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RESEARCH ARTICLE

CredibleExpertRank: Leveraging Social Network Analysis and Opinion Mining to Facilitate Reliable Information Retrieval on Knowledge-Sharing Sites

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ABSTRACT Asking and answering questions are common activities in both the workplace and everyday life. Knowledge-sharing websites have become a popular resource for obtaining instant and searchable answers. However, users of these sites may encounter challenges in acquiring timely and appropriate content from user-provided answers owing to factors such as limited expertise, spam, and time constraints. Identifying trustworthy experts who can provide relevant and reliable answers in knowledge-sharing communities is crucial to overcome this issue. In this study, we propose a solution to the problem of identifying credible experts on knowledge-sharing sites by introducing the CredibleExpertRank algorithm. Our algorithm calculates a CredibleExpert score based on two main factors: activity and credibility. The credibility score is determined by analyzing users' interactions related to questioning, answering, recommending, and mining users' opinions, while the activity score reflects the user's level of participation on the platform. We conducted experiments to evaluate the performance of the CredibleExpertRank algorithm, using user satisfaction measures for answers to given questions. Our findings confirmed that the credible experts identified by our algorithm provided more relevant and timely answers compared to other ordinary users. The timely nature of the credible experts' answers was due to the reflection of their activity factor, while the superior performance in relevance was attributed to the high recommendation rate of their answers and positive evaluations received from opinion mining results. Our study undertakes an extensive investigation focused on the identification and prioritization of credible experts, revealing their profound advantages in significantly enhancing the overall quality of knowledge-sharing platforms. We proposed the CredibleExpertRank algorithm as a powerful method for effectively identifying trustworthy experts and giving priority to their answers. Through a meticulous process of experimental evaluation, we provide compelling evidence that this approach leads to substantial improvements in both search efficiency and reliability on knowledge-sharing sites. By highlighting the potential benefits derived from the identification of credible experts, our study underscores their pivotal role in elevating the overall performance of knowledge-sharing platforms.

INDEX TERMS Knowledge sharing, social network analysis, opinion mining, expert recommendation system, social big data, social influence, ratings prediction, data mining.

I. INTRODUCTION

Knowledge-sharing sites serve as platforms for people to exchange information. Typically, they contain a vast repository of questions and answers on a wide range of topics, enabling users to access desired information quickly. However, a persistent challenge in these platforms is the time-sensitivity and credibility of user-provided answers, which can be affected by factors such as time constraints, limited expertise, and potential malicious intent. Ordinary users

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may not always possess the necessary knowledge or credibility to offer accurate and trustworthy information. Therefore, it is crucial to identify credible experts who can consistently provide reliable and timely answers to elevate the overall quality of knowledge-sharing platforms. The identification of trustworthy experts who can provide relevant and reliable answers has become essential in improving the quality of responses and enhancing user satisfaction.

Link analysis approaches such as PageRank [1] and the Hyperlink-Induced Topic Search (HITS) [2] can be used to identify authoritative users on knowledge-sharing sites. These methods use social networks to calculate a hub and authority scores for each user and rank users based on their authority scores. Other approaches, such as those used by Liu et al. [3], focus on building expert profiles for users based on the contents of their questions and answers, rather than on their reputations or a link analysis. The identification of trusted experts is essential to connecting them with questionnaires and increasing the visibility of experts on knowledge-sharing sites. Ultimately, the goal is to increase the visibility of experts and facilitate collaboration and knowledge-sharing among users.

Online customer reviews help consumers decide which products to buy and help companies understand consumers' buying behaviors. Anna et al. [4] proposed improving a recommendation system by using information such as opinions and suggestions extracted using natural language processing techniques from user reviews of products. Based on usage and satisfaction theory, Loc et al. [5] explained how to utilize online reviews for making purchasing decisions online. "SmartTips" [6] was built on an aspect-based sentiment analysis. It leverages customer feedback and applies aspect term extraction models to rate different products and extract user preferences. Several factors are considered, such as the reader voting, aspect term frequency, and opinion word frequency. With the development of e-commerce websites, user reviews have become an essential source of information for improving the performance of recommendation systems, as they generally contain user opinions reflecting product preferences. However, most classic recommendation systems do not accurately capture users' feelings regarding a product, as they often ignore users' opinions. Therefore, to overcome the above problems, Aminu et al. [7] proposed a recommendation system utilizing aspect-based opinion mining (ABOM).

We integrated Social Network Analysis (SNA) of users' behavior patterns with users' opinion mining technology to create a comprehensive model for understanding user interactions and behaviors within knowledge sharing sites.

A. MOTIVATION

Despite the recent use of commercial search engines that utilize Question-and-Answer information, it remains challenging to find good answers on knowledge-sharing sites. One way to address this issue is to return the best answer provided by a respondent, which would reduce the effort required to find good answers and minimize the need to post duplicate questions. Therefore, it is crucial to identify power users, who are users with high levels of activity, contribution, participation, popularity, and influence on knowledge-sharing sites.

B. OBJECTIVE

The aim of this study is to investigate methods for identifying power users (knowledgeable and credible users) on knowledge-sharing sites. Specifically, we explored whether a combined algorithm utilizing SNA and opinion-mining techniques could effectively identify groups of trustworthy users who are likely to provide accurate and relevant answers to a given question. Our primary objective is to capture the knowledge and reliability of users and determine whether combining analytical techniques, such as social network analysis and opinion mining, can help identify dependable groups of users for providing useful answers. By doing so, we aimed to enhance the search efficiency and reliability of knowledge-sharing platforms.

C. NOVELTY AND CONTRIBUTIONS

Previous research has extensively utilized SNA and opinion mining techniques to extract valuable information, identify influential users, and gain insights into social relationships, opinions, and attitudes on knowledge-sharing sites and social networking sites (SNS). These techniques have also been integrated into various domains, including but not limited to traffic accidents, transportation, healthcare monitoring, and more, to provide valuable insights and solutions. However, there has been limited research focused on enhancing information retrieval and information sharing by identifying reliable influencers through combined SNA and opinion mining algorithms or models, particularly in the context of knowledge-sharing sites. Therefore, our research is innovative and significant as it aims to address the challenge of finding reliable information on knowledge-sharing sites, which is often hindered by the presence of untrustworthy users who may post spam or irrelevant content with malicious intent. Our proposed solution, the CredibleExpertRank algorithm, aims to identify credible experts who can provide trustworthy information on knowledge-sharing sites.

D. ARTICLE ORGANIZATION

In this study, we propose the CredibleExpertRank algorithm as a novel approach to tackle this problem. The algorithm leverages the innovative integration of SNA [8], [9], [10], [11] and opinion mining techniques [12], [13], [14], [15] to effectively identify reliable and knowledgeable users in knowledge-sharing websites. This algorithm employs a two-pronged approach. First, it analyzes the relationships among users to construct a robust social network. Second, it evaluates the expertise and reliability of users through opinion mining, involving the analysis of their opinions and feedback. By combining these techniques, CredibleExpertRank offers a unique and differentiated approach to identifying credible experts within the knowledge-sharing community.

The CredibleExpertRank algorithm calculates a CredibleExpert score based on two main factors: activity and credibility. The credibility score is determined by analyzing users' interactions related to questioning, answering, recommending, and mining users' opinions, while the activity score reflects the user's level of participation on the platform.

We conducted experiments to evaluate the algorithm's performance based on user satisfaction measures for answers to given questions. Our findings confirmed that the credible experts identified by our proposed algorithm provided more relevant and timely answers compared to other ordinary users. The timely nature of the credible experts' answers was due to the reflection of their activity factor, while the superior performance in relevance was attributed to the high recommendation rate of their answers and positive evaluations received from opinion mining results.

What sets the CredibleExpertRank algorithm apart is its departure from conventional methods of evaluating expertise. Instead of relying solely on user-provided information or subjective ratings, it takes a data-driven approach that considers the interactions and opinions of users within the social network. This results in a more objective and reliable assessment of the expertise, as it considers the collective wisdom of the community rather than individual opinions. Therefore, prioritizing answers from trustworthy experts identified by the CredibleExpertRank algorithm can enhance the search efficiency and reliability of knowledge-sharing sites, as demonstrated by our experimental evaluation. In conclusion, our study highlights the potential benefits of finding credible experts and recommending their answers first to improve the overall quality of knowledge-sharing platforms.

In Section II, we review related works and provide background information. This includes an overview of link analysis approaches such as social influence and opinion mining-based methods for finding experts, as well as other approaches that focus on building user profiles based on the content of their questions and answers. In Section III, we introduce the CredibleExpertRank algorithm and detail the factors that are used to calculate a user's CredibleExpert score. The paper evaluates the proposed algorithm through experimental studies in Section IV, which showed that credible experts identified by the algorithm provided more relevant and timely answers compared to ordinary users. Finally, Section V concludes the paper by highlighting the potential of the proposed algorithm to enhance the search efficiency and reliability of knowledge-sharing platforms and facilitate collaboration and knowledge-sharing among users.

II. RELATED WORKS AND BACKGROUND

A. FINDING EXPERTS

The SNA is the most widely used method for finding experts on community-driven knowledge-sharing sites. A standard approach is to build a user social network and then use an algorithm to calculate each user's reputation. Chen et al. [16] proposed a reputation calculation mechanism for creating a social network graph with different weights for each edge type considering five types of user relationships potentially affecting the reputation; they then calculated the impact value(s) when the graph changed. Jurczyk et al. [17] created a social network graph based on a question-responder relationship between users and adopted the HITS algorithm to calculate the influence of each user. Zhang et al. [18] proposed "Expert Ranking," which ranks the experts in expert networks by considering how many people are involved and who has helped whom. Liu et al. [3] proposed a method for constructing an expert profile using the contents of a Q&A pair and discovered experts by comparing the similarity between the contents of questions and expert profiles. Zhang et al. [18] not only compared the similarities between queries and user profiles, but also considered differences in the level of expertise, time to post questions, and the number of responses to questions. Bouguessa et al. [19] proposed an approach for aggregating a mixture of a gamma distribution, the Bayesian information criterion, and an expectation maximization algorithm to address the shortcomings of link analyses.

- **Several challenges and major findings**: The literature on finding experts in knowledge-sharing platforms highlights challenges in reputation calculation and social network graph construction, while emphasizing the importance of user relationships, the effectiveness of social network analysis algorithms, and the potential of content-based approaches and advanced techniques for expert identification.

B. FINDING HIGH QUALITY ANSWERS

Su et al. [20] found that knowledge-sharing sites generally have good average response quality, but there are significant variations in the quality of specific responses. For example, when Yahoo! Answers surveyed reactions to a series of questions, the percentage of correct responses to specific questions ranged from 17% to 45%. Jeon et al. [21] developed an answer quality model based on features derived from specific answers (such as response length) from Naver Knowledge iN, a Korean Q&A site. Naver Knowledge iN was launched in October 2002 and was one of the earliest Q&A sites to leverage user-generated content to expand the amount of information available on the web. The site catered to South Koreans and allowed them to ask and answer questions on a range of topics. It is an early example of how user-generated content can enhance the web. By crowdsourcing knowledge from its users, the site provided a wealth of information that would otherwise be unavailable. In doing so, it helped pioneer a new model for web content and laid the foundation for subsequent Q&A sites such as Yahoo! Answers and Quora. Jeon et al. [21] generated a score by identifying useful features, such as certain best answers and the number of answers given. Agichtein et al. [22] expanded on Jeon et al.'s [21] work by exploring a much broader range of features, including structure, text, and community features, and evaluated the quality of questions, in addition to the question-and-answer pairs.

- **Several challenges and major findings**: The literature highlights challenges in response quality on knowledge-sharing sites and the need for models to assess answer quality based on specific features. Major findings indicate significant variability in response correctness and the success of user-generated content platforms like Naver Knowledge iN in crowdsourcing valuable information. Studies have investigated diverse features (structure, text, community aspects) to evaluate question and answer quality, contributing to the existing knowledge in this field.

C. SOCIAL INFLUENCE

The concept of social influence in social network services refers to the power by which interactions with others change an individual's thoughts, feelings, attitudes, or behaviors [23], [24]. Social influence takes many forms, including but not limited to conformity, socialization, peer pressure, obedience, leadership, persuasion, sales, and marketing. Deutsch et al. [25] proposed two psychological needs that drive humans to conform to the expectations of others: informational social influence and normative social influence.

Kellman [26] identified three broad variants of social influence: adherence, discernment, and internalization. In short, social influence can be understood as the impacts that interactions between members of a society can have on each other. Encouraging user participation is crucial for the success of Q&A social networks. One effective way to achieve this is by promoting collaboration among users to enhance the quality of the content and facilitate mutual learning. Correspondingly, it is essential to understand and measure the social influence of collaboration in Q&A social networks. Adaji et al. [27] conducted research on the social principles influencing cooperation. In a similar vein, Arora et al. [23] developed a mechanism for measuring influencer indexes on popular social media platforms, such as Facebook, Twitter, and Instagram, using machine learning algorithms such as ordinary least squares, k-nearest neighbor regression, support vector regression, and lasso regression. This mechanism calculated a cumulative score based on the influencer index.

- **Several challenges and major findings**: The literature highlights challenges in response quality on knowledge-sharing sites and the need for models to assess answer quality based on specific features. Major findings indicate significant variability in response correctness and the success of user-generated content platforms like Naver Knowledge iN in crowdsourcing valuable information. Studies have investigated diverse features (structure, text, community aspects) to evaluate question and answer quality, contributing to the existing knowledge in this field.

D. OPINION MINING

Opinion mining (and specifically ABOM) has gained significant attention in recent years owing to its potential applications in various fields such as marketing, customer service, and product development. As mentioned above, ABOM involves identifying and analyzing opinions and sentiments regarding specific aspects or features of a product or service, providing valuable insights for businesses to improve their offerings [12], [13], [14], [15].

The use of transfer learning in ABOM is an interesting approach. Transfer learning involves leveraging knowledge and models learned from one domain to improve performance in another related domain. It can be beneficial in cases where labeled data is limited. Using transfer learning, a model can potentially improve its performance in the aspect extraction and entity extraction tasks important in ABOM.

To further improve the accuracy of the recommendation process, Aminu et al. [7] suggested utilizing deep learning techniques for ABOM. User text reviews are a rich source of information for enhancing the performance of recommendation systems in e-commerce, as they provide valuable insights into users' preferences and opinions on products. Venkata et al. [28] developed a web-based system utilizing natural language processing to extract and present customer reviews in a graphical format, making it easier for users to make informed purchasing decisions. In another work, Noahman et al. [6] proposed a model called "SmartTips" which leveraged an aspect-based sentiment analysis to evaluate different products based on customer feedback and extract user preferences.

