Impacts of knowledge on online brand success: an agent-based model for online market share enhancement

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ABSTRACT

The dynamics of brands diffusion emerge partly from heterogeneous consumers’ interaction in social e-commerce and this social interaction influences adoption decisions. The agent-based simulation is a methodology that is well suited for modeling collective diffusion dynamics. Using optimal pricing mechanism and industry data, we introduce an agent-based model to replicate the evolution process of market share for multiple brands competing online. The proposed model helps understand the role of knowledge in the diffusion of competitive brands. It shows that when multiple brands face online competition, innovativeness, brand image, self-perceived utility and electronic word of mouth (e-WOM) all have significant effect on online shoppers’ decisions and have a bearing on brands’ market performance. Consumers often derive their value (utility) of a brand based on price, quality, rating, etc. When consumers rely more on self-perceived utility, e-WOM has more positive effects on market share. Depending on whether a firm’s competitive advantage is in innovation, price, web content, or use of social media, different online strategies should be employed for different brands to achieve market success.

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1. Introduction

Online review and social network are a daily routine for many web users. Sharing and inquiring product information online becomes an essential step in purchase decision-making. Through social media, social e-commerce (s-commerce) participants interact and contribute to the online buying and selling of products and services (Kim & Park, 2013). For example, members of Pinterest (https://www.pinterest.com/) and Fandongxi (http://www.fandongxi.com/) often browse and exchange information with other members interested in the same product or service. Stelzner (2013) reports that 86 percent of marketers consider social media vital for their business. The ascent of s-commerce and this social interaction influences adoption decisions. The agent-based simulation is a methodology that is well suited for modeling collective diffusion dynamics. Using optimal pricing mechanism and industry data, we introduce an agent-based model to replicate the evolution process of market share for multiple brands competing online. The proposed model helps understand the role of knowledge in the diffusion of competitive brands. It shows that when multiple brands face online competition, innovativeness, brand image, self-perceived utility and electronic word of mouth (e-WOM) all have significant effect on online shoppers’ decisions and have a bearing on brands’ market performance. Consumers often derive their value (utility) of a brand based on price, quality, rating, etc. When consumers rely more on self-perceived utility, e-WOM has more positive effects on market share. Depending on whether a firm’s competitive advantage is in innovation, price, web content, or use of social media, different online strategies should be employed for different brands to achieve market success.

Most simulation-based approaches extend the classical Bass model and complement its weakness. They can take into account the interactions between individual consumers within a social network. However, few simulation studies have focused on multi-brand online competition and diffusion; and no researchers have validated such a simulation model with actual online market data. We develop an agent-based simulation model to study diffusion and online brand competition, and perform validation for the proposed model using an industrial data set.

We assume consumers’ purchasing decision is influenced by their knowledge about the brand, which includes innovativeness, impression of the brand, self-perceived brand utility from web content, and e-WOM from social media (network externalities), etc. Chenavaz (2012) believes the demand of goods or service is a function of price and quality, while innovation is the main determinant of price.

There are two types of word-of-mouths (WOM) in diffusion process. One is the online customer review system, the most powerful
channel to generate online WOM (Dellarocas, 2003). The other is created by consumers using the social media. There has been a growing interest in examining the relationship between product sales and consumer reviews (Dellarocas, Zhang, & Awad, 2007; Duan, Gu, & Whinston, 2008; Forman, Ghose, & Wiesenfeld, 2008), in which perceived value through price is as important as perceived quality and service of product in influencing the purchase decision (Li & Hitt, 2010). In this research, instead of examining how price affects review, we examine the relationship between price and brand rating. On the other hand, network externalities suggest that consumption utility of one user in the network depends on the number of other users of the same or compatible product or service. The utility may increase with the number of actual buyers in the network (Katz & Shaprio, 1985).

Social media is such a platform that consumers could create and share product or service information and purchasing experience through network or mobile equipment. It is thus an important marketing tool for sales promotion in e-commerce. Stelzner (2013) finds 88 percent of marketers want to know the most effective social tactics and the best ways to engage shoppers via social media. In our study, we examine the effect of electronic word of mouth (e-WOM) on diffusion among consumers in social media.

We first develop a pricing model to determine the optimal price. Next, an agent-based model is developed incorporating the optimal price (derived from real data by the proposed revenue model) and four other factors: innovativeness, image (impression of prior market share), self-perceived utility (customer perceived value of an online brand based on price, rating, quality, etc.), and e-WOM in social media. Through agent-based simulation experiments, we address the following research questions:

1. How does innovativeness affect a brand’s market performance?
2. How does brand’ image impact market share?
3. How do the self-perceived utility and perceived e-WOM impact market share?

The organization of the paper is as follows. Section 2 reviews the literature and positions our research. In Section 3, we develop a revenue model to derive the optimal brand price. Section 4 incorporates optimal prices of different brands in the simulation model and replicates heterogeneous agents’ purchase decision making process. In Section 5, we conduct experiments on various scenarios to validate the model, and to develop insights into the effect of parameter changes on system performance. Conclusions and managerial implications are given in Section 6. Section 7 highlights the directions for future research.

2. Literature review

Price, quality, innovation, and online rating influence consumers’ purchasing decisions through WOM and other social norm (e.g. herd behavior). Price has an effect on online review and rating of product quality (Li & Hitt, 2010), which in turn impact consumer buying behavior (Li & Hitt, 2008). In brand diffusion, the knowledge perceived by consumers, including innovativeness, prior market share, self-perceived utility of brands (derived from price, quality rating, online ranking, etc.), and e-WOM may impact consumers’ adoption decision and brand performance. Thus, understanding how knowledge affects market share of online brands is critical for marketers. In this section, we review literature most relevant to our study: innovation diffusion, agent-based diffusion modeling, and pricing models.

