The Impact of Patient-Sharing Networks On Patient Outcomes in Acute Myocardial Infarction Patients

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ABSTRACT

The Impact of Patient-Sharing Networks on Patient Outcomes in Acute Myocardial Infarction Patients

Background: Acute myocardial infarction (AMI) is a leading cause of morbidity and mortality worldwide. Effective management of AMI patients requires timely and coordinated care, which is often facilitated through well-integrated hospital networks. However, the specific roles of network metrics, such as degree centrality and betweenness centrality, in patient-sharing networks have not been thoroughly investigated. This study aims to examine the impact of these network metrics on all-cause mortality (in-hospital, 1-year, and 3-year mortality) and readmission rates among AMI patients in South Korea.

Methods: The study targeted 107,595 hospitalized patients who had at least one claim with the primary diagnosis codes I21-I23. The primary dependent variables were three types of mortality. The secondary dependent variable was readmission for one year after discharge from the subject hospital. Network metrics were calculated based on patient-sharing patterns among hospitals, with degree centrality reflecting the number of referrals received and betweenness centrality indicating the extent to which a hospital acts as an intermediary in patient sharing. The incidence rate of mortality and readmission was calculated as the number of events divided by the total number of person-years of follow-up, and computed confidence intervals (CIs). This study employed the Cox proportional hazards model to analyze the association between network metrics and patient outcomes, adjusting for potential confounders such as age, sex, comorbidities, and hospital characteristics.

Results: Our analysis revealed that higher degree centrality was significantly associated with lower in-hospital mortality (aHR 0.64, 95% CI: 0.44–0.95, p=0.0263), 1-year mortality (aHR 0.73, 95% CI: 0.54–0.97, p=0.0307), and 3-year mortality (aHR 0.75, 95% CI: 0.58–0.96, p=0.0241). Similarly, higher betweenness centrality was linked to reduced in-hospital mortality (aHR 0.94, 95% CI: 0.89–0.90, p=0.0249), 1-year mortality (aHR 0.95, 95% CI: 0.90–0.90, p=0.0168), and 3-year mortality (aHR 0.91, 95% CI: 0.87–0.95, p<0.0001). Moreover, higher degree centrality was linked to reduced readmission within one year of discharge (aHR 0.73, 95% CI: 0.55–0.96, p=0.0260), whereas higher betweenness centrality was associated with higher readmission within one year (aHR 1.10, 95% CI: 1.05–1.15, p<0.0001).

Conclusion: This study highlights the vital role of hospital networks and the centrality of patient-sharing in determining the outcomes of AMI patients. Enhancing the integration and communication between hospitals can lead to significant improvements in patient outcomes.

Key words: Mortality, Regional Cardiocerebrovascular Centers, patient-sharing networks, Acute myocardial infarction

I. Introduction

1. Background

Cardiovascular disease (CVD) is a disease that occurs in the blood vessels of the heart and brain, such as acute myocardial infarction (AMI), cerebral infarction, and cerebral hemorrhage, and accounts for the second and fifth leading causes of death in Korea after cancer [1]. The annual number of patients with CVD is more than 2.9 million, and the annual medical expenses are close to 7 trillion won, and it is continuously increasing due to the aging population [2]. Although these diseases have a high severity and mortality rate, and the socioeconomic losses due to premature death are very large, deaths can be prevented by proper treatment within the golden hour, and emergencies can be prevented by managing pre-existing diseases [3, 4]. Because of the significant burden of CVD and the importance of tertiary prevention strategies, including prompt treatment and prevention of recurrence or complications in the management of CVD, many countries have specialized regional health service systems and evaluate their performance regularly [5].

In Korea, three Regional Cardio-cerebrovascular Centers (RCCVCs) were established for the prevention and treatment of CVD and initially funded by the Ministry of Health and Welfare in 2008 [6]. The province was divided into nine zones, except for the metropolitan areas, and then national hospitals or private university hospitals were designated as RCCVC in each region [6]. The program was continually expanded to up to 2023, and 14

RCCVCs are now in operation [7]. The Korean government has shown interest in forming networks for collaboration among providers by implementing pilot projects for health insurance coverage of cardio-cerebrovascular disease problem-solving clinical cooperation networks [8]. These networks are based on the RCCVCs and include both network-type collaborations centered around the RCCVCs and human network-type collaborations among specialists.

Studying the interaction of healthcare providers and associated teamwork is challenging. Most studies that addressed this issue are limited in scope to surveys and interviews [9], [10]. Although these studies are helpful to understand individual providers' perspectives, they typically include a costly design and dissemination, and have a low response rate [11]. Studying interactions of healthcare providers is essential to understand their working relations, referrals, hospital association, advice seeking, and how these relations impact their decision-making process and patient outcomes [12]. New approaches are needed to better capture these relationships, the associated impact on providers' teamwork, and associated patient outcomes.

Recent research has started utilizing social network analytic tools to describe the professional connections between providers, using the quantity of shared patients as a measure of the intensity of provider collaboration relationships [13-17]. The fundamental idea is rooted in the belief that healthcare providers exchange information and build a connection while delivering care to patients they have in common. Providers who have a larger number of shared patients are expected to have more robust collaborative relationships, resulting in improved coordination of care [14]. Importantly, they also represent informal connections between providers including referral patterns and advice seeking [15]. By reflecting both formal and informal connections that may shape clinical practice, patient-sharing networks may provide insight into variation in care [16]. Many studies have established a clear link between the expense of healthcare and the likelihood of patients being readmitted to the hospital, both on an individual basis and when considering the number of patients being attended to by the healthcare providers [17].

Despite previous efforts to assess the provider role, collaboration, and impact on patient outcomes, there is a lack of understanding about how healthcare providers interact with other healthcare providers in the community and how they can provide optimized care for patients [18]. The specific roles of network metrics, such as degree centrality and betweenness centrality, in patient-sharing networks for AMI patients have not been thoroughly investigated. It is necessary to evaluate the impact of hospital-level collaboration on patient outcomes for AMI patients using social network analysis.

2. Study objectives

The aim of this study is to investigate whether the structure of patient-sharing networks, defined by patient movements between hospitals, affects acute myocardial infarction patients' outcomes and readmission. The details of the study objectives are as follows:

To visualize the patient-sharing networks among healthcare providers involved in the care of AMI patients by region.

To investigate the association between patient-sharing network structures and the risk of all-cause mortality.

To investigate the association between patient-sharing network structures and the risk of readmission within a year.

To investigate the association between patient-sharing network structures and the risk of all-cause mortality among patients who underwent coronary intervention as a subgroup analysis.

II. Literature Review

1. Defining Access to Healthcare

Access to healthcare is a multifaceted concept with varying definitions, often taken for granted in specific contexts [19]. Fundamentally, it encompasses both a noun indicating the potential for healthcare utilization and a verb denoting the act of obtaining or receiving healthcare. The description of patient access includes the patient's entry into a healthcare system, their geographic proximity to the system, and their identification of an appropriate provider for their healthcare needs [20].

In the realm of public health, accessibility signifies the right of any individual to equitably utilize healthcare services, encompassing geographical accessibility, distribution considering healthcare needs, and the removal of barriers to access [21]. In essence, it guarantees that patients can access healthcare professionals or institutions regardless of their health issues [22].

Healthcare utilization is closely linked to the healthcare system and the supply and demand of healthcare services, with defining elements of healthcare accessibility varying based on the emphasized characteristics. Salkever (1976) identified economic and physical access as components of healthcare accessibility [23]. Penchansky & Thomas (1981) defined availability, physical accessibility, convenience, affordability, and acceptability as the elements of accessibility [24]. Availability refers to the adequate supply of healthcare relative to demand; physical accessibility pertains to transportation convenience, travel time, and distance; convenience denotes the degree to which provider efforts meet patient needs; affordability considers the relationship between patient income, health insurance, and service cost; and acceptability involves the attitudes of healthcare providers and patients towards each other [24]. Peters et al. (2008) defined the elements as quality of healthcare, geographic accessibility, availability, economic accessibility, and service acceptability [25].

Healthcare accessibility can be viewed as both a spatial concept, involving distance and region, and a non-spatial concept, involving social or economic factors. Studies focusing on the spatial concept of accessibility primarily examine regional healthcare utilization and the distribution of healthcare resources. In South Korea, the concentration of healthcare resources in metropolitan areas may lead to healthcare inequality in smaller cities or rural areas due to insufficient resource supply.

In this study, it aims to understand the accessibility to appropriate healthcare services following AMI through patient-sharing network structures and to investigate the impact of these network structures on patient outcomes.

2. Regional Cardiocerebrovascular Center (RCCVC) Project

The government launched Regional Cardiocerebrovascular Centers (RCCVCs) as a third preventive strategy within the Comprehensive Countermeasures for Cardiocerebrovascular Diseases framework. The purpose of the Regional Cardiocerebrovascular Centers (RCCVCs) is to establish a system that can provide prompt and intensive medical treatment within three hours, a crucial time when a disease strikes anywhere in the country. This is achieved by fostering regional base centers for the management of cardiocerebrovascular diseases, thereby reducing the inter-regional disparity in medical care [7]. They designated Kangwon National University Hospital, Kyungpook National University Hospital, and Jeju National University Hospital as RCCVCs in 2008, followed by Gyeongsang National University Hospital, Chonnam National University Hospital, and Chungbuk National University Hospital in 2009, Dong-a National University Hospital, Wonkwang Hospital, and Chungnam National University Hospital in 2010, and Seoul National University Hospital and Inha National University Hospital in 2021. Therefore, 11 regions across the country have designated and operationalized RCCVCs [7] (Fig. 1).

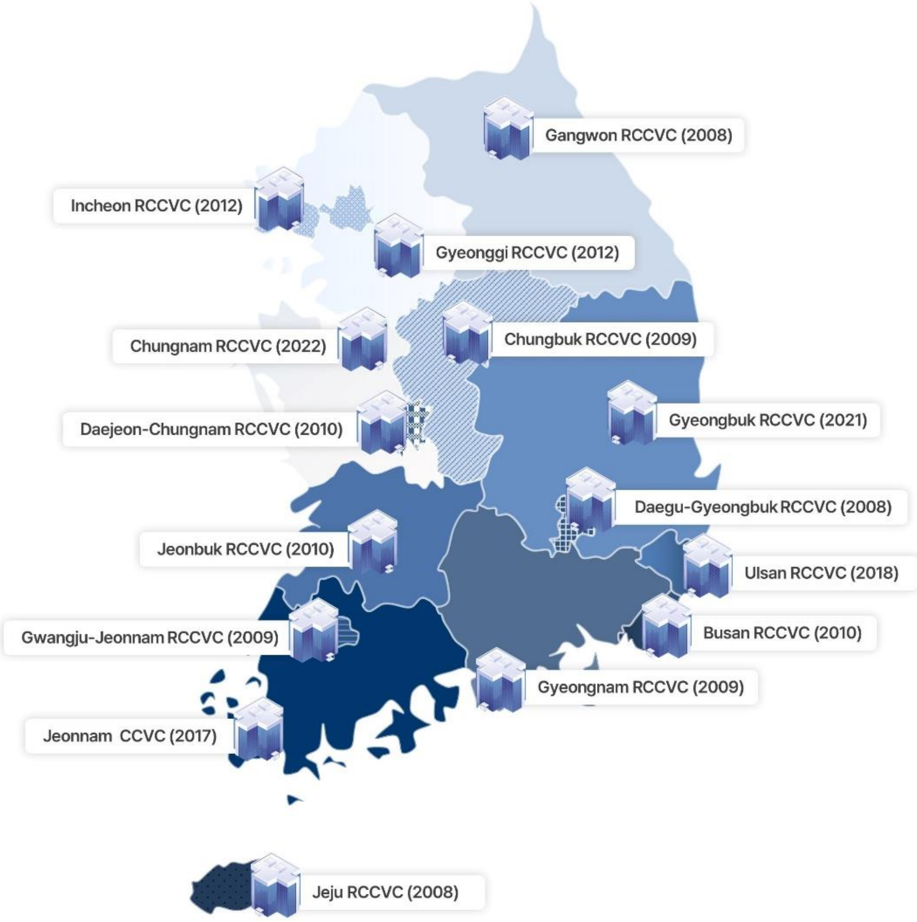


Figure 1. Current designation of regional cardiocerebrovascular centers

The RCCVC project can be broadly divided into the installation project for building facilities and equipment infrastructure and the operation project for developing and implementing programs for the operation of the workforce and essential functions of the centers. By 2013, about 167.4 billion won (95.9 billion won of government expenses and

71.5 billion won of hospital self-funding) had been invested, of which 102 billion was for the installation project and 65.4 billion for the operation project. The designated hospitals are reorganizing the medical treatment system by rearranging and centralizing the center's space through the construction of new facilities, expanding and remodeling existing facilities, supplementing major equipment and replacing obsolete equipment, increasing the workforce and reshuffling of organizations, and improving the treatment process [5, 6]. By doing this, they are developing and implementing hospital-centered preventive activities, which are based on the advancement of treatment activities that set them apart from the past.

Each RCCVC carries out such projects through its specialized organizational operation, comprising four sub-centers: three clinical centers, namely the Cardiovascular Center, the Cerebrovascular Center, and the Cardiocerebral Rehabilitation Center, and one prevention and control center (Figure 2) [7]. AMI and acute stroke are the main target diseases, and RCCVCs provide prompt and specialized care, such as the operation of a specialized medical care system (24-hour on-call), the development and dissemination of CP (critical pathway), and early rehabilitation. Moreover, the hospital implements patient education, follow-up and management services, and hospital-wide improvement projects to increase awareness of early symptoms. Education and publicity projects on using 119 in case of emergency symptoms, as well as preventive management projects for the local community, are also being promoted. Unlike other projects that only supported the existing hospital infrastructure, the RCCVC project fostered synergy in disease management projects by combining the adoption of building hardware through facility and equipment support, with the development of software through operation projects.

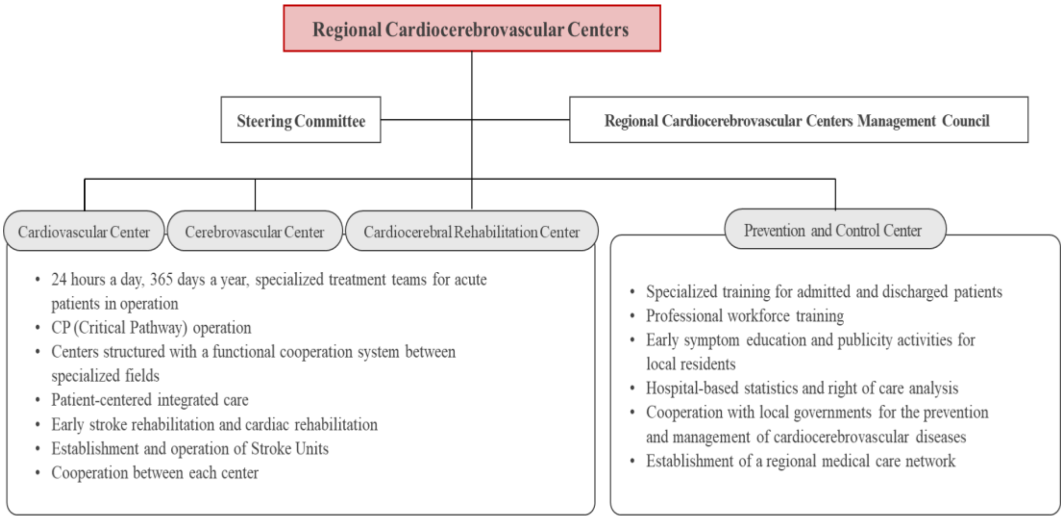


Figure 2. Structure and Functions of Regional Cardiocerebrovascular Center

The Korean government has shown interest in forming networks for collaboration among providers by implementing pilot projects for health insurance coverage of cardio-cerebrovascular disease problem-solving clinical cooperation networks in 2024 [8]. These networks are based on the RCCVCs and include both network-type collaborations centered around the RCCVCs and physician network-type collaborations. The introduction of a network model centered around RCCVCs, along with a complementary physician-centered network model, was implemented to facilitate rapid decision-making and treatment provision for the transfer of patients with cardio-cerebrovascular diseases [26]. The

RCCVC-centered institutional network aims to improve treatment outcomes by reducing the time from the onset of symptoms to the arrival at the final treatment facility. This is achieved through the establishment and strengthening of networks and cooperative systems between RCCVCs and local medical institutions [27]. The physician network, organized by disease and treatment method, aims to ensure the swift acceptance of referrals and rapid treatment provision by securing emergency resources, hospital beds, and operating rooms when a transfer is necessary for critically ill emergency cardio-cerebrovascular patients in the region [26].

3. Studies on Healthcare Accessibility

1) Effects of policies to increase access for serious and emergency diseases

There is some prior research on improving accessibility in healthcare. Previous studies primarily conducted their analyses at the regional level. Research results indicate a decrease in mortality among local patients when new emergency medical institutions establish or receive support through a national project.

According to Lee and Hong (2014), improving accessibility through the expansion of emergency medical facilities resulted in reduced emergency mortality rates and a decrease in the number of emergency deaths, contributing to lower emergency mortality costs [28]. The expansion of emergency medical facilities had a significant improvement effect, particularly in underdeveloped areas.

Based on the Second Basic Public Health Care Plan (2021–2025), Lim et al. (2020) split national regions into 70 intermediate medical regions. They then compared the self-sufficiency rates and severity-adjusted mortality ratios for cardiovascular and cerebrovascular diseases [29]. Regions with low self-sufficiency rates had higher severity-adjusted mortality ratios compared to those with high self-sufficiency rates.

Ko and Jo (2021) analyzed the impact of regional emergency medical resources on mortality among elderly ischemic heart disease patients [30]. Their study revealed that an increase in regional emergency medical resources was associated with a decrease in elderly ischemic heart disease mortality.

Bae et al. (2022) compared the crude mortality rates for stroke and AMI across the 70 intermediate medical regions, dividing them into Seoul, regions with cardiovascular disease centers, and regions without such centers [31]. The study found that the crude mortality rates were highest in Seoul, followed by regions with and then without cardiovascular disease centers.

Shin et al. (2023) investigated the impact of easier access to regional cardiovascular disease centers on the death rates from cardiovascular disease in a region [32]. They identified 11 of the 70 medical regions as having poor accessibility to regional cardiovascular disease centers. These regions exhibited higher average mortality ratios compared to those with better accessibility.

Table 1. Studies on Healthcare Accessibility

Author(s) (Year)	**Study Data**	**Key Findings**
Lee and Hong (2014)	Cause-of-death data from Statistics Korea	□ Enhancing accessibility by expanding emergency medical facilities led to a decline in emergency mortality rates and a reduction in the number of emergency deaths, hence leading to decreased expenses associated with emergency mortality. □ The growth of emergency medical facilities had a substantial positive impact, especially in undeveloped regions.
Lim et al. (2020)	NHIS database	□ Regions characterized by low self-sufficiency rates exhibited higher severity-adjusted mortality ratios in comparison to regions characterized by high self-sufficiency rates.
Ko and Cho (2021)	NEDIS database	□ The presence of an emergency medical resource per 100km^2 was associated with a decrease in the risk of death. □ The death rate decreased by 0.967, 0.970, 0.997, and 0.391 with the increase in the presence of a fire department, an ambulance, a paramedic, and a regional medical center, respectively. □ A reduction in the mortality rate was observed 0.844, 0.825, and 0.975 following the establishment of a local emergency medical center, a local emergency medical institution, and the implementation of an angiography device, respectively.

(Continue)

Table 1. Studies on Healthcare Accessibility (Continue)

Author(s) (Year)	Study Data	Key Findings
Bae et al. (2022)	NHIS database	□ The study found that the crude mortality rates were highest in Seoul, followed by regions with and then without cardiovascular disease centers.
Shin et al. (2023)	NHIS database	□ This study identified 11 of the 70 medical regions as having poor accessibility to regional cardiovascular disease centers. □ These regions exhibited higher average mortality ratios compared to those with better accessibility.

2) Effect of the establishment of regional cardiocerebrovascular centers

The previous studies consistently highlight the positive impact of the establishment of RCCVCs in Korea on the treatment of cardiovascular diseases, particularly AMI. Common findings include significant reductions in emergency room arrival-to-reperfusion times and improvements in treatment outcomes, such as increased proportions of patients receiving timely reperfusion therapy. Additionally, long-term evaluations underline the sustained benefits of improved infrastructure and operational practices, as evidenced by continued improvements in early reperfusion therapy times. The expansion of RCCVCs has generally led to higher treatment volumes without compromising care quality, emphasizing the role of enhanced medical infrastructure in managing increased patient loads effectively.

The RCCVCs have been established in Korea, and papers on the effect of the establishment of the center have been published. Lee et al. (2013) reported the initial experience of the Busan-Ulsan RCCVC project [33]. They analyzed a total of 132 patients with ST-segment elevation myocardial infarction who underwent primary coronary intervention from June 1, 2009, to June 30, 2011. After the start of the RCCVC project, the average emergency room arrival-to-reperfusion time was reduced from 72 ± 30 minutes to 59 ± 22 minutes, an average reduction of 13 ± 5 minutes ($p = 0.011$), and the proportion of patients with an emergency room arrival-to-reperfusion time of less than 90 minutes also significantly increased from 83% to 97% ($p = 0.005$). They reported that there was no difference in the survival discharge rate.

Kim et al. (2015) showed through a comparison between hospitals that the implementation of the RCCVC for AMI patients resulted in a reduction of hospital stay by 0.71 days and a total medical cost decrease of 800 dollars, demonstrating that the social burden of the disease decreased in the designated hospitals after the designation of the regional center [5].

The expansion and enhancement of medical infrastructure at RCCVCs have been crucial in improving patient outcomes. For instance, the establishment of RCCVCs improved the treatment volume and did not increase the mortality rate, suggesting that the infrastructure development helped in managing more cases effectively without compromising care quality [6].

Another study evaluated the decade-long impact of the Busan RCCVC project on the treatment of ST-segment elevation myocardial infarction (STEMI), noting improvements in early reperfusion therapy times, which is a direct outcome of improved infrastructure and operational practices [34].

