A Novel Use of Social Network Analysis and Routinely Collected Data to Uncover Care Coordination Processes for Patients with Heart Failure

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in Nursing in the Graduate School
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ABSTRACT

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Abstract

Effective patient care transitions require consideration of the patient's social and clinical contexts, yet how these factors relate to the processes in care coordination remains poorly described. This dissertation aimed to describe provider networks and clinical care and social contexts involved during longitudinal care transitions across settings. The overall purpose of this dissertation is to uncover the longitudinal patterns of utilization and relational processes needed for effective care coordination in transitional care, so we can redesign interventions that focus on informational and relationship networks to improve interaction patterns and system performance for people living with heart failure (HF) as they undergo transitions across settings and over time.

This dissertation was a retrospective exploratory study. Chapter 2 is an integrative review examining coordination processes in transitional care interventions for older adults with HF by integrating a social network analysis framework. We subsequently selected a cohort of patients aged 18 years or older (n = 1269) with an initial hospitalization for HF at Duke University Health System between January 1, 2016 and December 31, 2018 based on encounter, sociodemographic, and clinical data extracted from electronic health records (EHR). In Chapter 3, a latent growth trajectory analysis was used to identify distinct subgroups of patients based on the frequency of

outpatient, as well as emergency department (ED) and inpatient encounters 1 year before and 1 year after the index hospitalization; multinomial logistic regression was then used to evaluate how outpatient utilization was related to acute care utilization. Based on findings (described in Chapter 3), we purposively sampled 11 patients from the Chapter 3 cohort for a second empirical study (described in Chapter 4) with a mixed-methods sequential explanatory design. These 11 patients had a full spectrum of experience in socioeconomic disadvantages based on three strata (race, insurance, and Area Deprivation Index), but they had similar levels of comorbidity and average severity of illness and displayed the same change in the severity of illness during the study period. We used quantitative and qualitative data available from clinical notes in the EHR, and integrated results from quantitative and qualitative analysis to better understand the social and clinical context and social structure essential for care coordination.

High variability in transitional care is likely because care coordination processes are highly relational. The relational structure of transitional care interventions varied from triadic to complex network structures. Use of a network analysis framework helped to uncover relational structures and processes underlying transitional care to inform intervention development. Chapter 3 revealed that high heterogeneity exists in patients' utilization patterns.

A small subgroup of high users utilized a substantial amount of the resources. Patients with high outpatient utilization had more than 4 times the likelihood of also having high acute care utilization, and change in the severity of illness had the highest level of significance and strongest magnitude of effect on influencing high acute care utilization. Chapter 4 demonstrated the feasibility of using clinical notes and social network analysis (SNA) to assess the provider networks for patients with HF in care transitions. People who were experiencing more socioeconomic disadvantages and social instability were less likely to have densely connected provider teams and providers who were central and influential in the system network. Lacking consistent and reciprocal relationships with outpatient provider teams, especially primary care provider and cardiology teams, was precedent to poor care management and coordination. Turbulence in care transition can result from sources other than transitioning between settings. This dissertation demonstrated the (a) importance of understanding relational processes and structure during patients' utilization of acute and outpatient care services and (b) potential to capture structural inequalities that may influence the efficiency of care coordination and health outcomes for patients with HF.

Dedication

I dedicate this dissertation to my family, friends, mentors, and colleagues whose endless support made this work possible.

Contents

List of Tables

List of Figures

Acknowledgments

The completion of this dissertation would not have been possible without the expertise of and guidance from my dissertation committee: Bradi Granger, Eleanor McConnell, Kirsten Corazzini, James Moody, and Wei Pan. I would like to thank the Duke University School of Nursing and Duke University Graduate School for their generous support for training and research time needed to produce this dissertation. Work for this dissertation was partially supported by Duke University Graduate School Summer Fellowships (2017, 2018, 2019) and the Duke University School of Nursing PhD Student Pilot Fund. I wish to thank my colleagues (especially the 2016 PhD cohort) and the faculty and staff at the Duke University School of Nursing, Duke Network Analysis Center, and Duke Libraries. I would like to express my appreciation to Jamie Conklin for help with generating the search strategy for Chapter 2; Cory Miller, Preeti Bala, and Joseph Kelly for helping extract data from notes for Chapter 4; Tom Wolff and John Little for providing R coding consultation, and Donnalee Frega for providing editorial assistance. Last but not least, my parents, extended family, friends, and my ballroom dance coaches and partners have been a significant source of support and well-being during my time in the program. I am incredibly thankful to have had the support, guidance, and encouragement of so many wonderful people.

1. Introduction

Improving care transitions for people with heart failure (HF) presents a major clinical challenge due to the high prevalence, morbidity, health care expenditure, and readmission rates associated with HF. HF is one of the most common comorbid conditions (Heidenreich et al., 2011; Mozaffarian et al., 2016), affecting nearly 6.2 million Americans (Benjamin et al., 2019). Although the number of treatment options has increased and technologies have advanced significantly in recent years, HF remains a disease that is rarely cured (McIlvennan & Allen, 2016). One in eight Americans who died in 2013 had a medical history of HF (CDC, 2019; Mozaffarian et al., 2016). Older adults hospitalized with HF have an average life expectancy of 2.5 years (Huynh et al., 2006). By 2030, health care costs for HF are expected to more than double, rising from 32 to about 70 billion dollars (Benjamin et al., 2019; Heidenreich et al., 2013). HF is the most common cause of hospitalization and has the highest 30-day readmission rate compared with other diseases (Blecker et al., 2019). Patients with HF and their caregivers can suffer tremendous physical, psychosocial, and financial distress, especially during care transitions (Garlo et al., 2010; Gusdal et al., 2016; Selman et al., 2007).

Transitional care refers to “individual interventions and programs with multiple activities that are designed to improve shifts or transitions from one setting to the next, most often from hospital to home”(Albert et al., 2015). Difficulties in care transitions are often caused by complex medical and care needs, limited resources and support, poor self-care management, and fragmented health care systems (Arbaje et al., 2014; Ortiz, 2018). Poor transitional care is associated with poor health outcomes and creates huge financial burdens for both patients and the government (A. I. Arbaje et al., 2014; B. A. Daveson et al., 2014; Kansagara et al., 2015; Wang et al., 2016). One in five US Medicare beneficiaries (about 2.6 million older adults) is readmitted within 30 days of discharge from a hospital (A. I. Arbaje et al., 2014), costing Medicare more than $26 billion yearly (CMS, 2020).

The US health system had grown increasingly fragmented (A. I. Arbaje et al., 2014; Frandsen et al., 2015) as the fee-for-service model provides little incentive for hospitals to reduce readmissions or coordinate services across providers and care settings (McIlvennan et al., 2015; Novikov et al., 2018). Since 2010, health systems around the U.S. have increased their efforts to improve care coordination of patients who are transitioning from hospitals into the community due to the enactment of the Patient Protection and Affordable Care Act, which initiated the use of the 30-day readmission rate as a hospital quality measure, thus incentivizing hospitals to reduce 30-day readmission rates and increase care continuity and system efficiency (*Supreme Court decision to uphold the Affordable Care Act*, 2010). In 2012, the Centers for Medicare & Medicaid Services officially incorporated 30-day readmission rates into reimbursement decisions and penalized hospitals with higher than expected readmission rates through the Hospital Readmission Reduction Program (McIlvennan et al., 2015).

HF is one of the first three conditions included in the Hospital Readmission Reduction Program, because people with HF often experience rehospitalizations and nonlinear health trajectories (Luttik et al., 2016; Manemann et al., 2016) and are more likely to be transferred to a hospital (Bone et al., 2016). Although the national 30-day readmission rate for patients with HF decreased from 25% to around 22% after the enactment of the Affordable Care Act (Blecker et al., 2019; McIlvennan et al., 2015; Wasfy et al., 2017), it has remained at around 22% since 2012 (Blecker et al., 2019). The need for improvement in transitional care for patients with HF is a persistent problem that must be solved.

1.1 Gap: Relational and Longitudinal Processes

Care coordination is the key mechanism to ensure smooth care transitions (Albert, 2016; A. I. Arbaje et al., 2014; CMS, 2020) and achieve the Quadruple Aims: (1) improved patient experience, (2) improved provider work experience, (3) better quality of care, and (4) reduction in cost (Chen & Miller, 2016; Craig et al., 2011; B. A. Daveson et al., 2014; Sikka et al., 2015). "Care coordination involves deliberately organizing patient care activities and sharing information among all of the participants concerned with a patient's care to achieve safer and more effective care"(AHRQ, 2018). The Institute of Medicine has identified care coordination as a key strategy for improving the effectiveness and efficiency of the health care system (AHRQ, 2018; McDonald et al., 2007). The Agency for Healthcare Research and Quality emphasizes that effective care coordination processes require collective and connective efforts between various disciplines and departments as well as adaptivity to changes at individual and system levels, especially regarding transitions across settings that involve multiple teams (AHRQ, 2018; Albert et al., 2015; A. I. Arbaje et al., 2014; Coleman, 2003; Barbara A Daveson et al., 2014); however, existing research has focused primarily on care components, activities, or tasks, providing little understanding of the processes by which various participants can be connected to organize care activities or share information deliberately.

Although care coordination involves longitudinal and relational processes between multidisciplinary participants across settings, studies of care coordination or transitional care interventions have often focused on components of care, a single care setting, and a single episode of care (A. I. Arbaje et al., 2014; Hansen et al., 2011; Li et al., 2016). Extensive research has uncovered a wide range of care components for improving care transitions, including comprehensive assessment, discharge planning, medication reconciliation and management, patient education, post-discharge follow-ups, referrals for community-based resources, and technology-assisted self-management and monitoring (Coffey et al., 2017; Coleman, Parry, Chalmers, & Min, 2006; Hirschman et al., 2017; Hirschman et al., 2015; M. D. Naylor et al., 2011). Numerous intervention and implementation studies have evaluated the effects of these components (individually or in combination) for people with HF; however, consistent, reliable results have not been obtained (Albert, 2016; A. I. Arbaje et al., 2014; Li et al., 2016).

It is often difficult to determine which care components or activities may be effective because organizational processes are highly variable, relational, and dependent on the (a) engagement of multiple participants (e.g., providers, patients, family caregivers) and information sources across settings, (b) quality of interactions among participants, (c) system context, and (d) changes in patient context, needs, and condition over time. The lack of complete and explicit understanding of the longitudinal and relational processes needed to deliver care components or activities may be one major reason for the bottleneck of inconsistent results from transitional care studies, as well as the limited impact of policy and research efforts to reduce the 30-day readmission rate for patients with HF. To improve transitional care and care coordination processes for patients with HF and support the achievement of the Quadruple Aim, it is necessary to understand the relational processes and structures that enable the connection of participants and services for successful care continuity in their complexity.

