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RESEARCH ARTICLE

Use and Usefulness of Social Network Analysis in the Primary Health Context

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Abstract

Background and Objectives: While social network analysis has left a remarkable practical impact in the healthcare field, the potential implication of this methodology in the primary health domain is poorly researched. Hence, this study aimed to explore the use and usefulness social network analysis in the context of primary health care.

Methods: The health volunteers of Imam Ali Health Center in Isfahan city (situated in Central Iran) participated in a plan aimed at helping prevention of depression in 20-45-year-old mothers. Each health volunteer was asked to choose 5 to 20 individuals from the population they covered. Data were collected using a questionnaire in which each health volunteer determined which other volunteers they interacted, and what direction and frequency each interaction represented, during administration of the plan. An interaction was defined as the exchange of information related to the plan between volunteers. A series of network structure variables including degree centrality, betweenness centrality, density degree were calculated. A novel function-oriented network variable, termed activity performance was also introduced and calculated. The activity performance rank of the six lowest-betweenness-centrality-rank individuals were compared with their rank in gatekeeping list for validation of the new network variable.

Findings: The key members, gatekeepers and week members of the analysed social netwrok were identified. The network was revealed to be relatively homogenous. The average distance between individuals was 2.85 across the whole network and ranged from1.03 to 1.86 within the subnetworks. The individuals' activity performance ranks were congruent with their betweenness centrality ranks, suggesting the validity of the introduced network variables.

Conclusions: Social network analysis can help identify the strength and weaknesses of health-related networks in the primary health context. Elucidation of the network structural characteristics can help improve network interactions, reconciling the network paths, and reinforcing its structure, which in turn can lead to a higher performance of network-based health-related plans. The consistency between activity performance rank and betweenness centrality ranks indicate the validity of the former new variable as a complementary measure be used for a more informative social network analysis.

Keywords: Social Network Analysis, Primary Health, Health System, Health Services Delivery, Health Services Performance

Background and Objectives

Over the past two decades, the policy emphasizing the priority of prevention over treatment has promoted the status of primary health centers in the health system [1]. Health centers offer health coverage to areas of around 60000 populations in terms of disease control and prevention, health information collection, and health-related training. These centers typically need one health volunteer for every 50 to 100 households, who are chosen from among the community under coverage. These health volunteers establish a strong social network with the households under coverage and function as connecting bridges between households and the primary health centers. In this social network, health volunteers are dependent on and affected by the members of the network in terms of information exchange and quality of the services they delivered [2].

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Social network analysis is used to study the patterns of interactions among a set of individuals, organizations, and agencies [3]. For example, in a hospital, a physician may seek consultant in treatment of their patient or offer consultant to other physicians. Such communications induce a series of interactions in a particular medical ward or at the whole hospital level, potentially influencing other healthcare staff [4]. Evidence shows that the nature of these interactions can greatly influence the quality of services delivered, rendering analysis of the social networks important to promotion of community health [5, 6].

Social Network Analysis (SNA) is defined as a series of theories, tools, and processes allowing better understanding of the structure of a social network and the interactions within it [7]. Although the use of SNA within the health field has remained limited, it has left a remarkable impact in the healthcare domain [8, 9]. For instance, a study by Chen (2007) in Tiwan, titled "Incorporating geographical contacts into social network analysis for contact tracing of epidemiology of SARS", greatly contributed to successful control of SARS and diseases of similar epidemic pattern [10]. In another study, Pinquart (2010) identified an impact of social networks on reducing cancer mortality and helping cancer patients [9].

In the SNAs carried out in the field of health and heath care, individuals (physicians, nurses, and other staff) are denoted as nodes, and interactions among them are represented as ties [3]. The interactions can represent, for instance, as information exchange or advice-seeking [11-14]. Such interactions create a network structure, whose analysis would identify the strengths and weaknesses of the network operation from different perspectives, and facilitate planning to improve the network interactions, thereby enhancing the quality of care [3,4].

Lack of research on the potential impact of SNA on primary health system improvement motivated us to conduct a study of the kind. The data used in this study were extracted from a broader study by the same authors [14], aiming at identifying depression rate and helping its treatment among the population covered by a primary health center. The health volunteers worked for 10 months under full supervision of the researchers and the interactions among them were constantly analyzed. In the next step the obtained data were visualized and analyzed to yield insight into the potential contribution of SNA to health services improvement.