Table 2. Effects on Regional Cardiocerebrovascular Center designation

Author(s) (Year)	Study Data	Key Findings
Lee et al. (2012)	Single Regional Cardiocerebrovascular Center data	☐ The establishment of RCCVC significantly reduced the emergency room arrival-to-reperfusion time for patients with ST-segment elevation myocardial infarction, improving the timeliness of care. ☐ The proportion of patients receiving reperfusion therapy within 90 minutes increased notably post-RCCVC implementation, enhancing the immediate treatment response.
Kim et al. (2015)	National Health Insurance Service database.	☐ The implementation of RCCVCs was associated with reductions in hospital stays and total medical costs for acute myocardial infarction patients, indicating a decrease in the social and economic burden of the disease.
Cho et al. (2019)	National Health Insurance Service database.	☐ Despite the increase in treatment volume due to improved infrastructure, there was no corresponding increase in mortality, suggesting that care quality was maintained even as more patients were treated.
Lim et al. (2022)	Korean Registry of Acute Myocardial Infarction (KRAMI)	☐ Long-term evaluations of RCCVC showed sustained improvements in early reperfusion therapy times for myocardial infarction, reflecting the lasting benefits of the enhanced medical infrastructure and operational practices.

4. Social network analysis in healthcare settings

1) Methodological approach of social network analysis

(1) Overview

The methodological approach of social network analysis (SNA) aims to comprehend the relationships within a network [35]. It involves mapping and measuring relationships and flows between people, groups, organizations, computers, URLs, and other connected information entities [36]. The core idea is that social relationships carry a wealth of information that can be crucial for understanding behaviors, interactions, and influences [35]. Analysts use SNA to identify how relationships affect individual actions and decisions, the flow of information, and the diffusion of innovation [36]. SNA provides tools for measuring network dynamics, the influence of network actors, and the structure of relationships [37]. These insights can help in various fields such as sociology, anthropology, business networking, and more to optimize communication, improve organizational efficiencies, and understand social interactions at a deeper level [38].

Healthcare environments have employed SNA to understand the dynamics of communication and collaboration among healthcare professionals, the spread of innovative practices, and the exchange of knowledge among doctors [39, 40]. SNA provides a method for visualizing and uncovering communication and information exchange pathways among key groups within an institution [41]. It delves into the nature of connections that foster communication and knowledge acquisition, rather than emphasizing the intensity of individual relationships [42]. SNA allows for the study of complex communication and interaction patterns in healthcare environments [43]. Because communication and interaction among health care providers are crucial to improving patient safety and quality of care [44], SNA is an important analytic method that can help identify healthcare gaps affecting patient safety [35].

(2) Data measurement, collection, and processing

SNA is a tool to study the performance and interactions of teams and organizations. Networks are composed of a set of nodes that typically represent people or organizations, as well as a set of connections between the nodes defined by observed or reported communication [45]. People often use it as a synonym for collaboration and alliance, describing relationships between these entities [40]. Social networks are people or groups of people who reveal a pattern of interactions among individuals, groups, or organizations [46]. Table 3 displays the key social network analysis terms and definitions.

Several measures attempt to describe and assess properties of actor location in a social network and their prominence, indicating the actors' level of importance. Prominent actors are often situated in strategic network positions [47]. Centrality is a concept and measurement aimed at quantifying graph theoretic ideas about an actor's prominence in a complete network by summarizing structural relations among all nodes. An actor with high centrality participates extensively in various relations, whether by sending or receiving ties

[48]. Centrality helps researchers better identify key actors, those who are more visible and influential, and to better understand the concept's meaning [47]. Borgatti & Halgin (2011) described centrality as a family of properties related to node positions [49]. Specifically, actor centrality assesses the involvement of an actor with other network members. The centrality concepts measured in this study include degree, closeness, and betweenness.

Degree centrality measures how many connections a node has with other nodes in a social network [48]. In graphs, degree centrality is defined as the number of ties connected to a node i [49]. According to Wasserman & Faust (1994), degree centrality highlights the most visible network actors. An actor with a high degree is in direct contact with many others and becomes recognized as a major channel of relational information and a crucial network component, occupying a central position [47]. Conversely, an actor with low degree centrality is considered peripheral and less active in the network's relational processes. Degree centrality was significant in this study as it identified the most influential physicians based on their direct connections with others. This information is valuable to hospital leaders for sharing quality information within the physician network.

Closeness centrality was developed to show how close a node is to others in a social network, mathematically expressed as a function of its geodesic distance to all other nodes [48]. The idea is that an actor is central if they can quickly interact with all others and therefore depend less on others for information sharing. This concept was important to explore in this study as actors in central locations regarding closeness can efficiently communicate information to others [47]. Closeness centrality differs from degree centrality by not only recognizing a physician's reach but also measuring the distance of that reach, indicating the speed at which quality information might be disseminated. Wasserman & Faust (1994) illustrated this with a star network: the node at the center, connected to all other nodes, has the shortest paths to all other actors and thus has maximum closeness. This actor can reach all others in a minimum number of steps and does not rely on others for interactions.

Betweenness centrality in graph terminology refers to the share of shortest paths passing through a node i [49]. Knoke & Yang (2008) described it as how actors control or mediate relations between dyads not directly connected [48]. They explained that actor betweenness centrality measures the extent to which actors lie on the shortest path between pairs of actors in the network. Betweenness centrality is a crucial indicator of control over information exchange or resource flows within a network. Identifying betweenness centrality measurements pinpointed physicians that hospital leaders should rely on to ensure quality information flows from point A to point B.

Table 3. The key social network analysis terms and definitions

Measure name	Subcategories	Definition
Node		
Centrality	Betweenness, Closeness, Eigenvector, Bonacich	A measure that describes the importance of a node
Degree	Adjusted degree, In-degree, Out-degree	Quantifies the number of other connected nodes
Density		The number of ties in an ego's network divided by the number of possible ties among the other actors in the ego network
Dyadic and Triadic		
Assortativity		The extent patients are shared preferentially with providers who receive many patients
Distance		Shortest or longest geodesic distance between two nodes
Edge	Edge weight, Ties, shared patients	A tie (e.g., a shared patient) between two nodes)
Reciprocity		Whether patients are shared in both directions
Transitivity	Transitive Closure, Clustering coefficient, Cyclic Closure	The probability that two providers who are connected to a common provider are also connected
Patient		
Care Density		The ratio between the total number of patients shared by provider pairs within a patient's care team, and the total number of provider pairs within the patient's care team
Degree Centrality	Team Size	Numbers of providers connected to a particular patient

3) Effects of networks on healthcare utilization and outcome

The previous studies consistently highlighted the importance of patient-sharing networks and their impact on healthcare outcomes and costs. A common finding is that higher network centrality and density among healthcare providers are generally associated with better coordination of care, reduced healthcare costs, and improved patient outcomes, such as lower hospitalization and readmission rates. However, there are variations in the specific metrics and outcomes measured across studies. While some studies focus on reducing healthcare costs and improving clinical outcomes, others focus on the structural aspects of networks, such as degree centrality and tie strength, and their relationship to hospital performance. Additionally, certain studies report mixed results, indicating that the benefits of network structures might differ based on specific conditions or patient demographics, highlighting the need for context-specific analyses. Overall, the studies underline the critical role of well-structured provider networks in enhancing healthcare delivery and patient outcomes, despite differing methodologies and focal points.

Barnett et al. (2012) found that, across 51 hospital referral regions, the structure of hospital physician patient-sharing relationships was associated with hospital-level outcomes. To be more specific, Medicare spending on imaging and tests, doctor visits, and medical specialist visits went down when the relative centrality of primary care physicians (PCPs) went up by one standard deviation.

Landon et al. (2013) reported that, after adjusting for network size, physician communities accounted for a significantly greater share of hospital admissions, emergency room visits, physician visits, and PCP visits. Pollack et al. (2013) found that high care density was associated with lower total and inpatient health spending for patients with congestive heart failure and diabetes after adjustments.

Uddin et al. (2013) analyzed the structure of hospital-based physician networks treating total hip replacement patients and found associations with hospitalization costs and readmission rates. They reported that betweenness, centralization, and density were negatively associated with hospital cost, with positive and significant interaction terms between these measures and age. Lomi et al. (2014) found that patients in Italy tended to move to higher-performing hospitals based on readmission rates, with past organizational and relational effects driving patient transfers.

Pollack et al. (2014) noted that cancer survivors with the highest care densities had lower odds of hospitalization and higher odds of receiving diabetic eye examinations compared to those with the lowest care densities. Casalino et al. (2015) found that on a physician level, more ambulatory care-sensitive admissions (ACSA) were linked to higher levels of adjusted value degree and betweenness centrality. At the network level, a higher proportion of PCPs and an average adjusted value degree were also positively associated with ACSAs.

Hussain et al. (2015) found that an increase in shared patients between medical oncologists and surgeons caring for Stage III colorectal cancer patients was associated with a significant reduction in mortality hazard. Patient sharing did not have an impact on healthcare spending. Mascia et al. (2015) reported that hospital centrality was associated with readmissions, and that hospital ego-network density increased the likelihood of readmissions.

Pollack et al. (2015) suggested that individuals with higher care densities had significantly fewer hospitalizations, and those with the highest care densities had lower odds of preventable hospitalization or cervical cancer screening and higher odds of breast cancer screening. Individuals with diabetes who had access to a higher density of healthcare services were more likely to receive a diabetic eye exam and less likely to be readmitted to the hospital or experience unnecessary hospitalization.

In physician networks defined by shared total hip replacement patients, greater degree centrality and tie strength were positively associated with hospital length of stay, with patient gender moderating this relationship, according to Uddin et al. (2015). Another study by Uddin et al. (2015) revealed that the number of subgroups within a physician community was negatively associated with readmission rates, while the number of physicians per community was positively associated with readmission rates.

Hollingsworth et al. (2016) found that health systems with physicians who work together in tightly-knit groups during coronary artery bypass grafting (CABG) episodes achieved better surgical outcomes regarding hospital readmission, emergency department use, and mortality. Uddin (2016) reported that the number of physicians in a network was significantly associated with hospital costs.

Table 4. Previous studies on Social Network Metrics and Health Outcome

Author(s) (Year)	Study Design	Study Data	Social Network Metrics	Key Findings
Barnett et al. (2012)[39]	Cross -sectional	Medicare claims	Degree, PCP centrality	☐ Across 51 hospital referral regions, the arrangement of relationships between hospitals, physicians, and patients had an impact on the outcomes at the hospital level. ☐ After accounting for other factors, a significant decrease in total Medicare spending, Medicare spending on imaging and tests, physician visits, and medical specialist visits was observed for each one standard deviation increase in primary care physician (PCP) relative centrality.
Landon et al. (2013)[50]	Cross -sectional	Medicare claims	Adjusted degree, Shared patients, Relative betweenness, Clustering coefficient	☐ When accounting for network size, physician communities were shown to contribute a much larger proportion of hospital admissions, emergency room visits, physician visits, and PCP visits.
Pollack et al. (2013)[51]	Cross -sectional	SEER-Medicare	Care density	☐ a higher concentration of care was found to be linked to reduced overall health expenditure and hospitalization costs for patients diagnosed with congestive heart failure and diabetes.
Uddin et al. (2013)[52]	Cross-sectional	Australian Insurer	Edge, 2-star, 3-star, Triangle, Alt-K-Stars, Alt-K-Triangles, Alt-K-2-Paths	☐ Hospitalization costs and readmission rates for total hip replacement patients are linked to the structure of hospital-based physician networks, according to specialists. ☐ Regression models, which considered patient age and the interaction between age and network measure, revealed a negative correlation between betweenness centralization, density, and ho. These parameters interacted positively and significantly with age.

Table 4. Previous studies on Social Network Metrics and Health Outcome (Continued)

Author(s) (Year)	Study Design	Study Data	Social Network Metrics	Key Findings
Lomi et al. (2014)[53]	Longitudinal	Italian National Health Service (Abruzzo)	Reciprocity, Degree, Recurrence, Transitive closure, Out- degree, In-degree	☐ In Italy, patients who are transferred between hospitals typically move to institutions that have a greater level of performance, as determined by their readmission rate. ☐ The authors utilize longitudinal data on patient-sharing events to determine that previous organizational and relational factors influence patient transfers.
Pollack et al. (2014)[54]	Cohort	IMS Health Plan Claims Database	Care density	☐ Following adjustment, cancer survivors with the highest levels of care density exhibited a greater likelihood of reduced hospitalization rates and increased odds of receiving diabetic eye tests, in comparison to cancer survivors with the lowest care densities.
Casalino et al. (2015)[55]	Cross-sectional	Medicare claims	Mean adjusted value, PCP centrality, Percentage of PCP providers, Size	☐ Using a multi-level model, there was a positive association between a physician's adjusted value degree (which measures the number of connections to other physicians standardized by the number of patients seen in that network) and betweenness centrality, and ambulatory care sensitive hospital admissions (ACSA). ☐ At the network level, an increase of one standard deviation in the proportion of primary care physicians (PCPs) and the average adjusted value degree was found to have a positive association with Ambulatory Care Sensitive Admissions (ACSAs).
Hussain et al. (2015)[56]	Cohort	SEER-Medicare	Shared patients	☐ There was a notable reduction in the risk of death when there was an upsurge in the number of patients shared between medical oncologists and surgeons who treat individuals with Stage III colorectal cancer. ☐ There was no correlation between patient sharing and variations in healthcare expenditure.

Table 4. Previous studies on Social Network Metrics and Health Outcome (Continued)

Author(s) (Year)	**Study Design**	**Study Data**	**Social Network Metrics**	**Key Findings**
Mascia et al. (2015)[57]	Cross-sectional	Italian National Health Service (Abruzzo)	Bonacich Centrality, Ego- network density	☐ After adjustment, there was a correlation between the centrality of the hospital and readmissions. ☐ After making the necessary adjustments, an increase in the risk of readmissions was observed in hospitals with higher ego-network density.
Pollack et al. (2015)[58]	Cross-sectional	SEER-Medicare	Care density	☐ Bivariate analyses indicate that those with higher care densities have considerably fewer hospitalizations compared to those with lower care densities, across all patients and patients with congestive heart failure, diabetes, and chronic obstructive pulmonary disease. ☐ Individuals with higher care densities had a decreased likelihood of experiencing preventable hospitalizations or cervical cancer screenings, but an increased likelihood of receiving breast cancer screenings. ☐ Individuals with diabetes and higher care densities had an increased likelihood of receiving diabetic eye exams, but a decreased likelihood of hospital readmission and preventable hospitalizations.
Uddin et al. (2015)[59]	Cross-sectional	Australian Insurer	Degree centrality, Tie strength	☐ Higher degree centrality and tie strength in physician networks with a shared set of total hip replacement patients correlate with longer hospital stays. Patient gender affects network features like degree centrality and tie strength and hospital stay. ☐ ssssAn ERGM study found that physician networks with high readmission rates had more triangular structures, indicating a flat organizational structure. Centralization may increase performance, such as decreasing readmission rates.

Table 4. Previous studies on Social Network Metrics and Health Outcome (Continued)

Author(s) (Year)	Study Design	Study Data	Social Network Metrics	Key Findings
Uddin et al. (2015)[60]	Cross-sectional	Australian Insurer	Number of physician communities, Average number of physicians per community, Ratio of physicians to patients	☐ Simple linear regression models showed that readmission rate was negatively correlated with subgroups and positively correlated with physicians per community.
Hollingsworth et al. (2016)[61]	Cross-sectional	Medicare claims	Bipartite clustering coefficient	☐ Health systems with tightly-knit CABG physician teams have improved hospital readmission, emergency department utilization, and mortality results.
Uddin (2016)[62]	Cross-sectional	Australian Insurer	Average number of physicians per community, Density	☐ Number of physicians in a network greatly affected hospital cost.

III. Material and Methods

1. Data Source and Study Population

In this population-based cohort study, data were obtained from the Korean National Health Insurance Service (NHIS) database [63]. Since the implementation of universal health coverage in 1989, all South Korean citizens have been obliged to subscribe to the NHIS, and approximately 97% of the entire population (approximately 50 million) has been enrolled [64, 65]. Since the NHIS also manages the healthcare claims of the remaining 3% of the Korean population, the medical aid program beneficiaries, the NHIS database contains the medical records of the almost all Korean population. The data includes anonymized participant information (demographics, healthcare utilizations, and prescription records). All participants were followed up until their loss of eligibility due to death or emigration.

The NHIS database comprises a various type of data, such as medical check-up data, medical claims data, sociodemographic data, and mortality data for all Koreans. Among these, the medical claims data is the most extensive database provided by the NHIS, encompassing details about the medical utilization of the entire Korean population. This information includes International Classification of Diseases 10th revision (ICD-10) diagnostic codes, prescriptions for medications, lengths of hospital stays, medical expenses, and information regarding healthcare provisions. The NHIS provides researchers with customized cohort data for the purpose of policy making and academic research.

This study extracted the medical data of approximately 1.5 million patients, which is about 30% of the total patient with ischemic heart diseases (ICD-10 codes I20-I25) and cerebrovascular diseases (ICD-10 codes I60-I69), from January 1, 2005, to December 31, 2022, through random sampling. This study defined the first acute myocardial infarction (AMI) event as the first hospitalization episode that met the criteria. The AMI patient was defined when a hospitalization diagnosis code for AMI (ICD10; I21-I23) was identified in NHIS claims data. Among AMI patients, we identified those who underwent a therapeutic intervention, such as coronary angiography (CAG), percutaneous coronary intervention (PCI), or coronary artery bypass grafting (CABG) (Appendix 1) (Figure 3).

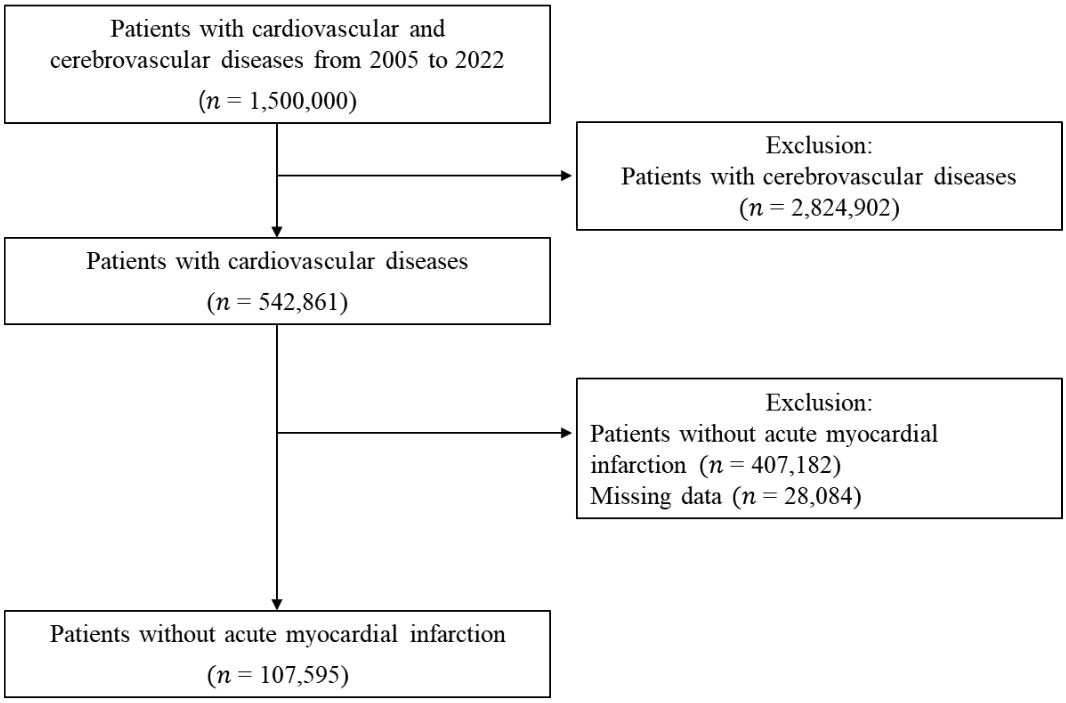


Figure 3. Flow chart of the study population

2. Definition of Variables

1) Dependent variables

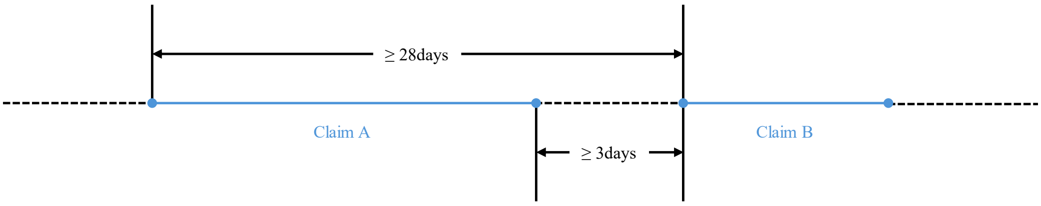
The primary dependent variables were three types of mortality. The death code was extracted from the NHIS insurance eligibility database. If a patient had a death code, they were considered deceased. The secondary dependent variable was readmission for one year after discharge from the subject hospital.

Table 5. Definition of dependent variables

Category	Variable Name	Definition
Outcome	In-hospital all-cause mortality	If the patient dies before discharge (within the end of the inpatient episode)
	1-year all-cause mortality	If the patient dies within 1 year from the onset of acute myocardial infarction
	3-year all-cause mortality	If the patient dies within 3 years from the onset of acute myocardial infarction
Healthcare utilization	Readmission within 1 year	Readmission within one year due to acute myocardial infarction after discharge

Multiple claims for a single disease episode are common in health insurance claims data [66]. This can occur in a variety of situations, such as during extended hospital stays or recurrent hospital admissions due to complications. For instance, when a patient undergoes a 30-day hospital stay for AMI, the insurance company submits claims for the event at separate 30-day intervals. Consolidating all interrelated insurance claims into a single disease episode becomes essential, given the distribution of claim codes for drug prescriptions, diagnostic tests, or medical procedures across these separate claims.

As such, we have introduced the concept of a “hospitalization episode” to address these complexities. Figure 4 outlines this term as the period of claims reasonably attributed to a single disease event. Specifically, we separated any two consecutive insurance claims A and B, both containing diagnosis codes for the disease of interest, into distinct hospitalization episodes if: (1) the gap between the first dates of claims A and B exceeded 28 days; and (2) the interval between the last date of claim A and the first date of claim B spanned 3 days or longer. In other words, a sequence of insurance claims for a disease was defined as a single hospitalization episode if no consecutive pair in the sequence met the conditions for episode separation.



