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A combined approach based on fuzzy AHP and fuzzy inference system to rank reviewers in online communities

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Abstract: Online product review communities allow users to share their ideas and opinions about various products and services. Although online reviews as user-generated content can be considered as an invaluable source of information for both consumers and firms, these reviews tend to be of very different quality. To tackle the problem of low quality reviews, we address reviewer credibility and propose an innovative framework. The framework comprises five critical phases for ranking reviewers in terms of credibility using a fuzzy analytic hierarchy process (AHP) and fuzzy inference system. To determine the weights of the features, a fuzzy AHP method was applied. In addition, according to the proposed framework, to compute a realistic credibility score based on trustworthiness and expertise, a cognitive approach was followed and a fuzzy inference system was designed. To illustrate an application of the proposed method, we conducted an experimental study using real data gathered from Epinions.

Key words: Social web, online reviews, reviewer credibility, trust network, fuzzy analytic hierarchy process, fuzzy inference systems

1. Introduction

Web 2.0 technologies [1–3] enable the creation of many social web applications such as online product review communities where users can share their ideas and opinions about various products and services. Websites such as Epinions.com, Yelp.com, and Ciao.com have become platforms on which users can write reviews about particular products. Online reviews produced in online communities can be considered as an invaluable source of information for both consumers and firms. However, they tend to be of very different quality [4]. In other words, due to the lack of a comprehensive mechanism to validate online reviews, some low quality, uninformative online reviews may be produced by nonprofessional reviewers [5]. To tackle the review quality problem, in this study, we address reviewer credibility since credibility assessments of the source (reviewer) and the message (review) are fundamentally and positively interlinked [5].

To effectively measure the credibility of reviewers, it is essential to identify source credibility dimensions and factors. Achieving this in this paper, we first identify source credibility dimensions and then use the dimensions to quantify the credibility of reviewers by mapping each qualitative dimension into some corresponding measurable features derived from three data sets including web of trust (WOT) [6] data, data about reviews written by users, and users' contribution data in the community. Afterwards, the value of each dimension is calculated using the weighted sum of features; as a contribution of this paper, we use a fuzzy analytic hierarchy

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process (AHP) [7–10] procedure to determine the weights of the utilized features. Finally, as another major contribution, we design a fuzzy inference system [11] to calculate credibility scores and then rank reviewers based on the output of the fuzzy system. To the best of our knowledge, this is the first study that proposes a combined approach based on fuzzy AHP and fuzzy inference to compute reviewer credibility.

The rest of the paper is organized as follows. Section 2 describes background and reviews related works on social webs, source credibility, fuzzy sets, and fuzzy AHP. In Section 3, we describe the proposed framework for reviewer ranking in terms of credibility. Section 4 demonstrates an implementation of the proposed framework using real data. In Section 5, we conclude the paper.

2. Related works

2.1. Source credibility

Credibility of online reviews is important as consumers and marketing departments are increasingly exploiting them to obtain information about certain products or services, which can help them make effective decisions. Credibility dimensions are categorized into three types: source credibility, message credibility, and medium credibility [5,12]. Credibility assessments of the source and message are fundamentally and positively interlinked [5]. Information quality and source credibility are predictors of information usefulness [12]. Credibility is a principal characteristic of information quality [12]. On a product review website, the review, reviewer, and website can be considered as the message, source, and medium, respectively.

Hovland et al. (as cited in [5,13]) defined source credibility as expertise and trustworthiness. Later studies identified different dimensions for source credibility; however, expertise and trustworthiness are still the essential dimensions [5].

2.2. AHP and fuzzy AHP

One of the most popular and widely used multiple criteria decision-making approaches is the AHP introduced by Saaty and Vargas [14] and Saaty and Peniwati [15]. Since in the conventional AHP human judgments are expressed in the form of crisp values, this method is unable to adequately handle uncertain and imprecise judgments of decision makers [16]. Therefore, fuzzy AHP methods have been proposed to deal with the uncertainty and impreciseness of decision makers' judgments [9]. The first fuzzy AHP method was presented by Laarhoven and Pedrycz [17]. Buckley [18] used trapezoidal fuzzy numbers to determine fuzzy scores. Chang [19] proposed a fuzzy AHP method by applying the extent analysis method.

2.3. The applied fuzzy AHP method

In this study, we apply the fuzzy AHP method proposed by Chang [19] to determine the weights of features identified for the quantifying reviewers' trustworthiness and expertise scores. Therefore, we employ the following steps to utilize the fuzzy AHP for assigning weights of features:

Step 1: Establish the fuzzy pairwise comparison matrix of m features.

