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A Reputation Bootstrapping Model for E-Commerce Based on Fuzzy DEMATEL Method and Neural Network

YAN WANG[1,2], LIQIN TIAN[3], AND ZHENGUO CHEN[3]
[1]College of Computer Science, Qinghai Normal University, Xining 810008, China
[2]College of Physics and Electronic Information Engineering, Qinghai University for Nationalities, Xining 810008, China
[3]College of Computer Science, North China Institute of Science and Technology, Beijing 101601, China

Corresponding author: Liqin Tian (wangy01028@126.com)

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ABSTRACT Reputation evaluation plays an important role in determining the credibility of online entities. Especially in e-commerce systems, consumers usually give priority to this indicator when choosing vendors. Reputation bootstrapping, which can determine the default reputation value of new entities, is still a challenging problem. Most current bootstrapping methods fail to consider the complexity, the ambiguity of trust, or the reputation and internal correlation characteristics of influential factors in the prediction process. Therefore, in this paper, a novel reputation bootstrapping model that combines the fuzzy decision-making trial and evaluation laboratory (DEMATEL) method with neural network prediction is established. First, we adopt a fuzzy multi-criteria decision-making model, named fuzzy DEMATEL method to discuss the intrinsic causal relationships between influential factors and identify the critical success factors (CSFs) for reputation estimation. Then, we adopt back propagation (BP) neural network to generalize the correlations between the CSFs and the initial reputation value. Finally, a case study is constructed to verify the proposed model. The experimental results indicate that the proposed model has better accuracy and efficiency compared with other reputation bootstrapping methods.

INDEX TERMS BP neural network, causal relationship, critical success factor, DEMATEL, fuzzy sets, reputation bootstrapping.

I. INTRODUCTION

Trust plays a prominent part in the context of physical stores and e-commerce [1]. There is no doubt that consumers will perceive more risk during the purchasing process if they lack trust with vendors [2]. As early researchers have declared, ‘‘trust, more than technology, promotes the development of e-commerce in all its forms’’ [3]. It is generally believed that reputation and feedback systems promote the trust, which makes consumers feel secure when purchasing through social e-commerce [4]. The basic idea of traditional reputation management is to encourage consumers to evaluate vendors, provide feedback after each transaction and aggregate ratings to obtain a reputation value that can assist consumers who are deciding whether to trade with a specific vendor [5].

However, rating information may not always be available [6], such as when a new vendor enters the e-commerce system and there is no transaction record available. In such cases, it is best for the system to assign an appropriate reputation value to the new vendor to enhance their visibility and to offer them an opportunity to compete with existing vendors. Thus, the system can provide a solution to the ‘‘cold start’’ problem. However, for most current reputation bootstrapping studies, only neutral or default initial reputation values are assigned to new vendors [7], [8]. The disadvantage of this assignment is that, when a minimum reputation value is assigned to a new vendor, it results in new vendors having no opportunity to be selected to provide transaction services to consumers; however, when a maximum or moderate value is

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set for new vendors, existing malicious vendors who have low reputation values can whitewash their bad transaction records by deleting their profiles and reregistering in the system as a new identity. Therefore, building an accurate reputation bootstrapping model for new vendors who have no rating history available is a necessary and challenging problem.

As far as we know, only a few researchers have attempted to handle the reputation bootstrapping problem without setting a default initial value [6], [9], [10]. The basic idea of most reputation bootstrapping models is that the correlations between quality of service (QoS) features and the performances of existing vendors are first learned through samples and then generalized to acquire the reputation values of new vendors. However, in China's largest C2C e-commerce site, Taobao, the reputation value is complicated, as it involves QoS value, type of product, brand effect, market strategy, various types of promotion, official certification and many other factors. Therefore, to assign the reputation values to new vendors accurately, we should examine the influencing factors from the root of the problem, analyze the intrinsic causal relationships, and identify the critical success factors (CSFs) for the reputation value. To address our research aim, we need input from professionals or experts with extensive experience in e-commerce domains, and we choose the DEMATEL (Decision Making Trial and Evaluation Laboratory) approach as our research method.

It is worth mentioning that fuzzy theory has great advantages in dealing with the uncertainty, dynamics, and vagueness of information [11]. Therefore, we combine fuzzy theory with the DEMATEL method to address this complex problem. To assign appropriate reputation values for new vendors, a reputation bootstrapping model based on fuzzy DEMATEL method and back propagation (BP) neural network is established in this paper. The contributions of this paper are as follows:

- A general model for C2C e-commerce websites that can solve the cold start problem for newly registered vendors is presented.
- To the best of our knowledge, we are the first to apply the fuzzy DEMATEL method to reputation prediction. Specifically, to assign an accurate reputation value to newly registered vendors, a large number of reputation-related factors are analyzed to explore CSFs that have a significant impact on reputation value.
- Reputation prediction accuracy is improved compared with reputation bootstrapping methods that considers only QoS features during initial reputation value assignment.

II. RELATED WORK

Reputation management has been studied in many computer science domains including e-commerce [12], multi-agent [13], peer-to-peer [14], and social network [15] systems. Reputation management can help entities choose a trustworthy and suitable partner so that risk can be minimized in future defective transactions [4]. Most existing studies [5], [12]–[15] concentrate on gathering and aggregating the ratings of consumers and encouraging honest feedback. However, few researchers have specifically studied the problem of reputation bootstrapping.

The proposed framework [16] assigned the reputation of the provider to newly deployed services. The authors assessed provider reputation according to past experiences. However, the framework cannot handle the problem that the provider is a newcomer during the reputation assessment process.

Burnett *et al.* [17] introduced the concept of stereotype based on the observable features and behaviors of partners. Subsequently, these stereotypes were applied to evaluate the unknown partners. This approach is fit for dynamic multi-agent systems and depends on cooperation among agents. In Jiao *et al.* [10], the concept of marginal reputation utility was introduced for the first time and combined with game theory to confirm the constraint of reputation formation to solve the reputation bootstrapping problem.