1.2 Theoretical Framework: The Lens of Complex Systems

The need to coordinate care implies that health care systems are becoming increasingly complex and should be studied as complex adaptive systems (Begun & Thygeson, 2014; McDaniel & Driebe, 2001). Successful care coordination in transitional care requires (a) a connected system of providers and essential services to ensure an unobstructed information flow and (b) cooperative care relationships (Albert et al., 2015; A. I. Arbaje et al., 2014; Barbara A Daveson et al., 2014; Gittell et al., 2013; McDonald et al., 2014; Toles et al., 2017). Rather than a Newtonian mechanistic view of care coordination in transitional care, a complex systems framework may provide a more enhanced understanding and explanation of the high heterogeneity in transitional care interventions, uncover the relational (interdependent) processes and structures that form the backbone of care coordination, and inspire more comprehensive approaches to the study of transitional care.

Care coordination is not comprised of individual factors and participants that function independently as assumed by a Newtonian mechanistic view, but rather has characteristics of complex adaptive systems like other social organizations. Participants interact with one another to establish relationships and connections and achieve goals (e.g., care plan revisions, medication changes). Coordinating care and overcoming challenges during transitions involves navigating the relationships among participants (e.g., health care providers, patients, caregivers) and enabling the transfer of information (e.g., discharge paperwork, education materials) between them (Anderson et al., 2015; Luttik et al., 2005; McDonald, 2007; McDonald et al., 2014; Meleis, 2015). Participants with different roles may find that their connections and interactions change as they adapt to new contexts, problems, or challenges over time; and conversely, shared feedback about issues may influence participants' behavior or opinions, resulting in new changes (Anderson et al., 2015; Begun et al., 2014; Braithwaite et al., 2017{Begun, 2014 #1520). Individual participants might adhere to certain formal or informal behavioral dictates, such as clinical procedures and standards of care, yet they might also self-organize based on responsibilities, internalized principles, or interactions with other participants and contexts (Begun & Thygeson, 2014; Braithwaite et al., 2017; Thompson et al., 2016).

By using a complex adaptive systems perspective, we can view care coordination in care transitions as the effect of influential interactions between participants in the system (Anderson et al., 2015; Begun & Thygeson, 2014; Ladyman et al., 2013; Thompson et al., 2016; Wilson et al., 2001). Care processes and outcomes not only depend on participants' interactions with others and their surroundings, but also influence their subsequent interactions (Anderson et al., 2015; Anderson & McDaniel, 2008; Ladyman et al., 2013; Thompson et al., 2016). A complex adaptive systems approach suggests that we should understand care coordination in care transitions through the perspectives of different participants while simultaneously considering the emergence of patterns at the system level. System-level and individual-level outcomes are interrelated in a complex science framework because macro-level (larger scale) behaviors or changes emerge from micro-level (finer scale) interactions (Bar-Yam, 2003, 2018; Begun & Thygeson, 2014; Thompson et al., 2016). The complex systems lens allows us to understand care coordination as an interdependent and collective effort that brings multiple sources of information and teams of care providers together, and it also allows us to view the care system from both individual and system perspectives.

By integrating a complex systems perspective, we propose to address care coordination in care transitions for people with HF as longitudinal and relational processes involving participants from hospital-based and community-based care settings (shown in Figure 1). The human figures in Figure 1 indicate participants who share information and interact both within and across settings. During care transitions, patients with HF and their caregivers utilize hospital-based and community-based care services to manage care; the linked and circling arrows in the model indicate the transitions that a patient with HF undertakes over time as they access and receive care from various services. The model demonstrates the composite of participant interaction as it develops and evolves.

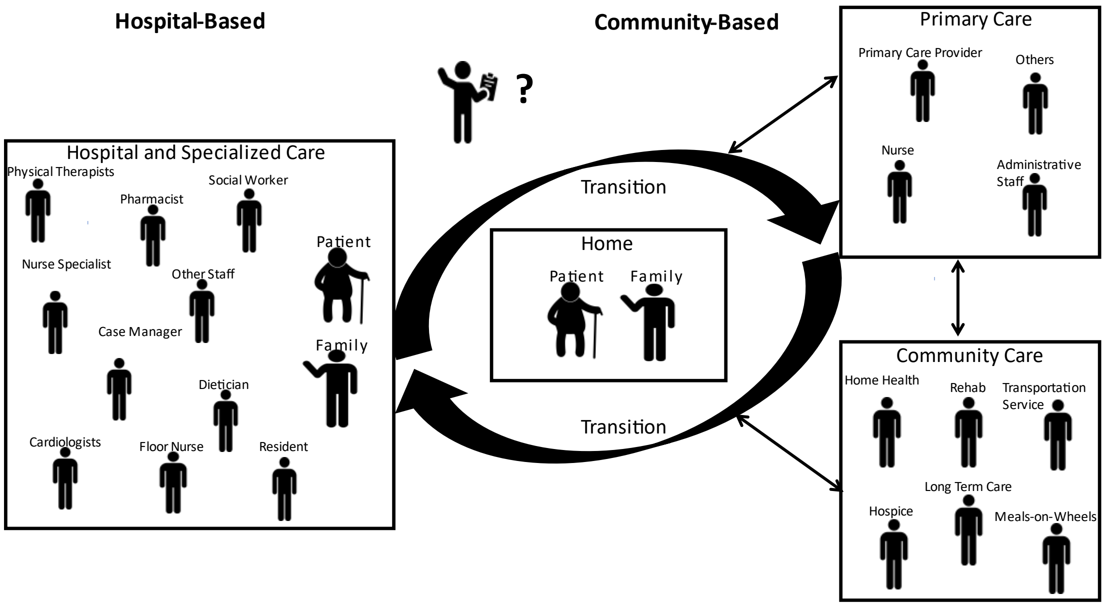


Figure 1: Care Coordination in Transitional Care

1.3 Social Network Analysis to Model Care Coordination

An understanding of care coordination in care transitions through a complex adaptive systems framework requires compatible analytics to capture the interconnected and interdependent nature of the relational processes and behavior patterns of the system (Thompson et al., 2016; Wilson et al., 2001). Social networks are inherent to complex adaptive systems, and the social network analysis (SNA) method is congruent with the theoretical principles of complex adaptive systems (Benham-Hutchins & Clancy, 2010; Clancy et al., 2008). SNA offers a way to understand the properties and qualities of relationships and information flow as well as the underlying social and information network structures in care transitions (Begun & Thygeson, 2014; Benham-Hutchins & Clancy, 2010; Valente, 2010). Care coordination relies heavily on networks of relationships and information (Coleman & Berenson, 2004; Barbara A Daveson et al., 2014; McDonald, 2007), so its processes can be best understood by considering the interactions of participants across settings as they work together through networks.

SNA captures the characteristics of individual participants as well as the qualities and quantities of their connections. In SNA, *node* is a term for people or things in the network (Valente, 2010); we can view the participants in care coordination across settings as nodes. *Ties* (also called *links* or *edges*) indicate connections, interactions, or relationships between nodes; we can view information transfers, clinical interactions, communications, and other forms of interactions for care coordination as ties. Characteristics of nodes (such as education and provider role) and characteristics of ties (such as mode and strength of interactions) are called *attributes* (Valente, 2010; Wasserman & Faust, 1994). Attributes can influence a participant's position within networks and thus can influence network structure, tie formation, and tie quality and quantity (Valente, 2010; Wasserman & Faust, 1994). In Figure 1, participants' interactions can be visualized and analyzed as networks. Figure 2 illustrates human figures as nodes, attributes of nodes as colors, ties as lines, and attributes of ties as solid or dash lines to model the participants.

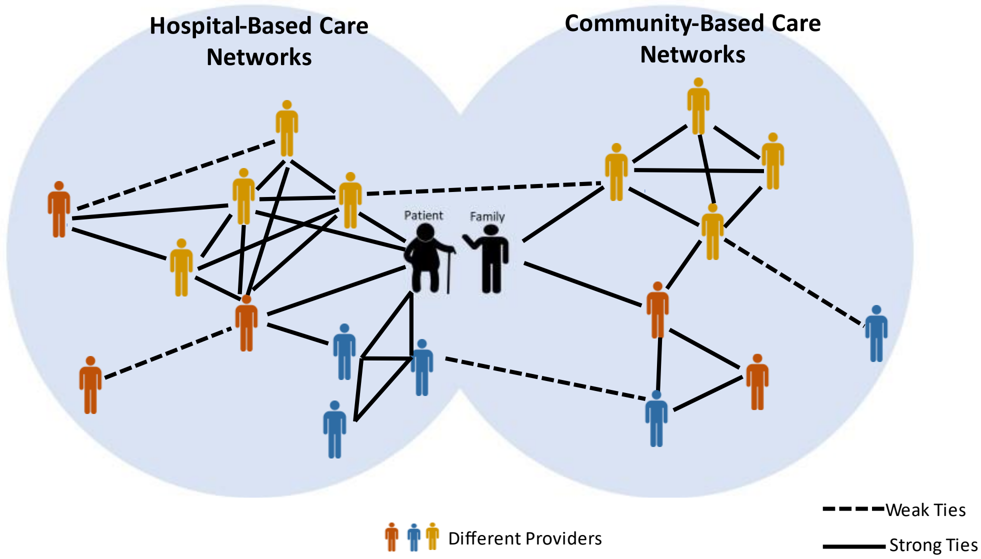


Figure 2: Using Social Networks to Model Participants and Their Interactions and Relationships Involved in Care Coordination

SNA allows us to evaluate care coordination from both individual-level (egocentric) and system-level (socio-centric or whole network) perspectives. Egocentric or individual-level network perspectives can provide important information on care processes to coordinate care, such as advice-seeking (Bae et al., 2015; Sabot et al., 2017). Studies have identified factors such as the setting of practice, patient characteristics, and personal characteristics that influence health professionals' social networks in workplaces (Bae et al., 2015). In relevant studies, providers primarily connected with other providers in the same clinical role (Creswick & Westbrook, 2007; Creswick et al., 2009). Communication networks for medication advice, discussion, and problem-solving were stronger within teams than between teams, and within a geographic setting than between geographic settings (Hossain & Kit Guan, 2012; Keating et al., 2007). Physicians tended to connect and share more often and fully when their patients had similar characteristics, such as race and health insurance (Landon et al., 2012). Nurses with older age tended to have higher network density (Van Beek et al., 2011). Providers with higher communication network density had a higher chance of adopting new information (Effken et al., 2013). Higher communication density was also related to higher job satisfaction (Van Beek et al., 2011). Increased network size and density were related to better coordination performance and care quality (Hossain & Kit Guan, 2012). When the process is considered from an egocentric perspective, each participant communicates and interacts within social networks that influence their ability to adapt to information, coordinate with others, and manage their work experience and the quality of care they provide (Bae et al., 2015; Benton et al., 2015; Chambers et al., 2012; Sabot et al., 2017).

