Administrative Claim Data to Learn About Effective Healthcare Collaboration and Coordination through Social Network

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Abstract

Previous studies have documented the application of administrative claim dataset for health services research purposes. In addition to administrative and billing details of healthcare services, insurance claim datasets can reveal important information regarding professional interactions or links that evolve among healthcare service providers through, for example, informal knowledge sharing. The aim of this study is to develop a research framework, which uses details of such professional interactions, to learn about effective healthcare coordination and collaboration. The proposed framework has been exercised to analyse Patient-centric Care Coordination Network and Physician Collaboration Network. The usefulness of this framework and its applications in exploring different collaborative efforts of healthcare service providers have been discussed in this paper.

1. Introduction

The ever growing computerised administrative claim dataset is the single largest source of utilisation data for different healthcare services. Since this type of claim datasets cover a wide variety of medical services and a broad geographic area, they have already gained wide acceptability for research investigation purposes [1, 2]. Prior research in the healthcare literature have already documented the application of this type of datasets to research questions that require market-level information on private health insurance transaction prices at a certain point of time or over a long period for a wide variety of medical services [3, 4]. Recently, researchers have been utilising health insurance claim datasets to explore informal networks that do not necessarily conform to the boundaries established by formal structures and have been emerged through informal discussions and observations (e.g. of patient records) among healthcare professionals. For example, Barnett et al. [5] utilise US Medicare administrative data to analyse Patient-Sharing networks of physicians. By exploiting the theory and methods of social network analysis, this study aims to propose a research framework to learn the structure of effective healthcare collaboration and coordination from the administrative health claim dataset.

Coordination is an abstract concept, which has an intuitive sense about its meaning [6, 7]. When we see, for example, a smoothly running factory or an effective healthcare-professional team in a hospital setting, we might say that workers of the factory or team members of the healthcare-professional team are well coordinated. The usefulness of coordination can be seen when there is a distinct need for managing simultaneous constraints such as task relationships. For instance, before having a hip replacement surgery by surgeons, a patient needs to be served by hospital imaging or pathology department. After surgery, that patient might need to be served by primary care unit for post-operative care. In such interdependent situations, coordination has the potential to act as an enabler to manage these interdependencies more efficiently. On the other hand, collaboration, which is a recurring process where multiple people or organisations work together towards common goals [8], enables individuals and organisations to work together more effectively and efficiently. There is a distinguished difference between collaboration and coordination in the sense that for efficient coordination harmonious functioning of parts are essential; whereas, prolific collaboration demands joint works with others on a common goal that is beyond what any single person or group can accomplish alone. To put this in a healthcare organisation or hospital perspective, for instance, a coordinative relation among different hospital units (e.g. primary care unit and medical test unit) is required for better patients’ outcomes where each of these units has separate immediate goal. These hospitals units do not necessarily need to work jointly or change the basic ways of doing business. On the other hand, the relation evolving between a nurse and a physician is a collaborative relation since both of them required to work jointly in providing healthcare services to patients.

Although administrative claim databases are mainly maintained for billing and administrative purposes,
they are found useful in a wide range of healthcare research areas including analysing healthcare utilisation [9, 10], measuring coordination performance of the hospital care network [6], exploring patterns of care and cost of care [11] and comparing disease prevalence and drug outcomes [12, 13]. First, they usually tend to be highly representative of a large population over a long period of time, which permits enhanced precision and study rare events. This further facilitates the ease of patient follow-up over a long period [13, 14]. Second, the data analysis is inexpensive as the data are already collected and computerised. Third, administrative data are free from certain bias that may put the validity of primary data collection in question. Due to the problems in obtaining a valid and representative sample of a population of interest, for instance, studies that require recruitment of subjects are vulnerable to selection bias. Fourth, administrative data bank permits flexibility in study design. Researchers can alter their study plans for more easily than with primary data collection efforts. Finally, administrative claim data preclude any imposition on patient, physicians or other providers.