Matrix $\tilde{A}$ is constructed by combining the experts' opinions.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1m} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{a}_{m1} & \tilde{a}_{m2} & \cdots & 1 \end{bmatrix} \tag{1}$$

Where

$$\begin{aligned} \tilde{a}_{ij} &= (l_{ij}, m_{ij}, u_{ij}) \\ \tilde{a}_{ji} &= (\tilde{a}_{ij})^{-1} = (u_{ij}^{-1}, m_{ij}^{-1}, l_{ij}^{-1}) \end{aligned} \tag{2}$$

$$\begin{aligned} l_{ij} &= \left(\prod_{t=1}^{s} A_{l_{ij}}^{t}\right)^{1/s}, \forall t = 1, 2, ..., s. \\ m_{ij} &= \left(\prod_{t=1}^{s} A_{m_{ij}}^{t}\right)^{1/s}, \forall t = 1, 2, ..., s. \\ u_{ij} &= \left(\prod_{t=1}^{s} A_{u_{ij}}^{t}\right)^{1/s}, \forall t = 1, 2, ..., s. \end{aligned} \tag{3}$$

$A^t = \left(A_{l_{ij}}^t, A_{m_{ij}}^t, A_{u_{ij}}^t\right)$ is the fuzzy comparison matrix from expert t when comparing features$i$ and j.

Step 2: For each feature, the value of the fuzzy synthetic extent can be calculated as follows [19]:

$$S_i = \sum_{j=1}^{m} a_{ij} \otimes \left[\sum_{k=1}^{m}\sum_{j=1}^{m} a_{kj}\right]^{-1} = \left(\frac{\sum_{j=1}^{m} l_{ij}}{\sum_{k=1}^{m}\sum_{j=1}^{m} u_{kj}}, \frac{\sum_{j=1}^{m} m_{ij}}{\sum_{k=1}^{m}\sum_{j=1}^{m} m_{kj}}, \frac{\sum_{j=1}^{m} u_{ij}}{\sum_{k=1}^{m}\sum_{j=1}^{m} l_{kj}}\right), i = 1, 2, ..., m. \tag{4}$$

Step 3: Compute the degree of possibility (V) for each S_i and obtain the weight vector [19]: as $S_1 = (l_1, m_1, u_1)$ and $S_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the degree of possibility (V) of $S_2 \geq S_1$ is defined by:

$$V(S_2 \geq S_1) = \begin{cases} 1 & m_2 \geq m_1, \\ 0 & l_1 \geq u_2, \\ \frac{l_1 - u_2}{(m_2 - u_2) + (m_1 - l_1)} & otherwise. \end{cases} \tag{5}$$

To compare $S_1\, and\, S_2$, we need both values of $V(S_1 \geq S_2)$ and $V(S_2 \geq S_1)$. The degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $S_i (i = 1, 2, ..., m)$ can be defined by the following.

$$\begin{aligned} V(S \geq S_1, S_2, ..., S_k) &= V\left[(S \geq S_1) \text{ and } (S \geq S_2) \text{ and ... and } (S \geq S_k)\right] \\ &= \min V(S \geq S_i), i = 1, 2, ..., k. \\ d(S_i) &= \min V(S_i \geq S_k) = W_i' k = 1, 2, ..., m \text{ and } , k \neq i \end{aligned} \tag{6}$$

Step 4: Normalize the weight vector.

After normalization of the weight vector, $W = (W_1', W_2', ..., W_m')^T$, the importance weights, are as follows [19]:

$$W = (W_1, W_2, ..., W_m)^T. \tag{7}$$

3. The proposed framework

The proposed framework for ranking reviewers in terms of credibility is shown in Figure 1. As illustrated in the figure, the framework comprises five phases or steps.

