information

MDPI

Article

Closed-Loop Feedback Computation Model of Dynamical Reputation Based on the Local Trust Evaluation in Business-to-Consumer E-Commerce

Bo Tian [1,*], Jingti Han [1] and Kecheng Liu [2]

[1] School of Information Management & Engineering, Shanghai University of Finance and Economics, Shanghai 200433, China; hanjt@mail.shufe.edu.cn
[2] Informatics Research Center, University of Reading, Reading RG6 6UD, UK; k.liu@henley.ac.uk
* Correspondence: youngtb@sina.com; Tel.: +86-21-6590-0518

Academic Editor: Willy Susilo
Received: 18 December 2015; Accepted: 27 January 2016; Published: 2 February 2016

Abstract: Trust and reputation are important factors that influence the success of both traditional transactions in physical social networks and modern e-commerce in virtual Internet environments. It is difficult to define the concept of trust and quantify it because trust has both subjective and objective characteristics at the same time. A well-reported issue with reputation management system in business-to-consumer (BtoC) e-commerce is the "all good reputation" problem. In order to deal with the confusion, a new computational model of reputation is proposed in this paper. The ratings of each customer are set as basic trust score events. In addition, the time series of massive ratings are aggregated to formulate the sellers' local temporal trust scores by Beta distribution. A logical model of trust and reputation is established based on the analysis of the dynamical relationship between trust and reputation. As for single goods with repeat transactions, an iterative mathematical model of trust and reputation is established with a closed-loop feedback mechanism. Numerical experiments on repeated transactions recorded over a period of 24 months are performed. The experimental results show that the proposed method plays guiding roles for both theoretical research into trust and reputation and the practical design of reputation systems in BtoC e-commerce.

Keywords: reputation computation; local trust rating; beta distribution; closed-loop feedback

1. Introduction

Credit, payment, logistics, and authentication compose the supporting system of e-commerce. According to the 35th China Internet development statistics report of China Internet Network Information Center (CNNIC) on 3 February 2015, 54.5% of Internet users thought information on the Internet was trustworthy [1], which has greatly improved compared with five years ago. However, the degree of acceptance of the Internet in China is still relatively low. Mature Internet and mobile communication technologies laid a solid technical foundation for the development of e-commerce and mobile commerce. However, consumers are still reluctant to accept e-commerce in China. The low degree of trust in the information on the Internet is one of the main reasons. How to improve the level of trust consumers have in the new type of virtual trading mode is an urgent issue to be solved. Trust theory research and trust evaluation system design have become hotspots in the field of e-commerce. The main methods used to research trust in e-commerce at present are derived from the conclusions of interpersonal trust relations of social networks. Relationships of trustees and agents in the network environment are discussed, factors that affect the perceived trust are analyzed, and causal relationships between perceived trust and decision-making of network transactions are theoretically reasoned and empirically researched [2–4]. Different methods of qualitative analysis and computational models of trust are proposed gradually [4–7]. In the application of e-commerce, the degree of trust is obtained by the method of evaluation or rating; calculation methods are simple such as average or summary [6,8,9]. In recent years, the evaluation methods of trust based on the theories of mathematics have attracted attention [4,10–12].

The difficulty of computing trust and reputation is that a trust relationship has subjective and objective dual characteristics at same time. In human social networks, trust is prone to be subjective [13]. In machine networks such as the Internet, trust is regarded as a supplementary mechanism of reducing uncertainty [14]. The motivation driving trust research in business-to-consumer (BtoC) e-commerce lies in the fact that trust is an effective mechanism for lowering transaction complexity, because of the span of time and space and information asymmetry during the process of online transactions. The goal of trust research is to provide a theoretical basis and direction for practical e-commerce development. Unfortunately, recently proposed computation approaches of trust and reputation are mainly focused on peer-to-peer networks, *ad hoc* networks, sensor networks, semantic Web, autonomic computing, grid computing, and multi-agent systems in pervasive computing environments [10,15–17]. In addition, a trust mining method through feedback comments for e-commerce was proposed last year [9]. Our previous work on trust and reputation has mainly investigated the factors of trust in BtoC e-commerce [18], proposed a recommended trust evaluation method for BtoC e-commerce based on the fuzzy analytic hierarchy process [19], and established a reputation evaluation computation model based on the relationship of trust and reputation [20]. In this paper, a new dynamical computation model of reputation based on trust evaluation in BtoC e-commerce is further proposed. Components and multi-dimensional characteristics of trust in BtoC e-commerce are analyzed firstly. The ratings of each customer are set as basic trust scores with four dimensions, and periods of ratings constitute the probability distribution of trust. The time series of massive feedback ratings of customers are aggregated to formulate the local trust and dynamical reputation values. Based on the conceptions of local trust and overall reputation, an iterative computation model of reputation is proposed. In order to achieve this objective, a logical model of trust and reputation is established in which the time series of ratings are consulted. As for the situation of single goods with repeat transactions, an iterative mathematical model of trust and reputation is established. In the computation model, Bernoulli probability described by Beta distribution function is used to formulate the trust values of certain time intervals. Lastly, numerical experiments on repeated transactions records over a period of 24 months on Dangdang and Amazon are performed. Representative commodities such as books are used in both Dangdang and Amazon. More than 4000 ratings with four dimensions of each commodity over two years on each website are separated into 24 months as time series. Ratings for each month are used for independent probability distribution estimation, and trust and reputation are renewed iteratively. Experimental results illustrated the dynamical variation processes of reputation effectively. As a result, the proposed computation model can tell customers which agent they should choose in concrete situations. The proposed iterative computation model, with local trust and overall reputation, could play a guiding role for both the theoretical research into computation of trust and the practical design of reputation systems in BtoC e-commerce.

The remainder of this paper is organized as follows. Related works about trust and reputation are reviewed in Section 2. Meanings of trust and reputation for BtoC e-commerce are discussed in Section 3. Multi-dimensional characteristics and composition of trust in BtoC e-commerce are also analyzed. Additionally, relationship and motivation are introduced in this section. Then the logical and computational model of reputation is further proposed based on the concept of trust and the relationship between trust and reputation in BtoC e-commerce in Section 4. In addition, the time series of ratings are consulted to establish the iterative mathematical model of trust and reputation, and the Bernoulli distribution is discussed to estimate trust values in this section. Experimental results of reputation and trust computation for representative commodities in both Dangdang and Amazon are reported in Section 5. Data collection, rating aggregation, model organization, and numerical computation results are discussed in this section. Finally, conclusions are drawn in Section 6.

2. Related Works

Many surveys of different disciplines to classify and characterize computational trust and reputation models exist in the literature. Some of them are based on online trust-related systems [6,7]. Some of them are about trust and reputation in multi-agent systems [4]. Some reviews focus on concrete aspects or functionalities of trust or reputation management [3,14]. Others deal with more general network environments [10,11]. In the following, related works will be reviewed and discussed from four perspectives: trust-related research approaches in pervasive network environments, trust-related research approaches in e-commerce, trust-related computation methods in e-commerce, and the probability method in trust computation, the topic of which is from large domain to small field.

2.1. Trust-Related Research in Pervasive Networks

Trust relationships occur in many diverse contexts such as pervasive systems, social interactions, semantic networks, *ad hoc* networks, distributed systems, sensor networks, and so on. In pervasive computing environment, trust can be used as a natural way to achieve the goals that enhance security and reduce uncertainty. A wide variety of trust and reputation theories and models with different features have been developed in recent years. The work in [4] reviewed computational trust and reputation models for open multi-agent systems. Current research on trust management in distributed systems is surveyed, and some open research areas are explored in [21,22]. The work in [23] presented a model of reputation management in collaborative computing systems. The work in [24] presented a framework for building distributed, dependable reputation management systems, with counter measures against vulnerabilities. In [9], the authors defined a reputation evaluation method based on reputation value and reputation prediction variance value based on the aggregation of feedback. In [25], the authors introduced an adaptive and dynamic reputation-based trust model to evaluate trustworthiness, based on community feedback about participants' past behavior. The paper [26] proposed a computational model for trust establishment based on a reputation mechanism, which incorporates direct experiences and information disseminated from past experiences in pervasive systems. The paper [27] proposed an adaptive and attribute-based trust model for service-level agreement guarantees in cloud computing. A more general social trust computational approach is researched in [10]. The objective of these research methods is the computation of general trust and reputation in network environments, which can provide a reference for research into trust and reputation in e-commerce.

2.2. Trust Research Approaches in E-Commerce

The range of theoretical research in e-commerce includes related technologies, application modes, value chains, legal ethics, consumption decision behavior research, and so on [28]. The research into trust in e-commerce mainly uses consumer decision-making theory and analyzes the role of perceived trust in consumer decision-making, in which trust acts as a sort of soft safety mechanism in the transaction procession. Empirical analysis is the main research method. The theory of consumer decision-making includes attitude intention behavior theory, innovation diffusion theory, Task-Technology Fit (TTF) theory and the Technology Acceptance Model (TAM) model, *etc*. [28,29]. The main research methods are borrowed from psychology, social science, economics, and marketing science. Based on the concept of general trust, the particularity of electronic commerce is incorporated. Related aspects and factors of trust during the transaction processes are analyzed. Conceptual models related to the roles of risk and trust in the purchase decision are established, and different hypotheses are put forward and empirically researched [30–33]. Computation methods of trust in e-commerce usually employ artificial intelligence, graph theory, game theory, probability, and stochastic process theories, in which the trust relationships are described and the trust evaluations are measured and forecast [4,7,11]. According to the difference of mechanisms, trust can be divided into identity-based trust models, role-based trust models, trust-negotiation models, and reputation-based trust models [28].