Methods

Population of the network

In an extensive research [14] from which the required data for the present study were provided, the health volunteers of Imam Ali Health Center in Isfahan city (situated in Central Iran) participated in a plan aimed at helping prevention of depression in 20-45-year-old mothers.

This health center has four local stations, each involving a number of health volunteers proportional to the population under their coverage (Table 1). Each health volunteer was asked to choose 5 to 20 individuals from the population they covered. Given that each health volunteer was responsible for more than 50 households, it was equally feasible for each to determine a samples size of up to 20. All 38 volunteers of the center were willing to participate in the study. A coding system comprising the ID of the local station the voluntary was applied, and the code of each volunteer (e.g. local X – code name) was used for identifying each volunteer.

Data Collection

Data were collected using a questionnaire in which each health volunteer determined which other volunteers they interacted, and what direction and frequency each interaction represented, during administration of the plan. An *interaction* was defined as the exchange of information related to the plan between volunteers.

Network Analysis

Each node (health volunteer) in the network was analyzed using two approaches: *Network Structure Analysis* and *Activity Performance Analysis*.

Network Structure Analysis

One of the most frequent applications of SNA is the identification of the *important* nodes in human social networks. To identify the importance and status of each node in the network, a number of network structure variables, including Degree Centrality (DC), Betweenness Centrality (BC) and Closeness Centrality (CC) has been introduced [15, 16], from which the first and the second were used in this study.

DC is defined as binary relationship between the nodes. This measure is categorized into two groups of *in-degree* and *out-degree* centralities. In our study, the in-degree centrality determines how frequently a health volunteer has been a receiver of interaction from the other volunteers, while out-degree centrality indicates how frequently a health volunteer has been an initiator of an interaction. In-degree centrality

$(C_{D,in})$ and out-degree centrality $(C_{D,out})$ of a specific node are generally calculated using the following formulas, respectively:

$$C_{D,in}(n_i) = \sum_{j=1}^{N} l_{ij.in} \quad (1)$$

$$C_{D,out}(n_i) = \sum_{j=1}^{N} l_{ij.out} \quad (2)$$

where l_{in} and l_{out} denote the number of inward or outward connections of node i respectively, and N denotes the number of nodes (vertexes) inside the network (mesh). In-degree centrality of a node i is calculated as the sum of the number of nodes j in the network that connect directly from node j to node i. Out-degree centrality of a node i is calculated as the sum of the number of nodes j in the network that connect outwardly from node i to node j [15].

Key members of a network are the members with

$$C_B(i) = \frac{\sum_{i \neq j \neq l} g_{jl}(i)}{g_{jl}} \quad (3)$$

the highest out-degree centralities. The following classification of the out-degree centrality scores facilitates identification and ranking of the network's key members: High (out-degree ≥ 5), Middle (3 ≥ out-degree ≥ 4), Low (1 ≥ out-degree ≥ 2) and Very Low (1 ≥ out-degree).

On the other hand, the BC is defined as the average number of times a particular node is located on an interaction path. The BC (C_B) of a node is formulated as follows:

$$C_{De} = \frac{n(ei)}{n(pi)} \quad (4)$$

Table 1 Distribution of the health volunteers in the health center's local stations

Station	Number of volunteers
1	13
2	6
3	5
Z	14
Total	38

where $g_j(i)$ is symmetric to the number of shortest paths that colligate node j and node l through node i.

BC can help identify the network's powerful members, called the *gatekeepers*.

This study also used another network structure variable, *i.e.*, Density Degree (DD), which is defined as proportion of existing interactions through a node to all corresponding potential interactions. DD (C_{De}) is formulated as the following:

where *n(ei)* is symmetric to the number of existing interactions and *n(pi)* is symmetric to the number of potential interactions.

Activity Performance Analysis

Activity performance accounts for a volunteer's *efficiency* and *effectiveness*. A volunteer's efficiency of activity is defined as the number of individuals introduced by them (that can vary from 5 to 20) to participate in depression preventive plan. A volunteer's effectiveness*,* on the other hand, is referred to as the level of influence each volunteer has on the depressed individuals under their coverage. This influence has is scored according to the Table 2. Since efficiency and effectiveness are measured by different criteria, they were normalized for the ease of comparison. These measures were then summed up to yield the Activity Performance score for each volunteer. The network was visualized using Net Drawand analysed using UCINET6 [15-17].

