A Classification of Healthcare Social Network Analysis Applications

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Abstract: As the web, social networks and the internet of things permeated our daily life; a new perspective for understanding the complexity of our interconnectedness has become necessary. One approach that has predominantly proven useful in discovering hidden relationships, connections and trends of complex systems through mathematical and graphical techniques is Social Network Analysis (SNA). This approach has become increasingly appeling for Healthcare in particular as many of this domain's problems examine systems with dynamic actors that interact with each other and exhibit emergent complex behaviors. However, due to their multiplicity, the application of SNA methodologies proves to be a complex and confusing endeavor. In an attempt to support the effort of applying SNA methodologies on Healthcare research problems, this paper offers firstly a categorization of SNA methodologies (structural and dynamic analysis), then inventories Healthcare SNA applications and classifies them into organizational and e-health related problems. The resulting categorization helps identify the Healthcare research problems most auspicious for SNA methodologies and should thus provide a guiding material of adequate SNA methodologies for a given Healthcare research problem.

1 INTRODUCTION

With the emergence of the web, online social networks, the internet of things etc., we are increasingly aware of our interconnectedness and its quantifiability. There is thus a growing realization that the behavior of a system is shaped by the interactions among its discrete components (Bullmore, 2009). Thereby, the study of the underlying network has become a stepping stone into understanding complex systems.

Social network analysis (SNA) has gained a lot of attention from both academia and practitioners of various domains (from social science (Lewis, 2008), economics (Krempel, 2002), politics (Klofstad, 2003), fight against crime and terrorism (Paulo, 2013), to neuroscience (Rubinov, 2010) and epidemiology (Chen, 2007)). SNA offers a new perspective for analysis and prediction as it focuses on the interconnectedness between the various constituents of the system and not on their inherent characteristics. It relies on Graph theory to express complex systems as a set of nodes (e.g. persons, organizations etc.) interconnected through social relationships (e.g. friendship, collaboration, transfer of funds, co-occurrence etc.). SNA aims to model, map, characterize and quantify topological properties of the network, identify patterns of relations and recognize the roles of sub-groups and nodes within it.

With the increasing availability of data and the advent and development of methods used to (a) collect, store and (b) visualize network data (Abraham, 2010), the interest in SNA has grown massively. Healthcare is among the chief domains where this particular approach is increasingly appealing. Many healthcare research problems examine systems with dynamic actors that interact with each other and exhibit emergent complex behavior. This makes these problems an auspicious application of SNA's methodologies and techniques.

The rest of the paper is organized as follows: Section II will introduce SNA and its underlying principles. It will also present the classification of the different SNA methodologies used throughout the literature into two main categories: structural and dynamics analysis. Section III will particularly focus on organizational healthcare and e-health SNA applications and then match them with the two SNA categories of section II. Section IV will summarize the results and enumerate different opportunities and challenges of the application of SNA in the

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healthcare domains. The last section will conclude the paper with providing hints on future work.

2 SOCIAL NETWORK ANALYSIS METHODOLOGIES

SNA is an interdisciplinary descriptive, empirical discipline that studies networks as a mathematical representation of complex systems by expressing them in terms of relationships among actors. SNA has four features: 1) It is motivated by a structural intuition based on ties linking social actors, 2) It is grounded in systematic empirical data, 3) It draws heavily on graphic imagery, and 4) It relies on the use of mathematical and/or computational models (Freeman, 2004). The body of research has used SNA methodologies in various domains to help validate theories made about the structure or the behavior of a social construct or complex system. These methodologies can be categorized in several ways. No matter how limited and flawed the effort, doing so is useful because it guides the first steps when attempting to answer a specific research question.

We propose a categorization based on the purpose of the SNA analysis. A review of seminal works on SNA {(Wasserman, 1994), (Albert, 2002), (Barabási, 2002), (Newman, 2003), (Watts, 2004), (Christakis, 2011), (Scott, 2012), (Blonder, 2012), (Barabási, 2016)} has rendered two distinct purposes of network analysis:

- **Structural Analysis:** describes in discrete time snapshots the topology of the network, the roles of particular nodes, communities and subgroups within the network etc.
- **Dynamics Analysis:** studies the changes of the network's topology through time (its evolution and growth, the removal and adding of nodes and edges, the change in link weight etc.) and examines the diffusion of processes within the network.