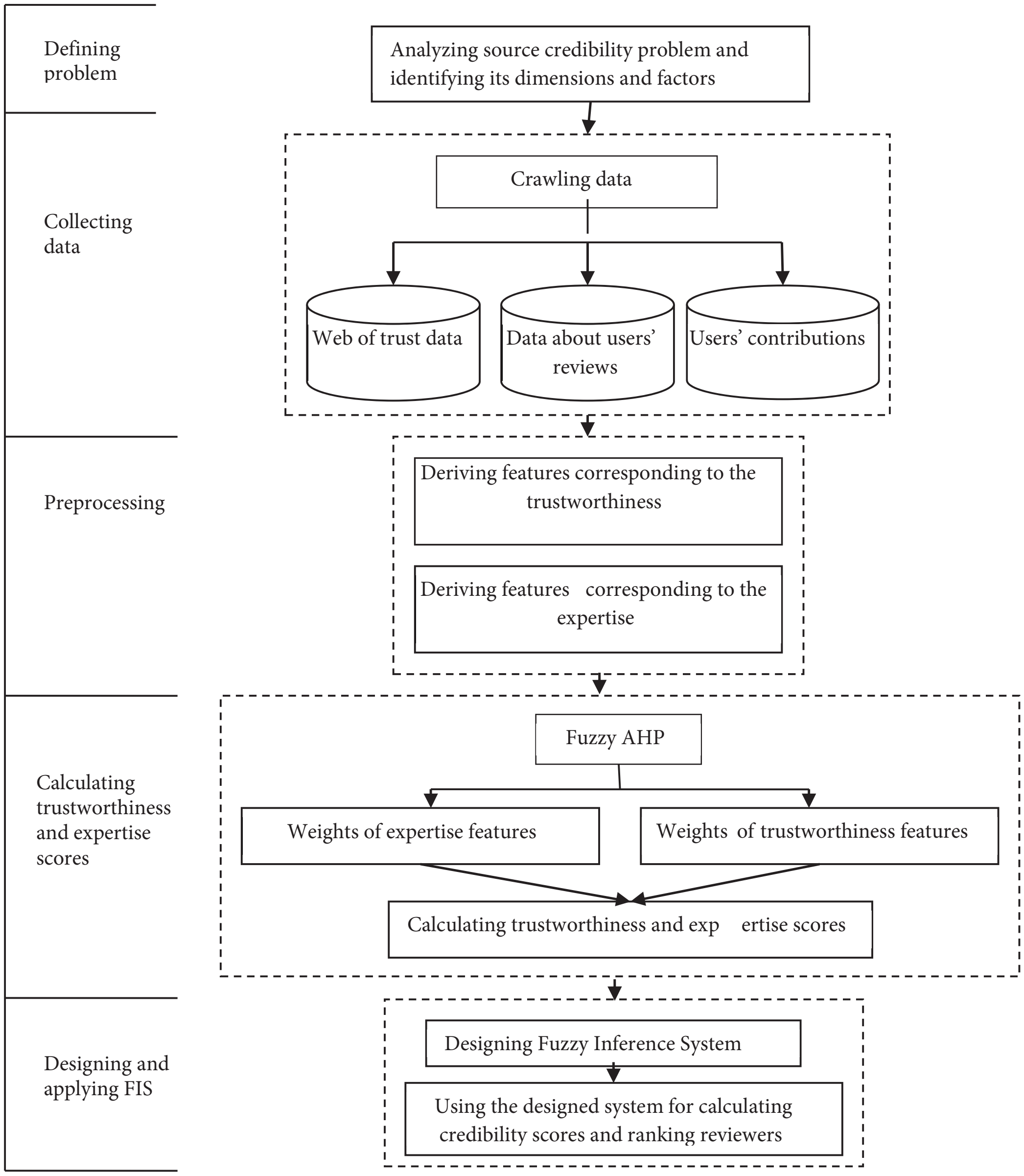

Figure 1. Research framework.

4. Implementation of the proposed framework

In this section, we implement the framework using a data crawl and provide an in-depth description of each phase.

4.1. Analyzing the source credibility problem of online reviews

In the first phase, we analyzed the problem of source credibility and identified its main dimensions through reviewing literature related to the credibility concept. As pointed out in the related works, trustworthiness and expertise are the focal dimensions of source credibility. Thus, to measure the source credibility of reviewers, it is essential to collect the data relevant to these dimensions.

4.2. Crawling data from web

As a case study, we selected Epinions.com, which is a well-known product review website. Epinions is a large community network that enables users to share their knowledge and experiences about products and services [20,21].

In this study, we were interested in collecting data of reviewers from the "Electronics" category. The data crawled fall into three categories: 1) data of the trust network among users (WOT); 2) data of user profiles, e.g., number of past reviews, number of user visits, length of activity, and number of personal information items disclosed; 3) data of reviews written, including the date on which the review was written, title, category, product rating, and helpfulness rating for the 1-year period.

In order to crawl the users' network, we started from the top reviewer in the Electronics product category and followed both the top reviewer's trusts and trusted by links to find other users. We used the breadth-first search strategy to crawl the users' trust network. We crawled the data of reviews from January 2013 to January 2014 from the Electronics category. The statistics of the crawled data are given in Table 1. The crawled data should be preprocessed before entering the next phase. Analysis of the crawled data indicated that a certain amount of users had not written reviews during the period of 1 year. Therefore, these users were filtered out. Some users did not contribute in the Electronics category, so we eliminated them from our data as well. After completing the preprocessing step, the number of active reviewers was reduced to 227.

Table 1. Statistics of the crawled data.

Description	Number
#Users	13,419
# Trust relations	475,574
# Reviews in one year	15,312

4.3. Deriving and constructing features corresponding to trustworthiness and expertise

According to what was mentioned in related works, source trustworthiness and expertise are the two primary determinants of source credibility [5,13]. In the following, we describe the derived features corresponding to the each of these two dimensions.

Table 2. Description of features utilized to estimate trustworthiness (F_1).

