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Mapping and Social Network Analysis of the Nurses of Razi Hospital

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Abstract

Background: Nurses frequently work as part of teams. High-quality care can only be delivered through effective communication among team members. Social network analysis (SNA) seeks to discover the connections. In a hospital, connection between nurses working in different departments is critical. In the same vein, groups of nurses and their social relationships in hospital settings are highly important. Networks play a significant role in work settings such as hospitals. The power of clusters (i.e. groups or teams of nurses) could be regarded as net capacity. If the power of a cluster increases, strength and quality of offered services will rise too. The social network analysis is intended to discover the associations and represent them graphically (i.e. qualitative representation). This means social connections are represented in a quantitative and mathematical language.
Objectives: The present study aims to examine the relationships between nurses working in Razi Hospital (Rasht, Iran), analyze the relationships through social network analysis, categorize as well as cluster the network of nurses at Razi Hospital, and represent the resulting data of social network analysis as network graphs.
Patients and Methods: This study employs soft system operation research as a qualitative research strategy to deal with the network of nurses working at Razi Hospital during 2016 in Iran as a case study. In terms of its area, Razi is the largest hospital of the Gilan Province of Iran. In this regard, 64 nurses engaged in the study through deep interviews with from 6 various departments of the hospital according to SNA procedure. The gathered qualitative data was analyzed using the Gephi software; ultimately, findings are depicted as network graphs in section 5.
Results: Nurses network of Razi Hospital (Rasht, Iran) includes 64 nodes/nurses and 168 edges/links, which are non-directional and weighted. After implementation of different steps in social network analysis, it can be state that, nurse network of the hospital includes 9 clusters out of which, 6 clusters belonged to studied departments. Due to the network low density, which is 0.083, the network has low coherence. This means that only 8.3% of the total potential and potential relationships in the network have been activated. Results concluded that, unfortunately, only members of different departments interact with each other and in the section, they work in.
Conclusions: In Razi Hospital, network of nurses is characterized by weak connections between different departments. However, the relationship between members (i.e. relationship between nurses in a department) is strong and this signifies that nurses of a cluster or department are related to each other. The findings suggest that members of a certain department as well as between departments should closely associate with each other. In addition, there is a significant association between those departments of the hospital in which nurses are working. We can use significant association in health care aspects that require organizational and organizational decision making. Nurses play an important and critical role in planning the main functions of hospital management.

Keywords: Graph Theory, Social Network Analysis, Centrality

1. Background

The present study aims to investigate the nurses' network of Razi Hospital of Iran. Nurses always work as part of teams or groups. The relationship that exists between team's members plays a key role in providing well services to patients. Created group among nurses and their social relationships are very important in the hospital environment. Networks play a vital role in workplaces such as hospitals. The strength of clusters can be defined as network capacity, meaning clusters, groups or teams that are nurses working in sections that are working or even in hospitals, such as friendships, etc. If cluster power increases, this will lead to increase in the power and quality of the provided services, which can ultimately affect the sector service quality as well as the nurses' job satisfaction. Social network analysis approach seeks to discover these relationships and eventually depict them in the form of a grid graph, that is to say, quantitatively, which means that social communication can be presented in a quantitative and mathematical language. The purpose of this study is to investigate the relationships between the nurses of Razi Hospital using the social network analysis approach, which leads to their networks clustering, which can be depicted in network graphs.

Therefore, this study aims to cope with the following research questions: firstly, what is the social network of nurses who work at Razi Hospital according to the social network analysis approach? Secondly, how many clusters exist in the social network map of nurses at Razi Hospital?

So far, the social network analysis approach in the hospital has not been used to discover the relationship between nurses.

1.1. Literature

Wasserman and Faust (1994, p. 21) believe that these methods change the main ideas of sociobehavioral theories and transform them into formal descriptions, presented as relational terms (1).