Okab *et al.* [9] combined QoS attributes with reputation values of similar services to estimate the reputation values of newcomer services based on regression models. Wu *et al.* [6] presented a reputation bootstrapping approach, where correlations between the QoS and reputation performance of existing services are first learned through artificial neural networks and then generalized to determine a reputation value of new and unknown services. However, determining appropriate reputation influencing factors from the root of the problem and analyzing the internal relationships between them is not discussed in the above literature.

Fombrun [18] evaluated a company's reputation by measuring its ability to provide value to shareholders; 6 indicators were introduced: company's charisma, product and service, social responsibility, vision and leadership, working environment, and financial performance. Oliveira *et al.* [19] used empirical testing and combined all trust dimensions (consumer characteristics, interactions, firm characteristics and website infrastructure) and the source of the trust of the path model to track the behavior trends of online consumers. Likewise, the estimation of the reputation of a vendor in e-commerce is a complicated problem. Therefore, it is of great concern to confirm CSFs that have a significant impact on reputation value during reputation prediction.

III. PRELIMINARIES AND PROPOSED MODEL

A. FUZZY SETS AND THE DEMATEL METHOD

In this section, background knowledge about DEMATEL and fuzzy theory method are discussed as follows:

The DEMATEL method is a synthetic approach used to establish and analyze structural models that involve causal relationships among complicated criteria [20]. It has been widely applied in many domains to help scholars address complex system problems, such as knowledge management [21], supplier selection [22], business intelligence [23], and emergency management [24]. The degree of influence between complex factors is often described by crisp values when building a structural model. However, in many real-world problems, crisp values are inadequate [21]. The relationships between factors tend to be ambiguous. Additionally, experts usually make assessments according to their accumulated experiences and expertise, and their estimations are often represented in equivocal linguistic terms. Therefore, transforming the linguistic estimation into fuzzy numbers is appropriate. Thus, fuzzy theory is applied to DEMATEL method to address this complex and uncertain problem.

Fuzzy logic provides a natural framework for handling uncertainty and the tolerance of imprecise data inputs for subjective tasks [25]. Since Zadeh [26] proposed fuzzy sets in 1965, fuzzy set theory has been the main theory used to address fuzziness, which is extremely useful for handling the vagueness of human thoughts and language when making decisions [27]. In fuzzy logic, numbers between 0 and 1 represent a partial truth, whereas crisp sets correspond to binary logic (0 or 1). Therefore, fuzzy logic can serve as the mathematical tool for expressing and handling fuzzy or imprecise judgements [25]. The basic structure of a fuzzy control system consists of four conceptual components: knowledge base, fuzzification interface, inference engine, and defuzzification interface [28]. A very significant feature of the fuzzy set is that an element belongs to a membership function with a certain degree, and the membership degree is denoted by a real value from 0-1.

Now, we briefly introduce some necessary definitions of fuzzy sets and the DEMATEL technique.

Definition 1: Let U be a universe of discourse, a fuzzy set$S$on$U$is characterized by a membership function $\mu_S : U \to [0, 1]$, for each $x \in U$, $\mu_S(x)$ represents the membership degree that x belongs to fuzzy set S.

Definition 2: In engineering, the membership function of a fuzzy random variable $\mu_S(x)$ generally satisfies the following format [29]:

$$\mu_S(x) = \begin{cases} G_1(x) & a \le x \le b \\ 1 & b \le x \le c \\ G_2(x) & c \le x \le d \\ 0 & else \end{cases}$$

where a, b, c and d are all real numbers that satisfy $a \le b \le c \le d$, $0 \le G_1(x) < 1$ is an increasing left continuous function in [a, b], and $G_1(a) = 0; 0 \le G_2(x) < 1$ is a decreasing right continuous function in [c, d], and $G_2(d) = 0$.

Specially, if the membership function satisfies the following equation:

$$\mu_S(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & \text{else} \end{cases} \quad (1)$$

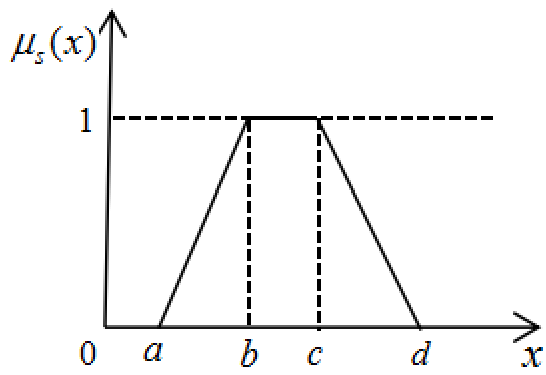

FIGURE 1. **Membership function of a fuzzy variable.**

Then, S is considered a set of trapezoidal fuzzy numbers, denoted as $N = (a, b, c, d)$. Figure 1 shows the trapezoidal membership function. Two operational laws and the CFCS defuzzification method are shown as follows:

1. Suppose $N_1 = (a_1, b_1, c_1, d_1)$ and $N_2 = (a_2, b_2, c_2, d_2)$ are two trapezoidal fuzzy numbers [26]. The addition operations of N_1 and N_2 are:

$$N_1 \oplus N_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2).$$

The multiplication operations of N_1 and N_2 are:

$$N_1 \otimes N_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2, d_1 \times d_2).$$

2. CFCS defuzzification method
Suppose $N_i = (a_i, b_i, c_i, d_i)$, $i = 1, \ldots n$ represents the trapezoidal fuzzy number and N_i^D represents its crisp value. Let $d^{max} = max_i d_i$, $a^{min} = min_i a_i$ and $\Delta = d^{max}$-a^{min}; then, the crisp value is computed as (2), as shown at the bottom this page [29], [30].