2.1 Structural Analysis

Structural analysis aims to examine the topology of the network in order to uncover the overall properties of the network and its constituents' characteristics. It offers two perspectives: a micro-view and a macro-view. The micro or Ego-centric view focuses on a select actor (ego) and examines its neighbors (nodes that are connected to it), their neighbors and so forth. It studies the features of personal networks. The macro or Socio-centric view, on the other hand, provides a bird's eye perspective of the network and helps examine the structural patterns of the interactions among nodes with the aim to explain and potentially generalize an outcome. Studying the structure of a network relies on a number of measures. Because of their ability to give an indication on the topology of the network (random, small world or scale free), the most studied concepts in contemporary network research are: degree distribution, clustering and Assortativity.

The *degree of a node* is the number of links it has in the network and thus reflects the size of a node's neighborhood. The average degree has been used to gauge the cohesion (Kratzer, 2005) or connectedness on the network level (Shrader, 1989). The degree distribution is often plotted, using histograms, to obtain insight into the overall structure of the network and detect potential heavy-tailed distributions.

The *clustering coefficient* represents the tendency of nodes to form tightly knit groups within the network. It is measured on the node level and on the network level (Watts, 1998). The local Clustering coefficient of a node is used to quantify the level of transitivity within the network, i.e. the chance that a node u is connected to w, when u is connected to v and v is connected to w (uvw form a triangle). The Network Clustering coefficient on the other hand is defined as the average of the local clustering coefficients of all the nodes.

Assortativity detects the level of *homophily* in a network and measures the similarity of connections in the graph with respect to the node degree (McPherson, 2001). Assortativity can hint to the existence of a core-periphery structure where a set of closely knit nodes constitute the core of a network and low degree nodes are left on the periphery.

Along these core concepts, many studies have focused on community detection where algorithms are applied to uncover locally dense connected subgraphs (barabasi, 2016). Community detection allows a deeper understanding of the network's structure and hidden connectivity patterns.

2.2 Dynamics Analysis

The study of network dynamics refers to two distinct phenomena. We borrow the classification given by (Blonder, 2012) in which they distinguish the dynamics of the network from the dynamics on the network. The first examines the growth of the network, the factors behind the creation or dissolution of new nodes and edges and the evolution of link strength through time. The second studies propagation phenomena and the transfer, throughout the network, of cascades such as information, trust, opinion, behavior, money, goods or pathogens etc.

2.2.1 Dynamics of the Network

The study of the dynamics of networks stems from the need to understand the rules of networks' growth in order to predict their evolution. Networks evolve by adding or removing nodes or links over time. Research on the evolution of networks focuses on the various dynamical processes that affect the change of the network's structure. The most popular evolving networks' models are Barabàsi and Albert's Preferential attachment (Barabàsi, 1999) and (McPherson, 2001)'s homophily model.

- In the preferential attachment model, nodes present a bias to connect to popular nodes that have a large number of connections. These hubs gain more connectivity as the network grows, following a rich-gets-richer model (Bollobás, 2003).
- Homophily represents the likeliness of nodes to connect to nodes that resemble them and which are generally the neighbors in the network. Nodes' connections are thus based on a conscious action with embedded bias (It's more likely for example to connect to a friend of a friend or an individual with common interests than it is to a random person).

While the main goal of these models is to predict the probability of link formation, enabling thus Link recommendations, nodes and links dissolution is another aspect of network evolution that is increasingly drawing interest. The goal here is to predict links that are more likely to be dropped from the network and to understand how it would affect the structure of the network.