System-level SNA can identify key players for CCTC as well as system-level characteristics and behaviors that might have implications for system changes. Participants in care networks vary in their structural positions and functional characteristics within networks (Antonucci, 1986; Antonucci & Akiyama, 1987; Valente, 2010). Providers may play key roles in networks for functions such as innovation diffusion, provision of medication advice, and knowledge-sharing (Anderson et al., 1990; Creswick & Westbrook, 2010; Wiemken et al., 2012). Networks with greater centrality were associated with higher work and patient satisfaction and with the ability to cope with work-related stressors (Anderson, 1991; Effken et al., 2013; Tsang et al., 2012). Differences in social network structures and types of teamwork may exist among teams of providers (Cott, 1997). Nursing teams were found to be more hierarchical than medical teams, possibly due to the task-oriented nature of nurses' work (Cott, 1997; West et al., 1999). Chase (1995) has suggested that nurses and doctors work in parallel hierarchies and structures that can validate information and judgment while simultaneously creating conflicts. Care teams differ according to setting and hierarchical structure; these variations can affect whether information flow and relationships are reciprocal or nonreciprocal, and they can influence teams' ability to coordinate care (Scott et al., 2005).

1.4 Purpose Statement and Aims

High heterogeneity and variability have been shown in transitional care. Existing research has predominantly focused on care components, but there is a need for a more explicit and comprehensive understanding of care coordination in care transitions across settings and over time. The overall purpose of this dissertation is to uncover the longitudinal and relational processes for care coordination in care transitions so we can design interventions that are more effective, person-centered, and sustainable to improve system performance and health outcomes of people living with HF as they transition across care settings and over time. Specifically, this dissertation aims to examine the (1) care coordination processes described in transitional care interventions for older adults with HF, (2) heterogeneity in the utilization of services across settings as well as how outpatient and acute care utilization are related among identified latent heterogeneous subgroups of patients, and (3) key patterns of social relationships important for care coordination processes in care transitions by evaluating quantitative and qualitative data available in clinical notes from electronic health records (EHR). The methods of this dissertation are grounded in the literature of social network analysis; a complex systems framework is applied with the goal of improving patient-centered care in care transitions for patients with HF.

1.4.1 Chapter 2

In Chapter 2, we will review transitional care interventions for patients with HF who are transitioning from hospital to home using a social network analysis framework. While many literature reviews have examined the components used in transitional care interventions, there exists a lack of understanding of the processes used by providers to carry out these components. This scoping review aims to map the characteristics, theoretical models, and components used in transitional care interventions. In addition, this study attempts to access the interdependent relationships among participants involved in the interventions by using a social network analysis framework based on their descriptions of intervention implementations. This social network analysis framework is used to provide a better understanding of the involved participants, care interactions, and network structures embedded in recent transitional care interventions.

1.4.2 Chapter 3

Because it is often assumed that 30-day readmissions imply incomplete treatment in hospitals, poor service arrangements or miscommunication at discharge, late or inadequate follow-ups, or inadequate access to care, most transitional care interventions focus on short episodes of care starting from before or immediately after hospital discharge to 30 days post-discharge; however, people's transitional care is a continuous and longitudinal process. Patients with HF interact with providers at different settings to obtain the information and support needed to manage their symptoms and care in the community both before and after being hospitalized. The Centers for Medicare and Medicaid Services incentivizes hospitals to improve 30-day readmission rates. Hospitals have been trying to improve their processes, such as better discharge planning, but there is a lack of comprehensive understanding about how patients use outpatient and acute care services over time and how outpatient utilization might influence acute care utilization.

Chapter 3 focuses on patients' longitudinal utilization of various services that influence which providers, provider settings, and provider specialties are involved in their care coordination. Chapter 3 provides the foundational knowledge about patient characteristics and their utilization of different services over time for Chapter 4. This understanding of patients' overall characteristics and their long-term trajectories of inpatient and outpatient use propels the research focus on short episodes of care after hospitalization to a more comprehensive view of care transitions and informs intervention development to address the issue of care fragmentation during care transition. The purpose of this study is to evaluate how outpatient and acute care utilization are related among identified latent heterogeneous subgroups of patients. Specific research questions are

1. What are the distinct trajectories of acute and outpatient care services utilization 1 year before and after the initial HF hospitalization?
2. How is outpatient utilization associated with acute care utilization after controlling for sociodemographic, health behavior, and clinical factors?

1.4.3 Chapter 4

The importance of improving system efficiency and preventing care fragmentation for patients with HF warrants studies of the patterns of interdependent relationships among the providers needed for care coordination in care transitions. SNA can model the interdependent relationships and care activities during care transitions and is a scalable and appropriate approach from a complex systems framework. Using a 2-mode network analysis approach and routinely collected clinical notes from EHR can help us understand the characteristics of patients' provider networks that may be related to patient care outcomes. In addition, routinely collected clinical notes contain rich longitudinal information about clinical and social context that can facilitate an in-depth understanding of care coordination processes in care transitions. The purpose of this mixed-methods pilot study is to test the feasibility of using clinical notes from EHR to understand care coordination processes during HF care transitions. Specific aims are to

1. Test the feasibility of 2-mode (patient-sharing) SNA to construct and characterize individual patients' provider networks.
2. Examine the quantitative and qualitative characteristics of the social and clinical context comprising care coordination during care delivery.

1.4.4 Chapter 5

In Chapter 5, we will synthesize and discuss key findings from the three studies conducted in my dissertation. We will also discuss the implications of our findings for future research and practice.

2. Care Coordination Processes in Transitional Care Interventions for Patients with Heart Failure: An Integrative Review through a Social Network Lens

2.1 Background

HF is one of the most common chronic illnesses among older adults, affecting 6.2 million Americans (Virani et al., 2020). Despite years of research and policy efforts to improve care during transitions following hospital discharge, rehospitalization remains a problem for older adults with HF (Jackson et al., 2018; O'Connor, 2017), often leading to poor health outcomes (Diop et al., 2017; Kilbourne et al., 2018). Since the enactment of the Affordable Care Act, which created financial incentives under the United States (U.S.) Centers for Medicare & Medicaid Services payment systems to reduce the 30-day hospital readmission rate, health systems in the U.S. have increased their efforts to improve transitional care for older adults with HF (Blecker et al., 2019). However, the national average readmission rate for people with HF has plateaued since 2012, despite transitional care interventions (Blecker et al., 2019).

Transitional care comprises "individual interventions and programs with multiple activities that are designed to improve shifts or transitions from one setting to the next, most often from hospital to home"(Albert et al., 2015). Meta-analyses have shown that nurse home visits (Feltner et al., 2014; Van Spall et al., 2017), nurse case management (Van Spall et al., 2017), disease management clinics (Feltner et al., 2014; Van Spall et al., 2017), and medication adherence programs (Ruppar et al., 2016) reduce readmission rates. One meta-analysis found that although telephone or ambulatory clinic follow-up visits alone did not reduce readmission, high-intensity interventions that combine home visits with telephone or clinic follow-up were efficacious (Vedel & Khanassov, 2015). Previous reviews have recognized care coordination as an important component (Albert, 2016; Bryant-Lukosius et al., 2015; Coffey et al., 2017; Naylor et al., 2018) or an implied aspect of successful transitional care (Stamp et al., 2014; Van Spall et al., 2017). However, care coordination as a process that occurs in response to care transitions (McDonald et al., 2014) has not been explicitly reviewed.

Care coordination "involves deliberately organizing patient care activities and sharing information among all of the participants concerned with a patient's care to achieve safer and more effective care"(AHRQ, 2018). Achieving well-coordinated care requires a collective effort by individuals from multiple professions, who may be located in different care settings, to work cohesively within and across teams over time (Coffey et al., 2017; Coleman & Berenson, 2004; Naylor et al., 2011). Deliberate organization of care activities requires a process involving interactions among interdependent individuals or groups (AHRQ, 2018; McDonald et al., 2014).

Social network analysis (SNA) is a theoretical perspective that describes and understands social systems through analysis of the patterns of relationships or connections (*ties*) formed among individuals, groups, or other entities (*nodes*) (Perry et al., 2018; Valente, 2010). Using SNA to describe and measure care coordination in the context of cardiovascular disease has recently gained acceptance in the literature (Carson et al., 2016; McDonald et al., 2014; Merrill et al., 2015; Uddin et al., 2016) and holds promise as a means of measuring team functioning, information transfer, and social structures inherent to care processes (Chambers et al., 2012; McDonald et al., 2014; Uddin et al., 2016). Individuals involved in care coordination processes can be viewed as *nodes*, and care coordination activities or interactions can be viewed as *ties* (Valente, 2010). Characteristics of nodes, such as provider role and work setting, and characteristics of ties, such mode of communication, can be considered as *attributes* (Valente, 2010). SNA allows investigators to analyze interdependent relationships, network roles of individuals, and social structure systematically (Turnbull et al., 2018; Valente & Fujimoto, 2010). Viewing transitional care through a SNA framework refocuses attention from a special set of tasks only to incorporating specific processes that foster a timely transfer of information and relationships to ensure a sufficient continuum of health care and social support for patients.

A better understanding of the care coordination processes involved in transitional care interventions may lead to new insights regarding essential features of successful interventions. Although SNA has not been used to guide the development or evaluation of care coordination processes in transitional care interventions, greater attention to how various individuals connect and share information to support the care of people with HF holds promise as a method for uncovering the social processes and structures crucial to transitional care (McDonald et al., 2014). Integrative reviews allow the synthesis of both experimental and non-experimental studies to evaluate a phenomenon of interest comprehensively (Whittemore & Knafl, 2005). This integrative review aims to examine care coordination processes in U.S.-based transitional care interventions for older adults with HF who are transitioning from hospital to home by integrating an SNA framework to more effectively extract and synthesize the roles, interactions, and social structures involved in care coordination processes.

2.2 Methods

This integrative review followed the guidance of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) checklist to systematically identify recent HF transitional care interventions for review (Page et al., 2021; Whittemore & Knafl, 2005). Although a protocol paper was not published, the consistent application of inclusion and exclusion criteria and systematic data extraction and comparison were ensured through use of the Garrard Matrix method (Garrard, 2014). We used the SNA theoretical perspective to guide the generation of codes for extracting data on care coordination processes involved in transitional care delivery as well as the critical review and synthesis of the data (Valente, 2010; Whittemore & Knafl, 2005). We decided not to include quality appraisal tools in our methods because our purpose was to examine care coordination processes in HF transitional care interventions rather than to evaluate the quality of evidence. Importantly, we wanted to include both experimental and non-experimental studies to comprehensively evaluate care coordination processes, especially quality improvements projects which may be less rigorous in design but are more flexible for adapting care coordination processes to patients' needs and system context.