Definition 3: The initial direct-relation matrix $Z = (z_{ij})$ is an $n \times n$ matrix, and z_{ij} is denoted as the degree to which the criterion C_i affects the criterion C_j. Specifically, $z_{ii} = 0$ $(i = 1, \ldots .n)$.

Definition 4: The normalized direct-relation matrix $X = (x_{ij})_{n \times n}$ can be obtained through $X = \frac{Z}{s}$, where

$$s = \max_{1 \le i \le n} \left(\sum_{j=1}^{n} z_{ij} \right) \quad (3)$$

Hence, matrix X resembles the sub-stochastic matrix by deleting all rows and columns associated with the absorbing states [20]. It was proven that $\lim_{p \to \infty} X^p = O$ and $\lim_{p \to \infty} \left(I + X + X^2 + \ldots X^p \right) = (I - X)^{-1}$, where O is the null matrix and I is the identity matrix [31], [32]. The total-relation matrix $T = (t_{ij})_{n \times n}$ can be calculated using the following formula:

$$T = \lim_{p \to \infty} \left(X + X^2 + \ldots + X^p \right) = X(I - X)^{-1} \quad (4)$$

$$N_i^D = a^{min} + \Delta \times \frac{(b - a^{min})(\Delta + d - c)^2(d^{max} - a) + (d - a^{min})^2(\Delta + b - a)^2}{(\Delta + b - a)(\Delta + d - c)^2(d^{max} - a) + (\Delta + b - a)^2(\Delta + d - c)(d - a^{min})} \quad (2)$$

TABLE 1. The influencing factors of the reputation bootstrapping.

aspects	The criteria/factors
vendor	Authenticity of the product description, product type/brand, vendor's attitude, speed of delivery, after-sale service, degree of advertising promotion, price advantage, product update speed, response time
consumer	Quality of the consumer
transaction platform	Convenience of interaction, comfort of using the platform, performance of the security system
external factors	Third-party authentication, privacy- preservation level, uncertain network environment

The sum of the rows and the sum of the columns, represented by R_i and D_j, respectively, can be computed using the following equations:

$$R_i = \sum_{j=1}^{n} t_{ij}, \quad i = 1, 2, \ldots, n \tag{5}$$

$$D_j = \sum_{i=1}^{n} t_{ij}, \quad j = 1, 2, \ldots, n \tag{6}$$

B. PROPOSED MODEL

Often, the reputation value is not very high for many vendors with good QoS performance on C2C e-commerce websites, and vendors with the same QoS performance may have different reputation values, which implies that the estimation of vendor reputation is a complicated problem that not only depends on QoS (e.g., response time and service attitude) but also other intrinsic criteria, such as product type, risk, brand effect and third-party authentication. Therefore, determining the factors that have a significant impact on reputation is crucial when predicting the reputation value of new vendors.

Our proposed model uses the fuzzy DEMATEL method in conjunction with neural network to solve the reputation bootstrapping problem. The fuzzy DEMATEL method generates CSFs that significantly impact reputation. These CSFs serve as the inputs for the neural network for estimating the reputation value. Our reputation bootstrapping mode has three main three stages:

- Apply a fuzzy DEMATEL method for group decision-making to aggregate group ideas, analyse the intrinsic causal relationships among the various factors related to reputation in social e-commerce and explore CSFs that significantly impact reputation.
- Estimate the new vendor reputation value based on the BP neural network. Focus on CSFs that can compress the data process scale, reduce the learning time and improve the predication accuracy; then, generalize the correlations between CSFs and reputation by learning the samples repeatedly to predict the reputation values of newly registered vendors.
- Conduct a case study to verify efficiency and accuracy. When evaluating the reputation value of a newly registered vendor, the system needs to survey and test it in advance to obtain the corresponding values of the CSFs and predict the reputation value based on the BP neural network.

The sequence of steps of the our proposed model is demonstrated in the following process 1. Exploring and identifying CSFs is discussed in detail in Section **IV.** After identifying CSFs, the system needs to extract the CSFs and reputation values from existing vendors as training set and testing set, respectively, to acquire the well-trained neural network. The system also needs to give a reasonable CSF value to newly registered vendors after testing and investigation to assign reputation values accurately. The content of grading each CSF for the newly registered vendor will be introduced in Section **VI**.

Inspired by several pioneering studies [4], [19], we confirm the reputation-related factors for new vendors in e-commerce by comprehensively considering four aspects: vendor, consumer, transaction platform and external factors. The factors are listed in Table 1.

IV. GENERATE CSFS BASED ON FUZZY-DEMATEL METHOD

To explore the intrinsic causal relationships among these criteria and grasp the essence of a complex problem, the fuzzy DEMATEL method is adopted in this paper. This method can explore the indirect relationships that result from the analysis of the perceived direct relationships [33], which generates unique information about the complex problem that would be otherwise ignored. Reputation-related criteria analysis based on the fuzzy DEMATEL method consists of the following steps:

Step 1: Set up a committee of experts and design the fuzzy linguistic scale.

An $l-$member committee of experts is formed. Suppose that a specific e-commerce reputation bootstrapping module contains a set of criteria, as shown in Table 2. And these experts should make pairs of comparisons about the direct influence between different C_i values in linguistic terms. The influence degree between different criteria is denoted as five linguistic terms (no influence, very low influence, low influence, high influence and very high influence), and the corresponding trapezoidal fuzzy numbers of these terms are shown in Table 3.

Process 1 The Sequence of Steps of the Proposed Model.