Claims A and B were considered as separate episodes when both conditions were met
(1) Interval between the first dates of claims A and B ≥23days
(2) Interval between the last dates of claim A and the first dates of claim B ≥3days

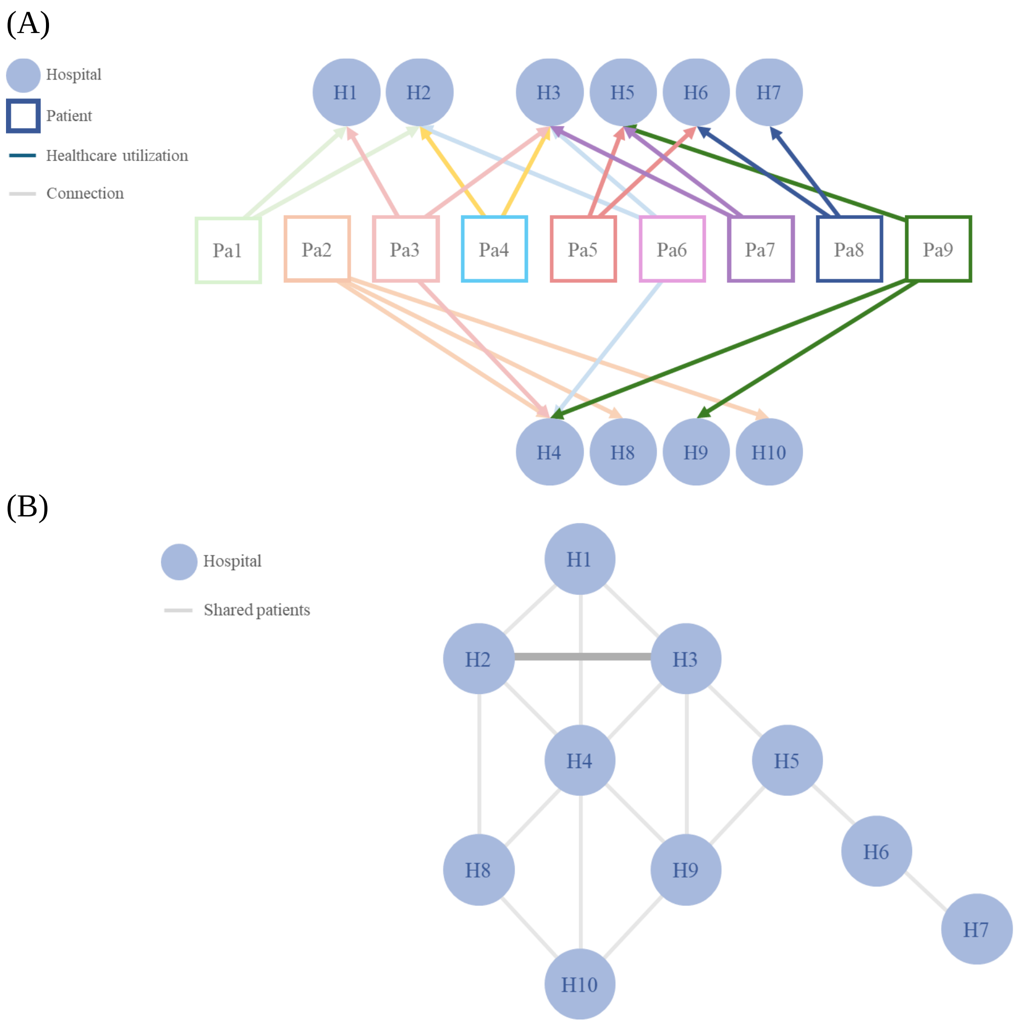
Figure 4. Definition of hospitalization episode

2) Variable of Interest

(1) Identifying the sharing of patients and constructing hospital networks

The network construction was based on patient-sharing relations between healthcare providers, an approach that has been previously validated [12]. Shared patients among providers were interpreted as representing an information-sharing relationship between those providers [67]. These shared patients were identified from health claims data. The network nodes represented healthcare providers, and an edge between two nodes indicated shared patients between those providers. The edge weights were determined by the number of shared patients, serving as a proxy for the strength of the relationships between providers (Figure 5).

The network was limited to patients with AMI and their associated healthcare providers. Previous research demonstrated that information-sharing relationships between healthcare providers were significant with link weights of two or more [12]. Hence, the network focused on providers who shared at least two patients. Excluding providers with only one shared patient has been recommended to eliminate chance relationships that may not provide meaningful information about the provider relationships [12, 68].



* Each node represents an individual hospital, and each edge (connection between two nodes) represents a connection through shared patients. Directed solid lines denote the observed connections between individual hospitals.

Figure 5. Illustrative model of patient sharing network

(2) Measuring Network-level metrics

This study focused on centrality measures, specifically betweenness and degree centrality. The aim was to understand how a provider′s connectedness, access, and control over information flow impacted patient outcomes. Density measured the cohesion and frequency of collaboration among healthcare providers [69]. Centrality measures identified nodes with important roles in the network and greater access to other nodes [70]. Two centrality measures were calculated: degree centrality and betweenness centrality. These measures were applied to the largest component of the network to identify the most influential providers and those with greater access and control over information flow.

Degree centrality indicated the number of providers directly connected to a given provider in the network [71]. The node with the highest degree might be regarded as the most prominent or dynamic node in a network. The degree of a node varies from 0 to N – 1, and is determined by the link between node i and j, denoted by α_{ij}.

$$degree\ centrality\ (i) = \sum_{i \neq j} a_{ij}$$

Betweenness centrality measured the extent to which a node acted as an intermediary between pairs of other nodes in the network. A node with higher betweenness centrality had more influence in distributing information within the network [39]. If this study envisions such paths as the transmission of information, hospitals that are located on several shortest paths are more likely to possess significant influence in the communication process. The most frequently employed measure of betweenness centrality is defined as follows:

$$betweenness\ centrality\ (i) = \sum_{i \neq s \neq t} \frac{\sigma(s,t|i)}{\sigma(s,t)}$$

σ (s, t |i) represents the total count of shortest pathways between s and t that traverse via i, while σ (s,t) denotes the total count of shortest paths between s and t, irrespective of whether or not they traverse through i.

3) Covariates

There were 14 control variables included. First, as sociodemographic factors, sex, age, region of residence, type of medical insurance subscription, and income level were included in the analysis. Income level was categorized based on income quintile, which is an indicator that divides the income level of all households in Korea from level 1 to level 20. Health insurance type was classified according to who pays the insured contribution. Second, as factors related health status and practice factor, this study adjusted for Charlson comorbidity index (CCI) score, hospitalization route, and surgery.

Multiple factors, including an individual's health status and the capabilities of the treating hospital, influence patient mortality. To adjust for the severity of comorbidities, which are significantly correlated with mortality, the CCI was calculated and utilized. The CCI score in this study was derived using five diagnostic codes, including the primary diagnosis code from the National Health Insurance Service claims data, to prevent underestimation of comorbidities. The CCI score was calculated by assigning weights to each condition according to Quan′s method (Appendix 2). Lastly, hospital type, RCCVCs designation, number of specialists, number of nurses, number of operating rooms, and number of ER Beds were selected as characteristics of the hospital treated. The RCCVCs designation status was classified according to whether the medical institution to which the patient was admitted was RCCVCs. The designation status of RCCVCs at the time of visit was defined as January of the year following the year of designation according to the following appendix 3. The controlled variables employed in this study are described in depth in Table 6:

Table 6. List of covariates

Variable	Definition
Sex	Male, Female
Age group	Under 50, 50-59, 60-69, 70-79, Over 80
Region	Seoul, Metropolitan, Urban/Rural
Medical Insurance	Insurance (Corporate) / Insurance (Regional)
Income	0-4th decile(Low), 5-8th decile, 9-12th decile, 13-16th decile, 17-20th decile(High)
Charlson Comorbidity Index (CCI) score	None, One, Two, Three or more
Hospitalization route	Emergency room, Other
Surgery	Yes, No
Hospital Type	Tertiary Hospital, General Hospital
RCCVCs designation	RCCVCs (Yes), Non-RCCVCs (No)
Number of specialists	Number of specialists
Number of nurses	Number of nurses
Number of operating rooms	Number of operating rooms
Number of ER Beds	Number of emergency room beds

4. Statistical Methods

A descriptive analysis was performed to see the general characteristics. The chi-square test was employed to examine the general characteristics of the study population with frequencies and percentages reported. T-test and analysis of variance were used to see the means and standard deviations of the covariates.

This study described the characteristics of the hospital network and then drew the graph according to the geographic scope and hospital grade. Selected networks were visualized using the Fruchterman-Reingold algorithm, a commonly used example of spring-embedder methods, which positioned nodes with stronger connections (i.e. hospitals with more shared patients) in closer physical proximity within the network graph [72]. This study calculated two centrality measures of the hospital network using the 'igraph' package (version 1.2.6) in R. To facilitate interpretation of this model, this study divided two network measures fairly neatly into two groups according to tertiles: low-middle (the first tertile to the second tertile) and high (the second tertile to the highest value). Coefficients

The incidence rate of mortality (and 95% confidence intervals) was calculated as the number of events divided by the total number of person-years of follow-up. The primary outcome of all-cause mortality was analyzed by constructing retrospective mortality cohorts, analyzed using a Cox proportional hazards model. The risk of mortality among AMI patients, with adjusted Hazard Ratios (aHR) and 95% CI reported. Time-zero was set to the date of their initial diagnosis, and survival time was defined as the number of days from the date of diagnosis (time-zero) to the date of death or December 31, 2022, whichever occurred first.

The incidence rate of readmission within one year (and 95% CI) was calculated as the number of events divided by the total number of person-years of follow-up. The risk of readmission within one year among AMI patients was analyzed using a Cox proportional hazards model, with aHR and 95% CIs reported. The survival time was defined as the number of days from the discharge date (time-zero) to the date of readmission or the one-year mark, whichever occurred first. All analysis was performed using SAS Enterprise Guide (version 7.1; SAS Institute, Care, NC). A P-value <0.05 was considered statistically significant.

5. Ethics Statement

The study protocol was reviewed and approved by the Institutional Review Board of Yonsei University's Health System in accordance with the principles of the Declaration of Helsinki (IRB Number: 4-2023-0181). The requirement for informed consent was waived since NHIS database we obtained (NHIS-2024-1-228) does not contain any personally identifiable information.

IV. Results

1. General Characteristics of the Study Population

1) Characteristics of the patients according to in-hospital mortality

This table 7 presented the characteristics of patients with in-hospital mortality compared to those who survived. The total sample size is 107,595 patients, with 91.8% surviving and 8.2% dying in the hospital. Males have a lower in-hospital mortality (6.4%) compared to females (12.9%), showing a significant difference (p<0.0001). Younger age groups have lower mortality, with the highest mortality observed in patients over 80 years (21.5%) (p<0.0001). Patients with higher household income had higher mortality (17-20th decile 9.3%) (p<0.0001). Higher CCI scores correlate with higher mortality (p<0.0001).

Tertiary hospitals have a lower mortality (7.3%) compared to general hospitals (9.0%) (p<0.0001). Patients treated with RCCVCs have a lower mortality (6.6%) compared to non-RCCVCs (8.5%). The average degree centrality was 0.73 (SD 0.42) and the average betweenness centrality was 293.02 (SD 326.74). Patients treated at hospitals with lower degree centrality had higher mortality (8.7%) (p<0.0001). Patients treated at hospitals with lower betweenness centrality had higher mortality (8.7%) (p<0.0001).

Table 7. Characteristics of the patients according to in-hospital mortality

Characteristics	Total		In-hospital death				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Total	107,595	100.0	98,748	91.8	8,847	8.2	
Sex							
Female	29,730	27.6	25,905	87.1	3,825	12.9	<0.0001
Male	77,865	72.4	72,843	93.6	5,022	6.4	
Age(year)	64.84	13.29	63.97	13.06	74.62	11.94	<0.0001
Age group							
Under 50	14,657	13.6	14,337	97.8	320	2.2	<0.0001
50-59	23,905	22.2	23,186	97.0	719	3.0	
60-69	27,094	25.2	25,561	94.3	1,533	5.7	
70-79	25,749	23.9	22,960	89.2	2,789	10.8	
Over 80	16,190	15.0	12,704	78.5	3,486	21.5	
Region							
Seoul	18,297	17.0	16,702	91.3	1,595	8.7	0.0056
Metropolitan	27,396	25.5	25,239	92.1	2,157	7.9	
Urban/Rural	61,902	57.5	56,807	91.8	5,095	8.2	

(Continue)

Table 7. Characteristics of the patients according to in-hospital mortality

Characteristics	Total		In-hospital death				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Medical Insurance							0.8640
Insurance (Regional)	40,547	37.7	37,221	91.8	3,326	8.2	
Insurance (Corporate)	67,048	62.3	61,527	91.8	5,521	8.2	
Household income							<0.0001
0-4th decile (Low)	18,245	17.0	16,694	91.5	1,551	8.5	
5-8th decile	14,868	13.8	13,778	92.7	1,090	7.3	
9-12th decile	18,285	17.0	16,920	92.5	1,365	7.5	
13-16th decile	23,102	21.5	21,329	92.3	1,773	7.7	
17-20th decile (High)	33,095	30.8	30,027	90.7	3,068	9.3	
Charlson Comorbidity Index score							
None	13,268	12.3	12,401	93.5	867	6.5	<0.0001
One	10,283	9.6	9,527	92.6	756	7.4	
Two	18,012	16.7	16,868	93.6	1,144	6.4	
Three or more	66,032	61.4	59,952	90.8	6,080	9.2	

(Continue)

Table 7. Characteristics of the patients according to in-hospital mortality

Characteristics	Total		In-hospital death				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Hospitalization route							0.7376
Other	25,032	23.3	22,987	91.8	2,045	8.2	
Emergency room	82,563	76.7	75,761	91.8	6,802	8.2	
Surgery							<0.0001
No	51,570	47.9	45,101	87.5	6,469	12.5	
Yes	56,025	52.1	53,647	95.8	2,378	4.2	
Hospital Type							<0.0001
Tertiary Hospital	51,495	47.9	47,713	92.7	3,782	7.3	
General Hospital	56,100	52.1	51,035	91.0	5,065	9.0	
RCCVC							<0.0001
No	94,530	87.9	86,541	91.5	7,989	8.5	
Yes	13,065	12.1	12,207	93.4	858	6.6	
Degree centrality	0.73	0.42	0.73	0.42	0.67	0.42	<0.0001
Degree centrality group							<0.0001
Low-middle	72,206	67.1	65,937	91.3	6,269	8.7	
High	35,389	32.9	32,811	92.7	2,578	7.3	

(Continue)

Table 7. Characteristics of the patients according to in-hospital mortality

Characteristics	Total		In-hospital death				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Betweenness centrality	293.02	326.74	296.00	328.70	260.20	301.50	<0.0001
Betweenness centrality group							<0.0001
Low-middle	68,268	63.4	62,307	91.3	5,961	8.7	
High	39,327	36.6	36,441	92.7	2,886	7.3	
Number of specialists	169.12	149.74	170.60	150.40	152.60	140.60	<0.0001
Number of nurses	611.10	549.88	615.50	551.00	562.10	534.70	<0.0001
Number of operating rooms	13.88	12.37	13.98	12.43	12.81	11.66	<0.0001
Number of ER Beds	31.30	13.16	31.41	13.13	30.02	13.44	<0.0001

2) Characteristics of the patients according to 1-year all-cause mortality

The table 8 presented the characteristics of patients according to one-year all-cause mortality. The total sample size is 107,595 patients, with 86.1% surviving and 13.9% dying within one year. Males have a lower one-year mortality (10.9%) compared to females (21.7%) ($p<0.0001$). Younger age groups have lower mortality, with the highest mortality observed in patients over 80 years (37.6%) ($p<0.0001$). Higher CCI scores correlate with higher mortality, with a notable increase in those with three or more scores (17.2%) compared to those with none (8.0%) ($p<0.0001$).

Patients treated with tertiary hospitals have a lower mortality (12.9%) compared to general hospitals (14.8%) ($p<0.0001$). Patients treated with RCCVCs have a lower mortality (11.5%) compared to non-RCCVCs (14.2%) ($p<0.0001$). Patients treated at hospitals with lower degree centrality had higher mortality (14.5%) ($p<0.0001$). Patients treated at hospitals with lower betweenness centrality had higher mortality (14.3%) ($p<0.0001$).

Table 8. Characteristics of the patients according to 1-year all-cause mortality

Characteristics	Total		1-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Total	107,595	100.0	92,649	86.1	14,946	13.9	
Sex							
Male	29,730	27.6	23,282	78.3	6,448	21.7	<0.0001
Female	77,865	72.4	69,367	89.1	8,498	10.9	
Age(year)	64.84	13.29	63.17	12.79	75.24	11.52	<0.0001
Age group							
Under 50	14,657	13.6	14,190	96.8	467	3.2	<0.0001
50-59	23,905	22.2	22,833	95.5	1,072	4.5	
60-69	27,094	25.2	24,683	91.1	2,411	8.9	
70-79	25,749	23.9	20,833	80.9	4,916	19.1	
Over 80	16,190	15.0	10,110	62.4	6,080	37.6	
Region							
Seoul	18,297	17.0	15,700	85.8	2,597	14.2	0.0017
Metropolitan	27,396	25.5	23,766	86.7	3,630	13.3	
Urban/Rural	61,902	57.5	53,183	85.9	8,719	14.1	

(Continue)

Table 8. Characteristics of the patients according to 1-year all-cause mortality

Characteristics	Total		1-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Medical Insurance							
Insurance (Regional)	40,547	37.7	35,043	86.4	5,504	13.6	0.0200
Insurance (Corporate)	67,048	62.3	57,606	85.9	9,442	14.1	
Household income							< 0.0001
0-4th decile (Low)	18,245	17.0	15,664	85.9	2,581	14.1	
5-8th decile	14,868	13.8	13,039	87.7	1,829	12.3	
9-12th decile	18,285	17.0	15,952	87.2	2,333	12.8	
13-16th decile	23,102	21.5	20,075	86.9	3,027	13.1	
17-20th decile (High)	33,095	30.8	27,919	84.4	5,176	15.6	
Charlson Comorbidity Index score							
None	13,268	12.3	12,209	92.0	1,059	8.0	<0.0001
One	10,283	9.6	9,319	90.6	964	9.4	
Two	18,012	16.7	16,431	91.2	1,581	8.8	
Three or more	66,032	61.4	54,690	82.8	11,342	17.2	

(Continue)

Table 8. Characteristics of the patients according to 1-year all-cause mortality

Characteristics	Total		1-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Hospitalization route							
Other	25,032	23.3	21,483	85.8	3,549	14.2	0.1368
Emergency room	82,563	76.7	71,166	86.2	11,397	13.8	
Surgery							
No	51,570	47.9	41,569	80.6	10,001	19.4	<0.0001
Yes	56,025	52.1	51,080	91.2	4,945	8.8	
Hospital Type							<0.0001
Tertiary Hospital	51,495	47.9	44,839	87.1	6,656	12.9	
General Hospital	56,100	52.1	47,810	85.2	8,290	14.8	
RCCVC							
No	94,530	87.9	81,093	85.8	13,437	14.2	<0.0001
Yes	13,065	12.1	11,556	88.5	1,509	11.5	
Degree centrality	0.73	0.42	0.73	0.42	0.68	0.42	< 0.0001
Degree centrality group							< 0.0001
Low-middle	72,206	67.1	61,757	85.5	10,449	14.5	
High	35,389	32.9	30,892	87.3	4,497	12.7	

(Continue)

Table 8. Characteristics of the patients according to 1-year all-cause mortality

Characteristics	Total		1-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Betweenness centrality	293.02	326.74	297.50	330.30	264.90	302.10	<0.0001
Betweenness centrality group							<0.0001
Low-middle	68,268	63.4	58,489	85.7	9,779	14.3	
High	39,327	36.6	34,160	86.9	5,167	13.1	
Number of specialists	169.12	149.74	171.60	151.20	153.60	139.50	<0.0001
Number of nurses	611.10	549.88	619.60	553.60	558.40	523.10	<0.0001
Number of operating rooms	13.88	12.37	14.04	12.48	12.90	11.63	<0.0001
Number of ER Beds	31.30	13.16	31.48	13.15	30.18	13.19	<0.0001

3) Characteristics of the patients according to 3-year all-cause mortality

The table 9 presented the characteristics of patients on three-year all-cause mortality. Out of 107,595 patients, 81.2% survived while 18.8% died within three years. Males have a lower three-year mortality rate (15.1%) compared to females (28.3%) ($p<0.0001$). Mortality increases with age, being highest in the over 80 group (49.4%) and lowest in the under 50 group (4.3%) ($p<0.0001$). Mortality increases with CCI score, reaching its peak in the group with a CCI of three or above (23.8%) ($p<0.0001$).

Tertiary hospitals show a lower mortality rate (17.9%) compared to general hospitals (19.6%) ($p<0.0001$). Patients treated with RCCVCs have a lower mortality rate (16.1%) compared to non-RCCVCs (19.2%) ($p<0.0001$). Patients treated at hospitals with lower degree centrality had higher mortality (17.6%) ($p<0.0001$). Patients treated at hospitals with lower betweenness centrality had higher mortality (18.2%) ($p<0.0001$).