According to the difference of mathematical tools used in the trust computation, the concrete methods can be based on deterministic mathematics theory, probability theories, and uncertainty theories [6,9,11]. The trust computation models mainly involve the expression of measurement of the concept of trust, a description of the relationship between reputation and trust, and a calculation of trust, which will be discussed thoroughly.

2.3. Trust-Related Computation Methods in E-Commerce

Computation methods of trust in e-commerce are analyzed as follows. Most practically applied methods of trust computation are based on simple operations such as average or sum [7,26]. This kind of method is widely used in the process of evaluation of e-commerce websites. The method refers to the trust evaluation among people in social networks, and the method is simple and easy to understand. At present, a weighted averaging method is used in Auction, Eigen, and Trust eBay. The main shortcomings of this method are that the evaluation is simple and cannot reflect the real trust values of the reviewers and the real trust status of the object to be evaluated.

Trust is a kind of psychological relationship; therefore, subjective logic can be used to describe it. Jøsang adopted the evidence space and the concept space to describe the trust relationships [34]. The author put forward that conjunction, consensus, and recommendation constitute the subjective logic operation associated with trust degree and integrated computation. Ternary group is used to express the degree of trust. However, the model cannot effectively eliminate the impact of malicious feedback evaluation. Evidence reasoning theory is used to compute reputation in [35].

Fuzzy reasoning is normally used to compute the uncertainty of research objects and has been used in trust computation in recent years. The paper [36] proposed a reputation-based trust system Regret. The paper [37] proposed a trust calculation framework that is based on fuzzy reasoning. The three stages of fuzzy reasoning are fuzzy processing, fuzzy reasoning, and defuzzification. The paper [38] proposed a P2P reputation system named Power Trust based on fuzzy logic reasoning. The authors illustrated that the number of user transactions follows a power-law distribution by analysis of a dataset of eBay, and, additionally, that only small parts of super nodes have a decisive role in the trust evaluation of a node. Zhou proposed a Gossip trust model for realizing trust computation by chat [39]. Wang proposed a fuzzy evaluation method of trust in the service environment [40]. The fuzzy inference methods solve the problem of imprecise input in the reasoning process, and simplify the reasoning process; however, prior knowledge is necessary to select the membership function.

Trust reflects the network relationships of human beings, so connective graph network methods can be used to describe trust. The paper [41] computed trust value through connectivity relationships of trust networks, in which the starting node sends a request to its neighboring nodes, and if the neighbors have no relevant information, the request gradually spreads to other neighbors. In the search path, trust evaluation provided by the node with low trust degree will be ignored, and all the trust values are averaged by the starting node finally. The model is based on t social networks between human beings. The paper [36] used the method of hierarchical structure of social networks to analyze different types of reputation in order to compute the trust value of the final node.

Different research methods have been proposed by others. Game theory is used in [42]. Cho [43] proposed a reputation computing system based on collaborative filtering. Gutowska [5] put forward a reputation simulation calculation model in BtoC e-commerce. Wang [44] proposed an evaluation method based on evidence probability. Liu [45] recently proposed a trust computing model based on a prototype. Furthermore, probability-related methods are an important kind of trust computation in e-commerce, which will be reviewed separately.

2.4. Probability Methods in Trust Computation

Trust is the expectation of behavior of the trustee in uncertain and incomplete environments [13]. Therefore, probability theory is adopted to evaluate trust and reputation. Despotovic proposed the method of maximum-likelihood estimation to calculate trust of nodes in P2P environment [46].

Beth [47] put forward a trust computing model based on experience and probability statistics. Experience is divided into two kinds: positive and negative, in the model. Trust is defined as the probability of a successful completion of the target entity. Based on Bayesian theory, posterior probability of the 0–1 events (satisfaction or dissatisfaction) is described by beta distribution function, which evaluates the trust scores [48,49], and trust is expressed by the expectation of the Beta probability density function. Jøsang [50] proposed the Dirichlet reputation system. A Bayesian network is used to model the trust under different conditions in [51]. By using Bayesian network, the requester can calculate the confidence probability of service providers according to the content he or she cares about. Each value of probability expresses the credibility of a node in the networks. Based on the concept of group, Bayesian model of trust and reputation was researched in [52]. We noticed that probability methods used in soft trust computation are employed mainly in general and broad network environments such as pervasive networks. In this paper, a trust-related computation method based on probability theory in BtoC e-commerce is proposed. Meanings, multi-dimensional characteristics, and composition of trust in BtoC e-commerce are analyzed. Based on the relationship of trust and reputation in BtoC e-commerce, iterative computation models of trust and reputation are established. Experimental results illustrated that the proposed model can effectively simulate the dynamical variation processes of reputation in BtoC e-commerce.

3. Relationship of Trust and Reputation

In order to establish a computational model of trust and reputation, the relative concepts, components, and hierarchical structure of trust are discussed. In addition, the logical relationship between trust and reputation in BtoC e-commerce is analyzed.

3.1. Meanings of Trust

The concept and meanings of trust have been defined by different disciplines. For instance, trust is considered as part of personal qualities, namely the beliefs, expectations, and feelings developed during individual psychological processes [7]. Trust is regarded as a form of organizational control used to reduce uncertainty as well as transaction cost in management [53]. Trust is essentially personal relationships, according to Mayer [54]. McKnight differentiates trust belief from trust intention [13]. It has been noted that trust in a person is a commitment to an action based on a belief that the future actions of that person will lead to good outcomes. Trust (or distrust) is the level of subjective probability with which an agent assesses that another agent will perform a particular action. Online trust refers to an individual's willingness to trust another individual (or entity) under the existence of uncertainties in e-commerce circumstances. BtoC e-commerce is the consumer purchase of products and services through online shopping or from firms on the Internet. So, trust in BtoC e-commerce is associated with the experience of consumers, asymmetry of information, interval of space and time of transaction, transaction risk, uncertainty, and so on. The concept of trust in BtoC e-commerce can be described as follows. Trust in BtoC e-commerce is the subjective psychological expectation of consumers that relies on the promise made by online firms, their websites, or a transaction environment under certain circumstances. The psychology of intuition and reliance are brought out from subjective beliefs, expectations, and feelings of consumers towards their trading counterparty, its website, and the virtual environment. The subjective psychological expectation of consumers can be described by probability formulation, which is determined by consumers, the trading counterparty, and the transaction environment. Its target is to reduce transaction risk and uncertainty because of information asymmetry, time-space interval, and trading vitality in BtoC e-commerce.

3.2. Components of Trust

The subjective probability of psychological expectation or trust in BtoC e-commerce is affected by consumers, goods, online companies, and their websites as well as the environment. Components of trust in BtoC e-commerce can be further established, as shown in Figure 1. Moreover, components relating to the trustor, trustee, and environment are shown in Table 1 in our previous work [18]. Three component factors of trust in BtoC e-commerce will be discussed separately.

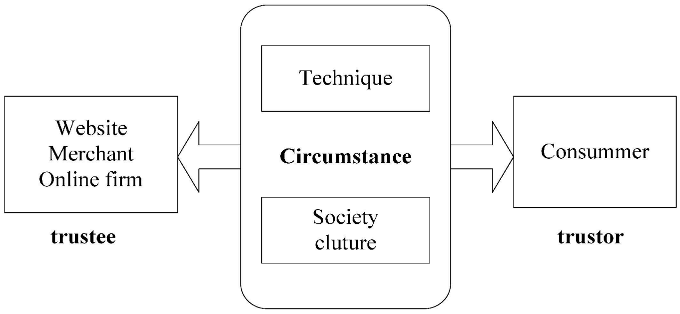


Figure 1. The components of trust system chart of business-to-consumer (BtoC) e-commerce.

Table 1. Components of the trust system of BtoC e-commerce.

Trustor	Consumer	Disposition to trust, purchase history ,attitude towards online shopping, attitude towards information technique, personal values, age, education and gender, subjective perceptive risk
Trustee	Online firm	Brand, reputation, offline presence, predictability, dependence, faith, cooperation, familiarity, benevolence, history of the firm
	Merchant	Quality, satisfaction, price, service, transference, familiarity
	Website	Likeability, convenience, usability, efficiency, reliability, portability, integrity, privacy, security, branding
Circumstance	Technique	Privacy, security, transparency, credibility of information, characteristics of computer technique, Internet technique, information technique, encryption, third-party certification
	Society	General attitude towards trust, Internet and e-commerce, policy, law, morality, culture

Components relating to the trustor include disposition to trust, purchase history, attitude towards online shopping, attitude towards information techniques, personal values, age, education, gender, subjective perceptive risk, and so on. Trustor-related factors can be further refined to include the following respects: (A1) experience of using the Internet, (A2) experience of trading online, (A3) attitude towards risk, which usually involves three types: risk preference, risk neutral, and risk aversion. People who belong to risk preference are more likely to accept online transactions. The final factor is (A4) trust propensity: the willingness to trust an individual, developed through long-term growth in society, which reveals the trend of consumers' trust towards general things, including their Internet trust trend.

