using data from Taobao [43]. Since we focused on SC from the perspective of information spread in social networks, Sina Weibo, as the most popular social media site in China, was an appropriate data sources for studying the information competition topic [4,32].

Users of Sina Weibo communicate with each other by posting, reposting, likes, and comments on contents; these features are similar to those used on Twitter. SC marketers and consumers form a network, where information diffuses through the process of users' interactions. In this study, we used a user (marketer)'s online post about the product, as a piece of information. We conducted a pre-test with a computer simulation based on Java script prior to collection of real data. We randomly chose a product, the loquat fruit. We used one piece of information, because if we had chosen two pieces of information, it would have been technically challenging for us to control other conditions to ensure the accuracy of the results. However, the situation of having only one piece of information to spread is covered in the proposed model (when  $M = 1$ ). Therefore, this did not fundamentally influence the verification of the effectiveness of the model. We also tested other product information spread datasets. The experience results were the same, so they are not included in this paper. We collected sales volume data related to the information spread data from the Taobao website, where social commerce transaction occurs. We took the information diffusion duration as the Maximal Lifetime ( $T$ ) of the information. In the dataset, the marketer released the original post at 10:02, 12 February 2019; after that, users reposted it until 23:00, 18 February 2019. The information diffusion duration was not fixed; instead, it differed among pieces of information. Nevertheless, no matter how long the real duration was, we matched it with the Maximal Lifetime (approximately 50,000) in the model. For example, the duration of information diffusion was 157 hours, which equals 56,520 ten-seconds, i.e.,  $T = 56,520$ .

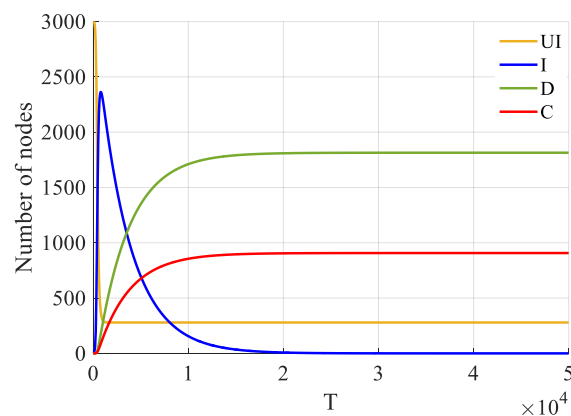
We treated online users' repost behavior as the signal that they had been informed by the original post. In the beginning of information diffusion, there was one  $I$  node; all the others were  $UI$  nodes. Generally speaking, when it came to the end of  $T$ , all the users in the network had been informed by the original post. Here, by the nodes that "have been informed", we mean  $C$  nodes as well as  $D$  nodes; that is to say, all nodes are either  $C$  or  $D$  nodes. We took the number of reposts as the approximate value of  $N$  in the model. This post had 2967 reposts in all, so we used  $N = 3000$ .

The parameters in epidemic models are variable [4], and accurate simulation requires situation-related parameter setting. Wu et al. (2012) set the parameter  $\lambda = 3.71 \times 10^{-6}$  based on the probability of taxis encountering each other; we applied this value in our work to depict the random meeting between online nodes [23]. For the other parameters,  $L$ ,  $\rho$ ,  $\sigma$ ,  $\alpha$ , and  $\mu$ , we determined the values of the parameters by using data fitting, that is, adjusting parameters according the actual dataset collected from the social media platform and keeping the relative error within a reasonable range.