Table 9. Characteristics of the patients according to 3-year all-cause mortality

Characteristics	Total		3-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Total	107,595	100.0	87,382	81.2	20,213	18.8	
Sex							
Female	29,730	27.6	21,304	71.7	8,426	28.3	<0.0001
Male	77,865	72.4	66,078	84.9	11,787	15.1	
Age(year)	64.84	13.29	62.49	12.57	75.04	11.39	<0.0001
Age group							
Under 50	14,657	13.6	14,033	95.7	624	4.3	<0.0001
50-59	23,905	22.2	22,440	93.9	1,465	6.1	
60-69	27,094	25.2	23,763	87.7	3,331	12.3	
70-79	25,749	23.9	18,961	73.6	6,788	26.4	
Over 80	16,190	15.0	8,185	50.6	8,005	49.4	
Region							
Seoul	18,297	17.0	14,850	81.2	3,447	18.8	<0.0001
Metropolitan	27,396	25.5	22,472	82.0	4,924	18.0	
Urban/Rural	61,902	57.5	50,060	80.9	11,842	19.1	

(Continue)

Table 9. Characteristics of the patients according to 3-year all-cause mortality

Characteristics	Total		3-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Medical Insurance							
Insurance (Regional)	40,547	37.7	33,140	81.7	7,407	18.3	0.0007
Insurance (Corporate)	67,048	62.3	54,242	80.9	12,806	19.1	
Household income							<0.0001
0-4th decile (Low)	18,245	17.0	14,763	80.9	3,482	19.1	
5-8th decile	14,868	13.8	12,415	83.5	2,453	16.5	
9-12th decile	18,285	17.0	15,143	82.8	3,142	17.2	
13-16th decile	23,102	21.5	18,995	82.2	4,107	17.8	
17-20th decile (High)	33,095	30.8	26,066	78.8	7,029	21.2	
Charlson Comorbidity Index score							
None	13,268	12.3	12,013	90.5	1,255	9.5	<0.0001
One	10,283	9.6	9,060	88.1	1,223	11.9	
Two	18,012	16.7	15,971	88.7	2,041	11.3	
Three or more	66,032	61.4	50,338	76.2	15,694	23.8	

(Continue)

Table 9. Characteristics of the patients according to 3-year all-cause mortality

Characteristics	Total		3-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Hospitalization route							
Other	25,032	23.3	20,227	80.8	4,805	19.2	<0.0001
Emergency room	82,563	76.7	67,155	81.3	15,408	18.7	
Surgery							
No	51,570	47.9	39,036	75.7	12,534	24.3	<0.0001
Yes	56,025	52.1	48,346	86.3	7,679	13.7	
Hospital Type							
Tertiary Hospital	51,495	47.9	42,300	82.1	9,195	17.9	<0.0001
General Hospital	56,100	52.1	45,082	80.4	11,018	19.6	
RCCVC							
No	94,530	87.9	76,423	80.8	18,107	19.2	<0.0001
Yes	13,065	12.1	10,959	83.9	2,106	16.1	
Degree centrality	0.73	0.42	0.74	0.42	0.69	0.42	
Degree centrality group							
Low-middle	72,206	67.1	58,237	80.7	13,969	19.3	<0.0001
High	35,389	32.9	29,145	82.4	6,244	17.6	

(Continue)

Table 9. Characteristics of the patients according to 3-year all-cause mortality

Characteristics	Total		3-year all-cause mortality				*P-value*
			Survival		Death		
	N, Mean	%	N, Mean	%	N, Mean	%	
Betweenness centrality	293.02	326.74	298.10	330.90	270.80	307.30	<0.0001
Betweenness centrality group							
Low-middle	68,268	63.4	55,220	80.9	13,048	19.1	
High	39,327	36.6	32,162	81.8	7,165	18.2	<0.0001
Number of specialists	169.12	144.44	168.8	146.2	152.0	135.2	<0.0001
Number of nurses	599.46	532.90	610.7	537.8	546.2	506.0	<0.0001
Number of operating rooms	13.63	12.01	13.80	12.13	12.80	11.41	<0.0001
Number of ER Beds	31.16	12.97	31.33	12.96	30.35	12.95	<0.0001

4) Characteristics of the patients according to readmission within one year after discharge

Table 10 presented patients' characteristics according to readmission within one year after discharge. AMI led to the readmission of 13.2% of the 107,595 patients within a year. The readmission rate was higher for females (14.1%) compared to males (12.8%) ($p<0.0001$). Readmissions increased with age, with the highest in the group aged 80 and over (14.6%) ($p<0.0001$). The group with a CCI score of three or more had the highest readmission rate (15.2%) ($p<0.0001$).

Tertiary hospitals show a lower mortality rate (12.7%) compared to general hospitals (13.6%) ($p<0.0001$). Patients treated with RCCVCs have a lower mortality rate (11.7%) compared to non-RCCVCs (13.4%) ($p<0.0001$). Patients treated at hospitals with lower degree centrality had higher mortality (13.7%) ($p<0.0001$). Patients treated at hospitals with lower betweenness centrality had higher mortality (13.3%) ($p<0.0001$).

Table 10. Characteristics of the patients according to readmission within one year

Characteristics	Total		Readmission within one year				*P-value*
			No		Yes		
	N, Mean	%	N, Mean	%	N, Mean	%	
Total	107,595	100.0	93,402	86.8	14,193	13.2	
Sex							
Female	29,730	27.6	25,525	85.9	4,205	14.1	<0.0001
Male	77,865	72.4	67,877	87.2	9,988	12.8	
Age(year)	64.84	13.29	64.71	13.30	65.70	13.2	<0.0001
Age group							
Under 50	14,657	13.6	12,867	87.8	1,790	12.2	<0.0001
50-59	23,905	22.2	20,981	87.8	2,924	12.2	
60-69	27,094	25.2	23,618	87.2	3,476	12.8	
70-79	25,749	23.9	22,111	85.9	3,638	14.1	
Over 80	16,190	15.0	13,825	85.4	2,365	14.6	
Region							
Seoul	18,297	17.0	15,901	86.9	2,396	13.1	<0.0001
Metropolitan	27,396	25.5	23,881	87.2	3,515	12.8	
Urban/Rural	61,902	57.5	53,620	86.6	8,282	13.4	

(Continue)

Table 10. Characteristics of the patients according to readmission within one year

Characteristics	Total		Readmission within one year				*P-value*
			No		Yes		
	N, Mean	%	N, Mean	%	N, Mean	%	
Medical Insurance							
Insurance (Regional)	40,547	37.7	35,136	86.7	5,411	13.3	<0.0001
Insurance (Corporate)	67,048	62.3	58,266	86.9	8,782	13.1	
Household income							0.7070
0-4th decile (Low)	18,245	17.0	15,803	86.6	2,442	13.4	
5-8th decile	14,868	13.8	12,925	86.9	1,943	13.1	
9-12th decile	18,285	17.0	15,919	87.1	2,366	12.9	
13-16th decile	23,102	21.5	20,024	86.7	3,078	13.3	
17-20th decile (High)	33,095	30.8	28,731	86.8	4,364	13.2	
Charlson Comorbidity Index score							
None	13,268	12.3	12,043	90.8	1,225	9.2	<0.0001
One	10,283	9.6	9,259	90.0	1,024	10.0	
Two	18,012	16.7	16,131	89.6	1,881	10.4	
Three or more	66,032	61.4	55,969	84.8	10,063	15.2	

(Continue)

Table 10. Characteristics of the patients according to readmission within one year

Characteristics	Total		Readmission within one year				*P-value*
			No		Yes		
	N, Mean	%	N, Mean	%	N, Mean	%	
Hospitalization route							
Other	25,032	23.3	21,589	86.2	3,443	13.8	<0.0001
Emergency room	82,563	76.7	71,813	87.0	10,750	13.0	
Surgery							
No	51,570	47.9	45,291	87.8	6,279	12.2	<0.0001
Yes	56,025	52.1	48,111	85.9	7,914	14.1	
Hospital Type							
Tertiary Hospital	51,495	47.9	44,956	87.3	6,539	12.7	<0.0001
General Hospital	56,100	52.1	48,446	86.4	7,654	13.6	
RCCVC							
No	94,530	87.9	81,872	86.6	12,658	13.4	<0.0001
Yes	13,065	12.1	11,530	88.3	1,535	11.7	
Degree centrality	0.73	0.42	0.73	0.42	0.70	0.41	
Degree centrality group							
Low-middle	72,206	67.1	62,331	86.3	9,875	13.7	<0.0001
High	35,389	32.9	31,071	87.8	4,318	12.2	

(Continue)

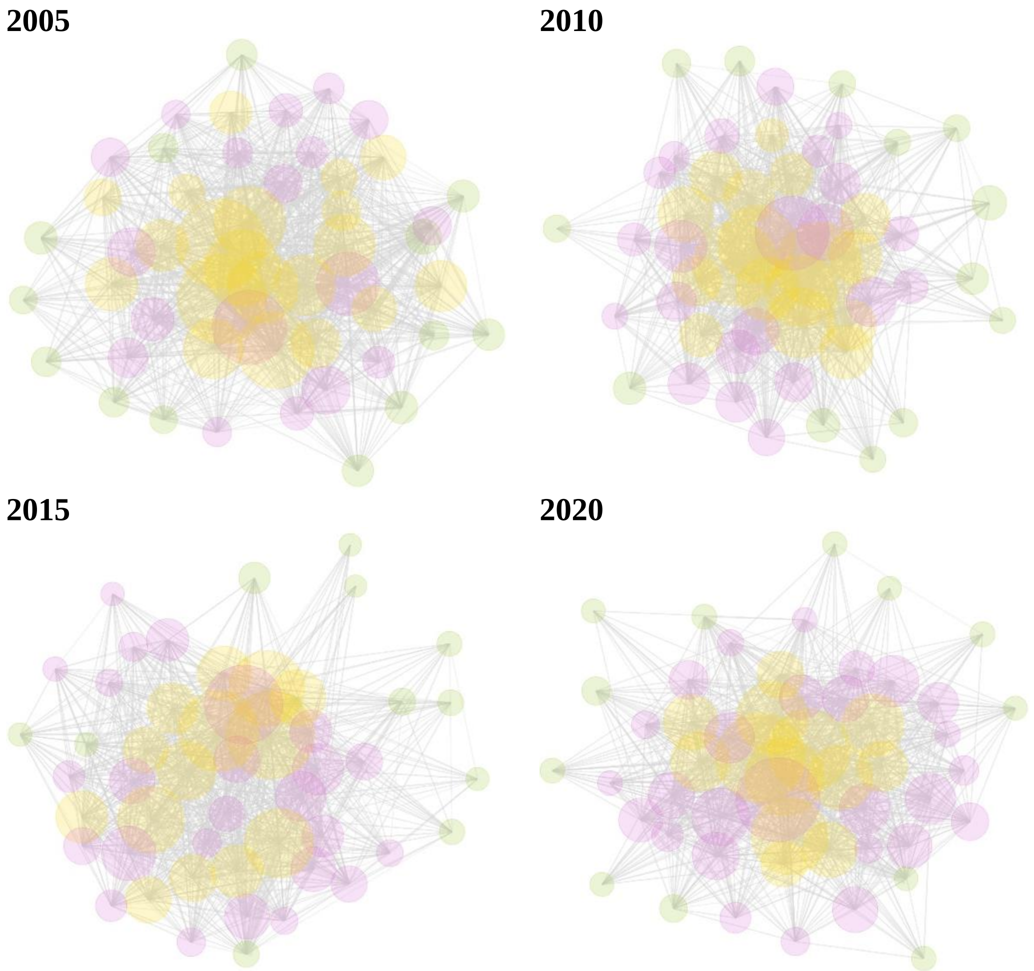
Table 10. Characteristics of the patients according to readmission within one year

Characteristics	Total		Readmission within one year				*P-value*
			No		Yes		
	N, Mean	%	N, Mean	%	N, Mean	%	
Betweenness centrality	293.02	326.74	294.70	329.20	282.00	309.70	<0.0001
Betweenness centrality group							
Low-middle	68,268	63.4	59,162	86.7	9,106	13.3	
High	39,327	36.6	34,240	87.1	5,087	12.9	<0.0001
Number of specialists	169.12	144.44	170.50	151.40	160.20	137.90	<0.0001
Number of nurses	599.46	532.90	618.20	557.00	564.60	498.10	<0.0001
Number of operating rooms	13.63	12.01	13.99	12.56	13.16	11.08	<0.0001
Number of ER Beds	31.16	12.97	31.35	13.26	30.94	12.52	<0.0001

2. Changes in the AMI patient sharing network by region from 2005 to 2020

1) Seoul Metropolitan City

Figure 6 showed changes in Seoul's AMI patient sharing network from 2005 to 2020. The network in Seoul was very dense, with many tertiary hospitals and general hospitals at its core. The centrally located tertiary and general hospitals had large node sizes. Over time, the roles of these tertiary and general hospitals within the network strengthened, and new hospitals joined the network. The central nodes grew larger, while the peripheral green nodes comparatively decreased in size.

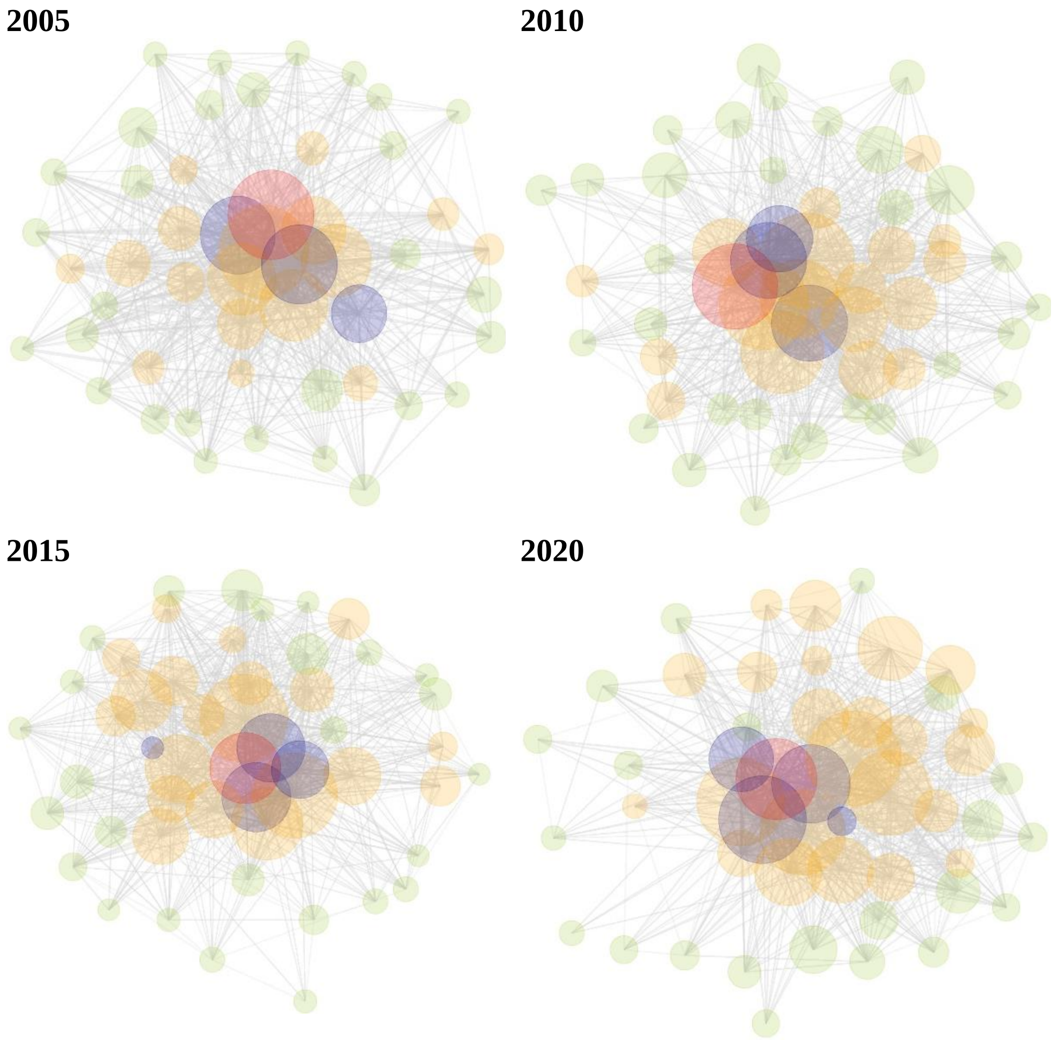


*The yellow nodes represent tertiary general hospitals in Seoul; the violet nodes represent general hospitals in Seoul; and the green nodes represent hospitals.

Figure 6. Changes in the AMI patient sharing network in Seoul in 2005–2020

2) Busan Metropolitan City

Figure 7 illustrated changes in the AMI patient sharing network in Busan from 2005 to 2020. The AMI patient sharing network in Busan underwent significant changes during this period. In the early stages, the network was primarily formed around local hospitals, with tertiary hospitals and general hospitals relatively separated. By 2010, the network had expanded, leading to increased connections between tertiary hospitals and general hospitals, and the influence of RCCVC and general hospitals grew. In 2015, the network density increased, with active patient sharing among various hospitals. Major nodes (RCCVC, tertiary hospitals) formed more connections, positioned themselves centrally, and grew in size. By 2020, the network had become even more complex, with strengthened cooperative relationships among RCCVC, tertiary hospitals, general hospitals, and other hospitals centrally located within the network.

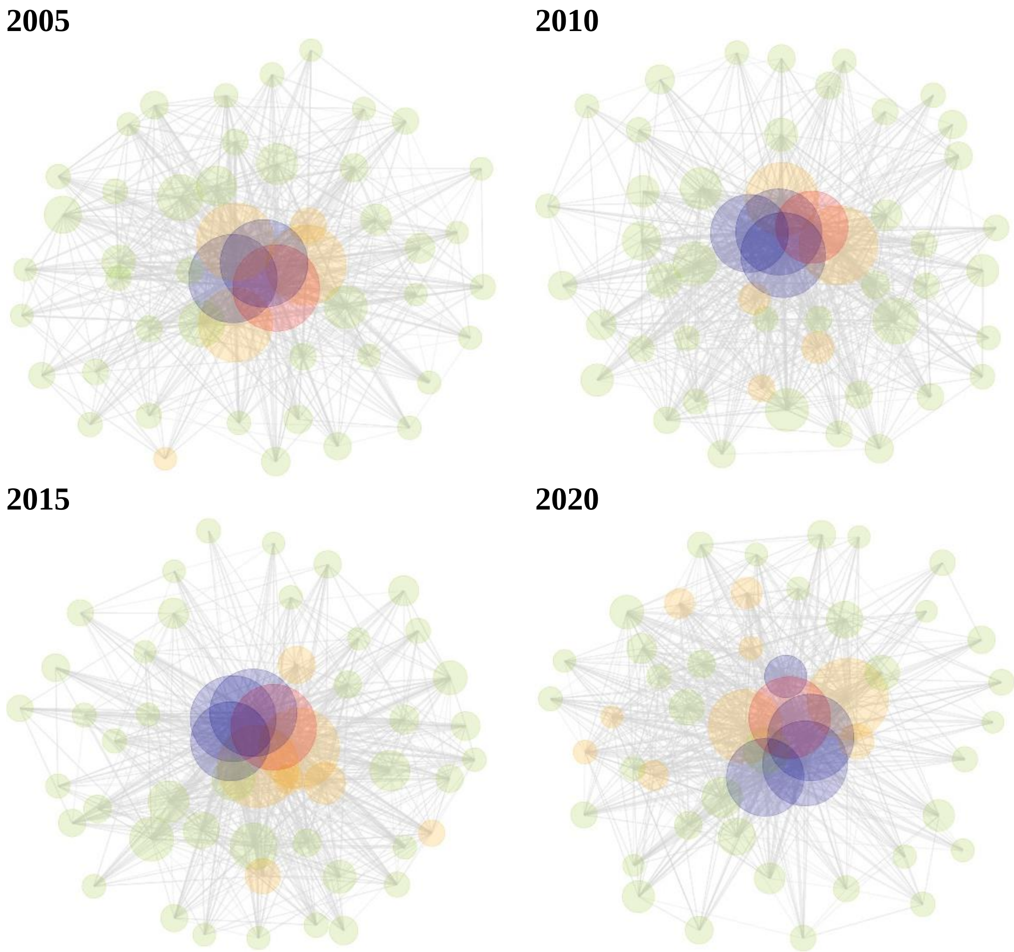


*The red node represents the RCCVC in Busan; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 7. Changes in the AMI patient sharing network in Busan in 2005–2020

3) Daegu Metropolitan City

Figure 8 illustrated changes in the AMI patient sharing network in Daegu from 2005 to 2020. In 2005, major hospitals (RCCVC, tertiary hospitals) in Daegu were centrally located in the network. Over time, the network expanded, and patient sharing became more active. Tertiary hospitals and general hospitals occupied the center of the network, and the node sizes were large.

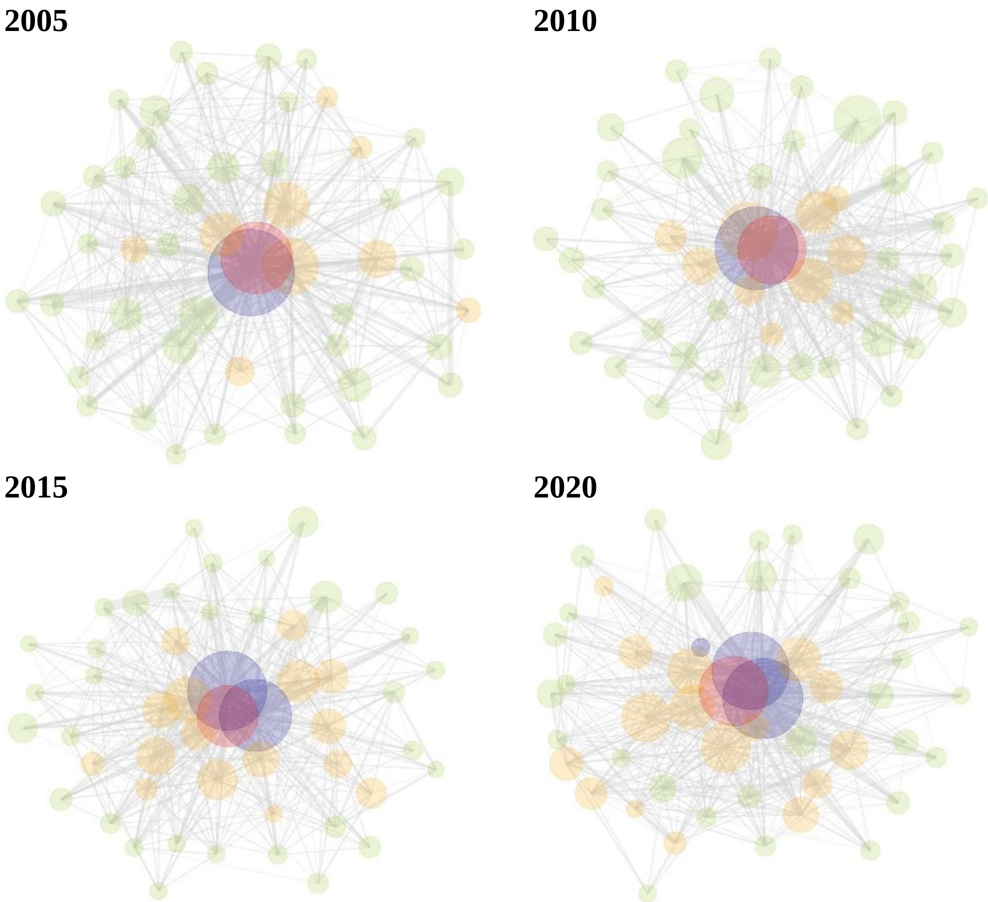


*The red node represents the RCCVC in Daegu; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 8. Changes in the AMI patient sharing network in Daegu in 2005–2020

4) Incheon Metropolitan City

Figure 9 showed changes in Incheon's AMI patient sharing network from 2005 to 2020. In the early stages, the network was simple, with limited connections among hospitals (green). RCCVC and tertiary hospitals were centrally located and large. From 2010 onwards, the network density increased. Major RCCVC and tertiary hospitals connected with various other hospitals (green), leading to increased patient sharing.