Table 2 Action of individuals under follow-up, following the activities of the volunteers

Action of individual under follow-up	Score
Doing nothing	0
Changing the lifestyle	1
Decided to make treatment plan but doing nothing yet	2
Referring to a consultant	3
Refer to a psychologist or psychiatrist	4

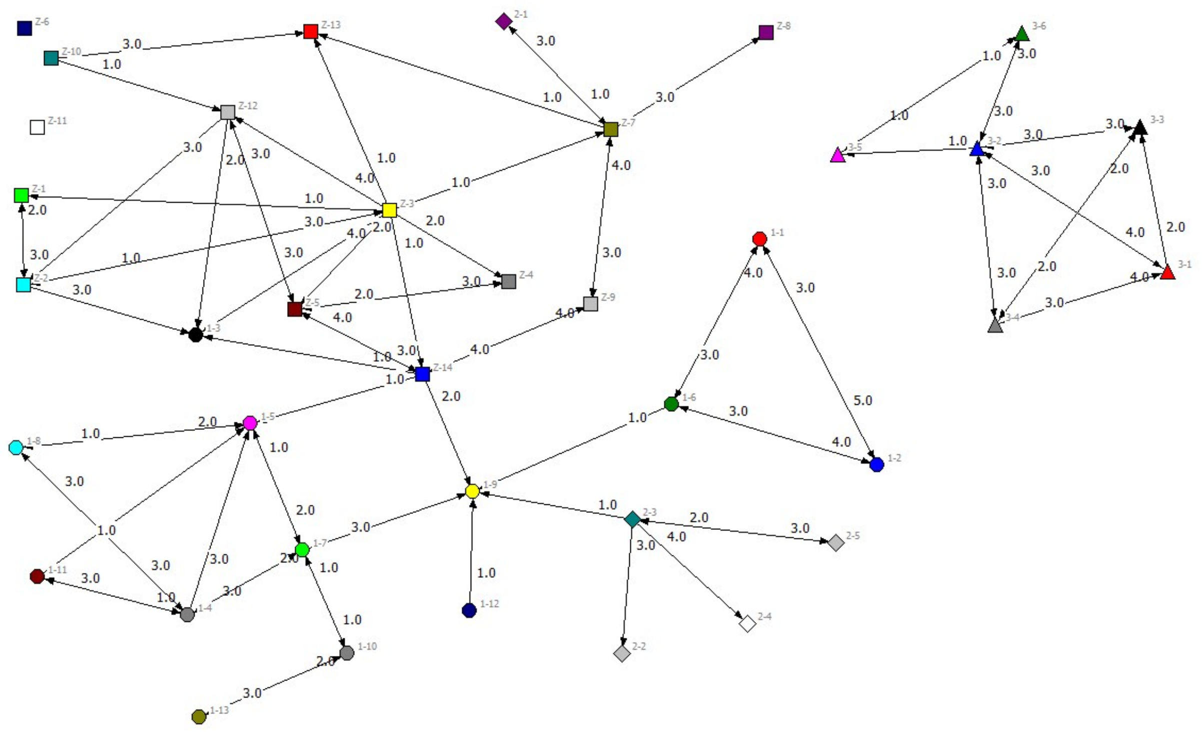

Figure 1 The network of health volunteers

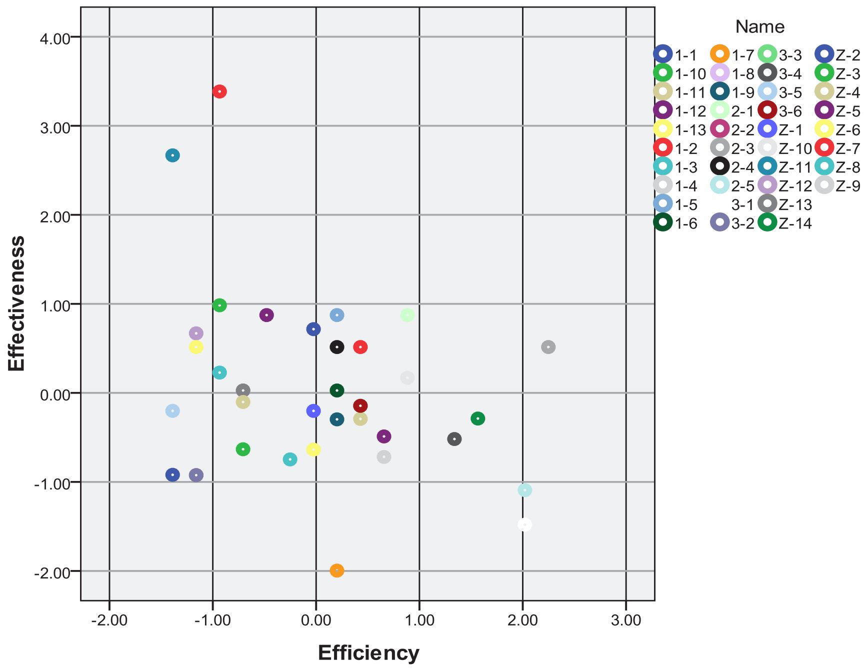

Figure 2 The scatter plot of effectiveness vs. efficiency of the health volunteers

Table 3 Seven health volunteers with the highest performance activity scores

Volunteer's code	Performance activity score	Rank
2-3	2.76	1
2-1	2.45	2
1-2	1.75	3
Z-11	1.29	4
Z-14	1.27	5
Z-10	1.05	6
1-5	1.04	7

Ethical issues

An approval of the Ethics Committee of Iran *University* of Science and Technology, and the Ministry of Health of Isfahan city was obtained for conduction of the study. All ethical issues concerning the rights of health centers and health volunteers were heeded.

Results

Network structure

Figure 1 displays an overall perspective of the network structure, where each node represents a health volunteer and each line represents an interaction between a particular volunteer and another one. The digits above each line show the number of interactions between volunteers. The efficiency and effectiveness scores of the volunteers are given in Figure 2 and the six top-ranked individuals are listed in Table 3.

Table 4 Density degree of the subnetworks in four stations of the health center

Station	Density degree
1	0.16
2	0.20
3	0.53
Z	0.14

Intuitive analysis of the network