- **Several challenges and major findings**: The literature highlights challenges in response quality on knowledge-sharing sites and the need for models to assess answer quality based on specific features. Major findings indicate significant variability in response correctness and the success of user-generated content platforms like Naver Knowledge iN in crowdsourcing valuable information. Studies have investigated diverse features (structure, text, community aspects) to evaluate question and answer quality, contributing to the existing knowledge in this field.

E. STRUCTURAL ANALYSIS IN Q&A SITES

Adamic et al. [29] analyzed Yahoo! Answers and categorized its content into three clusters ("Factual," "Advice," and "Discussion Forum") based on content characteristics and user interaction patterns. This analysis aimed to gain insights into knowledge-sharing activities in the Q&A corpus, as depicted in **Figure 1** [30].

In more detail, the "Factual" cluster includes categories related to scientific facts, programming, and academic disciplines. In this cluster, there are many askers, but only a few experts posting answers to their questions. The number of answers to questions is relatively low, but the content is accurate and contains a significant amount of text. The "Advice" cluster includes categories related to daily affairs, such as fashion, marriage, and pets. In this cluster, users find helpful information while attempting to provide advice and knowledge regarding others' questions. The text for this type of answer is relatively long. The "Discussion Forum"

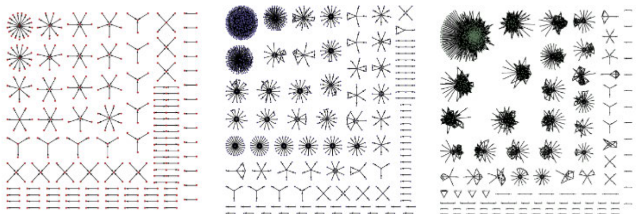


FIGURE 1. Sampled Ego Networks of Three Categories in Yahoo! Answers. a) Factual: Ego network of a user in the Factual category, depicting interactions related to information and knowledge. b) Advice: Ego network of a user in the Advice category, showcasing connections related to seeking and providing advice. c) Discussion Forum: Ego network of a user in the Discussion Forum category, illustrating interactions related to engaging in discussions and exchanging opinions. These ego networks visually represent connections and interactions within specific categories on Yahoo! Answers, offering insights into the social network structure and dynamics within each category [30].

cluster includes questions and responses concerning personal opinions or feelings, such as "Who will win the next baseball game?" and "What is your favorite movie?" Many users post questions and answers and the answers and interactions are often relatively long.

- **Several challenges and major findings**: The literature highlights challenges in response quality on knowledge-sharing sites and the need for models to assess answer quality based on specific features. Major findings indicate significant variability in response correctness and the success of user-generated content platforms like Naver Knowledge iN in crowdsourcing valuable information. Studies have investigated diverse features (structure, text, community aspects) to evaluate question and answer quality, contributing to the existing knowledge in this field.

F. COMBINATION OF SNA AND OPINION MINING

Farman et al. [31] conducted research on traffic accident detection and condition analysis using social networking data. They proposed methods for quickly detecting and responding to traffic accidents by analyzing social network interactions and relationships among users. They also utilized opinion mining techniques to extract valuable information from social networking data, such as user opinions, reviews, and feedback related to traffic accidents, providing insights into public opinions, perceptions, and attitudes toward traffic accidents.

In another study, Farman et al. [32] explored the use of multiple techniques, including SNA and opinion mining, along with word embedding and ontology-based topic modeling, to analyze sentiment in the field of transportation. By combining these techniques, they aimed to provide a comprehensive sentiment analysis of transportation-related text data, which could involve tasks such as sentiment classification, sentiment polarity analysis, and topic-based sentiment analysis. This analysis could provide insights into sentiment trends and topics of interest in the transportation domain, enabling better decision-making and insights for transportation-related businesses, policymakers, and researchers.

Farman et al. [33] focused on integrating SNA and opinion mining techniques in the context of healthcare monitoring using wearable sensors. They presented a framework that utilizes wearable sensor data and social networking data to provide an intelligent and comprehensive approach to healthcare monitoring. SNA is used to analyze social relationships and interactions among individuals, while opinion mining is employed to extract and analyze opinions expressed through social networking data. This integrated approach aims to provide personalized and effective healthcare interventions by leveraging both wearable sensor data and social networking data, and improving overall health outcomes for individuals.

On the other hand, Khan et al. [34] propose a hybrid Deep Neural Network (DNN) model with an attention mechanism for text sentiment classification. Although they do not specifically mention SNA or opinion mining, their focus on text sentiment classification is a common task in opinion mining. The proposed model considers both sentiment and contextual information in the text, incorporating an attention mechanism to automatically focus on important words or phrases during the classification process. The aim is to provide a more sophisticated and accurate approach to text sentiment classification by leveraging advanced deep learning techniques.

In summary, the research [31], [32], [33] focuses on integrating SNA and opinion mining techniques in various domains, such as traffic accidents, transportation, and healthcare monitoring, to provide insights into social relationships, opinions, and attitudes. Khan et al. [34] specifically focus on text sentiment classification, a key task in opinion mining, and propose a hybrid DNN model with an attention mechanism to improve the accuracy of sentiment classification. These studies demonstrate the diverse applications of SNA and opinion mining techniques in different domains and highlight their potential in extracting valuable insights from various types of data.

- **Several challenges and major findings**: The research conducted by Farman et al. [31], [32], [33], and Khan et al. [34] addresses challenges in various domains such as traffic accident detection, sentiment analysis in transportation, and healthcare monitoring. Their work introduces methods for rapid accident detection using social networking data, comprehensive sentiment analysis in transportation, integrated approaches for healthcare monitoring, and a hybrid DNN model with an attention mechanism for accurate sentiment classification. These findings emphasize the versatility of social network analysis (SNA) and opinion mining techniques in extracting valuable insights across diverse domains.

III. PROPOSED IDEA

In this section, we explain how to measure the CredibleExpert score among users in knowledge-sharing sites. **Figure 2** shows the architecture of CredibleExpertRank algorithm. The following subsections discuss each component in detail.

On knowledge-sharing sites, users can rate or review content and follow specific contributors. Credibility is a crucial factor in determining which answer to choose for a given

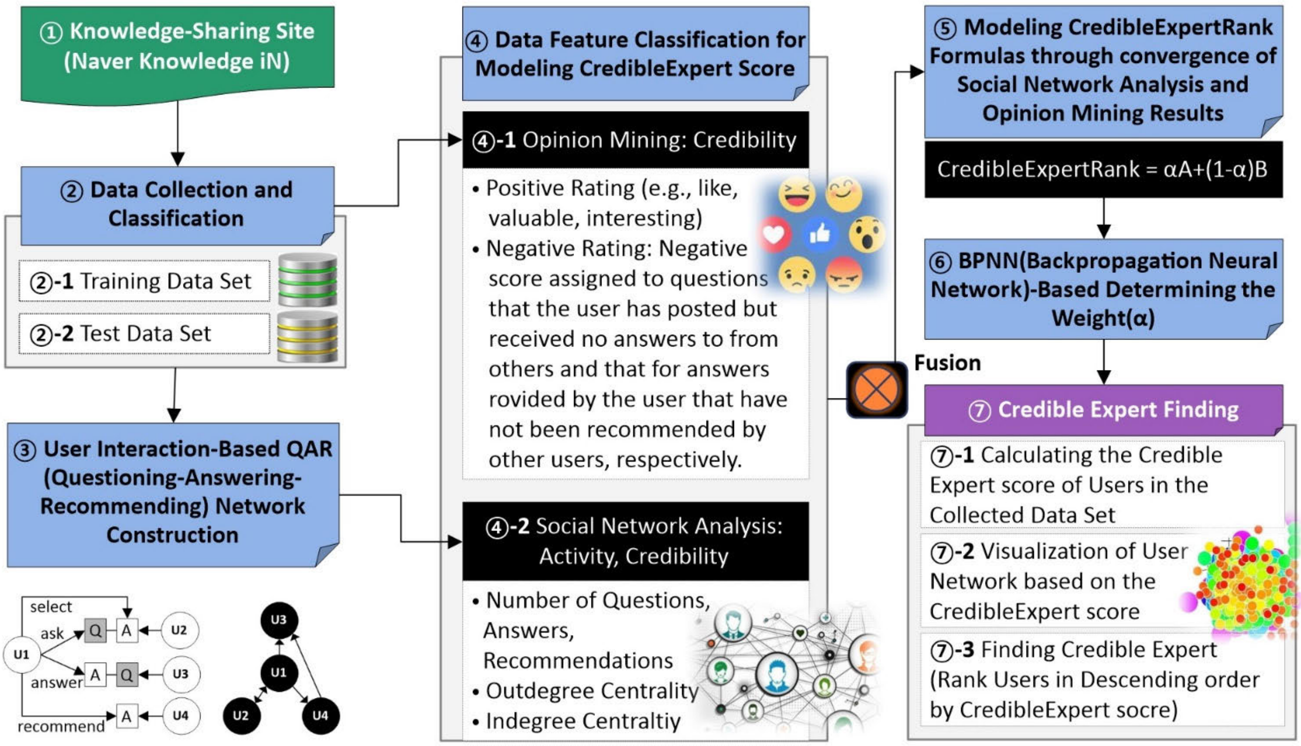


FIGURE 2. Architecture of the Proposed Model: CredibleExpertRank showcases the design and components of the proposed model, "CredibleExpertRank." The model follows several steps: ① selection of a knowledge sharing site, ② data collection from the site to create training and test datasets, ③ construction of a user interaction-based QAR (question-answering-recommending) network, ④ classification of data features for modeling CredibleExpert Score, including reliability-related features using opinion mining and activity- and credibility-related features using SNA, ⑤ integration of opinion mining and SNA techniques to model the CredibleExpertRank algorithm, ⑥ determination of feature weights using BPNN (Back Propagation Neural Network) to assess the influence of activity and credibility attributes, and ⑦ utilization of the CredibleExpertRank algorithm to calculate users' CredibleExpert scores on the knowledge sharing site, which are then used to identify and rank credible experts for users on the site.

question. SNA is a powerful tool for identifying influential contributors, while Opinion Mining (Sentiment Analysis) can provide insights into users' attitudes and emotions toward a given topic. By combining both methodologies, we can create a fusion model to identify credible experts on a knowledge-sharing site. This approach involves collecting and preprocessing data, applying Opinion Mining, constructing a user network, analyzing the network using SNA techniques, and then combining the Opinion Mining and SNA results to assign a score to each user. The resulting composite score can help to identify the most credible experts.

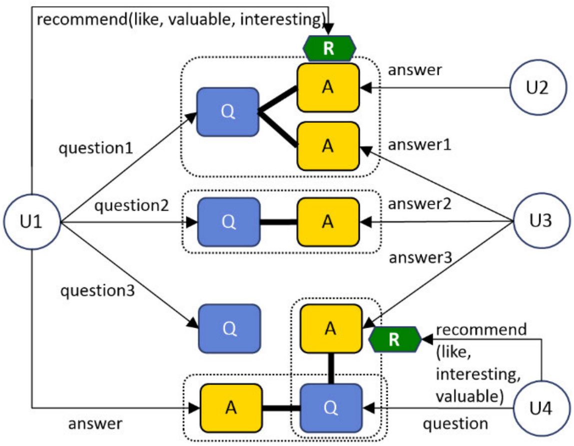
A. USER INTERACTION-BASED NETWORK CONSTRUCTION AND FEATURES

Figure 3(a) represents the structure of user interaction in a knowledge-sharing site. In this figure, nodes represent users, and edges represent interactions such as questions, answers, and recommendations exchanged between users. Users can post multiple questions simultaneously, and there can be multiple answers to a single question. Additionally, a questioner can express opinions, such as liking, finding valuable, or interesting, on a relevant answer. These interactions collectively form a dynamic network of connections among users. We can further explain the types of interactions and actions that are represented by the edges in **Figure 3(a)**, including how questions, answers, and recommendations are exchanged, and how users can express opinions on answers.

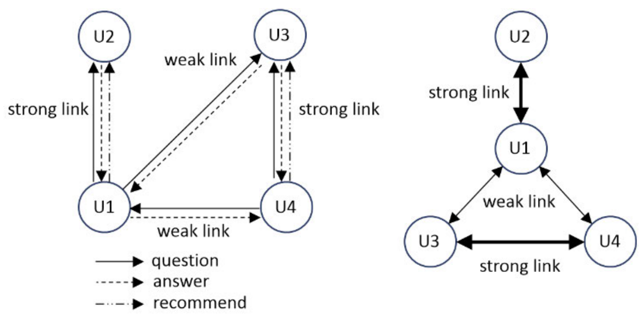
Figure 3(b) depicts the user interaction-based ego network. An ego network represents the connections of a specific user (the ego) with other users in the network. In this figure, we can highlight the ego user's connections with other users and their activities within the knowledge-sharing site. This can include details about the specific interactions or actions of the ego user, such as asking questions, providing answers, and giving recommendations. The ego network provides a visual representation of the immediate network of the ego user and their interactions within the knowledge-sharing site.

B. SOCIAL NETWORK ANALYSIS (SNA) ON THE NETWORK OF ASKER-ANSWERER-RECOMMENDER RELATIONS

Trust is essential in online communities as it influences people's belief in others' expertise [23], [35]. User activities such as asking and answering questions on knowledge-sharing sites provide insights into their reliability. Therefore, we can measure this reliability by considering various factors, including the number of questions and answers to user posts, how frequently a user responds to others' questions, and how many recommendations they receive for their answers. SNA



(a) User interaction in a knowledge-sharing site



(b) User interaction-based ego network

FIGURE 3. Structures of Knowledge-Sharing Sites According to Activity and Credibility. (a) User interaction in a knowledge-sharing site: This figure illustrates the structure of user interaction in a knowledge-sharing site, showcasing the connections and interactions among users. Nodes represent users, and edges represent interactions such as questions, answers, and recommendations exchanged between users. (b) User interaction-based ego network: This figure depicts the ego network of a user in a knowledge-sharing site, highlighting the user's connections with other users and their activities, such as asking questions, providing answers, and giving recommendations. The ego network provides a visual representation of a user's immediate network and their interactions within the knowledge-sharing site.