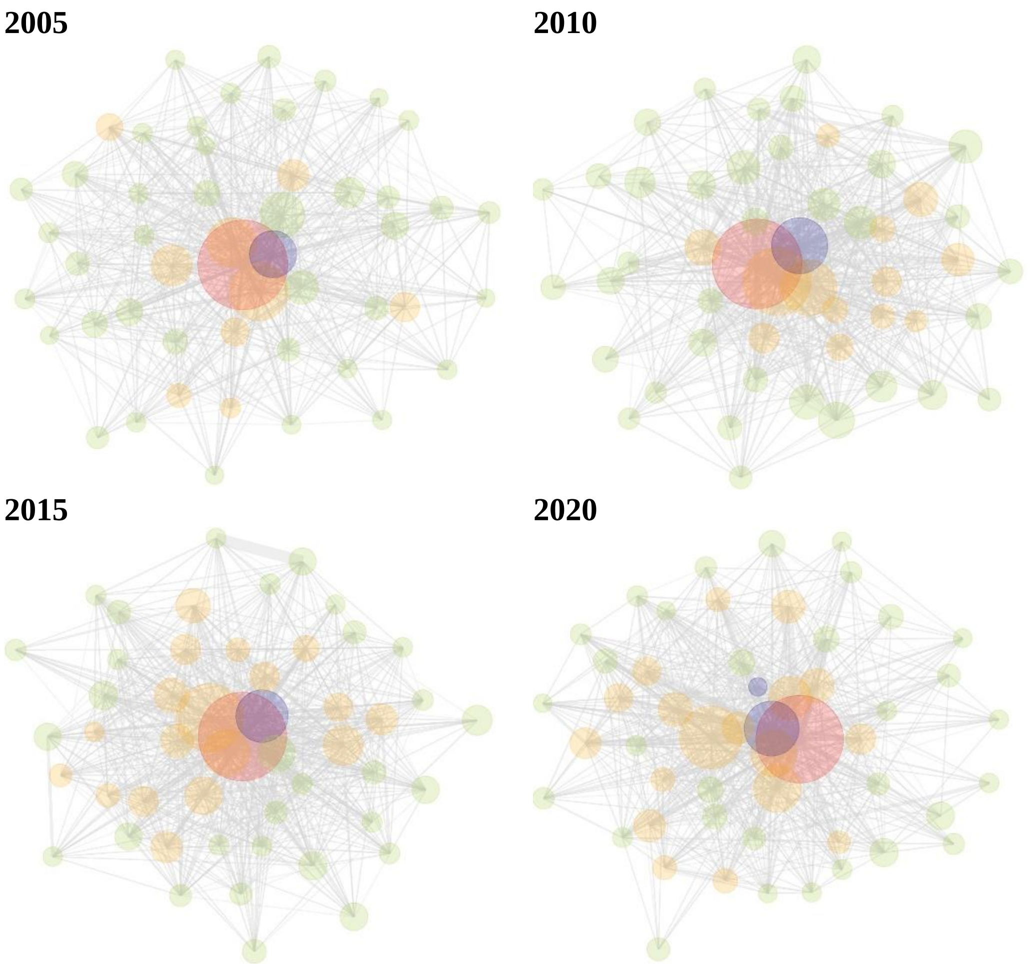


*The red node represents the RCCVC in Incheon; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 9. Changes in the AMI patient sharing network in Incheon in 2005–2020

5) Gwangju Metropolitan City

Figure 10 showed changes in Incheon's AMI patient sharing network from 2005 to 2020. In 2005, the network was relatively simple, with limited patient sharing among major hospitals (green). RCCVC and tertiary hospitals were centrally located and large within the network. Over time, connections among RCCVC (red), tertiary hospitals (blue), and general hospitals (orange) strengthened. There was a trend of increased patient sharing among hospitals and a rise in network density.

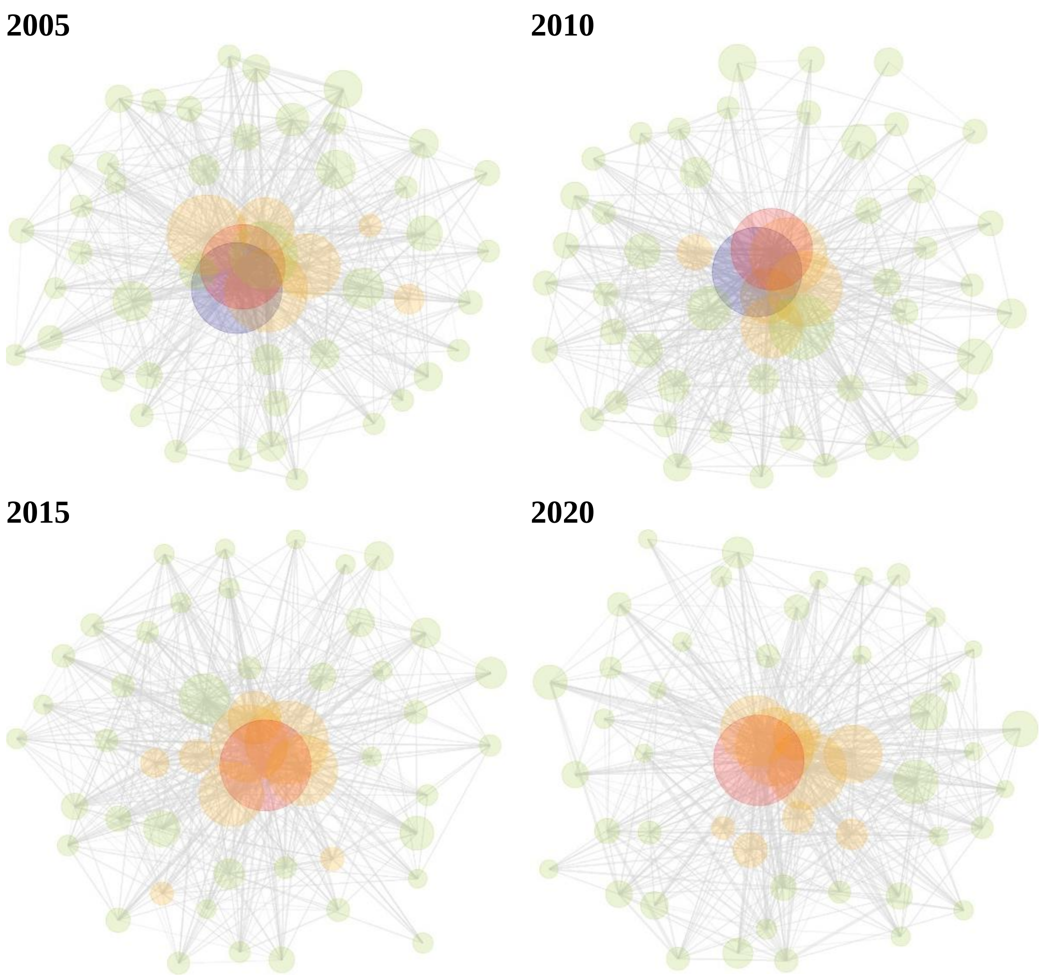


*The red node represents the RCCVC in Gwangju and Jeollanam-do; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 10. Changes in the AMI patient sharing network in Gwangju in 2005–2020

6) Daejeon Metropolitan City

Figure 11 illustrated changes in the AMI patient sharing network in Daejeon from 2005 to 2020. In 2005, the network was simple, with limited patient sharing among hospitals (green). The RCCVC and tertiary hospitals in Daejeon were centrally located and large. Over time, the network expanded, and various new hospitals (green) joined the network. The centrality of the RCCVC's connections was strengthened, positioning it at the center of the network.

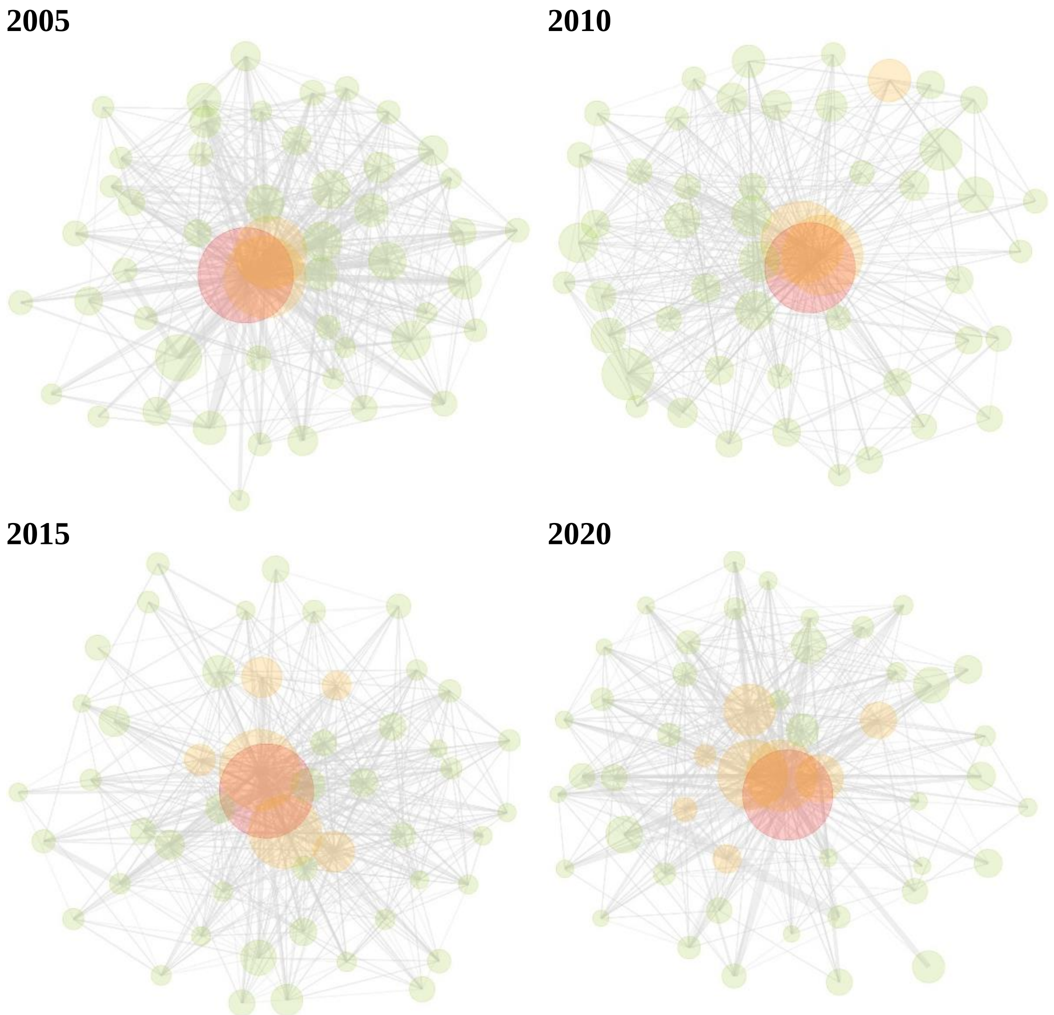


*The red node represents the RCCVC in Daejeon; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 11. Changes in the AMI patient sharing network in Daejeon in 2005–2020

7) Ulsan Metropolitan City

Figure 12 showed changes in the AMI patient sharing network in Ulsan from 2005 to 2020. The AMI patient sharing network in Ulsan involved a larger number of hospitals (green) compared to other regions. The RCCVC in Ulsan was centrally located in the network, sharing patients with general hospitals and other hospitals. Over time, connections among general hospitals and other hospitals increased, while the connections of the centrally located RCCVC remained strong.

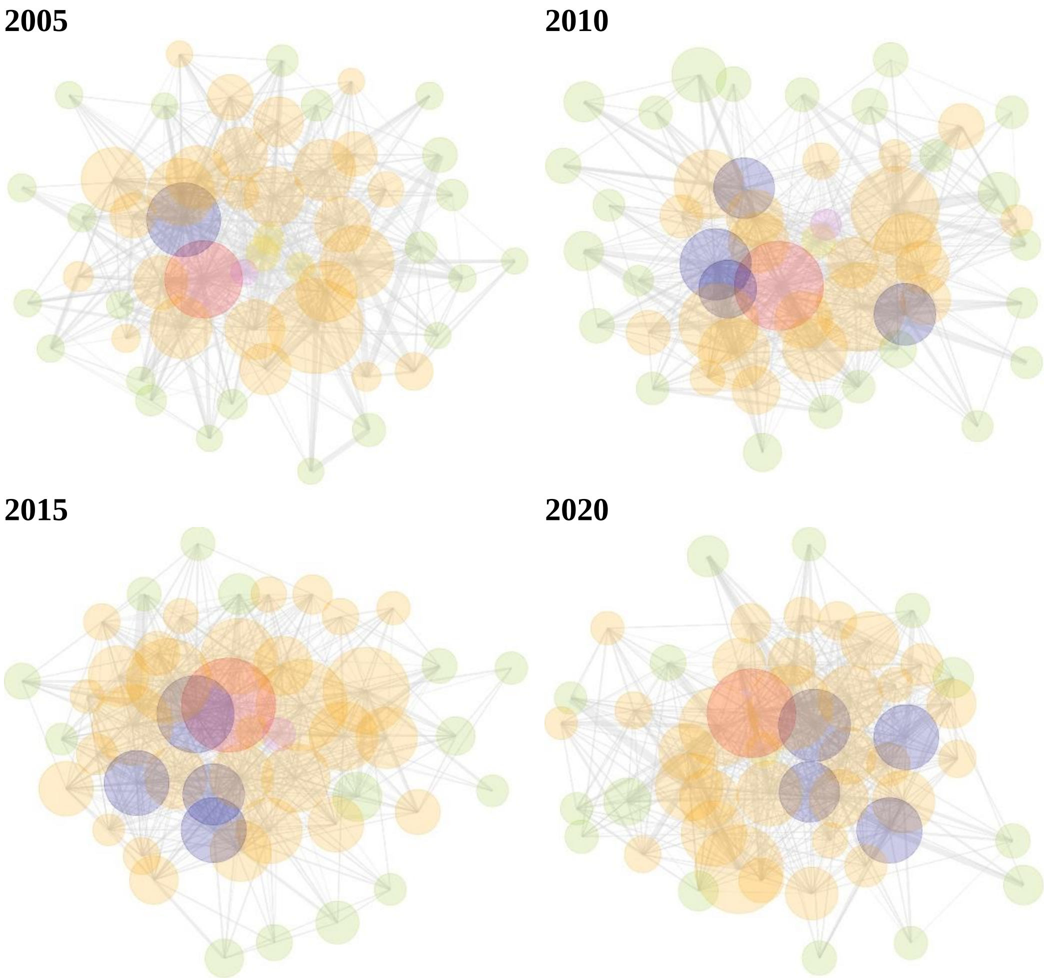


*The red node represents the RCCVC in Ulsan; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 12. Changes in the AMI patient sharing network in Ulsan in 2005–2020

8) Gyeonggi-do

Figure 13 showed changes in the AMI patient sharing network in Gyeonggi-do from 2005 to 2020. The AMI patient sharing network in Gyeonggi-do included a variety of healthcare institutions. The network featured nodes such as RCCVC, general hospitals, and hospitals located in Gyeonggi-do, as well as tertiary hospitals and general hospitals in Seoul. Compared to other regions, the network had a greater number of major nodes consisting of general hospitals and higher-level medical institutions rather than just hospitals (green). Over time, the connections between RCCVC and tertiary hospitals with general hospitals and hospitals in the region increased. The connections of the centrally located RCCVC remained strong.

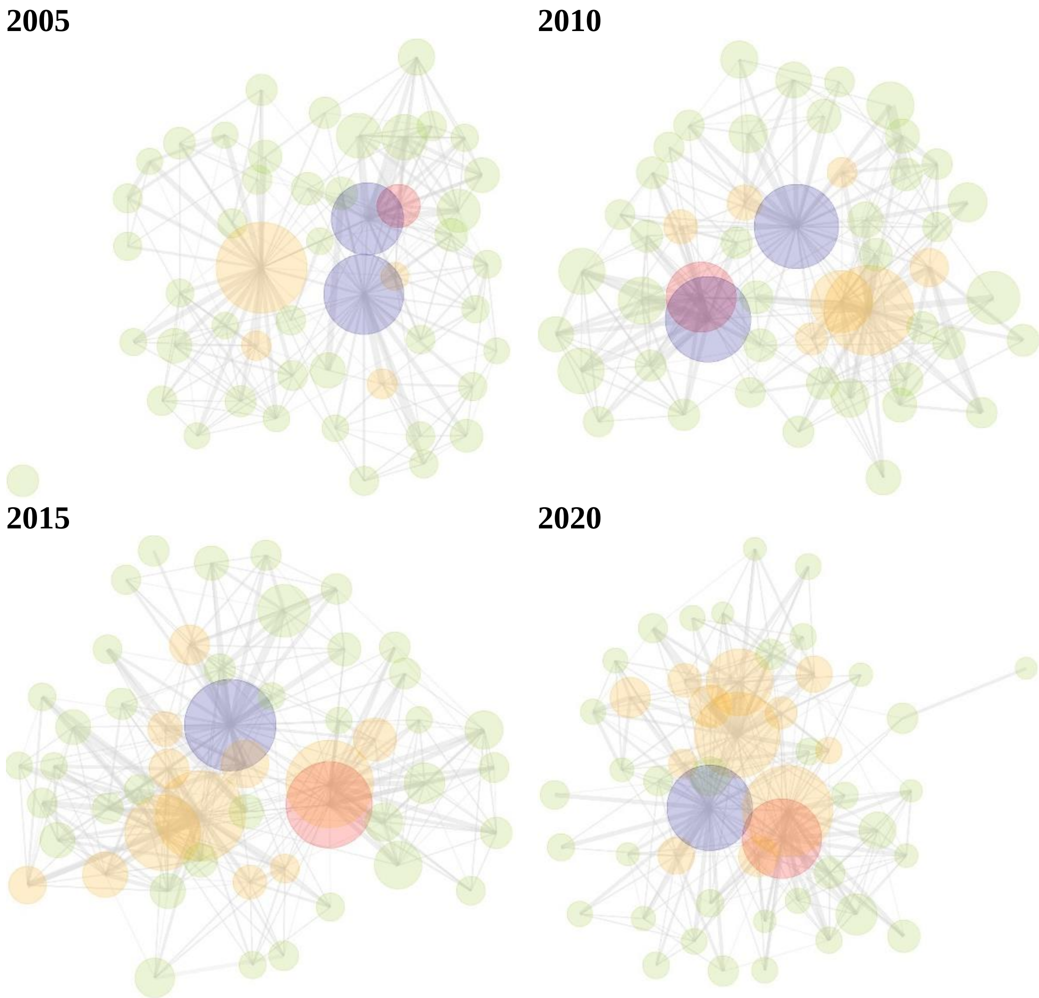


*The red node represents the RCCVC in gyeonggi-do; the yellow nodes represent tertiary general hospitals in Seoul; the violet nodes represent general hospitals in Seoul; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 13. Changes in the AMI patient sharing network in Gyeonggi-do in 2005–2020

9) Gangwon-do

Figure 14 showed changes in the AMI patient sharing network in Gangwon-do from 2005 to 2020. In 2005, the AMI patient sharing network in Gangwon-do featured tertiary hospitals and a single general hospital as the major institutions. The RCCVC in Gangwon-do was initially positioned at the periphery of the network. Over time, the RCCVC emerged as a major node within the network, shifting its position from the periphery to the center. In the recent network, strong connections can be observed among the RCCVC, tertiary hospitals, and major general hospitals. Additionally, connections among hospitals (green) have also increased.

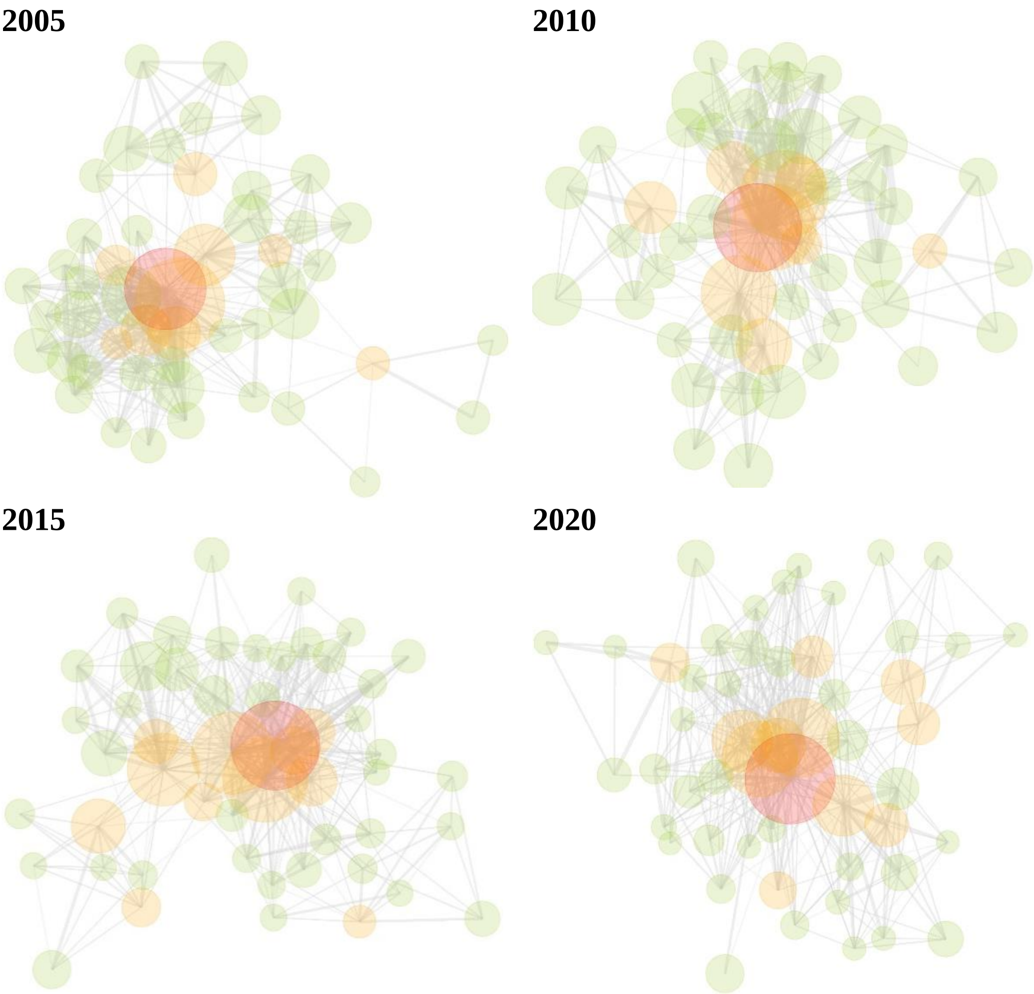


*The red node represents the RCCVC in Gangwon-do; the blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 14. Changes in the AMI patient sharing network in Gangwon-do in 2005–2020

10) Chungcheongbuk-do

Figure 15 showed changes in the AMI patient sharing network in Chungcheongbuk-do from 2005 to 2020. In 2005, a hospital that would later be designated as Chungcheongbuk-do's RCCVC was centrally located in the early network. This indicates that the hospital played a significant role in patient sharing. From 2010, as the network expanded, connections among general hospitals (orange) increased, bringing these hospitals to the center of the network. Over time, the hospitals located at the center of the network formed more connections, demonstrating their central role in patient movement.