1. Generating CSFs based on fuzzy-DEMATEL method

- Set a decision goal and set up a committee of experts
- Determine the evaluation criteria of the reputation and design the fuzzy linguistic scale.
- Acquire the initial fuzzy assessment matrices of experts and normalize them.
- Aggregate the evaluations of all experts, and obtain the total-relation fuzzy matrix.
- Establish and analyse the structural model.
- Explore the intrinsic relationship among these factors and identify the CSFs.

2. Predict the new vendor's reputation using BP neural network

- Normalize critical success factors (CSFs) and reputation values of the selected training set and testing set.
- Acquire the well-trained BP neural network by learning the samples, and verify the accuracy.
- The system survey and test the newly registered vendor and grade each CSFs.
- Normalize the values of CSFs of new vendors, and predict the reputation value.

TABLE 2. Reputation criteria.

Symbol	Definition
C_1	Authenticity of the product description
C_2	Vendor's attitude
C_3	Degree of advertising promotion
...	...
C_n	...

TABLE 3. Correspondence of linguistic terms and linguistic values.

Linguistic terms	Linguistic values
Very High influence (VH)	(0.75,0.75,1.0,1.0)
High influence (H)	(0.5,0.75,0.75,1.0)
Low influence (L)	(0.25,0.5,0.75,1.0)
Very low influence (VL)	(0,0.25,0.5,0.75)
No influence (N)	(0,0,0.25,0.5)

Step 2: Establish and normalize the initial direct-relation fuzzy matrices.

l fuzzy matrices can be obtained, and each is represented by $Z^{\langle w\rangle} = \left(z_{ij}^{\langle w\rangle}\right)_{n\times n}, w = 1, 2 \ldots l$, where $z_{ij}^{\langle w\rangle} = \left(a_{ij}^{\langle w\rangle}, b_{ij}^{\langle w\rangle}, c_{ij}^{\langle w\rangle}, d_{ij}^{\langle w\rangle}\right)$.

Then, we can obtain the normalized direct-relation fuzzy matrices $X^{\langle w\rangle}$ according to (3), which is denoted as $x^{\langle w\rangle} = x_{ij}^{\langle w\rangle} n \times n, w = 1, 2, \ldots l$.

$$x_{ij}^{\langle w\rangle} = \frac{z_{ij}^{\langle w\rangle}}{s} = \left(\frac{a_{ij}^{\langle w\rangle}}{s}, \frac{b_{ij}^{\langle w\rangle}}{s}, \frac{c_{ij}^{\langle w\rangle}}{s}, \frac{d_{ij}^{\langle w\rangle}}{s}\right) \tag{7}$$

Step 3: Aggregate the evaluations of l experts.

Theorem 1 is used to calculate the average matrix, which is denoted as:

$$\tilde{X} = \frac{\left(X^{\langle 1\rangle} \oplus X^{\langle 2\rangle} \ldots \oplus X^{\langle l\rangle}\right)}{l} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots & \tilde{x}_{2n} \\ . & . & \ldots & . \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \ldots & \tilde{x}_{nn} \end{bmatrix}$$

$$\tilde{x}_{ij} = \frac{\sum_{w=1}^{l} x_{ij}^{\langle w\rangle}}{l}, \quad w = 1, \ldots l \tag{8}$$

Then, the total-relation fuzzy matrix can be obtained by (4) and (8), denoted as $\tilde{T} = \left[\tilde{t}_{ij}\right]_{n\times n} = \tilde{X}(I - \tilde{X})^{-1}$, where each $\tilde{t}_{ij}$ represents the total influence from C_i on the other factors.

Step 4: Generate and analyse the structural model

The values of $\tilde{R}_i = \sum_{j=1}^{n} \tilde{t}_{ij}$, $\tilde{M}_j = \sum_{i=1}^{n} \tilde{t}_{ij}$ can be calculated by (5) and (6). $\tilde{R}_i$ indicates the overall direct and indirect influences of factor C_i on other factors, whereas $\tilde{M}_i$ indicates the overall influence that factor C_i receives from the other factors. Then, $\tilde{R}_i+\tilde{M}_i$ and $\tilde{R}_i-\tilde{M}_i$ can be calculated. By using the CFCS method for defuzzification (2), we can convert fuzzy numbers into crisp scores. Thus, we can acquire the crisp values $(\tilde{R}_i+\tilde{M}_i)^D$ and $(\tilde{R}_i-\tilde{M}_i)^D$, where $(\tilde{R}_i+\tilde{M}_i)^D$ is the "prominence" that reflects the importance of criterion C_i on the system and $(\tilde{R}_i - \tilde{M}_i)^D$ is the "relation", that indicates the net effect criterion C_i exerts on the system [24]. Furthermore, $(\tilde{R}_i - \tilde{M}_i)^D > 0$ indicates that factor C_i belongs to the cause group, whereas $(\tilde{R}_i - \tilde{M}_i)^D < 0$ indicates that factor C_i belongs to the effect group.

Step 5: Explore the intrinsic relationships among these factors and identify the CSFs

A causal relationship model of $((\tilde{R}_i + \tilde{M}_i)^D, (\tilde{R}_i - \tilde{M}_i)^D)$ can be established to explore the intrinsic relationships among these factors and provide valuable information for identifying CSFs. In addition, we calculate $(\tilde{R}_i)^D$ to assist the analysis.

