Research on social e-commerce reputation formation and state-introduced model

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Abstract

Purpose – This paper aims to solve the problem of information overload and reduce search costs. It proposes a social e-commerce online reputation formation model and community state-introduced model. A system dynamics trend simulation has been run to capture the relationship among the sellers, buyers, social e-commerce platforms and external environment to obtain an online reputation.

Design/methodology/approach – Empirical research relating to social e-commerce reputation has been used to confirm the influencing factors in social e-commerce, and a conceptual framework is developed for social e-commerce reputation formation. Thereafter, a trend simulation is generated to classify the relationship among the factors based on system dynamics. Also, the improved algorithm for community detection and a state-introduced model based on a Markov network are proposed to achieve better network partition for better online reputation management.

Findings – The empirical model captures the interaction effect of social e-commerce reputation and the state-introduced model to guide community public opinion and improve the efficiency of social e-commerce reputation formation. This helps minimize searching cost thereby improving social e-commerce reputation construction and management.

Research limitations/implications – There is no appropriate online reputation system to be constructed to test the relationship proposed in the study for a field experiment. Also, deeper investigation for the nodes' attributes in social networks should be made in future research. Besides, researchers are advised to explore measurement for the reputation of a given seller by using social media data as from Twitter or micro blogs.

Originality/value – Investigations that study online reputation in the social e-commerce are limited. The empirical research figured out the factors which can influence the formation of online reputation in social e-commerce. An SD model was proposed to explain the factors interaction and trend simulation was run. Also, a state-introduced model was proposed to highlight the effect of nodes' attributes on communities' detection to give a deeper investigation for the online reputation management.

Keywords System dynamics, Online reputation, Social e-commerce, State-introduced model

Paper type Research paper

1. Introduction

Social media developed rapidly these years, which offers the potential to form a social- and customer-orientation environment from the traditional good-orientation (Kaplan and

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Haenlein, 2010). Essentially, social media means computer applications or mobile phone applications which was built on Web 2.0, and Web 2.0 refers to a construct as a stage for value co-creation (Kaplan and Haenlein, 2010). Consumers can also consult their online community to seek advice when they make purchase decisions. In this circumstance, consumers can be available to product information and others' experience and evaluations via various social media platforms (Liang and Turban, 2011). Individuals are the producers of online content (user-generated content) which is the basis of social media. Also, they can make more informed and precise purchase decisions (Huang and Benyoucef, 2013). With the participation of online consumers and development of social media, consumers can create much more value for the company, not only economic value but also intangible value which may include word of mouth, referees and feedback (Zhao *et al.*, 2016). In this social climate, traditional e-commerce had been transformed into social e-commerce.

The Pew Research Center reported that roughly eight-in-ten Americans are now online shoppers: 79 per cent have made an online purchase of any type, whereas 51 per cent have bought something using a cellphone, and 15 per cent have made purchases by following a link from social media sites. In other words, currently, nearly many Americans have made purchases directly through social media platforms as had engaged in any type of online purchasing behavior 16 years ago. With the development of Web 2.0 technologies, lots of companies are getting worthy feedback or advice for their products or services with engaging their customers in social networks (Hajli *et al.*, 2014). Most consumers would get informational support before making purchase decision in social e-commerce. They can get valuable information via communicating with others in social media or scanning others' reviews about the product they want to buy (Lin and Huang, 2013).

Research suggests that the leading reasons that consumers do not purchase online are related to online security and policy, and credibility of companies (Gefen, 2000). Trust plays a significant role both in physical stores and e-commerce contexts (Jones and Jones, 2008). As consumers with little trust for commerce websites or online sellers, they may have more perceived risk about making purchase decisions. In fact, online trust often serves as the only foundation on which consumers base their purchase decisions, due to lack of further detailed information about firms and products (Urban *et al.*, 2009; Aguirre E *et al.*, 2015). As early researchers suggested, "trust, more than technology, drives the growth of e-commerce in all its forms" (Gefen, 2000). In social e-commerce, trust is also a key for the success of customer retention and customer loyalty. It has been argued that reputation and feedback systems foster the trust needed, making consumers feel comfortable purchasing in anonymous markets. Many studies show that consumers respond to a seller's reputation in intuitive ways (Klein, 2017). Online reputation systems have been extended to various professional domains in which people seeking products or services can see ratings and read reviews posted by people who have interacted with professionals in the past. All of these types of online reputation systems can help individuals predict the future behavior of other users and reach tentative answers to questions they have. However, threats to information quality are inherent in online reputation systems. For example, a person being rated may engage in dishonest behavior to manipulate ratings. Hence, identifying factors which influence the online reputation is a significant problem to be solved. The operational mechanism between factors from different parties should be clarified.

Besides, consumers have long relied on advice and recommendations from others before making purchasing decisions, and Americans currently have access to a vast library of customer ratings and reviews that they can consult when deciding if products or services are worth their money. Hence, consumers can seek information in brand communities or other social media communities when they have uncertain about their purchase decisions.

PEW's survey shows that an extensive majority of the public now incorporates these customer ratings and reviews into their decision-making processes when buying something new: Fully 82 per cent of US adults say they at least sometimes read online customer ratings or reviews before purchasing items for the first time, including 40 per cent who say they always or almost always do so. For online sellers, how to handle and explore the community is a vital problem for them. The optimum of the exploration of a group and community under given indexes is an NP hard problem. The current structural evaluation index, proposed by Newman, is modularity, in which a higher value of modularity indicates a more distinctive feature of the structure in the corresponding group or community (Girvan and Newman, 2002). Therefore, the goal of improvement of community detection algorithm based on modularity criterion optimization is to obtain a greater value of modularity criterion. The currently adopted algorithm strategy includes top-down splitting algorithm, down-top merging algorithms and other hybrid algorithms (Du *et al.*, 2011). However, Beckett (2016) believed that the pure optimization of modularity is difficult, particularly when the network being detected had a large scale and higher complexity. As a result, approaches to obtain a faster optimization result of a large-scale network had become a focus in the study of detecting social network structures (Stephen, 2015).

Therefore, on the foundation of complex network of social media, this paper treated each individual as an independent node in the dynamic network of social media and classified the nodes into different groups and communities according to the attributes of the nodes. Furthermore, the status-introduction model based on time series process was established aiming to enable an enterprise to achieve an optimal layout by controlling the influencing level in a dynamic social media group and community and, consequently, to influence other nodes and achieve the intended purpose and desired effect.