2.1. Traditional innovation diffusion models

Product diffusion has attracted much research attention. There are two main approaches to model diffusion (Schramm, Trainer, Shanker, & Hu, 2010). The first is an econometric approach (e.g. Bass model), which focuses on innovation and imitation. Innovation captures the external influence, while imitation refers to the internal influence (Bass, 1969). Yu et al. (2003) have since extended the Bass model to tackle competitive product diffusion, while Dewan et al. (2010) enhance it to address complementary product diffusion. Although the Bass-based econometric model can predict macro-level diffusion through dynamic systems, they cannot satisfactorily distinguish individual consumers’ characteristics. This indicates the heterogeneity in preferences and behaviors of consumers are usually neglected in these models. The other approach is the exploratory method (Galton & Robertson, 1985), which assumes consumers are heterogeneous and estimates the innovation diffusion by aggregating individual consumers’ adoption decisions. These models incorporate personal demographic information, decision traits and social influence (Galton & Robertson, 1985). However, they are not able to account for different degrees of interactions among consumers.

To overcome these limitations, researchers introduced the simulation-based approach. There are two types of simulation model: cellular automata models (Guseo & Guidolin, 2009; Moldovan & Goldenberg, 2004) and agent-based models (Schwarz & Ernst, 2009). The former uses cells to represent agents (e.g., consumers), while focusing on communication among consumers (Grassberger, 1984). It assumes a cell can be influenced by four- or eight-direct neighboring cells, but cannot interact with far-distanced units.

Our research belongs to the agent-based model, which has advantages in modeling complex systems (Gilbert, 2008). This bottom-up methodology, due to its ability to represent the macro-level dynamics of a system by aggregating individual behaviors and interactions among agents at the micro-level, has been applied to engineering, sociology, economics, and management fields. We discuss the agent-based models for collective diffusion dynamics next.

2.2. Agent-based diffusion modeling

Increasing number of researchers have tried to model agent-based social network (Kuandykov & Sokolov, 2010). Gunther, Stummer, Wakolbinger, and Wildpaner (2011) simulate the diffusion of biomass fuel to investigate the impacts of mass communications, targeted activities, and pricing strategies on diffusion. Kuandykov and Sokolov (2010) study how two network topologies (random and scale-free) impact diffusion of innovation, while Kim, Lee, Cho, and Kim (2011) model an agent’s car adoption decision as a multi-attribute decision-making process through fuzzy TOPSIS. Although the agent-based models for innovation diffusion are still in its infancy, they offer a promising direction for understanding innovation diffusion when consumers are heterogeneous. Fig. 1 provides a graphical example of agents and show how their social interactions influence purchase decisions in a social e-commerce.

In contrast to traditional agent-based models, which often require strict assumptions, we relax many presuppositions and employ real-world data to parameterize our simulation. Our model is illustrated and validated through real-life market share information.

2.3. Pricing model

Product diffusion is a multi-period process. To maximize profit, one needs to determine the optimal price during the product diffusion time horizon. Much has been done on optimal pricing. Bitran and Caldentey (2003) discuss dynamic pricing models and their relationship to revenue management. Elmaghraby and Keskinocak (2003) focus on dynamic pricing in the presence of inventory considerations, while Soon (2011) review the multi-product pricing models.

There are several online pricing strategies. From a game-theoretic perspective, Levina, Levin, McGill, and Nediak (2009) offer a dynamic pricing model. Mitra and Fay (2010) develop a signaling model to show how e-tailers can use prices to manage
customers’ expectations. Then again, Ehsani, Ghodsi, Khajenezhad, Mahini, and Nikzad (2012) use a weighted graph to model buyer network. From the perspective of customized bundling, Jiang, Shang, Ke, and Liu (2011) design a dynamic pricing strategy to maximize profits of e-trailer and customer savings. Ahmed and Kwon (2012) build a revenue model based on cost-per-impression for online display advertisement publishers. Finally, Yao and Zhang (2012) empirically show that e-tailers can determine the best selling price based on manufacturer’s suggested retail price, shipping price and other charges for shipping services.

The literature in this subsection paves the foundation for us to develop the pricing model in Section 3, which in turn offers the optimal dynamic pricing (as multi-period input variables) for the agent-based model we proposed in Section 4.

3. Pricing model
We consider a multi-period revenue optimization problem for competition of multiple brands in online market. It is obvious that better quality and innovative technology and service enhance brand attraction, increase product value, but also raise costs and reduce profits. In our model, the current price depends on the price in the previous time period. The demand of specific brands is a time-varied state variable. Its growth depends on natural growth rate, innovation degree and price change. Brand managers need to make decisions on price and innovation level in each planning horizon.

3.1. Profit and sale growth

Table 1 summarizes the parameters and variables necessary for our profit model.
Revenue of brand \( i \) is from sales at time \( t \). There are three associated costs:

(a) Total cost of brand \( i \) is \( c_i \cdot x_i(t) \).
(b) Total cost of brand \( i \)'s innovation is \( \alpha_i \cdot v_i(t) \), which rises with the brand’s innovativeness (technology and service innovation).
(c) Cost of the online price change, which is a positive value regardless of the rise or drop of the online price. Similar to Kumar and Sethi (2009), the cost is set as a quadratic function of the price change rate, i.e. \( \beta \cdot u(t)^2 \).

Therefore, the profit of brand \( i \) at time \( t \) can be written as

\[
\text{Profit } i(t) = (p_i(t) - c_i)x_i(t) - \alpha_i v_i(t) - \beta u_i(t)^2.
\]

Assume the demand is a linear function of price and innovation. Let \( x_i(t) \) be the number of online buyers of brand \( i \) at time \( t \), and \( \dot{x}_i(t) \) be the rate of change in that. The growth rate of online shoppers can be written as \( \dot{x}_i(t) = \eta_i + \pi v_i(t) - \varphi u_i(t) \), where \( \eta \) is the natural growth rate. The number of online shoppers increases with innovativeness \( \pi v_i(t) \), while that decreases with the price of brand \( i \) at the rate of \(-\varphi u_i(t)\).