Although social network analysis is seen today as a multidisciplinary pursuit, historical accounts tend to agree that the field was more or less started through the efforts of Jacob Moreno, a student of psychiatry from Vienna, who immigrated to the US in 1925 and developed the field of 'sociometry', widely considered the precursor to social network analysis (2). Moreno studied psychiatry, and through his studies, he became acquainted with Gestalt psychology, a sub- field in psychology that looks at the interplay between perceptions and larger structures of the human mind (2).

The pioneering work Moreno (1934) introduced an important graphical tool of sociogram, that is, "a graph that visualizes the underlying structure of a group and the position each individual has within it" (3-5). SNA is closely related to economics, political studies, medicine, and health care. On a parallel line of research, Wiener believed that this new science should become a powerful tool in studying social processes, arguing that "society can only be understood through a study of the messages and communication facilities, which belong to it" (1). This requires developing mathematical models that are sufficiently "rich" to capture the behavior of social actors, but are also "simple" enough to be rigorously analyzed. Mathematical methods of SNA have focused on graph-theoretic properties of social networks (6-8).

1.2. Graph Theory

Mathematically, a graph, G, is defined as a structure constituted by a finite and not empty set of nodes (vertices), $V(G) = \{V_1, V_2, \cdots, V_n\}$, and a finite set of edges (links) E(G), consisting of pairs of nodes from V (G) (not necessarily ordered or different).

The order or cardinality of a graph is the number of elements of the set of vertices V (G), i.e., #V (G). The edge set E (G) leads to a binary relation in V (G) and is called an adjacency relationship between the vertices of G. A network with n vertices is represented by an adjacency matrix A (G) with $n \times n$ elements, where:

$$a(v_i, v_j)\begin{cases}1, \ if\ v_i\ and\ v_j\ are\ connected\\ 0,\ otherwise\end{cases}$$

Equation 1

If an incident edge connects vertices v_i and v_j of a graph, then it is said that these vertices are neighbors or adjacent. The neighborhood of vertex vi is the set formed by all vertices adjacent to it (9).

A graph demonstrates the network structure. A set of nodes (vertices) as well as a set of lines (every line links 2 vertices) are needed for the graph (10).

Connections among the nodes are conveniently encoded by the graph's adjacency matrix $A = (a_{ij})$. In graph theory, the arc (i, j) usually corresponds to the positive entry $a_{ij} > 0$. In multi-agent control and opinion formation modeling, it is however convenient1 to identify the arc (i, j) with the entry $a_{ij} > 0$ (11).

1.3. Network Analysis

The term "network" has become a pervasive spatial and organizational metaphor for describing sets of complex interactions (12). Networks are typically represented as diagrams of node and links between these nodes (13).

A sociocentric network is composed of a single, bounded community that has complete or whole links among members. The whole structure of this network can be generalized for other networks having different patterns of interaction within defined groups (13).

Network analyses can be used to identify the organizations or actors in a network that serve as integral links to that network, also known as a key player(s). Like all network analysis, it is based on the assumption that there is importance in the relationship among the interacting units (14).

1.4. Social Network Analysis (SNA)

A social network can be defined as a set of people or actors, where each one of them has some sort of connection (link) to some or all other actors (15).

Recently, the study of the relationships present in social networks are receiving great attention with the aim of characterizing their topological complexities, namely: the analysis of their links' patterns, interactions, and implications. Such analysis has been facilitated through the use of Graph Theory and a set of mathematical algorithms (5). This approach is known as Social Network Analysis (SNA) (9).

The social network analysis constitutes the methodical framework of this paper as mentioned before. The structural components of a network - nodes, which are connected by edges, are in this setting the organizational units (nodes) connected with one another through 1 or more collaborative research projects (edges). More formalized the collaboration network is a weighted and undirected graph. The direction of an edge does not matter, however, capturing the number of shared projects is an essential condition (16).

In a social network, entities (e.g. people, organizations, countries, etc.) are connected in various ways with various levels of interaction. The entity is referred to as a node, while the connections between entities are known as links (14).