## 4. Results

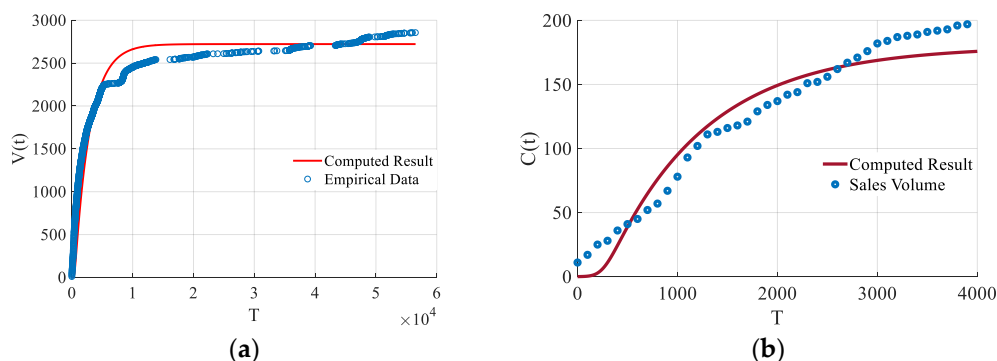
### 4.1. Empirical Evaluation

Four types of nodes were considered in this study:  $UI$ ,  $I$ ,  $D$ , and  $C$ . Figure 9 gives an overview of changes in all nodes' quantitative numbers. Initially, all nodes except the one in the network were  $UI$  nodes; the one that released the post was an  $I$  node. Information spread in a very short time. As a result, there was a significant decline in the number of  $UI$  nodes (the yellow line); most of them were informed and became  $I$  nodes (the blue line). After a peak in the number of  $I$  nodes, the number of  $I$  nodes declined, since nodes either purchased the product and entered the  $C$  state or discarded the product information and then transferred into the  $D$  state.



**Figure 9.** The change in number of all types of nodes.

Then, we specifically observed the number of nodes that had received production information, including *C* and *D* nodes, which is the most crucial index to reflect the effectiveness of product information diffusion. As shown in Figure 10, the blue scatters represent the dataset collected from the Sina Weibo and Taobao websites. The real data (blue spots) were consistent with the computed results (the red line). In both situations, the mean relative error between the two results was within 5%, verifying the accuracy of our proposed model. In the next section, we analyze the elements that influence the competitive information diffusion with the proposed model.

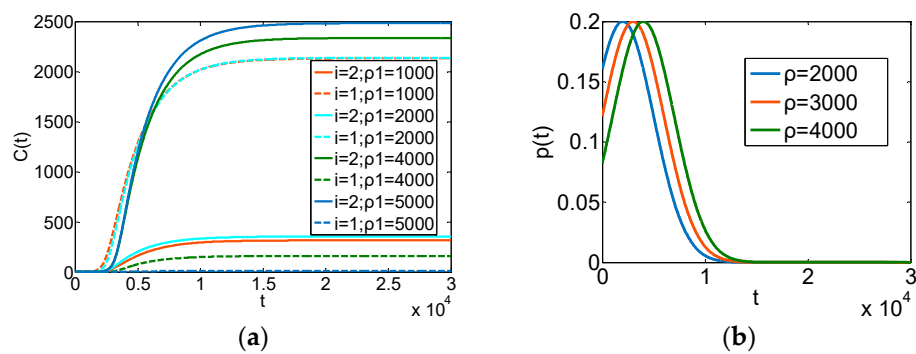


**Figure 10.** (a) Comparison of the number of nodes that were informed from the simulation and theoretical results; (b) comparison of the sales volume from the simulation and theoretical results.

#### 4.2. Separate Analysis of Parameters

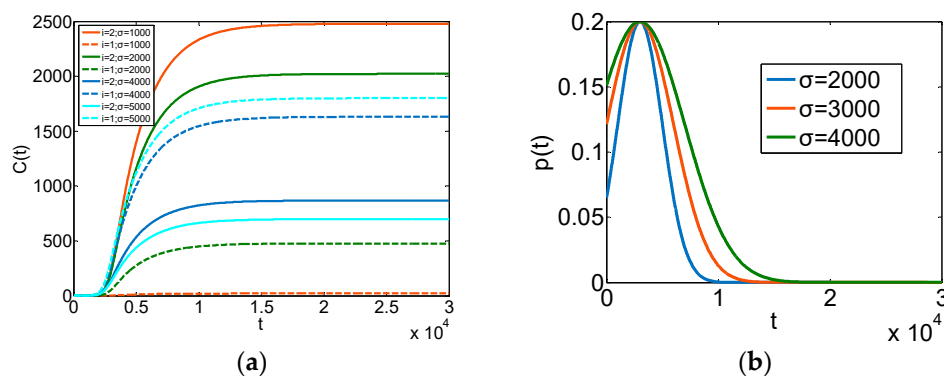
In this section, we depict the Matlab software (MathWorks, Natick, MA, US) computation results to explain the effect of parameters on the information diffusion effectiveness. We tested the influences of these parameters separately as well as jointly. In this process, we answered the research question for SC marketers of which strategy (the earlier release of the information or increased information duration compared with the competitor) is the more competitive in social commerce information diffusion.