2.2.1 Data Sources and Search Strategy

To identify recent publications on transitional care interventions in the U.S. for older adults with HF, three databases (PubMed, Scopus, and CINAHL) were searched. Search strategies were developed using keywords, MeSH terms, or subject headings related to care coordination, continuity of care, care transitions, older adults, and HF to capture existing articles published in English. In response to the enactment of the Patient Protection and Affordable Care Act in 2010, health systems have increased their efforts to improve care coordination in order to avoid rehospitalization-related financial penalties (Blecker et al., 2019); therefore only studies published after 2010 were included to capture the most recent studies influenced by the reform. Databases were searched on December 23, 2020 (Table 1). The references of included studies and of published literature reviews on transitional care interventions were reviewed for additional articles.

Table 1: Search Strategies for Databases and Filters and Limits Used

Databases and date	Search files	Number retrieved
PubMed searched on 12/23/2020	1. Transitional care[mesh] OR transition OR transitional OR transitions OR transitioned OR transitioning OR “patient transfer”[mesh] or transfer or transfers	1,091,541
	2. Aged[mesh] OR elderly OR geriatric OR geriatrics[mesh] OR “older adult” OR “older adults” or geriatrics	5,601,654
	3. Coordinat* OR “patient care management”[mesh] OR “care management” OR collaborat* OR communicat* OR communication[mesh] OR “patient-centered care”[mesh] OR “patient centered” or “patient centeredness” OR “continuity of patient care"[mesh] or “continuity of patient care"	2,040,036
	4 “heart failure” [mesh] OR “heart failure” OR "cardiac failure” OR “myocardial failure”	225,255
	#1 AND #2 AND #3 AND #4	439
	NOT (Editorial[ptyp] OR Letter[ptyp] OR Case Reports[ptyp] OR Comment[ptyp]), and limited to article in English	420
	Limited to 2010 to present	**333**
Scopus Searched on 12/23/2020	1. Transitional OR transition OR transitions OR transfer OR transfers	3,957,744
	2. Aged OR elderly or geriatric OR geriatrics OR "older adult" OR "older adults”	5,533,850
	3. coordinat* OR communicat* OR collaborat* OR “care management” OR “patient centered*”	3,720,652
	4. “heart failure” OR “cardiac failure” OR “myocardial failure”	331,662
	#1 AND #2 AND #3 AND #4, and limited to article in English	166
	Limited to 2010 to present	**143**
CINAHL searched on 12/23/2020	S1. Transitions OR (MH “Health Transition”) OR transition OR transitional OR (MH “continuity of patient care+”) OR (MH “Transfer, Discharge”) OR transfer OR transfers	113,525

S2. (MH "Aged+") OR MH "Geriatrics" OR eld* OR old* OR gero* OR geriatric OR senior OR aged OR aging OR geriatrics OR "older adult" OR "older adults"	1,200,009
S3. coordinat* OR collaborat* OR communicat* OR (MH "patient centered care") OR "patient centered" OR "patient centeredness"	371,340
S4. "heart failure" OR "myocardial failure" PR "cardiac failure" OR (MH "Heart Failure+")	66,303
S1 AND S2 AND S3 AND S4 and limited to English language	101
Limited to 2010 to present	**84**
Total	**560**
After screening duplication in Endnote (107 duplicates) plus manual screening (33 duplicates)	**420**

2.2.2 Selection Criteria

Studies were included if (a) the majority of participants were aged 65 or older (mean or median age ≥ 65) and had HF as their primary diagnosis, (2) the intervention was implemented in the context of care transitions from hospital to home, and (3) the intervention involved care coordination. Of the studies that included people with other diagnoses, such as chronic obstructive pulmonary disease, only those that conducted a subgroup analysis of people with HF were included. Interventions that had only one care activity, such as scheduling a primary care follow-up appointment within 7 days after discharge, or did not mention communication or collaboration with another health care provider during implementation were excluded. Because of the critical contextual factors of the larger health care system that would directly affect how care coordination would be developed and implemented, we limited eligible studies to those conducted in the U.S., and that evaluated 30-day readmission as an outcome. Articles were also excluded if they did not report results (i.e., protocol-only articles).

2.2.3 Study Selection

After articles were extracted from databases, duplicates were searched automatically and manually using EndNote version 9.2 (Clarivate Analytics, PA, USA) and were subsequently deleted. Titles and abstracts of the articles were imported into the Rayyan online screening platform (Ouzzani et al., 2016) and screened for relevance based on the title and abstract. After title and abstract screening, full text of these studies was reviewed in EndNote version 9.2 to ensure that they met inclusion and exclusion criteria. The first author independently reviewed the eligibility of all studies. The details of the screening process and reasons for exclusion can be found in the PRISMA flow diagram (Figure 3).

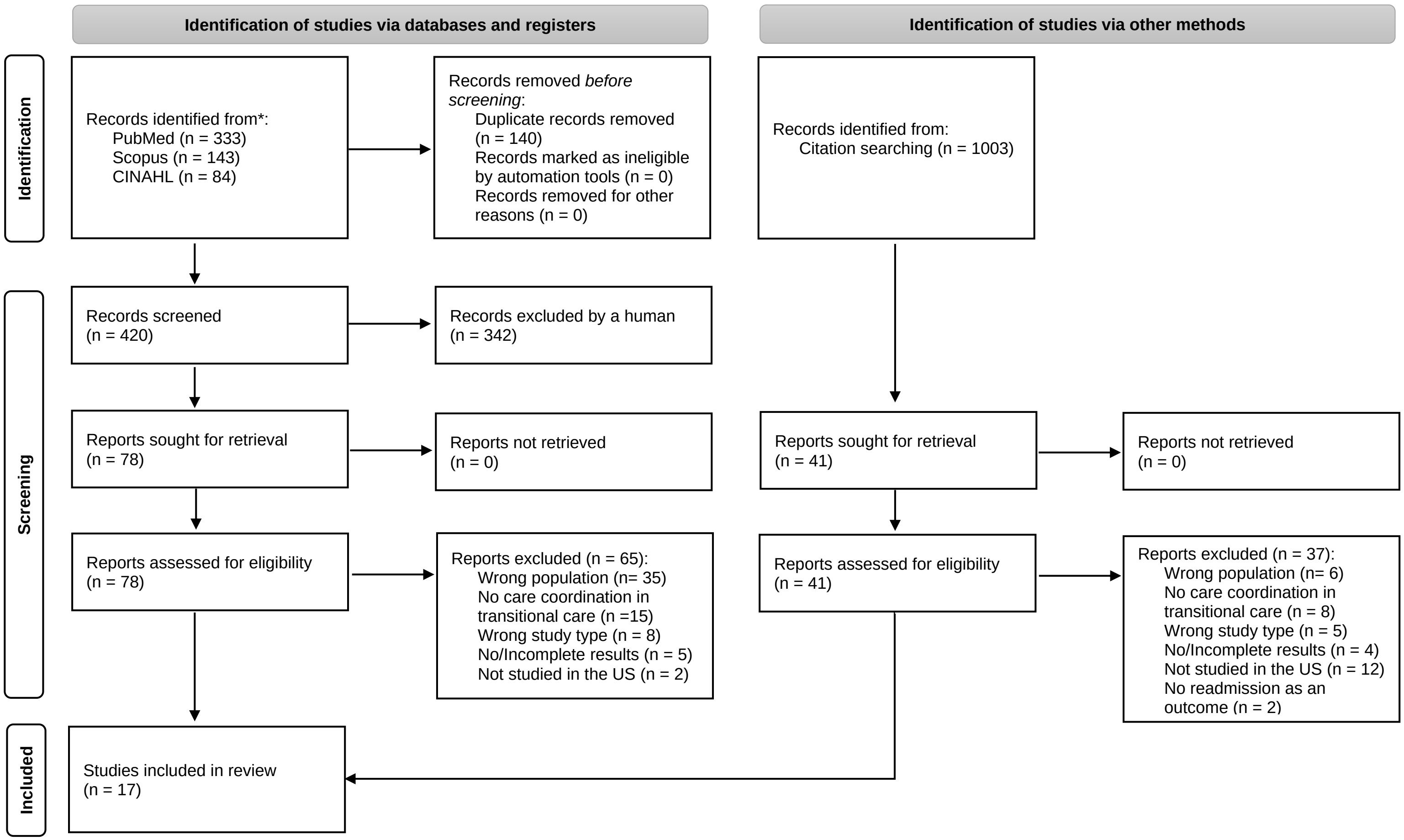


Figure 3: PRISMA Diagram of the Search and Selection Processes

2.2.4 Data Extraction and Synthesis

Following the Garrard Matrix method, we extracted data on the study characteristics and care coordination processes of included studies into matrices to ensure a systematic extraction of the data for this integrative review (Garrard, 2014; Whittemore & Knafl, 2005). Using an SNA framework, we examined each study's care coordination processes by identifying the *nodes*, individuals involved in the intervention (i.e., providers, patients, and informal caregivers); *ties,* the interactions between or among these individuals to coordinate care (e.g., exchanging information and visiting patients at their home); *node attributes* (e.g., provider role and setting); and *tie attributes* (e.g., interaction frequency and mode). We pilot tested the extraction matrices and revised the matrices based on consensus between two researchers (SW and EM) to ensure accurate extraction of care coordination processes before extracting all studies. We then compared differences among studies by identifying common nodes and ties, and mapped nodes and ties into networks to systematically abstract and compare the relational processes and structures.

2.3 Results

2.3.1 Search Outcomes

The database searches identified 560 articles. After 140 duplicates were removed, 420 titles and abstracts were reviewed for relevance. Full text review of 78 studies was performed to assess whether they met our inclusion and exclusion criteria. The initial screening of results from database searches resulted in 13 studies. A snowball sampling methodology using the 13 identified studies and 9 published systematic reviews of transitional care interventions identified an additional 41 studies for screening. Four studies were added to the review for a total of 17 studies that were included in the final review (Altfeld et al., 2013; Baecker et al., 2020; Bowles et al., 2011; Russell et al., 2011).

2.3.2 Study Characteristics

Four studies were randomized controlled trials (Altfeld et al., 2013; Bowles et al., 2011; Linden & Butterworth, 2014; Ong et al., 2016), and the remainder used quasi-experimental or retrospective observational designs (Arcilla et al., 2019; Baecker et al., 2020; Berman et al., 2019; Daley, 2010; Di Palo et al., 2017; Huntington et al., 2013; Milfred-LaForest et al., 2017; Miller et al., 2016; Murphy et al., 2019; Neu et al., 2020; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017). Sample sizes ranged from 21 (Berman et al., 2019) to 28,693 participants (Ong et al., 2016). The majority of the studies (n = 13) recruited more than 100 participants (Altfeld et al., 2013; Baecker et al., 2020; Berman et al., 2019; Bowles et al., 2011; Daley, 2010; Huntington et al., 2013; Linden & Butterworth, 2014; Milfred-LaForest et al., 2017; Miller et al., 2016; Murphy et al., 2019; Neu et al., 2020; Ong et al., 2016; Russell et al., 2011). The mean age of participants ranged from 67 (Neu et al., 2020) to 81 (Miller et al., 2016). All randomized controlled trials demonstrated no significant differences in 30-day readmission between intervention and control groups (Altfeld et al., 2013; Bowles et al., 2011; Linden &

Butterworth, 2014; Ong et al., 2016). Only four quasi-experimental studies reported statistically significant reductions in the 30-day readmission rate (Huntington et al., 2013; Miller et al., 2016; Neu et al., 2020; Russell et al., 2011). Although no effects on 30-day readmission were noted, some studies demonstrated significant improvement in quality of life (Whitaker-Brown et al., 2017), 14-day follow-up appointment compliance (Di Palo et al., 2017), 180-day readmission rate (Ong et al., 2016), and mortality (Ong et al., 2016). Key characteristics of the 17 included studies are summarized in Table 2.