2. Conceptual model and data analysis

To figure out the factors which can influence online reputation, empirical research and system dynamic analysis are used to simulate cumulative causation.

2.1 Online reputation model in social e-commerce

Reputation is what is generally said or believed about a person's or thing's character or standing (Sang *et al.*, 2007). Reputation can be regarded as a joint estimate of trustworthiness based on the referrals or ratings from members in a social media community. Obviously, in social e-commerce, buyers and sellers are the mainly members in the community, whereas they can interact with each other via the social media platform.

Fombrun (2001) mode comprehensively evaluates a company's reputation quotient by measuring the company's ability to provide value to its shareholders; six indicators are included, namely, company's charisma, product and service, social responsibility, vision and leadership, working environment and financial performance. Manfred (2004) split corporate reputation into two dimensions, a cognitive component called competence and an affective one called sympathy, covering four indexes of quality, responsibility, performance and attractiveness. The quality index included product quality, confidence/credibility, supreme service, reliability, respected level, customer orientation and value orientation. The responsibility index included fair play, information disclosure, sense of responsibility and view of reasonable profit. The performance index included strict management, stable environment, clear prospect, great growth potential and low operational risk. Attractiveness index included friendly working environment, excellent staff, strong attraction to loyal customers. Quality and responsibility were used to evaluate the perception of reputation during transaction, and performance are charisma were related to the company's strength reputation.

Companies' reputation means the extent to which a company is held in high esteem based on stakeholders' overall evaluation of the company (Fombrun *et al.*, 1990), and it may be regarded as a reliable bond between parties to a transaction, reducing transaction costs and customer perceived risk and increasing customer trust (Walsh *et al.*, 2007). In essence, building a strong reputation is a wisdom action that reduces customers' risks, as a good reputation is a signal of quality (Fombrun *et al.*, 1990). Also, Eisenbeiss *et al.* (2014) suggests that companies' reputation can be considered as a significant heuristic cue in consumers' post-purchase situations.

A number of operational definitions of corporate reputation have centered on the object specific components on which this overall evaluation is based, considering how well known a firm is; good or bad, reliable, trustworthy, believable and reputable (Brown, 1995; Hutton, 1997). Besides, companies' reputation can elicit a variety of favorable consequences for the company including the intention to purchase products (Grewal *et al.*, 1998). There is no doubt that consumers consider the reputation of the company before making a purchase decision (Zeithaml, 2000), also in social e-commerce the reputation of sellers should be considered. Thus, we derive the following hypothesis:

H1. In social e-commerce, sellers can influence online reputation formation.

From the perspective of a seller, the number of successful transactions, authenticity of the product description, value of accumulated reputation, value of favorable comment on service or product brand, seller's attitude and the speed of delivery can be used as effective measurements to evaluate the online reputation of social commerce.

Social e-commerce reaps its competitive advantage from the value of a product rather than from the price of the product. In social commerce, any person can play the role of a designer or a salesperson, not restricted to being a receiver of a certain product. Compared with the "broadcast" communication style of traditional e-commerce, social e-commerce focuses on user-generated content and relies on bilateral communication to realize infiltrated interpersonal communication and finally reaches a better persuasive effect of information.

Online reputation mechanisms have emerged as a viable alternative to the legal system in such settings in Resnick's research (Resnick *et al.*, 2000). Take e-bay for example: an online feedback mechanism that encourages buyers and sellers to rate one another seems to have succeeded in encouraging cooperative behavior in an otherwise very risky trading environment. Under social e-commerce circumstance, a user may have double roles as a buyer or as a seller and can switch the role. As a consequence, the reputation has two constituent parts corresponding to each of the roles: "selling reputation", coming from the previous selling records and "buying reputation", coming from the previous buying records (Zhang, 2006). We hypothesize that buyers can also influence the social e-commerce online reputation's formation. More formally:

H2. In social e-commerce, buyers can influence online reputation formation.

From the perspective of the consumer, amount of online shopping, authenticity of the sharing of shopping experience, credibility of product recommendation, value of accumulated reputation, quality of consumers and comment rates can be used as effective measurements to evaluate the online reputation of social commerce.

Perceptions about a specific object, are subject to the influence of individual's general attitudes and beliefs, also contextual factors through the mechanisms known as persuasion and social influence, for example, the privacy concerns on a social e-commerce website

(Wood, 2000). Extant studies show that a website's reputation can directly influence uses' privacy concerns and indirectly affect through the mediation of trust for the website (Kim *et al.*, 2008). In social e-commerce, it is resulted from the need of information exchange is necessary, which covers an economic contract and a social contract. We can easily find that some disreputable websites usually are smaller ones, which are scarcely ever the aims of the media for such misconduct, whereas it does not mean that they did a good performance than reputable companies in protecting privacy.

In social e-commerce, consumers may feel that reputable websites can operate consumer information with competence and commitment as a result of their common business practices, ethical standards and even the pressure from the media, whereas disreputable websites would lack the competence or commitment to protect users' privacy and other things (Li, 2013).

H3. In social e-commerce, platforms can influence online reputation formation.

From the perspective of a website platform, completeness of security system, reliability of fundamental design, convenience of interaction in communication and convenience of using the web site can be used as effective measurements to evaluate the online reputation of social e-commerce.

Taking China's largest online shopping platform Taobao as an example, the reputation system covered four indices: whether the description matches the product, the attitude of sellers, the speed of delivery and company's logic services. Customers can evaluate the four indices with a three-grade scale: positive, neutral and negative. Individual reputation and collective reputation constituted reputation. Collective reputation is the collection of individual reputations, and individual reputation will influence collective reputation. The social e-commerce website platform is composed of numerous online sellers, whereas the website provides a transaction platform and transaction service. It is the online sellers and customers between which the transaction actually is completed; therefore, the reputation of the website can be considered as collective reputation, whereas the reputation of each online seller should be regarded as individual reputation. Li's (2010) research indicated that there was a connection between individual reputation and collective reputation. The descended reputation had a fatal influence over the partnership or the cooperation among partners.