To explore and learn the performance of any collective effort, the social network view of any group endeavors has gained wide acceptability in the present healthcare literature [15-17]. The Bavelas theory of centrality [18], which is a classical network theory explaining how the communication structure among individuals affect their performance in achieving the desired goal in a complex work environment, has been the key factor for such acceptance. According to this theory, centralised structures such as the star or wheel are far more conducive to performance than the decentralised or flattened structures, such as a circle structure. The basic logic is that in decentralised networks information floats around inefficiently, thus less conducive to performance. Researchers have been utilising measures (e.g. centrality and density) and models (e.g. exponential random graph model) of social network analysis (SNA) to explore healthcare coordination and collaboration [19-21]. A social network is viewed as a set of actors that are linked by a set of links [22]. SNA can be seen as the mapping and measuring of relationships among participating actors that can provide both a visual and a mathematical analysis of network relations among actors [23]. SNA measures can explore the relative position of an actor in a social network. For example, centrality measure, which is a structural attribute of nodes in a social network, can determine how important a physician is within her professional collaboration network or how well-used a road is within an urban transport network. SNA models such as exponential random graph model (ERGM) are probabilistic models that have been utilised extensively in the social science literature to study the dynamics of network formation from underlying locally prominent micro structures [24]. Stochastic actor-based model is another type of simulation model that has been used by healthcare researchers [25].

This study aims to develop a research framework to learn about effective healthcare coordination and collaboration. By following this research framework, this study proposes a model to explore coordination among different hospital units during the course of providing care to hospitalised patients. The proposed research framework of this study is presented in the section 2. Examples of the application of this research framework for healthcare coordination and collaboration are illustrated in section 3. Finally, section 4 discusses the importance of the proposed research framework and its application in learning effective healthcare coordination and collaboration. This section also makes a conclusion of this paper.

2. Proposed research framework

In the course of providing healthcare services to patients, both coordination and collaboration among healthcare professionals are essential. The importance of coordination is highly reflected in case of task-dependency. For example, being seen by a specialist physician a patient has been asked to conduct further medical diagnoses (e.g. x-ray and blood test) in a Medical Diagnostic Centre. The physician also asks the patient to make a follow-up after two days. If the diagnostic centre does not provide the results of medical tests on time (i.e. within two days) then the physician cannot suggest any medication to that patient on the follow-up visit. This kind of task-dependency eventually creates an interdependent network among different participating service providers (e.g. physician and Medical Diagnostic Centre), which demands an efficient coordination for better outcomes. These service providers usually provide care in different ways (e.g. diagnostic centre conducts medical tests and physician prescribes medication to patients) and are not necessarily to work jointly. On the same side, healthcare professionals need to work jointly in order to provide other types of healthcare services to patients. A hospitalised chronic disease patient suffering from asthma and diabetes, for instance, could require multiple consultations from different specialist...
physicians. In this case, a proper collaboration among these physicians is mandatory since they work jointly to treat the patient and may need to change their prescriptions depending on the patient’s health condition and response to previous medications.

In general, health insurance claim datasets contain a large number of claims covering a wide variety of medical services, a broad geographic area and a long time period. In addition to utilisation statistics of different medical services and procedures, health insurance claim dataset reveals information about interactions among different health service providing units (e.g. physician and hospital) during the course of providing treatment to patients. For example, a hospital admission of a patient will generate many claims submitted to the health insurance provider. These claims will render details about for what services (e.g. physician consultation and hospital fees for accommodation) or procedures (e.g. surgery) they have been lodged. This will eventually reveal further information regarding coordination and collaboration among different hospital service units such as: (i) a given hospital service unit is coordinating with which other hospital service units; (ii) physicians who are collaborating to provide treatment to that patient; and (iii) amount of cost incurred for physicians’ visits, medical procedure and hospital accommodation separately. Similarly, health insurance claim details can provide details of over time care episode of patients who have been treated by multiple health service providers (e.g. a chronic disease patients who were served by hospital, rehab and multiple specialist physicians). Based on this information captured from health insurance claim dataset, this paper presents a research framework, as illustrated in Figure 1, to explore healthcare coordination and collaboration.