The social network of health volunteers (Figure 1) indicates that the links between nodes are weighted. These weights indicate the number of interactions among health volunteers. For instance, volunteer 1.2 has interacted with volunteer 1.1, in which 2.1 has been an initiator for five times towards 1.1 and has received interaction from 1.1 for three times. Figure 1 also shows the density of interactions in different parts of the network, both within and among local stations.

Table 5 Seven health volunteers with the highest frequency of out-degree interactions

Volunteer's code	Number of individuals the volunteer interacted outwardly	Rank
Z-3	9	1
3-2	5	2
Z-14	5	3
Z-7	4	4
1-7	4	5
1-4	4	6
2-3	4	7

Table 6 Seven health volunteers with the highest betweenness centralities

Volunteer's code	Betweenness centrality	Rank
Z-5	55.5	1
Z-14	48.75	2
Z-12	44.5	3
Z-9	42.5	4
Z-2	36.5	5
Z-7	28	6
1-7	24.25	7

Distance between individuals within the network

Geodesic distance of the network averages 2.85, which indicates that each individual within the network is only two to three steps away from another. On the other hand, the average distances in the subnetworks within the local stations ranged from 1.03 to 1.86. This observation indicates that within each local station, each individual is on average only one to two steps away from another.

The network density degree

The DD was calculated to be 0.05 throughout the network, indicating that only %5 of the potential interactions has been realized. On the other hand, the density of interactions is very high in some areas of the network. These areas correspond to the local station subnetworks, whose DDs are presented in the Table 4. As seen, although all the health volunteers have been trained and started their activity at the