Reputation's influence over the trust of a website as well as online sellers has been proved by many scholars. Research revealed that the reputation of an online seller was closely connected to a customer's initial trust (Alon and Liat, 2004). Jarvenpaa *et al.* (2000) also found that the quality of a website was a powerful instrument to earn customer's trust. Extant studies showed that reputation was an important predisposing factor of s customer's trust during B2C transaction (McKnight *et al.*, 2002). Moreover, reputation could be transmitted to other customers, making them also believe the website and online seller was honest, reliable and fair, as a result, community trust was produced. We predict that sellers' reputation can have effect on social e-commerce platform reputation. More formally:

H4. In social e-commerce, sellers' reputation can influence platforms' reputation.

As extant studies suggest that shoppers care about the shopping environment and how the store atmospherics can significantly influence purchase decisions (Donovan *et al.*, 1994; Spies *et al.*, 1997), we believe that how to create an aesthetic website that can let consumers enjoy their online shopping environment is a critical. Some studies focused on the impact and influence of trusted third-party referees and their seals-of-approval as mediators for building online consumer trust (Head and Hassanein, 2002). Hence, such as third-party authentication, authoritative legal provision, ability to secure privacy can be used as effective measurements to evaluate the online reputation of social e-commerce. Hence, the perspective of external environment should be taken into considered. We derive the following hypothesis:

H5. In social e-commerce, external environment can influence reputation formation.

2.2 Data analysis

We collected data from 300 respondents on survey platform (www.sojump.com), which were subjected to factor analysis (maximum likelihood estimation) (Figure 1). We choose oblique rotation over orthogonal because the factors were highly correlated with one another (Vieira, 2011). The data could satisfy the factor analysis standard, and the Kaiser–Meyer–Olkin measure of sampling adequacy was ideal at 0.921, also Bartlett's test of sphericity was ideal ($\chi^2(300) = 6048.58$, $p < 0.001$).

The loadings onto each factor ranged as follows (Table I): sellers (0.736-0.823), buyers (0.785-0.875), social e-commerce platform (0.783-0.810), external environment (0.852-0.859) and interaction (0.874-0.981).

The analysis also supported the reliability and validity of our scale. The reliability of all factor scales was examined by internal consistency analyses; the Cronbach's alpha for sellers (0.823), buyers (0.846), social e-commerce platform (0.818), external environment (0.865), all indicated high internal consistency (Table II).

Maximum shared variance (MSV) and average shared squared variance (ASV) were both lower than the average variance extracted (AVE) for all factors demonstrating discriminant validity of the scale (Table III).

The model fitting is evaluated by model fitting level (χ^2/df), ACFI, RMSEA, χ^2 statistics, CFI, IFI, SRMR and NFI. By using AMOS 20.0, the actual values of fit indices are shown

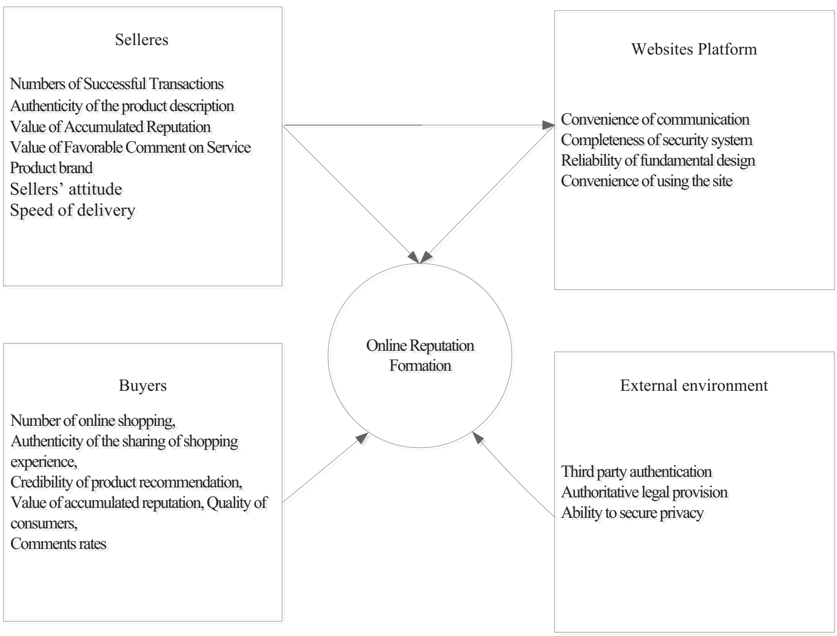


Figure 1.
Influencing model of online reputation in social commerce

Factor	Influencing factors of online reputation of social media commerce	Component 1	2	3	4
Sellers	Numbers of successful transactions	0.751			
	Authenticity of the product description	0.763			
	Value of accumulated reputation	0.748			
	Value of favorable comment on service	0.736			
	Product brand	0.788			
	Seller's attitude	0.823			
	The speed of delivery	0.819			
Buyers	Numbers of online shopping		0.836		
	Authenticity of sharing of online shopping		0.785		
	Credibility of product recommendation		0.786		
	Value of accumulated reputation		0.875		
	Comments rate		0.795		
Social e-commerce platform	Completeness of security system			0.798	
	Reliability of fundamental design			0.810	
	Convenience of interaction in communication			0.783	
External environment	Third-party authentication				0.852
	Authoritative legal provision				0.861
	Ability to secure privacy				0.859

Table I.
The factor analysis

Influencing factors	Indexes	Cronbach's α
Sellers	7	0.823
Buyers	5	0.846
Social e-commerce platform	3	0.818
External environment	3	0.865

Table II.
The reliability analysis

in Table IV. Structural equation modeling shows that the fit indicators of the model proposed by this study are acceptable, which presents that the model is consistent with data structure and have good validity.

To examine the statistical significance of the parameter used in the influencing model of online reputation formation of social e-commerce, a significance test of the path coefficient of the model is performed. The results are shown in Figure 2.

From Figure 2, we can see that sellers' factors, buyers' factors, social e-commerce platform and external environment was positively associated with social e-commerce reputation formation, which support *H1*, *H2*, *H3*, *H5*. Besides, seller's reputation can significantly have effects on social e-commerce platform reputation ($\beta = 0.21$, $p < 0.001$), which supports *H4*.