3.2. Profit maximization model

The marketer can optimize her total profit by deciding on \( u(t) \) and \( v(t) \). The following model optimizes the multi-period profit:

\[
\max \int_0^T \left[ \sum_{i} (p_i(t) - c_i)x_i(t) - \alpha_i v_i(t) - \beta u_i(t)^2 \right] dt
\]

subject to

\[
\begin{align*}
\dot{x}_i(t) &= \eta_i + \pi v_i(t) - \varphi u_i(t),\quad x_i(t) = x_i(0), \quad \forall t \\
p_i(t) &= u_i(t),\quad p_i(0) = p_i,0 \\
\sum_{i} x_i(t) &= 1 \\
x_i(t) &\geq 0, \quad \forall t,\quad p_i(t) \geq 0, \quad \forall t
\end{align*}
\]

Where \( x_i,0 \) and \( p_i,0 \) are respectively the market share and the online price of brand \( i \) at the beginning of the planning horizon. Without loss of generality, we assume the total market share is 1, with \( 0 \leq x_i(t) \leq 1 \), and the price change \( u_i(t) \) and innovation degree \( v_i(t) \) are the decision variables.

3.3. Dynamic pricing

Vendors regularly update and innovate technology to improve their products or service. Our goal is to find the optimal price in each time period given static innovation. A dynamic optimization method is used to solve Model (1). Like Fruchter (2009) and Kumar & Sethi (2009), we use a Hamiltonian function to obtain the necessary conditions for optimal solution:

\[
H = (p(t) - c)x(t) - \alpha u(t) - \beta u^2(t) + \lambda_x(t)(\eta + \pi v(t) - \varphi u(t)) + \lambda_p(t)u(t)
\]

where \( \lambda_x(t) \) and \( \lambda_p(t) \) are adjoint variables corresponding to \( x(t) \) and \( p(t) \) at time \( t \) respectively. They represent the shadow price associated with a unit change in state variables at time \( t \). Specifically, \( \lambda_x(t) \) is the marginal value of a change in \( x(t) \), while \( \lambda_p(t) \) is that in \( p(t) \).

Eq. (2) can be interpreted as the instantaneous profit rate, which indirectly contributes to the objective function. For the profit maximization problem in Model (1), the necessary condition is \( \frac{\partial H}{\partial u(t)} = 0, \)

Fig. 1. Agents, dynamics, and purchase decisions in a social e-commerce.
4.1. Overview in multi-period

In innovation theory, consumers are classified into five adoption types: innovators, early adopters, early majority, latemajority, and laggards. Different types of adopters have different levels of sensitivity to brand innovation, price and social influence from other agents.

4.1.2. Image and self-perceived value

Brand image is seen as an overall evaluation for a brand, it is a perceptual belief about a brand’s attribute, benefit, and attitudes associations (Faircloth, Capella, & Alford, 2001). Image of market share is a key for brand’s adoption. Most consumers will study market information of the product or brand they intend to purchase; hence image of market share or market size is an important cue for online shopping. It greatly influences consumer’s purchasing decision, and thus is essential for us to explore how an image of prior market share impacts its market performance.

Consumers often evaluate the value of a product by searching its online information, which includes price, online rating, quality ranking, etc. Quality of a brand refers to consumer’s perception of the brand, and such perception is affected by price (Li & Hitt, 2010) and the innovativeness of the brand. The online rating and comments greatly affect consumers’ perception about a product’s quality.

4.1.3. Network externalities (e-WOM in social media)

Word-of-mouth (WOM) is an influential driver that can affect consumers’ perception of a product (Yang, Hu, Winer, Assael, & Chen, 2012) and promote product diffusion (Rogers & Olaguera, 2003). However, conventional WOM is only effective within limited social communication margins, and the influence weakens quickly over time and space (Bhatnagar & Ghose, 2004). The online review (e-WOM) plays a more important role in consumers’ purchase decision as the online communities become more prevalent and “permanent”. Consumers can easily access the online reviews in social network to attain first-hand information about the product (Lee, Park, & Han, 2008). The empirical research literature also suggests that there exists a positive relationship between e-WOM and sales performance (Clemons, Gao, & Hitt, 2006; Duan et al., 2008; Li & Hitt, 2008).

Network externalities indicate that the value of a product to a consumer changes with the number of other consumers who adopt this product. Namely, the more adopters in one’s neighbor nodes within online social network, the more likely he/she is motivated to adopt the product. The effect of network externalities depends on the structure of the social network; the more connections (links) it has, the more information is spread. Barabási and Albert (1999) and Newman (2003) indicate that the structure of WWW and friendship network is a scale-free network, which has a short average path length and a large network clustering coefficient, and its degree distribution obeys the power law.

4.2. Agent and agents in the s-commerce

As a computational method, agent-based modeling enables a researcher to create, analyze, and experiment with the models. The
models are composed of interacted agents within an environment. Agents are either separate computer programs or distinct parts of a program used to represent social actors such as individuals or organizations (e.g., firms, or bodies (government, nation-states)). An agent has four leading features: autonomy, sociability, reactivity and proactivity (Gilbert, 2008). Agents are programmed not only to react to the located computation environment, but also can pass information to one another and act on the relevant messages.