Firstly, we tested the effect of the Information Breakout Time, which is reflected by parameter  $\rho$ . In Figure 11a, the dashed line indicates the diffusion of information 1, and the solid line indicates the diffusion of information 2. When the burst time of information 1 is earlier than 3000, the propagation effect of information 1 is better than that of information 2; however, when the burst time is earlier by 1000 or 2000, there is little effect on the final result (red and fluorescent blue). If the breakout time of information 1 is later than 3000, the effect of information 1 is poorer than that of information 2, and the difference between a later breakout time by 1000 and 2000 is significant (green and blue).



**Figure 11.** (a) The effect of  $\rho$  on the number of C nodes.  $\lambda = 3.71 \times 10^{-6}$ ,  $\alpha = \mu = 2 \times 10^{-4}$ ,  $N = 5000$ ,  $T = 30,000$ ,  $L_1 = L_2 = 0.2$ ,  $\sigma_1 = \sigma_2 = 2000$ ,  $\rho_1 = 1000, 2000, 4000, 5000$ , and  $\rho_2 = 3000$ . (b) The value of  $p(t)$  under different  $\rho$  values.

Then we tested the effect of the information diffusion duration, which is reflected by parameter  $\sigma$ . As shown in Figure 12a, the dashed line indicates the diffusion of information 1, and the solid line indicates the diffusion of information 2. When the information standard deviation of information 1 is greater than 3000 (blue and fluorescent blue), the propagation effect of information 1 is better than that of information 2. When the standard deviation of 1 is less than 3000 (red and green), then the effect of information 1 is worse than that of information 2. When the standard deviation of attraction is less than 3000, the same change has a more significant impact on the final number of consumers.



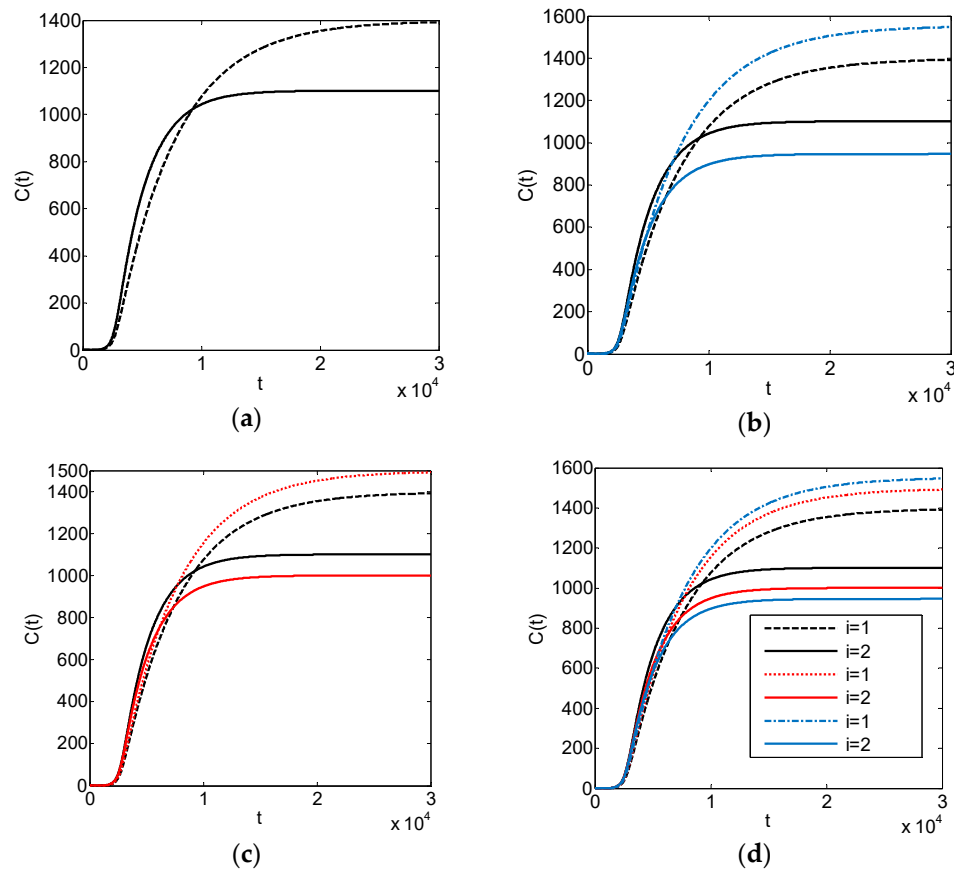
**Figure 12.** (a) The effect of  $\sigma$  on the number of C nodes.  $\lambda = 3.71 \times 10^{-6}$ ,  $\alpha = \mu = 2 \times 10^{-4}$ ,  $N = 5000$ ,  $T = 30,000$ ,  $L_1 = L_2 = 0.2$ ,  $\rho_1 = \rho_2 = 3000$ ,  $\sigma_1 = 1000, 2000, 4000, 5000$ , and  $\sigma_2 = 3000$ . (b) The value of  $p(t)$  under different  $\sigma$  values.