2.3 System dynamic trend simulation

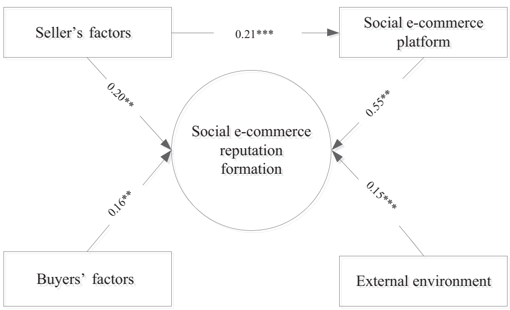
The above empirical research suggests that social e-commerce reputation formation is influenced by sellers, buyers, social e-commerce platform and external environment (Figure 3). Because the four objectives (sellers, buyers, social e-commerce platform and external environment) interact, we construct a causal interaction diagram with Vensim 6.3 based on system dynamic.

Table III.
Confirmatory factor analysis of the scale

Factor and items	AVE	MSV	ASV
Sellers	0.893	0.487	0.436
Numbers of successful transactions			
Authenticity of the product description			
Value of accumulated reputation			
Value of favorable comment on service			
Product brand			
Seller's attitude			
The speed of delivery			
Buyers	0.786	0.743	0.563
Numbers of online shopping			
Authenticity of sharing of online shopping			
Credibility of product recommendation			
Value of accumulated reputation			
Comments rate			
Social e-commerce platform	0.736	0.533	0.432
Completeness of security system			
Reliability of fundamental design			
Convenience of interaction in communication			
External environment	0.769	0.712	0.575
Third-party authentication			
Authoritative legal provision			
Ability to secure privacy			

Table IV.
Results of model fit indices

Fit indices	χ^2/df	NFI	CFI	IFI	SRMR	RMSEA
The actual value	1.698	0.923	0.989	0.943	0.051	0.056



Note: Only significant paths are shown here; $^{**}p < 0.01$; $^{***}p < 0.001$

Figure 2.
Conceptual model with standardized coefficient for each path

The system dynamic simulation is performed on Vensim; DT is set to 0.25 to discuss the trend of influence of online reputation in social commerce over a time span of two years.

Figure 4(a) shows the connection between the simulation sellers' factors and social e-commerce reputation, where 1 shows the trend of value of favorable comments on service,

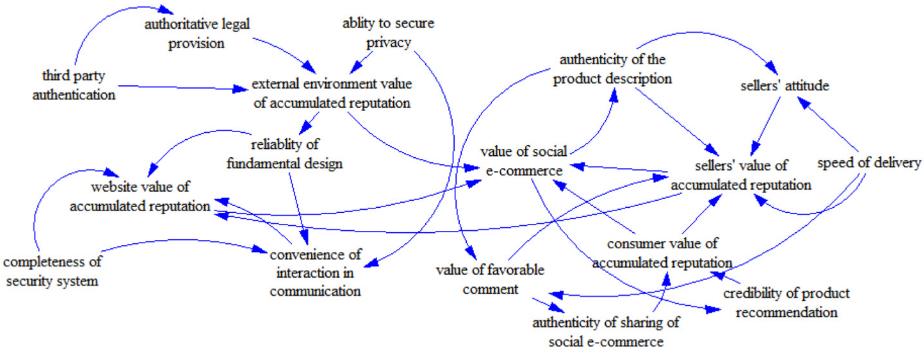


Figure 3.
Causal interaction diagram

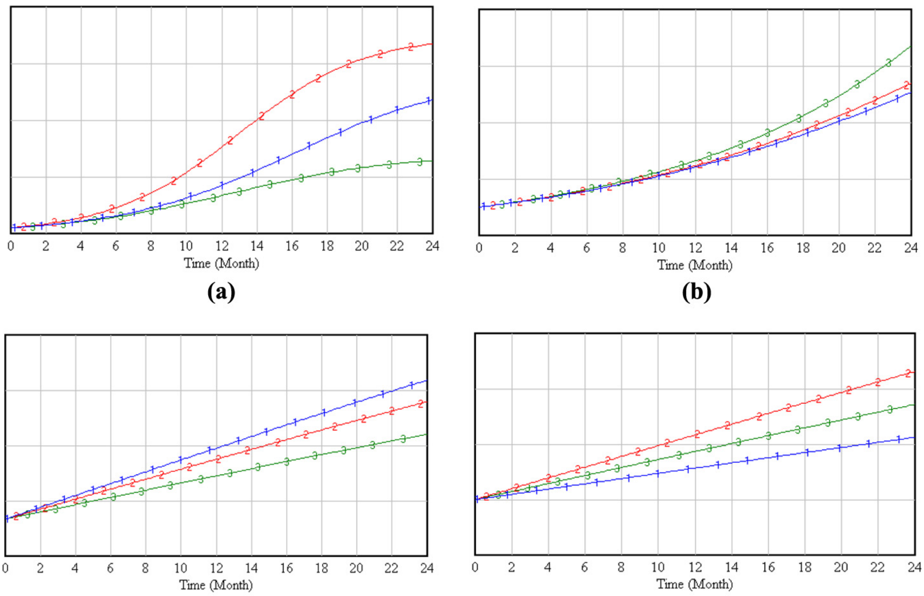


Figure 4.
Influencing trend of (a) seller, (b) buyers, (c) social e-commerce platform and (d) external environment

2 shows value of accumulated reputation and 3 shows authenticity of the product description. Within the duration of simulation, there is a significant rising trend in the online reputation of social commerce, influenced by the value of favorable comment on the service of online sellers, the value of accumulated reputation of online sellers and the authenticity of the product description of online sellers. This suggests that seller's reputation, service level and protection of consumer's privacy have confirmed influences on social e-commerce reputation.

Figure 4(b) shows the relation between the simulation of consumers' personal factors and online reputation, where 1 shows credibility of product recommendation, 2 shows the trend of authenticity of sharing on online shopping and 3 shows value of accumulated reputation.

In the span of the simulation, there is a significant rising trend in the online reputation of social commerce, influenced by credibility of product recommendation, authenticity of the sharing of online shopping experience and the value of accumulated reputation of consumer. This indicates that credibility of consumer's product recommendation, authenticity of sharing of online shopping experience and value of consumer's accumulated reputation have a perceivable influence on online reputation.