Feature	Description
PageRank (F_{11})	The page-rank of vertex i, $PR(i)$, is computed as follows: $PR(i) = c\sum_{j} \frac{PR(j)}{d_j} + 1 - c$, where j is the set of inbounding vertices of i, d_j is the out-degree of node j, and c is the "damping factor", a constant between 0 and 1 on the graph
User visits (F_{12})	The number of visitors who have viewed the reviews written by the user
Number of Personal information (F_{13})	The amount of personal information provided by a user about himself/herself
Recency (F_{14})	The time elapsed since the last review was written by reviewer

4.3.1. Trustworthiness

Trustworthiness is defined as the extent to which an information source is perceived as providing information that reflects the source's real opinions and attitudes regarding something [5, 22]. Trustworthiness is usually described by terms such as well-intentioned, truthful and unbiased [5]. Based on the data crawled from the website, several features relevant to the trustworthiness dimension can be derived. All of the features derived to compute the trustworthiness including "PageRank [23]", "User visits", "Number of Personal information", and "Recency" are described in Table 2.

4.3.2. Expertise

Expertise is the degree to which an information source is perceived as being able to know the truth or to present valid information [5,22]. It is often expressed with terms such as "experienced", "knowledgeable", and "competent" [5]. Expertise directly relates to knowledge about the goods or services, and it increases as related experiences increase [24]. The features derived from data for measuring the expertise of reviewers are shown in Table 3.

Table 3. Description of features utilized to estimate expertise (F_2).

Feature	Description
Experience (F_{21})	The length of time since reviewer's membership began
Level of contribution(F_{22})	The number of reviews written by reviewer in all categories during the period of 1 year
Level of contribution in the specific domain (F_{23})	The number of reviews written by reviewer in a specific category during the period of one year
General Knowledge score (F_{24})	$GKS(i) = \left(1 - \frac{1}{n+1}\right) \times \frac{\sum_{j \in R(u_i)} r_j}{n}$, where n is the number of reviews written by reviewer u_i in all categories during the period of 1 year,$R(u_i)$ is the set of reviews written by reviewer in all categories during the period of 1 year, and $r_j$is the helpfulness rating of a review R_j
Domain-specific Knowledge score (F_{25})	$DKS(i) = \left(1 - \frac{1}{n+1}\right) \times \frac{\sum_{j \in R(u_i)} r_j}{n}$, where n is the number of reviews written by reviewer u_i in a specific category during the period of 1 year, $R(u_i)$ is the set of reviews written by reviewer in a specific category during the period of 1 year, and $r_j$is the helpfulness rating of a review R_j

4.4. Calculating trustworthiness and expertise scores

As illustrated in the proposed framework, we use the fuzzy AHP technique in order to compute the weights of features corresponding to each dimension of source credibility. Afterwards, we calculate the trustworthiness and expertise scores as the weighted sum of their corresponding features.

4.4.1. Utilizing fuzzy AHP to compute the weights of features

To obtain the subjective weights of features, pairwise comparisons were performed. To perform pairwise comparisons, we utilized the set of linguistic terms employed in [25]. The linguistic terms are described by membership functions as depicted in Figure 2 and Table 4.

For features corresponding to both trustworthiness and expertise, we gathered fuzzy pairwise comparison matrices through interviews. A series of questions were designed and used for direct comparison. The result of interviewing each expert is a fuzzy pairwise comparison matrix, which indicates the expert's preferences regarding the features. After obtaining the opinions of five experts, we applied the fuzzy AHP method to calculate the weights.

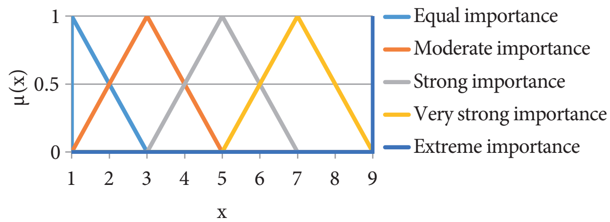

Figure 2. Linguistic scale for relative importance.

Table 4. Linguistic scale of importance.

Triangular fuzzy number	Linguistic scale of importance
(1, 1, 3)	Equal importance
(1, 3, 5)	Moderate importance
(3, 5, 7)	Strong importance
(5, 7, 9)	Very strong importance
(7, 9, 9)	Extreme importance

4.4.2. Calculation of the weights of features corresponding to trustworthiness

In this step, the fuzzy AHP method is applied to compute the weights of features corresponding to trustworthiness (Table 2). Based on the first step of fuzzy AHP (Eqs. (2) and (3)), for the features identified to quantify the trustworthiness, the results of aggregating opinions of three experts were obtained and are presented in Table 5. By tracing Eqs. (4), (5), (6), and (7), for each feature, the values of the fuzzy synthetic extent (S), the degree of possibility, and the weight were computed and are illustrated in Table 6.

4.4.3. Calculation of the weights of features corresponding to expertise

Similar to the previous step, in this step, the weights of features identified for quantifying the expertise dimension (Table 3) were calculated. The result of combining the opinions of the three experts is shown in Table 7. Furthermore, the calculated weights are given in Table 6.

Table 5. Pairwise comparison of the features corresponding to the trustworthiness dimension.

	F_{11}	F_{12}	F_{13}	F_{14}
F_{11}	(1,1,1)	(0.72,1.25, 2.95)	(4.08, 6.12, 8.14)	(2.67,4.83, 6.88)
F_{12}	(0.34,0.8, 1.38)	(1,1,1)	(3.68,5.72, 7.74)	(2.41, 4.51, 6.54)
F_{13}	(0.12,0.16, 0.25)	(0.13,0.17, 0.27)	(1,1,1)	(0.3, 0.8, 1)
F_{14}	(0.15,0.21,0.37)	(0.15, 0.22, 0.42)	(1,1.25, 3.32)	(1,1,1)

Table 6. The features weighting by fuzzy AHP procedure.

	F_{11}	F_{12}	F_{13}	F_{14}	F_{21}	F_{22}	F_{23}	F_{24}	F_{25}
$\min V(S_i \geq S_k)$	1.0	0.94	0	0.1530	0	0.1985	0.8131	0.0579	1.0
W	0.4769	0.4502	0	0.073	0	0.0959	0.3929	0.028	0.4832

4.4.4. Calculating trustworthiness and expertise score

In this stage, for each reviewer, we calculate trustworthiness and expertise scores as follows:

Table 7. Pairwise comparison of the features corresponding to the expertise dimension.

	F_{21}	F_{22}	F_{23}	F_{24}	F_{25}
F_{21}	(1,1,1)	(0.34,0.64,1.25)	(0.13,0.17,0.27)	(0.37,0.8,1.25)	(0.12,0.15,0.21)
F_{22}	(0.8,1.55,2.95)	(1,1,1)	(0.17,0.27,0.64)	(0.8,1,2.41)	(0.15,0.21,0.42)
F_{23}	(2.67,3.88,4.99)	(1.55,3.68,5.72)	(1,1,1)	(2.41,4.51,6.54)	(0.53,0.64,1.93)
$\boldsymbol{F_{24}}$	(0.8,1.25,2.67)	(0.42,1,1.25)	(0.15,0.22,0.42)	(1,1,1)	(0.14,0.19,0.34)
$\boldsymbol{F_{25}}$	(4.83,6.88,8.56)	(2.37,4.66,6.77)	(0.52,1.55,1.9)	(2.95,5.16,7.24)	(1,1,1)

$$\begin{aligned} trustworthiness\_Score(i) &= \sum_{j=1}^{m} x_{ij} * w_j^t \\ \exp ertise\_score(i) &= \sum_{j=1}^{m} x_{ij} * w_j^e \end{aligned} \tag{8}$$

Here, w^t and w^e are the weight vector of trustworthiness features and the weight vector of expertise features, respectively.

4.5. Fuzzy inference system for calculating credibility score

In reality, we generally do not use crisp numeric number values to evaluate credibility or other aspects of a person, but we use linguistic terms like “low” and “high”. Therefore, to build a realistic credibility rank for reviewers, we follow a cognitive approach. We convert the numeric values that were calculated for expertise and trustworthiness dimensions to linguistic terms and use them to reason about the credibility of reviewers.

We use a fuzzy inference system (FIS) [26] to calculate a comprehensive credibility rank for each reviewer. There are several studies related to the design techniques involving FISs. Among these techniques, the Mamdani fuzzy inference system [27–30] is one of the most popular algorithms, which is used in this paper. The advantages of the Mamdani system are its intuitiveness, popularity, and suitability to human input [31].

The FIS as portrayed in Figure 3 consists of four main parts: 1) fuzzification, 2) fuzzy rule base, 3) FIS, and 4) defuzzification. We will describe each part of the constructed fuzzy inference system in detail.

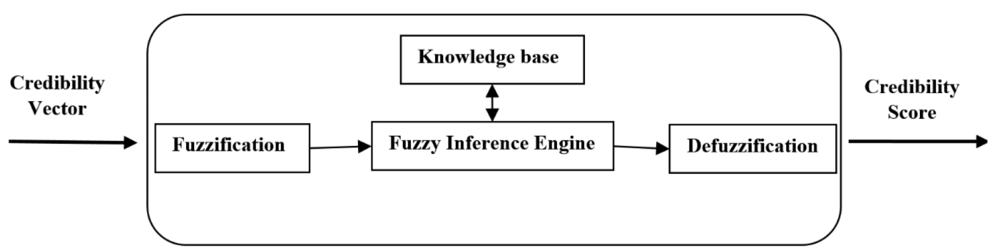

Figure 3. Fuzzy inference system designed for calculating credibility.

4.5.1. Fuzzification

In our system, corresponding to each input variable, we define a linguistic variable. Each linguistic variable consists of a set of linguistic terms, e.g., low, medium, and high. Each linguistic term is represented by a membership function (MF) which is denoted by μ. The fuzzifier uses these MFs to convert crisp input variables into linguistic terms.

As illustrated in Figure 3, in our system the input variables are the dimensions of credibility, including the trustworthiness and expertise values of reviewers. Therefore, in our system, we have two input variables and the output variable is credibility. The input variables are represented by the four Gaussian MFs applied in each variable as illustrated in Figures 4 and 5. In addition, the output variable (credibility) consists of five linguistic terms represented by five Gaussian MFs, as depicted in Figure 6.

4.5.2. Fuzzy rules

Since we have 2 input variables, each of which can have 4 different values, we will have $4^2 = 16$ different combinations. Each combination can potentially represent a class of credibility. In our proposed system, we have defined 16 rules for all possible combinations and we demonstrate them in Table 8.

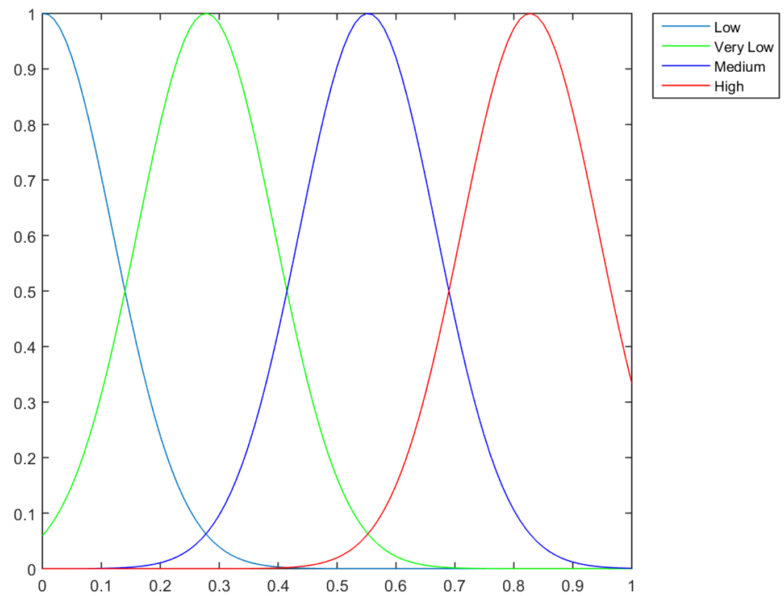

Figure 4. Membership function of the input variable trustworthiness.

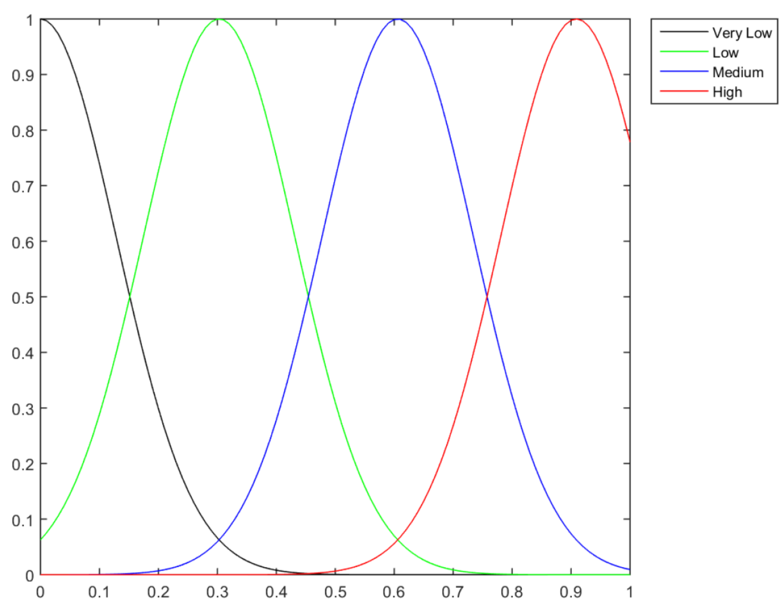

Figure 5. Membership functions of the input variable expertise.

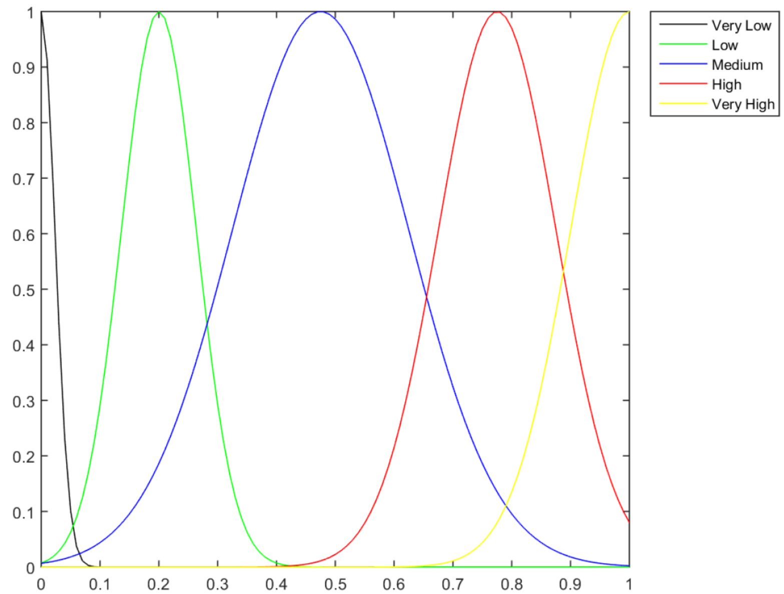

Figure 6. Membership functions of the output variable.

Table 8. The set of fuzzy rules defined in our system (VL = very low, L = low, M = medium, H = high, VH = very high).

Rule no.	Input variables		Output variable
	Trustworthiness	Expertise	Credibility
	H	H	VH
	H	M	H
	H	L	M
	H	VL	L
	M	H	H
	M	M	M
	M	L	L
	M	VL	L
	L	H	M
	L	M	L
	L	L	VL
	L	VL	VL
	VL	H	L
	VL	M	L
	VL	L	VL
	VL	VL	VL

4.5.3. Fuzzy inference engine

The fuzzy inference engine uses the defined fuzzy if-then rules to assign a map from fuzzy inputs to fuzzy outputs based on fuzzy composition rules [32]. This step is the key part of a fuzzy expert system that aggregates the facts derived from the fuzzification process with the rule base and caries out the modeling process.

Several FISs have been developed in various applications. The Mamdani FIS [27,33] is one of the most popular algorithms, which is utilized in this paper. The general "if-then" rule form of the Mamdani algorithm is given as follows [34]:

$$R_i\text{: IF } x_1 = A_{i1} \text{ AND } x_2 = A_{i2} \text{ AND } \cdots x_p = A_{ip} \text{ THEN } y = B_i, i = 1, ..., M,$$

where $x_1, ..., x_p$ are the p inputs of the fuzzy system gathered in the input vector $\underline{x}$, y is the output, M is the number of fuzzy rules, A_{ij} denotes the fuzzy set (linguistic term) used for input $x_j (j = 1, ..., p)$ in rule i, and B_i is the fuzzy set used for output in rule i.

In the inference engine, the following steps must be carried out [34]:

- Aggregation: in this step, for each rule i the degree of fulfillment is computed by applying the min operator as follows:

$$\mu_i(x) = \min[\mu_{i1}(x_1), \mu_{i2}(x_2), \cdots, \mu_{ip}(x_p)], \tag{9}$$

where $\mu_{ij}(x_j), i = 1, ..., M, j = 1, ..., p,$ are the degrees of membership for all linguistic terms computed in the fuzzification stage.

- Activation: in this step, the degrees of rule fulfillment that are calculated in the aggregation step are utilized to calculate the output activations of the rules by

$$\mu_i^{act}(\underline{x}, y) = \min[\mu_i(\underline{x}), \mu_i(y)], \tag{10}$$

where $\mu_i(y)$ is the output of the MF associated with fuzzy set B_i, and $\mu_i(\underline{x})$ is the degree of fulfillment for rule i.

- Accumulation: in this step, the output activations of all rules are combined using the max operator as follows:

$$\mu^{acc}(\underline{x}, y) = \max[\mu_i^{act}(\underline{x}, y)]. \tag{11}$$

4.5.4. Defuzzification

In the defuzzification step we use the centroid of area [35], which is one of the most prevalent methods for the defuzzification process; it is given by the following algebraic expression:

$$y^*_{COA} = \frac{\int\limits_{y_{\min}}^{y_{\max}} \mu^{acc}(\underline{x}, y) y dy}{\int\limits_{y_{\min}}^{y_{\max}} \mu^{acc}(\underline{x}, y) dy}, \tag{12}$$

where Y^*_{COA} is the crisp value for output variable y [34].

4.6. Method evaluation

The results of applying the proposed framework for ranking reviewers in terms of credibility are shown in Table 9. The table shows the top 10 credible reviewers.

Table 9. The top 10 credible reviewers identified using the proposed framework.

Rank									
1	2	3	4	5	6	7	8	9	10
R#95	R#29	R#75	R#57	R#103	R#166	R#206	R#157	R#194	R#162

In order to evaluate the effectiveness of the proposed fuzzy AHP-FIS that is used in the presented framework, we applied two different approaches including AHP-weighted aggregation (AHP-WA) and AHP-FIS. In the AHP-WA method, after obtaining the weights corresponding to the features derived from the data (features given in Tables 2 and 3) via the conventional AHP method [25], for each reviewer we calculate the ranking score (RS) as the weighted sum of the features using Eq. (13):

$$RS_{AHP-WA} = \sum_{i} w_i \times f_i, \tag{13}$$

where w_i is the weight corresponding to feature f_i obtained employing the conventional AHP method.