#### 4.3. Joint Analysis of Parameters

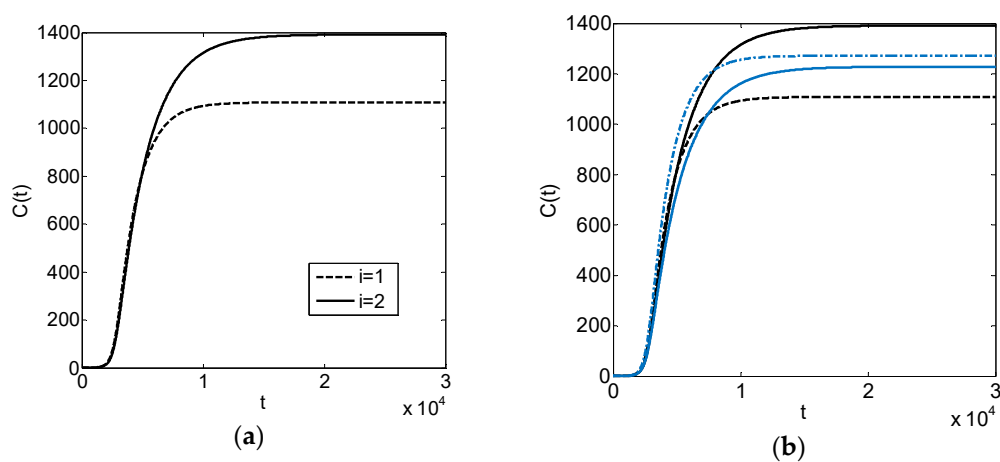
In this section, we explore the joint effects of parameters on the numbers of consumer nodes, including simultaneously decreasing the purchase probability  $\alpha$  and the discard probability  $\mu$ . Also, we compare the effects of bringing forward the information breakout time  $\rho$  and increasing the information diffusion duration  $\sigma$ . We can observe from Figure 13a, that in the competition for homogenous commodity information dissemination, parameters  $\alpha$  and  $\mu$  reduce simultaneously (Information 1, dashed line), resulting in poorer sales volume in the short term and better performance in the long term (Figure 13a). In this situation, decreasing parameter  $\rho$  (Figure 13b) and increasing parameter  $\sigma$  (Figure 13c) can both enhance the information propagation effect, wherein the effect of reducing parameter  $\rho$  is more significant (blue dashed line in Figure 13d).