This research framework first extracts different coordination and collaboration networks (e.g. coordination network among different hospital units and physician collaboration network) that evolve during the course of providing healthcare services to patients. These networks are then analysed using different social network analysis methods and approaches (e.g. social network centrality and exponential random graph model). For research analysis purposes, only social network analysis methods and approaches have been chosen since, according to Bavelas [18] experiment and Freeman’s [26] Centralisation Theory, network positions of actors have impact on their ability to perform. In this analysis, socio-demographic characteristics of the member actors of these networks are also considered, which will ultimately enable to explore the impact and influence of these characteristics on network formation and healthcare performance. This will extract positive and negative network features of these coordination and collaboration networks. Positive network features are the properties of coordination and collaboration

Figure 1: A research framework to learn about effective healthcare coordination and collaboration

Administrative claim dataset

- Socio-demographic information of patient, physician and hospital
- Capturing different coordination and collaboration networks, such as:
  - (a) Patient-centric care coordination network (PCCN) among different hospital
  - (b) Hospital-Rehab coordination network (HRCN)
  - (c) Physician collaboration network (PCN)

Socio-demographic information of patient, physician and hospital

Social network analysis approach, such as:
- (a) Measures of social network analysis (e.g. network centrality)
- (b) Exponential random graph model

Expected learning
- Structure (both positive and negative) and socio-demographical characteristics of effective healthcare coordination and collaboration

Application of learned knowledge
- Design effective and efficient healthcare environment
networks that are conducive to healthcare performance. For example, if a physician collaboration network with higher network density shows better healthcare performance in terms of less hospitalisation cost then the density is a positive network feature for that collaboration network. In contrary, negative network features are not causative to healthcare performance. Finally, this research framework shows the application of the learned knowledge in designing effective and efficient healthcare environment.

Table 1: Basic statistics of research dataset

<table>
<thead>
<tr>
<th>Item</th>
<th>Value (Std)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of patients</td>
<td>2352</td>
</tr>
<tr>
<td>Average LoS of patients</td>
<td>10.51 (12.11)</td>
</tr>
<tr>
<td>Average age of patients</td>
<td>65.02 (16.09)</td>
</tr>
<tr>
<td>Average value of degree centrality</td>
<td>29.98 (35.03)</td>
</tr>
<tr>
<td>Average value of tie strength</td>
<td>74.59 (14.11)</td>
</tr>
<tr>
<td>Gender distribution of patient</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1302</td>
</tr>
<tr>
<td>Male</td>
<td>1050</td>
</tr>
<tr>
<td>Number of different types of claims</td>
<td></td>
</tr>
<tr>
<td>Hospital claim</td>
<td>24559</td>
</tr>
<tr>
<td>Medical claim</td>
<td>69619</td>
</tr>
<tr>
<td>Ancillary claim</td>
<td>1388</td>
</tr>
</tbody>
</table>

