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Identification of Opinion Leaders and Followers— A Case Study of Green Energy and Low Carbons

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Abstract: In recent years, with the development of Web2.0, enterprises, government agencies, and traditional news media, which have been positively influenced by opinion leaders, have been dedicated to understanding leaders' opinions on the web in order to seek convergence. Specifically, with the increase of environmental awareness, the introduction of green energy and carbon reduction technology has become an important issue. Consequently, studies identifying opinion leaders and followers who are interested in green energy and low carbon have become important. This study aims to find a solution that can identify the characteristics of opinion leaders and followers that can be widely used, which will help certain public policies or issues to be more effectively disseminated in the future. To model the characteristics of opinion leaders and their influence on followers, this study uses a dual matrix. The interaction patterns are recognized among opinion leaders and followers, with the aim of developing public policy to promote green energy and low carbon emissions. A case is studied to validate the superiority of the proposed solution approach. With the proposed approach, a (business) organization can identify and access opinion leaders and their followers. Through communication, these organizations can absorb strain and preserve functions despite the presence of adversity. This study also clearly demonstrates its contribution and novelty through comparisons with the existing alternative method.

Keywords: green energy and low carbon; opinion leaders; followers; social media; matrix method; intelligent systems

1. Introduction

With the rise of communication technology, people are utilizing platforms such as content sharing sites, blogs, social networking, and wikis to create, modify, share, and discuss Internet content. Social media provides flexible platforms that play key roles in energizing collective action in movements [1]. This represents the social media phenomenon, which can significantly impact society and industry, e.g., firms' reputations, sales, and even survival [2]. Within the discussions on social media, certain individuals influence others and thus emerge as opinion leaders. Opinion leaders have great impacts and influence on social media. Organizations can take advantage of these predispositions through marketing research and public relations, nurturing opinion leaders or advocates, placing and creating advertisements, developing new products and lowering the cost-to-serve [3]. On the Internet, the power of these leaders is increasing larger and sequentially influencing entire societies through

calls to protest, promotion of policy and decision-making, which was defined as the fifth right in the “Towards a Civil Society” seminar [4].

The world must confront the energy crisis and air pollution. Discussions about energy issues are increasing. These discussions range from nuclear energy, thermal power, hydropower, and other forms of green energy and low carbon technology, including wind, solar, tidal, and biomass geothermal energy issues. In Taiwan, whenever an energy crisis occurs, energy charges increase. Anti-nuclear positions and other energy issues are discussed broadly. Therefore, the Taiwan government tries to understand people’s needs and questions.

On the Internet, the roles of opinion leaders and followers in the formation of these issues cannot be neglected. According to the “theory of two-step flow” [5] and Rosen’s definition of opinion leaders’ characteristics, “social media initially pass the information to opinion leaders, then opinion leaders spread the information to followers and influence their attitudes” [6]. Thus, when followers follow opinion leaders, the formers’ judgments and attitudes will be influenced and changed by opinion leaders. This study defines opinion leaders as people or social media with high social status who are able to influence followers. This study defines followers as the users who follow certain issues, publish related discussions and add their own ideas. They spread, repost or blindly follow the behaviors of opinion leaders.

Most previous research of opinion leaders focuses on the commercial domain rather than on nonprofit-related policies such as energy policy [7]. In the promotion of many public policies through online postings, it is difficult to clearly identify opinion leaders and followers, which greatly reduces the effectiveness of communication. Based on the community attributes of opinion leaders and whether they can successfully resonate, this study aims at providing a method to try to identify who are opinion leaders or who are likely to become opinion leaders in social media, and who are followers. Relational matrix analysis is used to represent the relationship between opinion leaders and followers in social media and to identify the collection of opinion leaders and potential opinion leaders.

Furthermore, previous studies [8] have used quantitative methods of analysis. One example is the SuperedgeRank algorithm. However, this algorithm not only has difficulty identifying potential opinion leaders effectively but also neglects how opinion leaders influence followers and how relationships between opinion leaders and followers are characterized. It also ignores the increasingly important role played by intelligent systems such as algorithms.

Although the literature on green energy is rapidly increasing, many studies suggest that this problem needs to be dealt with by considering a broader perspective [9]. This study not only examines the issue from the perspective of intelligent systems such as algorithms but also identifies the roles of opinion leaders and followers on social media in relation to the introduction of green energy and carbon reduction technology, with the aim of developing public policy to promote green energy and low carbon emissions. This study is novel not only because it takes quantitative factors and tradition clustering approaches into account but because it also analyzes posts, poster characteristics and their interactive relationships on social media. This study reviews relevant literature in Section 2. In Section 3, we propose a method to identify opinion leaders and their followers based on their interactions on social networks. The interaction patterns are also identified. An energy case is studied in Section 4 to validate the proposed solution approach and enhance communication effectiveness between government policymakers and people’s desires. The discussion is summarized in Section 5, and Section 6 concludes this study.