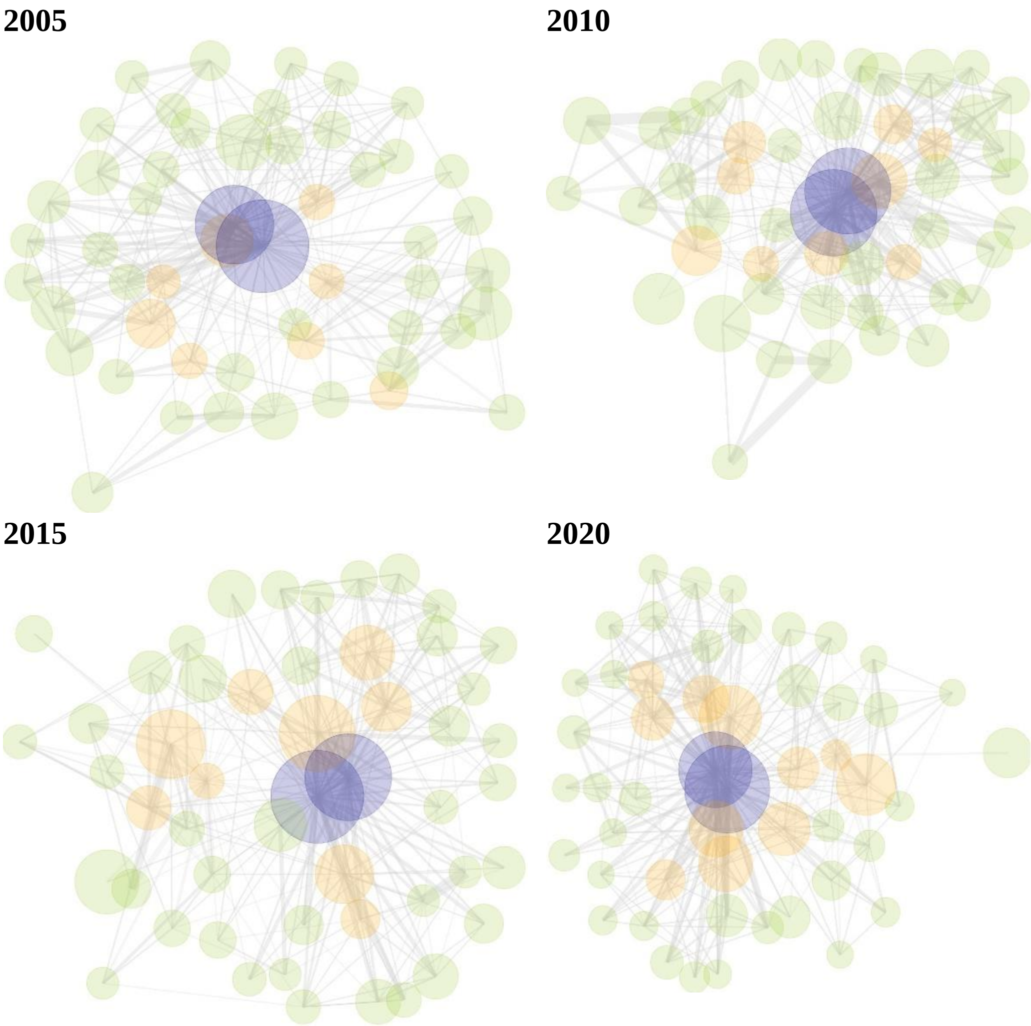


*The red node represents the RCCVC in Chungcheongbuk-do; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 15. Changes in the AMI patient sharing network in Chungcheongbuk-do in 2005–2020

11) Chungcheongnam-do

Figure 16 showed changes in the AMI patient sharing network in Chungcheongnam-do from 2005 to 2020. During this period, tertiary hospitals played a major role in patient sharing within the AMI patient sharing network in Chungcheongnam-do. Over time, connections among general hospitals (orange) increased, bringing these hospitals to the center of the network. The centrally located tertiary hospitals, major general hospitals, and other hospitals formed more connections, demonstrating their central role in patient movement.

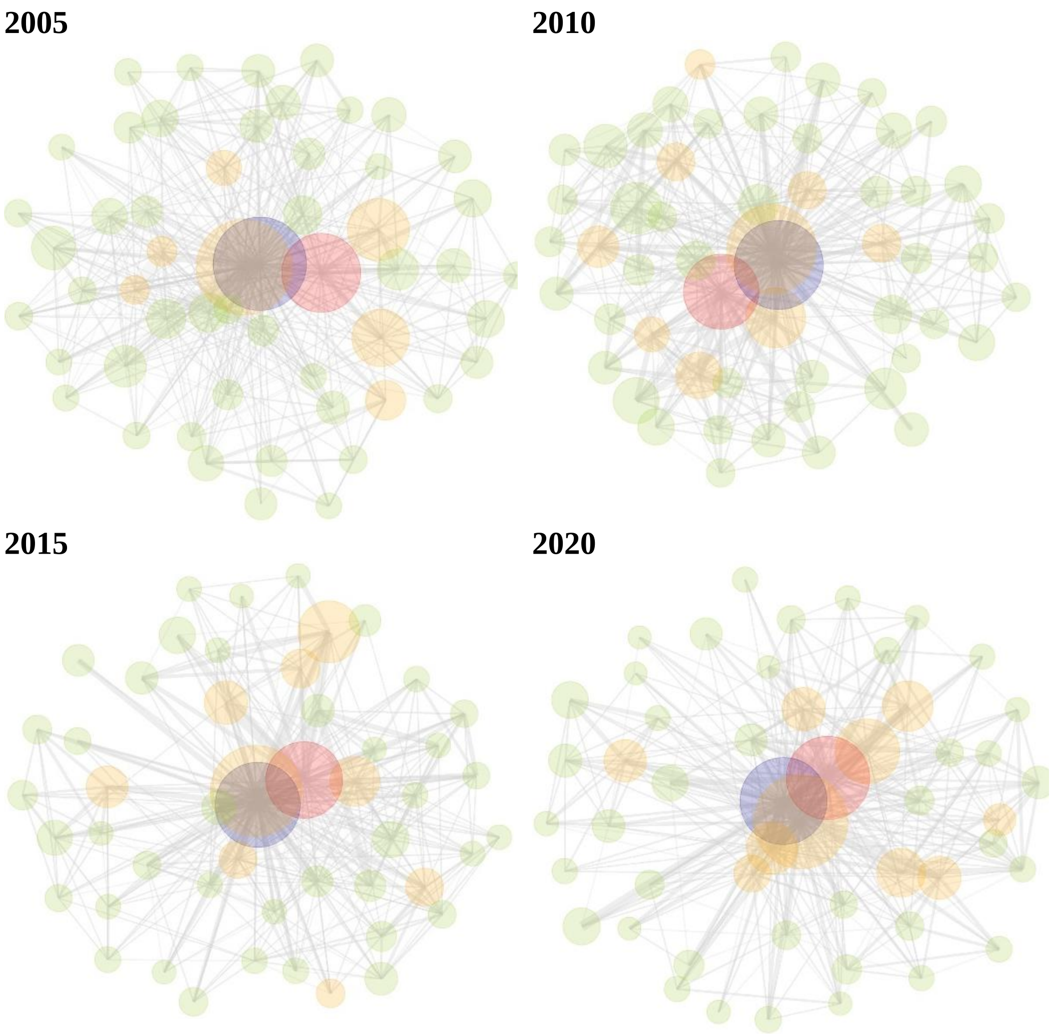


*The blue nodes represent tertiary general hospitals; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 16. Changes in the AMI patient sharing network in Chungcheongnam-do in 2005–2020

12) Jeollabuk-do

Figure 17 showed changes in the AMI patient sharing network in Jeollabuk-do from 2005 to 2020. In the AMI patient sharing network in Jeollabuk-do, tertiary hospitals and RCCVC played major roles in patient sharing. These hospitals formed many connections with general hospitals (orange) in the region. Over time, they formed even more connections not only with general hospitals but also with many other hospitals (green), demonstrating that tertiary hospitals and RCCVC were directly involved in patient movement with hospitals throughout the region.

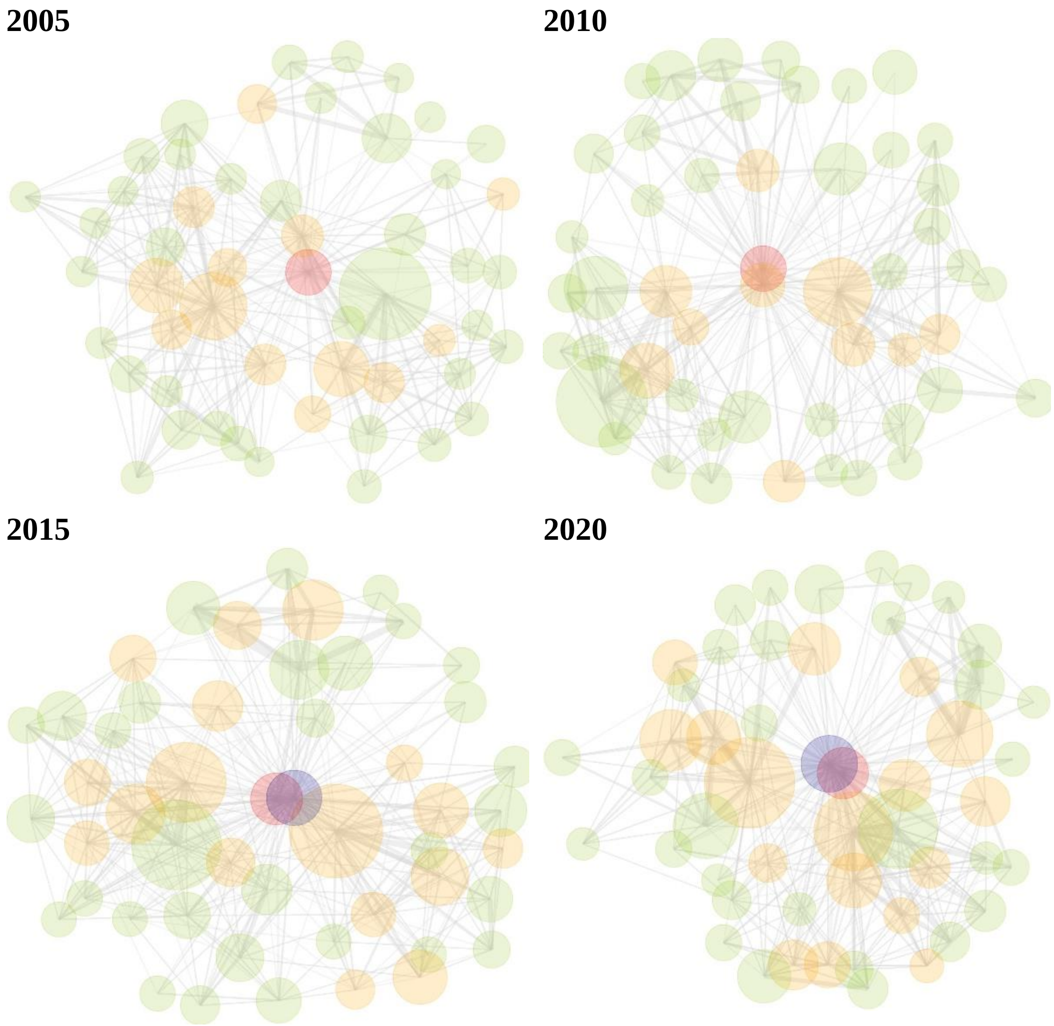


*The red node represents the RCCVC in Jeollabuk-do; the blue node represents tertiary general hospital; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 17. Changes in the AMI patient sharing network in Jeollabuk-do in 2005–2020

13) Jeollanam-do

Figure 18 illustrated changes in the AMI patient sharing network in Jeollanam-do from 2005 to 2020. In the AMI patient sharing network in Jeollanam-do, the hospital designated as the RCCVC for Gwangju and Jeollanam-do, located in Gwangju, played a major role in patient sharing. It had many connections not only with general hospitals but also with other hospitals in the region. Over time, general hospitals (orange) moved towards the center of the network. The RCCVC and major general hospitals centrally located in the network formed more connections with regional hospitals, demonstrating their central role in patient movement.

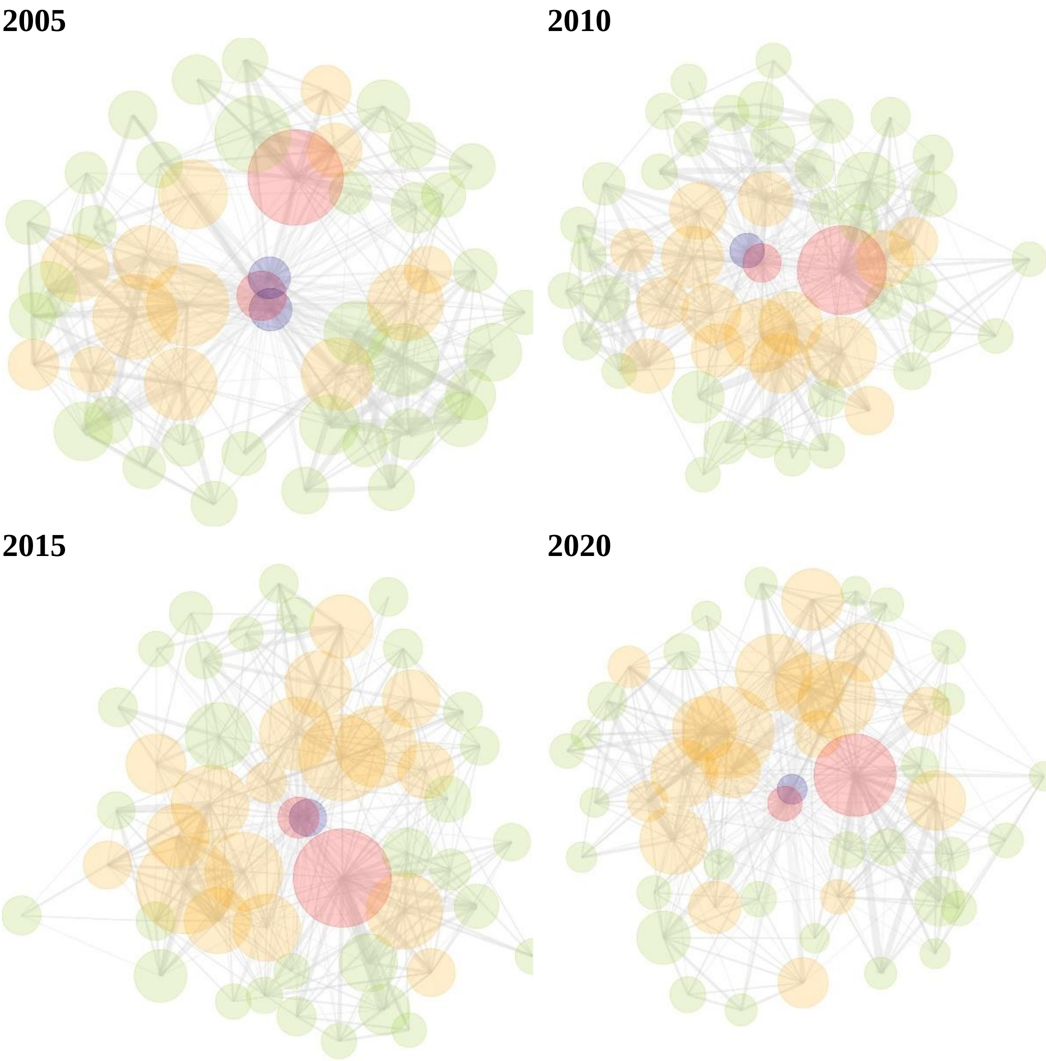


*The red node represents the RCCVC in Gwangju and Jeollanam-do; the blue node represents tertiary general hospital; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 18. Changes in the AMI patient sharing network in Jeollanam-do in 2005–2020

14) Gyeongsangbuk-do

Figure 19 illustrated changes in the AMI patient sharing network in Gyeongsangbuk-do from 2005 to 2020. In the AMI patient sharing network in Gyeongsangbuk-do, the conditionally designated RCCVC located in Gyeongsangbuk-do in 2017 appeared as a major node holding many patients. Additionally, the hospital designated as the RCCVC for Daegu and Gyeongsangbuk-do, located in Daegu, was connected to other hospitals in Gyeongsangbuk-do. Over time, general hospitals (orange) moved towards becoming major hospitals in the network. The RCCVCs located in both regions formed more connections with regional hospitals, demonstrating their central role in patient movement.

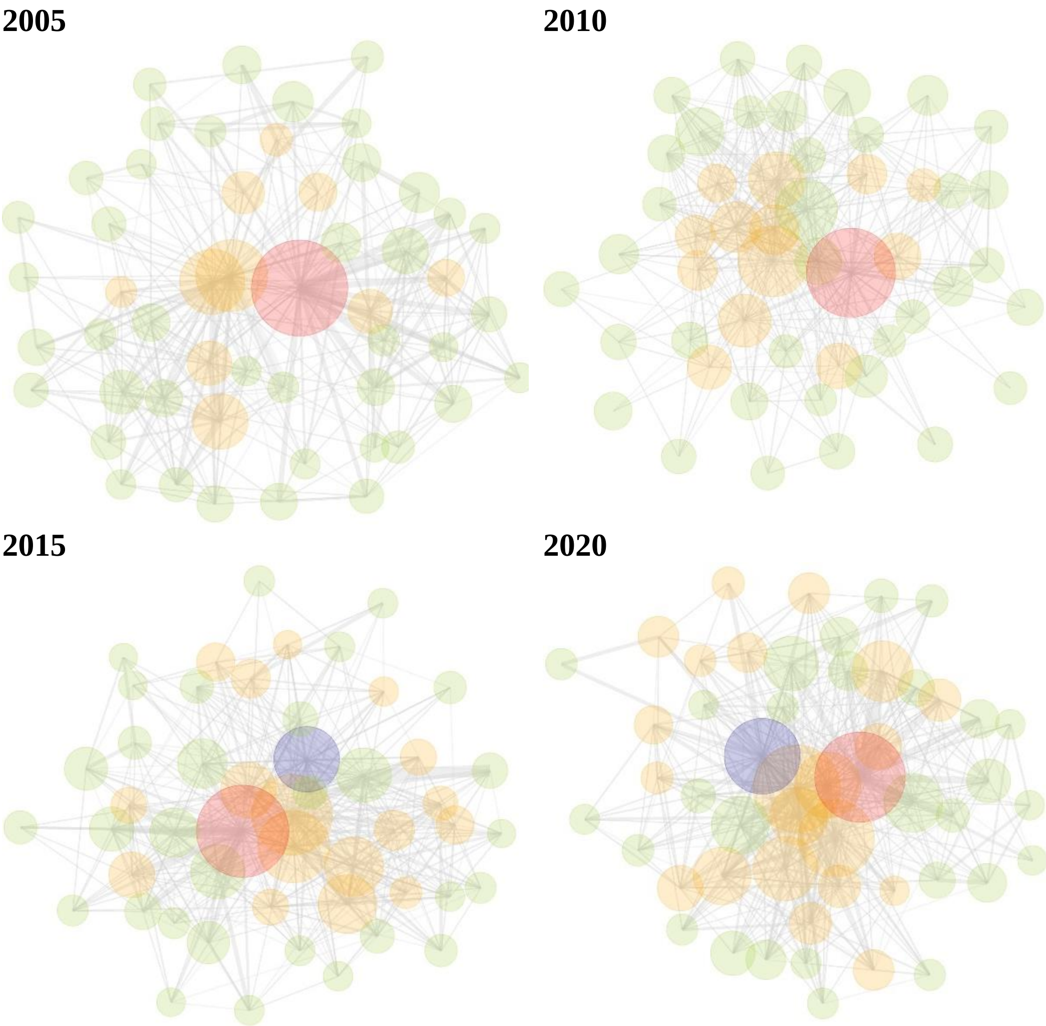


*The red nodes represent the RCCVCs in Daegu and Gyeongsangbuk-do; the blue node represents tertiary general hospital; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 19. Changes in the AMI patient sharing network in Gyeongsangbuk-do in 2005–2020

15) Gyeongsangnam-do

Figure 20 illustrated changes in the AMI patient sharing network in Gyeongsangnam-do from 2005 to 2020. In 2005, patient sharing among hospitals in Gyeongsangnam-do was limited. The hospital designated as RCCVC was centrally located in the network, indicating its significant role in patient sharing. From 2010 onwards, connections between the RCCVC and regional general hospitals (orange) increased, moving these hospitals towards the center of the network. As a result, the node sizes of these hospitals grew, demonstrating their important role in patient sharing.