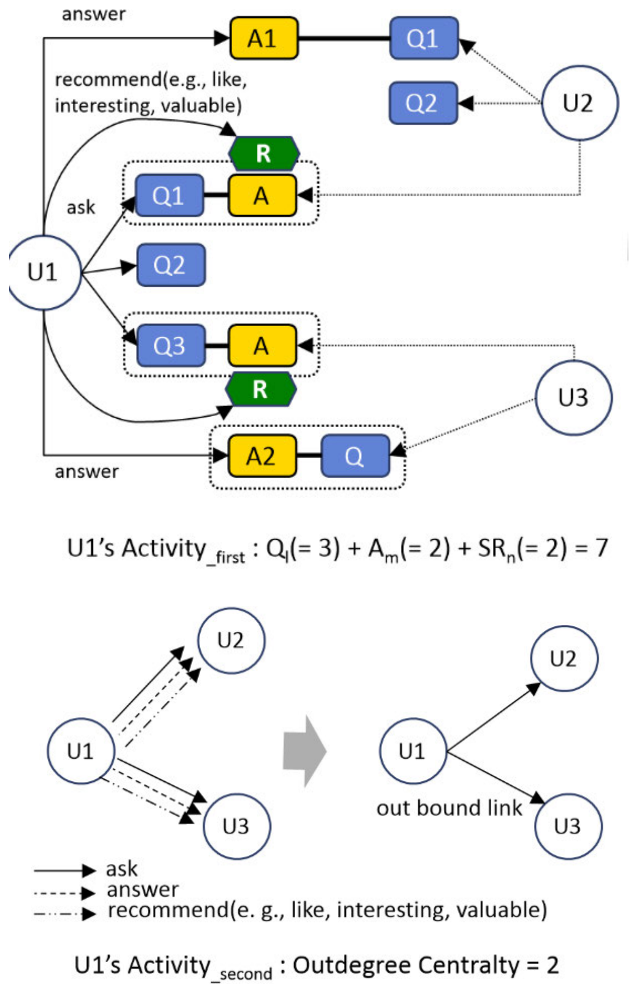


FIGURE 4. Activity Score Calculation: Social Network Analysis (SNA) of Ego Network Based on User Interactions. This figure showcases the process of calculating the Activity Score in a knowledge-sharing site. The calculation involves two steps: (1) counting the number of questions asked, answers provided, and recommendations given by a user, and (2) computing the outdegree centrality of the user's ego network based on their interactions with other users. The final Activity Score is obtained by summing the values obtained from these two steps, reflecting the user's activity level in the knowledge-sharing site.

is the most widely used method for identifying experts on community-driven knowledge-sharing sites because there is often a correlation between a user's prestige and expertise. Therefore, to calculate the user's "credibility score," we analyze the constructed Questioner-Answerer-Recommender (QAR) network using SNA [36], [37], [38]. Then, we combine opinion mining to identify experts, ultimately improving the accuracy of the credibility score [4], [5], [6], [28].

C. CALCULATING ACTIVITY SCORE BASED ON SNA

Figure 4 depicts the procedure for calculating the Activity Score in a knowledge-sharing site, which determines a user's level of activity. The calculation involves two steps:

Step 1: User contributions - The number of questions asked, answers provided, and recommendations given by a user are counted as indicators of their participation and contribution to the knowledge-sharing site. This step quantifies the user's active engagement with other users and their contributions to the community.

Step 2: Ego network analysis - The ego network refers to the immediate connections of a user with other users in the network. The outdegree centrality, which measures a user's influence within their network, is computed based on their interactions in terms of questions, answers, and recommendations. This step assesses the user's network position and influence.

The values obtained from Step 1 and Step 2 are then summed to obtain the final Activity Score, which reflects the user's overall activity level in the knowledge-sharing site. This quantitative evaluation allows for the identification of highly active or influential users within the network.

By following this procedure, the Activity Score can be systematically calculated, providing a quantitative measure of a user's participation and activity level in the knowledge-sharing site. This approach enables the identification of users who are actively engaged and influential in the community, making it a valuable tool for assessing user activity in a QAR network.

1) USER BEHAVIOR ANALYSIS

One way to determine a user's activity score is to count their engagement with various user behaviors, such as asking questions, answering other users' questions, and recommending other users' answers. The activity score is denoted as $ACT\_{first}(u_i)$ and can be calculated for each i[th] user using **Equation (1)** as follows:

$$\begin{aligned} ACT\_{first}\left(u_i\right) &= w_1 \times Q_l + w_2 \times A_m + w_3 \times SR_n \\ &= w_1 \times \sum\nolimits_{i=1}^{l} q_i + w_2 \times \sum\nolimits_{i=1}^{m} a_i \\ &\quad + w_3 \times \sum\nolimits_{i=1}^{n} sr_i \end{aligned} \tag{1}$$

In the above, weights are assigned to three metrics: the number of questions asked, the number of answers posted, and the number of recommendations received. These weights, represented by w_1, w_2, and w_3, respectively, can be adjusted to reflect the importance given to each metric.

For example, if asking questions is deemed more important than providing answers or receiving recommendations, a higher weight can be assigned to w_1. Similarly, if receiving recommendations is considered more important than asking questions or providing answers, then a higher weight can be assigned to w_3. By multiplying the number of questions asked by w_1, number of answers posted by w_2, and number of recommendations received by w_3, we can obtain a weighted sum representing the user's activity score. The higher the activity score, the more active the user on the knowledge-sharing site.

To normalize the $ACT\_{first}(u_i)$ score to a range between 0 and 1, we use **Equation (2)** as follows:

$$ACTn\_{first}\left(u_i\right) = \frac{ACT\_{first}\left(u_i\right) - \min\left(ACT\_{first}\left(u\right)\right)}{\max\left(ACT\_{first}\left(u\right)\right) - \min\left(ACT\_{first}\left(u\right)\right)} \tag{2}$$

Here, $ACT\_{first}(u_i)$ is the activity score of user u_i, min_{score} is the minimum activity score of the data, and max_{score} is the maximum activity score of the data. Subtracting the minimum score from the activity score of each user shifts the range of scores so that the minimum score becomes 0. Dividing by the range of scores (i.e., the difference between the maximum and minimum scores) will then scale the scores to a range between 0 and 1. This ensures that the scores are comparable and that the highest score in the data corresponds to a normalized score of 1.

2) OUTDEGREE CENTRALITY ANALYSIS

The second method for calculating activity scores involves using the outdegree centrality metric [39], [40], [41]. The outdegree centrality metric measures the quality of a node's connections to other nodes in the network. Highly central nodes with many connections are often considered trustworthy or strategically positioned.

Degree centrality is a way to measure the importance of a node based on the number of links it has to other nodes in the network. Nodes with many connections or edges have a higher degree centrality score than those with fewer connections. This metric is useful for identifying individuals who are popular and well-connected in the network. If the network is directional, the outdegree centrality metric measures the number of outgoing links or successors, whereas an indegree centrality metric can be used to measure the number of incoming links or predecessor nodes. A high outdegree centrality score indicates that a user is actively engaging with other users on the knowledge-sharing site by asking or answering questions and is seeking to attract more attention.

Users with high outdegree centrality tend to have frequent interactions with others or disseminate information quickly to many people. Therefore, we use the outdegree centrality as a measure of a user's activity in the QAR network. We follow the widely used approach of analyzing outdegree centrality to measure the authority and influence scores and then determine the activity scores.

To calculate the outdegree centrality, we consider a link created by recommending answers of other users or asking questions to other users as an outbound link from the perspective of a questioner and a link formed by answering other users' questions as an outbound link from the perspective of an answerer. The formula for calculating the outdegree centrality is presented in **Equation (3)** and shown in **Figures 4** and **5(a), (b)**.

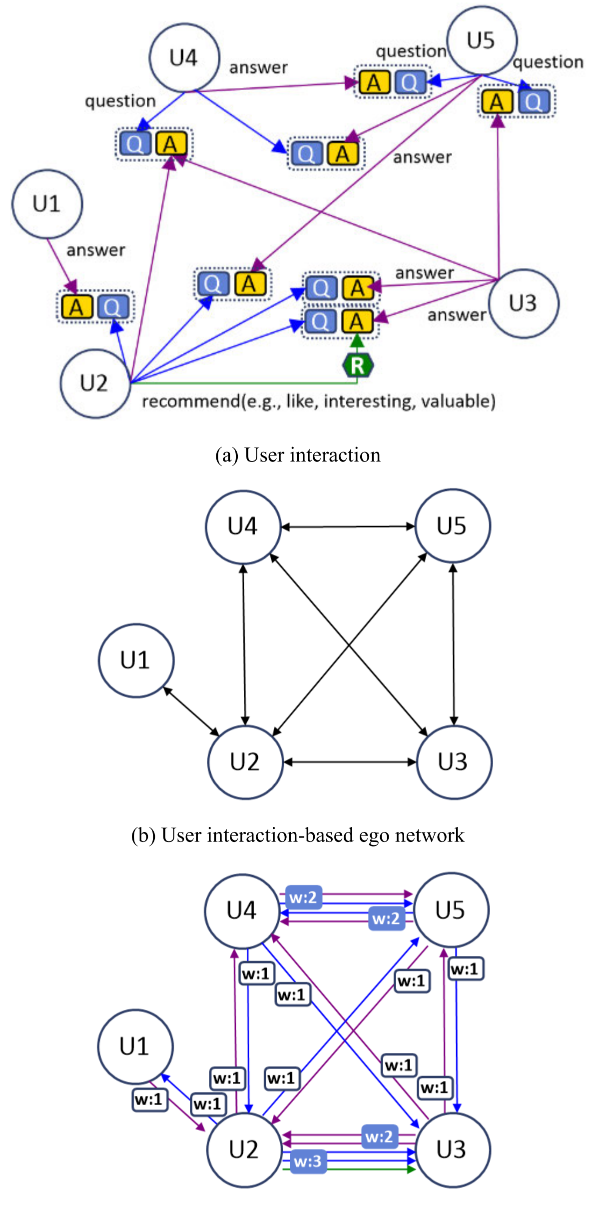
$$C_{outdegree}\left(u_i\right) = \sum\nolimits_{i=1}^{n} A_{ij} \tag{3}$$

Equation (3) involves summing the scores of the cells in matrix A corresponding to the row i and column j combinations. The process starts from column j = 1 and ends in the last column n (representing the total number of columns in the matrix). This calculation is performed for every user node $(u_1, u_2, \ldots, u_n)$ in the matrix to calculate the outdegree centrality for each user.

Table 1 provides an example of this calculation for each user node in the matrix. As shown in **Figure 5 (c)**, weights are assigned to the links based on the number of times a user engages in activities such as asking questions, providing answers, and making recommendations. Therefore, we use a weighted outdegree centrality method to calculate the second activity score. The formula for calculating the weighted outdegree centrality is given by **Equation (4)** as follows:

$$ACT\_{second}\left(u_i\right) = wC\_{outdegree}\left(u_i\right) = \sum\nolimits_{i=1}^{n} wA_{ij} \tag{4}$$

To calculate the weighted outdegree centrality score for each node (i.e., $u_1, u_2, \ldots, u_n$) in the matrix, we perform a similar calculation as in **Equation (3)** while considering the weights of the links based on the number of times the user asks questions, answers questions, or provides recommendations. Each calculation involves adding the scores of the cells



(a) User interaction

(b) User interaction-based ego network

(c) User interaction-based weighted ego network

FIGURE 5. Outdegree Centrality Calculation for Activity. This figure illustrates the process of calculating outdegree centrality for activity in a knowledge-sharing site. (a) User interactions, including actions such as asking questions, providing recommendations (e.g., interesting, valuable, like), and answering questions, are considered. (b) User interaction-based ego network is constructed, representing the connections between users based on their interactions. (c) User interaction-based weighted ego network is created, taking into account the weights assigned to different types of interactions. This process is used to compute the outdegree centrality, which reflects the user's level of activity and engagement in the knowledge-sharing site.

designated by the row i and column j combination in matrix A, as shown in **Table 2**.

The comparison of outdegree centrality between different networks using simple degree centrality can be difficult due to the tendency of the outdegree centrality value of a network to increase with its size, leading to unfair comparisons.

TABLE 1. Calculation of outdegree centrality: Adjacency matrix A (row sum).

node(u_i)	u_1	u_2	u_3	u_4	u_5
u_1	-	1	0	0	0
u_2	1	-	1	1	1
u_3	0	1	-	1	1
u_4	0	1	1	-	1
u_5	0	1	1	1	-
$C_{outdegree}(u_1) = u_1u_1 + u_1u_2 + u_1u_3 + u_1u_4 + u_1u_5 = 1$					
$C_{outdegree}(u_2) = u_2u_1 + u_2u_2 + u_2u_3 + u_2u_4 + u_2u_5 = 4$					
$C_{outdegree}(u_3) = u_3u_1 + u_3u_2 + u_3u_3 + u_3u_4 + u_3u_5 = 3$					
$C_{outdegree}(u_4) = u_4u_1 + u_4u_2 + u_4u_3 + u_4u_4 + u_4u_5 = 3$					
$C_{outdegree}(u_5) = u_5u_1 + u_5u_2 + u_5u_3 + u_5u_4 + u_5u_5 = 3$					
Outdegree Centrality	1	4	3	3	3

TABLE 2. Calculation of weighted outdegree centrality: Weighted adjacency matrix A.