2.2.2 Dynamics on the Network

In an attempt to understand the dynamic effect of network properties on diffusion, various studies relied on mathematical models originally used in fields such as epidemiology, sociology and economics. Louni et al. (Louni, 2014) classified the most popular information diffusion models into three categories:

- *Contagion Models*: these models build on the idea that a cascade flows in a network in the same way a contagious disease spreads through a population. The most widely used models for studying contagion are usceptible-infected (SI), susceptible-infected-susceptible (SIS) and susceptible-infected-recovered (SIR). The models consider cascades to spread from adopters (infected) to susceptible nodes and consider the possibility of retracting the cascade for recovered nodes.
- *Social Influence Models*: These models assume that the social influence between nodes affects the diffusion of cascades (opinions or behaviors for instance). The most widely studied and used social influence models are the Linear Threshold (LT) (Granovetter, 1978) and the Independent Cascade (IC) (Goldenberg, 2001).
- *Social Learning Models:* In contrast with previous models which ignore the actions and decision making of actors, the nodes in social learning models are considered rational agents who observe outcomes of prior behaviors and decide accordingly. The decision of a user to forward information is modeled using game theory concepts where the user maximizes some utility for himself (Jackson, 2008).

Studying the spread of cascades within a network offers theoretical and empirical tools to not only quantify the propagation process, but to forecast it as well.

3 A CATEGORIZATION OF HEALTHCARE SNA APPLICATIONS

Healthcare's purpose is to ensure the well-being of people by taking both proactive and active actions. Healthcare organizations take preventive actions like sharing information about healthy life styles, the vaccines in the market etc., providing psychological council, or conducting research for improving health services and the health life of people. They also take reactive actions by administrating drugs, doing surgery helping people with chronic illness etc.

Healthcare research covers a lot of areas such as clinical, biomedical, health systems and services and social, cultural, environmental and population health research. Healthcare research is undertaken to establish the foundation for developing effective therapeutic interventions to expose to individuals and communities, to support enhancing and understanding illness and health and safeguard and enhance the health of persons and populations (Steinwachs, 2008). Due to the complexity of the healthcare system, a methodological approach is needed to analyze, monitor and ensure the effectiveness of its endeavors. SNA is thus introduced as a powerful new way to discover valuable hidden connections, relationships, trends and insights.

3.1 Methods and Materials

The purpose of this work is to establish a matching between SNA methodologies, described in section II, and healthcare application domains in order to uncover trends of SNA applications in the healthcare field. To accomplish this, we classified SNA applications in healthcare according to their functional domain and finally assigned SNA methodologies to each healthcare domain.

To identify the SNA applications in healthcare, we scanned three databases (Scopus, Science Direct and IEEExplore Digital Library) for the last 10 years, using various research terms related to: (social network analysis OR graph analytics) AND (healthcare, e-health, health organization, behavioral OR epidemiology) in Title, keywords and abstract. The search was restricted to English scientific literatures that are in peer-reviewed venues and duplicated works were eliminated. A paper is selected when the algorithm and methodology of social network analysis in e-health or healthcare organizations. In this paper, the 16 works listed in Table 1 will be considered. During the data extraction process, we included information about the title of the article, the year of publication, the authors, the country, the application of healthcare research, the data sources, the applied methodology and the type of the modeled graphs.

3.2 Categories of Healthcare SNA Applications

There are many areas of healthcare that can apply SNA. In this paper, we focus on the areas that drew the most attention: healthcare organization and e-health.

3.2.1 Healthcare Organization

A report of the Institute of Medicine suggested six aspects for improvement of the healthcare system. It needs to be: Safe (healthcare services to patients should be secure and not cause any injuries), Effective (care services based on scientific evidence for increasing healthy outcomes), Patient-centered (present to the patient the care service that respect their needs, values and preferences), Timely (provide care assistance early on before any complications occur), Efficient (make healthcare services available with minimum costs and without waste), Equitable (people should have the same access to healthcare services).

To achieve these purposes, healthcare organizations need to collaborate to share information about their operational and research works, establish policies for more effective and safe treatments and manage their waste by detecting fraud of healthcare providers.

i. Health policy

The World Health Organization (WHO) defined health policy as “the decisions, plans, and actions that are undertaken to achieve specific health care goals within a society”. The specification of rules that healthcare stakeholders should follow in terms of defining characters for differing groups, making a reference for treatments and actions undertaken by healthcare practitioners and sharing this information with people, are the various things attained by a health policy institution.