According to the presented definitions, which promote the same concept, SNA focuses on the structure and pattern of interacting entities. Development of personal relations provides the chance of exposure to different types of information; these relations are essential to transfer knowledge and teach (1).

Social network analysis (SNA) is a technique that is increasingly used to identify the way information flows between different individuals, organizations, or entities (17). The analysis can be presented as a visualization of the relative spatial location of the individuals and the associated connections between them (18).

A basic concept in SNA indicates that group performance, as well as group's impact on its members, is dependent on the structure of relations in a network and to attain and maintain status (19, 20).

For Granovetter (21), the link's weight can be defined by the frequency of the relationship, emotional intensity, intimacy and mutual service between nodes (9), as well as organizational and industrial structures (22), subsidiary strategy, brand communities and customer relationships (23, 24). Furthermore, interest in the dynamic influence of social ties on organizational networks across and within different locations has been explored in the context of multinational companies (25, 26).

SNA has been extensively examined over the past years, particularly in the last decade considering the advances in graph theories (5, 27).

These networks can be presented as graphs, with actors described as nodes and relations among actors represented as arrows (28).

Social network analysis is the examination of the individual elements or nodes in a network and the nature and extent of connections and relationships, particularly social structures (13).

Mitchell defined SNA as "a specific set of linkages among a defined set of persons", with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the person's involved (29).

SNA is a method for mapping and evaluation of interactions and relationships among groups, organizations, websites, and other entities involved in information processing. In fact, the study of interactional patterns can present new information. The entities constitute the nodes in graphs. These graphs can provide valuable information for researchers and help them formulate hypotheses on the phenomena under study (1).

SNA is described as the assessment of social interactions, based on the network theory, where the actors are described as nodes and interactions are represented as arcs between the nodes (5, 27, 30).

Wasserman (1994) believes that SNA is developed based on important relations among communicating units. Freeman (1979) describes SNA as a technique, focusing on implicit interactional patterns. Moreover, Scott (2012) has introduced methods to examine different aspects of relations in the social structure; these strategies and methods are tailored to investigate relations in a given structure (31).

1.5. Centrality

In SNA, centrality describes the value of major nodes in a network (32). It describes the number of connections from 1 node to others. Centrality measures can provide useful information about the functioning of the social network (14).

Centrality in a network can be defined in different ways, including betweenness, closeness, degree, and eigenvector centrality. The prominent nodes have the highest weight of interactions and connections among users (33).

1.5.1. Degree Centrality

Degree centrality describes the number of relations, branching from a node (32). A node with various connections is considered as the central actor. In this study, the most popular people are those with the most friends; therefore, degree centrality is measured with respect to the number of connections (34).

Degree centrality is recognized as the easiest measure of centrality, which determines the number of ties between a node and others in a network. It is described as a measure of immediate connectivity of a node and its exposure to the information flow in the network (35).

The degree centrality coefficient denotes the actual number of possible relations for a person. The score is presented as proportion, ranging from 0 (each member is connected to all other members) to 1 (all members are connected to each member) (36).

1.5.2. Closeness Centrality

Closeness centrality is a measure, based on geodesic distance from a given node to all other nodes. The central node is the one, which is close to other nodes. Assessment of closeness centrality determines the safety, availability, and security (32).

Closeness centrality is a measure of the extent to which an individual node is connected to all other nodes and is an indicator of the extensiveness of involvement in communication relationships with other actors (37).

Pan (2007), based on various studies, closeness centrality may be an inefficient measure in some cases (particularly if the network is large) (34). Mean distance is from a given starting location to all the other reachable locations in the network (38).

1.5.3. Betweeness Centrality

Betweenness centrality is a measure, evaluating a node's ability to connect other nodes to one another through the shortest path. Therefore, in this approach, the number of shortest paths through the node is determined (5). The node with the greatest betweenness centrality can affect other nodes via communication (32).