Table 2: Characteristics of Reviewed Studies and Interventions

First Author (year), Model	Study Design	Sample Size (n) Age Mean ± SD	Outcomes (30-day Readmission)	Interventionist (Credential*)	Intervention Duration	Mode
Community-based interventions from the simplest to most complex network structures						
Huntington (2013), NR	Quasi-experimental (Two-group posttest only)	IG = 98 CG = 152 Age = 71-85 ± NR	IG = 15% CG = 26% (p = 0.043)	Nurse	Predischarge~ 30-day post discharge	In-person + telephone
Miller (2017), NR	Quasi-experimental (Historical group as comparison)	IG = 300 CG = 162 Age = 80.9 ±10.5	IG = 23.4% CG = 39.5% (p < .001)	Physical therapist, Nurse	During the 2 weeks post discharge	In-person + telephone
Bowels (2011), NR	Randomized controlled trial	IG = 101 CG = 100 Age = 71.3 ± 10.2	IG= 16% CG= 19% (p = 0.546)	Visiting nurse, Telehomecare nurse, Nurse manager	Within 2-week post discharge ~ 6 weeks or more	In-person + video visit + telemonitoring
Baecker (2020), Transitional Care Model	Retrospective cohort design	IG = 11,827 CG = 16,866 Age = 72.9 ±13.5	Hazard ratio = 0.95 (95% CI, 0.89-1.02, p >0.05)	Visiting or telecare nurses (RN), Case manager	Within 2 ~ 7-day post discharge	In-person + telephone
Berman (2019), NR	Quasi-experimental (Two-group posttest only)	IG = 21 CG = 454 Age = 76 ± NR (range = 65-93)	IG= 9.5%, CG= 11.9% (p = NR)	Pharmacist (PharmD)	At discharge ~ 30-day post discharge	In-person + telephone
Milfred-LaForest (2017), NR	Quasi-experimental (One-group pretest-posttest)	IG = 135 Age = 69.0 ±11.0	Pre = NR Post = 9% (p = NR)	Pharmacist (PharmD)	Within 2 days after discharge (One visit)	In-person
Arcilla (2019), Care Transitions Model	Quasi-experimental (One-group pretest-posttest)	IG = 47 Age = 71.85 ± NR (range = 22–95)	Pre = NR Post = 8.5% (p = NR)	Care Transition Coach (RN) at home health	Predischarge ~ 90-day post discharge	In-person + telephone + telemonitoring

First Author (year), Model	Study Design	Sample Size (n) Age Mean ± SD	Outcomes (30-day Readmission)	Interventionist (Credential*)	Intervention Duration	Mode
Russell (2011), NR	Retrospective observational study	IG = 223 CG = 224 Age = 79.7 ± 10.7	Odds ratio = 0.57 (Adjusted p < 0.01)	Home care nurse coordinator	Predischarge ~ 2-month post discharge	In-person + telephone
Whitaker-Brown (2017), Stetler Model of Research Utilization	Quasi-experimental (One-group pretest-posttest)	IG = 36 Age = 70.1 ± 11.7	Pre = NR Post = 5.6% (p = NR)	Nurse navigator, Nurse practitioner/ Physician assistant, Pharmacist (PharmD)	At Discharge ~ 4-week post discharge	In-person + telephone
Hospital-based interventions from the simplest to most complex network structures						
Ong (2016), Black (2014, protocol), NR	Randomized controlled trial	IG = 715 CG = 722 Age = 73.0 ± NR (25%-75% = 62-84)	IG = 22.7% CG = 21.6% (Adjusted p = 0.63)	Study nurse (RN), Call center nurse (RN)	Predischarge ~ 6-month post discharge	In-person + telephone + telemonitoring
Linden (2014), Care Transitions Model	Randomized controlled trial	IG = 129 CG = 128 Age = 67.7 ± 11.8	IG = 22.4% CG = 21.0% (Adjusted p = .828)	Nurse (RN)	Predischarge ~ 90-day post discharge	In-person + telephone + telemonitoring
Atfeld (2012), Enhanced Discharge Planning Program	Randomized controlled trial	IG = 360 CG = 360 Age = 74.5 ± 6.9	IG = 18.9% CG = 19.5% (p = 0.69)	Social Worker	Within 2 days after discharge (One call)	Telephone
Neu (2020), NR	Quasi-experimental (Historical group as comparison)	IG = 333 CG = 330 Age = 67.0 ± 16.6	IG = 10.5% CG = 17.3% (Adjusted p = 0.026)	Pharmacist (PharmD)	Admission ~ Discharge	In-person
Weeks (2020), NR	Observational	IG = 24 Age = 72.3 ± 1.3	IG = 25% (p = NR)	Nurse discharge navigator (RN)	Predischarge ~ 1–2-day post discharge	In-person + telephone + telemonitoring

First Author (year), Model	Study Design	Sample Size (n) Age Mean ± SD	Outcomes (30-day Readmission)	Interventionist (Credential*)	Intervention Duration	Mode
Murphy (2019), NR	Quasi-experimental (Historical group as comparison)	IG = 100 CG = 259 Age = 68.0 ± 15.0	IG = 24% CG = 18.2% (p = 0.238)	Nurse practitioner, Cardiologist, Pharmacists (PharmD and student), Dietitian	Admission ~ 30-day post discharge	In-person + telephone
Di Palo (2017), American College of Cardiology Patient Navigator Program	Quasi-experimental (Two-group posttest only)	IG = 51 CG = 43 Age = 69.7 ± 12.7	IG = 17.6% CG = 20.9% (p = 0.15)	Nurse (RN), Clinical pharmacist (PharmD)	Admission ~ Discharge	In-person
Daley (2010), A hybrid Care Transitions Model	Quasi-experimental (Two-group posttest only)	IG = 89 CG = 284 Age = 79.5 ± NR	IG= 15% CG= 20% (p = NR)	Nurse practitioner (HF management certificate)	Admission ~ 6 months post discharge	In-person + telephone + telemonitoring

* Only added if reported. When nurses' credential was not specified, we assumed that they were registered nurses.
NR = Not Reported, IG = Intervention Group, CG = Control/Comparison Group, SD = Standard Deviation, RN = Registered Nurse, PharmD = Doctor of Pharmacy

2.3.3 Care Coordination Processes

Intervention components were similar across 17 studies; they included but were not limited to patient education, medication reconciliation, telemonitoring, scheduling or referral for community-based services, and post-discharge follow-ups via telephone, home visits, or ambulatory clinic visits. However, care coordination processes varied considerably across studies in terms of the timeframe, setting of care delivery, number, and types of individuals involved as well as the location, frequency, and mode of interactions that occurred. The individuals involved and their interactions during care coordination processes and the social networks of reviewed studies are summarized in Table 3.

Table 3: Nodes and Network Characteristics in Care Coordination Processes

Study	Hospital-Based Nodes	Community-Based Nodes	Network Size, Structure
Community-based interventions from the simplest to most complex network structures			
Huntington (2013)	NR	Nurse (IN); PCP	3 Nodes, Triadic
Miller (2017)	NR	HH physical therapist (IN); HH nurse (IN); "Medical providers"	4 Nodes, Triadic
Bowles (2011)	NR	HH nurse manager (IN); HH telehomecare nurse (IN); HH visiting nurse (IN)	4 Nodes, Semi-Triadic
Baecker (2020)	NR	HH nurse (IN); HF case manager (IN); PCP/ cardiologist/ cardiology nurse practitioner; CG	5 Nodes, Triadic
Berman (2019)	Transition facilitator	Pharmacist (IN); HH nurse; PCP	5 Nodes, Triadic
Milfred-LaForest (2017)	NR	Pharmacist (IN); Nurse practitioner/ Cardiologist; Next provider of care; CG	5 Nodes, Triadic
Arcilla (2019)	Discharge planner; Inpatient staff	HH Care Transition Coach (IN); HH Dietitian; PCP; CG	7 Nodes, Triadic

Study	Hospital-Based Nodes	Community-Based Nodes	Network Size, Structure
Russell (2011)	Hospital staff; "Hospitals"	HH nurse (IN); PCP; Social services; Rehabilitative service; HH aide; Behavioral health specialists; Hospice/ palliative care; CG	11 Nodes, Complex
Whitaker-Brown (2017)	Inpatient coordinator	Nurse Practitioner/ Physician assistant (IN); Clinic nurse (IN); Pharmacist (IN); PCP; HF MD clinc; Telehealth; Home health care; Hospice/ palliative care; Rehabilitation care	11 Nodes, Complex
Hospital-based interventions from the simplest to most complex network structures			
Ong (2016)	Study nurse (IN); Call center nurse (IN)	"Health professionals"	4 Nodes, Triadic
Linden (2014)	Nurse (IN); Discharge staff	PCP	4 Nodes, Triadic
Altfeld (2012)	Social Worker (IN)	PCP; Transportation; Other services	5 Nodes, Triadic
Neu (2020)	Pharmacists (IN); Cardiologists/ Nurse practitioners; HF nurse navigator	CG	5 Nodes, Semi-triadic
Weeks (2020)	Nurse discharge navigator (IN); Pharmacist	PCP; Nurse at primary care; Community services	6 Nodes, Triadic
Murphy (2019)	Pharmacy personal (IN); Cardiologists (IN); Nurse practitioners (IN); Dietitians (IN)	Outpatient cardiology service	6 Nodes, Triadic
Di Palo (2017)	Nurse (IN); Pharmacist (IN); Physician assistants; Nurse managers; Cardiologists; Social workers; Nutritionists; Care transitions clinical coordinators; Staff nurses	PCP/ Cardiologist	11 Nodes, Complex
Daley (2010)	1: HF Coach (IN) 2-4: Senior leadership (Cardiovascular center director, Case management director, Department of Medicine chairman) 5-16: Interdisciplinary team members (Cardiology MD champion, Pharmacist, Case managers, Spiritual care, Dietary, Clinical nurse specialist, Operations manager, Staff nurse, Cardiology nurse practitioners, Physician assistants, Psychiatric nurse liaison, Psychiatrist) 17-18: ED triage nurse and physician	19: PCP 20-26: Home Health staff (HH supervisor, nurse, social worker, physical therapist, occupational therapist, dietician, telemonitoring nurse) 27: Cardiologist 28: Skilled nursing facilities 29: Assisted living facilities 30: Hospice 31: CG	32 Nodes, Complex