The study proposed by (Millard, 2015) adresses WHO's Essential Medicine List (EML). EML is a list of medicines that assists countries on selecting the treatments of each priority requirement. In this article, SNA is used to inspect the social, political and economic areas for adding the encouragement for Misoprostol’s use for preventing and treating a postpartum hemorrhage, especially in low income countries, according to the WHO's EML in 2011. A study the chronology of WHO misoprostol applications and evolution of related social networks are applied to evaluate the relation of health policy and this social area.

In (Takahashi, 2016), a descriptive analysis of duplicative prescription practices is performed. When patients take orders for the same state from two or more sources, we talk about duplicative prescription practices. This practice is the origin of medical waste. Some patients resell drugs for extra cash and can also cause adverse effects. The descriptive analysis was conducted by using the measurement of SNA and describing the prevalence (the rate of persons with an illness or characteristic) of duplicative prescription through ages. The study also calculated the density of the medical facilities and patients network for each class of drugs defined by their prevalence.

In (Bramhachari, 2016), the authors conducted a qualitative ego-network analysis to understand dominance of Rural Medical Practitioners (RMPs) in West Bengal, India. They inspected the genesis of RPMs’ social links with various actors in the health system and showed the operators donating their subsistence over the years, by using SNA. By identifying the ties in RMPs' network that are formal healthcare providers, the healthcare market and the community, we can comprehend the dynamics of the healthcare market.

Guo et al. use healthcare claims data of the Medical Insurance Association of Anhui Province to look into details of referrals social network. They design a referral social network where the nodes are hospitals and ties are patient-transferred between hospitals. The authors conduct a structural analysis to measure the degree and centrality to describe the relationship between this variable and other patients and hospital variables. Finally, they explore rules between the variables of the referral social network and variables of quality of the healthcare to help healthcare providers minimize cost and length of stay in the hospital and increase the efficiency of medical resources (Guo, 2015).

ii. Healthcare organizational collaboration

Healthcare organizations need to collaborate with each other in order to improve the quality of care to the patients, in term of efficient research, cost decrease, good management of resources etc.

- Intra-organizational Collaboration (actors)

Soulakis et al. made use of patients' Electronic Health Records (EHR) with heart failure to explore the collaboration between healthcare providers and patients in The Northwestern Memorial Hospital (NMH). The access to EHR provides a large amount of data about interactions between providers and patients (Soulakis, 2015). A structural SNA methodology is used to describe the collaboration between patients and providers through a bipartite network (the source node was a provider, the target node was a patient and the edge represented the patient record accessed by this provider), and a provider collaboration network which is a network of the common access of patient records by providers (the node represent providers and the edges are established when two providers have access to more than 10 common patient records). Data is extracted from the Enterprise Data Warehouse (EDW) of NMH. The network is afterwards visualized and clique formation is analyzed. A graph database is used to process queries and answer questions about care and provider-patient collaboration.

- Inter-organizational Collaboration (institutions)

Caniato et al. conducted a case study on management of healthcare waste in a region with specific characteristics: Gaza Strip (Caniato, 2015). They employ an SNA and stakeholder analysis to explore and comprehend the effects of a range of logistical and socio-economic factors on the effectiveness of stakeholder networks in the region. Caniato et al. applied a structural analysis of interaction frequency and information exchanged among stakeholders that are public authorities, health providers, supporting actors and others.

The study performed by (Schoen, 2014) used SNA to confirm the suggestion that when we take funding to concentrate on multi-sector collaboration in Social Innovation for Missouri (SIM) program, a public health program interventions to prevent obesity and stop tobacco, develop various partnership structures than other grantees. The authors explore different variables as the level of collaboration and frequency of contact by applying SNA. They measure the network descriptors such as average degree, density, betweeness centralization and degree centralization to evaluate the network of contacts and the collaboration of different stakeholders.