3. Application of the proposed framework

The proposed research framework of this study, as illustrated in Figure 1, has been exercised in this section to explore healthcare coordination and collaboration using a health insurance claim dataset. This dataset is provided by an Australian non-profit health insurance organisation. It includes member claim data from January 2005 to February 2009. In this dataset, there are mainly three different categories of claims lodged by patients, hospitals and physicians: (i) ancillary claim; (ii) medical claim; and (iii) hospital claim. Ancillary claims are auxiliary claims for medical services such as dental, optical, physiotherapy, dietician and pharmaceutical. All claims lodged by specialist physicians except of the ancillary type are medical claims. The claims for the services provided to hospitalised patients in private or public hospitals that are approved by the Department of Health, Australia are considered as hospital claims. In general, patients have medical claims, hospital claims and very few ancillary claims for their admissions to hospitals. For research analysis purpose, this study considers claim data of hospital admissions only for total hip replacement (THR) patients from 85 different hospitals. In these hospitals, 2229 patients get admitted during the data collection period. These patients lodged in total 1383 ancillary claims, 65871 medical claims and 23369 hospital claims. The basic statistics of this research dataset is presented in Table 1.
surgeons or specialist physicians. After the surgery that patient could be served by primary care unit for post-surgery care. At this stage, that patient might need to be seen by external physicians depending on her medical condition. This forms a Patient-centric Care Coordination Network (PCCN) as illustrated in Figure 2. The one-directional links between patient and different hospital units in this figure indicate that patients receive medical services from those service units. There are also relations and interdependencies among all hospital departments, as shown by two-directional dotted line in Figure 2. These types of interdependencies between the patient and service units, and among different service units have impacts on both network attributes (e.g. frequency of physician-visit) and performance measures (e.g. hospital length of stay and patient satisfaction) of PCCN. In order to find out positive network features, this coordination network is extracted from the health insurance dataset utilised in this study and has been explored using the measures of social network analysis, and socio-demographic characteristics of patients (i.e. gender and age).

In exploring PCCN, this study considers degree centrality and tie strength of social network analysis measures as independent variables, patients’ hospital Length of Stay (LoS) as the dependent variable, and gender and age of patients as moderating variables. In the context of network analysis, degree centrality of an actor is the count of the number of ties from that actor to other actors [22]. Tie strength defines the quality of relationship between two actors in a network [27]. The hypotheses that have been tested are related to (i) the impact of independent variables on the dependent variables; and (ii) the impact of moderating variables on the relations between independent and dependent variables. This is summarised in Figure 3. This study measures degree centrality for a patient by counting the total number of physician-visits to that patient during her hospitalisation period. Each physician-visit to a patient is responsible for a medical claim to the health insurance organisation. The total medical claims that a patient has during her hospitalisation period is therefore considered as the value for degree centrality. The ratio of the expenses for hospital claims and the total hospitalisation cost is the tie strength of a patient with hospital. For a patient, tie strength thus represents the proportion of the cost for the services that are covered by hospital claims (e.g. primary care, pathological test, medical examination, accommodation and so forth) compared to the total hospitalisation cost which has a significant portion for the expense of physician-visits.

This study finds positive correlation between degree centrality and LoS (rho = 0.763, p<0.01 at 2-tailed) and between tie strength and LoS (rho = 0.295, p<0.01 at 2-tailed). The corresponding simple linear regression models are presented in Table 2 (first two models). The finding regarding degree centrality suggests that patients need to have less physician-visit during their hospitalisation periods in order to make their hospital LoS shorter. At the same time, it has to be confirmed that patients receive proper treatment from healthcare providers or hospitals. Thus, in order to make patients’ LoS shorter healthcare managers or administrators have to give emphasis to make the number of physician-visits as minimum as possible whilst fulfilling patient’s expectation and providing right treatment. A positive correlation between tie strength and LoS conveys the message that less cost for services provided by hospitals makes LoS shorter. Alternatively, if the cost for medical claims (i.e. for physician-visits) increases then the percentage of hospital cost (i.e. tie strength) will decrease. Healthcare managers or hospital administrators can do it by emphasising increased number of physician-visits to patients. However, then the degree centrality value, which affect LoS positively, will increase. Another possible way is to encourage physicians to spend more time with patients during their visits, which will

**Table 2:** Simple linear regression model for checking (i) the relation of degree centrality and tie strength with LoS; and (ii) the controlling effect of gender and age of patients on the relation between degree centrality and LoS, and between tie strength and LoS