Components relating to the trustee include the e-commerce website, the merchant and the online service provider that include the brand, offline presence, faith, cooperation, familiarity, benevolence, history of the firm, quality of merchant, price, and website quality aspects such as convenience, usability, efficiency, reliability, privacy, and security. Merchant-related factors are as follows: (B1) types of goods—generally speaking, search goods have a lower perceived risk than experience goods; (B2) brand of goods—a good brand can reduce consumers' perceived risks; (B3) price of goods—under the premise of the law of value, the lower the price, the more attractive it is to consumers. On the contrary, too high or too low a price deviates from the law of value and will lead to consumers' distrust. Finally, (B4) is instructions about goods—appropriate instructions will improve consumers' purchase intention, while vague or exaggerated descriptions will easily cause distrust in certain consumers. Website-related factors are as follows: (C1) website reputation and popularity; (C2) website security, which includes transaction security, privacy protection, and third-party certification; (C3) navigation system, namely the ease of use of the website; (C4) transaction implementation convenience; and (C5) website style, consisting of layout design, image and content design, namely the usefulness of the website. Online company-related factors are as follows: (D1) reputation and popularity; (D2) history and business scale; (D3) willingness to make customized products for consumers; and (D4) consumer familiarity with the company.

Components of the environment of trust include technique and social factors. Components relating to techniques are privacy, security, transparency, credibility of information, Internet-relative technique, information technique, encryption, and third-party certification, among others. Social components include policy, law, morality, and culture, among others. As the information transmission medium, security of data transmission and privacy of transaction are prerequisites of online transaction [6]. Social environment, information technology, relevant laws and regulations, as well as trust management are effective means of lowering BtoC E-commerce information asymmetry [53,55]. The following environment-related factors have an influence on consumers' perceived trust: (E1) social and cultural; (E2) legal; and (E3) commercial and operational. The following technology environment-related factors have an impact on consumers' perceived trust: (E4) network technology maturity; (E5) information access facility; (E6) network system stability; and (E7) website authority safety certification.

3.3. Hierarchical Structure of Online Trust

The trust relationships between interpersonal social networks are established mainly through three channels, namely (1) objective institutional trust; (2) direct trust; and (3) indirect trust [28]. In BtoC e-commerce, objective institutional trust includes customary and trading rules, e-commerce related laws, third-party authentication, access control and guarantees, and other trust forms. The situational norm and structure guarantee are two facets of objective trust. Situational norms refer to trust that is judged through common habits and rules embedded in the transaction process. The structure guarantee means that there are factors such as legal norms, guarantees, or regulations in the specific transaction environment that influence trust.

In BtoC e-commerce, subjective direct trust of a customer is relative to their individual personality, psychological characteristics, and life experience. It is found that this personal factor is the most important factor for online perceived trust [6]. The recommendation information includes the local individual recommendation and the reputation of the public as a whole. The individual recommendation is also looked upon as one component that directs trust because individual recommendation trust is determined by life experience. If a person's friends are prone to trust more in BtoC e-commerce, he or she will be more prone to shopping online. Reputation is the expectation of the behavior of the object through the global trust in the historical behavior of the object [3,6]. Therefore, in BtoC e-commerce, the reputation of the public is regarded as the trust resource of general indirect recommendation, which contains other factors except the consumer's direct perceived trust.

Thus, trust in BtoC e-commerce is composed of subjective perceived trust and objective institutional trust. Subjective perceived trust includes direct perception trust and general recommendation trust. Objective trust is the environmental basis of trust in BtoC e-commerce. Direct perception trust is the inclination of the customer to trust an object. When direct trust is not enough to make a judgment regarding the trust objects or to determine the online trust of a strange transaction, other sources of information such as reputation or recommendation by friends will be applied to strengthen the trust so as to finish the transaction. Based on the analysis of the components of trust, a hierarchical structure of online trust in BtoC e-commerce can be constructed, as shown as Table 2. The components that influence trust in BtoC e-commerce can be classified as direct trust, indirect trust, and environment trust, based on which an integrated evaluation model of trust and reputation is established.

Table 2. Hierarchical structure of online trust in BtoC e-commerce.

Total Trust	**Objective Trust**	Institutional Trust	Situation norm	C1-C6, D3, E6-E7
			Structure guarantee	A8, C7-C9, D5, E1-E4, E8
	Subjective Trust	Direct Trust	Direct perceived trust	A1-A8, B1-B4, C1-C9, D1-D5, E1-E8
			Individual recommendation	A1, A7
		Indirect Trust	reputation	A1, A3, A8, B2, C1, D1

3.4. Logical Relationship between Trust and Reputation

Reputation systems collect, process, and aggregate information about participants or services to help future users make optimal decisions. In service-oriented network environments, reputation systems should encourage trustworthy behavior and punish dishonest participation. In the following, a general trust computation model for BtoC e-commerce is formulated to represent the relationship between trust and reputation. Based on the logical relationship between trust and reputation, iterative dynamical trust and reputation computation models will be derived in the next section.

In the hierarchical structure of online trust in BtoC e-commerce shown in Table 2, objective trust is invariable or changes slowly over a period, which constitutes the background knowledge of perceived trust during the transaction process. Direct perceived trust and individual recommendation trust compose direct trust. Reputation is often regarded as recommendation trust in the literature. Reputation and direct trust compose subjective trust. Subjective trust and objective trust compose the total trust. On the other hand, the factors of trust previously described (A1–E7) are usually considered in some practical trust and reputation evaluation systems such as Dang and Amazon. Therefore, these factors are refined to a multi-dimensional trust computation model, which includes reputation. Trust depends on potentially quantified trustworthiness qualities and context of transaction. Trustworthiness, or degree of trust, is the objective probability that the trustee performs a particular action on which the interests of the trustor depend. Reputation is a social evaluation or public estimation of standing for merit, achievement, reliability, *etc.* Reputation is the opinion of a community toward a person or someone else. Reputation may be used as a basis for trust. However, they are different notions, as pointed out by Jøsang [6]. Trust is local, temporary, and subjective, while reputation is global, long-term, and relatively objective. Both trust and reputation provide soft security mechanisms for online transactions. The relationship between trust and reputation constitutes the basic structure for the model of reputation computation, which is described by Figure 2.

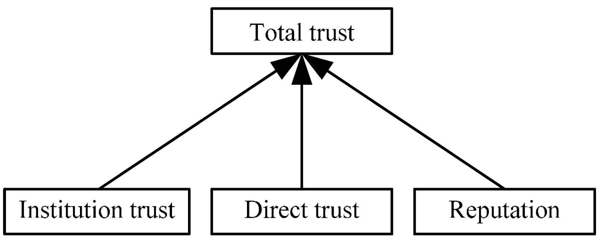


Figure 2. Schematic diagram of trust and reputation.

Based on the relationship between trust and reputation, a general mathematical description of the relationship of trust with reputation can be established as:

$$T = f(T_e, T_d, R) \tag{1}$$

where total trust T is the function of institutional trust T_e, direct perspective trust T_d, and reputation R. Linear function and product form are usually adopted to simulate the function relationship f of the total trust and its factor in the literature [17]. In our proposed method, the probability model is used. Because the objective institutional trust is slowly changing or invariable during a period, it is assumed to be constant and will not be considered when computing trust and reputation.

4. The Proposed Model

Based on the relationship of trust and reputation, a dynamical reputation and trust model will be proposed in this section. Firstly, the three variables denoted as total trust, direct trust, and reputation used in the proposed model are clarified, and the multi-dimensional trust concept of quantitative computation is derived. Then, the iterative mathematical relationship of trust and reputation is formulated. Finally, a probability computational model is established to compute reputation values.

4.1. Variables in the Model

Because the objective institutional trust T_e in Equation (1) is assumed to be constant, this factor will not be considered any more. The objective institutional trust is the total background trust factor from societies formulated over a long time, which has been mentioned in [13,28]. Thus, the total trust T is modeled on the function of direct perspective trust T_d and reputation R:

$$T = f(T_d, R). \tag{2}$$

In some practical reputation evaluation systems and research works, trust scores are used as basic elements in the computation of reputation [9,56–59]. However, direct trust and total trust are not distinguished. In the evaluation systems of Dangdang and Amazon, some examples of different aspects of evaluations are provided by customers, shown in Table 3, which correspond to the components of trust shown in Tables 1 and 2. Quality, price, logistics, and servers are the four different aspects of f trust in BtoC e-commerce transactions used in our proposed method.

Table 3. Examples of four aspects of evaluations provided by evaluation systems of Dangdang and Amazon.

Dimension	Dangdang	Amazon	Trust-Related Factors
Quality	Content is good	Quality is fine	B1–B2,B4,C1,D1–D3
Price	Price is reasonable	It is expensive, comparatively	B3
Logistics	Logistics are slow	Logistics are very fast	E2–E3,D1–D4
Servers	I connect to servers easily	Relative information is useful	A1–A4,B4,C1–C5,D1–D4,E4–E7

When we use the comments of customers to formulate trust and reputation, trust evaluation becomes a multi-dimensional concept. Furthermore, the evaluation-based trust is direct perceptive trust, which is expressed as the overall direct trust score T_d for the selling party of the transactions and the weighted aggregation of multi-dimensional trust scores for different aspects is shown as:

$$T_d = f(T_d^{(1)}, T_d^{(2)}, ..., T_d^{(k)}), \tag{3}$$

where $T_d^{(k)}$ represents the trust score for dimensions k ($k = 1, 2, ..., C$) such as quality, price, logistics, and convenience. Computation examples of multi-dimensional components of trust will be illustrated in Section 5.

From the relationship between reputation and trust discussed previously, reputation is the formation of long-term and global macro-concept. It is the result of the accumulation of trust. Therefore, reputation can be simplified as the representation of the average value of trust after a series of transactions for any given merchandise. If m transactions or transaction time units for the same merchandise occur, and the total trust of each transaction or transaction time unit is $T(i), i = 1, 2, ..., m$, then the reputation can be calculated as follows:

$$R = \frac{1}{m}\sum_{i=1}^{m} T(i). \tag{4}$$

The concrete form of the function relationship f of the total trust, direct perceptive trust, and reputation is a linear function in our proposed method, which is shown as:

$$T = \lambda * T_d + (1 - \lambda) * R, \tag{5}$$

where λ is the weighted factor that balances the roles of direct trust T_d and reputation R. If the values of total trust T, direct trust T_d, and reputation R are known, λ can be estimated by the regression method.