In our model, we let an agent as a consumer who may purchase from B2C site, is embedded in social networks and connected with other agents/consumers. Consumers within each group are heterogeneous in personal characteristics. We categorize different consumer agents’ sensitivity to innovativeness, price and social norm in Table 2. To replicate potential shoppers, we simulate consumers based on the probability distribution defined by Rogers and Olaquera (2003): innovators (2.5 percent), early adopters (13.5 percent), early majority (34 percent), late majority (34 percent) and laggards (16 percent). The relative size of these adopter groups can be easily modified to represent the true ratio.

### 4.3. Agent adoption decision rule

Agent j’s decision to accept brand i at time t depends on the evaluated value \( V_j^i(t) \) the agent receives from adopting the brand \( i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \), evaluated value from other brand \( V_j^{i-1}(t) \) and the threshold value \( V_{j, \text{min}}(t) \) of this agent. The agent will adopt the product or service if both conditions below can be satisfied,

(a) \( V_j^i(t) > V_j^{i-1}(t) \), i.e. \( V_j^i(t) = \max \{ V_j^1(t), V_j^2(t), \ldots, V_j^n(t) \} \).

If \( V_j^i(t) < 0 \), then we set \( V_j^i(t) = 0 \);

(b) \( V_j^i(t) > V_{j, \text{min}}(t) \), i.e. \( V_j^i(t) \) should be larger than the utility threshold, \( V_{j, \text{min}}(t) \), designated by agent j.

\[ V_j^i(t) = \psi_j + Z_j^i(t) + (1 - \psi_j) * V_j^i(t) \]  

where \( \psi \) is a weight. \( Z_j^i(t) \) is the perceived value by agent j who adopts brand i at time t. It is complementary to agent j’s perceived value from network externalities \( V_j^i(t) \) at time t.

\[ Z_j^i(t) = \beta_j^i(t) * q_j^i(t) - d_j^i(t) * p_j^i(t) - s_j^i(t) + (1 - \sigma(t)) \]  

The value of each variable in Eq. (8) is from 0 to 1, where \( \beta_j^i(t) \) is agent j’s sensitivity to the perceived quality of product i at time t. Similarly, \( q_j^i(t) \) is his sensitivity to perceived innovativeness of product i, \( d_j^i(t) \) is the discount of product i, and \( p_j^i(t) \) is a normalized price which equal with price divided by maximum price. In addition, \( q_j^i(t) \) is agent j’s perceived quality on product j at time t:

\[ q_j^i(t) = \text{fun}(t^i(t - 1), \delta(t)) \]  

After the consumer experiences the product, she posts the opinions and ratings online. Let \( r_j^i(t - 1) \) be the rating of product i given by agent j at time \( t - 1 \):

\[ r_j^i(t - 1) = \text{Min}(\text{Max}(0, \text{Min}(1, q_j^i(t - 1) - b(p_j^i(t - 1) - r(q_j^i(t - 1))))) - 5) \]  

The value of \( r_j^i(t - 1) \) is from 0 to 5, the parameter b captures the strength of the price effect (0 < b < 1), and \( r(q) \) denotes the reasonableness of the price given the perceived product quality q.

\[ r(t - 1) = \text{average}(\sum_j r_j^i(t - 1)) \]  

We denote the price of product i at time t as \( p_j(t) \), which is derived from Eq. (6). The innovativeness of product i is denoted as \( \sigma(t) \).

Barabási (2009) believes the real-world has scale-free network structures. Similar to the simulation study conducted by Schramm et al. (2010) and Van Eck, Jager, and Leeflang (2011), our network is a fixed structure (indicating no changes in links among agents) resided by agents. It is a preferential attachment network (i.e. scale-free network). Thus, the \( Y_j^i(t) \) in Eq (1) can be defined as:

\[ Y_j^i(t) = \frac{\sum_{j=1}^{m} \omega(\text{type}(j), k) \text{adopted_neighbour}_{jk}^i(t)}{\sum_{j=1}^{m} \text{neighbour}_{jk}^i(t)} \]  

Where \( \text{adopted_neighbour}_{jk}^i(t) \) is the number of agent j’s direct neighbors, who belongs to type k adoption group at time t, and have
pressed as contrary, the value of ω is a weight function, which can be expressed as

\[
\omega(type(j), k) = \begin{cases} 
  \text{very high} & \text{if } \left| \text{type}(j) - k \right| = 0 \\
  \text{high} & \text{if } \left| \text{type}(j) - k \right| = 1 \\
  \text{medium} & \text{if } \left| \text{type}(j) - k \right| = 2 \\
  \text{low} & \text{if } \left| \text{type}(j) - k \right| = 3 \\
  \text{very low} & \text{if } \left| \text{type}(j) - k \right| = 4 
\end{cases}
\]

In our model, we set ω as a constant, i.e. ω = \{1, 0.8; 0.6; 0.4; 0.2\}.

As a key indicator of competitive market performance, market share is defined as the percentage of market dominated by a specific entity. A seller’s market share depends on actions of other seller (Bell, Keeney, & Little, 1975). We define market share of online brand i (\(M_{si} \)) as follows,

\[
M_{si}(t) = \frac{\sum_{j} \text{isNew\_adopted}_i^j(t)}{\sum_{ij} \text{isNew\_adopted}_i^j(t)}
\]

Where isNew\_adopted_j^i(t) is a two-value function, when agent j begins to adopt brand i at time t, the isNew\_adopted_j^i(t) is 1. On the contrary, the value of isNew\_adopted_j^i(t) is 0 when agent j was not adopt brand i, or it is not first time to adopt band i.