Betweenness centrality is the number of times a person acts as a bridge between 2 other people or how probable it is for an individual to be the most direct route among people inside the network. It also determines how commonly a person plays an intermediary role (39).

Betweenness is used to identify which of the actors in a network are brokers of information between otherwise poorly connected groups or subgroups of people (37).

Betweenness centrality measures a node's ability to control the information flow. Nodes with high betweenness centrality can change or interfere with the information flow (35).

1.5.4. Eigenvector Centrality

Eigenvector centrality is a measure of prominent nodes in a network. It measures relative scores of the nodes, based on the concept that relations with high-scoring nodes increase the score of the node (40).

Overall, it is a measure of how connected the nodes are to a given node. It is also a measure of the influence of a node on the network (35).

1.6. The Concepts of Social Network Analysis

- Social Network: A set of relations that applies to a set of social entities and any additional information on those actors and relations (31).
- Actors: The social entities linked together according to some relation (31).
- Tie: What connects A to B, e.g. A is friend with B = A is tied to B (31).
- Density: There are a number of measures that can be used to assess the health of a network. Network density, which is the number of actual connections divided by the potential total number, provides a measure of the extent of the interactions within the structure and can be used to assess the degree to which a group is likely to be viewed as inclusive (41). A measure of the proportion of all movements in the network and is an indicator of cohesion and connectivity and the speed at which information diffuses in the social network (31). It is the proportion of all movements that are present in the network of all those that could be present. A complete network where all movements and locations are present has a density of 1 (38).
- Relation: A specified set of ties among a set of actors, e.g. friendship, family, etc. (31).
- Connected nodes: Number of locations connected by the movement of a commodity or people in the network (38).
- Directed movements: Total number of movements (unidirectional) between locations (38).
- Network diameter: The "network diameter" of a social network is the number of connections between the furthest pairs of nodes with the shortest path. It therefore provides a measure of how expansive a network is and the number of transmission steps it will take to ensure information is fully communicated to all individuals (37). The largest geodesic distance between all reachable pairs of nodes in the network (38).

2. Methods

2.1. Determination of Data Analysis Units and Levels and Sample

As it was mentioned before, this study aims to map the network of nurses in Razi hospital (Rasht, Iran), which includes 64 nurses, out of whom 54 nurses engaged in interviews. The remaining 10 nurses did not directly fill in a form; however, their colleagues mentioned them.

This means that these 10 nurses played a definite role in the network of nurses. The names of those 10 nurses should be expressed in the network since the hospital network considers relations between nurses. In essence, such relations are between humans and mutual. This implies that if a nurse is related to another nurse, the relation is mutual.

Razi Hospital is the largest public hospital in the province of Gilan in terms of its size, providing its most diverse services, poisoning, internal, and surgical (general and thoracic), as well as specialized specialties to its patients by its faculty members. Razi is the only hospital with 3 approved research centers and 13 departments. The complex has 281 approved hospital beds and 240 active beds. The responding nurses were from the departments such as infection, hematologic, surgical, pulmonary, digestive, and endocrinologic-rheumatologic.

2.2. Data Collection Method

This study interviewed the respondents to reach the needed qualitative data. Through this, some questions were also offered to the nurses in written form and then, they were asked to answer the questions. Sufficient explanation was given to all nurses.

2.3. Data Analysis Method

In the present study, data analysis method is premised on the social network analysis approach. The social network analysis approach is one of the common methods of studying soft operations.

2.4. Data Preparation

The intended gathered data was represented in Excel through a zero-one matrix. This implies that relation of a nurse with another nurse is represented by 1 and lack of relation is presented by 0. Then, software-runnable input was converted. The implemented software is Gephi. The set of network operators includes nurses of Razi Hospital.

First, set of relations between networks operators were represented as relations between arrayed pairs. Then, number of people with whom a nurse was related as well as extent of relation between them were represented. Each nurse was asked to attribute a score ranging from 1 to 9 to his/her relation with other nurses. In this case, the numbers 1, 3, 5, 7, and 9 refer to very low, low, moderate, high and very high relation respectively. The numbers play a significant role in development of edges (i.e. diameters). A larger number is correlated with higher thickness or diameter of intended edge as well as higher relation between 2 nodes that are connected by an edge. Therefore, edges are non-directional and weighted.