4.2. Iterative Model of Reputation and Trust

Reputation values are based on the average values of trust, which is usually calculated by the expectation function of probability variables [48]. Practical experience in BtoC e-commerce shows that a change in business reputation is caused by a change in trust of a large number of customers. Reputation influences consumers' perceived trust in return, and they both interact with each other. Therefore, by using closed-loop feedback control theory, the closed-loop evolution model of reputation and trust can be further illustrated as in Figure 3.

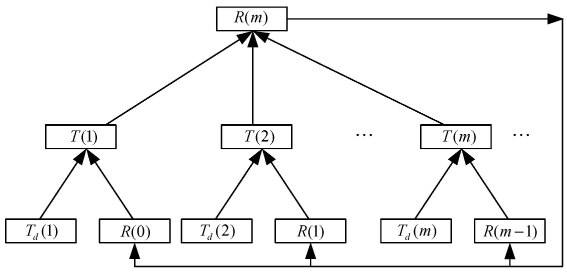


Figure 3. Iterative closed-loop computation model of reputation and trust.

In Figure 3, the values of reputation before the m-th transaction (or time interval) and after the m-th transaction (or time interval) are recorded as $R(m-1)$ and $R(m)$ respectively, the total trust of the m-th transaction (or time interval) is $T(m)$, and the direct trust of the m-th transaction (or time interval) is $T_d(m)$, $(m \in Z^+)$. As for repeated transactions of the same single commodity, the computational model can be established when considering the time series characteristics of the transactions. The reputation value of the last time is the basis of the next total trust calculation, and a renewal of trust will cause changes to the reputation. From Equation (4), the relationship of $R(m)$, $R(m-1)$ and the m-th total trust of $T(m)$ is shown as:

$$R(m) = \frac{m-1}{m}R(m-1) + \frac{1}{m}T(m), m \in Z^+. \quad (6)$$

From Figure 3 and Equation (5), the relationship of the m-th total trust of $T(m)$, $m \in Z^+$, direct trust T_d and the m-th reputation $R(m-1)$ is established as

$$T(m) = \lambda * T_d(m) + (1-\lambda) * R(m-1), m \in Z^+. \quad (7)$$

If the direct trust T_d of each transaction (or time interval) is known, and the parameters of Equations (6) and (7) are given, the iterative total trust and reputation values can be calculated. As discussed above, trust is the probability formulation for the counterpart of transactions. Therefore, the trust score on a dimension for a counterpart of a transaction is the probability that the consumer expects the seller to carry out transactions satisfactorily, which corresponds to the rating in practical evaluation systems. Following, the simple dimension direct trust component of T_d will be modeled by 0–1 distribution or Beta distribution, and the multi-dimensional direct trust component of T_d is computed by multi-dimensional probability distribution.

4.3. Computation of Direct Trust

A direct trust computation is performed when customers are attempting to interact with agents, making transactions, and giving their comments or star evaluations. In this situation, the direct trust computation is based on direct observation and derived from personal perception or the identity information embodied in online systems. Direct trust will be computed by using Beta distribution.

4.3.1. Characteristics of Beta Distribution

The Beta distribution is an important notion that describes the probability distribution of binary events in probability theory [48]. In Bayesian inference, Beta distribution can be used as a prior distribution by means of the probability density function, which in turn can be used for decision making. Bayesian inference is a statistical process through which the current state of the observed distribution is evaluated. Several researchers have exploited trust computation methods by using the Beta distribution and Bayesian frameworks [58]. Posterior probabilities of binary events can be represented as Beta distributions. The Beta-family of probability density functions is a continuous family of functions indexed by the two parameters α and β. The Beta probability distribution density function f can be expressed by using the gamma function as:

$$f(t;\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} t^{\alpha-1}(1-t)^{\beta-1}, 0 \leqslant t \leqslant 1, \alpha > 0, \beta > 0 \tag{8}$$

where $\Gamma(\alpha) = (\alpha-1)!$. In binomial distribution, it is desirable to compute the trust value of transactions. The notation T is used to represent the probability that a satisfactory evaluation will be provided by buyers. Considering repeated transactions for the same goods, the two parameters used in the beta distribution to represent the observations are α and β, respectively; n_s is the number of previous satisfactory evaluations; and n_u is the number of previous unsatisfactory evaluations. By setting $\alpha = n_s + 1$ and $\beta = n_u + 1$, the estimated value of T is obtained by computing the expectation value of the probability distribution function of the Beta distribution as:

$$T = E(f(t;\alpha,\beta)) = \frac{\alpha}{\alpha+\beta} = \frac{n_s+1}{n_s+n_u+2}. \tag{9}$$

In Equation (9), the values of n_s and n_u are obtained by counting the history of satisfactory and unsatisfactory evaluations. The local direct trust value is based on the expected value of the Beta distribution (see Equation (9)). For the same trust values, there may be several combinations of different values of n_s and n_u. In other words, if trust values are constant, large and small numbers of satisfactory evaluations and unsatisfactory evaluations may lead to the same level of trust. However, in practice, a greater number of evaluations would ensure more accurate trust computations. Therefore, a new characteristic parameter named confidence is used to distinguish between trust values that are estimated using different numbers of evaluations [17]. Level of confidence is denoted as $Conf$, and is defined via the variance of the Beta distribution as:

$$Conf(T) = 1 - Var(f(t;\alpha,\beta)) = 1 - \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} = 1 - \frac{(n_s+1)(n_u+1)}{(n_s +_u +2)^2(n_s +_u +3)} \tag{10}$$

where Var is the variation value of the probability distribution function. Considering the combination of values of n_s and n_u shown in Table 4, the result is equal trust and different levels of confidence. Figure 4 shows the same trust values with different variation values. It can be seen that the value of $Conf$ is higher when values of n_s and n_u increase. Therefore, the parameter $Conf$ is suitable to describe the level of confidence of trust.

Table 4. Same trust values with different samples of trust computation.

Total n	n_s	n_u	T	Var	$Conf$
6	2	4	0.375	0.0260	0.9740
14	5	9	0.375	0.0138	0.9862
22	8	14	0.375	0.0094	0.9906
30	11	19	0.375	0.0071	0.9929
38	14	24	0.375	0.0057	0.9943
46	17	29	0.375	0.0048	0.9952
54	20	34	0.375	0.0041	0.9959
62	23	39	0.375	0.0036	0.9964
70	26	44	0.375	0.0032	0.9968
78	29	49	0.375	0.0029	0.9971

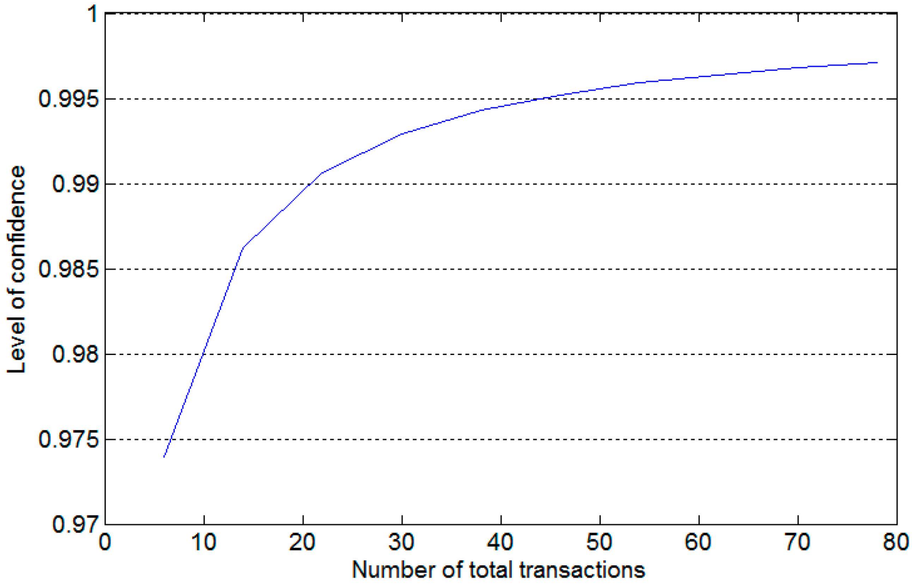


Figure 4. The relationship between level of confidence and transaction times.