5. The simulation study

5.1. Simulation flow

We develop an agent-based model to validate the proposed evolution model for consumers’ adoption decision, and to explore how knowledge impacts market share of online brands. When the simulation clock advances one time unit, consumers will make the purchase decision and trigger the choice event based on their value of utility. Consumers can retrieve product or brand information in e-commerce, and also obtain e-WOM from their social network. After the simulation clock starts, the simulation system will run continuously until the stop condition is met. Fig. 3 gives the simulation flow diagram. The simulation model was developed on a standard Lenovo laptop (Intel core i5-3230 M, CPU 2.6 gigahertz, and 4.00 gigabyte of RAM), with Microsoft Windows 8 operating system on Netlogo 5.0 environment. The interface of simulation system is shown in Fig. 4. All computational experiments were conducted in the same environment. Same as Jiang & Ma (2014) and Stummer, Kiesling, Günther, & Vetschera, 2015, for each scenario, we performed 50 replications. Table 3 summarizes the parameter settings for the simulation.

5.2. Validation through numerical experiments

Given that ABMs involve many parameters, the validation of ABMs is a challenging task (Fagiolo, Moneta, & Windrum, 2007; Yilmaz, 2006). Following Stummer et al. (Stummer et al., 2015), we perform conceptual validation, internal validation, micro validation, and macro validation to test our model.

Grounding in the conceptual framework for innovation diffusion by Rogers (Rogers & Olaguera, 2003), scale-free network, and other established theory, conceptual validation of our model is achieved.

In order to do internal validation, the simulation system was well tested to assure the system conformance with conceptual model. We first do unit test to test only some unit or sub-function, and then perform integration test in which the interaction between two or more “units” is explicitly tested. We also use extreme case to ensure simulation system working correctly (e.g. negative price, innovativeness, and other incorrect parameters).

There are two things toward establishing micro-level validity. Firstly, we carefully examined the empirical and secondary data used for parameterization. The other is that individual behavior data of agents are recorded by system logs, the data was analyzed to verify that individual agent decisions are reasonable and conform to results from the surveys and established theory.

We use the online refrigerator market in China as a base case to macro validates the proposed simulation model. The default settings for the parameters are given in Table 3 and the details of the consumer agents and environmental parameters used for the simulations can be found in Table 4.

The monthly market shares of six leading competing online refrigerator brands are extracted from http://www.enfodesk.com. It includes two high-end brands (brands 1 & 2), two mid-range brands (brands 3 & 4) and two low-end brands (brand 5 & 6). These brands are sold by top Chinese B2C e-tailors, such as 1mall (http://www.yhd.com), TMall (http://www.tmall.com), Jindong (http://www.jingdong.com), and Suning (http://www.suning.com).

Fig. 5a (5b) displays the actual (simulated) market share of brands. The summary statistics of the simulation results of Model 1 are shown in Table 5, where brands 3 and 5 have the highest market share, while brands 2 and 6 have the lowest market share. The parameters of the reference model (model 1 in Table 4) are set based on actual market shares of the six brands, and research and industrial reports from iResearch (2013). It reports that 72.6 percent shoppers are able to find merchandise information from e-commerce sites; 62.5 percent consumers recommend online shopping experiences to their friends; and 64.9 percent prefer to search novelty brand or information online.

In Fig. 5, we find that the ranks of the six brands’ actual market shares and that of the simulated ones are the same. ANOVA results
Table 3
The parameter settings.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of agents</td>
<td>500</td>
<td>Based on empirical data ([iResearch, 2013])</td>
</tr>
<tr>
<td>Weight of self-perceived value from evaluating brand-related information</td>
<td>$N(\mu, \sigma) = N(0.726,0.1)$</td>
<td>Based on empirical data ([iResearch, 2013])</td>
</tr>
<tr>
<td>Weight of perceived value from network externalities</td>
<td>$N(\mu, \sigma) = N(0.625,0.1)$</td>
<td>Based on empirical data ([iResearch, 2013])</td>
</tr>
<tr>
<td>Percentage of innovators, early adopters, early majority, late majority, &amp; laggards</td>
<td>2.5 percent, 13.5 percent, 34 percent, 34 percent, &amp; 16 percent</td>
<td>Based on Rogers’ innovation adoption theory ([Rogers &amp; Olaguera, 2003])</td>
</tr>
<tr>
<td>Percentage influence by each of the respective adoption types</td>
<td>0.975, 0.84, 0.50, 0.16, 0.025</td>
<td>Innovators and early adopters are opinion leaders, who would prefer to adopt novelty ([Rogers &amp; Olaguera, 2003])</td>
</tr>
<tr>
<td>Innovativeness of brands</td>
<td>0.8, 0.7; 0.9; 0.8; 0.85; 0.7</td>
<td>From market share</td>
</tr>
<tr>
<td>Discount of brands’ price</td>
<td>0.92; 0.87; 0.990; 0.83; 0.85</td>
<td>From secondary data</td>
</tr>
<tr>
<td>Initial rate</td>
<td>4.12; 3.96; 4.10; 4.05; 3.85; 3.55</td>
<td>From secondary data</td>
</tr>
<tr>
<td>Prior market share of brands</td>
<td>0.01; 0.08; 0.37; 0.17; 0.01; 0.09</td>
<td>From secondary data</td>
</tr>
</tbody>
</table>

Table 4
Initial values of parameters used for the simulation models.