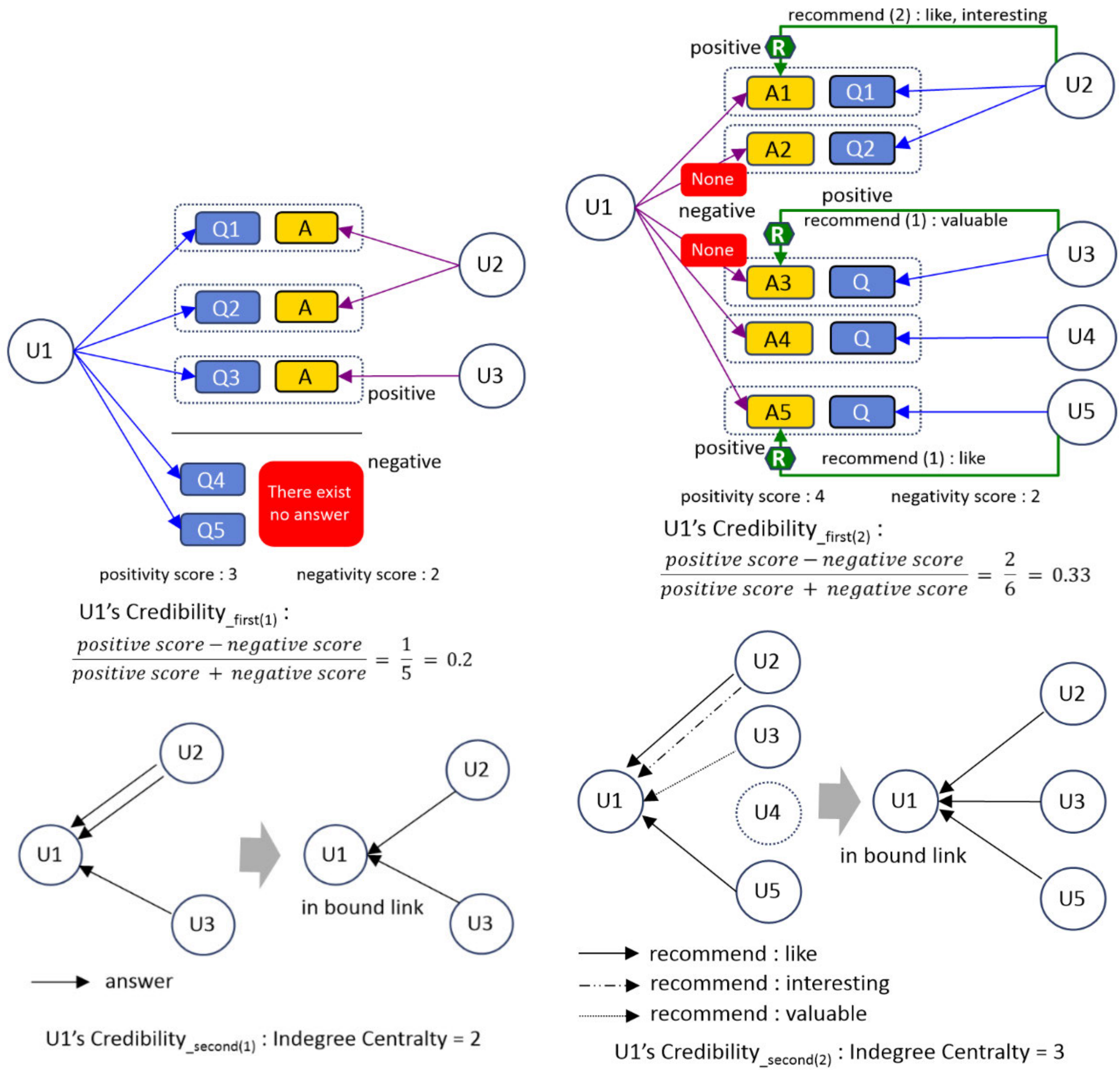
node(u_i)	u_1	u_2	u_3	u_4	u_5
u_1	-	1	0	0	0
u_2	1	-	3	1	1
u_3	0	2	-	1	1
u_4	0	1	1	-	2
u_5	0	1	1	2	-
$C_{outdegree}(u_1) = u_1u_1 + u_1u_2 + u_1u_3 + u_1u_4 + u_1u_5 = 1$					
$C_{outdegree}(u_2) = u_2u_1 + u_2u_2 + u_2u_3 + u_2u_4 + u_2u_5 = 6$					
$C_{outdegree}(u_3) = u_3u_1 + u_3u_2 + u_3u_3 + u_3u_4 + u_3u_5 = 4$					
$C_{outdegree}(u_4) = u_4u_1 + u_4u_2 + u_4u_3 + u_4u_4 + u_4u_5 = 4$					
$C_{outdegree}(u_5) = u_5u_1 + u_5u_2 + u_5u_3 + u_5u_4 + u_5u_5 = 4$					
Weighted Outdegree Centrality	1	6	4	4	4

Regularization is necessary to address this limitation. The normalization process involves dividing the outdegree centrality value of each node by the total sum of all of the outdegree centrality values in the network. This normalization method ensures that all link outdegree centrality indices have a value between 0 and 1, enabling the use of **Equation (5)**.

$$ACTn\_{second}\ (u_i) = \frac{weighted\_Outdegree\ Centrality\ of\ node(u_i)}{\sum_{i=1}^{n} weighted\_Outdegree\ Centrality\ of\ node(u_i)} = \frac{\sum_{i=1}^{n} wA_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} wA_{ij}} \quad (5)$$

D. CALCULATING CREDIBILITY SCORE BASED ON OPINION MINING AND SNA

With the increasing popularity of social networks, an increasing number of users can share their opinions and experiences regarding various products, services, and items. As a result, there has been a significant increase in user-generated content in the form of reviews, blogs, discussion forums, and social networking sites. Among these, reviews are



(a) Credibility in terms of question (b) Credibility in terms of answer

FIGURE 6. Credibility Score Calculation: Opinion Mining and SNA of Ego Network Based on User Interactions. This figure illustrates the process of calculating credibility scores in a knowledge-sharing site from two perspectives: (a) Credibility in terms of questions, where user interactions such as posting answers to questions (positive score) or not posting answers (negative score) are considered in the opinion mining aspect, and the ego network is constructed to calculate the indegree centrality. (b) Credibility in terms of answers, where user interactions such as receiving recommendations (e.g., like, interesting, valuable) for their answers (positive score) or not receiving recommendations (negative score) are considered in the opinion mining aspect, and the ego network is constructed to calculate the indegree centrality. These processes are used to compute the credibility scores, reflecting the perceived credibility of users' contributions based on their interactions and network centrality.

particularly valuable as data sources and are used extensively in marketing intelligence, social psychology, and other fields focused on analyzing opinions, attitudes, and sentiments [12], [13], [14], [15].

Reviews can be found on a variety of websites, such as those that are product-specific, as well as in newspapers, magazines, e-commerce sites, and sites that collect reviews from customers or experts in various fields. Opinions are a critical component of such content, as they are fundamental to almost all human activities and can significantly influence behavior [12], [13], [14], [15], [23], [35]. When people need to make decisions, they often rely on others' opinions. An individual's opinion regarding a product, service, or topic can reveal their level of satisfaction or dissatisfaction with it and their degree of concern regarding specific characteristics of the item. As a result, businesses and individuals are increasingly using reviews to inform their decision-making processes [5], [42], [43], [44].

Opinion mining is a widely used approach to identify, extract, and comprehend the credibility, authority, and preferences of web content [12], [13], [14], [15], [45], [46]. According to Dasgupta et al. [13], the objective of opinion mining is to infer a user's attitude, feelings, and emotions regarding a particular item. Thus, in the QAR network, we define a user's credibility as positive evaluations and feedback received from other users. We calculate the credibility score in two ways, as illustrated in **Figure 6**.

1) OPINION MINING FOR QUESTIONER-ANSWERER-RECOMMENDER (QAR) NETWORK

The first method involves computing a user's credibility score based on the rate of their answers to questions and the rate of their recommendations to answers. This credibility score is denoted as $CRD\_first(u_i)$ and is calculated using **Equation (6)** as follows:

$$\begin{aligned} CRD\_first\ (u_i) &= AQ\ (u_i) + RA\ (u_i) \\ &= \frac{\sum_{i=1}^{q} PA_{q_i} - \sum_{i=1}^{q} NA_{q_i}}{\sum_{i=1}^{l} q_i} \\ &\quad + \frac{\sum_{i=1}^{r} PR_{a_i} - \sum_{i=1}^{r} NR_{a_i}}{\sum_{i=1}^{m} a_i} \end{aligned} \tag{6}$$

In the above, $AQ(u_i)$ represents the ratio of questions with answers when user(i) asks a question to an unspecified number of other users on the Q&A site. $RA(u_i)$ refers to the ratio of how many recommendations user i's answers receive from the questioners when posting answers to questions from other users ($user_j$, $user_k$, $user_l$, etc.) on Q&A sites. q_i and a_i represent the total number of questions and answers posted by user i, respectively. PA_{qi} represents the total number of questions posted by user i for which they received answers from other users, and is a positive value. PR_{ai} is also a positive value that represents the total number of answers posted by user i that were recommended by the question askers. NA_{qi} and NR_{ai} are negative values that respectively indicate the total number of questions posted by user i that did not receive answers from other users, and the total number of answers posted by user i in response to questions asked by other users that were not recommended.

We consider answering a question as a positive factor and not answering a question as a negative factor. A recommended answer is also seen as a positive factor, whereas an unrecommended answer is a negative factor. Users with many posted answers or highly recommended answers have high credibility scores, whereas those who receive no answers to their questions or whose answers are not recommended have low credibility scores. Therefore, a user with a high positive rate has a high credibility score.

We also normalize the credibility score to account for variations in the data. The normalized score ranges from 0 to 1, where a score of 0 represents the lowest possible score and 1 represents the highest possible score. To achieve this normalization, we used **Equation (7)** as follows:

$$CRDn\_first\ (u_i) = \frac{CRD\_first\ (u_i) - \min\left(CRD\_first\ (u)\right)}{\max\left(CRD\_first\ (u)\right) - \min\left(CRD\_first\ (u)\right)} \tag{7}$$

Here, $CRD\_first(u_i) = (CRD\_first(u_1), \ldots, CRD\_first(u_n))$ and $CRD'\_first(u_i)$ is the i^{th} normalized $CRD\_first(u_i)$ score.

2) INDEGREE CENTRALITY ANALYSIS

The second approach to calculating a user's credibility score in the QAR network employs an indegree centrality analysis. We equate a user's credibility with the prestige of their knowledge as determined by user interactions such as likes, valuable recommendations, and interesting insights. Our algorithm assumes that users establish direct connections with prominent users; these serves as proxies for measuring their credibility scores. This prestige stems primarily from positive feedback, and users who consistently receive such feedback are considered as trustworthy and prominent in the network.

From an asker's perspective, the answer is an inbound link from the answerer. From the answerer's viewpoint, a recommendation from an asker creates inbound links to the answerer, as the recommendation serves as a valuable or interesting response to the asker's question.

Figure 7 (a), (b) illustrate how we define inbound links as answers from other users and recommendations from askers. The calculation of the indegree centrality is presented in **Equation (8)** as follows:

$$C_{indegree}\ (u_i) = \sum\nolimits_{i=1}^{n} A_{ji} \tag{8}$$

Equation (8) calculates the indegree centrality of each user node in a network using an adjacency matrix. Starting from the first row, the sum of all the entries in the column corresponding to a user node i is calculated, representing the total number of incoming links to user node i. This process is repeated for each node in the network by iterating over all possible columns in the matrix.

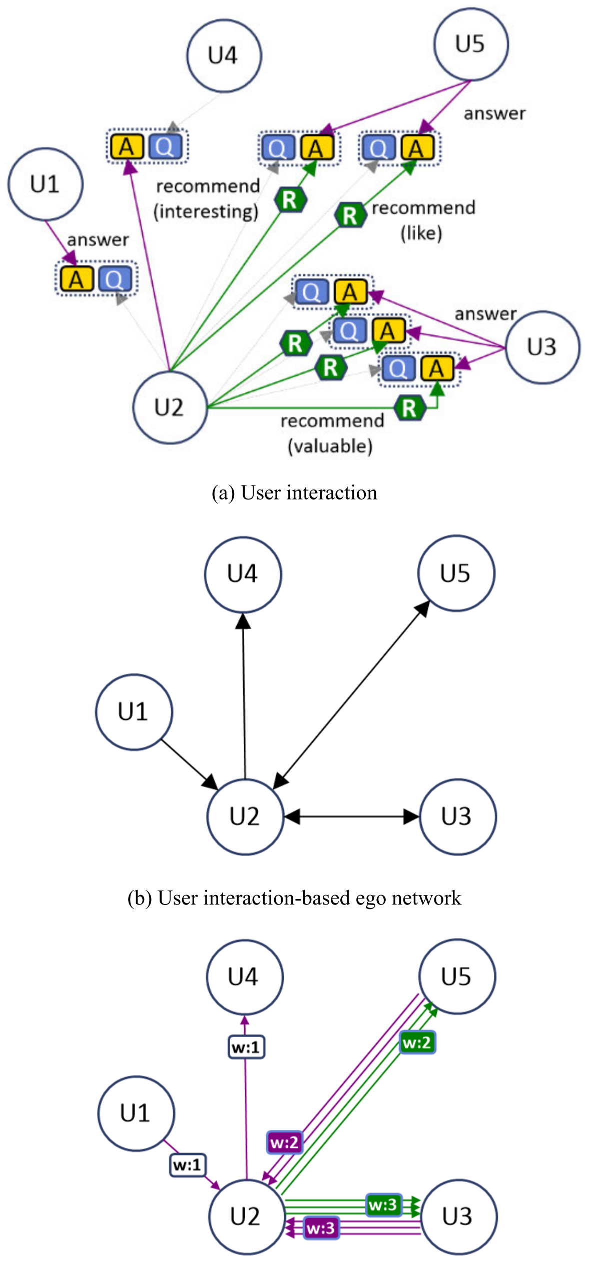
The result is a set of indegree centrality scores for each user node, providing a measure of the relative importance of each node in terms of the number of incoming links it receives. This approach is illustrated in **Table 3**.

The weight of a link in the network is determined by the number of times a user has either answered or recommended content created by another user, as illustrated in **Figure 7 (c)**. To calculate the $credibility\_{second}$ score of a $user_i$, we employ a weighted indegree centrality measure that considers these link weights. The $credibility\_{second}$ score for user i is given by **Equation (9)** as follows:

$$CRD\_second\ (u_i) = wC\_indegree\ (u_i) = \sum\nolimits_{i=1}^{n} wA_{ji} \tag{9}$$

The above represents the sum of the weights of all incoming links to user i. This calculation is performed for each user i in the network, as indicated in **Table 4**. Thus, the weighted indegree centrality measure is used to determine the relative importance of each user in the network based on the weighted connections to the user from other users in the network.

To normalize the indegree centrality measure, we use the same method as applied to the outdegree centrality. The normalized indegree centrality is shown in **Equation (10)** as



(a) User interaction

(b) User interaction-based ego network

(c) User interaction-based weighted ego network

FIGURE 7. Indegree Centrality Calculation for Credibility. This figure showcases the process of calculating indegree centrality for credibility in a knowledge-sharing site. It includes three steps: (a) User interaction, which involves user interactions such as posting answers, receiving recommendations, and other credibility-related actions; (b) User interaction-based ego network, which is constructed based on the connections formed by user interactions; and (c) User interaction-based weighted ego network, where the ego network is weighted based on the strength of user interactions. These steps are utilized to compute the indegree centrality, which represents the prominence and influence of users in the credibility assessment process.

follows:

$$CRDn\_second\ (u_i) = \frac{weighted\_Indegree\ Centrality\ of\ node(u_i)}{\sum_{i=1}^{n} weighted\_Indegree\ Centrality\ of\ node(u_i)} = \frac{\sum_{i=1}^{n} wA_{ji}}{\sum_{i=1}^{n}\sum_{j=1}^{n} wA_{ji}} \tag{10}$$

TABLE 3. CAlculation of indegree centrality: Adjacency matrix A (column sum).

node(u_i)	u_1	u_2	u_3	u_4	u_5
u_1	-	1	0	0	0
u_2	0	-	1	1	1
u_3	0	1	-	0	0
u_4	0	0	0	-	0
u_5	0	1	0	0	-
Indegree Centrality	0	3	1	1	1

$$C_{indegree}(u_1) = u_1 u_1 + u_2 u_1 + u_3 u_1 + u_4 u_1 + u_5 u_1 = 0$$
$$C_{indegree}(u_2) = u_1 u_2 + u_2 u_2 + u_3 u_2 + u_4 u_2 + u_5 u_2 = 3$$
$$C_{indegree}(u_3) = u_1 u_3 + u_2 u_3 + u_3 u_3 + u_4 u_3 + u_5 u_3 = 1$$
$$C_{indegree}(u_4) = u_1 u_4 + u_2 u_4 + u_3 u_4 + u_4 u_4 + u_5 u_4 = 1$$
$$C_{indegree}(u_5) = u_1 u_5 + u_2 u_5 + u_3 u_5 + u_4 u_5 + u_5 u_5 = 1$$

TABLE 4. Calculation of weighted indegree centrality: Weighted adjacency matrix A.

node(u_i)	u_1	u_2	u_3	u_4	u_5
u_1	-	1	0	0	0
u_2	0	-	3	1	2
u_3	0	3	-	0	0
u_4	0	0	0	-	0
u_5	0	2	0	0	-
Weighted Indegree Centrality	0	6	3	1	2

$$C_{indegree}(u_1) = u_1 u_1 + u_2 u_1 + u_3 u_1 + u_4 u_1 + u_5 u_1 = 0$$
$$C_{indegree}(u_2) = u_1 u_2 + u_2 u_2 + u_3 u_2 + u_4 u_2 + u_5 u_2 = 6$$
$$C_{indegree}(u_3) = u_1 u_3 + u_2 u_3 + u_3 u_3 + u_4 u_3 + u_5 u_3 = 3$$
$$C_{indegree}(u_4) = u_1 u_4 + u_2 u_4 + u_3 u_4 + u_4 u_4 + u_5 u_4 = 1$$
$$C_{indegree}(u_5) = u_1 u_5 + u_2 u_5 + u_3 u_5 + u_4 u_5 + u_5 u_5 = 2$$

This results in a normalized indegree centrality score for each user in the network (ranging from 0 to 1).