Timeframe. No consistent duration of care coordination processes was found across studies (Table 2); however, most interventions (n = 10) involved care coordination processes that occurred both during and after hospitalization (Arcilla et al., 2019; Berman et al., 2019; Daley, 2010; Huntington et al., 2013; Linden & Butterworth, 2014; Murphy et al., 2019; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017). Interventions were initiated at different points along the hospitalization trajectory, including shortly after admission (n = 4) (Daley, 2010; Di Palo et al., 2017; Murphy et al., 2019; Neu et al., 2020), right before or at discharge (n = 8) (Arcilla et al., 2019; Berman et al., 2019; Huntington et al., 2013; Linden & Butterworth, 2014; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017), and within 2 days (Altfeld et al., 2013; Baecker et al., 2020; Milfred-LaForest et al., 2017) or 2 weeks after discharge (Bowles et al., 2011; Miller et al., 2016). Likewise, the duration of transitional care interventions following hospital discharge varied: 1 or less (n = 4) (Altfeld et al., 2013; Baecker et al., 2020; Milfred-LaForest et al., 2017; Weeks et al., 2020), 2 weeks (n = 1) (Miller et al., 2016), 4 weeks or 1 month (n = 4) (Berman et al., 2019; Huntington et al., 2013; Murphy et al., 2019; Whitaker-Brown et al., 2017), 6 weeks (n = 1) (Bowles et al., 2011), 3 months (n = 2) (Arcilla et al., 2019; Linden & Butterworth, 2014), and 6 months (n = 2) (Daley, 2010; Ong et al., 2016).

Settings. Because providers can deliver transitional care in multiple settings, the setting where most in-person care activities were delivered by the provider was used to classify whether the provider was hospital- or community-based. We classified the setting of providers who only delivered care remotely based on their employer.

Interventionists commonly interacted with both hospital- and community-based providers (n = 9) (Arcilla et al., 2019; Berman et al., 2019; Daley, 2010; Di Palo et al., 2017; Linden & Butterworth, 2014; Murphy et al., 2019; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017). Categorizing the intervention as hospital- or community-based was determined by the interventionists' setting. Based on this classification method, 8 of the 17 studies were hospital-based (Table 2) (Altfeld et al., 2013; Daley, 2010; Di Palo et al., 2017; Linden & Butterworth, 2014; Murphy et al., 2019; Neu et al., 2020; Ong et al., 2016; Weeks et al., 2020). Among the 9 community-based studies, 6 studies were based in home health care services (Arcilla et al., 2019; Baecker et al., 2020; Bowles et al., 2011; Huntington et al., 2013; Miller et al., 2016; Russell et al., 2011); 2 were set in ambulatory transitional care clinics managed by hospitals (Milfred-LaForest et al., 2017; Whitaker-Brown et al., 2017); and 1 involved a hospital-employed pharmacist who conducted post-discharge home visits (Berman et al., 2019). Providers from primary care were involved in the processes but were not a focal point of transitional care interventions.

Nodes. The total number of nodes involved in care coordination processes varied from 3 to 32, including patients, informal caregivers or families, providers from multiple professions, and managerial or health system leadership (Table 3 and Table 4). Excluding the roles of patient and interventionist, the most common hospital-based node role was nurse or staff in charge of discharge planning or/and referrals (n = 7)

(Arcilla et al., 2019; Berman et al., 2019; Di Palo et al., 2017; Linden & Butterworth, 2014; Neu et al., 2020; Russell et al., 2011; Whitaker-Brown et al., 2017). The patient's primary care provider (PCP) (n = 11) (Altfeld et al., 2013; Arcilla et al., 2019; Baecker et al., 2020; Berman et al., 2019; Daley, 2010; Di Palo et al., 2017; Huntington et al., 2013; Linden & Butterworth, 2014; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017) or the next provider of care, such as an outpatient cardiologist (n = 4) (Milfred-LaForest et al., 2017; Miller et al., 2016; Murphy et al., 2019; Ong et al., 2016), were the most common community-based node roles. Only 7 of the 17 studies included informal caregivers in the processes, in which cases they participated in care management or discharge education sessions (Arcilla et al., 2019; Baecker et al., 2020; Daley, 2010; Di Palo et al., 2017; Milfred-LaForest et al., 2017; Neu et al., 2020; Russell et al., 2011).

Ties. Most studies established ties via a combination of in-person and telephone encounters (n = 7) (Baecker et al., 2020; Berman et al., 2019; Huntington et al., 2013; Miller et al., 2016; Murphy et al., 2019; Russell et al., 2011; Whitaker-Brown et al., 2017) or a combination of in-person meetings, telemonitoring, and telephone or video encounters (n = 6) (Arcilla et al., 2019; Bowles et al., 2011; Daley, 2010; Linden & Butterworth, 2014; Ong et al., 2016; Weeks et al., 2020). Few studies' ties were solely in-person (n = 3) (Di Palo et al., 2017; Milfred-LaForest et al., 2017; Neu et al., 2020) or via telephone (n = 1) (Altfeld et al., 2013). Most of the ties had a frequency of one. Telemonitoring ties often were daily during the post-discharge intervention period

(Arcilla et al., 2019; Bowles et al., 2011; Daley, 2010; Linden & Butterworth, 2014; Ong et al., 2016; Weeks et al., 2020).

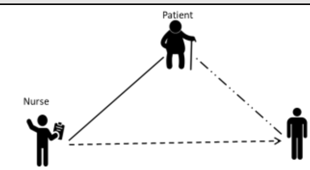
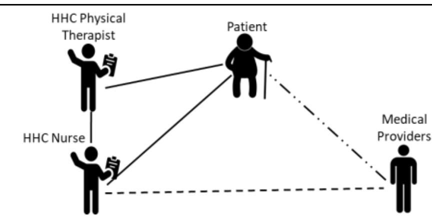
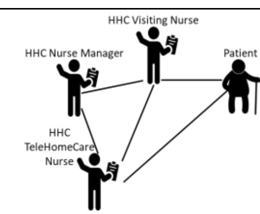
The most common pre- and post-discharge ties were in-person encounters between interventionist(s) and patients in the hospital before dicharge (Daley, 2010; Di Palo et al., 2017; Huntington et al., 2013; Linden & Butterworth, 2014; Murphy et al., 2019; Neu et al., 2020; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020) and in-person meetings either in the home setting (Arcilla et al., 2019; Baecker et al., 2020; Berman et al., 2019; Bowles et al., 2011; Daley, 2010; Huntington et al., 2013; Miller et al., 2016; Russell et al., 2011), or an ambulatory care setting (Arcilla et al., 2019; Baecker et al., 2020; Milfred-LaForest et al., 2017; Murphy et al., 2019; Whitaker-Brown et al., 2017), or remotely via telephone or telemonitoring after discharge {Altfeld, 2013 #2723}(Arcilla et al., 2019; Baecker et al., 2020; Bowles et al., 2011; Daley, 2010; Huntington et al., 2013; Linden & Butterworth, 2014; Milfred-LaForest et al., 2017; Murphy et al., 2019; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020) (Table 4). Pre-discharge ties between hospital- and community-based providers included referrals by hospital staff to community-based interventionists (Arcilla et al., 2019; Berman et al., 2019; Russell et al., 2011) or services such as home health care (Daley, 2010; Weeks et al., 2020). Connections made by hospital-based interventionists were to schedule or ensure follow-up appointments with PCPs or outpatient cardiologists (Daley, 2010; Di Palo et al., 2017; Murphy et al., 2019; Weeks et al., 2020). Post-discharge ties between hospital- and community-based providers (n = 9) were between the interventionist and PCPs, either to share information via telephone (Berman et al., 2019; Linden & Butterworth, 2014; Miller et al., 2016; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017) or in-person (Arcilla et al., 2019) or to ensure that the patient secured a follow-up appointment (Altfeld et al., 2013; Huntington et al., 2013; Milfred-LaForest et al., 2017). Ties involving caregivers happened in the hospital before the discharge (Di Palo et al., 2017; Neu et al., 2020), in the community after discharge (Arcilla et al., 2019; Baecker et al., 2020; Milfred-LaForest et al., 2017), or both (Daley, 2010; Russell et al., 2011).

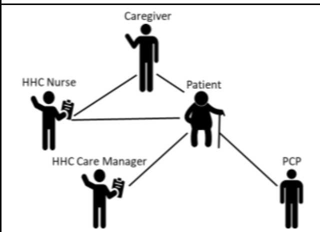
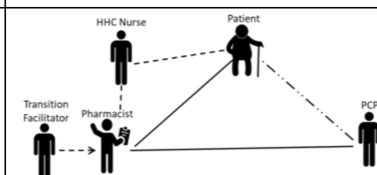
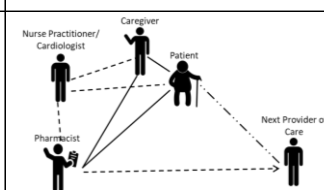
In-person ties were common among nodes located in the same settings: for example, among hospital-based interventionists, hospital-based providers (Daley, 2010; Di Palo et al., 2017; Murphy et al., 2019; Neu et al., 2020), and pre-discharge patients (Daley, 2010; Di Palo et al., 2017; Murphy et al., 2019; Neu et al., 2020; Weeks et al., 2020); or between community-based interventionists and post-discharge patients (Arcilla et al., 2019; Berman et al., 2019; Huntington et al., 2013; Milfred-LaForest et al., 2017; Miller et al., 2016; Whitaker-Brown et al., 2017). Although some studies had care activities that occurred across settings, interventionists' ability to deliver care in person across settings was low. Only four interventions involved interventionists who met patients in person both in the hospital before discharge and in the community after discharge (Arcilla et al., 2019; Daley, 2010; Murphy et al., 2019; Russell et al., 2011). Only three of the nine community-based interventionists met patients or hospital staff in the hospital before the patient's discharge (Arcilla et al., 2019; Huntington et al., 2013; Russell et al., 2011), and two of the eight hospital-based interventionists met patients in the community after discharge (Daley, 2010; Murphy et al., 2019). Some community- or hospital-based interventions did not involve or mention nodes from the other setting at all (Baecker et al., 2020; Bowles et al., 2011; Huntington et al., 2013; Milfred-LaForest et al., 2017; Miller et al., 2016; Neu et al., 2020). Telephone calls or telemonitoring devices were commonly used to communicate synchronously or asynchronously or transfer information across settings (e.g., between a hospital-based interventionist and person who had been discharged) (Altfeld et al., 2013; Daley, 2010; Linden & Butterworth, 2014; Murphy et al., 2019; Ong et al., 2016; Weeks et al., 2020).