1. $(\tilde{R}_i - \tilde{M}_i)^D > 0$, where criterion C_i belongs to the cause group, which means that criterion C_i has a net impact on the system. Furthermore, $(\tilde{R}_i + \tilde{M}_i)^D$ is the most important value to consider, and a high value of $(\tilde{R}_i + \tilde{M}_i)^D$ indicates that criterion C_i is key for the realization of the system objectives. Meanwhile, if $(\tilde{R}_i)^D$ is also relatively high, it indicates that C_i has an important impact on the other factors. In this case, we have sufficient confidence to confirm that criterion C_i can be recognized as a CSF. Here is another scenario: if $(\tilde{R}_i + \tilde{M}_i)^D$ is lower than the other factors, criterion C_i does not play a significant role in achieving the goal of the system, which shows that factor C_i is not sufficient to be recognized as a CSF.
2. $(\tilde{R}_i - \tilde{M}_i)^D < 0$, where criterion C_i belongs to the effect group, which means that criterion C_i tends to be affected by other factors. Furthermore, if $(\tilde{R}_i - \tilde{M}_i)^D$ is low, criterion C_i is easily impacted by other factors. Thus, its improvement can be achieved by adjusting other factors. If $(\tilde{R}_i - \tilde{M}_i)^D$ and $(\tilde{R}_i + \tilde{M}_i)^D$ are both relatively high, criterion C_i is slightly impacted by other factors, but its influence on achieving system goals is remarkable due to the high $(\tilde{R}_i + \tilde{M}_i)^D$. Therefore, the criterion C_i is a CSF.

Based on the above analysis, CSFs that play a key role in the realization of the system objective can be identified.

V. REPUTATION PREDICTION THROUGH THE BP NEURAL NETWORK

The artificial neural network is an abstract mathematical algorithm model that utilizes a physical device to model the structure and function of a biological neural network; it consists of multiple input and single output neurons connected according to certain topological structures [34]. Currently, the BP neural network has been widely used in regression [35], recognition [36], and prediction analysis [37] due to its ability to address nonlinear and complex system problems; it has advantages for dealing with problems of fuzzy and inaccurate information while considering many factors. Theoretically, it has been proven that the three-layer BP neural network can realize arbitrary nonlinear mappings [34]. Therefore, it is employed to learn the correlations between the CSFs and the reputation value in this model.

TABLE 4. Linguistic assessment data.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
C_1	-	H	H	N	VH	VH	N	N	N	H	N
C_2	VH	-	H	L	N	VH	N	VH	VH	VH	VH
C_3	L	N	-	L	N	VH	L	H	L	N	N
C_4	H	VH	H	-	H	L	N	L	L	VH	H
C_5	N	VH	VH	H	-	H	H	VH	N	N	H
C_6	H	H	H	L	VH	-	H	L	N	N	N
C_7	N	N	N	L	VH	H	-	N	N	N	VH
C_8	N	VH	L	VH	N	H	N	-	N	N	L
C_9	N	VH	N	N	N	L	N	N	-	N	N
C_{10}	VH	VH	H	VH	L	H	N	N	L	-	L
C_{11}	H	L	H	H	N	VH	H	H	L	L	-

First, the output value is calculated according to the current connection weight, threshold and input vector. Then, according to the difference between the output value and the target value, the connection weights and thresholds are modified. The learning process is repeated until the mean square error is less than a given value. The selection of initial values of the connection weights and thresholds is critical to the training time but has no effect on the training results. In this proposed model, initial values are randomly assigned, and all neurons employ a sigmoid activation function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

The input vector is (C_1) tuple (C_1), which denotes the CSFs derived from the previous step. The output value is the corresponding reputation value. The CSFs and the corresponding reputation of the existing entities are used as the training sets and testing sets, respectively, and the neural network is trained using the effective error BP algorithm. To speed up neural network training, input vectors and output values are normalized through the following formula:

$$Y^{'} = \frac{Y - min(Y)}{max(Y) - min(Y)} \tag{10}$$

Note that some of the criteria have values that are interpreted inversely. Thus, the normalized value (C_1) is calculated as follows:

$$Y^{'} = 1 - \frac{Y - min(Y)}{max(Y) - min(Y)} \tag{11}$$

In this paper, we adopt a fast optimization algorithm, called the Levenberg-Marquardt (LM) algorithm to train the neural network; LM uses the following equation to iteratively revise the connection weights and thresholds.

$$x(k+1) = x(k) - [J^T J + \mu I]^{-1} J^T e \tag{12}$$

TABLE 5. Values of $\tilde{R}_i, \tilde{M}_i, \tilde{R}_i+\tilde{M}_i, \tilde{R}_i-\tilde{M}_i$.

	$\tilde{R}_i$	$\tilde{M}_i$	$\tilde{R}_i+\tilde{M}_i$	$\tilde{R}_i-\tilde{M}_i$
C_1	(0.22, 0.78, 3.87, 6.95)	(0.69, 1.86, 4.59, 8.34)	(0.91, 3.64, 8.46, 15.29)	(-0.47, -1.08, -0.72, -1.39)
C_2	(0.36, 1.42, 4.64, 6.22)	(0.21, 1.14, 4.57, 5.22)	(0.57, 2.56, 9.21, 11.44)	(0.15, 0.28, 0.07, 2.00)
C_3	(0.68, 1.57, 5.69, 9.22)	(0.55, 1.44, 4.25, 7.66)	(1.23, 4.01, 9.94, 16.88)	(0.13, 013, 1.44, 1.56)
C_4	(0.58, 1.52, 4.32, 8.10)	(0.63, 1.74, 4.02, 6.68)	(1.21, 3.26, 8.34, 14.78)	(-0.05, -0.18, 0.22, 1.42)
C_5	(0.37, 1.19, 3.21, 4.27)	(0.43, 1.45, 4.12, 6.84)	(0.80, 2.64, 8.39, 11.01)	(-0.06, -0.26, -0.91, -2.57)
C_6	(0.42, 1.49, 4.21, 6.27)	(0.62, 1.41, 4.30, 6.89)	(1.04, 2.90, 8.51, 13.16)	(-0.20, 0.09, -0.09, -0.62)
C_7	(0.54, 1.58, 4.33,8.23)	(0.43, 1.79, 4.21, 6.65)	(0.97, 3.27, 8.54, 14.88)	(0.07, -0.21, 0.12, 1.58)
C_8	(0.59, 0.99, 4.52, 8.53)	(0.48, 1.70, 4.65, 6.88)	(1.07, 2.69, 9.17, 15.41)	(0.11, -0.71, -0.13, 1.65)
C_9	(0.39, 1.29, 3.11, 4.27)	(0.53, 1.55, 4.02, 6.33)	(0.92, 2.84, 7.13, 10.60)	(-0.14, -0.26, -0.91, -2.06)
C_{10}	(0.33, 1.12, 2.57, 3.86)	(0.19, 1.42, 4.61, 5.22)	(0.52, 2.52, 7.18, 9.08)	(0.14, -0.28, -2.04, -1.36)
C_{11}	(0.25, 1.22, 4.84, 6.22)	(0.23, 1.15, 4.43, 5.72)	(0.48, 2.27, 9.27, 11.94)	(0.02, 0.07, 0.41, 0.50)