Dianas et al. studied an excellence program in low and middle-income countries provided by the National Heart, Lung, and Blood Institute-UnitedHealth to fund 11 centers of excellence (Dianis, 2016). In order to prove the effect of collaboration with a federal support, they used SNA. They created a network of the program's stakeholders by considering links as collaborations on administrative support and research projects. They later compared the resulting network before the development of the Centers of Excellence Program and after.

Kawonga et al. presented a case study of HIV monitoring and evaluation to examine and understand the way that Disease Control Program(DCP) and General Health Services(GHS) managers communicate when they make a health reform to make an administrative integration in South Africa (Kawonga, 2015). For this purpose, they described the entire network by using density, degree and betweenness centrality. They also used density and a measure of homophily to analyze sub-groups networks. A block-model analysis was used to identify the connections between management committees and manager groups.

The paper presented by Khosla et al. introduced a study of collaboration between HIV agencies in Baltimore (Khosla, 2016). SNA and relation coordination were used to analyze the quality of coordination between HIV agencies when they accessed resources like information, around seven dimensions such as accuracy of communication, knowledge of agencies' work, frequency, problem-solving communication, timeliness, shared goals and mutual respect. Density and centrality of the network of agencies collaboration were calculated as part of an SNA structural analysis. For the study of relation coordination, a questionnaire was used among these seven dimensions about communication and relationships between HIV agencies. SNA measures were used to describe the whole network: density and degree centralization and to describe a position of an actor in the network: degree, indegree, centrality, degree centrality, weighted degree centrality, betweenness centrality and closeness centrality.

Wang et al. apply SNA to explore the collaboration between surgeons, assistants and anesthetist working at different hospitals by using data from Private Health Insurance (PHI) claims in Australia. They also studied their impact on quality and cost of care (Wang, 2014). SNA is used to analyze the collaboration among the three healthcare providers, study the topologies of the network to see how doctors work while treating patients and examine the effect of these topologies on quality and cost of care for patients. The effect of network structure on quality and cost is analyzed around efficiency metrics that are Length of Stay (LoS), Medical costs and Complication rate. They thereafter designed two kind of networks: one for collaboration between surgeons, assistant surgeons and anesthetists; and the second centered on a surgeon collaboration network to study the connections of each surgeon. The measures of SNA used in this paper are: the size of node (charged number of this provider), tie strength (total of common admission between two providers), centrality to have an idea on the influence of a vertex in the network) and density.

- Research collaboration

Collaboration research is important to enhance the quality of research by determining the leaders in a subject and affording reasonable proposals and scientific evidence to make a finance of specific area of research policy (Wu, 2015).

Bien et al. presented a case study of the use of SNA in the context of biomedical research grants collaboration at the University of Arkansas for Medical Sciences (UAMS) (Bian, 2013). The objective of this study was to evaluate the research collaboration networks (RCNs) for both level inter- and intra-institution in the community of the Clinical Translational Science Award (CTSA) and examine the effectiveness of CTSA funded at UAMS and their influence on environment of research collaboration in an institution. For categorizing the network, the authors calculated the network's path length and its clustering coefficient. They also measured the structural characteristics such as centrality to identify the important (the influencer or contributor) node in the research community. They examined the structural characteristics and the network dynamics of the RCNs.

Wu et al. (Wu, 2015) performed a study on the scientific research collaboration in the specialty of psychiatry. This work applied SNA to analyze the structure of scientific collaboration in psychiatry by using the notion of co-authorship, which can determine the authors, institutions and countries involved in the scientific collaboration network. In each level of authors, institutions and countries, the author characterized psychiatry research collaborative behaviors, K-plex analysis and Core-periphery are the methods used in this paper to describe the collaborative connections. The authors measure centrality to detect the central, the core position and actor with control and possession of valuable research resources in each collaboration network.

3.2.2 E-health

WHO defines e-Health as "the use of information and communication technologies (ICT) for health"(WHO, 2016). By using ICT in this area, we can assist patients for treatments; share information about healthy life styles, follow people with diseases etc.