<table>
<thead>
<tr>
<th>Model</th>
<th>Dependent Variable</th>
<th>R² value</th>
<th>Constant</th>
<th>Independent Variable</th>
<th>B</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>LoS</td>
<td>0.573</td>
<td>2.694</td>
<td>Degree centrality</td>
<td>0.757</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>LoS</td>
<td>0.053</td>
<td>-4.184</td>
<td>Tie strength</td>
<td>0.230</td>
<td>0.000</td>
</tr>
<tr>
<td>3</td>
<td>LoS</td>
<td>0.578</td>
<td>2.129</td>
<td>Degree centrality</td>
<td>0.822</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Degree centrality*Age</td>
<td>-0.063</td>
<td>0.416</td>
</tr>
<tr>
<td>4</td>
<td>LoS</td>
<td>0.595</td>
<td>2.167</td>
<td>Degree centrality</td>
<td>0.858</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Degree centrality*Gender</td>
<td>-0.164</td>
<td>0.000</td>
</tr>
<tr>
<td>5</td>
<td>LoS</td>
<td>0.314</td>
<td>-1.640</td>
<td>Tie strength</td>
<td>0.020</td>
<td>0.580</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Tie strength*Age</td>
<td>0.297</td>
<td>0.000</td>
</tr>
<tr>
<td>6</td>
<td>LoS</td>
<td>0.268</td>
<td>-4.034</td>
<td>Tie strength</td>
<td>0.274</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Tie strength*Gender</td>
<td>-0.085</td>
<td>0.000</td>
</tr>
</tbody>
</table>
eventually increase total medical cost because the charge for physician-visit to a patient depends on the duration of visiting time. This will increase cost for medical claims and, eventually, reduce the percentage of hospital cost (i.e. tie strength). Furthermore, longer physicians’ visiting hour will increase patient satisfaction [28], keep degree centrality value unchanged and decrease patients’ tie strength with hospitals – all of these enable to manage hospital LoS effectively. According to the fourth and sixth regression models of Table 2, the gender of patient moderates the relation between degree centrality and LoS, and between tie strength and LoS. However, age of patient does not show any moderating effect as indicated by the model 3 and 5 of Table 2. This finding will further enable healthcare managers or administrators in implementing effective and efficient hospital setting.

3.2. Physician collaboration within hospital

Collaborations among physicians, which is termed as Physician Collaboration Network (PCN), emerge when they visit common hospitalised patients [1, 20]. When physicians visit common patients within the same hospital or healthcare organisation PCN emerges among them. Figure 4 illustrates an example of such a PCN construction. In a hospital (say $H1$), patient $Pa1$ is visited by $Ph1$, $Ph2$ and $Ph4$ physicians, patient $Pa2$ is visited by $Ph2$, $Ph3$ and $Ph4$ physicians, patient $Pa3$ is visited by $Ph3$ and $Ph4$ physicians, and physician $Ph2$ and $Ph4$ visit patient $Pa4$. This is depicted in the patient-physician network in Figure 4(a). The corresponding PCN for this patient-physician network is demonstrated in Figure 4(b). In this PCN, there are network connections with weight 1 between $Ph1$ and $Ph2$, between $Ph1$ and $Ph4$, and between $Ph2$ and $Ph3$ because they visit a common patient. The weight of the links between $Ph3$ and $Ph4$ are 2 as they have two common patients. Since $Ph2$ and $Ph3$ have three common patients, the weight between them is 3. As people have hospital admissions for a wide range of illness and patients with a particular disease need to be seen by particular specialist physicians, different types of PCNs (e.g. a PCN for knee surgery patients and a PCN for heart surgery patients) are being evolved inside a hospital for hospitalised patients suffering from different types of diseases. Since the research dataset of this study contains health insurance claim data for THR patients from 85 different hospitals, 85 PCNs evolve during the data collection period. Out of these 85 PCNs this study compares the top-5 PCNs having higher readmission rate with the top-5 PCNs having lower readmission rate using exponential random graph (ERG) model in order to explore prominence of micro-structures within these two types of PCNs.