4.3.2. Multi-Dimensional Beta Distribution

As for multi-dimensional trust scores with different respects $T_d^{(1)}, T_d^{(2)}, ..., T_d^{(k)}$, when each aspect is assumed to be independent from the others, the probability distribution density function f of $T_d^{(1)}, T_d^{(2)}, ..., T_d^{(k)}$, can be expressed as:

$$f(t_1, \alpha_1, \beta_1; t_2, \alpha_2, \beta_2, ..., t_C, \alpha_C, \beta_C) = \frac{\Gamma(\alpha_1+\beta_1)}{\Gamma(\alpha_1)\Gamma(\beta_1)} t_1{}^{\alpha_1-1}(1-t_1)^{\beta_1-1} \frac{\Gamma(\alpha_2+\beta_2)}{\Gamma(\alpha_2)\Gamma(\beta_2)} t_2{}^{\alpha_2-1}(1-t_2)^{\beta_2-1} \cdots \frac{\Gamma(\alpha_C+\beta_C)}{\Gamma(\alpha_C)\Gamma(\beta_C)} t_C{}^{\alpha_C-1}(1-t_C)^{\beta_C-1}, \ 0 \leqslant t_i \leqslant 1, \ \alpha_i > 0, \beta_i > 0, i = 1, 2, ..., C. \tag{11}$$

Therefore, the estimated value of T_d with multi-dimensional factors is obtained by computing the expectation of probability distribution function $f(t_1, \alpha_1, \beta_1; t_2, \alpha_2, \beta_2; ...; t_C, \alpha_C, \beta_C)$ as:

$$T_d = E(f(t; \alpha, \beta)) = \prod_{i=1}^{C} T_i = \prod_{i=1}^{C} \frac{n_{s_i}+1}{n_{s_i}+n_{u_i}+2}, \tag{12}$$

The level of confidence $Conf$ defined from the variance of the beta distribution is shown as:

$$Conf(T) = 1 - Var(f(t; \alpha, \beta)) = (\prod_{i=1}^{C} \frac{n_{s_i}+1}{n_{s_i}+n_{u_i}+2})^2 - \prod_{i=1}^{C} \frac{(n_{s_i}+1)(n_{s_i}+2)}{(n_{s_i}+n_{u_i}+2)(n_{s_i}+n_{u_i}+3)} + 1. \tag{13}$$

4.3.3. Dynamical Reputation Computation Processes

From Equations (4) and (11), it can be seen that the values will not change with an increase in the number of transactions if the reputation is stable. When the number of transactions increases, trust values only become more accurate. However, the reputation of trustees in the process of transactions changes gradually in practice. Especially in BtoC commerce, there are so many competitors. As a result, the number of transactions may change drastically. Therefore, in order to establish the dynamical reputation computation model, the transactions are regarded as a time series of events, and divided into equal time intervals. For example, there are $N_1, N_2, ..., N_m$ transactions in m equal time intervals. After each transaction, the customer provides a binomial distribution evaluation (good or bad). In the i-th time interval, there are $n_s(i)$ satisfactory evaluations and $n_u(i)$ unsatisfactory evaluations. The direct local $T_d(i)$ can be calculated with Equation (9). Given the value of parameter λ and initial value of

$R(0)$, the total trust value $T(i)$ can be computed, $i = 1, 2, ..., m, m \in Z^+$. The cumulative reputation can be computed using Equation (8).

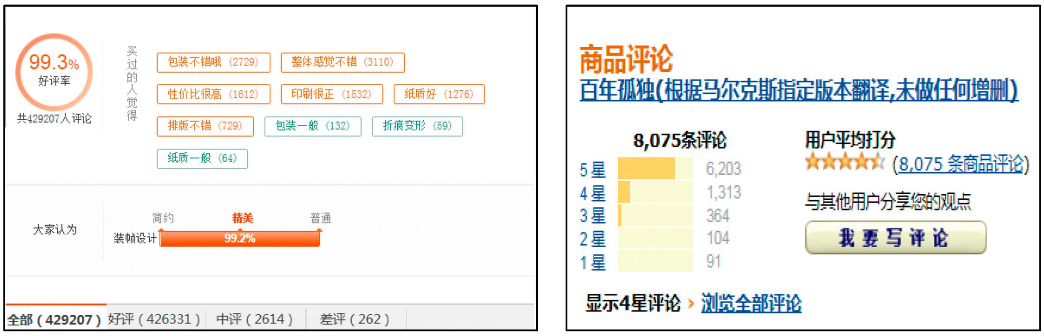
As for multi-dimensional components of trust, similar computation steps will be completed. After each transaction, the customer provides a binomial distribution evaluation (good or bad) for each dimensional component of trust. In the *i*-th time interval, there are $n_{sj}(i)$ satisfactory evaluations and $n_{uj}(i)$ unsatisfactory evaluations for the$j$ dimension, $j = 1, 2, ..., C$, where C is the number of dimensions. The direct local $T_d(i)$ can be calculated by Equation (11). Similarly, total trust values and cumulative reputation can be computed using Equations (8) and (9).

5. Experimental Results

In this section, numerical experiments are performed to illustrate the variation of total dynamic reputation with local computed trust. Firstly, data are collected on two online firms. Original two-year language evaluations of four aspects of trust in relation to online transactions are collected and these transaction evaluations are separated into 24 different time intervals. Then the value of direct trust is estimated by using the expected value of the probability distribution function of the Beta distribution, and the values and reputation are renewed by an iterative algorithm. The reputation of the same commodity from two online business firms is computed. From the computational results, it is noted that there are different characteristics of different firms.

5.1. Data Collection

In most BtoC transaction platforms, consumers can write reviews about a variety of topics from consumer durables to household electrical appliances. In China, Dangdang (http://www.dangdang.com/) and Amazon (http://www.amazon.cn/) are two famous BtoC firms especially with regard to the sale of books. Therefore, the proposed computational method of reputation was used to analyze the trust and reputation of these two firms. Piracy has become a serious problem in China in the 10 ten years, and online book sales have become an important channel for pirated books, which are inferior in quality to the genuine books. For this study, the same books with more than 4000 effective evaluations in the last three years were chosen. If readers want to know the details of the evaluation systems, please visit the website. The evaluations are divided into 24 monthly periods. In each month, positive and negative evaluations of quality, price, logistics, and servers are counted manually from the language evaluations of the different aspects of comments provided for customers in the evaluation systems of Dangdang and Amazon. In our experiment, evaluations of quality, price, logistics, and servers are assumed to be independent. Therefore, the multi-dimensional expected value of the probability distribution function of the Beta distribution can be used to compute the values of trust. Figure 5 shows the evaluation interference of Dangdang and Amazon. Table 5 shows the positive (marked "+") and negative (marked "−") evaluations of the four factors of trust of Dangdang and Amazon. The data are from June 2013 to May 2015. There are a total of 33,632 and 4057 effective evaluations of trust in the books on Dangdang and Amazon from June 2013 to May 2015.



(**a**) (**b**)

Figure 5. Evaluation interference of the same book on Dangdang and Amazon (Both in Chinese language). (**a**) Evaluation interference on Dangdang. (**b**) Evaluation interference on Amazon.

5.2. Computation Results

In order to compute the total local trust for a time interval by iterative formulation Equations (6) and (7), the initial value of reputation should be given in advance. In our method, the initial value of reputation $R(0)$ is set the same as $T_d(1)$, and the value of the parameter weighted factor λ is 0.6. By using the data shown in Table 5, direct trust for dimension k ($k = 1, 2, 3, 4$) named $T_d^{(k)}$ can be calculated using Equation (9), and total multi-dimensional direct trust T_d can be calculated using Equation (12). Computation results of one of four values of different dimensions of trusts (quality trust (Q-Tru), price trust (P-Tru), logistics trust (L-Tru), and servers trust (S-Tru)), different dimensions of reputation such as quality reputation (Q-Reput), price reputation (P-Reput), logistics reputation (L-Reput), and servers reputation (S-Reput), total trust (Total-Tru), and total reputation (Total-Reput) are shown in Table 6. In the last row of Table 6, there are values for the confidence of multi-dimensional direct trust computed using Equation (13). Figure 6 shows the dynamical variation of reputation, total multi-dimensional trust, and one of four different dimensions of trust (quality, price, logistics, and servers) for the book on Dangdang. Figure 7 shows the dynamical values of reputation, values of total multi-dimensional trust, and values of one of four dimensions of values of trust for the same book on Amazon. Finally, Figure 8 shows the variation of confidence of multi-dimensional direct trust of Dangdang and Amazon over 24 months from June 2013 to May 2015.

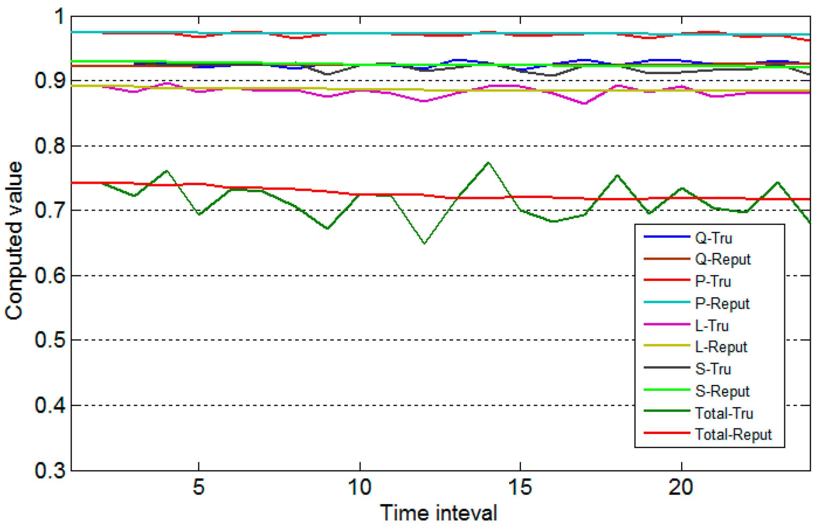


Figure 6. Dynamical reputation and trust for books on Dangdang over 24 months.