In Figure 14, we can see that in the competition between information transmission of homogeneous commodities, parameters  $\alpha$  and  $\mu$  increase (Information 1, dashed line), which at the same time, will lead to worse information transmission performance (Figure 14a). In this situation, reducing the value of parameter  $\rho$  (Figure 14b) and increasing the value of parameter  $\sigma$  (Figure 14c) can enhance

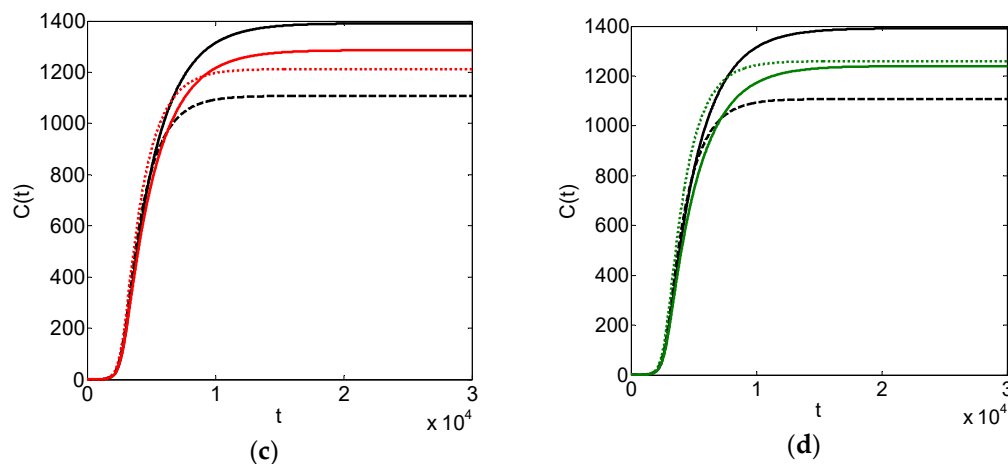
the information transmission effect, in which the effect of reducing the value of parameter  $\rho$ , is more significant and even flips the outcome. The effect in Figure 14c is not as good as that in Figure 14b. If the degree of increase of parameter  $\sigma$  is larger than that of the decrease in parameter  $\rho$ , as we can see in Figure 14b,d the effects are the same.



**Figure 13.** The effects of different parameter values on the number of consumers:  $\lambda = 3.71 \times 10^{-6}$ ,  $\alpha_1 = \mu_1 = 1 \times 10^{-4}$ ,  $\alpha_2 = \mu_2 = 2 \times 10^{-4}$ ,  $N = 5000$ ,  $T = 30,000$ ,  $L_1 = L_2 = 0.2$ ,  $\rho_2 = \sigma_2 = 3000$ , (a) The original value  $\rho_1 = \sigma_1 = 3000$ , (b)  $\rho_1 = 2800$ ,  $\sigma_1 = 3000$ , (c)  $\rho_1 = 3000$ ,  $\sigma_1 = 3200$ , (d)  $\rho_1 = 2800$ ,  $\sigma_1 = 3200$ .



**Figure 14.** Cont.



**Figure 14.** The effects of different parameter values on the number of consumers:  $\lambda = 3.71 \times 10^{-6}$ ,  $\alpha_1 = \mu_1 = 3 \times 10^{-4}$ ,  $\alpha_2 = \mu_2 = 2 \times 10^{-4}$ ,  $N = 5000$ ,  $T = 30,000$ ,  $L_1 = L_2 = 0.2$ ,  $\rho_2 = \sigma_2 = 3000$ ; (a) the original value,  $\rho_1 = \sigma_1 = 3000$ , (b)  $\rho_1 = 2800$ ,  $\sigma_1 = 3000$ , (c)  $\rho_1 = 3000$ ,  $\sigma_1 = 3200$ , (d)  $\rho_1 = 3000$ ,  $\sigma_1 = 3100$ .

## 5. Discussion and Implications

### 5.1. Discussion of Results

This work has four main findings in the domain of competitive information diffusion in social commerce. Firstly, the information breakout time has a significant effect on the number of consumers in the competitive product information environment. Specifically, the earlier a piece of information breaks out, the better the diffusion outcome will be; that is, more nodes turn into consumers in the end. However, the degree of earlier diffusion does not matter that much.

Secondly, the information diffusion duration positively influences the effectiveness of the information spread, which means that the longer a piece of product information diffuses, the more purchase volume it will attain in the end.

Thirdly, a product with a lower purchase rate also has the chance of beating its competitors in the long term, as long as it keeps its discard rate lower than theirs, while a product with a higher purchase rate is very likely to lose out in terms of sales volume if its discard rate is also high.