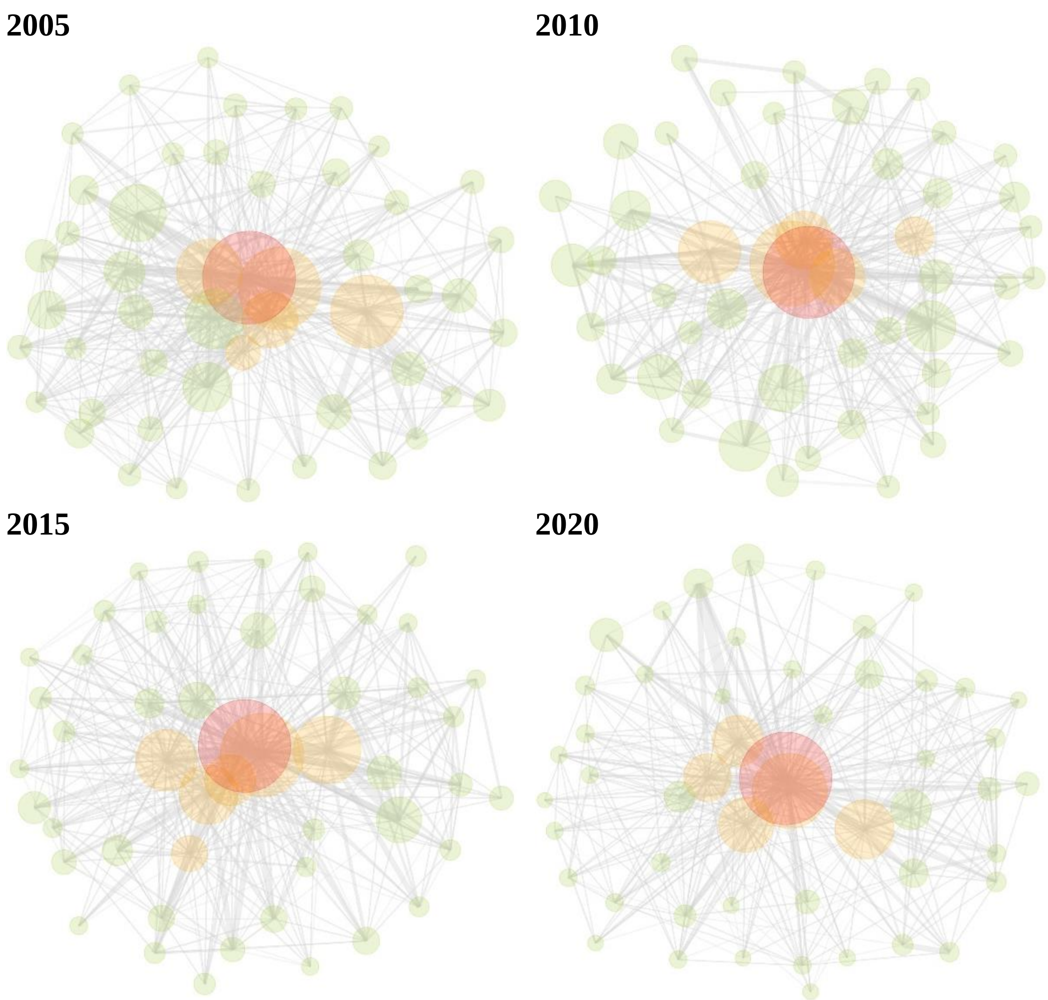


*The red nodes represent the RCCVCs in Gyeongsangnam-do; the blue node represents tertiary general hospital; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 20. Changes in the AMI patient sharing network in Gyeongsangnam-do in 2005–2020

16) Jeju-do

Figure 21 showed changes in the AMI patient sharing network in Jeju-do from 2005 to 2020. The AMI patient sharing network in Jeju-do consisted of the hospital designated as RCCVC, a few general hospitals, and many other hospitals. The hospital designated as RCCVC was centrally located in the network, indicating its significant role in patient sharing. The connections between the RCCVC and regional general hospitals (orange) and other hospitals (green) increased, confirming the RCCVC's central position in the patient sharing network.



*The red node represents the RCCVC in Jeju-do; the orange nodes represent general hospitals; and the green nodes represent hospitals.

Figure 21. Changes in the AMI patient sharing network in Jeju-do in 2005–2020

3. Results of the impact of patient-sharing networks on mortality

1) Results of the incidence ratios and hazard ratios for in-hospital mortality

Table 11 presents the incidence ratios and hazard ratios for in-hospital mortality. Among patients treated at RCCVCs, there were 1,362 in-hospital deaths per 100,000 person-years, while among patients not treated at RCCVCs, there were 1,378 in-hospital deaths per 100,000 person-years. In terms of degree centrality, patients treated at hospitals with high degree centrality experienced 1,202 in-hospital deaths per 100,000 person-years, whereas patients treated at hospitals with low to middle degree centrality experienced 1,467 in-hospital deaths per 100,000 person-years. Regarding betweenness centrality, patients treated at hospitals with high betweenness centrality had 1,132 in-hospital deaths per 100,000 person-years, compared to 1,541 in-hospital deaths per 100,000 person-years for patients treated at hospitals with low to middle betweenness centrality.

Males have a decreased risk of mortality compared to females, with an adjusted Hazard Ratio (aHR) of 0.88 (95% CI: 0.84 – 0.92, $p<0.0001$). Patients aged 50-59 have an increased risk of mortality compared to those under 50, with an aHR of 1.41 (95% CI: 1.24 – 1.61, $p<0.0001$). Patients aged 60-69 have an aHR of 2.75 (95% CI: 2.44 – 3.11, $p<0.0001$), indicating a significantly higher risk compared to those under 50. Patients aged 70-79 have an aHR of 5.50 (95% CI: 4.89 – 6.19, $p<0.0001$). Patients over 80 have the highest increased risk, with an aHR of 11.43 (95% CI: 10.15 – 12.88, $p<0.0001$). The risk of mortality for patients living in the metropolitan region is lower compared to patients living in Seoul (aHR = 0.88, 95% CI: 0.82–0.95, p = 0.0004). Patients with corporate insurance have a higher risk, with an aHR of 1.09 (95% CI: 1.05 – 1.13, p<0.0001), compared to those with regional insurance. Patients in higher income deciles have a lower risk of mortality compared to the lowest decile. Higher scores are associated with higher risk compared to those with three or more scores. Patients admitted through the emergency room have a higher risk, with an aHR of 1.13 (95% CI: 1.08 – 1.19, p<0.0001), compared to other routes.

Patients in general hospitals have a higher aHR of 1.07 (95% CI: 1.01 – 1.13, p=0.0202) compared to those in tertiary hospitals. Patients treated in RCCVCs have a lower risk, with an aHR of 0.84 (95% CI: 0.78 – 0.90, p<0.0001), compared to those treated in non-RCCVCs. A higher degree centrality group is associated with a lower risk of mortality, but the hazard ratio is not significant (aHR 0.64, 95% CI: 0.44 – 0.95, p=0.0263). A higher betweenness centrality group is associated with a lower risk of mortality (aHR 0.94, 95% CI: 0.89 – 0.99, p=0.0249).

Table 11. Results of the incidence ratios and hazard ratios for in-hospital mortality

Variables	In-Hospital Mortality						
	100,000 person-year	**Event**	**Incidence Ratio per 100,000 person-year (95% CI)**		**aHR**	**95% CI**	***P-value***
Sex							
Female	158267	3,825	2416	(2340 – 2493)	Ref		
Male	483277	5,022	1039	(1010 – 1068)	0.88	(0.84 – 0.92)	<0.0001
Age group							
Under 50	119347	320	268	(240 – 299)	Ref		
50-59	175569	719	409	(380 – 440)	1.41	(1.24 – 1.61)	<0.0001
60-69	173163	1,533	625	(521 – 751)	2.75	(2.44 – 3.11)	<0.0001
70-79	129158	2,789	955	(700 – 1302)	5.50	(4.89 – 6.19)	<0.0001
Over 80	44307	3,486	1458	(939 – 2264)	11.43	(10.15 – 12.88)	<0.0001
Region							
Seoul	114739	1,595	1390	(1323 – 1459)	Ref		
Metropolitan	166810	2,157	1293	(1239 – 1348)	0.88	(0.82 – 0.95)	0.0004
Urban/Rural	359995	5,095	1202	(1090 – 1326)	0.83	(0.78 – 0.88)	0.0942
Medical Insurance							
Insurance (Regional)	254540	3,326	1306	(1262 – 1351)	Ref		
Insurance (Corporate)	387004	5,521	1426	(1389 – 1464)	1.09	(1.05 – 1.13)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 11. Results of the incidence ratios and hazard ratios for in-hospital mortality

Variables	In-Hospital Mortality						
	100,000 person-year	**Event**	**Incidence Ratio per 100,000 person-year (95% CI)**		**aHR**	**95% CI**	***P-value***
Household income							
0-4th decile (Low)	103288	1,551	1501	(1428 – 1577)	Ref		
5-8th decile	91019	1,090	1197	(1128 – 1270)	0.97	(0.9 – 1.05)	0.4337
9-12th decile	111662	1,365	955	(839 – 1086)	0.95	(0.89 – 1.03)	0.2059
13-16th decile	141460	1,773	761	(621 – 934)	0.93	(0.87 – 0.99)	0.0274
17-20th decile (High)	194114	3,068	607	(459 – 804)	0.94	(0.88– 1.00)	0.0338
Charlson Comorbidity Index score							
None	105620	867	821	(768 – 877)	Ref		
One	76415	756	989	(921 – 1062)	0.83	(0.76 – 0.92)	0.0003
Two	119224	1,144	1192	(1018 – 1395)	0.78	(0.71 – 0.85)	<0.0001
Three or more	340284	6,080	1436	(1117 – 1848)	0.75	(0.69 – 0.81)	<0.0001
Hospitalization route							
Other	155480	2,045	1315	(1259 – 1373)	Ref		
Emergency room	486084	6,802	1399	(1366 – 1432)	1.13	(1.08 – 1.19)	< 0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 11. Results of the incidence ratios and hazard ratios for in-hospital mortality

Variables	In-Hospital Mortality						
	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
Hospital Type							
Tertiary Hospital	323823	3,782	1167	(1131 – 205)	Ref		
General Hospital	317721	5,065	1593	(1550 – 1638)	1.07	(1.01 – 1.13)	0.0202
RCCVC							
No	579484	7,989	1378	(1348 – 1409)	Ref		
Yes	63952	858	1342	(1251 – 1433)	0.84	(0.78 – 0.90)	<0.0001
Degree centrality group							
Low-middle	427235	6,269	1467	(1431 – 1503)	Ref		
High	214309	2,578	1202	(1157 – 1250)	0.64	(0.44 – 0.95)	0.0263
Betweenness centrality group							
Low-middle	386762	5,961	1541	(1502 – 1580)	Ref		
High	254782	2,886	1132	(1092 – 1174)	0.94	(0.89 – 0.99)	0.0249

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

2) Results of the incidence ratios and hazard ratios for 1-year all-cause mortality

Table 12 presented the incidence ratios and hazard ratios for 1-year all-cause mortality. Among patients treated at RCCVCs, there were 2,360 deaths within one year per 100,000 person-years, while among patients not treated at RCCVCs, there were 2,318 deaths within one year per 100,000 person-years. In terms of degree centrality, patients treated at hospitals with high degree centrality experienced 2,097 deaths within one year per 100,000 person-years, whereas patients treated at hospitals with low to middle degree centrality experienced 2,445 deaths within one year per 100,000 person-years. Regarding betweenness centrality, patients treated at hospitals with high betweenness centrality had 2,027 deaths within one year per 100,000 person-years, compared to 2,527 deaths within one year per 100,000 person-years for patients treated at hospitals with low to middle betweenness centrality.

Males have a decreased risk of mortality compared to females, with an aHR of 0.94 (95% CI: 0.91 – 0.98, p<0.0001). Patients aged 50-59 have an increased risk of mortality compared to those under 50, with an aHR of 1.41 (95% CI: 1.27 – 1.57, p<0.0001). Patients aged 60-69 have an aHR of 2.81 (95% CI: 2.54 – 3.10, p<0.0001), indicating a significantly higher risk compared to those under 50. Patients aged 70-79 have an aHR of 6.21 (95% CI: 5.64 – 6.84, p<0.0001). Patients over 80 have the highest increased risk, with an aHR of 13.34 (95% CI: 12.10 – 14.71, p<0.0001). The risk of mortality for patients living in the metropolitan region is lower compared to patients living in Seoul (aHR = 0.91, 95% CI:

0.86–0.96, p = 0.0005). The risk of mortality for patients living in the urban/rural region is lower compared to patients living in Seoul (aHR 0.89, 95% CI: 0.85–0.93, p<0.0001). Patients with corporate insurance have a lower risk, with an aHR of 0.93 (95% CI: 0.90 – 0.96, p<0.0001), compared to those with regional insurance. Patients in higher income deciles have a lower risk of mortality compared to the lowest decile. Higher scores are associated with higher risk compared to those with three or more scores. Patients admitted through the emergency room have a higher risk, with an aHR of 1.08 (95% CI: 1.04 – 1.13, p<0.0001), compared to other routes.

Patients treated in RCCVCs have a lower risk, with an aHR of 0.80 (95% CI: 0.76 – 0.85, p<0.0001), compared to those treated in non-RCCVCs. A higher degree centrality group is associated with a lower risk of mortality (aHR 0.73, 95% CI: 0.54 – 0.97, p=0.0307). A higher betweenness centrality group is associated with a lower risk of mortality (aHR 0.95, 95% CI: 0.90 – 0.99, p=0.0168).

Table 12. Results of the incidence ratios and hazard ratios for 1-year all-cause mortality

Variables	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
	1-year all-cause mortality						
Sex							
Female	158267	6,448	4072	(3974 – 4173)	Ref		
Male	483277	8,498	1758	(1721 – 1795)	0.94	(0.91 – 0.98)	0.0006
Age group							
Under 50	119347	467	391	(357 – 428)	Ref		
50-59	175569	1,072	610	(575 – 648)	1.41	(1.27 – 1.57)	<0.0001
60-69	173163	2,411	952	(820 – 1107)	2.81	(2.54 – 3.10)	<0.0001
70-79	129158	4,916	1486	(1151 – 1918)	6.21	(5.64 – 6.84)	<0.0001
Over 80	44307	6,080	2319	(1614 – 3332)	13.34	(12.10 – 14.71)	<0.0001
Region							
Seoul	114739	2,597	2262	(2177 – 2351)	Ref		
Metropolitan	166810	3,630	2175	(2106 – 2247)	0.91	(0.86 – 0.96)	0.0005
Urban/Rural	359995	8,719	2091	(1939 – 2255)	0.89	(0.85 – 0.93)	<0.0001
Medical Insurance							
Insurance (Regional)	254540	5,504	2161	(2105 – 2219)	Ref		
Insurance (Corporate)	387004	9,442	2439	(2390 – 2488)	0.93	(0.90 – 0.96)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation:CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 12. Results of the incidence ratios and hazard ratios for 1-year all-cause mortality

Variables	1-year all-cause mortality						
	100,000 person-year	**Event**	**Incidence Ratio per 100,000 person-year (95% CI)**		**aHR**	**95% CI**	***P-value***
Household income							
0-4th decile (Low)	103288	1,551	1501	(1428 – 1577)	Ref		
5-8th decile	91019	1,090	1197	(1128 – 1270)	0.98	(0.92 – 1.04)	0.5426
9-12th decile	111662	1,365	955	(839 – 1086)	0.98	(0.93 – 1.04)	0.4391
13-16th decile	141460	1,773	761	(621 – 934)	0.94	(0.89 – 0.99)	0.0168
17-20th decile (High)	194114	3,068	607	(459 – 804)	0.91	(0.87 – 0.96)	0.0002
Charlson Comorbidity Index score							
None	105620	867	821	(768 – 877)			
One	76415	756	989	(921 – 1062)	0.86	(0.79 – 0.94)	0.0006
Two	119224	1,144	1192	(1018 – 1395)	0.89	(0.82 – 0.96)	0.0024
Three or more	340284	6,080	1436	(1117 – 1848)	1.16	(1.09 – 1.24)	<0.0001
Hospitalization route							
Other	155480	2,045	1315	(1259 – 1373)			
Emergency room	486084	6,802	1399	(1366 – 1432)	1.08	(1.04 – 1.13)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation:CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 12. Results of the incidence ratios and hazard ratios for 1-year all-cause mortality

Variables	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
	1-year all-cause mortality						
Hospital Type							
Tertiary Hospital	323823	6,656	2055	(2006 – 2104)	Ref		
General Hospital	317721	8,290	2608	(2552 – 2665)	0.98	(0.94-1.03)	0.3964
RCCVC							
No	579484	13,437	2318	(2279 – 2357)	Ref		
Yes	63952	1,509	2360	(2241 – 2479)	0.80	(0.76 – 0.85)	<0.0001
Degree centrality group							
Low-middle	427235	10,449	2445	(2398 – 2492)	Ref		
High	214309	4,497	2097	(2037 – 2160)	0.73	(0.54 – 0.97)	0.0307
Betweenness centrality group							
Low-middle	386762	9,779	2527	(2478 – 2578)	Ref		
High	254782	5,167	2027	(1973 – 2083)	0.95	(0.90 – 0.99)	0.0168

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

3) Results of the incidence rate ratios and hazard ratios for 3-year all-cause mortality

Table 13 showed the incidence ratios and hazard ratios for all-cause mortality over three years. Among patients treated at RCCVCs, there were 3,392 deaths within three years per 100,000 person-years, while among patients not treated at RCCVCs, there were 3,123 deaths within three years per 100,000 person-years. In terms of degree centrality, patients treated at hospitals with high degree centrality experienced 3,292 deaths within three years per 100,000 person-years, whereas patients treated at hospitals with low to middle degree centrality experienced 3,268 deaths within three years per 100,000 person-years. Regarding betweenness centrality, patients treated at hospitals with high betweenness centrality had 2,811 deaths within three years per 100,000 person-years, compared to 3,372 deaths within three years per 100,000 person-years for patients treated at hospitals with low to middle betweenness centrality.

Patients aged 50–59 have an increased risk of mortality compared to those under 50, with an aHR of 1.44 (95% CI: 1.31–1.58, p<0.0001). Patients aged 60–69 have an aHR of 2.91 (95% CI: 2.67–3.17, p<0.0001), indicating a significantly higher risk compared to those under 50. Patients aged 70–79 have an aHR of 6.55 (95% CI: 6.03–7.12, p<0.0001). Patients over 80 have the highest increased risk, with an aHR of 14.42 (95% CI: 13.25–15.68, p<0.0001). The risk of mortality for patients living in the metropolitan region is lower compared to patients living in Seoul (aHR = 0.93, 95% CI: 0.89–0.97, p = 0.0019). The risk of mortality for patients living in the urban/rural region is lower compared to patients living in Seoul (aHR 0.93, 95% CI: 0.91–0.96, p<0.0001). Patients with corporate insurance have a lower risk, with an aHR of 0.93 (95% CI: 0.91–0.96, p<0.0001), compared to those with regional insurance. Patients in higher income deciles have a lower risk of mortality compared to the lowest decile. Higher scores are associated with a higher risk compared to those with three or more scores. Patients admitted through the emergency room have a higher risk, with an aHR of 1.07 (95% CI: 1.04–1.11, p<0.0001), compared to other routes.

Patients treated in RCCVCs have a lower risk, with an aHR of 0.81 (95% CI: 0.77–0.85, p<0.0001), compared to those treated in non-RCCVCs. A higher degree of centrality is associated with a lower risk of mortality (aHR 0.75, 95% CI: 0.58–0.96, p = 0.0241). A higher betweenness centrality group is associated with a lower risk of mortality (aHR 0.91, 95% CI: 0.87–0.95, p<0.0001).

Table 13. Results of the incidence ratios and hazard ratios for 3-year all-cause mortality

Variables	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
	3-year all-cause mortality						
Sex							
Female	158267	8,426	5321	(5209 – 5436)	Ref		
Male	483277	11,787	2438	(2394 – 2482)	0.99	(0.96 – 1.02)	0.3150
Age group							
Under 50	119347	624	523	(483 – 565)	Ref		
50-59	175569	1,465	834	(792 – 878)	1.44	(1.31 – 1.58)	<0.0001
60-69	173163	3,331	1331	(1170 – 1514)	2.91	(2.67 – 3.17)	<0.0001
70-79	129158	6,788	2124	(1706 – 2646)	6.55	(6.03 – 7.12)	<0.0001
Over 80	44307	8,005	3390	(2482 – 4632)	14.42	(13.25 – 15.68)	<0.0001
Region							
Seoul	114739	3,447	3003	(2904 – 3105)	Ref		
Metropolitan	166810	4,924	2951	(2869 – 3034)	0.93	(0.89 – 0.97)	0.0019
Urban/Rural	359995	11,842	2899	(2716 – 3094)	0.92	(0.88 – 0.96)	<0.0001
Medical Insurance							
Insurance (Regional)	254540	7,407	2909	(2843 – 2976)	Ref		
Insurance (Corporate)	387004	12,806	3307	(3251 – 3365)	0.93	(0.91 – 0.96)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: IRR, Incidence rate ratio; CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 13. Results of the incidence ratios and hazard ratios for 3-year all-cause mortality

Variables	3-year all-cause mortality						
	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
Household income							
0-4th decile (Low)	103288	3,482	3370	(3259 – 3483)	Ref		
5-8th decile	91019	2,453	2694	(2589 – 2803)	0.97	(0.92 – 1.02)	0.2078
9-12th decile	111662	3,142	2154	(1976 – 2347)	0.97	(0.92 – 1.02)	0.1980
13-16th decile	141460	4,107	1722	(1503 – 1973)	0.93	(0.89 – 0.97)	0.0013
17-20th decile (High)	194114	7,029	1377	(1142 – 1660)	0.91	(0.87 – 0.94)	<0.0001
Charlson Comorbidity Index score							
None	105620	1,255	1188	(1124 – 1255)	Ref		
One	76415	1,223	1600	(1513 – 1692)	0.92	(0.85 – 0.99)	0.0310
Two	119224	2,041	2155	(1902 – 2442)	0.99	(0.92 – 1.06)	0.7274
Three or more	340284	15,694	2902	(2373 – 3550)	1.44	(1.36 – 1.53)	<0.0001
Hospitalization route							
Other	155480	4,805	3089	(3003 – 3178)	Ref		
Emergency room	486064	15,408	3168	(3119 – 3219)	1.07	(1.04 – 1.11)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 13. Results of the incidence ratios and hazard ratios for 3-year all-cause mortality

Variables	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
	3-year all-cause mortality						
Hospital Type							
Tertiary Hospital	323823	9,195	2838	(2781 – 2897)	Ref		
General Hospital	317721	11,018	3466	(3402 – 3531)	0.98	(0.94-1.02)	0.2358
RCCVC							
No	579484	18,107	3123	(3078 – 3169)	Ref		
Yes	63952	2,106	3392	(3250 – 3540)	0.81	(0.77 – 0.85)	<0.0001
Degree centrality group							
Low-middle	427235	13,969	3268	(3214 – 3323)	Ref		
High	214309	6,244	3292	(3151 – 3435)	0.75	(0.58 – 0.96)	0.0241
Betweenness centrality group							
Low-middle	386762	13,048	3372	(3218 – 3327)	Ref		
High	254782	7,165	2811	(2837 – 2981)	0.91	(0.87 – 0.95)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

4) Subgroup analyses for the incidence rate ratios and hazard ratios for mortality among AMI patients who received coronary interventions

The table 14 presented the incidence rate ratios and hazard ratios for all-cause mortality at different time points (in-hospital, one-year, and three-year) for patients who received coronary interventions.

In in-hospital mortality, a higher betweenness centrality group is associated with a significantly lower in-hospital mortality risk (IRR 0.83, 95% CI: 0.74 – 0.92, p=0.0005; aHR 0.88, 95% CI: 0.79 – 0.98, p=0.0225). Patients treated in RCCVCs have a lower risk, with an aHR of 0.81 (95% CI: 0.70–0.93, p=0.0041), compared to those treated in non-RCCVCs.

In one-year mortality, a higher betweenness centrality group is associated with a significantly lower in-hospital mortality risk (IRR 0.91, 95% CI: 0.84 – 0.98, p=0.0111). Patients treated in RCCVCs have a lower risk, with an aHR of 0.80 (95% CI: 0.72–0.88, p<0.0001), compared to those treated in non-RCCVCs.