Figure 4(c) shows the association between the simulation of website factors and online reputation, where 1 shows the trend of security system completeness, 2 shows reliability of fundamental design and 3 shows convenience of interaction in communication. Over the period of simulation, there is a significant rising trend in the online reputation of social commerce, under the influence of security system completeness, reliability of fundamental design and convenience of interaction in communication. This means that the completeness of the website security system, the credibility of fundamental design and the convenience of interaction in communication have substantial influence on online reputation.

Figure 4(d) shows the connection between the simulation of web site factors and online reputation, where 1 shows the trend of ability to secure privacy, 2 shows authoritative legal provision and 3 shows third-party authentication. With time changes, in the length of time of simulation, there is a significant trend of rising in online reputation of social commerce, under the influence of authoritative legal provisions, third-party authentication and the ability to protect privacy. This means that authoritative legal provisions, third-party authentication and the ability to protect privacy have definite influences on online reputation.

3 State-introduced model and simulation

3.1 Community detection

Based on empirical research and system dynamic simulation, we find that buyers can seek information and advice from their own joined communities in social e-commerce. So the problem for the sellers or the platform is how to detect the community and the leading node is of great significance to manage the community and social e-commerce reputation. Also, the state-introduced model was established to optimize the communities' nodes distribution.

Community detection requires the partition of a network into communities of densely connected nodes, with the nodes belonging to different communities being few and scattered connected (Ferreira *et al.*, 2015). Accurate formulation of local optimization problem is obviously known to be computationally abstruse. Therefore, some arithmetic has been proposed to find reasonably efficient partitions in a fast way. Fast algorithms studies have attracted much interest lately owing to the growing applicability of large network data sets, as well as the impact of networks on daily life (Xin *et al.*, 2016) Many forms of community detection algorithms can be distinguished: divisive algorithms detect inter-community links and remove them from the network, agglomerative algorithms combine with similar nodes/communities recursively and optimization techniques are on the strength of the utility maximization of an objective function (Wang *et al.*, 2016). The quality of the partitions rooting in these techniques is often measured by the what is called modularity of the partition. The modularity of a partition is a scalar value between −1 and 1 that measures the density of links in the communities as compared to links between communities (Jakalan *et al.*, 2016). Considering the weighted networks, it is defined as (Hu *et al.*, 2016):

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j)$$

where A_{ij} represents the weight of the edge between i and j, $k_i = P_j A_{ij}$ is the sum of the weights of the edges attached to vertex i, c_i is the community to which vertex i is assigned, the δ-function $\delta(u, v)$ is 1 if $u = v$ and 0 otherwise and $m = \frac{1}{2}\sum_{ij} A_{ij}$.

As shown in Figure 5, each pass is composed of two steps: First, modularity is optimized by allowing only local changes of communities, then the found communities are aggregated to build a new entity.

The process can be described as follows:

3.1.1 Phase 1. Each node in initial network is taken as a community structure. Then destination nodes are chosen, and the sets which are made of their adjacent nodes are computed. Computing the gain of modularity in which node i is classified into its own community, then i is removed from its own community and put in the community of j; as a result, node i would be placed in the community in which the gain is maximum only when this gain is positive. Otherwise, node i would stay in its original community. After that, it is determined whether the ergodic has been terminated and a stable network community structure is obtained. If it does not meet the condition, the process is applied repeatedly and sequentially for all nodes, until no further improvement can be achieved and Phase 1 is then complete.

3.1.2 Phase 2. According to the new network whose nodes are the communities found during Phase 1, the weight of the new community is given by the sum of the links among nodes in the accompanying community. Then the sum of original nodes weights is computed in the new network. After that, the weights of new community and the new network comes into being. Meanwhile, Phase 1 restarts.

This algorithm is a community detection algorithm. Its essence is to make the same attribute node merge into the suitable community, and the process is re-expressing the network structure. While a kind of modularity optimization algorithm, its process of community merging only by controlling the node degree, neglects other nodes' message. As a consequence, in the process of actual network detection, only taking the modularity as the standard consolidation standard cannot be accepted. The process is faced with numerous

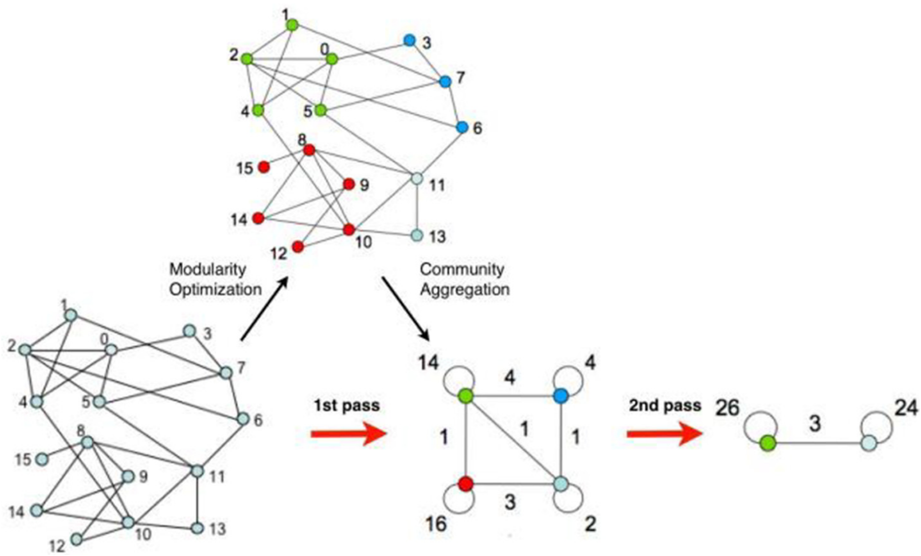


Figure 5.
Visualization of the steps of Blondel's algorithm

uncertainties. With the purpose of clearly revealing the feature of network structure and effectively distinguishing the nodes in community which possess the same attributes, it is necessary to bring in a priori knowledge such as the relative nodes' attributes into the process in community detection and merger.