Last but not least, earlier information breakout time and longer information diffusion duration could both increase sales. The former has a better effect than the latter. Also, the effect is significant, no matter how much earlier than the competitor the breakout time is.

### 5.2. Theoretical and Practical Implications

This work is a combination of the model method and data mining technology. It contributes to the existing literature in three aspects. First of all, we pioneered the exploration of the mechanism of competition in social commerce from the perspective of information diffusion. Secondly, we created a model to simulate the mechanism of competitive product information diffusion and verified it with real data collected from social commerce platforms. Lastly, by using the proposed model, we analyzed the influences of the information breakout time, diffusion duration, online users' purchase rate, and discard rate on the size of sales. The results showed that an early breakout time had a more positive effect on the purchase volume. Decreasing the purchase rate could have a positive effect through a lower discard rate. These results not only shed light on the theoretical research of social commerce, but are also practically meaningful for the industry.

According to the theoretical results, we have two suggestions for social commerce marketers in order to win out among the fierce competition. One of them is ensuring a low discard rate; that is, if marketers fail to control consumers' discard information rate, even a high purchase rate cannot make up for the sales lost. The other is making a great effort to release the product information before the

competitors; when it comes to securing market share, being even a tiny step ahead in terms of timing is much more efficient than increasing the information duration. As for answering the research question raised in the beginning, combining the research results, we would say it is better to act early than to act for longer.

### 5.3. Strategies for Marketers

According to the simulation results, products can win out over their peer competitors by merely announcing information one step earlier. For those who have high purchase and discard rates, this is even more effective. We used the term “target product” to refer to the product we want to apply the strategies to. The “competitor product” is the product in competition with the “target product.” Specifically, the developed strategies for marketers are as follows:

**Strategy 1:** In the long term, keeping the discard rate low (discard refers to behavior that causes a node to receive the product information but not purchase the product afterward) could help a target product with a low purchase rate gain more sales volume than the competitor product.

**Strategy 2:** For a target product with a high purchase rate, it is crucial to control the discard rate, otherwise, the competitor product may achieve more sales volume.

**Strategy 3:** For a target product with a low purchase rate and low discard rate, releasing the product information earlier is more effective in boosting the sales volume than increasing the information duration.

**Strategy 4:** For a target product with a high purchase rate and high discard rate, releasing the product information earlier is even more useful (to a more significant degree than the low/low target product) in boosting the sales volume than increasing the information duration.

## 6. Limitations and Future Research

### 6.1. Limitations

Due to the technical challenges involved in controlling the competitive information spread conditions, we only used one piece of product information in the empirical test. This is a limitation of this work since it weakens the arguments to some degree. Nevertheless, the situation of only one piece of information spread is covered in the proposed model (when  $M = 1$ ). Therefore, it would not have fundamentally influenced the verification of the effectiveness of the model.

The other limitation of this research is that we simplified the model to include only two competitors in the market. While the real situation is more complex, it is also possible that three or more competitive products exist at the same time. Thus, we believe the findings in this work could also act as a guide.

Despite such limitations and the complexity of the real-world situations, our findings regarding the competitive information are empirically supported and provide valuable knowledge for researchers and marketers in the SC field. Furthermore, this study is first on the SC competitive information spread subject and therefore is also exploratory in nature. In that regard, our work has been successful in uncovering some interesting starting points for future research.

### 6.2. Future Research

Social e-commerce is an important trend in e-commerce. It is ubiquitous in our lives and has a significant share in social and economic development, although theoretical research as well as practical supervision in this discipline are still in the early stages. Furthering the research of social commerce is crucial from both theoretical and practical perspectives. To provide a better understanding of this industry, we need to deeply explore the following aspects of SC.:

One direction that researchers should adopt is the use of mixed methods and technologies to ensure the accuracy of the results and avoid model bias. The majority of the existing literature is empirical, with the survey method being the most popular. We give an explanation of the SC mechanism by introducing the model as a method of empirical observations, which provides a direction to study the



marketing competition in SC. Future studies could explore the phenomenon in SC by combining a more extensive data set, field studies, and qualitative methods.

The other consideration would be predicting the performance of SC and exploring its underlying mechanism by taking more independent variables into consideration. This may include, but is not limited to, product and platform features.

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