The study presented by Chomutare et al. adresses weight loss performance by monitoring online interaction behaviors for forcast them (Chomutare, 2014). The authors captured data from a sub-forum of two online communities concerned with obesity. The first was for people older than 50 years and the second was for people that needed surgical interventions as they interacted before and after the intervention for weight loss performance. Structural SNA is used to create a classification of people who lose significant weight (performers) and the others (non-performers) to predict weight loss. Authors remarked that the top performers were connected at different sub-community and were more active online.

Pachucki et al. measure objectively the social interaction between 6th-grade students at a private K-8 School in the State of California by using accelometers and RFID technology. The purpose of this paper is to study the relations between social interaction and mental health behaviors such as self-esteem and depressive symptoms of early adolescences. Due the focus on health behaviors, health status and changes in network structure; the authors measure the characteristics of social environment, health behavior, social interaction network and mental health to analyze them using bivariate associations. They use a stochastic actor-based modeling (SABM) framework to join the dynamic co-evolution of social ties and self-esteem or depressive symptoms (Pachucki, 2015).

Goodall et al. explored the importance of ICT for searching information behavior by older migrants with Culturally And Linguistically Diversity (CALD) (Goodall, 2014). They determined factors that leverage the use of ICT to locate information. These factors can be education, migration, socio-economic status, ethnicity and English proficiency of older migrants. The study undertook by Goodall et al. focused on the search of cancer-related information by the group. The authors used SNA and a constructivist grounded theory method to analyze the data captured in the interviews, and then they studied the preferences and uses of traditional information sources compared to modern ones (PC, Internet and mobiles).

Table 1: A methodological classification of each healthcare application represented in this paper.

Reference of paper and the country	The SNA application	Healthcare categorization	Methodological categorization	Dataset/Size of the network	Algorithms/Metrics
(Millard, 2015), UK	They establish a chronology of WHO misoprostol applications and they examine the evolution of related social networks and the nested subset network of the WHO EML misoprostol applications	Healthcare organization: Health policy	Dynamics of the network	238 organizations and individuals	Chronological approach combined with SNA (evolution of social network) : density, geodesic distance, diameter, centrality, nesting, clique formation
(Takahashi, 2016), Japan	They conduct a descriptive analysis of medical waste by studying duplicative prescription practices	Healthcare organization: Health policy	Structural	Data are from health insurance claims database 1,243,058 insured people and their dependents	Statistical analyses: correlation by using scatter plots and the Pearson correlation coefficient SNA: bipartite networks, density
(Bramhachari, 2016), India	They use a qualitative ego-network method to understand the RMP network	Healthcare organization: Health policy	Structural	35 participants	Qualitative Ego-network method
(Guo, 2015), China	They analyze the healthcare claims data of the Medical Insurance Association of Anhui Province to design a referral social network.	Healthcare organization: Health policy	Structural	72 hospitals and 8856 patients in the claim data from Medical Insurance Bureau	Community detection: spinglass, edge betweenneess, label propagation, optimal, walktrap. Simple linear regression: Los, Medical cost, Degree, closeness centrality, betweenness centrality, eigenvector centrality, rank of Hospital. Rules exploration: Decision tree.

Table 1: A methodological classification of each healthcare application represented in this paper (cont.).

