# Studying the Complex Inter-relationships amongst various SNA Metrics and SEA Metrics using ISM Methodology

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## ABSTRACT

Social Network Analysis is the process of investigating social structures through the use of networks and graph theory. It characterizes networked structures in terms of nodes which includes individual actors, people, or things within the network and the ties, edges, or links which include relationships or interactions that connect them. Examples include friendship and acquaintance networks , business networks , difficult working relationships, knowledge networks , diseases transmissions , sexual relationships etc. On the other hand, sentiment analysis helps in determining the emotional temperament of reviewers and writers and helps to identify, extract or portray intuitive information, such as opinions, which may be expressed in a certain given piece of text or topic. Present research work attempts to explore the various metrics associated with the success of social media network analysis as well as sentiment analysis and thereafter it tries to establish the inter-relationships between the various sentiment analysis metrics through ISM methodology.

## Keywords

Social Media Metrics , Social Network Analysis, Sentiment Analysis , ISM Methodology ; SNAM , SeAM

## 1. INTRODUCTION

In the last decade, social media has seen a phenomenal growth and billions of people across the globe use it for sharing ideas and feedback and exchanging information with each other. Various social media channels like blogs, social networking sites like Facebook, Twitter etc. have made it easier for people to stay connected and updated. Businesses make use of recommendations, reviews and other online expressions to market their products, capture upcoming opportunities and manage their goodwill over social media . It is quite obvious that online opinion polls can either make or break an enterprise’s reputation. It is here, sentiment analysis comes into the picture.

### 1.1 Social networks

Social scientists have used the concept of "social networks" since early in the 20th century to connote complex sets of relationships between members of social systems at all scales, from interpersonal to international. Networks can consist of anything from families [1], project teams, classrooms, sports teams, legislatures, nation-states, disease vectors, twitter or face book memberships . Networks can consist of direct linkages between nodes or indirect linkages based upon shared attributes, shared attendance etc. These levels could be individual nodes, dyads, triads, ties and/or edges, or the entities. For example, node-level features for example , can include network phenomena such as betweenness and centrality, or individual attributes such as age, sex, or income [2].

#### *1.1.1 Modelling and Visualizing social networks*

Visual representation of social networks is important to understand the network data and convey the result of the analysis. Exploration of the data is done through displaying nodes and ties in various layouts, and attributing colors, size and other advanced properties to nodes. For example , signed graphs can be used to illustrate good and bad human relationships. A positive edge between two nodes denotes a positive relationship (friendship, alliance, dating) and a negative edge between two nodes denotes a negative relationship (hatred, anger). Signed social network graphs can be used to predict the future evolution of the graph. These graphs works on the concept of "balanced" and "unbalanced" cycles. Unlike balanced graphs which represent a group of people who are unlikely to change their opinions of the other people in the group , unbalanced graphs represent a group of people who are very likely to change their opinions . Metrics or measures from different perspectives could help the researchers on this ground. Present research focuses on exploring various metrics that could be helpful in analyzing social network. Paper is arranged as follows . Section 2 presents the literature review associated with social metrics for analyzing social network . ISM methodology which can be used to establish these relationships have been explained in section 3. Section 4 presents the observations and future directions .

### 1.2 Social Network Analysis (SNA)

Georg Simmel and Émile Durkheim, who wrote about the importance of studying patterns of relationships that connect social actors could be considered as early sociologists who conducted social network analysis. In 1954, John Arundel Barnes started using the term systematically to denote patterns of ties in tribes or families . For example , the term bounded groups for tribes, families etc. and social categories for gender, ethnicity etc. Social network analysis has found applications in various academic disciplines such as anthropology, biology, demography, communication studies [2] economics, geography, history, information science, political science, public health [2] social psychology, development studies, sociolinguistics, computer science [3] and literature [4-5] .

### 1.3 Sentiment Analysis (SeA)

Sentiment analysis, also known as opinion mining, is the analysis of the *feelings* (i.e. attitudes, emotions and opinions) behind the words using natural language processing tools. In other words **, Sentiment analysis** [1] helps in determining the emotional temperament of reviewers and writers and helps to identify, extract or portray intuitive information, such as opinions, which may be expressed in a certain given piece of text or topic.

The goal of this paper is to identify various measures or metrics that can be used in social network analysis as well as sentiment analysis to evaluate the performance and success of social media posts and to further study the possible interrelationship amongst them. The paper is organized as follows: Section 2 presents the literature review on media metrics used for social network analysis as well as sentiment analysis . These metrics can also be obtained from various social media metrics evaluation tools available in market. Thereafter in section 3, ISM methodology is presented. Section 4 deals with managerial implications.

# 2. CASE PROBLEMS [1-6]

# 2. Literature Review on media metrics

## 2.1 Metrics associated with analyzing Social Network

Social media metrics could be a brilliant way to gain deeper insights from social network and critically analyzing the relationships from different perspectives . Following section discusses some of these metrics based on the associated researches . Google scholar , Research gate and other search engines have been used for exploration.

### *2.1.1 On the basis of connections*

2.1.1.1 Homophily (Ho): The extent to which actors form ties with similar versus dissimilar others. Similarity can be defined by gender, race, age, occupation, educational achievement, status, values or any other salient characteristic[6].

2.1.1.2 Multiplexity (Mu): The number of content-forms contained in a tie[7]. For example, two people who are friends and also work together would have a multiplexity of 2 [8]. Multiplexity has been associated with relationship strength and can also comprise overlap of positive and negative network ties [9].

2.1.1.3 Mutuality/Reciprocity (Re): The extent to which two actors reciprocate each other's friendship or other interaction [9] .

2.1.1.4 Propinquity (Pr): The tendency for actors to have more ties with geographically close others [9].

### *2.1.2 On Basis of Distributions*

2.1.2.1 Bridge (Br): An individual whose weak ties fill a structural hole, providing the only link between two individuals or clusters. It also includes the shortest route when a longer one is unfeasible due to a high risk of message distortion or delivery failure [10] .

2.1.2.2 Centrality (Ce): Centrality refers to a group of metrics that aim to quantify the "importance" or "influence" (in a variety of senses) of a particular node (or group) within a network [11] ; [12-13]. "Centrality" could be commonly measured through betweenness centrality [14] closeness centrality, eigenvector centrality, alpha centrality, and degree centrality[15].

2.1.2.3 Density (De): The proportion of direct ties in a network relative to the total number possible [16].

2.1.2.4 Distance (Di): The minimum number of ties required to connect two particular actors, as popularized by Stanley Milgram's small world experiment and the idea of 'six degrees of separation'.

2.1.2.5 Structural holes (Sh): The absence of ties between two parts of a network. Finding and exploiting a structural hole can give an entrepreneur a competitive advantage.

2.1.2.6 Tie Strength (TS): Defined by the linear combination of time, emotional intensity, intimacy and reciprocity (i.e. mutuality) [10]. Strong ties are associated with homophily, propinquity and transitivity, while weak ties are associated with bridges.

### *2.1.3 On the basis of Segmentation*

Groups are identified as 'cliques' if every individual is directly tied to every other individual. Similarly they could be identified as 'social circles' if there is less stringency of direct contact [16].

2.1.3.1 Clustering coefficient (CC): A measure of the likelihood that two associates of a node are associates. A higher clustering coefficient indicates a greater 'cliquishness' [17] .

2.1.3.2Cohesion (Co): The degree to which actors are connected directly to each other by cohesive bonds. Structural cohesion refers to the minimum number of members who, if removed from a group, would disconnect the group [19-20] .

### *2.1.4 Social networking potential (SNP)*

Social Networking Potential (SNP) is a numeric coefficient, derived through algorithms to represent both the size of an individual's social network and their ability to influence that network. SNP coefficients have two primary functions:

1. The classification of individuals based on their social networking potential, and
2. The weighting of respondents in quantitative marketing research studies.

Variables used to calculate an individual's SNP include but are not limited to: participation in social networking activities, group memberships, leadership roles, recognition, publication/editing/contributing to non-electronic media, publication/editing/contributing to electronic media (websites, blogs), and frequency of past distribution of information within their network.

### *2.1.5In computer-supported collaborative learning metrics*

One of the most current methods of the application of SNA is to the study of computer-supported collaborative learning (CSCL). When applied to CSCL, SNA is used to help understand how learners collaborate in terms of amount, frequency, and length, as well as the quality, topic, and strategies of communication. There are several key terms associated with social network analysis research in computer-supported collaborative learning such as **density**, **centrality**, **indegree**, **outdegree**, and **sociogram**.

## 2.2 Metrics associated with Sentiment Analysis

The following sections discusses various metrics that can either be collected through online or market metrics tools or can also be collected through interviews and questionnaires.

#### *2.2.1Metrics that can be collected through Social Mention*

Social Mention is a free social media analysis tool that provides users with various useful metrics such as the *ratio of people speaking positively about your keyword versus those who are speaking of it negatively*. It can also tell you *what percentage of people are likely to continue mentioning your keyword and how popular your brand is on social media*. While you can't really analyze individual pieces of data, Social Mention is a great option for people looking to get a brief synopsis of their social media reputation.

#### *2.2.2Metrics that can be collected through Sentiment analyser*

Sentiment Analyzer makes use of "computational linguistics and text mining" to determine the sentiment behind your piece of text. It then compounds and compares its findings to produce an overall score.

#### *2.2.3Metrics that can be found through Brandwatch software*

Brandwatch's software provides interesting insights into metrics like it mention volume, aggregate followers, and latest activity. With Brandwatch, your team sees where your brand's images are appearing and how those images are performing with your target audience.

**[2] https://blog.hubspot.com/service/sentiment-analysis-tools**

#### *2.2.4Metrics that can be found through Repustate2*

Repustate has a sophisticated text-analysis API that accurately assesses the *sentiment behind customer responses*. Its software can pick up on short-form text and slang like lol, rofl, and smh. It also analyzes emojis and determines their intention within the context of a message.

## 2.5 Metrics that can be found through Quick search

Quick Search looks at your *mentions, comments, engagements*, and other data to provide your team with an extensive breakdown of how customers are responding to your social media activity.

**2.7 Quality metrics (QM) :** Quality metrics include *opinions, feelings, satisfaction ratings, the quality of shares, comments, re-tweets, replies, ratings or conversations*, as well as the quality of engagement over time.

**2.8 Metrics that can be found through People Browser**: Find all the mentions of your brand, industry and competitors and analyze sentiment. This tool allows you to compare the *volume of mentions before, during and after your marketing campaigns.*

**2.9 Metrics that can be measured through Facebook Insights** [3]: If you have more than 30 Likes on your Facebook Page you can start measuring its performance with Insights. Some of the metrics include *total page Likes, number of fans, daily active users, new Likes/Unlikes, Like sources, demographics, page views and unique page views, tab views, external referrers, media consumption etc.*

## 3. INTERPRETIVE STRUCTURAL MODELLING METHODOLOGY

Interpretive structural modelling methodology or ISM [warfield, 1974] is a known technique to map the relationships amongst the relevant elements as per decision maker's problems in a hierarchical manner. Starting with the identification of elements , it proceeds with establishing the contextual relationships between elements (by examining them in pairs ) and move on towards developing the structural self-interaction (SSIM) matrix using VAXO [warfield , 1974] and then initial reachability matrix and final reachability matrix and rearranging the elements in topological order using the level partition matrices . A *Mic-Mac* analysis is performed afterwards which categorize the variables as per the driving and dependence power in to autonomous, dependent, driver and linkage category. Finally, a diagraph can be obtained.

## 4. CASE EXAMPLE

Some 15 metrics have been explored in section 2 above *viz. Percentage of people who are likely to continue mentioning your keyword (PoP); Popularity of brand on social media(POB);* S*entiment behind the piece of text (SBT)/ sentiment behind customer responses ; Volume of brand in terms of its aggregate followers (VoB); Latest activity to the brand website (LAW) ; sentiment behind customer responses (SBCR) ; Customer or visitor's mentions, comments and engagements (CCE); Increase in Quality metrics (IQM) ; Number of shares of posted contents (NoS); Number of likes (NoL) and comments ; Number of fans, daily active users (NoF); Volume of mentions before, during and after your marketing campaigns (VoM); Total page Likes, new Likes/Unlikes, (TPL/NL); Like or similar sources, demographics (LS/De); Page views and unique page views, tab views (PV/TV); Number of external referrers (NoR).*

***Explanation :*** The more the percentage of people who are likely to mention your keywords, the more could be the popularity as well as volume of brand in terms of aggregate followers. This could also lead to increased activity to the brand website . This is also directly related to increased number of new likes/ dislikes as well as total page likes.

Similarly, page views is directly linked to total page likes , the more the number of people are going to like your webpage , the more they may referred them to others . This could increase the number of external visitors . Number of external referrers is directly linked to number of fans . Number of fans lead to total number of page likes. Increase in the number of fans also increases the quality metrics of the post and improve the quality of website . Not only this , number of shares of posted comments as well as customer's /visitors mention and comments also improve the quality metrics , increase the page views , positively increase the traffic to the websites , increase the number of referrers and ultimately increase the number of fans .

Latest activity to the brand website could be the result of influence of external referrers , popularity of brand in social media , new page likes , page views . This may lead to volume of brand in terms of followers . Finally sentiments behind piece of text or sentiment behind customer responses is directly resulted from their experience of brand , page likes , percentage of people who would continue mentioning your keywords as they relate their sentiments with those keywords . This could also be the result of like sources or demographics. Volume of mentions before and after the marketing campaigns is directly related to latest activity to the brand website. This also contributes to popularity of brand on social media and will indirectly affect the fan following . page views are directly related with number of external referrers and also on demographics. Sometimes , the fan following also depend on demographics . for example , webpage posted on web targeting the elite class of metro will target to capture a specific segment and therefore quite possible that the number of likes / dislikes etc. depends largely on the demographics selected .

Sentiment behind customer response is directly linked to the success and popularity of brand on social media. If customer does not like the content [which is a combination of CCE , POP as well as SBCR, TPS, TPL and Demographics ] resulting in greater number of dislikes and decrease number of page views[PV, NoF] . Like sentiments and number of shares of posted comments will enhance the traffic to the website , creates its brand image , results in more likes and page views.

It is quite common now days , that demographics play a major role , be it in getting job or popularising your music video . Also when you are playing a sport like cricket etc. , various sources of media , particularly social media now days are becoming popular . people are emotionally captured by the player of their region and promote heavily on that. Not only that people usually select an upcoming singer in a music show from their own region.

### 4.1 Construction of Structural self-interaction Matrix (SSIM)

This matrix gives the pair-wise relationship between two variables *i.e. I and j* based on VAXO. SSIM has been presented below in Fig 1.

### 4.2 Construction of Initial Reachability Matrix and final reachability matrix

The SSIM has been converted in to a binary matrix called the initial reachability matrix shown in fig. 2 by substituting V, A, X, O by 1 or 0 as per the case. After incorporating the transitivity, the final reachability matrix is shown below in the Fig 3.

| S. No. | Barriers | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PoP | POB | SBCR | VoB | LAW | CCE | IQM | NoS | NoL | NoF | VoM | TPL | PV/TV | NoR | Demo |
| 1 | PoP | | V | A | V | V | X | V | V | V | V | V | V | V | A | A |
| 2 | POB | | | A | V | V | A | V | X | V | A | A | A | A | A | A |
| 3 | SBCR | | | | V | V | A | V | V | V | V | V | V | V | V | A |
| 4 | VoB | | | | | V | A | V | A | V | A | X | A | A | A | A |
| 5 | LAW | | | | | | A | V | V | V | A | A | A | A | A | A |
| 6 | CCE | | | | | | | V | V | V | V | V | V | V | A | A |
| 7 | IQM | | | | | | | | X | V | X | A | A | A | A | A |
| 8 | NoS | | | | | | | | | V | X | X | V | A | A | A |
| 9 | NoL | | | | | | | | | | X | V | V | A | X | A |
| 10 | NoF | | | | | | | | | | | V | V | A | A | A |
| 11 | VoM | | | | | | | | | | | | V | A | A | A |
| 12 | TPL | | | | | | | | | | | | | X | A | A |
| 13 | PV/TV | | | | | | | | | | | | | | A | A |
| 14 | NoR | | | | | | | | | | | | | | | A |
| 15 | Demo | | | | | | | | | | | | | | | |

**Fig 1: SSIM matrix for pair wise relationship amongst barriers**

| S. No. | Barriers | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PoP | POB | SBCR | VoB | LAW | CCE | IQM | NoS | NoL | NoF | VoM | TPL | PV/TV | NoR | Demo |
| 1 | PoP | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | POB | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | SBCR | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 4 | VoB | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 5 | LAW | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | CCE | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| 7 | IQM | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 8 | NoS | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 9 | NoL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 |
| 10 | NoF | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 11 | VoM | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| 12 | TPL | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| 13 | PV/TV | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 |
| 14 | NoR | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 15 | Demo | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Fig 2: Initial reachability matrix**

| S. No. | Barriers | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PoP | POB | SBCR | VoB | LAW | CCE | IQM | NoS | NoL | NoF | VoM | TPL | PV/TV | NoR | Demo | D.P |
| 1 | PoP | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 |
| 2 | POB | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 8 |
| 3 | SBCR | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 |
| 4 | VoB | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 8 |
| 5 | LAW | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 8 |
| 6 | CCE | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 14 |
| 7 | IQM | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 5 |
| 8 | NoS | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 8 |
| 9 | NoL | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 8 |
| 10 | NoF | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 10 |
| 11 | VoM | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 9 |
| 12 | TPL | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 8 |
| 13 | PV/TV | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 10 |
| 14 | NoR | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 14 |
| 15 | Demo | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 |
| | De.P | 5 | 14 | 5 | 14 | 13 | 5 | 15 | 15 | 15 | 10 | 15 | 15 | 9 | 7 | 3 | |

**Fig 3 : Final reachability matrix**

D.P : Driving power ; De.P : dependence power

## 4.3 Level Partition

From the final reachability matrix, reachability and final antecedent set for each factor are found. The elements for which the reachability and intersection sets are same are the top-level element in the ISM hierarchy. After the identification of top level element, it is separated out from the other elements and the process continues for next level of elements. Reachability set, antecedent set, intersection set along with different level for elements have been shown below in table 1.

**Table 1: Iteration I**

| S. No. | Reachability set | Antecedent set | Intersection set | Level |
|---|---|---|---|---|
| **1.** | **7,8,9,11,12** | 1,2,3,4,5,6,7,8,9, 10,11,12,13,14,15 | **7,8,9,11, 12** | |
| 2. | 2,4,7,8,9,11, 12 | 1,2,3,4,5,6,8,9,10 ,11,12,13,14,15 | 2,4,8,9,11, 12 | |
| 3. | 2,4,5,7,8,9, 11,12 | 1,2,3,4,5,6,8,10,1 1,12,13,14,15 | 2,4,5,8,11, 12 | |

| | | | | |
|---|---|---|---|---|
| 4. | 2,4,5,7,8,9, 11,12,13 | 1,3,6,11,12,13,14 ,15 | 11,12,13 | I |
| 5. | 2,4,5,7,8,9, 10,11,12,13 | 1,3,6,13,14,15 | 13 | |
| 6. | 1,2,3,4,5,6,7, 8,9,10,11, 12,13,14 | 1,3,6,14,15 | 1,3,6,14, 15 | |
| 7. | 1,2,3,4,5,6,7, 8,9,10,11, 12,13,14,15 | 1,15 | 1,15 | |

**Table 2: Iteration II**

| S. N o. | Reachabilit y set | Antecedent set | Intersecti on set | Level |
|---|---|---|---|---|
| 2. | **2,4** | 1,2,3,4,5,6,8,9, 10,13,14,15 | 2,4 | II |
| 3. | 2,4,5 | 1,2,3,4,5,6,8,10, 13,14,15 | 2,4,5,8 | |
| 4. | 2,4,5,13 | 1,3,6,13,14,15 | 13 | |
| 5. | 2,4,5,10,13 | 1,3,6,13,14,15 | 13 | |
| 6. | 1,2,3,4,5,6, 10,13,14 | 1,3,6,14,15 | 1,3,6,14, 15 | |
| 7. | 1,2,3,4,5,6, 10,13,14,15 | 1,15 | 1,15 | |

**Table 3: Iteration III**

| S. N o. | Reachabilit y set | Antecedent set | Intersecti on set | Lev el |
|---|---|---|---|---|
| 3. | **5** | 1,2,3,4,5,6,8,10, 13,14,15 | **5** | III |
| 4. | 5,13 | 1,3,6,10,13,14, 15 | 13 | |
| 5. | 5,10,13 | 1,3,6,10,13,14, 15 | 13 | |
| 6. | 1,3,5,6,10, 13,14 | 1,3,6,14,15 | 1,3,6,14, 15 | |
| 7. | 1,3,5,6,10,1 3,14,15 | 1,15 | 1,15 | |

**Table 4: Iteration IV**

| S. N o. | Reachabilit y set | Antecedent set | Intersecti on set | Lev el |
|---|---|---|---|---|
| 4. | **13** | 1,3,6,10,13,14,1 5 | 13 | IV |
| 5. | 5,10,13 | 1,3,6,10,13,14,1 5 | 13 | |
| 6. | 1,3,5,6,10, 13,14 | 1,3,6,14,15 | 1,3,6,14, 15 | |
| 7. | 1,3,5,6,10,1 3,14,15 | 1,15 | 1,15 | |

**Table 5: Iteration V**

| S. N o. | Reachabilit y set | Antecedent set | Intersecti on set | Lev el |
|---|---|---|---|---|
| 5. | 5,10,13 | 1,3,6,10,13,14,1 5 | 13 | V |
| 6. | 1,3,5,6,10, 13,14 | 1,3,6,14,15 | 1,3,6,14, 15 | |
| 7. | 1,3,5,6,10, 13,14,15 | 1,15 | 1,15 | |

**Table 6. Iteration VI**

| S.No. | Reachability set | Antecedent set | Intersection set | Level |
|---|---|---|---|---|
| 6. | **1,3,6,14** | 1,3,6,14,15 | 1,3,6,14 | **VI** |
| 7. | 1,3,6,14,15 | 1,15 | 1,15 | |

**Table 7. Iteration VII**

| S.No. | Reachability set | Antecedent set | Intersection set | Level |
|---|---|---|---|---|
| 7. | **15** | 15 | 15 | **VII** |