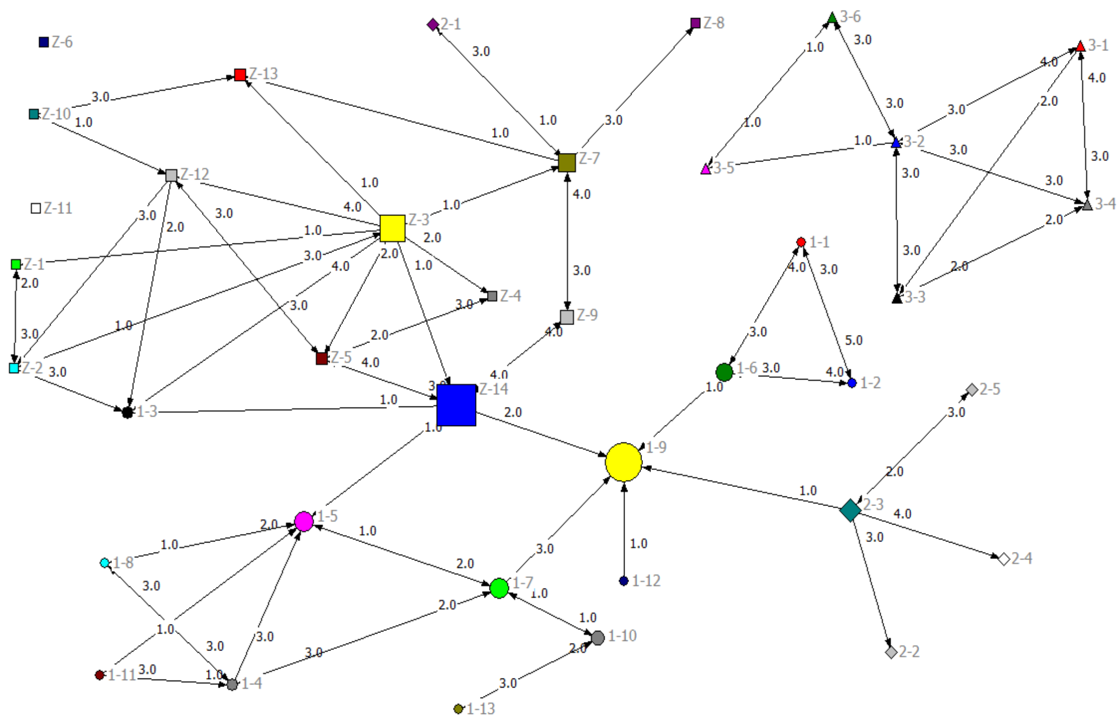

Figure 3 The health volunteers' network structure with the node sizes proportional to BC

Table 7 Comparison of network variable scores of seven weakest health volunteers

Volunteer's code	Key-members rank	Activity performance rank	Gatekeeping rank
1-3	Very low	32	38
1-9	Very low	23	37
2-2	Very low	37	36
Z-6	Very low	26	35
Z-8	Very low	30	34
Z-13	Very low	28	33

same place, the DD within the local station subnetworks is greater than that within the whole network. The highest density of interactions was observed in local station 3. The DD of the subnetwork of this station is 0.53, which indicates that more than half of the potential interactions in this station have taken place. Similarly, the station Z shows a DD of 0.14, indicating that only %14 of the possible interactions have been realized in this station.

Average frequency of interactions within the network

While the frequency of in-degree interactions within the network averages 2.05, the out-degree interactions show an average frequency of and 2.1. These values imply that, each individual has been an initiator and a receiver of interactions for average twice.

Reciprocal interactions in the network

Average frequency of the reciprocal interactions throughout the network was calculated to be 0.49, indicating that almost half of the possible interactions within the entire network have been of bi-directional.

Identification of the key members

The key members among health voluntaries are those who had the largest number of out-degree interactions. Table 5 shows seven individuals with the highest frequency of out-degree interactions. The volunteer Z-3 has managed to develop 9 out-degree interactions, receiving the first rank in the network.

Identification of the powerful members

The powerful members of the network, the *gatekeepers* (Table 6), are identified by BC. Figure 3 shows the BC of health volunteers, where the size of each node is proportional to its BC. The individuals with the highest BC scores have been more frequently present on the path of interactions as compared with the other members, and hence exert higher influence on the network interactions.

Identification of week members

Table 7 shows activity performance rank, key-members rank, and gatekeeping rank for the six lowest-BC-rank volunteers. As seen, the individuals with low gatekeeping ranks, also gain the lowest key-members rank and record a very low activity performance.

Discussion

The chief objective of this study was to tailor the use of SNA to the study of health-related networks developed in the primary health context. Our analysis of the network of health volunteers calculated several network variables that can be used for better and multi-faceted understanding of the network structure and interactions. For instance, our analysis identified the most powerful and the weakest members of the network, the average distance between the nodes, the density of interactions within the network, and the share of the bi-directional interactions from the total. These data can be used for improving network interactions, reconciling the network paths, and reinforcing its structure, which in turn can lead to a higher performance of network-based health-related plans.

Comparison of our network quantities with those of other networks can provide further insight into the latent characteristics the study network. In our network, an average geodesic distance of 2.87 was calculated between each individual, which is considerably higher than the 1.78 value in the network analyzed by Crewick. This indicates that our network is a less cohesive one, and the information flow throughout the network takes more time when compared with the Crewick's network.

While the DD in the Crewick's network was computed to be 30%, our network represented a DD of only 5%. However, when evaluated in the local stations, this figure changes. While in the Crewick's network [4] a local DD of 64% at best, our network's highest local DD was calculated to be 53%. The fact that distance and density are different in different parts of the network when compared to the whole could be attributed to the presence of the network clusters. Crewick found clusters of interactions between individuals with similar educational background and Meltzer et al. (2010) identified clusters of interaction between individuals of identical previous workplace. As these clustered are formed naturally based on the background characteristics of the network members, they usually reflect robust and potentially effective interactions. Hence, it is recommended that these clusters are conserved when restructuring the network for new plans [19].

In our network, more reciprocal communications was observed in comparison to the previously studied networks, in which the relationships between physicians and other staff in medical departments were analyzed. For instance, in the Crewick's network [4], reciprocal relationships accounted for only 30% of all the interactions, which was considered by authors as very low. However, in the present study, 50% of the relationships were of reciprocal nature. In the organizations with strict hierarchy, limited reciprocal interactions can form, because the individuals at higher levels are often reluctant to initiate an interaction with the lower level members. Boyer *et al* [3], in a hospital SNA study showed that while individuals' age and gender had not a significant impact on the nature of network interactions, individuals with more important position and higher degree of education are less incline to make outward interactions. However, in our study, volunteers' uniform organizational position and similar level of education create a flat organizational structure and a homogenous network allowing for development of reciprocal interactions.

Calculation and ranking of the DC of the network nodes led to identification of key members of the network. The networks, key members should receive especial attention, as their performance can highly impact the quality of overall network interactions [19].

Our analyses also identified the network's gatekeepers, *i.e.* the powerful members of the network. Such members can effectively contribute to expanding and controlling the interactions. The particular importance of these nodes is related to their ability to connect different parts of a network. For instance, the health volunteer Z-14 (Figure 1) who has the highest BC, has been able to link three major areas in the network, reside on their interaction path, and control the interactions.

On the other hand, some members of the network were identified as weak. These are members who either have not developed any interaction or have been merely the receivers of the interactions. For instance, voluntary 1.3 who has the lowest BC, had developed only four interactions, all of which being one-way inward, creating no functional pathway for transferring information. The information exchange in this part of the network can hence be improved by removing the current obstacles or substituting the week members by more powerful members.

According to Boyer *et al.* (2008) [3] incorporating more variables into SNA would allow deriving more insights from such of an analysis. Our study introduced a novel network variable with the potential to expand the scope of SNA: node activity performance. Using such measures in scoring the nodes of a network can help functional evaluation of the network members. Table 7 shows that the individuals with the lowest gatekeeping scores have also received the lowest scores among the key members, and recorded a very low activity performance as well. This observation implies that the members with limited ability to develop adequate interactions with other members, have also limited ability to perform their function, in terms of introducing the depression-prone individuals to the health center or positively influencing their health. We can therefore conclude that individuals with low network measures would have low performance as well. This consistency validates the network variable introduced in this study to be used as complementary measures for a more informative social network analysis.

Conclusions

This study exemplified the use and usefulness of social network analysis in the context of primary health care. Using SNA techniques, a series of network variables, including degrees centrality, betweenness centrality, and density degree were calculated for a network of health volunteers seeking to support the health of a depression-prone population. Computation of these network variables revealed the key members, gatekeepers, as well as the week members of the network, whose identification can lead to better and multi-faceted understanding of the network structure and interactions. Calculation of the average distance between network members yields a measure for the speed at which the information can flow through the network. Enumeration of the reciprocal interactions reflected the underlying homogeneity of the network. Elucidation of these network characteristics can help improve network interactions, reconciling the network paths, and reinforcing its structure, which in turn can lead to a higher performance of network-based health-related plans. In addition, our study introduced a new network variable, *i.e.* node activity performance which can be used in functional evaluation of the network members. Showing consistency with the previously established network measures, this new measure can be used for a more informative social network analysis.

Abbreviations

(SNA): Social Network Analysis

Abbreviations

(SNA): social network analysis; (DC): degree centrality; (BC): betweenness centrality; (DD): density degree

Competing Interests

The authors declare no competing interests.

Authors' Contributions

SMHM designed the study, coordinated provision of the requirements, and contributed to the revision of the manuscript. MMRP had the major contribution to data collection, network analysis, interpretation of the network analysis results, and drafting and revising of the manuscript. EB contributed to network analysis and the interpretation of the results. FN assisted in medical and psychological aspects of the study. All authors read and approved the final manuscript.

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