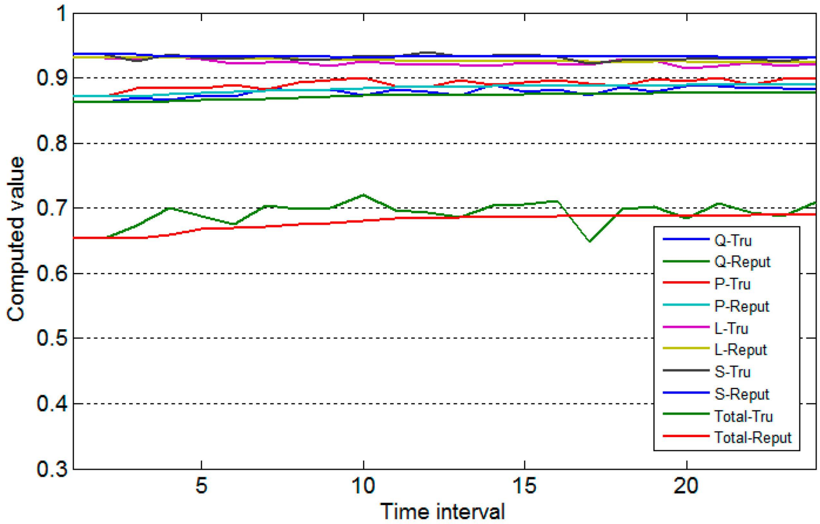


Figure 7. Dynamical reputation and trust for books on Amazon over 24 months.

Table 5. Number of evaluations of trust in books on Dangdang and Amazon during the 24 months.

Time Interval	Number of Evaluations of Dangdang								Number of Evaluations of Amazon							
	Quality		Price		Logistics		Servers		Quality		Price		Logistics		Servers	
	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−
2013.06	223	18	324	08	285	34	327	24	24	3	26	3	26	1	28	1
2013.07	353	25	285	07	149	27	261	19	35	3	42	2	33	2	23	2
2013.08	395	17	427	09	392	35	298	31	22	2	29	1	47	2	44	2
2013.09	264	26	250	14	264	42	235	25	46	4	42	3	46	3	37	2
2013.10	354	29	418	11	317	39	173	16	35	3	43	2	37	4	41	3
2013.11	469	30	367	07	185	28	372	35	41	1	35	3	25	2	32	1
2013.12	358	41	294	18	378	52	264	19	64	4	52	2	53	5	37	3
2014.01	596	47	425	03	421	87	287	55	39	2	47	1	71	9	52	4
2014.02	397	32	358	10	258	34	232	21	22	2	39	0	45	3	32	1
2014.03	286	23	261	06	274	46	359	23	47	3	28	2	27	2	45	2
2014.04	243	28	174	05	152	39	285	41	35	3	31	3	34	3	37	0
2014.05	378	11	282	12	250	41	252	28	34	4	42	2	33	3	29	1
2014.06	412	25	467	02	376	32	274	15	53	2	37	3	38	4	48	2
2014.07	258	32	365	15	311	27	327	43	26	2	54	4	45	3	35	1
2014.08	395	28	391	12	285	43	163	30	41	3	40	2	31	2	42	2
2014.09	406	13	226	05	128	36	270	22	30	4	29	2	36	3	21	2
2014.10	378	29	362	08	380	29	361	27	51	3	30	3	57	2	36	3
2014.11	312	14	254	16	294	41	235	35	48	5	43	2	65	3	28	2
2014.12	659	31	258	05	459	40	196	28	39	2	58	4	46	6	31	2
2015.01	875	69	467	01	396	74	452	51	52	3	69	3	72	8	80	6
2015.02	457	32	357	19	238	37	239	27	21	1	32	3	47	3	34	2
2015.03	485	21	274	08	165	24	368	21	30	2	54	3	25	2	27	2
2015.04	266	19	187	14	271	36	227	35	27	2	41	2	42	3	43	2
2015.05	425	28	382	09	318	33	185	26	42	3	48	3	39	2	27	1

Table 6. Computational results of reputation and trust for books on Dangdang over 24 months.

Time Interval	Q-Tru.	Q-Reput.	P-Tru.	P-Reput.	L-Tru.	L-Reput.	S-Tru	S-Reput.	Total-Tru	Total-Reput	$Conf$
2013.06	0.9218	0.9218	0.9731	0.9731	0.8910	0.8910	0.9292	0.9292	0.7426	0.7426	0.99943
2013.07	0.9218	0.9218	0.9731	0.9731	0.8910	0.8910	0.9292	0.9292	0.7426	0.7426	0.99919
2013.08	0.9238	0.9218	0.9730	0.9731	0.8813	0.8910	0.9292	0.9292	0.7227	0.7426	0.99958
2013.09	0.9288	0.9225	0.9739	0.9730	0.8960	0.8877	0.9240	0.9292	0.7611	0.7376	0.99933
2013.10	0.9195	0.9240	0.9672	0.9732	0.8823	0.8898	0.9235	0.9279	0.6933	0.7423	0.99939
2013.11	0.9236	0.9231	0.9730	0.9720	0.8895	0.8883	0.9245	0.9270	0.7322	0.7341	0.99939
2013.12	0.9261	0.9232	0.9734	0.9722	0.8837	0.8885	0.9240	0.9266	0.7283	0.7339	0.99949
2014.01	0.9176	0.9236	0.9657	0.9724	0.8863	0.8878	0.9272	0.9262	0.7052	0.7332	0.99954
2014.02	0.9269	0.9229	0.9715	0.9715	0.8757	0.8876	0.9084	0.9263	0.6716	0.7301	0.99942
2014.03	0.9230	0.9233	0.9713	0.9715	0.8863	0.8863	0.9238	0.9244	0.7248	0.7242	0.99944
2014.04	0.9232	0.9233	0.9720	0.9715	0.8798	0.8863	0.9270	0.9243	0.7215	0.7243	0.99913
2014.05	0.9174	0.9233	0.9706	0.9715	0.8676	0.8857	0.9138	0.9245	0.6481	0.7240	0.99938
2014.06	0.9325	0.9228	0.9685	0.9715	0.8799	0.8842	0.9191	0.9236	0.7170	0.7182	0.99962
2014.07	0.9264	0.9235	0.9759	0.9712	0.8913	0.8839	0.9279	0.9233	0.7746	0.7181	0.99944
2014.08	0.9162	0.9237	0.9686	0.9716	0.8906	0.8844	0.9150	0.9236	0.6998	0.7219	0.99927
2014.09	0.9253	0.9232	0.9708	0.9714	0.8809	0.8848	0.9071	0.9231	0.6832	0.7205	0.99899
2014.10	0.9319	0.9234	0.9719	0.9713	0.8633	0.8846	0.9228	0.9221	0.6930	0.7183	0.99960
2014.11	0.9240	0.9239	0.9722	0.9714	0.8931	0.8833	0.9233	0.9221	0.7541	0.7169	0.99936
2014.12	0.9300	0.9239	0.9646	0.9714	0.8817	0.8839	0.9112	0.9222	0.6944	0.7188	0.99945
2015.01	0.9299	0.9242	0.9726	0.9711	0.8907	0.8837	0.9121	0.9216	0.7352	0.7176	0.99965
2015.02	0.9246	0.9245	0.9760	0.9711	0.8752	0.8841	0.9167	0.9211	0.7045	0.7185	0.99939
2015.03	0.9261	0.9245	0.9663	0.9714	0.8798	0.8837	0.9160	0.9209	0.6969	0.7178	0.99934
2015.04	0.9309	0.9246	0.9708	0.9711	0.8808	0.8835	0.9255	0.9207	0.7430	0.7169	0.99927
2015.05	0.9257	0.9248	0.9621	0.9711	0.8828	0.8834	0.9093	0.9209	0.6798	0.7180	0.99938

Table 7. Computational results of reputation and trust for books on Amazon over 24 months.

Time Interval	Q-Tru.	Q-Reput.	P-Tru.	P-Reput.	L-Tru.	L-Reput.	S-Tru	S-Reput.	Total-Tru	Total-Reput	$Conf$
2013.06	0.8621	0.8621	0.8710	0.8710	0.9310	0.9310	0.9355	0.9355	0.6540	0.6540	0.99372
2013.07	0.8621	0.8621	0.8710	0.8710	0.9310	0.9310	0.9355	0.9355	0.6540	0.6540	0.99479
2013.08	0.8697	0.8621	0.8837	0.8710	0.9286	0.9310	0.9262	0.9355	0.6739	0.6540	0.99494
2013.09	0.8666	0.8646	0.8843	0.8752	0.9331	0.9302	0.9359	0.9324	0.7006	0.6589	0.99626
2013.10	0.8724	0.8651	0.8832	0.8775	0.9285	0.9309	0.9313	0.9333	0.6874	0.6673	0.99575
2013.11	0.8721	0.8666	0.8892	0.8786	0.9215	0.9304	0.9292	0.9329	0.6748	0.6706	0.99508
2013.12	0.8842	0.8675	0.8829	0.8804	0.9237	0.9290	0.9349	0.9323	0.7040	0.6712	0.99674
2014.01	0.8797	0.8699	0.8936	0.8807	0.9232	0.9282	0.9268	0.9326	0.6979	0.6753	0.99701
2014.02	0.8819	0.8711	0.8966	0.8824	0.9182	0.9276	0.9289	0.9319	0.7000	0.6778	0.99504
2014.03	0.8738	0.8723	0.9010	0.8839	0.9261	0.9265	0.9341	0.9316	0.7203	0.6800	0.99527
2014.04	0.8825	0.8724	0.8884	0.8856	0.9219	0.9265	0.9330	0.9318	0.6976	0.6837	0.99528
2014.05	0.8780	0.8734	0.8863	0.8859	0.9207	0.9261	0.9403	0.9319	0.6932	0.6849	0.99527
2014.06	0.8737	0.8737	0.8957	0.8859	0.9198	0.9256	0.9330	0.9326	0.6856	0.6855	0.99619
2014.07	0.8885	0.8737	0.8897	0.8867	0.9178	0.9252	0.9346	0.9326	0.7037	0.6855	0.99574
2014.08	0.8790	0.8748	0.8927	0.8869	0.9241	0.9246	0.9356	0.9328	0.7056	0.6867	0.99589
2014.09	0.8824	0.8751	0.8959	0.8873	0.9226	0.9246	0.9332	0.9330	0.7110	0.6879	0.99412
2014.10	0.8723	0.8755	0.8916	0.8878	0.9202	0.9245	0.9224	0.9330	0.6482	0.6893	0.99583
2014.11	0.8861	0.8753	0.8874	0.8880	0.9297	0.9242	0.9269	0.9324	0.6991	0.6870	0.99613
2014.12	0.8785	0.8759	0.8977	0.8880	0.9279	0.9245	0.9271	0.9321	0.7024	0.6876	0.99611
2015.01	0.8868	0.8761	0.8948	0.8885	0.9137	0.9247	0.9285	0.9318	0.6845	0.6884	0.99764
2015.02	0.8868	0.8766	0.9000	0.8888	0.9178	0.9242	0.9295	0.9316	0.7078	0.6882	0.99486
2015.03	0.8846	0.8771	0.8894	0.8894	0.9239	0.9239	0.9295	0.9315	0.6923	0.6891	0.99468
2015.04	0.8840	0.8774	0.8979	0.8894	0.9184	0.9239	0.9259	0.9314	0.6886	0.6892	0.99568
2015.05	0.8826	0.8777	0.8982	0.8897	0.9221	0.9236	0.9324	0.9312	0.7089	0.6892	0.99596