In the final step, intended data is represented pairwise in a matrix so as to determine relation of each operator with other operators.

3. Resuls

Adopting social network analysis approach (SNA), social network of nurses working in Razi is as depicted in Figure 1. The resulting graph includes 64 nodes and 168 edges. As it is clear, the graph is non-directional:

Figure 1 depicts the network of nurses working in Razi Hospital of Rasht. The nurses' network is a low-density, while nurses related mostly to other nurses in their own departments, which means their relation with other departments is very low. The resulting network contains 9 clusters, out of which 6 clusters refer to 6 departments of the hospital studied within the present research. The departments include infection, hematologic, surgical, pulmonary, digestive, and endocrinologic-rheumatologic departments. The remaining 3 clusters are related to 6 nurses working in the infections department. These 6 nurses are not related with other nurses and Gephi Software considers them to be 3 distinct clusters. Here, we call them "recluses of infection department". Those 6 nurses are only related with another nurse in their own department and not with others. After collected, intended data was used as an input to Gephi Software. The software performs clustering and analyzes the number of clusters in the whole network. It should be noted that the data accessed by the software does not distinguish between nurses of different departments and general data are made available to the software.

3.1. Degree of Centrality

Degree of centrality refers to the number of direct links that an operator has with others. Degrees of centrality for different departments of the hospital are as detailed in the following.

In digestive department, nurses' degree of centrality ranges from 1 to 8. In the department, degree of centrality is low, which means that the number of direct links between nurses (operators) working in this department is low. Only 1 out of 11 nurses in this department has a high degree of centrality (i.e. 8). This implies that the nurse is the most popular nurse in his/ her department.

In the Endocrinology department, degree of centrality ranges from 3 to 10. The degrees of centrality for the Endocrinology department is high and this implies that relations between operators are high and there are direct relations between nurses. Out of 11 nurses working in the endocrinology department, 2 nurses have high degree of centrality (i.e. 8). The department has 2 popular nurses.

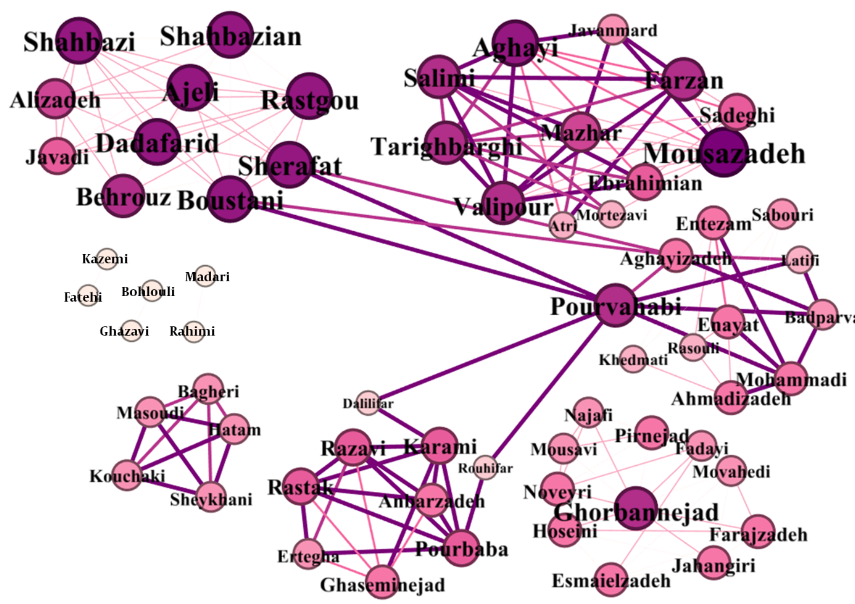

Figure 1. Razi hospital nurses network

In the Infection department, degree of centrality ranges between 1 and 9. Out of 16 nurses working in the Infection department, 4 nurses have a top degree of centrality (i.e. 9). The degree of centrality for the Infection department is sparse. About 10 nurses have high degrees of centrality and a remaining 6 nurses have a low degree of centrality.