<table>
<thead>
<tr>
<th>Model#</th>
<th>Innovativeness of brands</th>
<th>Initial brands image of market share</th>
<th>Weight of self-perceived value $N(\mu; \sigma)$</th>
<th>Weight of perceived e-WOM $N(\mu; \sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.8</td>
<td>0.7</td>
<td>0.9</td>
<td>0.89</td>
</tr>
<tr>
<td>2 (a)</td>
<td>0.8</td>
<td>0.7</td>
<td>0.65</td>
<td>0.85</td>
</tr>
<tr>
<td>2 (b)</td>
<td>0.65</td>
<td>0.9</td>
<td>0.65</td>
<td>0.85</td>
</tr>
<tr>
<td>2 (c)</td>
<td>0.8</td>
<td>0.85</td>
<td>0.9</td>
<td>0.85</td>
</tr>
<tr>
<td>3 (a)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0</td>
<td>0.08</td>
</tr>
<tr>
<td>3 (b)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.15</td>
<td>0.37</td>
</tr>
<tr>
<td>3 (c)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>0.17</td>
</tr>
<tr>
<td>3 (d)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>0.11</td>
</tr>
<tr>
<td>3 (e)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>0.09</td>
</tr>
<tr>
<td>4 (a)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.15</td>
<td>N(0.05;0.1)</td>
</tr>
<tr>
<td>4 (b)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>N(0.05;0.1)</td>
</tr>
<tr>
<td>4 (c)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>N(0.05;0.1)</td>
</tr>
<tr>
<td>4 (d)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>N(0.05;0.1)</td>
</tr>
<tr>
<td>4 (e)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>N(0.05;0.1)</td>
</tr>
<tr>
<td>4 (f)</td>
<td>Same as Model 1</td>
<td>0</td>
<td>0.05</td>
<td>N(0.05;0.1)</td>
</tr>
</tbody>
</table>

Note that: "Weight" is the proportion (percentage) of agent’s exposure to online information (price, rating, quality ranking, etc.), while 1-weight is the proportion (percentage) of agent’s exposure to e-WOM in social media. The parameters in Model 1 are from the actual data reported in: [http://report.iResearch.cn/1868.html](http://report.iResearch.cn/1868.html) and [http://www.enfodesk.com](http://www.enfodesk.com). It serves as a base model for reference.

Table 5
Descriptive statistics of Model 1’s simulation results.

<table>
<thead>
<tr>
<th>Brand #</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand_s1</td>
<td>0.06</td>
<td>0.21</td>
<td>0.13</td>
<td>0.05</td>
</tr>
<tr>
<td>Brand_s2</td>
<td>0.02</td>
<td>0.08</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>Brand_s3</td>
<td>0.18</td>
<td>0.45</td>
<td>0.36</td>
<td>0.08</td>
</tr>
<tr>
<td>Brand_s4</td>
<td>0.10</td>
<td>0.22</td>
<td>0.18</td>
<td>0.04</td>
</tr>
<tr>
<td>Brand_s5</td>
<td>0.11</td>
<td>0.43</td>
<td>0.22</td>
<td>0.08</td>
</tr>
<tr>
<td>Brand_s6</td>
<td>0.02</td>
<td>0.13</td>
<td>0.07</td>
<td>0.04</td>
</tr>
</tbody>
</table>

5.3. Sensitivity analyses

We now conduct experiments to examine how innovativeness, brand’s image (customers’ perception of a brand’s prior market share), self-perceived value, and e-WOM (network externality) impact the diffusion of multiple brands competing online. The simulation results are summarized in Table 7–10.

5.3.1. Innovativeness on market share

To test the effect of brand innovativeness on market share, we vary the innovativeness of two brands at a time in Model 2 (see Models 2a-c in Table 4). As brands 3 & 5 belong to the highest innovative class, we vary them together in Model 2a. Similarly, Brands 1 & 4 are
altered jointly due to their medium innovativeness (Model 2b); and brands 2 & 6 are changed together due to low innovativeness (Model 2c). In Table 4 model 2a, the innovativeness of brands 3 & 5 are reduced to (0.65, 0.65); other parameters remain at the same level as Model 1. The ANOVA in Table 7 shows that brand innovativeness has a significant effect on market share (p-value < 0.01) for all brands in Model 2a. The market share of brand 3 decreases from 0.36 in model 1 to 0.21 in Model 2a, while that of brand 5 drops from 0.22 to 0.08, indicating lower innovativeness hurts market performance.

In Table 4 Model 2b, we reduce the innovativeness of brands 1 & 4 to 0.65. Compared with the market shares of brand 1 (0.13) and brand 4 (0.18) in Model 1, their shares have significantly decreased to 0.06 and 0.08 respectively (Table 7, Model 2b). Similarly, Model 2c increases the innovativeness level of brand 2 & 6 to 0.85, the market shares of which have significantly increased from (0.04, 0.07) to (0.09, 0.12) respectively.

Similar to the literature on Brick and Mortar firms, we find from Table 7 that innovativeness of an online brand is highly correlated with a brand’s market performance under s-commerce. A brand can gain market share by improving its innovativeness, and novel firms will derive competitive advantages both online and offline.

| Table 6 |
| ANOVA test for the simulated results and the real-world data. |
| Sum of square | df | Mean square | F | Sig. |
| Brand1 Between-group | .001 | 1 | .001 | 0.693 | 0.414 |
| Within group sum | .043 | 22 | .002 |
| Brand2 Between-group | .001 | 1 | .001 | 3.120 | 0.091 |
| Within group sum | .008 | 22 | .000 |
| Brand3 Between-group | .000 | 1 | .000 | 0.045 | 0.834 |
| Within group sum | .130 | 22 | .006 |
| Brand4 Between-group | .005 | 1 | .005 | 3.989 | 0.058 |
| Within group sum | .025 | 22 | .001 |
| Brand5 Between-group | .000 | 1 | .000 | 0.031 | 0.862 |
| Within group sum | .145 | 22 | .007 |
| Brand6 Between-group | .004 | 1 | .004 | 4.096 | 0.055 |
| Within group sum | .023 | 22 | .001 |