ERG model simplifies a complex structure down to a combination of basic parameters. It can effectively identify structural properties in social networks [29]. This theory-driven modelling approach also allows to test the significance of structural parameters in the process of the formation of a given network [22, 29]. For instance, a given cost effective PCN may be explored using ERG model to examine what micro structures play a statistically significant role in the development process of this PCN. A commonly used sub-class of ERG models is the Markov random graph in which a possible tie from $i$ to $j$ is assumed conditionally dependent only on other possible ties involving $i$ and/or $j$ [14]. This sub-class of ERG models is also known as the low-order model which is utilised to explore PCNs having higher and lower readmission rates. The configurations and parameters of low-order model are shown in Figure 5. These parameters relate to some well-known structural regularity in the network literature and represent

![Figure 4: (a) Patient-physician network, and (b) Corresponding PCN (Pa stands for patient, and Ph stands for physician.)](image)

![Figure 5: Configurations and parameters for lower order ERG models](image)
structural tendencies in the network (e.g. mutuality and transitivity). They were chosen because they are conceptualised as forces which drive the formation of the network itself. For example, transitivity is conceptualised as a force which drives the formation of the network itself (the friends of our friends are more likely to be our friends). An example of a Markov random graph model for non-directed networks, with edge (or density), 2-star, 3-star and triangle parameters, is given below [30]:

\[ Pr(X=x) = \frac{1}{k} \exp(L(x) + \sigma_2 S_2(x) + \sigma_3 S_3(x) + \tau T(x)) \ldots \] (1)

In Eq. (1), \( \theta \) is the density or edge parameter and \( L(x) \) refers to the number of edges in the graph \( x \); \( \sigma_k \) and \( S_k(x) \) refer to the parameter associated with \( k \)-star effects and the number of \( k \)-stars in \( x \); while \( \tau \) and \( T(x) \) refer to the parameter for triangles and the number of triangles, respectively. Goodness-of-fit (GOF) measure is used to test whether a given model fits the network data. A parameter estimate in the model can be assumed to have converged if the GOF index is below 0.10 [29].

Using Pnet\(^1\), all PCNs (i.e. top-5 higher readmission rate PCNs and top-5 lower readmission rate PCNs) have been fitted with a low-order model (i.e. 2-star, 3-star and triangle model). Out of three parameter of this model, only the triangle parameter is found to have significant effect for all PCNs. The significance for each parameter is replicated by another variable, called t-statistics. A t-statistics value of \( \geq 2 \) is considered to have significance effect for a given parameter. Only triangle parameter shows t-statistics value \( \geq 2 \) for all 10 PCNs. The positive triangle parameter can be interpreted as providing evidence that the ties tend to occur in triangular structures and hence will cluster into clique-like forms. A t-test further reveals that there is a significant difference of the triangle parameter between PCNs with higher readmission rate and PCNs with lower readmission rate (t(10) = -3.05, \( p < 0.05 \)). The result shows that, on average, the triangle parameter for PCNs with higher readmission rate (\( M = 16.49, SE = 1.47 \)) is more positive than the parameter for PCNs with lower readmission rate (\( M = 5.90, SE = 1.48 \)). The presence of a higher number of triangle structures in PCNs with higher readmission rate indicates that most actors are likely to have more connections with others. That means all network actors have almost same number of connections with others. That means PCNs with higher readmission rate are less centralised. On the other hand, PCNs with lower readmission rate do not have prevalence of such actors in the network structures, indicating that the possibility of the presence of some actors that have more connections (i.e. network hub) within the network compared to others. In these PCNs, few actors have very higher number of connections and the rest have lower number of connections; thus, making them more centralised. This eventually leads these PCNs to show better outcomes (i.e. low readmission rate) since, according to the Bavellas theory [18], centralised structures are more conducive to performance. The underlying mechanism is that a centralised PCN eases the sharing of professional knowledge among its member physicians.