TABLE 6. The values of $(\tilde{R}_j+\tilde{M}_j)^D, (\tilde{R}_j-\tilde{M}_j)^D, (\tilde{R}_i)^D$.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
$(\tilde{R}_i+\tilde{M}_i)^D$	4.079	2.902	4.221	3.905	3.809	3.780	3.965	4.120	2.857	2.660	2.206
$(\tilde{R}_i-\tilde{M}_i)^D$	-0.023	0.035	0.145	0.033	-0.031	-0.087	0.190	0.103	-0.221	-0.209	0.038
$(\tilde{R}_i)^D$	2.785	1.273	2.886	2.067	2.301	2.150	2.377	2.676	1.955	1.574	1.631

$x(k)$ is the connection weight and threshold vector in the $k-th$ iteration, J is the Jacobian matrix of the first derivative of the neural network error to the connection weights and thresholds, μ is the adjustment factor, which should be reduced after a successful iteration (i.e., the error decreases) and increased if the error increases after an iteration. I is the identity matrix, and e is the error vector. Repeat the learning process until the mean square error is not greater than 0.001.

VI. A CASE STUDY

A. ANALYSIS OF CAUSAL RELATIONSHIPS AND IDENTIFICATION OF CSFs

In the C2C e-commerce website Taobao, many new vendors enter the system every day and are assigned a default minimum value. Thus, these vendors have no advantages over existing vendors, even if they have better QoS or products. Therefore, it is necessary to solve the reputation bootstrapping problem in this system. Through the literature review and the evaluation basis given by e-commerce experts, we confirm the following reputation-related factors: speed of delivery (C_1), product type (C_2), vendor attitude (C_3), degree of promotion (C_4), quality of consumers (C_5), after-sale service (C_6), security and privacy protection (C_7), authenticity of the product description (C_8), price advantage (C_9), product update speed (C_{10}), and third-party authentication (C_{11}). Note that we analyse the vendors from the same transaction platform only, and they are equally affected by the transaction platform; therefore, we do not consider the impact of the platform in this study case. In this section, three experts studying the reputation of e-commerce are invited to form a committee, and they provide the influence degree among criteria based on trapezoidal fuzzy numbers (Table 3). Subsequently, initial direct-relation fuzzy matrices are generated, denoted by $Z^{\langle k \rangle}, k = 1, 2, 3$. For example, the assessment data of one of the experts are shown in Table 4. In the next step, the normalized direct-relation fuzzy matrices and the average fuzzy matrix $\tilde{X}$ are calculated according to (3), (7). Correspondingly, the total fuzzy matrix $\tilde{T}$ can be obtained, and $\tilde{R}_i = \sum_{j=1}^{n} \tilde{t}_{ij}$, $\tilde{M}_j = \sum_{i=1}^{n} \tilde{t}_{ij}$, and $\tilde{R}_i + \tilde{M}_j, \tilde{R}_i - \tilde{M}_j$ are shown in Table 5. Finally, by using the CFCS method for defuzzification according to (3), we can convert fuzzy information into crisp scores. Thus, we can acquire the crisp values $(\tilde{R}_i+\tilde{M}_i)^D$, $(\tilde{R}_i-\tilde{M}_i)^D$ and $(\tilde{R}_i)^D$, as shown in Table 6.

According to the value of $(\tilde{R}_i - \tilde{M}_i)^D$, the eleven factors can be divided into a cause group and an effect group.

The cause group ($(\tilde{R}_i - \tilde{M}_i)^D > 0$) contains C_2, C_3, C_4, C_7, C_8, C_{11} and the effect group($(\tilde{R}_i - \tilde{M}_i)^D < 0$) consists of $C_1, C_5, C_6, C_9, C_{10}$.

The identification process of the CSFs is analyzed as follows:

1) ANALYSIS OF THE CAUSE GROUP

From Table 6, it is obvious that the factor ''vendor' attitude'' (C_3) has the highest value of $(\tilde{R}_i + \tilde{M}_i)^D$ and $(\tilde{R}_i)^D$, indicating that C_3 has a great impact on the reputation value and other factors. Therefore, C_3 can be identified as a CSF. The factor ''product type'', C_2, has a relatively low value of $(\tilde{R}_i + \tilde{M}_i)^D$, indicating that C_2 has little effect on the realization of the system goal; therefore, C_2 cannot be recognized as a CSF. The factor C_8 has the second highest value of $(\tilde{R}_i + \tilde{M}_i)^D$ and the third highest value of $(\tilde{R}_i)^D$, which indicates that the ''authenticity of the product descriptions'' (C_8) plays a significant role in the online transactions. Therefore, C_8 can be identified as a CSF. Similarly, the factor C_4 also has a relatively significant impact on the whole system due to its relatively high value of $(\tilde{R}_i + \tilde{M}_i)^D$, and this factor can be deemed as a CSF. The values $(\tilde{R}_i + \tilde{M}_i)^D$ and $(\tilde{R}_i)^D$ of the factor C_{11} are lower than other factors; thus, C_{11} cannot be recognized as a CSF.