$V = \{v_1, v_2, v_n\}$ are defined as n nodes in network, E is defined as the set of edges in network and $E = \{e_1, e_1, e_m\}$ denotes m links. $C = \{c_1, c_2, c_m\}$ denotes K communities into which the network is divided. First, adjacent matrix $M \in R^{n \times n}$, n is defined as the sum of nodes. The link relationship between two nodes is the value of element of matrix. That is to say, when the node i and node j have interlinkages, $M(i,j) = 1$, otherwise, $M(i,j) = 0$. And in general, G denotes the sparse matrix in social network. Subsequently, the attribution matrix is defined as $Q \in R^{k \times n}$ and the j^{th} rank of Q denotes node v_j membership degree in K communities. Hence, it can depict the structure and characteristic for raw information. Immediately following, the similarity matrix is defined as $S \in R^{n \times n}$, n is the sum of nodes. The value of an element is the index of similarity between the two nodes in similarity matrix, and it can describe attribute similarity between the nodes.

When just conlinkring the link structure information, the interlinkage between nodes in network invariably is negative, whereas the weights of links are nonnegative. Thus, it adopts nonnegative matrix factorization (NMF) as appropriate to community detection. What is more, basis vector matrix W which is divided by NMF shows the community features that reduce dimensional analysis of network and that it has sparsity and linear independence. Meanwhile, Q represents the degree of membership of corresponding node and community. Nonnegative matrix is defined in community detection as follows: Assume a certain single mode $G(V, E)$, whose adjacent matrix is $M \in R^{n \times n}$. By means of searching the maximum approximate net raw data M's a couple of low rank factor matrix can realize community detection. If Euclidean distance is applied, optimized objective function O^l (E) can be described as follows:

$$\min O^l(E) = \min_{W,H} \|A - NM\|_F^2$$
$$s.t.\ \ N \geq 0, M \geq 0,$$

In that, $\|\cdot\|_F$ is Frobenius norm (a F norm), which is used for measuring the degree of approximation; $N \in R^{n \times k}$ and $M \in R^{k \times n}$ are basis matrix and attribution matrix based on divisional node mode. n denotes node number in network, whereas r denotes clustering number of related mode node subspaces. That can reveal the number of communities in network G.

3.2 The model of status-introduction based on time-series processing

In our research, we establish the model of state-introduction on account of time series processes. We denote O are the whole leaf nodes, and X are all the parent nodes.

H1. The state variables evolve with the mode of Markov, which is described as follows:

$$\left(\boldsymbol{X}^{(t+1)} \perp \boldsymbol{X}^{(0:(t-1))} \middle| \boldsymbol{X}^{(t)} \right)$$

H2. In given time t, the introduced variables in time t are independent of the whole state sequence condition:

$$\left(\boldsymbol{O}^{(t)} \perp \boldsymbol{X}^{(0:(t-1))}, \boldsymbol{X}^{(t+1:\infty)} \middle| \boldsymbol{X}^{(t)}\right)$$

MOD:

$$\psi_{i,j}(o_{i,j}, o_{i,k}) \propto \exp\left\{\begin{array}{l} \sum_{j=1,\cdots,m} \boldsymbol{E}_{\{O_{i,j},O_{i,j+1}\}\sim Q}\left[In\,\phi_{(i,j)}(X_{i,j}, X_{i,j+1})|x_{i,j}, x_{i,k}\right] \\ +\sum_{j=1,\cdots,m+1} \boldsymbol{E}_{\{O_{1,j},O_{2,j+1}\}\sim Q}\left[In\,\phi_{(i,j)}(X_{i,j}, X_{k,j})|x_{i,j}, x_{i,k}\right] \\ -\sum_{j=1,\cdots,m} \boldsymbol{E}_{\{O_{1,j},O_{1,j+1}\}\sim Q}\left[In\,\psi_{(i,j)}(O_{i,j}, O_{i,j+1})|o_{i,j}, o_{i,k}\right] \end{array}\right\}$$

Among of them, the general form of Q is Gibbs parametric family.

If and only if:

$$\psi_j(o_j) \propto \exp\left\{\sum_{\phi\in \boldsymbol{X}_j} \boldsymbol{E}_{x\sim Q}[In\,\phi|o_j] - \sum_{\psi_k \in A_j}[in\,\psi_k|o_j]\right\}$$

Among of them:

$$X_j = \{\phi \in \Phi : Q| \neq (U_\phi \perp O_j)\}$$

$$A_j = \{\psi_k : Q| \neq (O_k \perp O_j)\} - \{O_j\}$$

U represents the scope, whereas Z represents the normalization constant. We can draw the conclusion that:

$$Q(X) = \frac{1}{Z_Q}\prod \psi_j$$

ψ_j is the local optimization. In this case, we can introduce the model.

3.3 Experimental results

Based on the model proposed above, experiments were conducted on the online social network. A total of 1,500 nodes in a brand community were chosen in a micro-blog; the nodes in original state are as shown in Figure 6(a). By means of the proposed model, the nodes can be seen as in a steady state as shown in Figure 6(b). Thus, the model is applicable.

This model (as A in Figure 7) is compared with Blondel's (as B in Figure 7). A is more stable than B, and the strategy adoption of A is much higher than B.

4. Discussion

Reputation plays an increasingly salient and active role for both brick-and-mortar and online businesses and tends to feature primarily in corporate communications literature (Albert *et al.*, 2010). The current study has several substantial contributions. First, the systematic literature review on online trust, reputation and social e-commerce in the introduction fills the gap in the social e-commerce reputation literature. The test on sellers,