| Table 7 |
| Innovativeness vs. market share (Model 2a-c). |
| Model # | Brand 1 | Brand 2 | Brand 3 | Brand 4 | Brand 5 | Brand 6 |
| Mean(SD) | p | Mean(SD) | p | Mean(SD) | p | Mean(SD) | p | Mean(SD) | p | Mean(SD) | p |
| 1 | 0.13 (0.05) | - | 0.04 (0.02) | - | 0.36 (0.08) | - | 0.18 (0.04) | - | 0.22 (0.08) | - | 0.07 (0.04) | - |
| 2a | 0.23 (0.07) | 0.001 | 0.09 (0.02) | 0.000 | 0.21 (0.06) | 0.000 | 0.28 (0.09) | 0.002 | 0.08 (0.04) | 0.000 | 0.12 (0.04) | 0.006 |
| 2b | 0.06 (0.05) | 0.003 | 0.08 (0.03) | 0.001 | 0.36 (0.07) | 0.86 | 0.08 (0.03) | 0.000 | 0.33 (0.1) | 0.009 | 0.05 (0.04) | 0.176 |
| 2c | 0.12 (0.06) | 0.62 | 0.09 (0.04) | 0.002 | 0.28 (0.06) | 0.006 | 0.17 (0.05) | 0.699 | 0.22 (0.07) | 0.918 | 0.12 (0.06) | 0.01 |
5.3.2. Brand image on brand market share

To test whether image (perceived prior market share) has impacts on the adoption of a brand, we conducted experiments using Models 3a-b. In Table 4 Model 3a, the consumers have no impression of brands’ prior market share, while consumers in Model 3b have partial (inaccurate) perceptual information. Table 8 shows that except for brand 5, the market shares differ significantly between models 1 and 3a (p-values < 0.002) is.

We find the larger the gaps of a brand’s image are from Model 1, the greater the differences in market shares are. Specifically, Model 3b shows that market shares of brand 2 (changed from 0.04 to 0.08) and brand 6 (changed from 0.07 to 0.16) have significantly improved. Brand’s image has significant impacts on market share. This explains why brands with less innovativeness at times disseminate exaggerated market information through market campaign.

Brand image/reputation is of critical importance as it impacts consumers’ purchasing decisions and brands’ market performance. To innovative firms, if biased information is presented by competitors, the dynamic market cannot automatically recover from it through consumers’ perceptual knowledge on firm (image). Therefore, an extrinsic mechanism needs to be developed to rectify the incorrect/unfair brand perception and restore its reputation.

5.3.3. Self-perceived utility and e-WOM on market share

In Models 4a-c, we test if lower self-perceived utility results in lower adoption rate and market share. We also test if e-WOM has such effects using Models 4d-f.

Lower self-perceived utility

In Table 4 Models 4a-c, we set the weight of self-perceived utility (the chance of exposure to online information, e.g. price, online rating, quality ranking) to be less than that of e-WOM (the rightmost column). From models 4a-c in Table 5, we find market shares of many brands are significantly different from that in model 1. We can conclude that low weight of self-perceived utility (relative to e-WOM) has negative effect on the market share of innovative brands (brands 3 & 5); and even if e-WOM increases, the market share will not increase. For low innovative brand (brand 2 & 6), we find marketers should promote through e-WOM (social media) extensively, and aggressively develop new client market.

Lower weight of e-WOM

Alternatively, in Models 4d-f, the weight of self-perceived utility is greater than that of e-WOM. It means that consumers mainly depend on self-derived perception toward the brand’s value, and has little exposure to e-WOM. The simulation result in Table 10 shows that higher weight on self-perceived value and lower weight on e-WOM have positive effect on mid- and high-end brands, and have negative effect on low-end brands. Thus, pushing valuable online information to customers of the mid- and high-end brands can moderate the effects of negative e-WOM. Marketers of mid- to high-end brands should increase shoppers’ exposure to online product information (e.g. quality, price, online rating), and give them the incentive to circulate the positive e-WOM through social media.

6. Discussions and conclusions

Many researchers have studied innovation diffusion. However, most models developed hitherto focus on single product and are subject to strict assumptions. Very few have paid attention to multiple brands online competition. To address the gap between complex collective dynamics in online market and existing innovation theory, we develop an agent-based simulation model based on real-world data. The proposed simulation model can fairly accurately predict online market share of multiple brands under e-commerce.

The contributions of this research are twofold. First, the proposed agent-based simulation model advances the study of innovation diffusion of multiple brands. Second, the simulation experiments provide insights to the roles of knowledge in online brand competition. Managers can thus better understand the impacts of knowledge and develops fitting strategies to improve brand success.

Innovation improves technology and service. Technology innovation, which enhances efficacy, ease of use and other functional characteristics, can significantly impact the quality and price of products. Similarly, service innovation for online products plays an important role in market share (Miles, 1993). Online consumers are
Concerned about delivery time, quality, trustworthiness of recommendation, and responsiveness to customer questions. When brands do not outperform in technology, they may excel in services innovation to win the game. Our findings suggest innovation is positively associated with market share. Despite conventional emphasis on market promotion and WOM in the social media era, innovation is in fact the most powerful tool to gain competitive advantage.

Personality traits, knowledge and social connectivity are important factors that influence consumer adoption decisions (Goldenberg, Han, Lehmann, & Hong, 2009). However, the extant literature focuses on connectivity, network structure and hubs. None has systematically investigated the role of knowledge among heterogeneous consumer agents. We consider four factors: innovativeness, image (market share); self-perceived utility from online information; and network externalities (e-WOM). We investigate how such factors influence consumers’ decision on online shopping and explore the relationship of self-perceived utility and e-WOM.

We find that image (market share) has significant effect on brands’ market performance. When customers do not have enough prior knowledge about the brand image or reputation (market share), the market share of brands differs from that with complete information (knowledge). Thus, marketers of successful brands should disseminate timely the actual market information to all potential buyers by mass media; offer incentives to repeat customers, and inspire them to spread brand knowledge to their friends.