3.3. Summary of previous two examples

By following the proposed research framework PCCN and PCN, which are being extracted from health insurance claim dataset, have been analysed by using SNA measures and exponential random graph models respectively. These analyses reveal network structures of these two coordination and collaboration networks that are conducive to healthcare performance. In accordance of the proposed framework, the summary of these two research examples and the corresponding research outcomes are illustrated in Table 3.

4. Discussion

This study presents a research framework to learn about effective healthcare coordination and collaboration using health insurance claim datasets. This framework has further been exercised to learn Patient-centric Care Coordination Network (PCCN) and Physician Collaboration Network (PCN). From the analyses of PCCN and PCN, this study illustrates the structure of networks for effective coordination and collaboration. It also illustrates how to capture PCCN and PCN, and their different network attributes (e.g. degree centrality) from various types of claims that have been lodged to the health insurance providers by healthcare providers and patients. For PCCN and PCN, this study develops prediction models to estimate healthcare outcome measures (i.e. LoS and readmission rate respectively). Based on the outcomes of these models, this study then proposes suggestive guidelines for healthcare administrators and managers.

Although the proposed research framework is designed for health insurance claim dataset it can be adopted for public health services datasets (e.g. Medicare Australia). These datasets are usually maintained by the governments of the corresponding countries. Because of the differences in privacy policies across different countries, governments of some countries (e.g. Taiwan) can disclose de-identified public health services datasets; whereas, some other

\(^{1}\) http://www.sna.unimelb.edu.au/pnet/pnet.html
Table 3: Summary of the analyses of Patient-centric Care Coordination Network (PCCN) and Physician Collaboration Network (PCN)

<table>
<thead>
<tr>
<th></th>
<th>Patient-centric Care Coordination Network (PCCN)</th>
<th>Physician Collaboration Network (PCN)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Data Source</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claim type</td>
<td>Hospital claim and medical claim</td>
<td>Medical claim</td>
</tr>
<tr>
<td><strong>Methods</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Approach followed for data analysis</td>
<td>Measures of social network analysis</td>
<td>Exponential random graph model</td>
</tr>
<tr>
<td>Socio-demographic statistics used</td>
<td>Patient age and gender</td>
<td>None</td>
</tr>
<tr>
<td><strong>Results</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning outcomes</td>
<td>(a) effective structure of coordination networks</td>
<td>Effective PCNs are attributed with the presence of less number of triangle structures.</td>
</tr>
<tr>
<td></td>
<td>(b) Gender of patient has impact on coordination performance</td>
<td></td>
</tr>
<tr>
<td>Suggestion based on outcomes</td>
<td>Lessen number of physician-visits to patients but physicians visits should have longer time duration and be comprehensive in nature</td>
<td>Some (but not all) physicians should have higher-level of collaborations with their colleagues</td>
</tr>
</tbody>
</table>

The health insurance claim dataset could be in varied formats from one country to another since different countries follow various standards for the maintenance of this type of datasets [32]. However, in general health insurance claim datasets contain basic information of claim details regardless of their country-source and the standards followed to collect them. This study uses the health insurance claim dataset from an Australian health insurance organisation. The standard followed in Australia eases this study to capture Patient-centric Care Coordination Network (PCCN) and Physician Collaboration Network (PCN). Other countries could follow different standards that will enable to extract different coordination and collaboration networks. The standard followed in USA, for instance, facilitates researchers to elicit and explore hospital-based professional networks based on patient-sharing ties [5]. The variation in the standard for the maintenance of health insurance claim dataset will therefore impose constraints to the application of the proposed research framework in the context of some countries compared to others.