(Soulakis, 2015), USA	They make a bipartite network of providers accessing patients' records and a provider collaboration network to describe collaboration between patients and providers.	Healthcare collaboration intra-organization	Structural	Collaborative electronic health record (HER) 1504 nodes and 83 998 edges	Bipartite network Module and clique identification: heuristic community detection algorithm, kCliques algorithm
(Caniato, 2015), Italy	They conduct a Stakeholder analysis and structural SNA of interaction frequency and information exchanged between stakeholders	Healthcare collaboration inter-organization	Structural	Dataset constructed from 16 structured and two semi-structured interviews	SNA and stakeholder analysis
(Schoen, 2014), USA	They apply structural SNA to both contact and collaboration networks	Healthcare collaboration inter-organization	Structural	23 Missouri communities in early 2012	SNA: average degree, density, degree centralization, and betweenness centralization
(Dianis, 2016),USA	They conduct structural SNA on the network of all stakeholders in an excellence program	Healthcare collaboration inter-organization	Structural	11 contracts in 10 countries 128 nodes	SNA: density, average distance
(Kawonga, 2015), South Africa	They apply structural and dynamic methodologies on the communication network of GHS and DCP managers	Healthcare collaboration inter-organization	Dynamics of the network	51 managers in two provinces during 2010-2011 Dataset: HIV data collation and HIV data use	SNA: density, degree, betweenness centrality and E-Index (measure of homophily) Block modelling
(Khosla, 2016), USA	They combine SNA and relational coordination to measure the quality of coordination among HIV agencies	Healthcare collaboration inter-organization	Structural	57 agencies	SNA: density, degree centralization, weighted degree centralization, closeness centrality, betweenness centrality Relational coordination: frequency, timeliness and accuracy of communication, problem-solving communication, knowledge of agencies' work, mutual respect and shared goals
(Wang, 2014), Australia	They use SNA to explore the collaborative network and surgeon centric collaboration network to analyze the impact of collaboration on the quality and cost of care	Healthcare collaboration inter-organization	Structural	Health insurance claims: 59256 admissions performed by 870 surgeons	SNA: degree centrality, closeness centrality, betweenness centrality , density, clustering coefficient, number of triangles

Table 1: A methodological classification of each healthcare application represented in this paper (cont.).

(Bian, 2013), Arkansas, United States	They apply structural and dynamic methodologies on the network to identify leaders and influencers in a research collaboration network	Healthcare research collaboration	Dynamics of the network	The Automated Research Information Administrator (ARIA) and the Translational Research Institute (TRI)	SNA: measures of centrality, mean path length, clustering coefficient, characteristic path length, diversity Temporal evolution: average number of new edges, centrality leaders
(Wu, 2015), China	They use the measure of centrality to conduct an SNA on authors, institutions and countries collaborating on psychiatric research	Healthcare research collaboration	Structural	36557 papers about psychiatry from Science Ciation Index Expanded (SCI-Expanded) in web of science	SNA: centrality, K-plex analysis, Core periphery Hierarchical clustering
(Goodall, 2014), Australia	They use Grounded theory and a qualitative SNA on the egocentric network of individuals and their sources of information, and compare the resulting networks	E-health: Information technology access	Structural	Interview with 54 participants aged 63–94 years	Constructivist grounded theory method (CGTM) SNA: egocentric network
(Chomutare, 2014), Norway	They use structural SNA to classify people according to their ability to lose weight significantly	E-health: Social influence and behavior analysis	Structural		Binomial classification: Bayes and decision tree method SNA: bipartite graph , degree centrality, betweenness centrality Expansion-reduction method Community detection: hierarchical clustering
(Pachucki, 2015) USA	They measure the association between social interactions and depressive symptoms and self-esteem of early adolescences at a private K-8 School in the State of California	E-health: Behavioral analysis	Dynamics on the network	40 students of sixth-graders at a private K-8 school	Measures of Social environment, Health behaviors (physical activity and food choice), Social interaction networks, dependent variables (self-esteem and depressive symptoms) to make bivariate associations and SNA (size of personal networks, transitivity and closeness centrality)

4 SYNTHESIS AND DISCUSSION

The following table represents the matching between the categorization of healthcare SNA applications and the SNA methodologies.

Figure 1 shows that the highest number of the included research works studied healthcare collaboration and focused on collaboration between institutions. This might be due to the accessibility of inter-collaboration data compared to intra-collaboration data (insurance claims vs. EHRs). E-health is a new area of SNA application and can thus present new opportunities to researchers, although the lack of data especially in low-income countries may be problematic.