In the case of Hematology department, degree of centrality ranges between 1 and 6. In the department, 3 nurses had top degree of centrality (i.e. 6). However, degree of centrality for the department is at a moderate level.

Out of 11 nurses working in the pulmonary department, 1 nurse had a high degree of centrality (i.e. 8). This implies that the department has a popular nurse. The department has a medium degree of centrality.

Out of 5 nurses working in the surgical department, all nurses had a degree of centrality 3. In the department, the degree of centrality is low.

3.2. Betweenness Centrality

Distribution of betweenness centrality for network of nurses working in Razi Hospital suggests that only 1 nurse had high centrality (i.e. 268). The nurse belongs to the pulmonary department and he/she imposes the highest control over nurses of the department. With high betweenness, the nurse plays a significant role in network connection, has a central position in the network, and is critical to flow of data in the network. This implies that the intended nurse is located between lots of other nodes. The figure and numbers of the following table signify that a large number of nurses (i.e. 17 nurses) had 0 betweenness centrality. As a result, those nurses had no control over other nurses. As the figure suggests, a lot of nurses are in the range of 0 to 2.5, which implies that they have low betweenness centrality and exert low control over other nurses. In addition, the top 6 nurses with highest degrees of betweenness centrality are in the range of 0 to 2.5. This means that betweenness centrality is low and their control over other nurses is low. In addition, the top 6 nurses with the highest betweenness centrality belong to the Pulmonary department of the hospital. This problem suggests that nurses of the Pulmonary department control each other.

3.3. Closeness Centrality

In regard to the hospital, the highest and lowest closeness centralities are 1 and 0.239669, respectively. This implies that a nurse with closeness centrality “1” is closer to other nurses of his/her own cluster or the department in which he/she is working. As the relevant figure suggests, 11 nurses had close-to-one closeness centrality. The Surgical and Infection departments have the highest number of nurses with closeness centrality “1”. In this case, 5 nurses belonged to the Surgical department and 6 nurses were from the Infection department. The closeness centrality of the Surgical department suggests that communication and relation between nurses are identical and high.

High closeness centrality suggests that intended nurses are closer to other nurses in their own cluster and have higher levels of communication and relation. As value of closeness centrality reduces, level of communication between such nurses and others reduces.

In the case of network of nurses working in Razi Hospital, closeness centrality ranges between 0 and 1. There is distribution of closeness centrality for different departments of the hospital.

3.4. Eigenvector Centrality

Measuring significance of a node in a network is done based on relations between nodes. The network includes non-directional graphs. In the hospital network, there are 100 iterations.

Eigenvector centrality seeks to find central operators that are least distant from others. In this regard, a point with the highest eigenvector centrality has more central neighbors.

The network includes non-directional graphs. There are 100 iterations in the hospital network. In the network of nurses working in the Razi Hospital, 5 nurses have the highest eigenvector centrality. This means that 5 nurses have more central neighbors and all of those nurses belong to the Infection department of the hospital. The highest and lowest eigenvector centrality for network of nurses working in Razi Hospital are 1 and 0.02187, respectively. For all departments of the hospital, eigenvector centrality ranges from 0 to 1.

4. Conclusions

Social network analysis is a useful means of mapping existing networks and evaluating them. It is a simple to use technique, which could offer fruitful perceptions. Essentially, it is a tool for targeting managerial measures that aim to improve communicative links in a group or network of nurses. SNA is a powerful and flexible tool, as it can be a great asset for nurses. The nurses are the ones that aim to realize a situation and take opportunities of the group, department, or network in which they are a member.