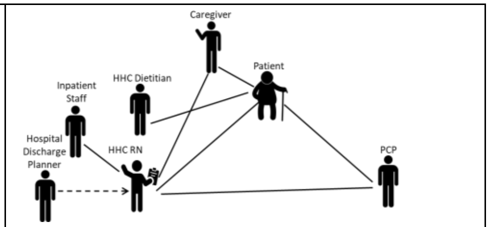
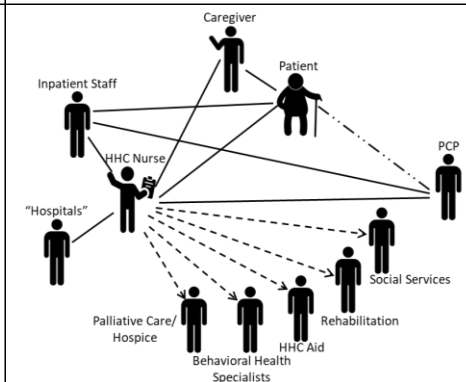
From triadic to complex network structures. Combining nodes, ties, and attributes, care coordination processes can be visualized as networks (Table 4). Care coordination network structures varied across studies from a simple tradic (Huntington et al., 2013) to more complex networks (Daley, 2010). Although no one study had an identical configuration of networks, one common triadic pattern (n = 14) was found: The interventionist(s) (a) met patients in person before or after hospitalization to assess health status and needs and reinforce education on care management, (b) connected with the next provider of care (i.e., PCPs or outpatient cardiologists) by telephone (Baecker et al., 2020; Berman et al., 2019; Daley, 2010; Di Palo et al., 2017; Huntington et al., 2013; Linden & Butterworth, 2014; Milfred-LaForest et al., 2017; Miller et al., 2016;

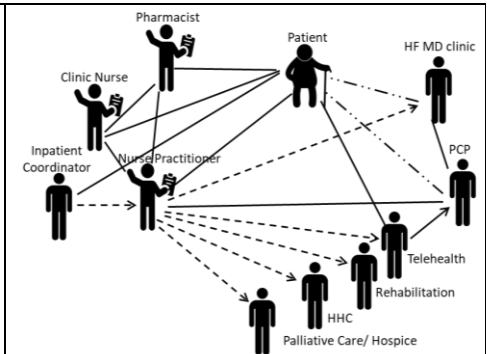
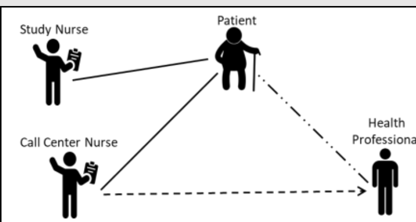
Murphy et al., 2019; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017) or in person (Arcilla et al., 2019) to transfer discharge information and/or appointment set-ups, and (c) facilitated or encouraged connections between patients and their next provider of care.

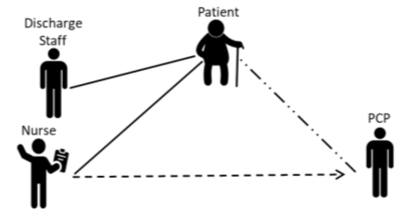
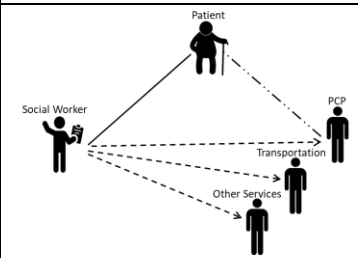
Table 4: Individuals, Individuals' Relationships (Mode: Frequency), and Networks in Care Coordination Processes

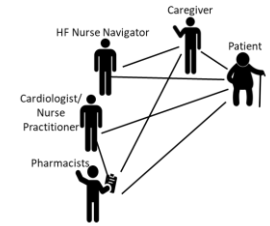
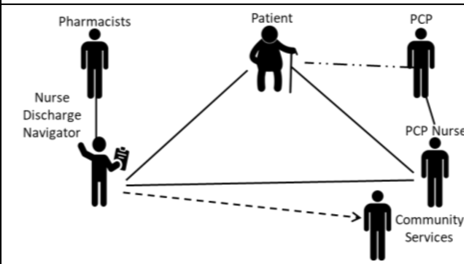
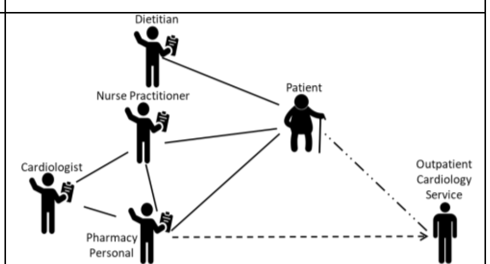
Study	Hospital Nodes	Community Nodes	Within Hospital/Community Ties	Across-Setting Ties	Network Mapping and Structure
Community-based interventions from the simplest to most complex network structures					
Huntington (2013), Triadic	NR	1. Nurse (IN) 2. PCP	<u>Post-discharge</u> • IN—Patient (In-person within 48-hr post discharge: 1 + telephone/in-person: ≥ 4 person: Daily) • IN—PCP (Ensure appointment: 1)	<u>Pre-discharge</u> • IN—Patient (In-person: 1)	
Miller (2017), Triadic	NR	1. HH physical therapist (IN) 2. HH nurse (IN) 3. "Medical providers"	<u>Post-discharge</u> • IN (HH nurse)—Patient (Home visits: Mean = 3.4) • IN (HH physical therapist)—Patient (Home visits: Mean = 1.2) • INs—Medical providers (Telephone: As needed)	NR	
Bowles (2011), Semi-Triadic	NR	1. HH nurse manager (IN) 2. HH telehomecare nurse (IN)	<u>Post-discharge</u> • IN (Visiting nurse)—Patient (Home visits: 1-2 per week) • IN (Telehomecare nurse)—Patient (Video visit: 1-2 per week + Telemonitoring: daily)	NR	

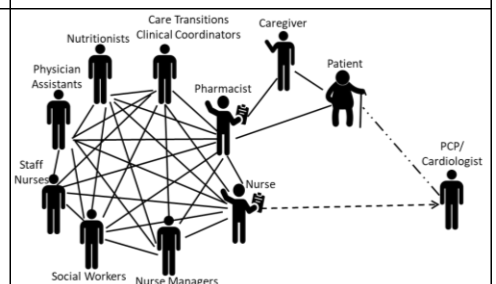
		3. HH visiting nurse (IN)	• All INs (NR: Regularly)		
Baecker (2020), Triadic	NR	1. HH nurse (IN) 2. HF case manager (IN) 3. PCP/ cardiologist/ cardiology nurse practitioner 4. CG	<u>Post-discharge</u> • IN (HH nurse)—Patient/ CG (Home visit/telephone: 1) • IN (HF case manager)—Patient (Telephone: 1) • PCP/ cardiologist/ cardiology nurse practitioner—Patient (Clinic visit: 1)	NR	
Berman (2019), Triadic	1. Transition facilitator	2. Pharmacist (IN) 3. HH nurse 4. PCP	<u>Post-discharge</u> • IN—Patient (Home visit: 1 + Follow up: 1) • IN—PCP (Telephone: "Works in close contact") • IN—HH nurse (Telephone: As needed)	<u>Pre-discharge</u> • Transition facilitator—IN (Referral: 1)	
Milfred-LaForest (2017), Triadic	NR	1. Pharmacist (IN) 2. Nurse practitioner / Cardiologist 3. Next provider of care 4. CG	<u>Post-discharge</u> • IN—Patient/ CG (In-person: 1)—Nurse practitioner/ Cardiologist (In-person: As needed) • IN—Next provider of care (Share information: 1)	NR	

Arcilla (2019), Triadic	1. Discharge planner 2. Inpatient staff	3. HH Care Transition Coach (IN) 4. HH Dietitian 5. PCP 6. CG	<u>Post-discharge</u> • IN—Patient/ CG (In-person: 1) • IN—Patient (Telephone: Weekly + Telemonitoring: Daily to weekly) • HH Dietitian—Patient/ CG (In-person: 2) • IN—PCP—Patient (In-person at PCP office: 1)	<u>Pre-discharge</u> • IN—Patient (In-person: 1) • IN—Inpatient staff (In-person training: 1) • IN—Discharge planner (Referral: 1)	
Russell (2011), Complex	1. Hospital staff 2. "Hospitals"	3. HH nurse (IN) 4. PCP 5. Social services 6. Rehabilitative service 7. HH aide 8. Behavioral health specialists 9. Hospice/ palliative care 10. CG	<u>Pre-discharge</u> • Inpatient coordinator—Patient (In-person: 1) <u>Post-discharge</u> • IN—Patient (Home visits and telephone: Weekly) • IN—PCP (Telephone: 2) • IN—Social services (Referral: As needed) • IN—Rehabilitation (Referral: As needed) • IN—HH aide (Referral: As needed) • IN—Behavioral health specialists (Referral: As needed) • IN— Hospice/ palliative care (Facilitate transfer: As needed)	<u>Pre-discharge</u> • Inpatient staff—IN (Referral: 1) • IN —CG—Patient (In-person: 1) • Inpatient staff—IN—PCP (Ensure appointment: 1) <u>Post-discharge</u> • IN—Hospitals (Report and case reviews: Monthly)	

Whitaker-Brown (2017), Complex	1. Inpatient coordinator	2. Nurse Practitioner/ Physician assistant (IN) 3. Clinic nurse (IN) 4. Pharmacist (IN) 5. PCP 6. HF MD clinic 7. Telehealth 8. Home health care 9. Hospice/ palliative care 10. Rehabilitation care	<u>Pre-discharge</u> • Inpatient coordinator—Patient (In-person: 1) <u>Post-discharge</u> • IN (Nurse practitioner)—Patient (In-person: 4) • All INs(In-person: 4) • INs—PCP (Telephone: ≥ 2) • INs—Telehealth (Referral: 1) • Telehealth—Patient (Telemonitoring: daily) • IN—HF MD clinic (Referral: As needed) • IN (Nurse practitioner)—Rehabilitation (Referral: As needed) • IN (Nurse practitioner)—Home health care (Referral: As needed) • IN (Nurse practitioner)—Palliative care/ hospice (Referral: As needed)	<u>Pre-discharge</u> • Inpatient coordinator—IN (Referral: 1)	
Hospital-based interventions from the simplest to most complex network structures					
Ong (2016), Triadic	1. Study nurse (IN) 2. Call center nurse (IN)	3. "Health professionals"	<u>Pre-discharge</u> • IN (Study nurse)—Patient (In-person: 1)	<u>Post-discharge</u> • IN (Call center nurse)—Patient (Telephone: 9 + Telemonitoring: Daily)	