Self-perceived utility from online information and perceptual knowledge from e-WOM have effects on some brands. Different brands should adopt different brand strategy. For example, the mid- and high-end brand marketers should increase customers’ exposure to online product information, and then incentivize them to spread positive WOM through social media. Alternatively, low-end brands should promote sale by using e-WOM to persuade potential consumers to purchase. Brands with high innovativeness can easily gain market shares by means of stronger e-WOM. An advisable path for low-end brands with low innovativeness is to target the products to special interest group customers.

These findings are valuable for marketers since they help to understand the roles of knowledge in online brand competition, as well as to adjust strategies for winning market share. Our study suggests that innovativeness is critical for winning market share for online brand. The self-perceived utility and network externality (e-WOM) impact consumers’ online shopping decision at various degrees. When consumers have more self-perceived knowledge, e-WOM would positively impact a product’s market share. Therefore, marketers should not only rely on social media to promote the brands. They should not only focus on website design (attending to structure, navigation, visual landscape, functionality, interactivity, and overall experience), but also frequently update (publish) valuable online information to provide timely incentive to attract customers.

7. Limitations and further research

Although our models have predicted market share of online brands well and provided insights to online brands competition, there are some limitations in this study. First, because we only have average monthly market share rather than daily market data, the limited samples might result in bias in data fitting, and influence the simulation model. Future study with daily data or weekly data may help validate the simulation model better, and more accurately predict online market share of multiple brands in the competitive market.

Second, we do not have dynamic innovativeness data directly associated with market share. Hence, we cannot identify the relationship between dynamic innovation and market share. Future research should explore the impact of dynamic innovation on market share empirically or through simulation.

Finally, the pricing scheme developed in this research is from the perspective of multi-period revenue optimization. Other pricing models such as customized bundling and online auction may be employed in the future. Through different pricing models, we can study how different pricing strategies impact customers’ image or perception on brand, and how various pricing strategies influence consumer online purchase decisions.

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Appendix

For Eq. (2), let $\frac{\partial u}{\partial p(t)} = -2\beta u(t) - \psi \lambda_x + \lambda_p = 0$. Then we have

$$u(t) = -\frac{\psi}{2\beta} \lambda_x + \frac{1}{2\beta} \lambda_p.$$  

From Eqs. (1), (4), (5), we find

$$p'(t) = -\frac{\psi}{2\beta} \lambda_x + \frac{1}{2\beta} \lambda_p + \frac{\psi}{2\beta} (p(t) - c) - \frac{1}{2\beta} \pi(t).$$  

Taking the derivative of (A1), we have

$$p''(t) = -\frac{\psi}{2\beta} \pi(t) - \frac{1}{2\beta} \pi'(t) = \frac{\psi}{2\beta} (p(t) - c) + \frac{1}{2\beta} \eta(t).$$  

Taking the integral of (A2), we have

$$p''(t) - \frac{\psi}{2\beta} p(t) = -\frac{1}{2\beta} (\eta(t) + \pi(t)) t - c_1.$$  

The equation above is a 2nd-order linear nonhomogeneous differential equation with constant coefficients. Its solution can be obtained by the method of undetermined coefficient as fellow,

$$p''(t) = c_1 e^{\frac{\psi}{2\beta} t} - c_2 e^{\frac{-\psi}{2\beta} t} + \frac{1}{2\psi} (\eta + \pi(t)) t - \frac{\beta}{\psi} c_1.$$  

Let $t = 0$ for (A4), then we have

$$p_0 = p(0) = c_1 + c_2 - \frac{\beta}{\psi} c_1.$$  

Taking the derivative of (A4), we find

$$p'(t) = c_1 e^{\frac{\psi}{2\beta} t} \frac{\psi}{2\beta} - c_2 e^{\frac{-\psi}{2\beta} t} \frac{\psi}{2\beta} + \frac{1}{2\psi} (\eta + \pi(t)).$$  

From Eqs. (A1) and (A6), we have,

$$0 = u(T) = p'(T) = c_1 e^{\frac{\psi}{2\beta} T} \frac{\psi}{2\beta} - c_2 e^{\frac{-\psi}{2\beta} T} \frac{\psi}{2\beta} + \frac{1}{2\psi} (\eta + \pi(t)).$$  

and

$$p'(t) = c_1 e^{\frac{\psi}{2\beta} t} \frac{\psi}{2\beta} + c_2 e^{\frac{-\psi}{2\beta} t} \frac{\psi}{2\beta}.$$  

Let $t = 0$, then we have

$$p'(0) = c_1 \frac{\psi}{2\beta} + c_2 \frac{\psi}{2\beta}.$$  

Given (A1), let $t = 0$, then we have

$$p'(0) = \frac{\psi}{2\beta} (p_0 - c) - \frac{1}{2\beta} \lambda_p.$$
Combine (A9) and (A10), we find

$$c_{11} \frac{\varphi}{\beta} + c_{12} \frac{\varphi}{\beta} = \frac{\varphi}{2\beta} (P_0 - c) - \frac{1}{2\beta} x_0$$

(A11)

From (A7) and (A11), we have

$$c_1 = \frac{\varphi}{2\beta} (P_0 - c) - \frac{1}{2\beta} x_0$$

(A12)

$$c_{12} = \left[ \left( \frac{1}{2} (P_0 - c) - \frac{1}{2\varphi} x_0 \right) e^{\sqrt{T/T}} + \frac{j + \pi v}{2\varphi} \sqrt{T/\beta} \right]$$

Form (A4) and (A11)–(A13), we find

$$p^*(t) = \left[ \frac{\varphi (P_0 - c) - x_0}{(j + \pi v) t + x_0} \right] \left[ \frac{j + \pi v}{2\varphi} \sqrt{T/\beta} \right]$$

This completes the proof.

References