The network of nurses working in the Razi Hospital (Rasht, Iran) includes 64 nodes/nurses and 168 edges/links between nurses. The edges are non-directional and weighted. The diameter of the longest graph is the distance between 2 nodes in a network. In this network, diameter of graph and mean length of longest path are 6 and 8172231.2, respectively.

Degrees of centrality for different hospital departments are as detailed in the following. In the Digestive department, centrality degree is low and this implies that there are few direct links between nurses of the department. In the case of the Endocrinology department, a high degree of centrality is observed, which signifies many communications between operators as well as direct relations between nurses. The degree of centrality for the Infection department is sparsely distributed, due to the fact that 10 nurses have high centrality degrees and 6 nurses have low centrality degrees. In regards to the Surgical department, the degree of centrality is low. However, the degree of centrality for the Hematological department is medium and the same is the case for the pulmonary department. Low, medium, and high degree of centrality are determined based on value of centrality and comparison of different departments. The betweenness centrality for all 6 departments of the hospital ranges from 1 to 10. The number 1 signifies low relation between 2 nurses while number 10 signifies a high level of relation between 1 nurse and another.

In regard to the betweenness centrality of network of nurses working in Razi Hospital, one may note that only 1 nurse has high centrality (i.e. 268). The nurse is working in the Pulmonary department and he/she imposes the highest level of control over nurses of the department. As a relevant figure and table suggest, a large number of nurses (i.e. 17 nurses) have 0 betweenness centrality. This implies that none of those 17 nurses have any type of control over other nurses. The top 6 nurses with the highest degrees of betweenness centrality belong to the Pulmonary department of the hospital. This signifies that nurses working in the pulmonary department control each other to a certain degree. One should note that a nurse with the highest degree of betweenness centrality is the head nurse of the department and his/her job position might have affected the extent of control over other nurses.

The highest and lowest closeness centralities for Razi Hospital are 1 and 0.239669, respectively. This suggests that a nurse with closeness centrality 1 is closer to other nurses of the cluster or the department where he/she works. In this case, surgical department and infections department had the highest number of nurses with maximum closeness centrality. In other words, 5 nurses of the Surgical department and 6 nurses of the Infections department have top limit of closeness centrality. The value of closeness centrality for the Surgical department suggests that communication and relation between nurses are identically high because value of closeness centrality for those nurses is the maximum value among all nurses and in the whole hospital network. A high centrality of proximity signifies that intended nurses are closes to other nurses of the same cluster or the department where they work. As a result, one could state that they are better connected and more related to each other. As the value of closeness centrality reduces, relation of nurses with others declines too. In relation to the Razi Hospital, centrality of proximity ranges from 0 and 1. The closeness centrality is distributed all over the hospital departments and no department has 0 closeness centrality.

Measurement of significance of a node in a certain network is done based on relations between nodes. Here, the network includes non-directional graphs and there are 100 iterations of hospital network. The centrality seeks to identify central operators with the least distance from others. In the network of nurses working in the Razi Hospital, 5 nurses have top values of eigenvector centrality. This suggests those 5 nurses have more central neighbors. All of those nurses were working in the Infections department. The maximum and minimum values of eigenvector centrality are 1 and 0.002187, respectively. The eigenvector centrality for all hospital departments ranges from 0 to 1.

In the Razi Hospital, nurses' network is a network with weak relations between different departments. However, there are strong relations between members or nurses of a definite department. Considering the low density of nurses' network (i.e. 0.083), the network has a low level of integration since 8.3% of all possible and potential network relations were realized. In the hospital network, the average clustering coefficient is equal with 0.714, which signifies relatively high inclination of network members to form different clusters. The study results suggest that nurses of different departments as well as nurses working in a certain department need more communication. Implementing social network analysis, as one of the soft operation research methods, in the field of hospital management can be regarded as the most advantageous of this study while lack of nurses' accurate information to design a SNA questionnaire is the main weaknesses of the present study. This shortage forced the use of the interview instead.

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