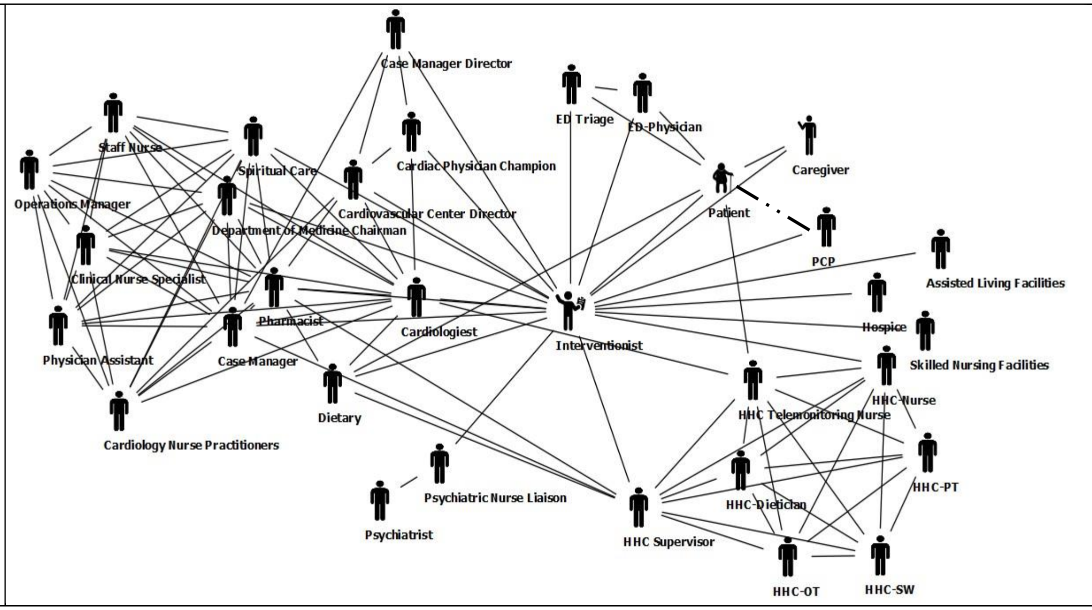
				• IN (Call center nurse)—health professionals (Telephone: As needed)	
Linden (2014), Triadic	1. Nurse (IN) 2. Discharge staff	3. PCP	<u>Pre-discharge</u> • IN—Patient (In-person: 1) • Discharge staff—Patient (In-person discharge planning: 1)	<u>Post-discharge</u> • IN—Patient (Interactive voice response: Daily for 30 days post discharge + Motivational interview via telephone: >1 as needed for 90 days post discharge) • IN—PCP (Telephone: As needed)	
Altfeld (2012), Triadic	1. Social Worker (IN)	2. PCP 3. Transportation 4. Other services	NR	<u>Post-discharge</u> • IN—Patient (Telephone: 1) • IN—transportation (Referral: As needed) • IN—Other services (Referral: As needed) • IN—PCP (Ensure follow-up appointment: 1)	

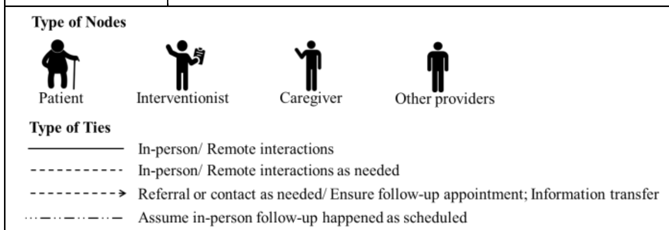
Neu (2020), Semi-triadic	1. Pharmacists (IN) 2. Cardiologists/ Nurse practitioners 3. HF nurse navigator	4. CG	<u>Pre-discharge</u> • IN—Patient (In-person: 1) • IN —Cardiologist—Patient (In-person medication reconciliation: 1) • IN—Patient/CG (In-person: 1) • HF nurse navigator—Patient/CG (In-person: 1)	NR	
Weeks (2020), Triadic	1. Nurse discharge navigator (IN) 2. Pharmacist	3. PCP 4. PCP Nurse 5. Community services	<u>Pre-discharge</u> • IN—Patient (In-person: 1) • IN—Pharmacists (Consult: 1)	<u>Pre-discharge</u> • IN—PCP (Ensure follow-up appointments: 2) • IN—Community services (referral: NR) <u>Post-discharge</u> • IN—Patient (Telephone: 1) • IN—Nurse at PCP (Telephone: As needed)	
Murphy (2019), Triadic	1. Pharmacy personal (IN) 2. Cardiologists (IN) 3. Nurse practitioners (IN)	5. Outpatient cardiology service	<u>Pre-discharge</u> • IN (Pharmacy personal)—Patient (In-person: 3) • IN (Dietitian)—Patient (In-person:1-2) • IN (Pharmacy personal)—IN (Cardiologist/ Nurse	<u>Pre-discharge</u> • IN (Pharmacy personal)—Outpatient cardiology service (Ensure follow-up appointment: 1) <u>Post-discharge</u>	

	4. Dietitians (IN)		practitioner)—Patient (In-person: 1)	• IN (Pharmacy personal)—Patient (In-person at outpatient pharmacy: 1-2) • IN (Nurse practitioner)—Patient (Telephone: 1) • IN (Pharmacy personal)—Patient (Telephone: 1) • IN (Dietitian)—Patient (Telephone: 1) • INs (Pharmacy personal)— IN (Nurse practitioner)—Outpatient cardiology service (Referral: As needed)	
Di Palo (2017), Complex	1. Nurse (IN) 2. Pharmacist (IN) 3. Care transitions clinical coordinators 4. Staff nurses	10. PCP/ Cardiologist	<u>Pre-discharge</u> • INs—Care transitions clinical coordinators —Staff nurses—Physician assistants —Social workers—Nurse managers—Cardiologists—	<u>Pre-discharge</u> • IN (Nurse)—PCP/ Cardiologist (Obtain follow-up appointment:1)	

	5. Physician assistants 6. Cardiologists 7. Social workers 8. Nurse managers 9. Nutritionists		Nutritionists (In-person: Daily) • IN (Pharmacist)—Patient (In-person: >1)—CG (In-person: encourage to be present)		
Daley (2010), Complex	1. HF Coach (IN) 2. Pharmacist 3. Cardiovascular center director 4. Case management director 5. Cardiac physician champion 6. Case managers 7. Spiritual care 8. Dietary 9. Department of Medicine chairman 10. Clinical nurse specialist	19. PCP 20. HH supervisor 21. HH nurse 22. HH social worker 23. HH physical therapist 24. HH occupational therapist 25. HH dietician 26. HH telemonitoring nurse 27. Cardiologist 28. Skilled nursing facilities	<u>Pre-discharge</u> • IN—Patient (Daily: In-person) • IN—Pharmacist (Reconciliate Meds: At admission & discharge) • IN—Cardiovascular center director—Case management director—Cardiac physician champion (In-person: Bi-weekly) • IN—Case manager—Department of Medicine Chairman—Spiritual care—Dietary—Clinical nurse specialist—Operations manager—Pharmacist—Staff nurse (In-person: twice a week)—Cardiology nurse practitioners—Physician	<u>Pre-discharge</u> • IN—CG—Patient (In-person education: once) • IN—In-hospital case managers—HH Supervisor—Pharmacist—HH Dietician (In-person: Bi-weekly) • IN—PCP (Remotely: Upon hospitalization and enrollment) • IN—Case managers—HH nurse—HH physical therapist—HH dietician (Referral for homebound: As needed)—HH occupational	See below

	11. Operations manager 12. Staff nurse 13. Cardiology nurse practitioners 14. Physician assistants 15. Psychiatric nurse liaison 16. Psychiatrist 17. ED triage 18. ED physician	29. Assisted living facilities 30. Hospice 31. CG	assistants (In-person: Vary) • IN—Psychiatric nurse liaison—Psychiatrist (Referral: as needed) <u>Post-discharge</u> • Patient—HH telemonitoring nurse (Telemonitoring: Daily) • HH telemonitoring nurse—Cardiologist (Data transfer: Bi-weekly)	therapist or social worker (Referral: As needed) • IN—Hospice (Referral: As needed) <u>Post-discharge</u> • IN—Patient—CG (Telephone: 4 times the first month to monthly + In-person: As needed for patients without HH) • IN—ED triage—ED physicians—Patient (In-person: As needed) • IN—Skilled nursing facilities (Education sessions: NR) • IN—Assisted living facilities (Education sessions: NR)	

Daley (2010), Complex	



NR = Not Reported, IN= Interventionist, HH= Home health care, CG= Caregivers (Friends, family, or relatives that are supportive or have an influence on patients' care), PCP= Primary Care Provider, ED = Emergency Department

All randomized control trials had a simple network structure that had five or fewer total nodes or ties. Studies without randomized controlled designs were more likely to have more complex network structures involving large numbers of individuals and showing network clusters (Daley, 2010; Di Palo et al., 2017; Russell et al., 2011; Whitaker-Brown et al., 2017). In particular, one quality improvement project involved 33 nodes, including both clinical and managerial stakeholders from different settings (e.g., the director of a cardiovascular center and a home care supervisor), to address gaps in clinical and system processes for transitional care (Daley, 2010). This was the only study that established processes with the emergency department to improve communication so that the interventionist could reconnect quickly with people who were readmitted to the hospital as well as interact with them during their subsequent transition back to the community after rehospitalization (Daley, 2010).

Network role of interventionists. Similar to the high variability in network structures for care coordination, various types of providers were chosen for the interventionist role to initiate and/or facilitate care coordination processes: nurses alone (n = 9) (Arcilla et al., 2019; Baecker et al., 2020; Bowles et al., 2011; Daley, 2010; Huntington et al., 2013; Linden & Butterworth, 2014; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020), multidisciplinary teams (n = 4) (Di Palo et al., 2017; Miller et al., 2016; Murphy et al., 2019; Whitaker-Brown et al., 2017), pharmacists alone (n = 3) (Berman et al., 2019; Milfred-LaForest et al., 2017; Neu et al., 2020), or social workers alone (n = 1)

(Altfeld et al., 2013). Multidisciplinary teams included nurses (n = 4) (Di Palo et al., 2017; Miller et al., 2016; Murphy et al., 2019; Whitaker-Brown et al., 2017), pharmacists (n = 3) (Di Palo et al., 2017; Murphy et al., 2019; Whitaker-Brown et al., 2017), dieticians (n = 2) (Murphy et al., 2019; Whitaker-Brown et al., 2017), physical therapists (n = 1) (Miller et al., 2016), and cardiologists (n = 1) (Murphy et al., 2019). Nurses were the most common provider type to serve either as the interventionist or as part of a multidisciplinary team; most were registered nurses (n = 11) (Arcilla et al., 2019; Baecker et al., 2020; Bowles et al., 2011; Di Palo et al., 2017; Huntington et al., 2013; Linden & Butterworth, 2014; Miller et al., 2016; Ong et al., 2016; Russell et al., 2011; Weeks et al., 2020; Whitaker-Brown et al., 2017), and the remainder were advanced practice nurses (n = 3) (Daley, 2010; Murphy et al., 2019; