International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Unveiling the Network Properties of Peer Alcohol Network: A Novel Understanding of Alcohol Consumption Behaviour of Adult Network of a small Village

Kimasha Borah*[1], Prof. Kalyan Bhuyan[2], Ankumon Sarmah[3]

Submitted: 15/01/2024 **Revised**: 23/02/2024 **Accepted**: 01/03/2024

Abstract: Alcohol use disorder is a global phenomenon which has been linked with various kinds of harms including physical, psychological, social, financial and legal harms. The global statistics related to alcohol use, deaths and morbidity associated with alcohol is very alarming which warrants for an effective strategy to deal with the menace of alcohol use. Though apparently alcohol consumption is an individual behaviour, drinking is often influenced by peers. In fact, alcohol consumption is influenced by peers and similarly peer selection is also influenced by alcohol use thus making it a potential area of research from social network analysis (SNA). Therefore, studying the alcohol use from the network analysis perspective definitely will shed light on initiation and progression of alcohol use in the community the knowledge of which might be helpful in formulating the strategies to treat and prevent the excessive alcohol use. Hence this study is undertaken to examine the network behaviour and properties of Peer Alcohol Network in a rural area using snowball technique of sampling.

Keywords*: Alcohol use, Random network, Scale free network, Social network*

1. Introduction:

Alcohol consumption has been a global phenomenon with more than 2.4 billion people across the globe is estimated to be the current users and as per the National Survey on extent and pattern of substance use in India 14.6% individuals aged between 10 and 75 years consume alcohol [1, 2]. Alcohol use has been identified as one of the major contributors of death, disability, and ill health [3] There have been several reasons of initiating alcohol use ranging from, peer influence, psychological stress and some others view it just as a way to socialize[4], [5].

Alcohol consumption is linked to various kinds of harm including physical, psychological and financial and these harms are not only confined to the person engaged in drinking but also to the family members, friends and society [6]-[8].

Alcohol consumption though may apparently be viewed as an individual behaviour, drinking is often influenced by others and has rarely been considered as a unitary act. Alcohol consumption can influence the choice of relationships and vice versa. Selecting drinking buddies as friends and initiating and maintaining drinking behaviour on being influenced by these buddies are often observed in real life situations. Hence examining these social ties can provide us the important information regarding initiation and maintenance of drinking behaviour in individuals as well as in groups. One such approach to examine the roles of individuals is the social network analysis (SNA) which utilizes the theories, methods and techniques to study social ties and how they could affect individual and group behaviour. These theories share the tenet that people get influenced by the people they interact with and that their positions within larger social systems can affect or constrain their behaviour. In order to operationalize network constructions, particular mathematical algorithms (and related software) are used, together with recognised methods for evaluating the properties and dimensions of these relationships [9].

From the social network perspective, drinking has been explained by theories of social influence, according to which a person's family and friends have a significant influence on their behaviour. Peers appear to have a significant impact on individual drinking behaviours, according to empirical research in this field. Social learning and social control theorists contend that social context and network norms shape individual behaviour. However, numerous studies on the drug use and abuse patterns of adolescents suggest that such relationships may really be the outcome of selection procedures in which people select social network members who have drinking habits that are similar to their own. These results are consistent with theories on social network

[1]Assistant Professor, Centre for Computer Science and Applications, Dibrugarh University,Dibrugarh, Assam, India
[2]Professor, Department of Physics, Dibrugarh University, Dibrugarh, Assam, India
[3]Assistant Professor, Centre for Computer Science and Applications, Dibrugarh University, Dibrugarh, Assam, India
** Corresponding author Email: kimashaborah@dibru.ac.in*

development that contend that people seek out others who share their interests or who are similar to them on a social level. Although the social selection contention is gaining support in studies focusing on adult populations have not been studied so far. Although life stage changes may cause variances between adults and adolescents in the mechanisms that drive drinking behaviours and social network formation, adults exhibit considerable connections between networks and individual drinking patterns. Alcohol consumption can both influence choice of relationships (e.g. selecting drinking buddies as friends) and be influenced by them (e.g. being pressured by peers to drink alcohol), suggesting that this is a potential field for investigation into the role of peer network in initiation and maintenance of alcohol use disorder and also the possible mechanism to halt the progress of the disorder from social point of view.

However, there are very few researchers in this area, particularly on the adult population in this region of the country. This has motivated us to use the opportunity to conduct this study with the objectives:

1. To construct peer adult network using social network analysis.

2. To examinethe network characteristics of peer adult network.

3. To explore the small world property of the peer adult network.

4. To explore the scale free property of the peer adult network.

1.1 Preliminaries:

Centrality of the nodes (alcohol user) in the network:

Centrality indicates individual position within a network. It also shows how influential a node or a participant within the network.Measures of centrality focus on individual actor's (nodes) position inside the network. They make an effort to define the actors and identify individuals who take on significant structural roles inside the social network or how and to what extent influential a node is. Degree centrality, closeness centrality, betweenness centrality and eigen vector centrality are the four primary types of centralities that can be calculated.

Degree centrality:

The first mathematical model for centrality was created by Freeman (1978) and is based on the linkages or connections that connect a node. Opsahl et al. (2010) defined node strength as degree centrality. A node's degree centrality is a measure of how many other nodes are directly connected to it[10],[11]

Closeness centrality:

The concept of proximity or closeness centrality was initially proposed by Bavelas (1948) and defined by Sabidussi (1966) as the inverse of the sum of the geodesic distances from each vertex in the network to all other vertices. Closeness centrality is Freeman's (1979) second mathematical metric [10]. It implies that someone in a central position is typically closer to everyone else. It analyses the effectiveness of communication as well.

Eigenvector centrality:

This centrality measure is based on the idea that a node is important if its neighbour is important. An influential node in the network is one with a high eigen centrality score. It is helpful since it implies power over nodes more than "hop" distant one in addition to direct impact over those nodes [12].

Betweenness centrality:

In network analysis, it's not only important to consider how far one actor is from other actors; it's also important to consider which actors are continuing along which shortest pathways among pairs of other actors. Betweenness centrality was first introduced by Shaw (1954) as a measure for the management of human network in communication with other humans in social networks by Freeman (1978)[10].

PageRank:

Similar to Eigen Centrality, PageRank can assist in identifying significant or influential nodes whose influence goes beyond merely their direct connections [12].

Density:

The degree of connectivity in a network was measured by its network density. The actual number of ties in a network, represented as a percentage of the total number of ties, is what is referred to as density. Network density is a numeric value that ranges from 0 to 1.0. The network is considered dense when density is close to 1.0; otherwise, it is considered sparse [13], [14].

Network model:

There are two basic types of network models: regular and random, each based on a different assumption about the network topology. In actuality, random network models exhibit small-world characteristics and high connectedness, which manifests as a logarithmic increase in the number of degrees of separation with the size of the network (Newman 2003). Regular networks have stronger clustering, but lesser connectedness as compared to random networks. Since social networks frequently contain cliques or clustering, they are neither totally random nor completely regular in nature.

Small World Network:

Small-world networks, developed by Watts and Strogatz in 1998, are highly clustered like regular networks but highly connected like random networks. According to empirical investigations, many networks specially real world complex networks are highly clustered and strongly connected in nature, much like the small-world network. Small world networks are unique in the sense that like regular networks small world networks are highly clustered but have a short global separation a feature similar to that of random network. Unlike regular and small world networks random networks don't have clustering [15].

Scale Free network:

A connected graph or network that has the feature that the number of links k coming from a certain node displays a power law distribution $P(k) \sim k^{-\gamma}$ is known as a scale-free network. By gradually adding nodes to an already-existing network and adding links to nodes that already have preferred attachment, one can create a scale-free network in which the likelihood of connecting to a given node (i) is proportional to the number of links (k_i) the node currently has.

$$P\text{ (node linkingi) } \sim (k_i)/\textstyle\sum_j k_j \qquad [16]$$

The work of Barabási and Albert (1999) highlighted the applicability of scale-free networks to model real-world networks. They looked at the architecture of several massive networks, including the Internet and the network of coauthorship among scientists. Scholars have noted that many real-world networks, such as social interaction networks or the Internet, exhibit topologies that are similar to this type of network [17].

The average path length L and clustering coefficient C are two statistics that Watts and Strogatz used to quantify the structural characteristics of networks.

Average path length (L) : The number of edges in the shortest path between any two vertices in the network.

Clustering coefficient (C): The ratio between the existing edges among neighbors of a vertex and the possible edges in this neighbourhood [15].

2. Materials and Methods:

2.1 Participants:

Participants were the people who drink alcohol in a village named Hiloidhari Gaon of Dibrugarh District, Assam, India. All the male individuals aged 18 and above who drink alcohol regularly were eligible to participate in the study. Out of 76 individuals who drink alcohol regularly, only 60 consented to participate and completed the survey.

2.2 Sampling:

Our sampling techniques was chain -referral or snowball method. Snowball sampling methods are particularly useful when attempting to map a network with unknown boundaries, where researchers do not know a priori who belongs to the group and who does not [18]. We have non-random study population where individual were recruited only on being nominated by the index case identified subject to the fulfilment of set of inclusion criteria

2.3 Procedure:

This study was conducted in the district of Dibrugarh. The list of villages in the District of Dibrugarh was prepared and a village named Hioloidhari Gaon was selected randomly for collection of data. Initially, the village headman was approached and briefed about the purpose of the study and permission was taken to conduct the study. At first, a person known to consume alcohol regularly was identified with the help of the village headman and other influential leaders of the village. He was explained about the purpose of the study, written informed consent was taken and he was designated as the index case for our study. All the relevant information regarding his habit of consumption of alcohol was gathered which included his companions of drinking. Then he was asked to name or refer a person/persons who drink who in turn will name someone else. Thus a list of persons who drink with him and any other person whom he knows to have the habit of drinking alcohol regularly i.e. seeds and recruits was prepared and each and every individual from that list was interviewed and responses were recorded.

2.4 Measures:

Demographics

Information regarding participants' age, religion, educational status, income, and marital status are collected by using a semi-structured proforma.

2.5 Alcohol use:

The questionnaire used to collect the data included information like the amount of alcohol, frequency of drinking, whether taken in groups or in solitary, who takes the initiative, where they meet to drink and whether he drinks in the absence of the leader. For the current investigation, a list of alcohol users were used based on participants' responses. In this exercise, participants were asked to list the names of the friends they are drinking with. Each person was then asked to mention their drinking companions from the list, and so on. A list of participants was made therefrom.

3. Network Definition:

Peer Alcohol Network:

We propose a social network called the Peer Alcohol Network, where the nodes are the study participants. The nodes' degree of connectivity is determined by the companion's drinking behavior. Thus, in this social network model, relationships (social ties) between two actors can only develop if they partake in alcohol use together. The participants are coded as P (1 to 60) to maintain confidentiality and anonymity.

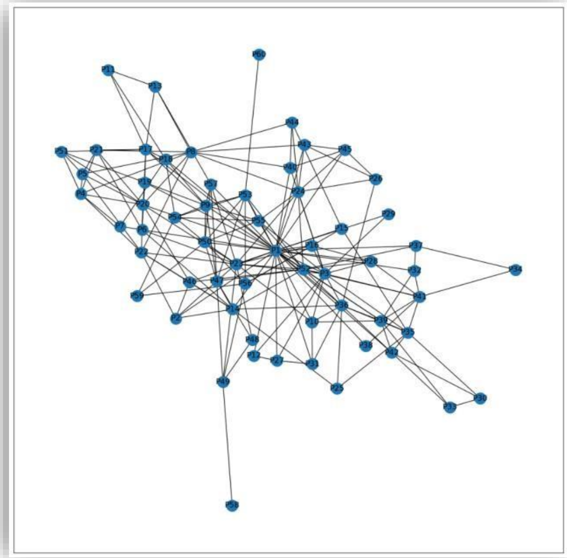

Fig. 1. Peer Alcohol Network

As mentioned above the participants (P) are asked to list the names of their companions they would drink alcohol with. Based on their responses, network linkagesare created. As shown in Fig1, the current social network comprises of 60 nodes (alcohol user) with 195 number of potential edges or social ties.

Data analyses are conducted by the following steps:

1. We prepare an adjacency matrix by using the information obtained from the study population.

2. From the adjacency matrix, we construct social network namely Peer AlcoholNetwork.

3.1 Adjacency matrix:

We construct an adjacency matrix of the participants (N=60). The adjacency matrix is a matrix containing rows and columns which is used to represent a simple graph, with 0 or 1 in the position of $(V_{i,}V_j)$ according to the condition whether V_i and V_j are adjacent or not. Each pair of participants (P_i,P_j) are either connected or disconnected with the connection being undirected i.e., if $P_i \rightarrow P_j$then $P_j \rightarrow P_i$ (RM Christley et al). The matrix ($\Delta=\delta_{ij}$) is defined as

$$\delta_{ij} = \begin{cases} 1 & \text{if } P_i \leftrightarrow P_j \\ 0 & \text{otherwise} \end{cases}$$

4. Analysis of Peer Alcohol Network:

The network analysis is done by calculating different network measures such as graph density, Page Rank etc. One of the most used network measurements is centrality measures which consist of degree centrality, betweenness centrality, closeness, and eigenvector centrality. In order to do various statistical analyses, such as average clustering coefficient, average shortest path length, degree centrality, betweenness centrality, eigenvector centrality, proximity centrality, Page Rank, robustness etc., several built-in features of Python are used from the adjacency matrix.

The proposed network model has an average clustering coefficient of 0.4207, and an average shortest path length of 2.4079.The density of the current network is 0.1101.

Table 1. Centrality measures of the current study. Based on their centrality scores, table 1 displays the centrality measures of sixty participants in ascending order.

Person	Degree centrality	Person	Closeness centrality	Person	Eigenvector centrality	Person	Betweenness centrality	Person	PageRank
P1	0.559322034	P1	0.686046512	P1	0.463838451	P1	0.463838451	P1	0.073277
P3	0.254237288	P23	0.536363636	P23	0.10889465	P23	0.10889465	P3	0.034422
P52	0.254237288	P52	0.531531532	P52	0.067276542	P52	0.067276542	P52	0.03287
P23	0.237288136	P3	0.522123894	P3	0.05423053	P3	0.05423053	P23	0.031268
P8	0.169491525	P24	0.5	P20	0.053036553	P20	0.053036553	P8	0.023871
P9	0.169491525	P14	0.487603306	P17	0.049801642	P17	0.049801642	P47	0.023738

P24	0.169491525	P20	0.479674797	P53	0.047732718	P53	0.047732718	P50	0.02337
P47	0.169491525	P50	0.479674797	P24	0.042812865	P24	0.042812865	P24	0.023126
P50	0.169491525	P17	0.475806452	P50	0.040968077	P50	0.040968077	P9	0.022983
P14	0.152542373	P53	0.468253968	P42	0.037395174	P42	0.037395174	P53	0.02294
P17	0.152542373	P55	0.468253968	P49	0.036475515	P49	0.036475515	P39	0.022343
P20	0.152542373	P57	0.468253968	P14	0.032743176	P14	0.032743176	P17	0.022176
P36	0.152542373	P36	0.464566929	P47	0.031412221	P47	0.031412221	P36	0.021917
P39	0.152542373	P39	0.464566929	P8	0.031275973	P8	0.031275973	P41	0.02152
P53	0.152542373	P10	0.4609375	P39	0.027275352	P39	0.027275352	P35	0.02104
P22	0.13559322	P46	0.4609375	P36	0.02562161	P36	0.02562161	P14	0.020927
P35	0.13559322	P2	0.457364341	P9	0.022601055	P9	0.022601055	P20	0.020789
P41	0.13559322	P18	0.457364341	P35	0.022560889	P35	0.022560889	P22	0.018782
P55	0.13559322	P19	0.457364341	P18	0.021383844	P18	0.021383844	P55	0.018377
P4	0.118644068	P16	0.453846154	P37	0.020501184	P37	0.020501184	P4	0.017569
P6	0.118644068	P40	0.453846154	P41	0.018959276	P41	0.018959276	P56	0.016895
P5	0.101694915	P15	0.450381679	P15	0.018898366	P15	0.018898366	P6	0.016749
P10	0.101694915	P47	0.450381679	P22	0.018087004	P22	0.018087004	P49	0.016653
P18	0.101694915	P42	0.446969697	P57	0.017127271	P57	0.017127271	P42	0.016462
P21	0.101694915	P43	0.446969697	P55	0.014943853	P55	0.014943853	P18	0.016087
P42	0.101694915	P7	0.443609023	P56	0.014386163	P56	0.014386163	P54	0.015606
P46	0.101694915	P9	0.440298507	P6	0.011436978	P6	0.011436978	P5	0.015095
P54	0.101694915	P28	0.440298507	P19	0.011057952	P19	0.011057952	P21	0.014996
P56	0.101694915	P32	0.430656934	P40	0.010395233	P40	0.010395233	P10	0.014945
P57	0.101694915	P37	0.430656934	P7	0.00864627	P7	0.00864627	P57	0.014866
P2	0.084745763	P45	0.430656934	P16	0.007874791	P16	0.007874791	P46	0.014477
P16	0.084745763	P31	0.427536232	P43	0.007758985	P43	0.007758985	P45	0.013508
P19	0.084745763	P27	0.424460432	P13	0.006610028	P13	0.006610028	P40	0.013333
P28	0.084745763	P12	0.421428571	P4	0.005777998	P4	0.005777998	P43	0.013315
P40	0.084745763	P38	0.421428571	P54	0.005619008	P54	0.005619008	P51	0.013245
P43	0.084745763	P29	0.418439716	P46	0.00507385	P46	0.00507385	P16	0.013056
P45	0.084745763	P22	0.415492958	P10	0.004056618	P10	0.004056618	P19	0.012953
P49	0.084745763	P6	0.409722222	P2	0.003796291	P2	0.003796291	P28	0.01294
P51	0.084745763	P8	0.404109589	P45	0.003780762	P45	0.003780762	P2	0.012677
P13	0.06779661	P41	0.401360544	P44	0.003736516	P44	0.003736516	P37	0.012395
P15	0.06779661	P35	0.398648649	P51	0.003706534	P51	0.003706534	P13	0.011813
P26	0.06779661	P49	0.383116883	P21	0.003400196	P21	0.003400196	P15	0.011783
P27	0.06779661	P44	0.375796178	P28	0.002160497	P28	0.002160497	P32	0.011727

P31	0.06779661	P4	0.373417722	P32	0.001858011	P32	0.001858011	P27	0.0117
P32	0.06779661	P21	0.373417722	P5	0.001744145	P5	0.001744145	P44	0.011583
P37	0.06779661	P48	0.373417722	P26	0.001636238	P26	0.001636238	P26	0.011423
P44	0.06779661	P54	0.373417722	P25	0.001282449	P25	0.001282449	P31	0.011391
P7	0.050847458	P56	0.373417722	P38	0.001254076	P38	0.001254076	P30	0.010374
P11	0.050847458	P13	0.371069182	P30	0.000614357	P30	0.000614357	P33	0.010281
P12	0.050847458	P5	0.366459627	P59	0.000611705	P59	0.000611705	P11	0.009812
P25	0.050847458	P25	0.364197531	P11	0.000599065	P11	0.000599065	P48	0.009684
P30	0.050847458	P26	0.364197531	P31	0.00059002	P31	0.00059002	P59	0.009537
P33	0.050847458	P51	0.355421687	P27	0.000487045	P27	0.000487045	P12	0.009286
P48	0.050847458	P59	0.34502924	P33	0.000409117	P33	0.000409117	P7	0.009262
P59	0.050847458	P11	0.33908046	P34	0.000243522	P34	0.000243522	P25	0.009246
P29	0.033898305	P30	0.329608939	P12	0	P12	0	P34	0.007964
P34	0.033898305	P33	0.324175824	P29	0	P29	0	P38	0.007262
P38	0.033898305	P34	0.320652174	P48	0	P48	0	P29	0.006946
P58	0.016949153	P60	0.320652174	P58	0	P58	0	P58	0.005998
P60	0.016949153	P58	0.278301887	P60	0	P60	0	P60	0.005372

Degree centrality:

Table 1 shows that person 1(P1) has highest degree centrality followed by P3,P52 and P23.It indicates that these participants are the ones who mostly use alcohol with many partners.

Closeness centrality:

Table 1 shows that P1 has highest closeness centrality followed by P23, P52 and P3.It implies that P1,P23,P52 and P3 in a central position are typically closer to everyone else.

Eigenvector centrality:

The eigenvector centrality of P1 is highest, followed by P23, P52, and P3. If a node's neighbour is significant, then so is the node itself. The fact that person 1 is related to other people who made large contributions to the peer alcohol network suggests that person 1 has the highest eigen vector centrality.

Betweenness centrality:

Like earlier centrality values, it is noted that P1 has the highest betweenness centrality, followed by P23, P52, and P3.It suggests that all of the other network participants can readily access these participants.

Page Rank:

P1 has the greatest page rank, followed by P3, P52, and P23, according to Table 1. P1, P3, P52, and P23 are thus recognised as powerful individuals whose influence extends beyond just their ties.

The index case is the most crucial and important participant, according to the study's findings above, and it is noticed that Person 3, Person 23, and Person 52 are the key nodes or contributing nodes in the suggested network model.

4.1. Analysis of small world property of Peer Alcohol Network:

Small-world networks are often identified by comparing a network's average path length (L) and clustering coefficient (C) to those of a completely random network of the same size. A small-world network has a significantly higher C while having a L that is very similar to a random network. In order to analyse the current network model, we must compute the regular lattice's average path length (ln(N)/ln(k)) and clustering coefficient (N/k) and compare them to the Peer Alcohol network's L and C. N is the number of network nodes, and K is the average number of edges or connections.Average path length on a regular lattice is 3.4737, and the clustering coefficient is 0.0541. Since the Average path length and clustering coefficient of Peer

Alcohol Network are 2.4079 and 0.4207 respectively so, the Peer Alcohol Network exhibit small world property.

4.2. Analysis of scale free property of Peer Alcohol Network:

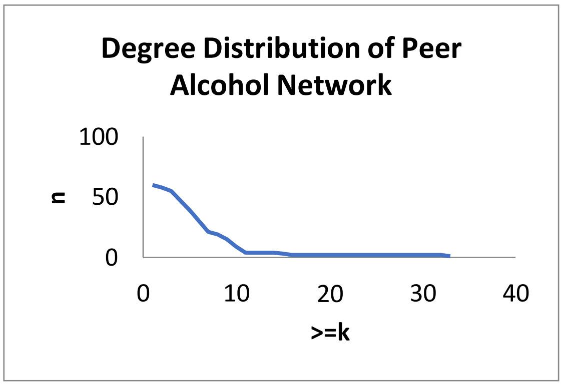

Fig.2. Degree distribution of Peer Alcohol Network

5. Robustness analysis of Peer Alcohol Network:

To examine its robustness characteristic, we conduct an experiment using the same network model. Based on the degree of centrality of each node, we exclude five nodes from this experiment. First, the highest degree node in the existing network architecture is removed. To calculate the network parameters, five nodes are gradually removed based on their connections (degree centrality).Table 2 displays statistics such as size of the network,network density, average path length, average clustering coefficient, percentage change in average path length, percentage change inaverage clustering coefficient.

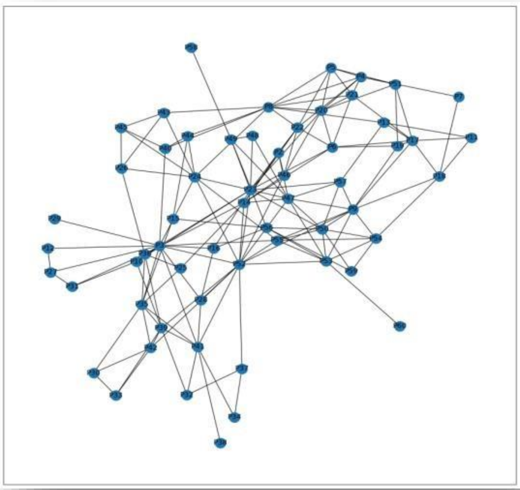

Fig. 3. After removing index case

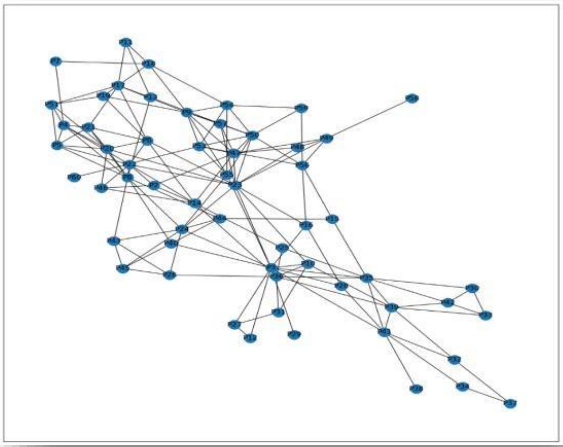

Fig. 4. Removal of two highest central persons(P1,P52)

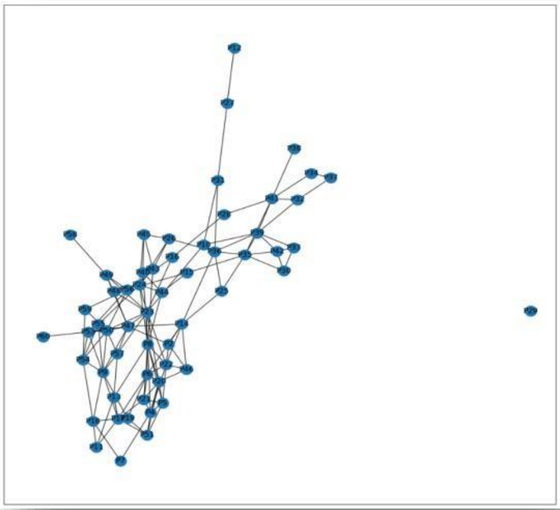

Fig. 5. Removal of three highest central persons (P1,P52,P3)

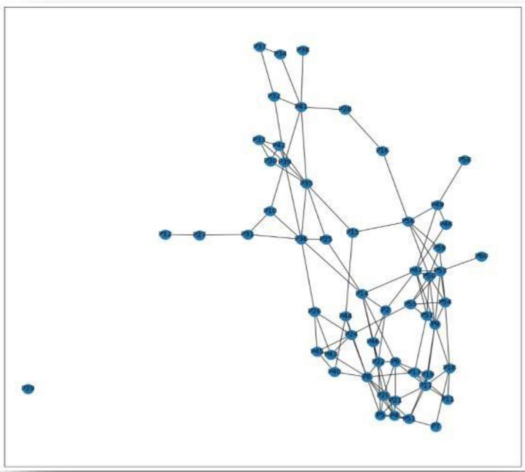

Fig. 6. Removaloffour highest central persons (P1,P52,P3 and P23)

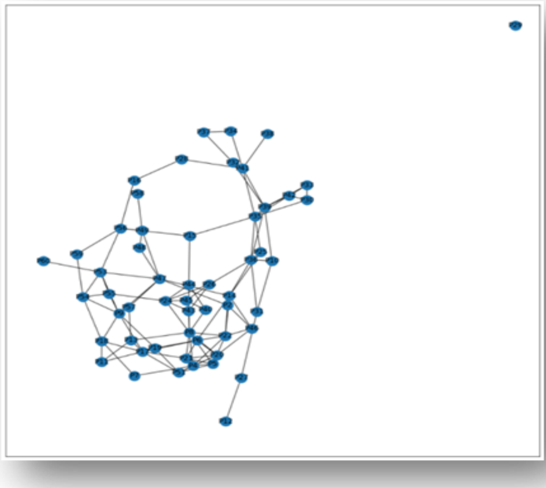

Fig. 7. Removal of five highest central persons (P1,P52,P3,P23,P50

Table 2. Change of network parameters after removal of key participants

Removal of nodes	size of network		Density	Average clustering coefficient(C)	Average path length (L)	Percentage Change in C	Percentage Change in L
	No. of nodes	No. of edges					
Removal of P1(index case)	59	162	0.0947	0.3661	2.7808	12.978	-15.487
Removal of P1and P52	58	148	0.0895	0.3698	2.9661	12.099	-23.182
Removal ofP1, P52and P3	57	135	0.0846	0.3352	Disconnected Reduced network (3.2418)	20.323	-34.632
Removal ofP1, P52, P3 and P23	56	124	0.805	0.3455	Disconnected Reduced network (3.4741)	17.875	-44.279
Removal of P1, P52, P3, P23 and P50	55	116	0.0781	0.3162	Disconnected Reduced network (3.5031)	24.840	-45.484

6. Discussion:

Humans are vulnerable to react under peer pressure. Role of peers are significant in the lives of many people, particularly in late childhood and adolescence when young people are trying to establish their independent existance, find acceptance, and create an identity. Peer pressure affects people of all ages, and studies have shown that even adults may change their drinking habits in response to it [19].Shushtari et al (2018) stated that a social network or personal network is a group of connections (ties) between people (actors) who communicate and share interests.[20] In the present study, a social network is constructed considering participants as individual nodes, with connections between nodes established based on friendship or shared interests (in our context of drinking). The main goal of our study is to investigate the peer relationships amongst adult people living in a village that are built on friendship and drinking together behaviour. Several network parameters are examined in this study, including as centrality measurements, density, average shortest path length, average clustering coefficient, robustness etc., which provides a good understanding of the Peer Adult Network model. Moreno et al (1934) stated that some nodes in a graph are classified as "stars" because of their particular significance and influence and there have been numerous methods for determining a node's centrality. Within this group of parameters, four metrics—degree, proximity, betweenness, and eigenvector centralities—stand out as being fundamental to the area of SNA. They all have solid yet distinctive theoretical foundations (Freeman, 1979; Bonacich, 1972, 1987), and they are commonly employed for empirical research of social systems, which contributes to their importance within the field of network analysis [21]In the current study, we also identify central(star) individuals who hold influential positions within the network using SNA. The positions of the individuals of the proposed network model are calculated by calculating different centrality measures as mentioned above and showed in table 2.Current findings demonstrate that the individual from whom our investigation began is the most crucial, influential, and important contribution node of the suggested network model. Person 3, Persons 23 and Person 52 are the other major contributing and influential participants along with the index case, which is shown in Table1, but interestingly, when we look at the degree of connectivity, we discover that the majority of the participants have significant roles to play within the network. Knox J et al. (2019) systematically reviewed empirical studies that used social network analysis to assess the influence of social network characteristics on drinking behaviours in adults and demonstrated how patterns of relationships between social actors and peer drinking behaviour affect an individual's drinking behaviour. [1]. Barnett et al. also constructed peer network to examine associations between peer behaviours and alcohol use, marijuana use. They formed clusters and found that the drinking volume of nominated peers was significantly positively associated with participant drinking volume.[22] In the current study we only examine the influence of peer on drinking. Various centrality measures of the proposed network model have suggested the influence of key nodes on drinking behaviour of others as shown in table1.

Numerous real-world networks were empirically examined as small-world networks by Watts and Strogatz (1998), who concluded that many real-world networks meet the criteria being small-world networks. Similar to that, empirical research reveals that many networks in nature are highly connected and highly clustered, much like the small world network. The current study compares the Peer Alcohol Network's clustering coefficient's (0.4207) and path length's (2.4079) values with the clustering coefficient (0.0541) and average path length (3.4737) of a regular lattice of similar size. And it is found that the Peer Alcohol Network is highly clustered and has short global connections, which shows that it exhibits small world property. Again, the degree distribution of the Peer Alcohol Network (see Fig 2) suggests that it is a scale free network. That means there are very few people with large number of peers and also number of people with very few peers is also low in the network.

Understanding the robustness of basic network measures is extremely important in order to assess the validity of network (Carley et al., 2001; Carley, 2003). According to Gunasekara et al (2012) it's crucial to analyse interactions between network members, such as those in the alcohol or criminal industries, in order to uncover hidden relationships and power structures. Knowing a network's model or pattern can help determine how robust a network is and what activities might make it robust. [23] Figures 3 and figure 4 depict how participants are interconnected as observed during the removal of important characters or actors. The subgraphs are still connected after three or four of the network's most significant contributors are removed. Only one (person 29) of the 60 participants is cut off from the network as shown in figure 5, figure 6 and figure 7. The values of density, average clustering coefficient, and average path length, percentage change in average clustering coefficient and percentage change in average path length following the deletion of significant contributing nodes (based on degree centrality) from the graph, are shown in the table 2. After elimination of three members, the shortest path length is not reached, but the graphs indicate that the subgraph is still entirely connected. Table 3 also displays the reduced networks' average path lengths.It is expected that average path lengths should increase, and average clustering coefficients should decrease after high degree nodes are removed [24] In our investigation, we have found that average path length has increased, and average clustering coefficient has decreased. Positive signs suggest an increase in values, whereas negative signs indicate a decrease in the parameter. (see table 2). One of the important findings of the current study is that though the formation of network began with the identification of index case and other persons nominated by him, removal of index case from the proposed network is not sufficient to disrupt the network (fig2). Only one node disconnects when three nodes P1, P52, and P3 are removed, but the connections between the other nodes remain, as seen in figure 4. The proposed network mode is not changed even after the removal of four nodes (P1, P52, P3, and P23) and five nodes (P1, P52, P3, P23, and P50). Figures 5 and figure 6 also demonstrate that only one node (P29) is disconnected. This means persons continues to drink even in the absence some of the persons who drink from their network. This finding is similar to the findings of Havassy et al (1991) who commented that having even a single person drinking in a social network can predict high chances of relapse of alcohol. Barnett et al. (2014a) examined five distinct social network characteristics for alcohol consumption and alcohol-related problems in a college residential network but in our case the population are primarily adults [25]. Numerous research demonstrated that edge deletion or node deletion techniques can both be used to examine the robustness of a network. They observed that the four community-based metrics of robustness are the average degree inside the communities (ADC), average community size (ACS), average clustering co-efficient (ACC), and average distance between all the nodes in a community (ADB). Average shortest path length reveals whether the social network's size has grown or reduced. nonetheless, the clustering coefficient reveals how tightly connected a network's nodes are (*Borgatti* et al 2006), Gunasekara et al 2012) [21], [23]. The current study, which is comparable to them, employed the node removal technique. Measures of the average shortest path length, average clustering coefficient, and density are displayed in Table 2. Such community-based measures to calculate robustness of networks are also employed in other fields also including airlines network [24] thus proving its utility. In the present study, we specifically design the adult social network, and our study is limited to investigating the several network parameters of the proposed network. It is noted from the existing literature that the majority of the substance use disorder networks were constructed based on frequency and period of consumption, social, physical harms of substance use etc. On the other side, robustness testing was done on several networks, including aviation and criminal networks. Nevertheless, the current study is unusual because, to the best of our knowledge, it is the first in this region of the country to test the durability of the adult alcohol network.

7. Conclusion:

This study provides the unique insight into the behaviour of alcohol use such as: (i) Peer Alcohol Network exhibits small world property, that means the accessibility among the peers is very high, (ii) the network possesses scale free property, that meansformation of hubs is very likely and one can identify the hubs and counselling may be easier through the hubs,

(iii) the network is robust, that means removal of high centrality individuals is not going to alter or destroy the formation of the network easily.The findings are of importance in knowing the spread of alcohol use in the community. Knowing the key persons in the community who drink alcohol is important in the sense that they play a pivotal role in influencing others around him to initiate and continue drinking. However, disruption of this network is not possible only by removing the key person from the network. From the psychosocial perspective, even after treatment of cases with alcohol use disorder, the chance of relapse increases when they mingle with peers who drinks alcohol. Complete disruption of network is possible only when most of persons in the network are targeted for intervention in the form of treatment both medical and psychological so as to prevent the spread of alcohol use disorder along with other strategies like demand reduction.

Acknowledgement:

We extend our heartfelt gratitude to Dr. Ankur Bharali, Professor of Mathematics, Dibrugarh University for his guidance.

Conflict of Interest: None

Reference:

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