Figure 6.
The results of experiment

Notes: (a) Original state; (b) steady state

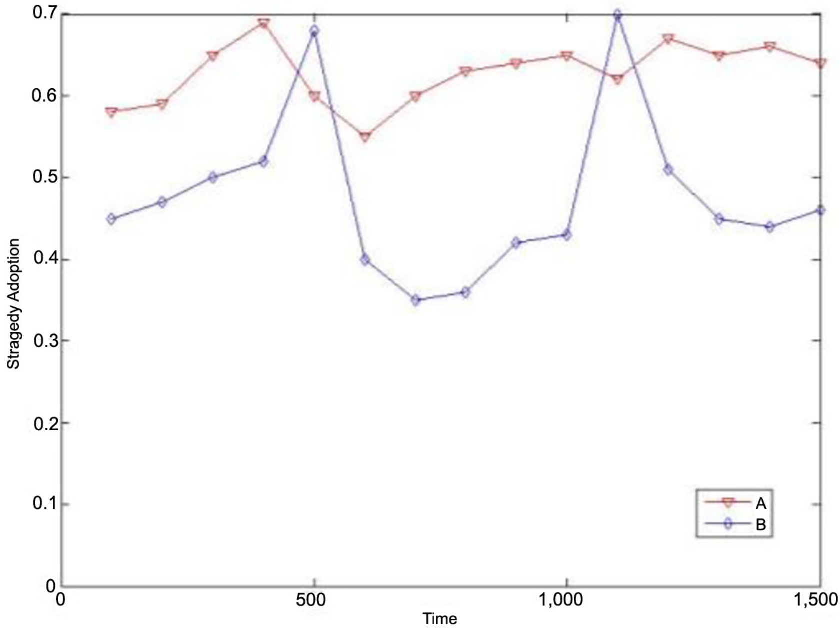


Figure 7.
The comparison of models

buyers, social e-commerce platforms and external environment's direct impact on social e-commerce reputation formation highlights its importance to online reputation, calling for more attention to this critical concept in further research. For example, sellers' attitude and speed of delivery play decisive roles in the development of sellers' online reputation, suggesting the need to study how the attributes from the four objectives interact within it. Second, system dynamic trend simulation fills the gap in social e-commerce reputation-simulated experiment research. The causal interaction map was constructed of the social e-commerce reputation formation based on the empirical research. The cause-and-effect graph clearly reflects the internal relations among the social e-commerce system. The findings are consistent with the results found by Manaman *et al.* (2016), who shows that various companies are willing to use these media to raise their reputation and, particularly, that comments on social e-commerce has either negative or positive impact on the company's reputation or product.

Additionally, taking the characteristics of social media into consideration, this paper has established a model of state-introduction on the analysis of the characteristics of network nodes. By introducing nodes' dynamic characteristics into a current community detection algorithm, this research, based on the analysis of the degree of the node, adapts the clustering coefficient as the reference index of node community central position. The influence of node attribute over community detection should not be overlooked because its influence is particularly noticeable in the variability of nodes' relative positions in the community. Nodes are taken as a Markov message source which evolves in Markov method, and the state-introduced model is established. Then the optimal solution has been given. Compared with node centricity, this research consummates the explanation of the position of community centricity and also provides a creative method to improve the algorithm of community detection. The model established takes advantage of a Markov network to yield the optimization. What is more, this model not only uses the property of Markov and expands the Markov Chain to Markov Network but also applies the model to guide community public opinion and improves the efficiency of social media marketing.

4.1 Implications of the study

This study has implications for theoretical development and practice. From the perspective of behavioral decision-making, it is critical to identify the factors that influence formation of social e-commerce reputation. The study confirms four sources of critical influences for social e-commerce reputation concerns, suggesting that both sellers (i.e. numbers of successful transactions), buyers (i.e. authenticity of sharing on online shopping), social e-commerce platform (i.e. authenticity of sharing on online shopping) and external environment (i.e. third-party authentication) should be included in consideration to construct a reputation in social e-commerce. In addition, the study shows that the significance of sellers' factors has an effect on social e-commerce platforms' reputation. Sellers' related factors must be taken into consideration seriously when a better social e-commerce reputation is to be built. Sellers in social commerce should apprehend the significance of the protection of consumers' privacy as well as others' sensitive information. To prohibit leakage of information, the limelight of protection should be on the security of online shopping information. Online sellers' ability to protect consumer's privacy should be supervised and certificated by third-party certification, which is in need of promotion and perfection.

Additionally, the proposed community detection algorithm and state-introduced model highlight the effect of nodes' attributes on communities' detection. Compared with Blondel's research, the degree of proportional relationship of nodes can clearly reveal the degree of relationship between nodes and community.

4.2 Future directions

In future research, some questions could be addressed related to the design of reputation systems' framework for social e-commerce service, such as the optimal amount of information to be shown to users in the social e-commerce. The other related research direction is to explore measurement for the reputation of a given seller by using social media data, such as from Twitter or microblog. Future research can apply some mechanisms to match the microblog with sellers by use of N-Gram (a language-independent method) together with other classification methods such as support vector machine.

With the rapid development of social networks, more messages are provided to community detection. Hence, the priority for future research can be effective methods for handling heterogeneous multi-source data, filtering and selection of invalid messages and the optimization of various message sources for community detection and social network analysis. Meanwhile, in different types of data fusion methods, the acquisition of equilibrium parameters mostly aims at a particular data set of tuning parameters and lacks a theoretical model derivation. As a result, the relationship between node attribute and community detection should be analyzed to explore an improved algorithm with higher efficiency.

Reference

Aguirre, E., Mahr, D. and Grewal, D. (2015), "Unraveling the personalization paradox: the effect of information collection and trust-building strategies on online advertisement effectiveness", *Journal of Retailing*, Vol. 91 No. 1, pp. 34-49.

Alon, H. and Liat, E. (2004), "The development of initial trust in an online company by new customers", *Information & Management*, Vol. 41 No. 3, pp. 377-397.

Beckett, S.J. (2016), "Improved community detection in weighted bipartite networks", *Royal Society Open Science*, Vol. 3 No. 1, pp. 140-536.

Brown, S.P. (1995), "The moderating effects of insupplier/outsupplier status on organizational buyer attitudes", *Journal of the Academy of Marketing Science*, Vol. 23 No. 3, pp. 170-181.

Du, H., Cai, M. and Yuan, T. (2011), "Development and prospect on the study of community structure", *Zhejiang Social Sciences*, No. 2, pp. 116-122.

Eisenbeiss, M., Cornelißen, M. and Backhaus, K. (2014), "Nonlinear and asymmetric returns on customer satisfaction: do they vary across situations and consumers?", *Journal of the Academy of Marketing Science*, Vol. 42 No. 3, pp. 242-263.

Fombrun, C.J. (2001), "Corporate reputations as economic assets", *Blackwell Handbook of Strategic Management*, pp. 289-312.

Gefen, D. (2000), "E-commerce: the role of familiarity and trust", *Omega*, Vol. 28 No. 6, pp. 725-737.

Girvan, M. and Newman, M.E. (2002), "Community structure in social and biological networks", *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 99 No. 12, pp. 7821-7826.