This research contributes to finding a solution to easily identify the characteristics of opinion leaders and followers in the case of online posts related to green energy and low-carbon policies. Once certain public policies need to be effectively disseminated, they can be widely used. Using the same model and the solution approach, the results of this study can be extended from the green energy low carbon issue to other social issues. Furthermore, this study provides a new perspective to deal with the effective identification of opinion leaders and followers, at the same time, promotes the “theory of two-step flow” to add another research perspective in the academic field.

2. Literature Review

2.1. Green Energy and Low Carbon

Global warming, unexpected climate change, dwindling energy resources and unprecedented amounts of air pollution have become critical problems. The United Nations' 2030 Sustainable Development Goals show that a sustainable modern electricity grid [10], reduction of CO₂ emissions [11] and the carbon footprint of human mobility to a sustainable level [12] etc., are key parts. In addition, exhaustion of fossil fuel is viewed as a big challenge of human development [13] since energy is an expensive resource that is becoming more scarce with increasing population and demand [14]. Green energy could help governments reduce the dependency on energy importation, improve the variety of production resources and advance sustainable environmental development. Moreover, the usage of rich green energy could benefit economies significantly [15].

In the past, studies of green energy and low carbon have focused on issues of energy itself and energy systems, for example, integration of energy systems [16], reliability of the power distribution system [17], uptake of biomass energy [18], and so on. Few studies have focused on social opinions about green energy and low carbon. In recent years, due to awareness of the environment, the public has started to care more about the environment and quality of life [19]. Social media has strengthened community among people and emerged as a platform to spread messages quickly and powerfully. In the era of Web 2.0, massive public opinion is increasingly generated on the Internet [20]. Therefore, the study of the role of social media in green energy and low carbon social issues is very important.

2.2. Opinion Leaders

In the era of the Internet, opinion leaders enhance content sharing. In fact, almost all of the content is generated by opinion leaders (the 90–91% law) [21]. What makes opinion leaders so important on social networks is their ability to informally influence others' attitudes and behaviors [22–25]. Opinion leaders usually have access to far more information on a certain topic and have professional experience with the topic. Rosen defined the characteristics of opinion leaders proposed the acronym ACTIVE. ACTIVE stands for the six characters of opinion leaders: ahead in adoption, connected, travelers, information-hungry, vocal, and exposed to the media [6].

In a recent qualitative survey carried out through focus groups, Katz and Lazarsfeld proposed the "theory of two-step flow" in 1995 and pointed out that opinion leaders are situated between social media and the majority of people. The information first reaches the opinion leaders or influencers [26], who then introduce it to the wider population [5]. Followers are those who are affected and change their behaviors and attitudes when receiving the information [27]. The followers are enormously influenced by opinion leaders in terms of changing their attitudes and behaviors [25].

Based on the above study, we elaborate on the attributes of opinion leaders as follows: Their life experience and understanding of knowledge are rich and thorough and a majority of them are highly educated. Moreover, they have strong social skills, strong connections with the broad masses, and good reputations due to their professionalism and knowledge. They have great influence and appealing power. They exhibit sensitivity to information, willingness to accept new things and an innovative spirit.

2.3. Opinion Leaders Identification

Many theories have been put forward about social networks, but few address the issue of opinion leader identification [28]. According to a previous literature review, opinion leaders are simply determined based on some visible user activities, and other factors that allow a user to become an opinion leader are ignored [28,29]. Studies of Internet opinion leaders have also mainly focused on the role of Internet opinion leaders in spreading the news and in the Internet world of word mouth marketing [23]. Consensus has not yet been reached in the analysis of Internet opinion leaders. Few efforts have been taken to create a computer-based model to identify and analyze the

opinion leaders in an Internet community, and the studies that have been undertaken on this issue have failed to reach an in-depth level [30]. At present, studies related to the TwitterRank algorithm based on PageRank [29] and the contribution of information to InfluenceRank [31] and weighted Page-Rank [32] make use of the network construction of user interaction, but they neglect the users' inherent features [33].

In addition, from the perspective of data mining, the identification of opinion leaders is a cluster problem. However, the aforementioned studies consider the relationships of people to be a social network. Engagement is used as an effective degree to measure user interaction with an organization. Basic interactions include commenting on contents, sharing contents, or "liking" or "favoriting" content. A core KPI for social media is that engagement is high, as this would indicate that organizations are producing content that users find interesting enough to spend additional time on [34]. Unfortunately, when applying the cluster problem to social networks, previous studies have only taken quantitative factors, and traditional clustering approaches into account, e.g., support vector machines [35], k-means [36], partitioning around medoids [37], fuzzy c-means [38], and so on have been used to resolve quantitative clusters. However, qualitative characteristics are not yet considered, and only static data have been analyzed. To study the qualitative characteristics of opinion leaders and the impact of opinion leaders on followers, [39] evaluates whether every speaker in social media satisfies the characteristics of an opinion leader. By observing the relational matrix, the interacting relations between users in social media are analyzed, and opinion leaders and followers are identified. However, there are no theoretical background axioms implied in [39], specifically from the perspective of communication to validate the results.

2.4. Opinion Leaders Identification Algorithms

Ma and Liu [40] used the SuperedgeRank algorithm to analyze the attributes of three seed networks and identify opinion leaders on the Fukushima nuclear issue. In another study, Jiang et al. [41] designed and implemented a BBS opinion leader mining system based on an improved PageRank algorithm using MapReduce. Ziyi et al. [30] adopted the core algorithm of the Internet searching–PageRank model and, by combining the analysis of the influence of linguistic data and sentimental preference, put forward a method to identify Internet opinion leaders; they also verified the method by carrying out an empirical study. Cheng et al. [42] combined influence with sentimental analysis based on the content of posts and filtered opinion leaders by combining the PR values of the PageRank algorithm and recognition degree, abbreviating the IS Rank algorithm. Deng et al. [43] constructed a SINA Micro Blog APIs based Micro Blog crawling and analysis tool, and a node betweenness approximation computation method was proposed, offering better accuracy and less running time to detect core opinion leaders on Micro Blog graphs.

PageRank is an excellent sorting algorithm, but its running speed decreases significantly with the increase of the number of data nodes. Jing and Lizhen [33] proposed a hybrid data mining approach based on user features and interaction networks, which includes three parts: a way to analyze users' authority, activity and influence, a way to consider the orientation of sentiment in an interaction network and a combined method based on the HITS algorithm for identifying microblog opinion leaders [33]. Chu et al. [44] researched social networks to access the influence of tobacco opinion leaders on followers and found that followers are a vulnerable group. They are young and low educated. Followers are easily influenced by opinion leaders. Therefore, anti-smoking education to stay away from tobacco can educate them on social media. Obviously, opinion leaders on the Internet have considerable influence on followers, and opinion leaders are often used in marketing in the e-commerce industry. The research of Lin et al. [45] found that opinion leaders can use their influence to act as important promoters of products and services. It is recommended that companies or corporate managers choose to cooperate with opinion leaders of a certain type of forum to promote products or services. What is the impact of the levels of followers' trust in opinion leaders on the resulting influence? Zhao et al. [46] used opinion dynamics theory to study the influence of trust in opinion

leaders. His research found that followers' trust in opinion leaders determines opinion leader influence. It is suggested that if the communication effect of e-commerce is pursued, the key premise can increase the trust of opinion leaders.

Not only have many studies investigated opinion leaders in the e-commerce field, but the role and function of opinion leaders have attracted attention in politics and the public domain. Aleahmad et al. [43] examined the political field by proposing the effective OLfinder algorithm. The researchers found that this algorithm can not only find opinion leaders in social networks but also calculate their popularity. Many people are curious about why opinion leaders like to play the role of opinion leaders. Winter et al. [47] examined people who disseminate opinions about politics or public affairs on the Internet and identified these people as opinion leaders who try to influence the psychological motivations and personality characteristics of followers. This study found that opinion leaders have strong psychological motivations to actively express themselves and persuade others, making them like to play the role of opinion leaders. In addition, in social network analysis, centrality methods have been applied to measure the importance of nodes in a network whereby nodes with higher centrality can influence others more significantly [48,49].

All in all, past relevant research either used a certain social measurement method based on interview self-reports or questionnaire surveys or used quantitative clustering techniques to identify opinion leaders. Few studies have actually investigated online posts to identify opinion leaders and the social patterns of interaction between opinion leaders and followers. Thus, it is important to propose a method to analyze posts, posters' characteristics and their interactive relationships in social media.

3. Methodology

3.1. Modeling Interaction between Opinion Leaders and Followers

Between users, matrix M is a relational matrix.

$$M = [T|I] \quad (1)$$

We set the row index as i and the column index as j in the matrix. The n users in the set are represented by $C = \{1 \dots n\}$. In the matrix T , the elements are composed of counts of responses and being responded to. Additionally, between users and social community support level, the elements in the matrix I are the influence factors

Matrix T shows us the counts of both responses and being responded to between n users. T_{ij} refers to counts of responses of $user_i$ to $user_j$ where $i \neq j$. When T_{ij} refers to counts of total posts of $user_i$ where $i = j$. i refers to the index of the users who responds to other user's opinions, and j refers to the index of the users whose opinions are responded to.

Matrix I indicates the power of users to influence and be influenced. I_{ij} refers to the influence of $user_i$ on $user_j$ where $i \neq j$, i refers to the index of a user who influences other people, and j refers to the index of a user who is influenced by others. The influence power can be classified into three different patterns, including job position, professional knowledge and social community support level [39]. Each criterion has three levels, no influence (NI), general influence (GI), and high influence (HI) (Table 1). For a higher job title with more professional knowledge and a high social community support level, we define influence power as high influence (HI). For a general job title with popular professional knowledge and neutral social community support level, the overall influence power is general (GI). If the user has no job and inaccurate professional knowledge or social community support, we define that the influence level as having no influence (NI). However, some users have privacy settings or discuss issues anonymously, so our study could not gather their background information. Fortunately, the proposed approach can serve as a flexible model with the missing part left blank.

Table 1. Influence power table (NI: No Influence, GI: General Influence, HI: High Influence.).

		Social Status				
		–	General	+		
Professional knowledge	Wrong knowledge	NI	NI	NI	Low social community support	Social community Support
	Popular knowledge	NI	NI	GI	Low social community support	
	Professional knowledge	NI	GI	GI	Low social community support	
Professional knowledge	Wrong knowledge	NI	NI	GI	Neutral social community support	Social community Support
	Popular knowledge	NI	GI	GI	Neutral social community support	
	Professional knowledge	GI	GI	HI	Neutral social community support	
Professional knowledge	Wrong knowledge	NI	GI	HI	High social community support	Social community Support
	Popular knowledge	GI	HI	HI	High social community support	
	Professional knowledge	HI	HI	HI	High social community support	

In matrix I , I_{ij} refers to a user’s social community support level where $i = j$. In this study, social community support is divided into three levels. These three levels are relatively well-known, and well-followed social media that receives good attention are which are classified as having high social community support (H). Less-followed, less-known social media with low attention is classified as low (L). However, we were unable to gather users’ social community support levels because of some users’ anonymous discussions or privacy settings. Our study defines the social community support level of these users as missing (O).

A non-follower, a user with a negative speech count, is defined in this study. Meanwhile, when contents are responded to negatively, the user is listed as a non-opinion leader. The relationship between opinion leaders and followers refers to a mutual relationship between users. However, one user may not respond to or express ideas to others’ speech content on social media. One opinion leader may not be an opinion leader of all users. Therefore, if there is no relationship between users, we cannot distinguish whether they are opinion leaders or followers. In this study, the groups of opinion leaders and followers are be judged base on interaction. The users with mutual influence are classified as one group to analyze whether there is an opinion leader and a follower in the group. If there is no mutual influence, no group is formed.

3.2. Opinion Leaders and Followers’ Social Patterns

Six axioms are proposed to classify opinion leaders, influencers, followers and interaction patterns. Notations are presented in Table 2.

Table 2. Notations table.

Notations:
N_{rsp} : The total number of responses in matrix T .
\bar{N}_{rsp} : The average total number of responses in matrix T .
N_g : The total number of members that respond in group g .
\bar{N}_g : The average total number of members’ responses in group g .
$T(US_i)$: The number of $user_i$ ’s posts, the total counts of $column_i$ in matrix g .
$T(UR_i)$: The number of $user_i$ ’s responses, the total counts of row_i in matrix T .

Table 2. Cont.

Notations:

USI_{ij} : The influence of $user'_i$'s speech to $user_j$, where i is the index of the column, and j is the index of the row.
 URI_{ij} : The influence of $user'_i$'s responses from $user_j$, where j is the index of the column and I is the index of the row.
 $SI_i\{INFLUENCE\}$: The number of $user'_i$'s influences (NI, GI, HI).
 SI_{ol} : Number of the opinion leaders' posts in matrix I .
 SI_f : Number of followers' posts in matrix I .
 $SI_{ol}\{influence\ power\}$: The number of opinion leaders' influences (NI, GI, HI).
 $SI_f\{NI\}$: The number of opinion leaders' influences (NI, GI, HI).
 UNI_i : The number of $user'_i$'s posts with NI influence power and responses in matrix T are zero.

The axioms formulated by the systematic rolling analysis of big data over the years. Experts determine the criteria and select thresholds for them, for example, the positive or negative degree of the counts of responses to and responded to. The following axioms are proposed to recognize opinion leaders, influencers, and followers.

Axiom1—Opinion leader.

If $\bar{N}_{rsp} < UR_i$ and $UR_i > 2 \times \bar{N}_g$ and $UNI < 1/2 \times N_g$, then the $user_i$ is an opinion leader.

To be an opinion leader, $user'_i$'s (UR_i) response total must be higher than the average total response (\bar{N}_{rsp}), and $user_i$ must have more than twice the number of responses in the group (\bar{N}_g). Moreover, $user'_i$'s NI speech and the count in matrix $T(US_i)$ less than 1 cannot be more than half of the total number of members' responses in group g .

Axiom 2—Influencer.

If $\bar{N}_g < UR_i < 2 \times \bar{N}_g$ and $UNI < N_g$, then $user_i$ is an influencer. If the $user'_i$'s responses (UR_i) are more than the average number of total responses in the group and lower than twice the average number of total responses in the group. Moreover, $user'_i$'s speech which is NI and the count in matrix $T(US_i)$ which is less than 1 cannot more than the number of the member which is in the group. Influencers also have the power to influence others and have the potential to become opinion leaders. Hence, this study also offers a way to find influencers.

Axiom 3—Followers.

If $UR_i > 0$, then the user is a follower.

A follower needs to support or agree with someone, so the $user_i$ must have a positive count in matrix T . In other words, the user in row_i is the follower's leader.

Three social community patterns are classified: In the *criterion* pattern, the opinion leaders broadly influencing many followers usually obtain high social community support and posts professionally. The criterion social community, the most common pattern. In the argument pattern, the pattern's emergence is caused by the discussion space provided for users of social community platforms. Users can give specific advice to influence each other or influence other users. The bandwagon pattern arises when followers follow closely due to opinion leaders' personal charisma. In this pattern, followers usually do not care whether the content posted by opinion leaders is correct.

The following axioms are used to define three patterns.

Axiom 4—Criterion pattern.

According to *group_k* with opinion leaders in *set_ol*, (1) if the number of posts influencing followers who post to *set_ol* in *group_k* is more than half of the number ($\geq 1/2 \times SI_f$), and (2) if the number of posts influencing opinions directed to followers in *group_k* is more than half of the number ($SI_{ol}\{HI,GI\} \geq 1/2 \times SI_{ol}$), then *group_k* is a criterion pattern.

According to the criterion pattern, an enterprise can promote its products effectively, and the government can sharp public opinion in favor of a particular policy by utilizing the function of opinion leaders. Furthermore, finding opinion leaders and tracking them over the long term can prevent an explosion of potential issues. In the criterion pattern, the opinion leader is very professional.

If a government or enterprise wants to negotiate or cooperate with them, the contractor must also be professional.

Axiom 5—Argument pattern.

After grouping with the CI Algorithm, we find different groups. According to $group_k$ with opinion leaders in set_ol , (1) if the number of posts influencing {HI,GI} followers who post to set_ol in $group_k$ is more than half of the number (if $SI_f \{GI,HI\} \geq 1/2 \times SI_f$) and (2) if the number of posts influencing {HI, GI} opinions directed to followers in $group_k$ is more than half of the number ($SI_ol \{HI,GI\} \geq 1/2 \times SI_ol$), then we recognize that $group_k$ can be characterized as an argument pattern.

On the basis of the argument pattern, the character of the interaction between opinion leaders and followers is not significant; consequently, the cost of marketing is high and may even have little impact on promotion. Moreover, in the argument pattern, the viewpoints are diverse. Thus, it is desirable to provide a platform and sufficient information and domain knowledge for uses to engage in dialog with each other.

Axiom 6—Bandwagon pattern.

After grouping with the CI Algorithm, then we have different groups. According to $group_k$ with opinion leaders in set_ol , (1) if the number of posts influencing {NI} followers who post to set_ol in $group_k$ is more than half of the number (if $SI_f \{NI\} \geq 1/2 \times SI_f$) and (2) if the number of posts influencing {NI} opinions directed at followers in $group_k$ is more than half of the number ($SI_ol \{NI\} > 1/2 \times SI_ol$), then we recognize that $group_k$ can be characterized as a bandwagon pattern.

According to the bandwagon pattern, opinion leaders and followers are not professional in most cases. Enterprises and governments can utilize social media to promote their products and public policy effectively by enhancing the roles of these opinion leaders and followers. If the government or an enterprise wants to negotiate or cooperate with them, the contactors need not be professional but must be a decision-maker who can promise to provide resources.

3.3. Problem with Identification of Opinion Leaders and Followers

The problem of identifying opinion leaders and followers is formulated as follows:

Decompose a user-user interaction matrix into mutually separable submatrices (modules) with (1) the minimum number of non-empty high-value entries outside the block-diagonal matrix T , and (2) the maximum number of strongly desired entries (HI) and the minimum number of strongly undesired entries (NI) included in the submatrices of the block diagonal matrix I .

Subject to the following constraints:

Constraint C1: Empty groups of users are allowed, and

Constraint C2: The number of users in a group cannot exceed the upper bound N_u .

Constraint C3: Satisfy the following assumptions:

- (1) Continuous posts are defined as one post.
- (2) Users who respond negatively to posts cannot be regarded as followers.
- (3) The content of the post and the level of social community support determine the influence of the user's post.
- (4) Expert posts are prioritized as reasonable posts.
- (5) If users have a low influence on each other, judge it as "NI".
- (6) If users have a great influence on each other, judge it as "HI".

In matrix T , we count input post, responses and being responded to. In the matrix I , (1) input the highest influence power HI. Moreover, (2) input the lowest influence power NI. Combined with observation results, identify the opinion leader set and follower set.

3.4. Identification of Opinion Leader and Follower

In this study, the relationship between opinion leaders and followers is the mutual relationship between users. When a user satisfies the characteristics of opinion leaders, our study defines the user

as an opinion leader. Followers will change their own ideas and attitudes according to opinion leaders' characteristics, including social status, accuracy of post contents and social community support level. The algorithm is described as follows:

- Step I. Collect data from social media, such as users, posts, and response information.
- Step II. Compute the counts of total posts of $user_i$ in matrix $[T_{ii}]$
- Step III. For all users, put the responses which $user_i$ gives to $user_j$ in matrix $[T_{ij}]$ until there are no responses from $user_i$ to other users.
- Step IV. If $column_i$ and row_i in matrix T are NULL then remove the meaningless $user_i$ by deleting row_i and $column_i$ in matrix T and I until there are no meaningless $user_i$
- Step V. According to the data of social media, matrix T and social community support level, the social community support level marked with $user_i$ at $[I_{ii}]$.
- Step VI. For all users i and j , according to expert judgment, assign $user_i$ the influence power level $[I_{ij}]$ of $user_j$.
- Step VII. If $[T_{(i-1)(i-1)}] > [T_{ii}]$, exchange the columns of $user_i$ and $user_{i-1}$. until there is no $[T_{ii}] < [T_{(i-1)(i-1)}]$ in matrix T .
- Step VIII. The CI algorithm is applied to group users.
- Step IX. If $[I_{ij}]$ is not NULL, then check whether the $user_i$ and $user_j$ is in the same group or not; if they are not in the same group, then put them in the same group matrix until all users in the matrix I have been checked.
- Step X. In each group, sum up all positive responses to N_{rsp} and compute the average \bar{N}_{rsp} .
- Step XI. Count the responses of $user_i$ by $\sum_{j=1}^n [T_{ij}]$ and posts of $user_i$ by $\sum_{i=1}^n [T_{ij}]$. Additionally, count the influence of each $user_i$, If $user_i$ satisfies Axiom 1, then $user_i$ is identified as an opinion leader. If $user_i$ satisfies Axiom 2, then $user_i$ is identified as an influencer. If $user_i$ satisfies Axiom 3, then $user_i$ is identified as a follower. Continue until all users in matrix T have been checked.
- Step XII. Check each group matrix. Count all opinion leaders' $[I_{ij}]$ and followers' $[I_{ij}]$. Recognize the pattern based on Axioms 4–6.
- Step XIII. When there are positive responses or influence between users, we classify these users in the same group.

4. Case Study

The ABC network platform is taken as an example to describe the application of our research in practice. The ABC network platform is a discussion platform created by the government to promote community communication. This platform was created as part of a public policy proposal to improve policy communication and make policy public.

This case study is taken from the National Energy Conference organized by the Energy Bureau of Taiwan's Ministry of Economic Affairs. However, there are still many disagreements when it comes to choosing opinions due to value divergence. To discuss and clarify issues with the public, the proposition, "Where does future electric power come from?" is open on the policy consultant forum (People Talk), with three sub-issue forums including, 'environment low carbon sustainable development', 'stable supply and open source' and 'reduce expenditures effectively'. In particular, 'stable supply and open source' is the focus of this case study.

The proposed solution approach is applied in this case.

Step I. Collect materials: Judging by the forum (posts, fan pages) on social media about green energy and low carbon, we collected materials, including text and response information. This study collected materials from users' discussion contents related to the "stable supply" issue on the ABC network platform between May 2019 and the end of 2019. The data collection is implemented with the Python-Jieba crawler program, which is particularly suitable for Chinese text analysis automatically. The collected materials are listed below: Post users: 36; total posts: 205 (total posts have been deducted from the number of administrator responses and consecutive posts); effective responses: 61; effective count of being responded to 47.

Step II. Input matrix elements: Input elements in matrix *T*. The elements include general posts, counts of responses and being responded to as judged by experts.

Step III. Remove meaningless users: Remove users whose posts are never responded to.

Step IV. Tag the user’s category: Input social community support

Step V. Influence analysis: We analyze a user’s influence by comparing the levels of influence power according to three characteristics and input the influence into the matrix *I*.

Step VI. If the count of users’ posts, responses, and influence power, reaches a certain level of relevance, then move forward. If the users have greater counts of responses or respondents, list them in front. (Figure 1).

Matrix *I*

1	18	19	20	21	24	26	27	28	29	30	31	34	35
18	5												
19		8											
20			1										
21				3									
24					1								
26						1							
27							1						
28								1					
29									1				
30										1			
31											1		
34												1	
35													1

Matrix *T*

1	16	18	19	20	21	24	26	27	28	29	30	31	35
16													
18													
19													
20													
21													
24													
26													
27													
28													
29													
30													
31													
34													
35													

Figure 1. Matrix element conversion. Note1: the criterion of influence power: NI = no influence; GI = general influence; HI = high influence. Note2: The level of social community support: H: high social community support; L: low social community support; O: missing social community support.

Step VII. According to matrix *I* and *T* based on Equation (1), group the users by their relationships. Group A {1, 2, 3, 4, 5, 6, 18, 20, 21, 24}; Group B {2, 16, 24, 26, 27, 34, 36}; Group C {17, 18, 19}; Group D {19, 20, 21, 36}; Group E {2, 27, 28, 29, 30, 36}; Group F {7, 20, 26}; Group G {2, 9, 27, 31, 34}; Group H {7, 27}; Group I {7, 8, 15}; Group J {21, 22, 23}; Group K {25, 26}; Group L {34, 35}.

Step VIII. Identification: Determine the interaction between users, followers, and opinion leaders, according to the definition of each group of opinion leaders.

In Group A, opinion leader 1 is recognized by Axiom 1, and the influencers are Users 3 and 5. This group is identified as an argument group based on Axiom 5.

In Group B, User 16’s post contents are usually meaningless. According to Axiom 1, User 16 is not an opinion leader. Moreover, the group does not belong to any pattern.

Group C is an argument pattern. Users 18 and 19 are influencers. In this pattern, no opinion leaders and followers are identified. The influencers influence each other without focusing on any particular key person.

In group D, the response of User 19 has a great influence on Users 20 and 21. However, the influence of the posts responded to by Users 20 and 21 is not great. There is a discussion relationship between Users 19 and 20, so it is a social pattern.

In Group E, the post contents of User 36 are valuable. However, other users’ responses are not good. Thus, User 36 is an opposing opinion leader.

In Group F, according to Axiom 6, User 26 is an influencer, and the group represents an argument pattern. User 20 is the follower of User 26.

In Group G, Users 27 and 34 are the influencers, and it is a bandwagon pattern. Moreover, User 2 is the follower.

In Group H, Users 27 and 7 have a discussion relationship, and both of them are influencers.

In Group I, the social community support level of the group is high. They should be opinion leaders, in theory. However, in this case, study, since they do not play the role of opinion leaders, they cannot be recognized as opinion leaders. User 7 is an opinion leader, and this is an argument pattern.

In Group J, there are no opinion leaders or followers. User 21 is an influencer.

In Group K, User 26 is opposed to the opinions of User 25. There are no opinion leaders or followers in this group.

Group L: In this group, there are no opinion leaders or followers.

According to the summary of group analysis, Users 1 and 36 are obviously opinion leaders. The five groups A, C, D, F, and H can all be characterized as argument patterns, which shows that in the forum, most post contents influence other users through discussion.

The case was also analyzed with a traditional network approach, i.e., the Ward method, named after its creator, focuses on the allocation of profiles to groups equally. Ward [50] pointed out that grouping in this manner makes it easier to consider and understand relations in large collections. The principle of this method is to minimize heterogeneity, and the important goal is to find the greatest similarity. The comparison between the proposed approach and Ward’s approach is shown in Table 3. The results show that Users 1, 7, 36 are identified as opinion leaders. However, User 19 has not been identified through the traditional method due to the threshold.

Table 3. Analysis results.

	The Proposed Approach		Ward’s Approach	
Opinion leader	1,7,19,36		1,7,36	
Influencer	18,24,20,21,22,27		N/A	
Leader/followers	1	18,24,21,3,5,6,20	1	18,24,21,3,5,6,20
	7	8,15,20,27	7	8,15,20,27
	19	8,15,20	36	20,27,28
	36	20,27,28		
Pattern	Criterion argument bandwagon	D, E A, C, F, H, I G	N/A	

The identification of opinion leaders by Ward’s method only identifies opinion leaders who participate in the whole conversation. However, in the proposed approach, this study uses two identification methods: the whole conversation and group conversation. The latter can clarify which user is the group’s opinion leader. In addition, the proposed approach can discover different patterns. Although the traditional network approach of Ward’s is considered to be the best one among the hierarchical clustering methods [51–53], it cannot identify these patterns.

Through the perception of social community patterns among users, this study successfully distinguished opinion leader and defined social patterns in the complex social communities, which contains highly controversial users and many of them are anonymous, where few persons are involved in the discussion and users’ support level could not be obtained because users disagree with each other.

After identifying opinion leaders and followers, in a criterion pattern, opinion leaders have a higher degree of professionalism than followers. In that case, if green energy and low-carbon related policies are to be disseminated through opinion leaders, it is necessary to send personnel with a certain degree of professionalism. After contacting and negotiating with them, you must

first obtain the approval of the opinion leaders before you can persuade them to influence followers through their platforms or social media. It is expected that they will achieve rapid dissemination, higher dissemination effect, and avoid costly but ineffective dissemination. In addition, a follower may also become another opinion leader, generating multiple diffusion of innovations.

Second, in the argument pattern, due to the comparably equal status between opinion leaders and followers, issues are quite diverse, and it is not easy to focus on specific issues. If opinion leaders wanted to disseminate relevant policies on energy conservation and low carbon to influence followers, the dissemination effect would be poor. Therefore, in order to make the issue of green energy and low-carbon attract more attention, opinion leaders can package the issue into lifestyles and features, thereby achieving a higher diffusion effect (Diffusion of innovations) on followers.

In addition, in the bandwagon pattern, because opinion leaders and followers are less professional, they are more vulnerable to each other. In order to disseminate green energy and low-carbon policies, policies can be packaged as simple, interesting or lifestyle issues, while social media or platforms are often used by opinion leaders or followers to achieve better diffusion of innovations.

5. Discussion

In this study, three interactive patterns and their characteristics are identified, which can help how to find opinion leaders more effectively and grasp the characteristics of opinion leaders and followers when want to spread (Diffusion of innovation) new policies or marketing new products. Opinion leaders and followers both have different levels of knowledge, social community support, and influence power. Therefore, this study summarizes the interactions on social media into three patterns, and the characteristics of three patterns have also been explored. Furthermore, based on the characteristics of users in these patterns, it can be used to provide opinion leaders with specific and clear topics/issues to influence their followers, thereby obtaining effective dissemination or commercial marketing purposes in the green energy domain.

In addition, the results of this study can also be applied to the political dissemination of democratic elections or the shaping of the opinion climate, which can more efficiently lead the electoral issues and win elections. In other words, the issues or political opinions that candidates are trying to market can be differentiated based on different communication modes so that the information can be segmented, and the impact of effective agenda-setting goals can be achieved. This study not only has the possibility of expanding and deeper research, but it is also the relative value of this research.

Most previous studies used different algorithms or improved algorithms to identify opinion leaders [28–31,33,37]. In other words, most of the above-mentioned studies only used various algorithms to identify opinion leaders or followers, and consequently, apply them to political communication and commercial marketing related fields. There has recently been an exploration of the psychological motivation of actively acting as opinion leaders to understand which users are active communicators or passive recipients of social issues. However, the related study on the interaction patterns between the opinion leaders and followers and their characteristics have not been explored.

In addition, the opinion dynamics of current popular research are interested. The classic model of opinion dynamics is derived from the research of DeGroot's and Friedkin–Johnsen's models of opinion dynamics, which aims at the integration and consistency of opinions in social networks, carried out very enlightening modeling and exploration [54]. DeGroot's model describes the process of reaching consensus in social networks, while Friedkin–Johnsen's model further introduces the degree of "stubborn individual" to explain the phenomenon of inconsistent opinions in social networks. The models clearly depict the dynamic process of opinion integration and consistency, as well as the obstacles caused by "stubborn individual" factors to the process of opinion integration [55,56]. However, the two models are very instructive to explore how individuals (or Internet users) should be controlled if they are affected by certain characteristics or stubbornness in the process of opinion integration. Our study more specifically explores how opinion leaders and followers can find out the characteristics of users and the patterns of interaction between them in the process of consensus,

which can be applied to precision marketing in actual operation, and even give opinion leaders with different characteristics use differentiated topic content to increase the influence of consensus. Since the research of DeGroot's and Friedkin–Johnsen's models of opinion dynamics are in conceptual level only, some difficulties in practical application are challenged [57].

This study extends the idea of [39] to the domain of green energy and low carbons, where roughly qualitative characteristics of opinion leaders and matrix of interaction between users are considered. To make this study more solid and applicable, the theories of “two-step flow”, “bandwagon effect”, “agenda-setting” and “innovation diffusion theory” from the theoretical perspective of communication and the axioms are used to validate the results. In addition, this study does not focus on a single discipline only but a cross-disciplinary study of the fields of green energy and low carbons, intelligent systems, and communication to provide numerous management implications discussed in this section. The core novelty and contribution is shown in that the solid theoretical part makes this study applicable to other social media and industry sectors.

6. Conclusions

Nowadays, networks are the most important media among broad masses, and almost everyone is closely related to networks, which results in many social issues as virtual networks are reflected in the real world. Opinion leaders play a very important role in spreading media for many issues. Previous research used some social measurement methods based on interview self-reports or questionnaire surveys [23,24,32,33] or used quantitative clustering techniques to identify opinion leaders [30,40–43]. In fact, few studies have investigated online posts to determine the social patterns of opinion leaders and interactions between opinion leaders and followers. Therefore, it is valuable that this study proposes a method to analyze the characteristics of social media posts, posters and their interaction relationships.

Furthermore, this study identifies opinion leaders on the issue of green power in social communities based on social community support level and influence power level. As a result of users cannot express positive and negative opinions on the issue; it is not enough to consider only the user's posts. For example, when a user has a large number of posts, if the user cannot get support from others, he/she cannot be classified as an opinion leader.

Using the same model and the solution approach, the results of this study can be extended from the green energy low carbon issue to other social issues, e.g., the domain of marketing to make better CRM. It also provides an efficient and operable application model for online marketing or public issue communication in practical applications, which can more easily identify opinion leaders and followers. Furthermore, this study not only examines from the perspective of intelligent systems such as different algorithms but provides a new perspective to deal with the effective identification of opinion leaders and followers, at the same time, promotes the “theory of two-step flow” [5] to add another research perspective in the academic field.

The level of community support and influence proposed in this study uses a relational matrix to analyze the relationship and the community pattern between users in this study. If it is applied to analyze social media with higher data volume and discussion volume, it should consider the computation speed, but which is usually not an issue in the current IT world. In addition, this study uses static data for analysis. This model can also be added or removed from dynamic data and evolution modeling for analysis in the future, and it is expected that it can be identified as more timely and faster. For example, the advantages of DeGroot and Friedkin–Johnsen models are taken into consideration for further study

However, this research's reproducibility to other industry sectors is interested and requires further investigation. In addition, this study focuses on a single case study of a country's green energy and low-carbon policy in Taiwan. If the results of this study are used to infer whether there will be differences in other countries with different levels of development, knowledge and education, it is

worthwhile to explore further. In any case, despite the above negotiable points, it does not detract from the valuable results obtained in this study.

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