In three-year mortality, a higher degree centrality group is associated with a significantly lower in-hospital mortality risk (IRR 0.59, 95% CI: 0.36 – 0.98, p=0.0412). Patients treated in RCCVCs have a lower risk, with an aHR of 0.82 (95% CI: 0.76–0.88, p<0.0001), compared to those treated in non-RCCVCs.

Table 14. Subgroup analyses for the incidence rate ratios and hazard ratios for mortality among AMI patients who received coronary interventions

Variables	aIRR	95% CI	*P-value*	aHR	95% CI	*P-value*
In-hospital mortality						
Degree centrality group						
Low-middle	Ref					
High	0.58	(0.23 – 1.47)	0.2484	0.59	(0.22 – 1.58)	0.4104
Betweenness centrality group						
Low-middle	Ref					
High	0.83	(0.74 – 0.92)	0.0005	0.88	(0.79 – 0.98)	0.0225
RCCVC						
No	Ref					
Yes	0.95	(0.83 – 1.10)	0.4851	0.81	(0.70 – 0.93)	0.0041
1-year all-cause mortality						
Degree centrality group						
Low-middle	Ref					
High	0.67	(0.36 – 1.22)	0.1868	0.70	(0.38 – 1.32)	0.2734
Betweenness centrality group						
Low-middle	Ref					
High	0.91	(0.84 – 0.98)	0.0111	0.96	(0.89 – 1.03)	0.2845
RCCVC						
No	Ref					
Yes	0.94	(0.85 – 1.04)	0.2043	0.80	(0.72 – 0.88)	<0.0001

*Results adjusted for all control variables.
*Abbreviation: aIRR, Adjusted Incidence rate ratio; CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference, RCCVC: Regional Cardiocerebrovascular Center

(Continue)

Table 14. Subgroup analyses for the incidence rate ratios and hazard ratios for mortality among AMI patients who received coronary interventions

Variables	aIRR	95% CI	*P-value*	aHR	95% CI	*P-value*
3-year all-cause mortality						
Degree centrality group						
Low-middle	Ref					
High	0.59	(0.36 – 0.98)	0.0412	0.64	(0.38 – 1.08)	0.0922
Betweenness centrality group						
Low-middle	Ref					
High	0.95	(0.90 – 1.01)	0.1159	1.01	(0.95 – 1.07)	0.7241
RCCVC						
No	Ref					
Yes	0.96	(0.89 – 1.04)	0.3658	0.82	(0.76 – 0.88)	<0.0001

*Results adjusted for all control variables.
*Abbreviation: aIRR, Adjusted Incidence rate ratio; CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference, RCCVC: Regional Cardiocerebrovascular Center

4. Results of the readmission within one year after discharge

Table 15 showed the incidence ratios and hazard ratios for readmission within one year after discharge. Among patients treated at RCCVCs, there were 12,640 readmissions within one year per 100,000 person-years, while among patients not treated at RCCVCs, there were 14,523 readmissions within one year per 100,000 person-years. In terms of degree centrality, patients treated at hospitals with high degree centrality experienced 13,163 readmissions within one year per 100,000 person-years, whereas patients treated at hospitals with low to middle degree centrality experienced 14,850 readmissions within one year per 100,000 person-years. Regarding betweenness centrality, patients treated at hospitals with high betweenness centrality had 14,011 readmissions within one year per 100,000 person-years, compared to 14,455 readmissions within one year per 100,000 person-years for patients treated at hospitals with low to middle betweenness centrality.

Patients treated in RCCVCs have a lower risk, with an aHR of 0.87 (95% CI: 0.83–0.93, $p<0.0001$), compared to those treated in non-RCCVCs. A higher degree of centrality is associated with a lower risk of readmission (aHR 0.73, 95% CI: 0.55–0.96, $p = 0.0260$). A higher betweenness centrality group is associated with a higher risk of readmission (aHR 1.10, 95% CI: 1.05–1.15, $p<0.0001$).

Table 15. Results of the incidence ratios and hazard ratios for readmission within one year after discharge

Variables	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
	Readmission within one year after discharge						
Sex							
Female	26913	4,205	15577	(15114 – 16055)	Ref		
Male	72096	9,988	13813	(13545 – 14086)	0.99	(0.95 – 1.03)	0.5400
Age group							
Under 50	13742	1,790	12988	(12400 – 13603)	Ref		
50-59	22358	2,924	13040	(12576 – 13521)	0.98	(0.92 – 1.04)	0.4166
60-69	25076	3,476	13092	(12013 – 14268)	0.98	(0.92 – 1.03)	0.4062
70-79	23359	3,638	13145	(11395 – 15163)	1.04	(0.98 – 1.11)	0.1855
Over 80	14473	2,365	13197	(10796 – 16133)	1.07	(1.00 – 1.14)	0.0632
Region							
Seoul	16965	2,396	14082	(13529 – 14657)	Ref		
Metropolitan	25189	3,515	13913	(13461 – 14381)	0.98	(0.93 – 1.04)	0.4887
Urban/Rural	56855	8,282	13747	(12724 – 14851)	1.01	(0.96 – 1.06)	0.7388
Medical Insurance							
Insurance (Regional)	37287	5,411	14469	(14088 – 14859)	Ref		
Insurance (Corporate)	61721	8,782	14186	(13893 – 14486)	0.97	(0.94 – 1.01)	0.1113

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: IRR, Incidence rate ratio; CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 15. Results of the incidence ratios and hazard ratios for readmission within one year after discharge

Variables	Readmission within one year after discharge						
	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
Household income							
0-4th decile (Low)	16726	2442	14556	(13990 – 15145)	Ref		
5-8th decile	13716	1943	14124	(13510 – 14761)	0.98	(0.92 – 1.04)	0.4702
9-12th decile	16841	2366	13705	(12433 – 15106)	0.97	(0.91 – 1.02)	0.2172
13-16th decile	21257	3078	13298	(11386 – 15530)	0.99	(0.94 – 1.04)	0.6726
17-20th decile (High)	30469	4364	12903	(10417 – 15982)	0.96	(0.91 – 1.01)	0.0959
Charlson Comorbidity Index score							
None	12686	1225	9629	(9104 – 10183)	Ref		
One	9769	1024	10452	(9831 – 11112)	1.08	(0.99 – 1.17)	0.0848
Two	17031	1881	11345	(9915 – 12981)	1.15	(1.07 – 1.24)	0.0001
Three or more	59523	10063	12315	(9931 – 15272)	1.74	(1.64 – 1.85)	< 0.0001
Hospitalization route							
Other	22947	3443	14959	(14468 – 15468)	Ref		
Emergency room	76062	10750	14091	(13828 – 14360)	0.98	(0.94 – 1.02)	0.3203

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

(Continue)

Table 15. Results of the incidence ratios and hazard ratios for readmission within one year after discharge

Variables	Readmission within one year after discharge						
	100,000 person-year	Event	Incidence Ratio per 100,000 person-year (95% CI)		aHR	95% CI	*P-value*
Hospital Type							
Tertiary Hospital	47477	6,539	13732	(13403 –14069)	Ref		
General Hospital	51532	7,654	14809	(14481 – 15144)	0.98	(0.94 – 1.03)	0.4407
RCCVC							
No	86900	12,658	14523	(14272 – 14778)	Ref		
Yes	12109	1,538	12640	(12023 – 13288)	0.87	(0.83 – 0.93)	<0.0001
Degree centrality group							
Low-middle	66302	9,875	14850	(14560 – 15146)	Ref		
High	32707	4,318	13163	(12776 – 13562)	0.73	(0.55 – 0.96)	0.0260
Betweenness centrality group							
Low-middle	62809	9,106	14455	(14161 – 14755)	Ref		
High	36199	5,087	14011	(13631 – 14402)	1.10	(1.05 – 1.15)	<0.0001

*Results adjusted for the numbers of specialists, nurses, operating rooms, and Emergency room beds.
*Abbreviation: CI, Confidence Interval; aHR, Adjusted Hazard ratio; Ref: Reference

V. Discussion

1. Discussion of the Study Method

1) Study design, participants and variables

This study aimed to investigate the impact of patient-sharing networks on the mortality and readmission of AMI patients. Specifically, this study examined the effects of network metrics, namely degree and betweenness centrality, on all-cause mortality (in-hospital mortality, 1-year mortality, and 3-year mortality) and readmission.

The study utilized a retrospective cohort design, leveraging the extensive data available in the Korean National Health Insurance Service (NHIS) database. This study collected data from 2005 to 2022, which accounts for approximately 30% of patients with cardiovascular disease during this period. Although some previous studies have used cohort data, most relied on hospital-collected data with small sample sizes. This study achieved high external validity because it used a relatively large sample size compared to previous studies. Additionally, the data used in the current study included medical treatment records with diagnosis codes and exact dates of treatment or diagnosis.

This study considered using multilevel analysis for group-level variables such as individual and hospital levels. However, the intraclass correlation coefficient, which is a criterion for determining model fit, was less than 5%. Therefore, this study proceeded with analysis using the Cox proportional hazards model for single-level analysis. The Cox proportional hazards model is a commonly used statistical tool in clinical research to investigate the association between predictor variables and patient survival time. This study modeled the survival analysis of AMI patients after onset with specified factors, including the characteristics of the primary treatment hospital (network metrics). The purpose was to simultaneously examine the effect of these specified factors on the rate at which a particular event (mortality) occurs at a specific point in time. This study calculated and interpreted the mortality rates as hazard ratios after adjusting for several known quantities (covariates).

The methodological approach included SNA, which provided significant advantages in understanding the organizational context of healthcare delivery and the interactions within patient-sharing networks. SNA offers several strengths that were crucial to this study. First, SNA allowed us to map and quantify the relationships between hospitals based on patient-sharing patterns, helping to identify key hospitals within the network that play a central role in patient care coordination. Second, SNA of the strength and direction of hospital ties shed light on the coordination of care among various healthcare providers, underscoring the significance of collaborative efforts in improving patient outcomes. Third, SNA enabled the identification of hospitals that are central to the network (high degree and betweenness centrality), which often serve as major referral centers and play critical roles in setting care standards and influencing outcomes across the network. Fourth, understanding network dynamics helped identify potential gaps and inefficiencies in the system, providing valuable information for policymakers to optimize resource allocation and improve the overall effectiveness of healthcare delivery.

The inclusion of SNA in our methodological approach significantly strengthened the study by providing a deeper understanding of inter-hospital relationships and their effects on patient outcomes. The ability to visualize and analyze the network structure allowed us to identify critical nodes and connections that influence care delivery. Additionally, SNA facilitated the examination of both formal and informal networks, providing a comprehensive perspective on the organization and delivery of healthcare in real-world settings.

2) Limitations of the study

This study had certain limitations. Firstly, the potential inaccuracy of administrative data has been a topic of debate for decades, potentially limiting its use. For instance, ICD-10 codes in cohort data may not always represent patients' actual disease status because their primary purpose is to facilitate health insurance claims. To address this, we supplemented the data with procedure codes to obtain additional evidence for AMI.

Second, because this study used administrative data, the present analyses could not control for potential confounders that could affect mortality, such as health-related behaviors like smoking, drinking, and physical activity; household composition and marital status; and the presence of caregivers. It is important to note that the potential impact of unmeasured variables could not be eliminated.

Thirdly, there could be concerns about outliers when calculating degree and betweenness centrality. Extreme maxima or minima, if they exist, can influence the entire measurement. However, since these indices provide relative status for specific regions, the maximum or minimum values can have their own significance. Additionally, when calculating the patient-sharing numbers necessary for degree and betweenness centrality, this study only included medical utilization cases of cardiovascular and cerebrovascular diseases their risk factors (ICD-10: E10-E14, E78, I10-I13, I15, I20-25, I60-I69), which may lead to concerns about underestimation. Future studies could expand this to include medical utilization for antecedent cardiovascular diseases. Additionally, the network metrics were derived from patient-sharing patterns, which may not fully reflect the quality of inter-hospital collaborations. Future research should explore more granular aspects of hospital interactions, including qualitative assessments of collaboration quality.

2. Discussion of the Results

By specifically examining the impact of network centrality metrics, such as degree and betweenness centrality, this study builds on existing knowledge. The analysis revealed that hospitals with higher degree centrality, indicating more direct connections with other hospitals, had lower in-hospital mortality rates. This suggests that hospitals more integrated into the patient-sharing network are better equipped to provide timely and coordinated care, which is crucial for acute conditions like AMI. High betweenness centrality, which measures the extent to which a hospital acts as a bridge within the network, was also associated with lower in-hospital mortality. This is consistent with findings by Barnett et al. (2012), who reported that hospitals with higher centrality in patient-sharing networks had better clinical outcomes [39]. The similarity underscores the importance of centrality in improving immediate patient outcomes through enhanced information flow and resource allocation [73, 74].

For 1-year mortality, the findings were consistent with those for in-hospital mortality. Patients treated in hospitals with higher degree centrality had lower mortality rates within one year of discharge. This aligns with the results of Pollack et al. (2013), who found that higher care density, a related concept, was associated with lower mortality and better health outcomes one year post-discharge [75]. The consistent findings across different studies highlight the critical role of hospital networks in ensuring sustained patient care post-discharge [76, 77].

The impact of network metrics on 3-year mortality followed a similar pattern. Higher degree centrality was linked to lower long-term mortality, suggesting that well-connected hospitals can provide sustained quality care and effective management of chronic conditions that may arise post-AMI. High betweenness centrality also correlated with lower 3-year mortality, indicating the lasting benefits of hospitals that facilitate extensive collaboration and information exchange within the network. These findings support those of Casalino et al. (2015), who demonstrated that strong physician networks are associated with better long-term health outcomes [55].

The analysis of hospital readmission rates in relation to network centrality metrics—specifically degree centrality and betweenness centrality—reveals nuanced impacts on readmission. Hospitals with high degree centrality, which reflects the number of direct connections to other hospitals, was associated with reduced readmission within one year. This suggests that hospitals with more connections and those acting as key intermediaries in the network can better manage patient care transitions, provide comprehensive discharge planning, and ensure follow-up care, thereby reducing the likelihood of readmissions [59]. This aligns with previous research, which noted that higher network centrality was linked to lower readmission rates due to improved care coordination [78, 79]. High betweenness centrality can lead to increased readmission rates due to potential inefficiencies in handling high patient traffic and information bottlenecks [80]. This indicates that hospitals serving as key intermediaries may experience higher readmissions, potentially due to the complexities and challenges in managing information flow and patient transitions between multiple hospitals [57].

The findings of this study reveal that the risk of death among AMI patients is significantly lower when treated at RCCVCs. This outcome suggests that RCCVCs, with their specialized resources, protocols, and expertise in managing cardiovascular emergencies, provide a superior standard of care that leads to better patient outcomes [6]. Our findings are consistent with previous research that highlights the benefits of specialized centers and high-volume hospitals in managing critical conditions. Studies have shown that hospitals with higher patient volumes tend to have better outcomes due to their accumulated experience and specialized resources [81, 82]. The centralized and focused care available at these centers likely plays a critical role in improving survival rates for AMI patients [31]. These centers may also benefit from more advanced medical technologies, highly skilled healthcare professionals, and a more structured and systematic approach to emergency care, all of which contribute to enhanced patient management and treatment efficacy [5].

This study also corroborates findings from studies that investigate the role of healthcare networks in patient outcomes. For instance, Barnett et al. (2012) found that healthcare networks play a crucial role in managing patient care and improving outcomes through shared resources and collaborative practices [39]. Researchers highlight hospitals' ability to function within a network, share best practices, and appropriately refer patients as a critical factor in achieving better health outcomes.

Furthermore, this research contributes to the existing literature by examining the specific roles of degree and betweenness centrality in healthcare networks. While previous studies focused on the overall benefits of network participation, this study provides a more detailed analysis of how hospitals' position and connectivity within these networks influence patient outcomes. This level of analysis helps to identify key nodes within the network that are crucial for effective patient management and can inform policy decisions aimed at optimizing healthcare delivery.

3. Implications

The study highlights the value of hospital networks and the importance of centrality in patient-sharing. Policies promoting better integration and communication between hospitals could lead to improved patient outcomes. Establishing more robust referral systems and incentivizing hospitals to develop strong collaborative relationships is crucial. Healthcare policies should encourage data sharing, coordinated care plans, and the development of integrated care networks to ensure that patients receive timely and appropriate interventions. This could involve creating regional health networks that facilitate patient transfers, resource allocation, and collaborative care planning.

Furthermore, the findings suggest that it is not only the presence of specialized centers like RCCVCs that matter but also how well hospitals are connected within the healthcare network. Policymakers should consider strategies to strengthen these networks, such as regional collaborations or national frameworks that facilitate effective patient transfers and shared expertise. Encouraging hospitals to participate in regional health networks and providing incentives for collaboration and data sharing can enhance the overall efficiency and effectiveness of the healthcare system.

VI. Conclusion

This study provides valuable insights into the impact of hospital networks and the centrality of patient-sharing on the outcomes of AMI patients. By analyzing network metrics such as degree centrality and betweenness centrality, we demonstrated that hospitals with higher centrality in patient-sharing networks are associated with lower mortality rates and reduced readmission rates. By fostering stronger inter-hospital connections and enhancing collaborative care efforts, healthcare systems can achieve better patient outcomes, more efficient resource utilization, and overall improved public health. Future research should continue to explore the dynamics of hospital networks and develop strategies to optimize healthcare delivery through enhanced collaboration and connectivity.

Abbreviations

AMI	Acute myocardial infarction
CVD	Cardiovascular disease
CCI score	Charlson Comorbidity Index score
CP	Critical pathway
NHIS	National Health Insurance Service
RCCVCs	Regional Cardio-cerebrovascular Centers
SNA	Social Network Analysis
STEMI	ST-segment elevation myocardial infarction

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Appendix

Appendix 1. Procedure code of PCI and CABG

Procedure	Code
Percutaneous transluminal coronary angioplasty	M6551, M6552, M6571, M6572
Percutaneous transcatheter placement of intracoronary stent	M6561, M6562, M6563, M6564
Coronary artery bypass graft	O1641, O1642, O1647, OA641, OA642 OA647

Appendix 2. Weighted index applied to calculate CCI score

Conditions	**Assigned weights for each condition**
Myocardial infarction	1
Congestive heart failure	1
Peripheral vascular disease	1
Cerebrovascular disease	1
Dementia	1
Chronic pulmonary disease	1
Connective tissue disease	1
Ulcer disease	1
Mild liver disease	1
Diabetes	1
Hemiplegia	2
Moderate or severe renal disease	2
Diabetes with end organ damage	2
Any tumor	2
Leukemia / lymphoma	2
Moderate or severe liver disease	3
Metastatic solid tumor	6
Acquired Immune Deficiency Syndrome	6

Appendix 3. Year of Designation as Subject Centers according to RCCVCs Designation Information

Year & month of designation	Year of designation as the subject center	Designated hospitals
2008.11	2009	Kangwon National University Hospital Kyungpook National University Hospital Jeju National University Hospital
2009.03	2010	Gyeongsang National University Hospital Chonnam National University Hospital Chungbuk National University Hospital
2010.04	2011	Dong-A University Hospital Wonkwang University Hospital Chungnam National University Hospital
2012.12	2013	Seoul National University Bundang Hospital Inha University Hospital
2017.12 (Conditional designation)	2018	Andong Medical Group Hospital* Mokpo Jung Ang Hospital
2018.03	2019	Ulsan University Hospital

*In January 2022, Andong Medical Group Hospital, which had been conditionally designated, was officially designated as RCCVC following a reassessment.

Korean Abstract (국문 요약)

급성 심근경색 환자의 주 치료 병원의 네트워크 중심성이 환자 결과에 미치는 영향

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김봄결

서론: 급성 심근경색은 전 세계적으로 이환율과 사망률의 주요 원인이다. 급성 심근경색은 환자의 효과적인 관리는 시기적이고 조정된 치료가 필요하며, 이는 잘 통합된 환자 공유 네트워크를 통해 촉진될 수 있다. 그러나 급성 심근경색 환자 공유 네트워크에서 연결중심성과 매개중심성 같은 네트워크 지표의 구체적인 역할은 충분히 조사되지 않았다. 이 연구의 목적은 네트워크 지표가 한국의 급성 심근경색 환자들의 모든 원인 사망 및 재입원에 미치는 영향을 조사하는 것이다.

연구방법: 이 연구는 주 진단 코드 I21-I23 으로 적어도 한 번의 청구를 한 107,595 명의 급성 심근경색 입원 환자를 대상으로 하였다. 주요 종속 변수는 세 가지 유형의 사망률이었고, 이차 종속 변수는 연구 대상 병원에서 퇴원 후 1 년 내 재입원이었다. 네트워크 지표는 병원 간 환자 공유 패턴을 기반으로 계산되었으며, 연결중심성은 받은 환자 수를 반영하고 매개 중심성은 병원이 환자 공유 네트워크에서 중개 역할을 하는 정도를 나타낸다. 사망률 및 재입원율 발생률은 총 추적 관찰 인년수로 나눈 사건 수로 계산하고, 신뢰 구간(CI)을 계산했다. 이 연구는

네트워크 지표와 환자 결과 간의 연관성을 분석하기 위해 잠재적 혼란 변수(연령, 성별, 동반 질환, 병원 특성)를 조정한 Cox 비례 위험 모델을 사용했다.

연구결과: 분석 결과, 높은 연결중심성은 병원 내 사망(aHR 0.64, 95% CI: 0.44 - 0.95, p=0.0263), 1 년 내 사망(aHR 0.73, 95% CI: 0.54 - 0.97, p=0.0307), 3 년 내 사망(aHR 0.75, 95% CI: 0.58-0.96, p=0.0241)과 유의미하게 연관이 있었다. 유사하게, 높은 매개중심성도 병원 내 사망(aHR 0.94, 95% CI: 0.89 - 0.99, p=0.0249), 1 년 내 사망(aHR 0.95, 95% CI: 0.90 - 0.99, p=0.0168), 3 년 내 사망(aHR 0.91, 95% CI: 0.87-0.95, p<0.0001) 감소와 연관이 있었다. 또한, 높은 연결중심성은 퇴원 후 1 년 이내 재입원율이 낮았다(aHR 0.73, 95% CI: 0.55-0.96, p=0.0260). 반면 높은 매개중심성은 퇴원 후 1 년 이내 재입원(aHR 1.10, 95% CI: 1.05-1.15, p<0.0001) 증가와 유의미하게 연관이 있었다.

결론: 이 연구는 급성 심근경색 환자의 결과를 결정하는 데 있어 병원 네트워크와 환자 공유의 중심성이 중요한 역할을 한다는 것을 강조한다. 병원 간의 통합과 의사소통을 강화함으로써 환자 결과를 크게 개선할 수 있다.

핵심어: 사망, 환자공유네트워크, 연결중심성, 매개중심성, 급성 심근경색