The application of different SNA measures (e.g. closeness centrality) and models (e.g. stochastic actor-based models) depend on the research questions that are being aimed to response. In exploring PCCN, this study uses degree centrality and tie strength since it intends to examine the impact of the number of times a patient is being visited by physicians and the proportion of hospital expenses compared to the total hospitalisation cost of a patient on LoS. Network density has to be used when the aim will be to explore the impact of the level of connectivity among different actors of Patient-centric Care Coordination Network (PCCN) on LoS. To analyse the network formation of Physician Collaboration Network (PCN) and its effect on hospital readmission rate, this study utilises ERG models. If this study aims to examine the longitudinal dynamics of these two networks (i.e. PCCN and PCN) then it will need to consider models and methods that are designed for exploring over time network dynamics such as stochastic actor-based models [33] or topological methods for longitudinal social networks [34].

Computerised health claim dataset could have few demerits. This type of dataset allows limited insight into errors of omission and the appropriateness of care. Moreover, claim datasets do not provide sufficient clinical details. For example, a claim for diagnosing a disease indicates that a diagnosis is done for a particular patient. It does not say anything about the outcome of the diagnosis as well as the severity of that disease. Further, problems are inherent in health insurance claim dataset from measurement errors, as like, a diagnosis could be missed or miscoded which may lead to wrong estimation of healthcare utilisation. These limitations could generate biased results if they will be utilised, for example, to compare healthcare utilisation statistics. However, they are not relevant to this study since we consider network measures, LoS and readmission rate to show an instantiation of our proposed framework.

5. Conclusion, limitation and future research direction

In summary, although health insurance datasets are mainly collected and stored for claim processing purpose, they contain information regarding interactions, which evolve during the course of providing healthcare to patients, among healthcare professionals. This study proposes a research
framework to learn about effective healthcare coordination and collaboration by considering these interactions. This framework highlights the application of health insurance claim dataset in extracting and exploring healthcare coordination and collaboration networks, which will eventually lead to developing policies for effective and efficient healthcare environments.

This study is subject to several limitations. First, the proposed research framework incorporates only a few examples of coordination and collaboration networks that can be extracted from health insurance claim dataset. Subject to the various standards followed for the maintenance of claim datasets in different countries, it may need to exclude few of the existing networks or include new networks (e.g. physician and health insurance organisation network to study cost effectiveness) to apply this research framework in the context of any other country. Similarly, in order to explore coordination and collaboration networks from different perspectives, additional SNA measures and methods may need to be included to the proposed research framework. Second, this study ascertains PCCN and PCN based on the information about physician-patient direct link and shared patients among physicians respectively using health insurance claim dataset. Although this technique has been validated [2, 35], it cannot be known what information or behaviour, if any, pass across the ties of these networks. Third, we report our results for coordination among hospital units by considering only two confound factors (i.e. Los and Gender). However, other factors (e.g. seriousness of patient condition and comorbidity) could affect these results. Finally, in exploring PCCN and PCN this study considers only 2352 THI patients who have been admitted to 85 hospitals. By considering patients having other diseases, further work is needed to confirm the findings from the analyses of PCCN and PCN.

The limitations of this study provide some future research opportunities. First, by considering the proposed research framework as a guideline, other collaboration networks (e.g. Hospital-Rehab coordination network) that evolve during the course of providing treatment to patients can be explored to learn about their effective structures. Second, we could consider other confounding factors to adjust our findings. The dataset that we have contains some other relevant information regarding patient hospitalisation, such as, infection rate and International Classification of Diseases (ICD10) details of service provided to patients. By utilising ICD10 information, we could consider Charlson-Deyo index [36], which is a comorbidity measure, to adjust our findings from PCCN and PCN. Third, in analysing various networks we could use more sophisticated network modelling method such as stochastic actor-level model. Originated from logistic regression, this modelling approach considers actor-level interactions in a network to understand the network evolution and dynamicity. On top of that, this modelling method can explore how socio-demographic attributes of member actors influence the future network growth and change.

6. References


Adherence to Glaucoma Medications: Methodology and Findings of the Glaucoma Adherence and Persistence Study (Gaps)