Grewal, D., Krishnan, R. and Baker, J. (1998), "The effect of store name, brand name and price discounts on consumers' evaluations and purchase intentions", *Journal of Retailing*, Vol. 74 No. 3, pp. 331-352.

Hajli, N., Lin, X. and Featherman, M.S. (2014), "Social word of mouth: how trust develops in the market", *International Journal of Market Research*, Vol. 56 No. 5, pp. 673-689.

Head, M.M. and Hassanein, K. (2002), "Trust in e-commerce: evaluating the impact of third-party seals", *Quarterly Journal of Electronic Commerce*, No. 3, pp. 307-326.

Hu, Y., Yang, B. and Wong, H.S. (2016), "A weighted local view method based on observation over ground truth for community detection", *Information Sciences*, Vols 355/356, pp. 37-57.

Huang, Z. and Benyoucef, M. (2013), "From e-commerce to social commerce: a close look at design features", *Electronic Commerce Research and Applications*, Vol. 12 No. 4, pp. 246-259.

Hutton, J.G. (1997), "A study of brand equity in an organizational-buying context", *Journal of Product & Brand Management*, Vol. 6 No. 6, pp. 428-439.

Jakalan, A., Gong, J. and Su, Q. (2016), "Social relationship discovery of IP addresses in the managed IP networks by observing traffic at network boundary", *Computer Networks*, Vol. 100, pp. 12-27.

Jarvenpaa, S.L., Tractinsky, N. and Vitale, M. (2000), "Consumer trust in an Internet store", *Journal of Computer-Mediated Communication*, Vol. 1 No. 2, pp. 45-71.

Kaplan, A.M. and Haenlein, M. (2010), "Users of the world, unite! the challenges and opportunities of social media", *Business Horizons*, Vol. 53 No. 1, pp. 59-68.

Kim, D.J., Ferrin, D.L. and Rao, H.R. (2008), "A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents", *Decision Support Systems*, Vol. 44 No. 2, pp. 544-564.

Klein, B.D. (2017), "On the development and application of a framework for understanding the properties and information quality of online reputation systems", *Journal of the Midwest Association for Information Systems*, No. 1.

Li, Y. (2013), "The impact of disposition to privacy, website reputation and website familiarity on information privacy concerns", *Decision Support Systems*, Vol. 57 No. 1, pp. 343-354.

Li, Y. (2010), "A review of reputation theories", *Management Review*, Vol. 22 No. 10, pp. 3-11.

Liang, T.P. and Turban, E. (2011), "Introduction to the special issue social commerce: a research framework for social commerce", *International Journal of Electronic Commerce*, Vol. 16 No. 2, pp. 5-14.

Lin, M.J. and Huang, C. (2013), "The impact of customer participation on NPD performance: the mediating role of inter-organisation relationship", *Journal of Business and Industrial Marketing*, Vol. 28 No. 1, pp. 93-106.

Manaman, H.S., Jamali, S. and AleAhmad, A. (2016), "Online reputation measurement of companies based on user-generated content in online social networks", *Computers in Human Behavior*, Vol. 54, pp. 94-100.

McKnight, D.H., Choudhury, V. and Kacmar, C. (2002), "The impact of initial consumer trust on intentions to transact with a web site: a trust building model", *Journal of Strategic Information Systems*, Vol. 11 No. 3, pp. 297-323.

Resnick, P., Kuwabara, K. and Zeckhauser, R. (2000), "Reputation systems", *Communications of the ACM*, Vol. 43 No. 12, pp. 45-48.

Sang, A., Ismail, R. and Boyd, C. (2007), "A survey of trust and reputation systems for online service provision", *Decision Support Systems*, Vol. 43 No. 2, pp. 618-644.

Spies, K., Hesse, F. and Loesch, K. (1997), "Store atmosphere, mood and purchasing behavior", *International Journal of Research in Marketing*, Vol. 14 No. 1, pp. 1-17.

Urban, G.L., Amyx, C. and Lorenzon, A. (2009), "Online trust: state of the art, new frontiers, and research potential", *Journal of Interactive Marketing*, Vol. 23 No. 2, pp. 179-190.

Vieira, V.A. (2011), "Experimental designs using ANOVA", *Revista De Administração Contemporânea*, Vol. 15 No. 2, pp. 363-365.

Wang, Z., Li, Q. and Xiong, W. (2016), "Fast community detection based on sector edge aggregation metric model in hyperbolic space", *Physica A Statistical Mechanics & Its Applications*, Vol. 452, pp. 178-191.

Wood, W. (2000), "Attitude change: persuasion and social influence", *Annual Review of Psychology*, Vol. 51 No. 1, pp. 539-570.

Xin, Y., Xie, Z.Q. and Yang, J. (2016), "The adaptive dynamic community detection algorithm based on the non-homogeneous random walking", *Physica A Statistical Mechanics & Its Applications*, Vol. 450, pp. 241-252.

Zeithaml, V.A. (2000), "Service quality, profitability, and the economic worth of customers: what we know and what we need to learn", *Journal of the Academy of Marketing Science*, Vol. 28 No. 1, pp. 67-85.

Zhang, J. (2006), "The roles of players and reputation: Evidence from eBay online auctions", *Decision Support Systems*, Vol. 42 No. 3, pp. 1800-1818.

Zhao, W.X., Li, S. and He, Y. (2016), "Connecting social media to e-commerce: cold-start product recommendation using microblogging information", *IEEE Transactions on Knowledge and Data Engineering*, Vol. 28 No. 5, pp. 1147-1159.

Further reading

Caruana, A. and Ewing, M.T. (2010), "How corporate reputation, quality, and value influence online loyalty", *Journal of Business Research*, Vol. 63 No. 9, pp. 1103-1110.

Jones, K. and Leonard, L.N.K. (2008), "Trust in consumer-to-consumer electronic commerce", *Information & Management*, Vol. 45 No. 2, pp. 88-95.

Li, L.I., Tadelis, S., and., and Zhou, X. (2016), "Buying reputation as a signal of quality: evidence from an online marketplace", Working Paper No. w22584, National Bureau of Economic Research.

Robert, D. and John, R. (1982), "Store atmosphere: an environmental psychology approach", *Journal of Retailing*, Vol. 58 No. 1, pp. 34-57.

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