2) ANALYSIS OF THE EFFECT GROUP

The factors in the effect group tend to be influenced by other factors. The factor ''speed of delivery'' (c_1) has a high value of $(\tilde{R}_i - \tilde{M}_i)^D$, indicating that it is slightly affected by other factors. Meanwhile, its values of $(\tilde{R}_i + \tilde{M}_i)^D$ and $(\tilde{R}_i)^D$ are high, suggesting that it has a certain impact on the realization of the overall goal of the system. Therefore, the factor c_1 can be deemed as a CSF. The factor ''quality of consumers'' (C_5) has the second highest value of $(\tilde{R}_i - \tilde{M}_i)^D$ in the effect group, which indicates that it is also slightly affected by other factors. Additionally, its values of $(\tilde{R}_i + \tilde{M}_i)^D$ and $(\tilde{R}_i)^D$ are relatively high, and the influence of the factor ''quality of consumers'' (e.g., malicious consumers' feedback rating) for the reputation value in e-commerce deserves attention and in-depth study. Therefore, C_5 can be deemed as a CSF. There is another factor, C_6, that is similar to the condition of the factor C_5, thus, the factor C_6 is also a CSF. The factor C_9 has the lowest value of $(\tilde{R}_i - \tilde{M}_i)^D$, suggesting that it is easily influenced by other factors, which means that it can be improved by adjusting other factors. Therefore, the factor C_9 is not a CSF. Likewise, the factor C_{10} cannot be identified as a CSF.

From the above analysis, we obtain 6 CSFs in this study case. In addition to QoS (vendor attitude, speed of delivery, after-sale service and authenticity of the product description), the influence from the quality of consumers and the degree of promotion also cannot be ignored. Therefore, we will assign initial reputation values to newly registered vendors based on these six CSFs.

B. DATA PREPARATION AND DESCRIPTION

To evaluate the effectiveness of our reputation bootstrapping model, we collected 100 existing vendor samples registered in the same month in China's largest C2C website, Taobao, and extract the CSFs, i.e., speed of delivery, vendor attitude, degree of promotion, quality of consumers, after-sale service, authenticity of the product description and the corresponding reputation value calculated from feedback ratings, from each vendor. Afterward, to speed up neural network training, the input vector (CSFs) and output reputation value should be normalized according to (10), (11). Then, we randomly divided the samples into 80 training samples and 20 testing samples. For the CSFs of new vendors, the system needs to provide reasonable CSFs values after testing and investigation. The characteristics of the CSFs used in the system are listed in Table 7. Note that malicious users are determined by the deviation between feedback ratings and overall quality of the vendor. Each vendor has an actual performance level (overall quality), denoted by $OqVal$, which is calculated according to the following equation:

$$OqVal = 5 \times \frac{\sum_{i=1}^{n} Y'(q_i)}{n} \tag{13}$$

$q_i (i = 1 \ldots .4)$ refers to the four CSFs (speed of delivery, vendor attitude, after-sale service, and authenticity of the product description) related to the overall quality of the vendor, and $Y^{'}(q_i)$ refers to the normalized value of q_i based on (10), (11). We assume that honest consumers rate a vendor based on his/her $OqVal$ within the interval $[Max(0, OqVal - 1), Min(Oqval + 1, 5)]$. For example, if $OqVal = 4$, fair feedback ratings should belong to 3-5. A deviation of ± 1 from $OqVal$ represents natural variation, and malicious users give ratings outside this interval [9]. Additionally, the value of the factor ''after-sale service'' has to be determined for new vendors. We select existing sellers who have the same value of $OqVal$ as the new vendors, calculate their average value of the factor ''after-sale service'', and assign it to new vendors. Because it is difficult to judge the benefit the promotion will bring, we can rate the''degree of advertising promotion'' through consultation and investigation.

C. EVALUATION METRICS

The goal of the experiment is to verify the feasibility of our proposed model and ensure the accuracy and efficiency in predicting the reputation values of the new vendors. In this system experiment, we compare the estimated reputation values and the calculated reputation values from the feedback rating in the test sets. We adopt the mean absolute error (MAE) and the root mean squared error (RMSE) metrics to measure the performance of our model compared with other methods. Specifically, the comparisons are conducted under the same contexts. MAE is a measurement of how close the estimated value is to the eventual value, and it is denoted

TABLE 7. CSF metrics and characteristics.

Number	CSF	Description	Data types
1	Speed of delivery	Time taken from placing an order to receiving the goods.	Number of days
2	Vendor's attitude	Consumers' judgement about the service attitude of vendor	Five grades(1,2,3,4,5)
3	Degree of promotion	Advertising promotion in various ways in the system	Five grades(1,2,3,4,5)
4	After-sale service	The number of system intervention/total number of applications for refunds	%
5	Authenticity of the product description	The extent to which products match the descriptions	Five grades(1,2,3,4,5)
6	Quality of consumers	The ratio of malicious users	%

TABLE 8. Comparison of MAE and RMSE.

Metrics	FDMNN	IVM	AVM	QoS-ANN	REM
MAE	0.0383	0.1941	0.1691	0.0717	0.0511
RMSE	0.0452	0.2282	0.1904	0.0812	0.0598

as follows:

$$MAE = \frac{\sum_{i=1}^{n} \left| R_i - \hat{R}_i \right|}{n} \tag{14}$$

RMSE is used to measure the deviation between the estimated value and the eventual value, and it is denoted as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(R_i - \hat{R}_i \right)^2}{n}} \tag{15}$$

D. EVALUATION AND COMPARISON

To evaluate the performance of our proposed model, we compare our reputation prediction model (labeled FDMNN) with the following four methods.