E. CredibleExpertRank ALGORITHM

We focus on analyzing the relationships between users, specifically between the asker and answerer where the provided answer is considered as relevant by the asker, as well as the feedback provided by other users. Users can post multiple questions simultaneously and there can be multiple answers to a question. The asker can choose the most suitable answer as the best one. We assume that trust networks exist among askers, answerers, and recommenders, which serve as the basis for identifying credible users. As more answers from other users are posted to questions posed by an i^{th} user, and as more of an i^{th} user's answers are recommended as a good answer and receive positive feedback from other users, the credibility of the i^{th} user is enhanced. As demonstrated in **Figure 3 (in Section III-C)**, the centrality degree in the trusted network established on the knowledge-sharing platform can play a valuable role in determining credibility. Building on this insight, we develop the CredibleExpertRank algorithm, which calculates a CredibleExpert score ($CRank(u_i)$) for the i^th user as shown in **Equation (11)**:

$$CRank\ (u_i) = \alpha \left[ACTn\_{first}\ (u_i) \times ACTn\_{second}\ (u_i)\right] + (1-\alpha)\left[CRDn\_{first}\ (u_i) \times CRDn\_{second}\ (u_i)\right] \tag{11}$$

Here, $ACTn\_{first}(u_i)$ represents the total number of questions, recommendations, and answers that the i^th user has posted; it is a measure of their activity level. $CRDn\_{first}(u_i)$ denotes a combination of the rate of answers to questions and rate of recommendations to answers of the same user; it is used to evaluate the credibility of the user. $ACTn\_first(u_i)$ and $CRDn\_first(u_i)$ are normalized to a range between 0 and 1. In contrast, $ACTn\_{second}(u_i)$ and $CRDn\_{second}(u_i)$ are weighted measures of the outdegree centrality and indegree centrality in the QAR network, respectively. The QAR network is a network of relationships between askers, answerers, and recommenders. The weights assigned to the outdegree centrality and indegree centrality measures are based on their importance in the network. The parameter α is a balance parameter for determining the relative importance of the activity and credibility measures, with values between 0 and 1.

The following is the CredibleExpertRank Algorithm for calculating the CredibleRank score:

```
FUNCTION calculate_credible_rank_score(users, qar_network, alpha):
    // Calculate ACTn_first and CRDn_first for each user
    FOR each user in users:
        ACTn_first = calculate_ACTn_first(user)
        CRDn_first = calculate_CRDn_first(user)
        user.ACTn_first = ACTn_first
        user.CRDn_first = CRDn_first
    // Calculate ACTn_second and CRDn_second for each user using qar_network
    FOR each user in users:
        ACTn_second = calculate_ACTn_second(user, qar_network)
        CRDn_second = calculate_CRDn_second(user, qar_network)
        user.ACTn_second = ACTn_second
        user.CRDn_second = CRDn_second
    // Normalize ACTn_first and CRDn_first
    ACTn_first_normalized = normalize([user.ACTn_first for user in users])
    CRDn_first_normalized = normalize([user.CRDn_first for user in users])
    // Calculate CRankui for each user using normalized values
    FOR i from 0 to length(users) - 1:
        user = users[i]
        CRankui = alpha * ACTn_first_normalized[i] * user.ACTn_second + (1 - alpha) * CRDn_first_normalized[i] * user.CRDn_second
        user.CRankui = CRankui
    // Sort users in descending order of CRankui
    users.sort(key=lambda x: x.CRankui, reverse=True)
    RETURN users // Return the sorted users
// Helper functions for calculation and normalization
FUNCTION calculate_ACTn_first(user):
    // Calculate the total number of questions, recommendations, and answers posted by the user
    RETURN user.num_questions + user.num_recommendations + user.num_answers
FUNCTION calculate_CRDn_first(user):
    // Calculate the combination of answer-to-question rate and recommendation-to-answer rate
    RETURN (user.num_answers / user.num_questions) * (user.num_recommendations / user.num_answers)
FUNCTION calculate_ACTn_second(user, qar_network):
    // Calculate the weighted measure of outdegree centrality in the QAR network
    RETURN qar_network.outdegree_centrality[user]
FUNCTION calculate_CRDn_second(user, qar_network):
    // Calculate the weighted measure of indegree centrality in the QAR network
    RETURN qar_network.indegree_centrality[user]
FUNCTION normalize(values):
    // Normalize the values to a range between 0 and 1
    min_value = min(values)
    max_value = max(values)
    normalized_values = [(value - min_value) / (max_value - min_value) for value in values]
RETURN normalized_values
// Usage example
users = [...] // List of user objects
qar_network = [...] // QAR network representation
```

ranked_users = calculate_credible_rank_score(users, qar_network, alpha)
// The 'ranked_users' list now contains the users sorted scending order of their CRankui values

The algorithm calculates the CredibleRank score for each user by combining various metrics related to their activity, participation, and centrality in the QAR network. These metrics include the total number of questions, recommendations, and answers posted by the user (ACTn_first), the combination of answer-to-question rate and recommendation-to-answer rate (CRDn_first), the weighted measure of outdegree centrality (ACTn_second), and the weighted measure of indegree centrality (CRDn_second).

To ensure comparability across users, the ACTn_first and CRDn_first values are normalized using the normalize function. The CRankui score is then calculated as a weighted combination of the normalized ACTn_first and ACTn_second values and the normalized CRDn_first and CRDn_second values.

After calculating the CRankui scores for all users, the algorithm sorts the users in descending order based on their CRankui values. The sorted list, ranked_users, is then returned.

The algorithm can be applied by providing the appropriate data for the users list (containing user objects) and the qar_network representation. The alpha parameter can be adjusted to control the balance between the different metrics. The resulting ranked_users list will contain the users sorted in descending order of their CRankui values, enabling further analysis or actions based on the ranking.

F. OPTIMIZING PARAMETER

The parameter α considers the activity and credibility in each category. We optimize α using a backpropagation neural network (BPNN) learning algorithm that has shown good performance in Artificial Neural Network (ANN) analyses [47].

IV. EXPERIMENT AND EVALUATION

A. EVALUATION METRICS

We assessed the effectiveness of our algorithm using the normalized discounted cumulative gain (NDCG) [48], which is a common measure for evaluating the accuracy of web search result rankings. To ensure the reliability of our evaluation, we carefully selected fifty editors[1] who considered the range of topics when grading the answers posted by users [49]. Using a three-point measurement scale, we evaluated the relevancy of each answer and classified them as "Suitable," "Common," or "Unsuitable," according to **Table 5**.

[1]Two Instructors, seven Ph. D Students and thirty-six Master's Students in Dept. of Library & Information Science, and Dept. of Computer Science at University, one Postdoctoral Research Fellow in Dept. of Computer Science at University, one Ph. D Student in Dept. of Social Informatics, Graduate School of Informatics at University, and three researchers from the Korea National Information Society Agency.

TABLE 5. Evaluation criteria of answer's relevancy [49].

Relevancy	Score	Guidelines	Questioner's Confidence Index
Suitable	2	• All matters in the question are answered and have sufficient data • Some matters of the question are not answered, but have sufficient data to support the answer	More than 60%
Common	1	• Some matters of the question are answered.	30–60 %
Unsuitable	0	• All matters in the question are not in the answer and have insufficient data to support the answer • Partially useful to support the answer, but matters in the question do not match with the answer	Less than 30 %

To calculate credibility (trust), we divided the questions into two groups: intellectual questions requiring specialized knowledge and trivial questions requiring little knowledge, such as hints and tips for daily life. The trustworthiness score was then classified as "High," "Normal," or "Low," depending on the level of answers required for each question. The trust assessment guidelines are presented in **Table 6**.

The editors assigned a "*rel* score" to each answer based on a three-point measurement system for relevancy and trust. The cumulative gain score was calculated by summing the three values ($rel_{\text{total}} = rel_{\text{relevancy}} + rel_{\text{trust}} + ratio_{\text{selected\_answers}}$). We applied the user ranking by CredibleExpertRank to calculate the discounted cumulative gain score of the question, and applied the same approach in the other baseline methods.

B. BASELINE METHODS

We set three baseline methods: PageRank, HITS, and Point System [29]. To compare the performance of our approach with those of PageRank and HITS, we calculated the authority score.

- **PageRank**: PageRank is a well-known SNA algorithm originally developed by Google to rank web pages. It can be used to identify the most influential contributors on a knowledge-sharing site based on their network of connections and the quality of those connections. **Equation (12)** shows the PageRank algorithm as applied in a Q&A user network. PageRank only uses the outbound links among users (also used as a factor in our CredibleExpertRank algorithm).

$$PR(u_a) = c\sum\nolimits_{u_b:u_b\rightarrow u_a}\frac{PR(u_b)}{O(u_b)} + (1-c)\frac{1}{N} \qquad (12)$$

TABLE 6. Evaluation criteria of answer's credibility [49].

Credibility	Score	for Intellectual Questions	for Trivial Questions
High	2	• Accurate source corresponded with public trust • Firm objectives and basis (theoretic/ scholarly source) • Logical organization (pictures, graphs) • Affirmative answer to the question	• Logical, personal opinion • Proverb, maxim, hints /tips in daily life • Not scholarly, but practically make sense • Affirmative answer to the question
Normal	1	• Answered but insufficient source	• Answered logically but insufficient source
Unsuitable	0	• Slanders, curses, lascivious comments • Disrespectful comments • Assuming comments • Useless opinions • Answer which is not concerned with question • Advertisements	

In the above, $PR(u_a)$ is user u_a's PageRank score; $O(u_b)$ is user u_b's outdegree; c is a damping factor (set to 0.85 in our experiment); and N is the total number of users.

• **HITS**: The HITS is another SNA algorithm for identifying influential contributors on a knowledge-sharing site. It is based on the idea that influential contributors are those who are not only well-connected but who are also associated with high-quality content. The HITS was developed to predict the importance of web pages by assigning each page a hub and authority score. A page is considered a good hub if it links to many good authoritative pages, and authoritative pages are in turn linked by many good hubs. This idea has an intuitive parallel with Q&A sites. In a user relationship graph, poorly formulated or nonsense questions will have few or no answers (resulting in a low outdegree for the questioning user nodes). In contrast, good questions tend to have many answers. In turn, users answering many questions from "good" users will have high indegrees. This immediately suggests that nodes representing question authors act as "hubs" while nodes representing answer authors correspond to "authorities." **Equation (13)** shows the HITS algorithm. $H(u_b)$ denotes user u_b's hub score, and $A(u_a)$ denotes user u_a's authority score.

$$H\left(u_b\right)=\sum\nolimits_{u_a:u_b\rightarrow u_a} A\left(u_a\right); \quad A\left(u_a\right)=\sum\nolimits_{u_b:u_b\rightarrow u_a} H\left(u_b\right); \tag{13}$$

Here, $H(u_b)$ is the hub score of each u_b from a set of users posting questions; $A(u_a)$ is the authority score of each u_a from a set of users posting answers. If one has a high hub score, it means that he/she is a good asker, and if one has a high authority score, it means that he/she is a good answerer.

• **Point System**: Point System is an opinion mining-based algorithm for identifying the relevancy of posts, comments, and reviews on a knowledge-sharing site. It can be used to identify experts with a high level of positive or negative sentiment, as well as to understand the sentiments of users toward specific topics or contributors. Point System is powered by the expert value algorithm used as the evaluation system of "Naver Knowledge iN." This algorithm is based on the activity of the users. The calculations are shown in **Equation (14)** as follows:

$$E_i = \{(A_{selected} + RW_{relay\_mvp}) \times 10\} + A_{non\_selected} + (W_{writen} \times 15) + (W_{extra} \times 3) + RW_{relay} \tag{14}$$

Here, A_{selected} refers to the number of answers given by user i on the Q&A site and selected by the asker as the most helpful or relevant. $W_{\text{relay\_mvp}}$ is the number of suggestions made by the user in professional reviews where the user has been selected as the most valuable user. $A_{\text{non\_selected}}$ represents the number of answers that user i has given on the Q&A site that are not selected by the asker as the most helpful or relevant. W_{writen} is the number of articles written by users in professional reviews. W_{extra} refers to the number of other posts that user i has made on the Q&A site; these can include comments on other people's questions or answers or new questions or discussions. RW_{relay} is the number of comments made by users in professional reviews. These variables are used to analyze the activity and contributions of users in both Q&A websites and professional reviews.

• **Influencer Score (IS) [50]:** The formula to identify influencers or mavens is expressed as **Equation (15)**:

$$\begin{aligned}
&\text{Influencer Score (IS)}\\
&\quad = (0.4 * \text{Number of followers})\\
&\qquad + (0.2 * \text{Number of posts}) - (0.1 * \text{Automated}\\
&\qquad \times \text{Readability Index}) + (0.3 * \text{Average percentage of}\\
&\qquad \times \text{uppercase letters}) - (0.2 * \text{Average percentage of}\\
&\qquad \times \text{distinct words}) + (0.4 * \text{Average percentage of}\\
&\qquad \times \text{hashtags})
\end{aligned} \tag{15}$$

The variables used in the formula are as follows: Number of followers (NF) refers to the number of people who follow the user on social media. Number of posts (NP) is the total number of posts or tweets posted by the user. Automated Readability Index (ARI) is a measure of the average readability of the user's posts, approximating the US school grade level needed to comprehend the text. Average percentage of uppercase letters (UCL) represents the average percentage of uppercase letters in the user's posts, calculated as (number of uppercase letters / total post length) * 100. Average percentage of distinct words (DW) denotes the average percentage of distinct words in the user's posts, calculated as (number of distinct words / total post length) * 100. Average percentage of hashtags (HT) indicates the average percentage

TABLE 7. Test data component ratio according to number of answers per question.