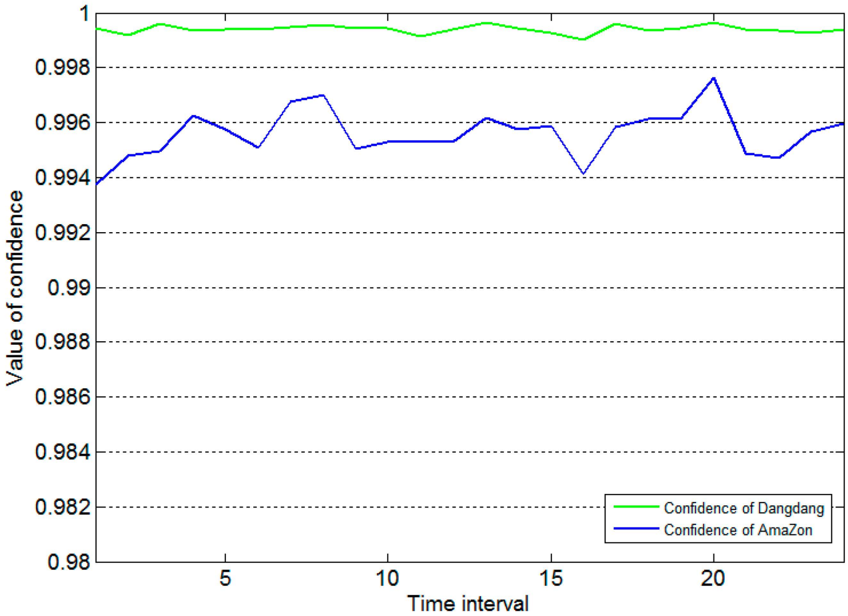


Figure 8. Variation values of confidence of multi-dimensional direct trust over 24 months.

5.3. Discussion

From Figures 6 and 7 the following conclusions can be drawn. In the case of Dangdang, single dimension values of reputation are, from high to low, price reputation (P-Repu), server reputation (S-Repu), quality reputation (Q-Repu), and logistics reputation (L-Repu). In the case of Amazon, single dimension values of reputation are, from high to low, server reputation (S-Repu), logistics reputation (L-Repu), price reputation (P-Repu), and quality reputation (Q-Repu). It can be noted that trust changed quickly because it was based directly on evaluations, whereas reputation changed slowly. Therefore, the model can correctly simulate local trust and global reputation. Comparing the total reputation shown in Figures 6 and 7 we can see that the reputation of Dangdang is higher than that of Amazon, and the former is decreasing slowly. The reputation of Amazon is lower than that of Dangdang and is increasing slowly. It can also be observed from Figure 8 that the values of confidence of total direct trust in Dangdang are higher than those of Amazon because there are more evaluations of Dangdang compared with Amazon.

6. Conclusions

A new closed-loop feedback computation model of dynamical reputation based on the trust evaluation in BtoC e-commerce has been proposed in this paper. Three concepts, namely direct trust, total trust, and reputation, are discussed initially. Based on the probability theory of evaluations of different dimensions of trust, a new dynamical computational model of trust and reputation is established. Multi-dimensional characteristics and the composition of trust in BtoC e-commerce are analyzed and the ratings of each customer are used as basic trust score events in the probability distribution. A logical model of trust and reputation is established based on the relationship between trust and reputation, and an iterative computation model of dynamical reputation is further proposed by using a closed-loop feedback mechanism. Furthermore, a time series of massive feedback ratings of customers are aggregated to formulate the sellers' local temporal trust scores using Beta distribution. Computational experiments on repeated transactions for the same commodity over a period of 24 months on Dangdang and Amazon are also performed. The results show that the proposed computational model can effectively simulate a variation in reputation. The proposed computational model for local trust and overall reputation can play a guiding role in both theoretical research into computational models of trust and reputation and the practical design of reputation systems in e-commerce. How to design a series of comparative experiments with a suitable method is not easy because of different mechanisms. Thus we did not design more comparative experiments. The information processing method derived in this paper is a trial. An advanced time-series signal processing method can also be used in the future. These directions are our next further research topics.

Acknowledgments: This research is supported by the National Natural Science Foundation of China (71302080), the Shanghai Natural Science Foundation (12ZR1409900), Ministry of Education Research of Social Sciences Youth Foundation projects (13YJC630149), and the Special Research Foundation for the Doctoral Program of Higher Education of China (20120078120001).

Author Contributions: All authors have made significant contributions to the paper. Bo Tian carried out a literature survey, proposed the trust and reputation computation system, and wrote the paper. Jingti Han and Kecheng Liu contributed to simulations and modification of the manuscript. All authors have read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. China Internet Network Information Center. The Thirty-Fifth China Internet Network Development Status Report in February, 2015. Available online: https://www.cnnic.cn/hlwfzyj/hlwxzbg/hlwtjbg/201502/t20150203_51634.htm (accessed on 28 January 2016). (In Chinese).
2. Lin, W.-S.; Wang, C.-H. Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Comput. Educ.* **2012**, *58*, 88–99. [CrossRef]
3. Wu, X.; Chen, Q.; Zhou, W.; Guo, J. A review of mobile commerce consumers' behavior research: Consumer acceptance, loyalty and continuance (2000–2009). *Int. J. Mob. Commun.* **2010**, *8*, 528–560. [CrossRef]
4. Pinyol, I.; Sabater-Mir, J. Computational trust and reputation models for open multi-agent systems: A review. *Artif. Intell. Rev.* **2013**, *40*, 1–25. [CrossRef]
5. Gutowska, A.; Sloane, A.; Buckley, K.A. On Desideratum for B2C E-Commerce Reputation Systems. *J. Comput. Sci. Technol.* **2009**, *24*, 820–832. [CrossRef]
6. Jøsang, A.; Ismail, R.; Boyd, C. A survey of trust and reputation systems for online service provision. *Decis. Support Syst.* **2007**, *43*, 618–644. [CrossRef]
7. Wang, Y.D.; Emurian, H.H. An overview of online trust: Concepts, elements, and implications. *Comput. Hum. Behav.* **2005**, *21*, 105–125. [CrossRef]
8. Qin, T.; Liu, X. DSRtrust: A dynamic trust model of distinguishing service and recommendation for internet-based virtual computing environment. *Int. J. Grid Distrib. Comput.* **2014**, *7*, 135–147. [CrossRef]
9. Zhang, X.; Cui, L.; Wang, Y. Commtrust: Computing multi-dimensional trust by mining e-commerce feedback comments. *IEEE Trans. Knowl. Data Eng.* **2014**, *26*, 1631–1643. [CrossRef]
10. Urbano, J.; Rocha, A.P.; Oliveira, E. An approach to computational social trust. *AI Commun.* **2014**, *27*, 113–131.
11. Sabater, J.; Sierra, C. Review on computational trust and reputation models. *Artif. Intell. Rev.* **2005**, *24*, 33–60. [CrossRef]
12. Kant, V.; Bharadwaj, K.K. Fuzzy computational models of trust and distrust for enhanced recommendations. *Int. J. Intell. Syst.* **2013**, *28*, 332–365. [CrossRef]
13. Marsh, S.P. Formalizing Trust as a Computational Concept. Ph.D. Thesis, University of Stirling, Stirling, UK, 1994.
14. Shankar, V.; Urban, G.L.; Sultan, F. Online trust: A stakeholder perspective, concepts, implications, and future directions. *J. Strateg. Inf. Syst.* **2002**, *11*, 325–344. [CrossRef]
15. Che, S.; Feng, R.; Liang, X.; Wang, X. A lightweight trust management based on Bayesian and entropy for wireless sensor networks. *Secur. Commun. Netw.* **2015**, *8*, 168–175. [CrossRef]
16. Shi, X.; Zhang, Y. Design and implementation of P2P trust model based on the classic Bayesian networks theory. *J. Theor. Appl. Inf. Technol.* **2012**, *45*, 129–135.
17. Denko, M.K.; Sun, T.; Woungang, I. Trust management in ubiquitous computing: A Bayesian approach. *Comput. Commun.* **2011**, *34*, 398–406. [CrossRef]