Structural SNA methodologies are the most used, whereas dynamic methodologies are mainly used in problems related to healthcare organization (cf. Table 2). The prevalence of structural analyses could be due to the complexity of dynamic methodologies compared to structural ones. Associations between SNA structural metrics and domain-specific metrics are however rarely examined; which constitutes a research question that deserves further attention. There is also a pressing need to move beyond the static view of the network, visualized in snapshots, to a visualization that captures more accurately the dynamic processes that reshape the network (a movie-like visualization for instance). Another research opportunity relates to the application of dynamics on the network methodologies such as propagation and diffusion models. While these methodologies have been exclusively used in behavioral analysis, they have the potential to examine the propagation of information in social networks and uncover hidden processes shaping collaboration or policy making endeavors.

With respect to data collection, a third of the included studies gathers data from questionnaires. This raises data completion issues and inaccuracies arising from informant bias and stresses the pertinence of alternative data collection methods relying on RFID technologies, accelerometers or EHRs etc. Online social networks (OSN) such as Facebook, Twitter etc. are widely used nowadays and can help perform social behavioral analyses. We can comprehend e-health tools and design future IPC to promote effective interaction behaviors in OSNs by correlating interaction behaviors and a specific disease (Chomutare, 2014). However, many challenges could face such studies. When SNA methodologies are used on OSNs' social data, it is difficult to distinguish between the effects of Homophily and those of peer influence. Questions relating to the sufficiency of collected data and its representativeness of a given behavior to infer conclusions remain unanswered. There are also the pressing issues of privacy and ethics regarding data collection and which are consequences of the inherent processes of the social graph's construction and design. Anonymization, consent and privacy are among the issues that need further attention.

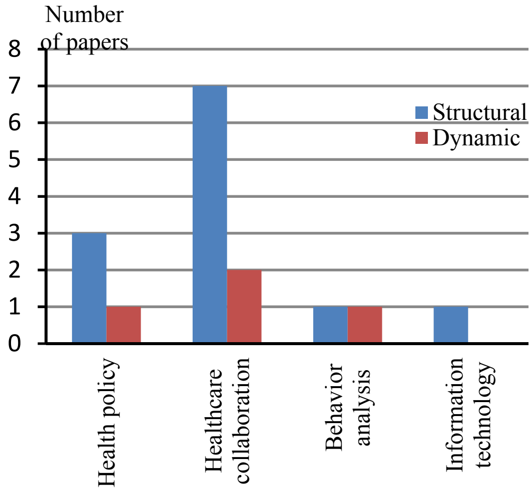

Figure 1: Number of papers of each healthcare application and methodological classification (Dynamic, Structural).

Table 2: The SNA methodology used in each healthcare domain.

Healthcare categorization	**Functional Sub-categorizing**	**Methodological categorization**
Healthcare organization	Health policy	Dynamics of the network, Structural
	Healthcare collaboration intra-organization	Structural
	Healthcare collaboration inter-organization	Structural, Dynamics of the network
	Healthcare research collaboration	Dynamics of the network, Structural
E-heath	Information technology access	Structural
	Social influence and behavior analysis	Structural, Dynamics on the network

Furthermore, social media provides a large amount of data. The resulting networks are thus very large and new tools are needed to process them. Big data network analysis is increasingly drawing the attention of researchers. However, due to the complexity of healthcare research problems, further research is needed in order to produce domain-specific tools.

5 CONCLUSIONS

The purpose of this paper was to propose a classification of healthcare SNA applications based on a review of papers that used structural and dynamic SNA methodologies to answer healthcare-related research problems. We classified these research works into two categories: One concerning healthcare organizations and pertaining to policy making, communication, and collaboration and a patient-oriented category which concerns patients' behaviors, social influence and healthcare information access.

The proposed classification of healthcare SNA applications is preliminary and requires further enrichment through the inclusion of other research works. The level of adequacy of a chosen SNA methodology to a given Healthcare research problem is yet to be examined. Experimental studies will have to be conducted to establish comparative analyses between variations of a given methodology for a particular problem. For instance, different subsets of metrics can be used and compared for structural SNA methodologies, various propagation models can be simultaneously tried for dynamic SNA methodologies.

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