Number of Answers	Test Set1		Test Set2		Test Set3	
	Number (%)	Cumulation (%)	Number (%)	Cumulation (%)	Number (%)	Cumulation (%)
1	6,459	6,459	3,768	3,768	2,691	2,691
	(1.2)	(1.2)	(0.7)	(0.7)	(0.5)	(0.5)
2	9,689	16,148	8,074	11,842	6,459	9,150
	(1.8)	(3)	(1.5)	(2.2)	(1.2)	(1.7)
3	252,461	268,609	264,304	276,146	278,838	287,988
	(46.9)	(49.9)	(49.1)	(51.3)	(51.8)	(53.5)
4	122,193	390,802	142,649	418,795	162,027	450,015
	(22.7)	(72.6)	(26.5)	(77.8)	(30.1)	(83.6)
5	70,517	461,319	82,359	501,154	58,674	508,689
	(13.1)	(85.7)	(15.3)	(93.1)	(10.9)	(94.5)
6	31,759	493,078	16,687	517,841	15,072	523,761
	(5.9)	(91.6)	(3.1)	(96.2)	(2.8)	(97.3)
7	20,455	513,533	12,919	530,760	7,536	531,297
	(3.8)	(95.4)	(2.4)	(98.6)	(1.4)	(98.7)
8	11,842	525,375	4,844	535,604	3,768	535,065
	(2.2)	(97.6)	(0.9)	(99.5)	(0.7)	(99.4)
9	9,689	535,064	1,614	537,218	2,691	537,756
	(1.8)	(99.4)	(0.3)	(99.8)	(0.5)	(99.9)
10+	3,234	538,298	1,080	538,298	542	538,298
	(0.6)	(100)	(0.2)	(100)	(0.1)	(100)

of hashtags used in the user's posts, calculated as (number of hashtags / total post length) * 100.

These variables are combined in the Influencer Score formula to create a composite score that can help identify influencers or mavens from public social media accounts. The formula takes into account various factors related to user network, user behavior, message readability, and message structure, providing a quantitative measure for evaluating users' influencer potential on social media. This formula can be integrated into a decision support system for marketing and information systems managers to identify potential influencers for marketing campaigns or information dissemination strategies.

C. DATASETS

We obtained three types of networks (Factuality, Advice, and Discussion Forum) and collected Q&A pairs, questions, answers, and recommendations from Naver Knowledge iN [30]. To obtain an unbiased dataset, the users were selected using a sampling method. The dataset included 1,357 users and 1,345,745 Q&A pairs collected between March 2022 and January 2023. We used 60% of the Q&A pairs (807,447 pairs) as a training set to adjust the parameter α and the remaining 40% (538,298 pairs) as a test set to demonstrate the effectiveness of the algorithm. We organized three test sets with a similar ratio of answer(s) per question. The dataset statistics are listed in **Table 7**. Notably, a large proportion (more than 80%) of the Q&A data had three to five answers per question; we considered these Q&A cases as important and analyzed them closely.

D. PARAMETER ESTIMATION

Parameter α in **Equation (11) (in Section III-E)** is the balance parameter considering the activity and credibility. For optimizing α, we use the BPNN learning algorithm which has shown good performance in ANN analysis [47]. and the summary is as follows. The BPNN is a type of artificial neural network that employs a supervised learning algorithm. It consists of simple processing elements or nodes organized into different layers, including an input layer, one or more hidden layers, and an output layer. The architecture

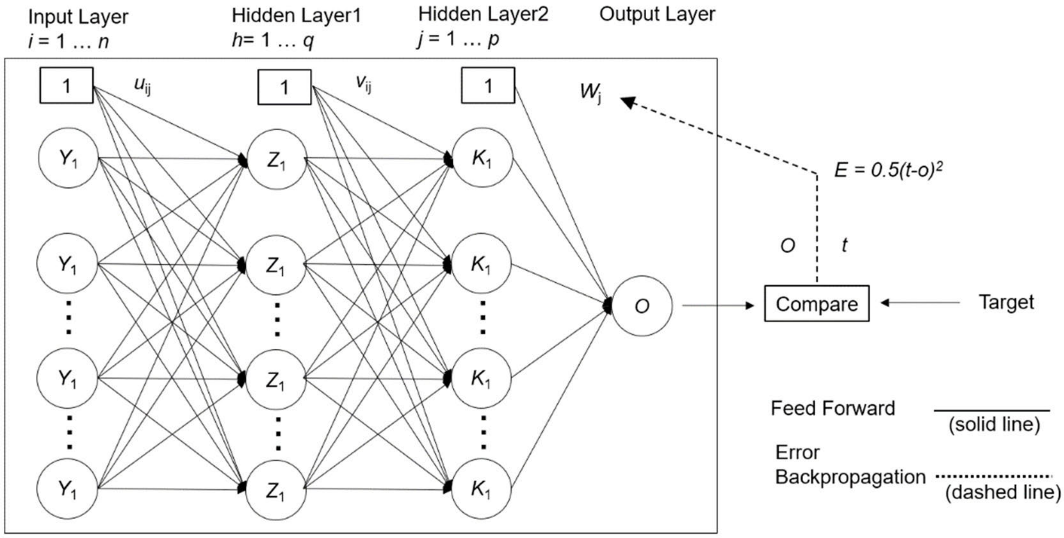


FIGURE 8. Flow Chart of a typical two hidden Layers BPNN. The flow chart of a typical two-hidden-layer backpropagation neural network (BPNN) starts with the input layer, followed by preprocessing of the input data. The data then passes through multiple hidden layers with activation functions, and the output layer produces the final prediction. Prediction error is calculated and used for weight updates through backpropagation. The network is trained iteratively using a training dataset, and once trained, it can make predictions on new data. The flow chart may also include additional steps or optimizations depending on the implementation.

commonly used in this research involves two hidden layers, as illustrated in **Figure 8**. To optimize α using the BPNN algorithm, we follow the standard backpropagation process. This process involves the following steps:

1. Present an input to the network.
2. Propagate forward the computed activation network output and compare it with the target.
3. Propagate backward the computed error signal.
4. Update the weights connecting the nodes based on the error signal using the generalized delta rule.

Repeat steps 1 to 4 for each training pattern until the stopping condition is met.

By iteratively adjusting the weights based on the error signal, the network gradually improves its accuracy in approximating the desired input-output mapping. This optimization process enables us to determine the optimal value of α in **Equation (11)**.

In summary, we utilize the BPNN learning algorithm to estimate the parameter α. This algorithm, based on backpropagation, adjusts the weights of the network to minimize the difference between the computed output and the target output. By following the steps of the backpropagation algorithm, we optimize α and achieve an accurate approximation of the desired input-output mapping.

The SPSS Clementine tool was utilized to determine the optimal value of α. For the training set, a total of 814 users were selected. As shown in **Figure 9**, the training method employed a two hidden-layered BPNN, where the input layer consisted of two neurons and the hidden layers had two or three neurons. The output scores from the CredibleExpertRank calculation were used as the target outputs for the BPNN.

To maximize training efficiency, two input variables were used:

• Input 1, which was calculated as the product of outdegree and the number of questions.

• Input 2, which was calculated as the product of indegree, the ratio of selected answers, and the ratio of recommended answers.

The weights of the output layer and the hidden layers were updated during training to minimize the mismatches between the output scores and the predicted outputs based on the training data of the BPNN. The training procedure converged to the minimal error after 15 iterations, and α was subsequently adjusted to 0.27 in order to optimize the performance of the system.

This approach allowed for the fine-tuning of the BPNN by adjusting the value of α, which was determined using the SPSS Clementine tool, and optimizing the input variables to achieve the best possible training efficiency and accuracy in predicting the output scores.

E. ANALYSIS OF USER CONNECTIONS AND VISUALIZATION OF USER NETWORK STRUCTURE

We analyzed the network based on user connections, questions, answers, and recommendations to determine the relevance of the categories selected for experimentation and calculate reliable expert scores. Then, we ranked them based on the link analysis. To identify an efficient network structure for this study, we attempted to cluster the main categories in Naver Knowledge iN using an SNA. To analyze and cluster the structure of a given network of users, we selected 500 users from each category.

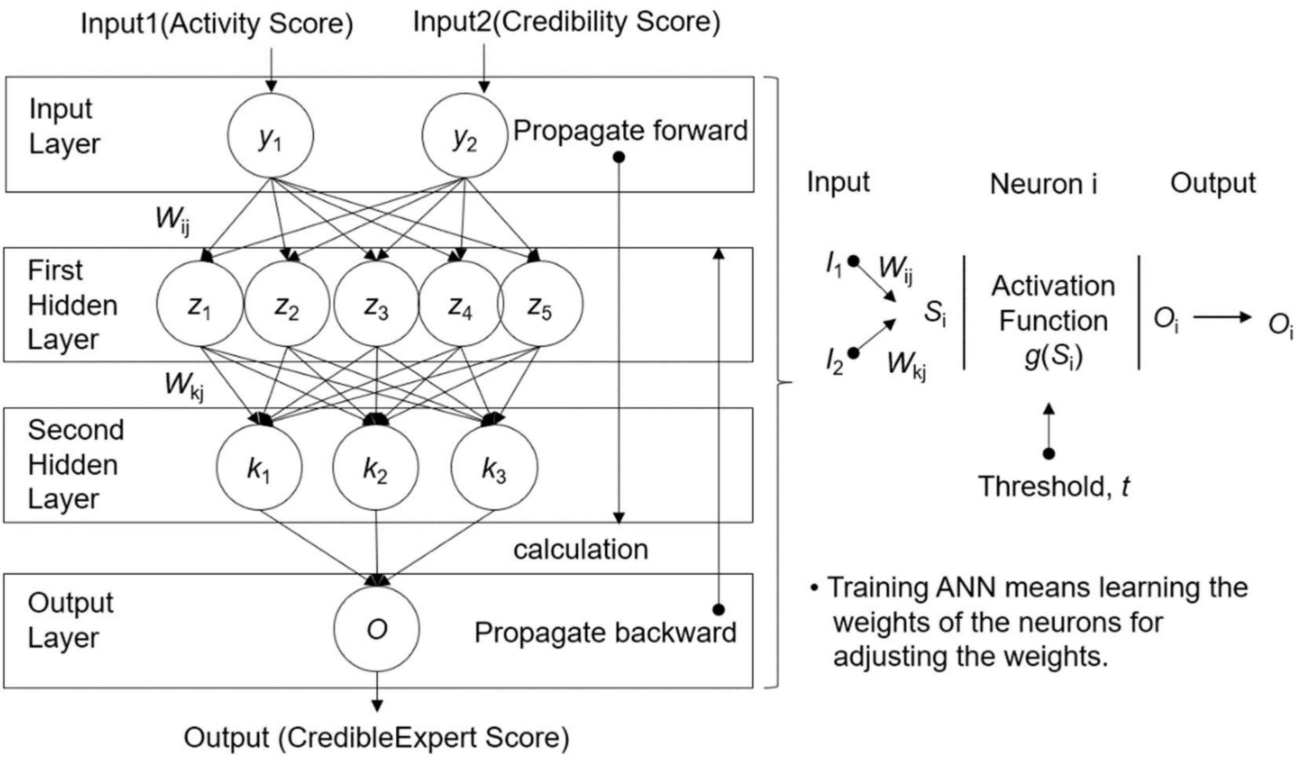


FIGURE 9. Estimating Optimized Parameter α. The training method utilized a two hidden-layered BPNN with an input layer consisting of two neurons and hidden layers containing two or three neurons. The output scores from the CredibleExpertRank calculation were used as target outputs for the BPNN. To maximize training efficiency, two input variables were used, calculated as the product of outdegree and the number of questions (Input 1), and the product of indegree, the ratio of selected answers, and the ratio of recommended answers (Input 2). The weights of the output layer and hidden layers were updated during training to minimize mismatches between output scores and predicted outputs based on the training data of the BPNN.

TABLE 8. Evaluation criteria of answer's credibility.

Cluster	Categories in Naver Knowledge iN
Factuality	Computer/Communication, Game, Business/Economy
Advice	Shopping, Health/Medical, Home/Life, Education/Study
Discussion	Sports, Entertainment, Society/Culture, Travel/Leisure

The user connections based on the questions and answers were analyzed using Python and then visualized as three types of ego networks [30]. **Table 8** shows the clustering results.

Figure 10 shows an example of network visualization (the color of a circle denotes the degree of credibility; the closer the circle is to navy, the fewer connections there are, and the closer to yellow, the more connections there are.). As can be seen from the visualization, the results show characteristics similar to those of existing studies [30], indicating that the collected dataset well-reflects the behavioral patterns of users of knowledge-sharing sites.

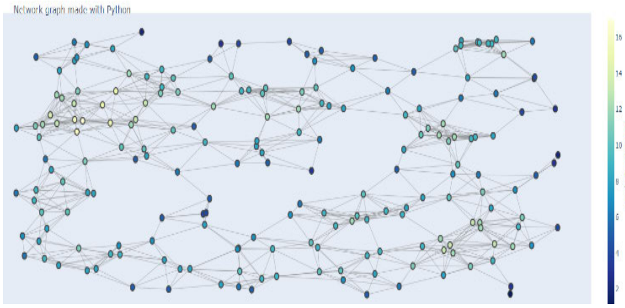
F. FINDING AND RANKING CREDIBLE EXPERTS

Based on the CredibleExpertRank algorithm, we identified trusted experts, visualized and showed the trusted experts corresponding to the top-k ranks, and ranked them according to the CredibleExpert score, as shown in **Table 9**. **Table 9** shows the results for the credibility score for the top 10 users based on the CredibleExpertRank algorithm.

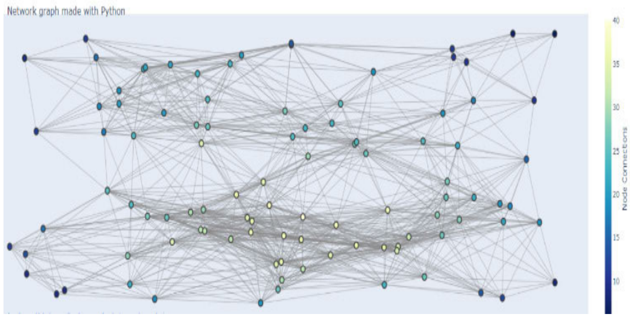
We analyzed and visualized the network structure of the users to identify credible experts using Python. **Figure 11** shows an example of a network structure based on the top-k credible experts. The size of the circle and width of the link denote the degree of credibility; the larger the circle, the wider the link, and the more credible it is. As can be seen in **Figure 11**, we can easily find credible experts on knowledge-sharing sites based on the credibility scores as calculated using the CredibleExpertRank algorithm.