18. Zheng, Q.; Tian, B. A Trust Evaluation Model for B2C E-Commerce. In Proceedings of the 2007 IEEE International Conference on Service Operations and Logistics, and Informatics, Philadelphia, PA, USA, 27–29 August 2007.
19. Tian, B.; Yang, L. Dynamic Reputation Model in Service-Oriented Computing Environment. In Proceedings of the 2011 International Conference on Transportation, Mechanical, and Electrical Engineering (TMEE), Changchun, China, 16–18 December 2011.
20. Tian, B.; Wang, J.; Yang, L. Recommended trust evaluation in B2C E-commerce based on fuzzy analytic hierarchy process. *Int. J. Knowl. Syst. Sci.* **2012**, *3*. [CrossRef]
21. Ramchurn, S.D.; Huynh, D.; Jennings, N.R. Trust in multi-agent systems. *Knowl. Eng. Rev.* **2004**, *19*. [CrossRef]
22. Li, H.; Singhal, M. Trust management in distributed systems. *IEEE Comput.* **2007**, *40*, 45–53. [CrossRef]
23. Alvaro, E.A.; Benjamin, A.; Gheorghe, C.S. Reputation management in collaborative computing systems. *Secur. Commun. Netw.* **2010**, *3*, 546–564.
24. Srivatsa, M.; Liu, L. Securing decentralized reputation management using TrustGuard. *J. Parallel Distrib. Comput.* **2006**, *66*, 1217–1232. [CrossRef]
25. Xiong, L.; Liu, L. PeerTrust: Supporting reputation-based trust for peer-to-peer electronic communities. *IEEE Trans. Knowl. Data Eng.* **2004**, *16*, 843–857. [CrossRef]
26. Kraounakis, S.; Demetropoulos, I.N.; Michalas, A.; Obaidat, M.S.; Sarigiannidis, P.G.; Louta, M.D. A robust reputation-based computational model for trust establishment in pervasive systems. *IEEE Syst. J.* **2015**, *9*, 878–891. [CrossRef]
27. Li, X.; Du, J. Adaptive and attribute-based trust model for service level agreement guarantee in cloud computing. *IET Inf. Secur.* **2013**, *7*, 39–50. [CrossRef]
28. *Mobile Commerce and Wireless Computing Systems (Chin. Transl.)*; Chen, Z.B., Translator; Higher Education Press: Beijing, China, 2006.Elliott, G.; Phillips, N. Addison-Wesley: Boston, MA, USA, 2003.
29. Ponte, E.B.; Carvajal-Trujillo, E.; Escobar-Rodríguez, T. Influence of trust and perceived value on the intention to purchase travel online: Integrating the effects of assurance on trust antecedents. *Tour. Manag.* **2015**, *47*, 286–302. [CrossRef]
30. Hong, I.B. Understanding the consumer's online merchant selection process: The roles of product involvement, perceived risk, and trust expectation. *Int. J. Inf. Manag.* **2015**, *35*, 322–336. [CrossRef]
31. Moody, G.D.; Galletta, D.F.; Lowry, P.B. When trust and distrust collide online: The engenderment and role of consumer ambivalence in online consumer behavior. *Electron. Commer. Res. Appl.* **2014**, *13*, 266–282. [CrossRef]
32. Kim, K.; Hong, E.; Rho, S. The study of defined buying factors affecting trust building and service performance in financial management systems. *Math. Comput. Model.* **2013**, *58*, 38–48. [CrossRef]
33. Yen, D.C.; Wu, C.S.; Cheng, F.F.; Huang, Y.W. Determinants of users' intention to adopt wireless technology: An empirical study by integrating TTF with TAM. *Comput. Hum. Behav.* **2010**, *26*, 906–915. [CrossRef]
34. Jøsang, A. The Right Type of Trust for Distributed Systems. In Proceedings of the 1996 Workshop on New Security Paradigms (NSPW '96), Lake Arrowhead, CA, USA, 17–20 September 1996.
35. Yu, B.; Singh, M.P. An Evidential Model of Distributed Reputation Management. In Proceedings of the First International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS '02), Bologna, Italy, 15–19 July 2002.
36. Sabater, J.; Sierra, C. REGRET: A Reputation Model for Gregarious Societies. In Proceedings of the fifth International Conference on Autonomous Agents (AGENTS '01), Montreal, QC, Canada, 28 May–1 June 2001.
37. Schmidt, S.; Steele, R.; Dillon, T.S.; Chang, E. Fuzzy trust evaluation and credibility development in multi-agent systems. *Appl. Soft Comput.* **2007**, *7*, 492–505. [CrossRef]
38. Song, S.; Hwang, K.; Zhou, R.; Kwok, Y.K. Trusted P2P transactions with fuzzy reputation aggregation. *IEEE Internet Comput.* **2005**, *9*, 24–34. [CrossRef]
39. Zhou, R.; Hwang, K.; Cai, M. GossipTrust for fast reputation aggregation in Peer-to-Peer networks. *IEEE Trans. Knowl. Data Eng.* **2008**, *20*, 1282–1295. [CrossRef]
40. Wang, Y.; Lin, K.-J.; Wong, D.S.; Varadharajan, V. Trust management towards service-oriented applications. *Serv. Oriented Comput. Appl.* **2009**, *3*, 129–146. [CrossRef]

41. Golbeck, J.; Hendler, J. Accuracy of Metrics for Inferring Trust and Reputation in Semantic Web-Based Social Networks. In Proceedings of the 14th International Conference on Knowledge Engineering and Knowledge Management, Northamptonshire, UK, 5–8 October 2004.
42. Buragohain, C.; Agrawal, D.; Suri, S. A Game Theoretic Framework for Incentives in P2P Systems. In Proceedings of the Third International Conference on Peer-to-Peer Computing (P2P '03), Linköping, Sweden, 1–3 September 2003.
43. Cho, J.; Kwon, K.; Park, Y. Q-rater: A collaborative reputation system based on source credibility theory. *Expert Syst. Appl.* **2009**, *36*, 3751–3760. [CrossRef]
44. Wang, Y.; Hang, C.W.; Singh, M.P. A probabilistic approach for maintaining trust based on evidence. *J. Artif. Intell. Res.* **2011**, *40*, 221–267.
45. Liu, X.; Datta, A.; Rzadca, K. Trust beyond reputation: A computational trust model based on stereotypes. *Electron. Commer. Res. Appl.* **2013**, *12*, 24–39. [CrossRef]
46. Despotovic, Z.; Aberer, K. Maximum Likelihood Estimation of Peers' Performance in P2P Networks. Available online: http://www.eecs.harvard.edu/p2pecon/confman/papers/s2p3.pdf (accessed on 28 January 2016).
47. Beth, T.; Borcherding, M.; Klein, B. Valuation of trust in open networks. In Proceedings of the Third European Symposium on Research in Computer Security, Brighton, UK, 7–9 November 1994.
48. Ismai1, R.; Jøsang, A. The Beta Reputation System. In Proceedings of the 15th Bled Electronic Commerce Conference, Bled, Slovenia, 17–19 June 2002.
49. Mui, L.; Mohtashemi, M.; Halberstadt, A. A Computational Model of Trust and Reputation. In Proceedings of the 35th Annual Hawaii International Conference on System Sciences, Big Island, HI, USA, 7–10 January 2002.
50. Jøsang, A.; Haller, J. Dirichlet Reputation Systems. In Proceedings of the Second International Conference on Availability, Reliability and Security (ARES '07), Vienna, Austria, 10–13 April 2007.
51. Wang, Y.; Vassileva, J. Bayesian Network-Based Trust Model. In Proceedings of the IEEE/WIC International Conference on Web Intelligence (WI 2003), Halifax, NS, Canada, 13–17 October 2003.
52. Teacy, W.L.; Luck, M.; Rogers, A.; Jennings, N.R. An efficient and versatile approach to trust and reputation using hierarchical Bayesian modeling. *Artif. Intell.* **2012**, *193*, 149–185. [CrossRef]
53. Kim, D.J.; Song, Y.I.; Braynov, S.B.; Rao, H.R. A multidimensional trust formation model in B-to-C e-commerce: A conceptual framework and content analyses of academia practitioner perspectives. *Decis. Support Syst.* **2005**, *40*, 143–165. [CrossRef]
54. Mayer, R.C.; Davis, J.H.; Schoorman, F.D. An integrative model of organizational trust. *Acad. Manag. Rev.* **1995**, *20*, 709–734.
55. Tian, B.; Zheng, Q. Recommended Trust Evaluation Model in Business-to-Consumer E-Commerce Based on DS Evidence Fusion Theory. *J. Manag. Sci.* **2008**, *21*, 98–104.
56. McKnight, D.H.; Choudhury, V.; Kacmar, C. Developing and validating trust measures for e-commerce: An integrative typology. *Inf. Syst. Res.* **2002**, *13*, 334–359. [CrossRef]
57. Tian, B.; Liu, K.C.; Chen, Y.Z. Dynamical Trust and Reputation Computation Model for B2C E-Commerce. *Future Internet* **2015**, *7*, 405–428. [CrossRef]
58. Thirunarayan, K.; Anantharam, P.; Henson, C.; Sheth, A. Comparative trust management with applications: Bayesian approaches emphasis. *Future Gener. Comput. Syst.* **2014**, *31*, 182–199. [CrossRef]
59. Kravari, K.; Bassiliades, N. HARM: A Hybrid Rule-Based Agent Reputation Model Based on Temporal Defensible Logic. In Proceedings of the 6th International Symposium on Rules: Research Based and Industry Focused, Montpellier, France, 27–29 August 2012.