The AHP-FIS method is similar to the proposed fuzzy AHP-FIS method, except that it utilizes the conventional AHP method to determine the importance weight of each derived feature. The results of comparison are represented in Tables 10 and 11. To analyze the results of experiments conducted in this study, we define a distinguishability measure. The distinguishability measure is computed based on the distance between the ranking scores of any two consecutive items in an ordered list. Suppose that the ranking scores for the two reviewers R_1 and R_2 are rs_1 and rs_2. The distinction value between reviewers R_1 and R_2 is defined as:

$$d_{R_1,R_2} = rs_1 - rs_2. \tag{14}$$

It is clear that a higher distinction value indicates a better performance in terms of ranking as it makes the ranking task easier due to the larger distinguishability. In the following we use the defined distinction value in Eq. (14) to analyze the results.

Table 10. Results of comparison of AHP-WA and fuzzy AHP-FIS.

AHP-WA			Fuzzy AHP-FIS		
Reviewer ID	Ranking score	Distinction value	Reviewer ID	Rank score	Distinction value
R#95	0.6450	0.026	R#95	0.6710	0.05
R#75	0.6190	0.029	R#29	0.6210	0.026
R#29	0.5900	0.006	R#75	0.5950	0.025
R#103	0.5840	0.031	R#57	0.5700	0.12
R#119	0.5530	0.022	R#103	0.4500	0.041
R#57	0.5310	0.064	R#166	0.4090	0.095
R#166	0.4670	0.01	R#206	0.3140	0.005
R#94	0.4570	0.023	R#157	0.3090	0.006
R#177	0.4340	0.028	R#94	0.3030	0.013
R#206	0.4060		R#162	0.2900	

First we compare the performance of AHP-WA with that of fuzzy AHP-FIS using the distinguishability measure. As shown in Table 10, fuzzy AHP-FIS and AHP-WA obtained different ranking results. Regarding the distinction value, fuzzy AHP-FIS performs slightly better than AHP-WA. In 5 of 9 cases, fuzzy AHP-FIS has higher distinction values compared to AHP-WA.

The results of comparison of fuzzy AHP-FIS and AHP-FIS (as seen from Table 11) indicate that fuzzy AHP-FIS performs significantly better than AHP-FIS. In 7 of 9 cases, fuzzy AHP-FIS obtains higher distinction values compared to AHP-FIS.

4.7. Discussion

One of the main advantages of the presented framework is that it exploits three types of data to derive features pertinent to the source credibility dimensions to calculate reviewers' credibility scores. This is in contrast with

Table 11. Results of comparison of AHP-FIS and fuzzy AHP-FIS.

AHP-FIS			Fuzzy AHP-FIS		
Reviewer	Ranking score	Distinction value	Reviewer	Ranking score	Distinction value
R#95	0.6470	0.023	R#95	0.6710	0.05
R#29	0.6240	0.024	R#29	0.6210	0.026
R#103	0.6000	0.017	R#75	0.5950	0.025
R#57	0.5830	0.054	R#57	0.5700	0.12
R#75	0.5290	0.09	R#103	0.4500	0.041
R#166	0.4390	0.064	R#166	0.4090	0.095
R#38	0.3750	0.016	R#206	0.3140	0.005
R#206	0.3590	0.003	R#157	0.3090	0.006
R#79	0.3560	0.001	R#94	0.3030	0.013
R#162	0.3550		R#162	0.2900	

the existing studies [5,24], which considered only the number of reviews posted by a reviewer and the number of "helpful" votes received by each review to compute credibility of reviewers. The essential part of the framework, which is responsible for ranking reviewers based on the features extracted from data in the preprocessing stage, is the fuzzy AHP-FIS method. This method was compared with the AHP-WA and AHP-FIS methods. The results of the experiments conducted in this study indicated that fuzzy AHP-FIS performs better than the others. The other interesting characteristic of the framework is following a cognitive approach in calculating credibility scores. Since concepts like credibility or trust are usually expressed using linguistic terms such as "high" or "low" rather than numeric values, our proposed approach can better quantify such characteristics. Moreover, the ability of defining different membership functions and inference rules allows the proposed method to be customized depending on the area of application.

5. Conclusion

In an online product review website, due to the lack of a comprehensive mechanism to validate online reviews, some low quality and uninformative online reviews may be generated. In this paper, to tackle the review quality problem, we addressed reviewer credibility since credibility assessments of a reviewer and a review are fundamentally and positively interlinked. Therefore, a novel framework to rank reviewers in terms of credibility was presented. To illustrate an application of the proposed method, we carried out an experimental study using real data gathered from Epinions.

The main contributions of this paper are: utilizing three types of data including user WOT data, data about reviews written by users, and users' contribution data in measuring reviewers' credibility dimensions; using fuzzy AHP to calculate feature weights; and designing a FIS to compute credibility scores. The proposed framework can be exploited by companies and business enterprises in obtaining credible customer reviews in order to gain insights about customers' opinions and sentiments regarding their products and services in an efficient and effective manner. In the future, we plan to use our method to develop an opinion analyzer system that will combine the concepts of source credibility and aspect-based opinion mining. Our presented method will act as a preprocessing component to select the reviews from the most credible reviewers for mining purposes.

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