G. EVALUATION RESULTS

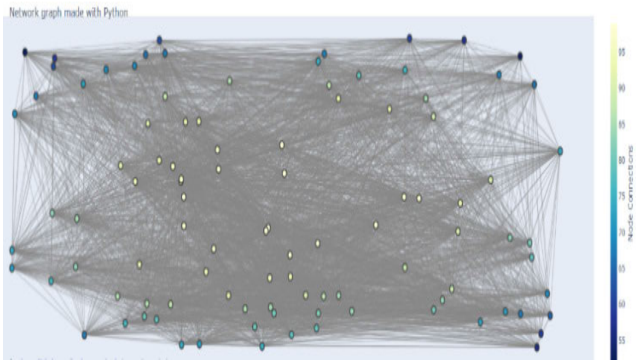
We evaluated the effectiveness of our approach by calculating the NDCG@k score, which measures the suitability of our answers compared to those from experts identified by other baseline methods. We compared the performance of our proposed algorithm with that of baseline methods, such as the HITS, PageRank algorithm, and Point System. The results, presented in **Table 10** and **Figure 12**, demonstrate that the CredibleExpertRank outperforms all other baseline methods by achieving a higher NDCG@k score. This suggests that



(a) Factuality



(b) Advice



(c) Forum

FIGURE 10. Ego Networks of Three Selected Categories in Naver Knowledge iN. (a) Factuality: This figure shows the ego network for the category of "Factuality" in Naver Knowledge iN. The ego network represents the central user (ego) and the users with whom they have interactions (neighbors) in the "Factuality" category. The nodes represent users, and the edges represent interactions between users. (b) Advice: This figure shows the ego network for the category of "Advice" in Naver Knowledge iN. (c) Forum: This figure shows the ego network for the category of "Forum" in Naver Knowledge iN. These ego network diagrams provide a visual representation of the user interactions within the three selected categories in Naver Knowledge iN, showcasing the relationships and connections between users in each category.

our proposed algorithm successfully identifies more credible experts and provides better answers.

The average improvement in NDCG@k(All) shows a 14.407% ~ 19.499% improvement over PageRank, 12.690% ~ 18.799% improvement over HITS, 11.473% ~ 17.319% improvement over Point System, and 6.781% ~ 5.747% improvement over IS.

The average improvement for NDCG@3 ~ 5 (85.57% to 94.5% of the dataset) is 19.263% ~ 38.795% over PageRank, 18.438% ~ 37.631% over HITS, 17.393% ~ 35.992% over Point System, and 8.318%~8.872% over IS.

The maximum improvements for NDCG@3 (note that the three-answer case is approximately half of the entire set of data): are 25.961% ~ 40.280% over PageRank, 33.435% ~ 39.401% over HITS, 32.667% ~ 37.400% over Point System, and 9.031% ~ 9.729% over IS.

Thus, CredibleExpertRank cases significantly outperform all baseline methods in all cases: PageRank (average 17.072%, maximum 40.280% in NDCG@3), HITS (average 15.688%, maximum 39.401% in NDCG@3), Point System as currently used in Naver's Knowledge iN (average 14.464%, maximum 37.400% in NDCG@3), and IS (average 6.972%, maximum 9.729% in NDCG@3).

In particular, CredibleExpertRank shows the highest performance in the case of questions with three to five answers, which constitutes a major part of the test dataset (29.379% average, 38.795% maximum over PageRank, 27.827% average, 37.631% maximum over HITS, 26.784% average, 35.992% maximum over Point System, and 10.298% average, 13.705% maximum over IS), shown in **Figure 13**.

- **Discussion:** Although PageRank is an effective graph ranking algorithm for identifying important pages or nodes based on the number and quality of inbound links, it has limitations when it comes to finding credible experts in social networks. In social networks, not all links or relationships are equal, and different types of links can have different levels of influence on other nodes. For example, inbound links from other authoritative nodes may have a greater impact on a node's credibility and authority than outbound links. Therefore, using only PageRank-based links to identify credible experts may not be sufficient, and alternative algorithms considering other factors such as the quality and nature of the links may be needed. Additionally, social networks can be complex and multidimensional, and different types of relationships or interactions between nodes may need to be considered to accurately identify credible experts.

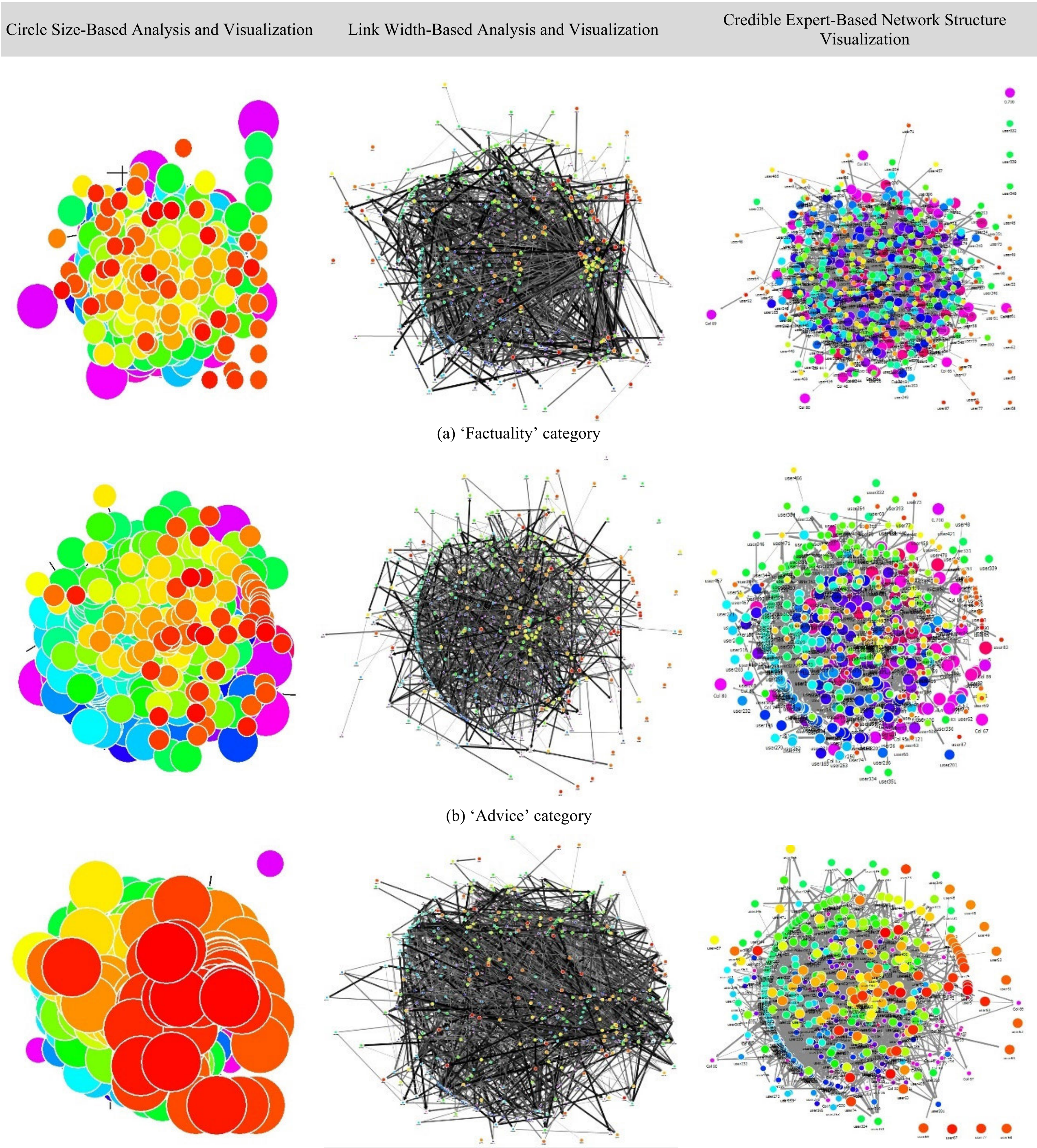
The HITS algorithm uses link structure analysis to locate authoritative web pages on the internet. HITS considers two aspects of link relationships: authority and hubs. Authority pages provide important information and receive many links from high-quality hubs, while hub pages link to authoritative pages. Therefore, the algorithm can identify high-quality web pages on a particular topic by analyzing both inbound and outbound links. However, the algorithm does not distinguish between the degree of influence of inbound and outbound links or levels of influence on a person's credibility in a social network. Therefore, while the HITS algorithm effectively identifies popular web pages, it has limitations in identifying credible and authoritative experts in a network structured by people.

PageRank and HITS do not consider a weighted graph structure for reflecting the actual strengths among users; thus, they can result in inaccurate identifications of authoritative users. Although Point System uses a confidence element based on user voting points, it does not apply weights to the

TABLE 9. CredibleExpertRank algorithm-based top 10 users recommendation.

Category	Number of Questions	Number of Answers	Number of Recommend	Number of Questions Posted Answer	Number of Recommended Answers	Weighted Indegree	Weighted Outdegree	CRank score	Rank (user)
Factuality	21	104	75	20	98	0.864	0.932	0.960	1
	33	89	42	31	87	0.871	0.927	0.905	2
	17	67	51	15	60	0.943	0.821	0.778	3
	18	112	62	16	87	0.827	0.878	0.773	4
	45	32	17	42	31	0.894	0.836	0.755	5
	37	34	23	32	33	0.912	0.882	0.733	6
	21	48	56	18	48	0.794	0.856	0.722	7
	19	56	43	15	53	0.885	0.896	0.706	8
	41	27	16	37	26	0.865	0.813	0.692	9
	29	43	13	26	41	0.819	0.878	0.668	10
Average	28.1	61.2	39.8	25.2	56.4	0.867	0.872	0.769	
Advice	12	88	94	11	81	0.864	0.937	0.917	1
	8	88	81	8	77	0.867	0.876	0.882	2
	15	72	72	13	68	0.877	0.908	0.829	3
	9	58	62	8	50	0.975	0.898	0.790	4
	18	27	39	16	26	0.943	0.875	0.744	5
	22	43	35	21	39	0.887	0.829	0.735	6
	11	43	98	8	42	0.843	0.881	0.720	7
	18	28	65	17	26	0.806	0.857	0.716	8
	16	39	77	13	33	0.891	0.896	0.697	9
	23	31	33	21	28	0.859	0.853	0.673	10
Average	15.2	51.7	65.6	13.6	47	0.881	0.881	0.770	
Forum	8	217	136	8	112	0.813	0.884	0.983	1
	9	103	78	8	88	0.892	0.956	0.879	2
	9	212	143	8	98	0.782	0.824	0.870	3
	13	189	89	12	81	0.895	0.943	0.840	4
	11	89	97	10	71	0.798	0.964	0.824	5
	6	112	85	6	78	0.876	0.869	0.819	6
	24	65	43	22	61	0.851	0.871	0.777	7
	29	58	35	26	54	0.868	0.895	0.759	8
	12	87	29	11	81	0.833	0.841	0.746	9
	15	56	23	14	50	0.889	0.893	0.717	10
Average	13.6	118.8	75.8	12.5	77.4	0.850	0.894	0.821	

behavior of each vote. The CredibleExpertRank algorithm is proposed as a solution to the limitations of PageRank, HITS, and Point System in identifying credible experts on knowledge-sharing sites. By assigning different weights to an importance measure based on indegree and outdegree centralities, CredibleExpertRank compensates for the disadvantages of PageRank and HITS. CredibleExpertRank addresses these limitations by assigning different weights based on



(a) 'Factuality' category

(b) 'Advice' category

(c) 'Forum' category

FIGURE 11. Visualization of CredibleExpertRank Score-Based Credible Experts. We analyzed and visualized the network structure of users to identify credible experts using Python. The figure shows an example of a network structure based on the top-k credible experts. In this visualization, the size of the circle represents the degree of credibility, with larger circles indicating higher credibility, and the width of the links denotes the level of credibility, with wider links indicating higher credibility. This visualization allows us to easily identify credible experts on knowledge-sharing sites based on the credibility scores calculated using the CredibleExpertRank algorithm.

indegree and outdegree centralities and incorporating opinion mining for links in social networks on knowledge-sharing sites, resulting in improved performance compared to existing methods.

To address these limitations, we propose the CredibleExpertRank algorithm for identifying credible experts on knowledge-sharing sites. CredibleExpertRank assigns different weights based on indegree and outdegree centralities and incorporates opinion mining for links in social networks, resulting in improved performance compared to existing methods. With this approach, CredibleExpertRank compensates for the disadvantages of PageRank, HITS, and

TABLE 10. **Normalized discounted cumulative gain (NDCG)@k evaluation result.**

	Classification	NDCG											
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10	Average (@3-5)	Average (@All)
Set1	PageRank	0.792	0.739	0.732	0.651	0.626	0.627	0.599	0.595	0.571	0.565	0.670	0.6497
	Hyperlink-Induced Topic Search (HITS)	0.803	0.768	0.691	0.682	0.65	0.633	0.608	0.607	0.577	0.577	0.674	0.6596
	Point System	0.808	0.778	0.695	0.691	0.655	0.639	0.622	0.609	0.589	0.582	0.680	0.6668
	Influencer Score (IS)	0.812	0.793	0.753	0.741	0.718	0.677	0.643	0.629	0.603	0.592	0.737	0.6961
	CredibleExpertRank	0.862	0.859	0.821	0.801	0.774	0.728	0.691	0.671	0.631	0.595	0.799	0.7433
	Improvement over baselines (%)												
	PageRank	8.848	16.241	25.961	24.59	23.565	16.151	15.38	12.704	10.408	5.425	19.263	14.407
	HITS	7.356	11.852	33.435	18.926	19.002	15.05	13.612	10.505	9.192	3.249	18.438	12.690
	Point System	6.692	10.414	32.667	17.376	18.094	13.969	11.08	10.124	7.148	2.273	17.393	11.473
	IS	6.158	8.323	9.031	8.097	7.799	7.533	7.465	6.677	4.643	0.507	8.318	6.781
Set2	PageRank	0.814	0.76	0.666	0.646	0.646	0.641	0.638	0.614	0.598	0.574	0.653	0.6597
	HITS	0.815	0.78	0.677	0.668	0.654	0.652	0.646	0.629	0.6	0.575	0.666	0.6696
	Point System	0.825	0.791	0.687	0.669	0.65	0.653	0.647	0.634	0.608	0.589	0.669	0.6753
	IS	0.827	0.802	0.762	0.751	0.727	0.702	0.669	0.664	0.637	0.599	0.747	0.714
	CredibleExpertRank	0.873	0.868	0.872	0.855	0.82	0.777	0.729	0.693	0.651	0.601	0.849	0.7739
	Improvement over baselines (%)												
	PageRank	7.223	14.212	30.907	32.414	26.999	21.102	14.188	12.824	8.988	4.807	30.082	17.311
	HITS	7.144	11.327	28.857	28.014	25.407	19.083	12.823	10.162	8.558	4.452	27.414	15.576
	Point System	5.845	9.778	26.925	27.823	26.179	18.901	12.634	9.257	7.127	2.054	26.969	14.601
	IS	5.562	8.229	14.436	13.848	12.792	10.684	8.969	4.367	2.198	0.334	13.705	8.389
	PageRank	0.824	0.784	0.635	0.634	0.623	0.649	0.652	0.637	0.601	0.582	0.631	0.6621
	HITS	0.824	0.786	0.639	0.642	0.627	0.649	0.655	0.644	0.607	0.587	0.636	0.666