## 4.4 ISM Diagraph

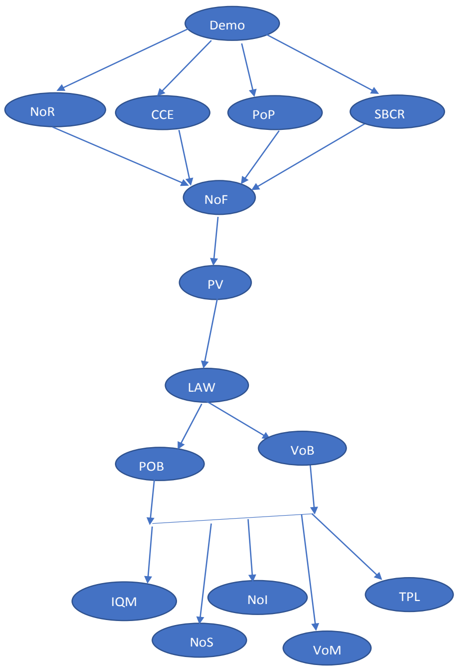


**Figure : Interpretive Structural Model**

**Fig 5. ISM Diagraph**

# 5. PRACTICAL APPLICATIONS AND RESEARCH IMPLICATIONS OF SOCIAL NETWORK ANALYSIS (SNA)

## 5.1 Applications of Social network analysis

### *4.1.1 Practical applications*

Social network analysis is used extensively in disciplines which include data aggregation and mining, network propagation modeling, network modeling and sampling, user attribute and behavior analysis, community-maintained resource support, location-based interaction analysis, social sharing and filtering, recommender systems development, and link prediction and entity resolution.

### *4.1.2 Security applications*

Social network analysis is also used in intelligence, counter-intelligence and law enforcement activities. This technique allows the analysts to map covert organizations such as an espionage ring, an organized crime family or a street gang. The National Security Agency (NSA) uses its clandestine mass electronic surveillance programs to generate the data needed to perform this type of analysis on terrorist cells and other networks deemed relevant to national security.

### *4.1.3 Textual analysis applications*

Large textual corporations can be turned into networks and then can be analyzed with the method of social network analysis. In these networks, the nodes are Social Actors, and the links are Actions. The resulting networks, which can contain thousands of nodes, are then analyzed by using tools from network theory to identify the key actors and general properties such as robustness or structural stability of the overall network, or centrality of certain nodes [6].

### *4.1.4 Unique capabilities*

Researchers employ social network analysis in the study of computer-supported collaborative learning in part due to the unique capabilities it offers through the study of interaction patterns within a networked learning community.

## 5.2 Research implications of Social Network Analysis

### *5.2.1 Other methods used alongside SNA*

- Qualitative method – The principles of qualitative case study research constitute a solid framework for the integration of SNA methods in the study of CSCL experiences.
- Quantitative method – This includes simple descriptive statistical analyses on occurrences to identify particular attitudes of group members who have not been able to be tracked via SNA in order to detect general tendencies.

*5.2.2 Other than ISM methodology,* other MCDM techniques such as AHP , Fuzzy AHP , DEMATEL approach etc. could be used to study the hierarchical relationships amongst the metrics as well as the relative importance of these metrics.

# 6. FUTURE DIRECTIONS AND RESEARCH IMPLICATIONS OF SENTIMENTS ANALYSIS

## 6.1 Sentiment analysis techniques

*Lexicon based methods* [13]*and machine-learning methods* [11] are the two widely known sentiment analysis techniques. Lexicon-based methods rely on a sentiment lexicon, a collection of known and pre-compiled sentiment terms. Machine learning approaches make use of syntactic and/or linguistic features, and hybrid approaches are very common, with sentiment lexicons playing a key role in the majority of methods.

## 6.2 Fusion of Social network analysis and Sentiment analysis

Shams *et al*. [13] employed a combination of sentiment analysis and social network analysis for extracting classification rules for each customer. These rules represent customers' preferences for each cluster of products and can be seen as a user model. The combination helps the system to classify products based on customers' interests.

## 6.3 NLP and social media sentiment analysis

NLP refers to computer systems that process human language in terms of its meaning . Apart from common word processor operations that treat text like a mere sequence of symbols, NLP considers the hierarchical structure of language . By analysing language for its meaning, NLP systems have long filled useful roles, such as correcting grammar, converting speech to text and automatically translating between languages .

## 6.4 The Limits of NLP in Social Media

- As with most computer systems, NLP technology lacks human-level intelligence, at least for the foreseeable future. On a text-by-text basis, the system's conclusions may be wrong — sometimes very wrong. For instance, the tweeted phrase "You're killing it!" may either mean "You're doing great!" or " You're a terrible gardener!"
- Much of social media interaction is personal, expressed between two people or among a group.

# 7. ACKNOWLEDGEMENTS

Authors are thankful to DCAL, IIM Bangalore for disseminating knowledge on social network analysis . Co-author Remica Aggarwal also extend her sincere thanks to Prof. S.P. Singh for disseminating knowledge about ISM Methodology .

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