1. The intermediate value method (labelled IVM) proposed by Wang *et al.* [7] allocates the median value (0.5) to the reputation of all newcomers.
2. The average value method (labelled AVM) proposed by Huang *et al.* [8] calculates the average reputation value of all existing services and allocates this value to the newcomer.
3. The QoS-ANN methods proposed by Wu *et al.* [6] predicts the reputation value of a newcomer using neural network by considering only QoS.
4. The REM methods proposed by Tibermacine *et al.* [9] predicts the reputation value of a newcomer using a multiple regression model based on QoS and similar services, and considers malicious density (i.e., malicious user ratio).

Note that we only consider the QoS characteristics (after-sale service, response time, vendor attitude, and authenticity of the product descriptions) as the reputation-related factors that emerge in the QoS-ANN and REM methods. The MAE and RMSE values of these methods are listed in Table 8. Meanwhile, a contrast between the calculated reputation values and the estimated reputation values (FDMNN) is shown in Figure 2. Comparison curves of the prediction deviations among FDMNN, IVM, AVM, REM and QoS-ANN are shown in Figure 3.

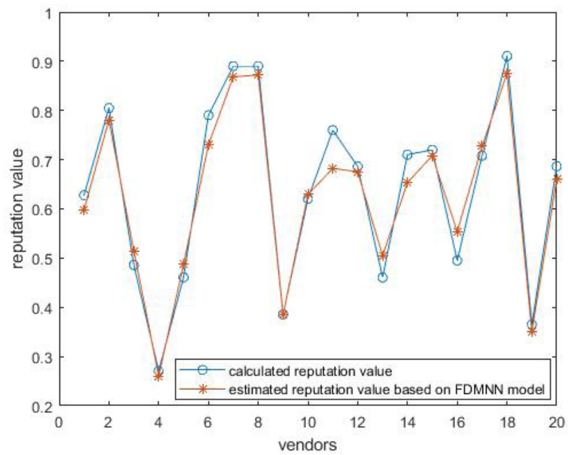

FIGURE 2. Comparison curves of the estimated reputation values and the calculated values.

From the comparison results, we can observe that our model (FDMNN) has lower MAE and RMSE values (i.e., higher accuracy) than other methods. From Figure 3, we observe that the QoS-ANN and REM methods are very accurate for most vendors in the test sets but have a large prediction deviations for the remaining vendors. Through analysis, we conclude that the QoS-ANN method is less accurate than our model in terms of predicting the reputation values of vendors with high degrees of promotion or high proportions of malicious users. The REM method, which considers the malicious density, is not as accurate as our model in terms of predicting the reputation value of vendors with high degrees of promotion.

From the above results, we can conclude that the proposed model can more efficiently assign new vendors' reputations.

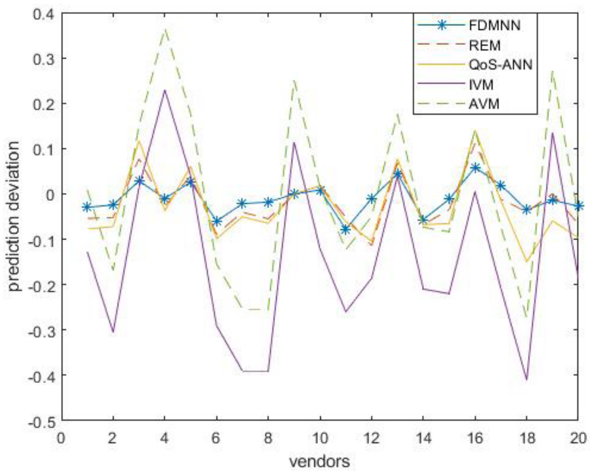

FIGURE 3. Prediction deviation comparison curves of FDMNN, IVM, AVM, QoS-ANN, and REM.

This result is because our model comprehensively considers all reputation-related factors (vendors, consumers, platforms and external factors) and then explores the CSFs through the fuzzy DEMATEL method rather than considering only QoS factors.

VII. CONCLUSIONS

In this paper, we propose a novel reputation bootstrapping model based on fuzzy DEMATEL method and neural network. The proposed model explores the intrinsic causal relationships from the root of the problem among all influencing factors and identifies the CSFs for reputation. Afterwards, the correlations between these factors and the eventual reputation values are generalized by repeated learning. A case study was conducted to verify efficiency, and the experimental results show that the proposed model has better accuracy than other methods.

Although our method considers the uncertainty and ambiguity of expert evaluation in the CSF identification process, the evaluation mainly relies on the experience and expertise of experts; thus, the result is somewhat subjective. Therefore, identifying CSFs by combining subjective and objective methods will studied in our future work. Furthermore, combining the initial reputation value with the feedback ratings provided by consumers after normal transactions to obtain complete reputation management will also be a future research direction.

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YAN WANG received the B.S. degree in electronic and information engineering from Qinghai Normal University, in 2003, and the M.S. degree in electronic and information engineering from South China Normal University, in 2007. She is currently pursuing the Ph.D. degree with the College of Computer Science, Qinghai Normal University.

LIQIN TIAN received the M.S. degree from the Department of Computer Science and Technology, Tsinghua University, in 2003, and the Ph.D. degree from the Information Engineering School, Beijing University of Science and Technology, in 2009. He did a Postdoctoral Research at Tsinghua University, from 2009 to 2011. He is currently a Professor with the North China Institute of Science and Technology, China, where he is also the New Century Excellent Talents. His current research interests include computer networks, performance evaluation, and network security.

ZHENGUO CHEN received the M.S. degree from Xidian University, in 2005, and the Ph.D. degree from Northeastern University, in 2018. He is currently with the North China Institute of Science and Technology, where he is an Associate Professor. His main research areas include network security and the Internet of Things.