TABLE 10. *(Continued.)* **Normalized discounted cumulative gain (NDCG)@k evaluation result.**

	Point System	0.827	0.791	0.649	0.648	0.634	0.657	0.672	0.648	0.614	0.604	0.644	0.6744
	IS	0.873	0.832	0.812	0.803	0.797	0.749	0.7	0.674	0.641	0.601	0.804	0.7482
Set3	CredibleExpertRank	0.89	0.889	0.891	0.878	0.857	0.803	0.741	0.698	0.656	0.609	0.875	0.7912
	Improvement over baselines (%)												
	PageRank	8.037	13.342	40.28	38.422	37.496	23.655	13.785	9.524	9.055	4.589	38.795	19.499
	HITS	8.011	13.068	39.401	36.804	36.706	23.639	13.264	8.416	8.006	3.716	37.631	18.799
	Point System	7.658	12.353	37.4	35.597	35.279	22.208	10.363	7.759	6.792	0.78	35.992	17.319
	IS	1.947	6.851	9.729	9.340	7.528	7.210	5.857	3.561	2.340	1.331	8.872	5.747

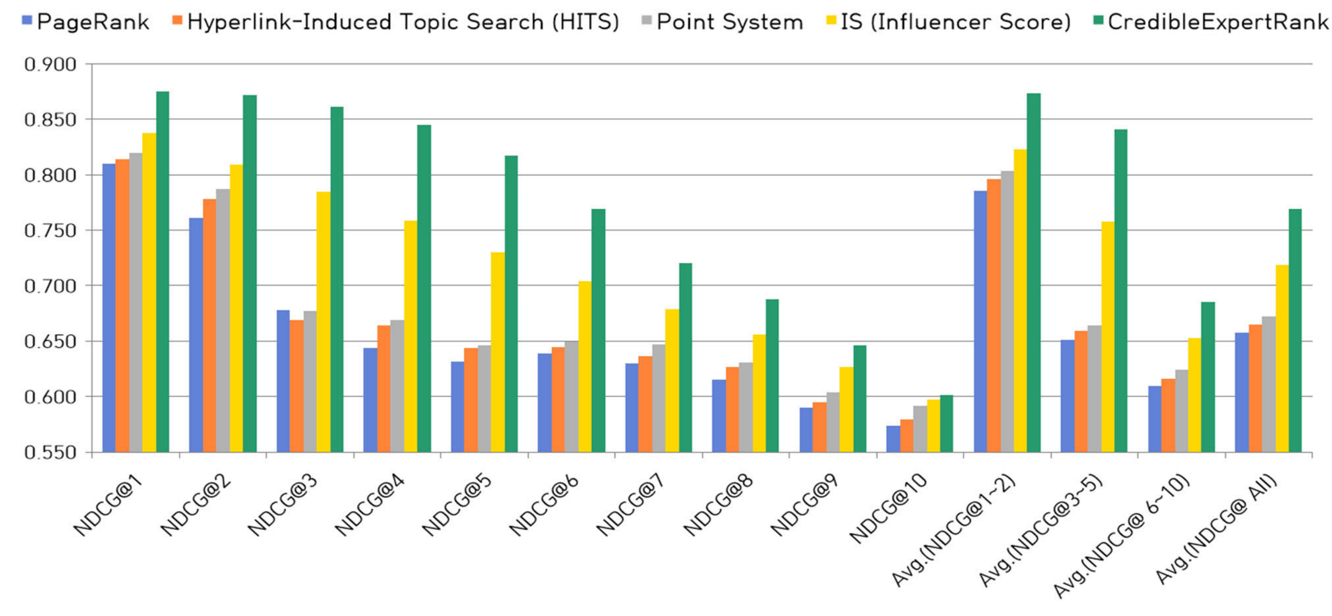
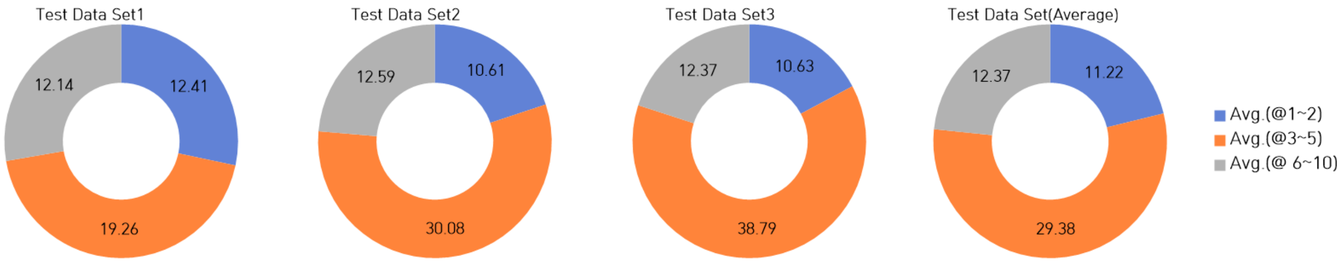


FIGURE 12. **Visualization of CredibleExpertRank Score-Based Credible Experts. In this figure, we present the performance comparison of our proposed algorithm with baseline methods, including HITS, PageRank algorithm, and Point System. The results clearly show that our CredibleExpertRank algorithm outperforms all other baseline methods, achieving a higher NDCG@k score. This indicates that our algorithm successfully identifies more credible experts and provides superior answers compared to the baseline methods.**

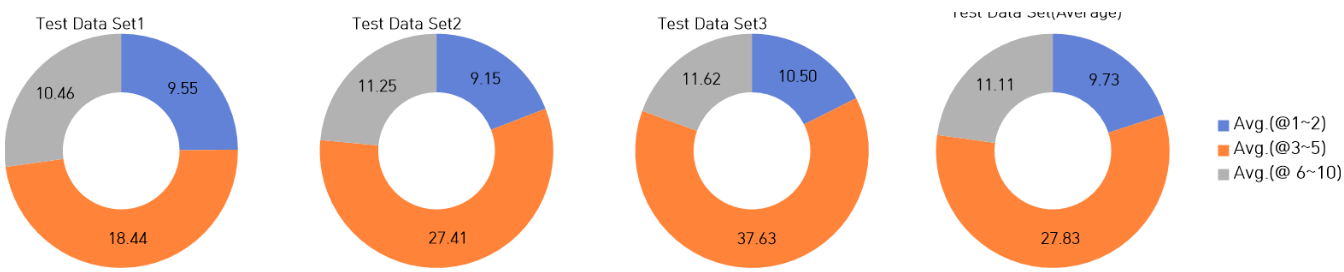
Point System and provides a more accurate and reliable measure of credible experts.

IS has several shortcomings that need to be addressed. Firstly, it lacks consideration for network centrality, content quality, and user interactions, which are crucial factors in identifying influencers. Secondly, the IS does not incorporate variables such as degree centrality and opinion mining, which can provide a more comprehensive analysis of a user's influence. Additionally, the IS may not accurately capture the relevance and timeliness of the information shared by influencers, as it does not account for user interactions such as likes, comments, and shares. However, the advantage of the IS is that it provides a quantitative measure for evaluating users' influencer potential on knowledge sharing sites by considering factors such as the number of followers, readability of posts, use of uppercase letters, distinct words, and hashtags. This can be useful in identifying potential influencers for information dissemination strategies.

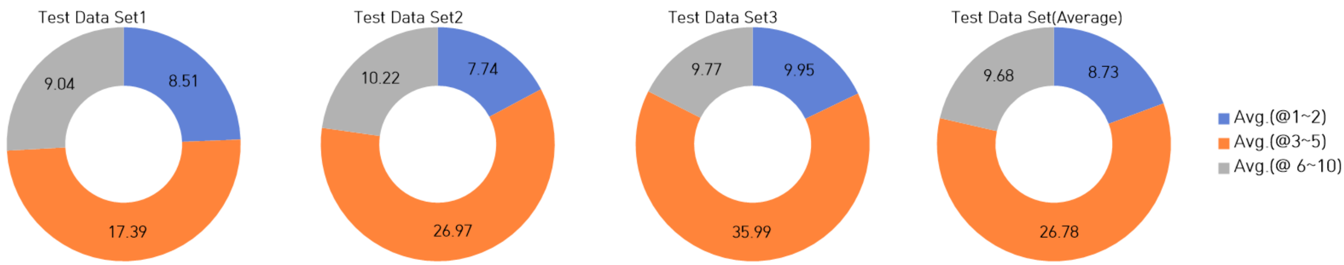
To address the shortcomings mentioned above, the CredigleExpertRank algorithm can be enhanced by incorporating additional variables such as degree centrality and opinion mining. Degree centrality, which measures a user's



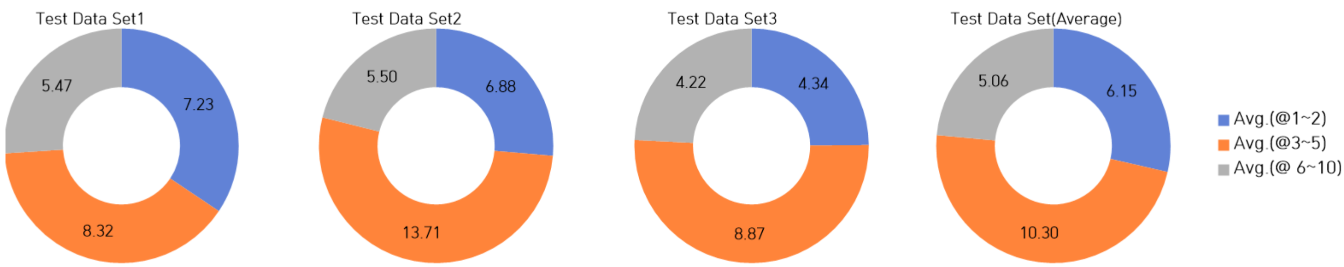
(a) Improvement Rate of CredibleExpertRank over PageRank



(b) Improvement Rate of CredibleExpertRank over HITS



(c) Improvement Rate of CredibleExpertRank over Point System



(d) Improvement Rate of CredibleExpertRank over IS

FIGURE 13. Performance in the Case of Questions with Answers. CredibleExpertRank demonstrates superior performance, particularly in the case of questions with three to five answers, which constitute a significant portion of the test dataset.

centrality in the social network, can provide insights into the user's overall influence within their network. Opinion mining, which evaluates user behavior patterns such as likes, shares, and comments, can provide a more comprehensive understanding of user interactions and engagement levels. By integrating these variables into the formula, the algorithm may result in better accuracy in identifying influencers and providing more relevant and timely information from the identified influencers.

Experimental evaluations have shown that the CredigleExpertRank algorithm, which incorporates degree centrality and opinion mining, performs better in identifying influencers on knowledge sharing sites compared to traditional information retrieval methods. The information provided by the identified influencers is more appropriate and timely, likely due to the inclusion of additional variables that capture the user's centrality in the network and their engagement levels. The enhanced algorithm may offer improved decision support for marketing and information systems managers, allowing for more effective targeting of influencers for marketing campaigns or information dissemination strategies.

V. CONCLUSION AND FUTURE DIRECTIONS

In this study, we present a novel algorithm, CredibleExpertRank, which combines SNA and opinion mining to identify credible experts on knowledge-sharing sites. The CredibleExpertRank algorithm involves several steps, including data collection, SNA network analysis, opinion mining, and credibility score calculation, which ranks the experts based on their credibility.

We evaluated the CredibleExpertRank algorithm using real-world data from a knowledge-sharing site and found that it effectively identified credible experts. Furthermore, the combination of SNA and opinion mining resulted in better performance than using either method alone. Our experiments demonstrated that answers from trusted experts were more relevant than those from regular users. By using our algorithm to recommend trusted experts to users or to rank their answers higher, we can enhance the search effect and improve information sharing.

In conclusion, our proposed approach offers a new and effective method for identifying credible experts on knowledge-sharing sites. The CredibleExpertRank algorithm has potential applications in various fields, such as expert recommendation systems and knowledge management in online communities.

- **Future Directions:** To further enhance the accuracy and reliability of the CredibleExpertRank algorithm, several additional considerations can be taken into account. First, expand the range of experiments: In addition to analyzing the frequency of interactions, further research can be conducted to identify and incorporate other trust factors that could potentially affect the reliability of the algorithm. For example, exploring factors such as user profile similarity, hop distance, and social relationships between users, and assigning appropriate weights to these factors could provide a more comprehensive understanding of user credibility. Second, incorporate additional factors: Consider integrating other relevant trust factors, such as the quality and accuracy of a user's past answers or their reputation on other knowledge-sharing platforms. Incorporating such factors could provide a more nuanced assessment of user expertise and credibility, leading to more accurate identification of credible experts. Third, consider contextual information: Take into consideration the context of questions being asked, and assign greater weight to questions that require specialized knowledge or expertise. Users who have a proven track record of answering such questions correctly could be given higher credibility scores, leading to improved identification of credible experts. Fourth, utilize advanced machine learning algorithms: Explore the use of more advanced machine learning algorithms, such as deep learning or ensemble methods, to learn the most relevant features for identifying credible experts. This could potentially improve the accuracy and robustness of the algorithm in identifying credible experts based on factors such as user activity, content quality, and social network structure. Lastly, incorporate user feedback: Consider incorporating user feedback to dynamically adjust the weights assigned to different trust factors or to update the rankings of users over time. Additional user feedback, such as rating scores or reviews of users who are sensitive to topics and have similar interests, can provide valuable insights into the credibility and reliability of experts, leading to more adaptive and accurate rankings.

By implementing these suggestions, the CredibleExpertRank algorithm has the potential to become a more advanced and reliable tool for identifying credible experts on knowledge-sharing sites, leading to improved search efficiency and reliability of knowledge-sharing platforms. However, it is important to thoroughly validate and evaluate any modifications using appropriate benchmarks and real-world data to ensure the effectiveness and robustness of the algorithm.

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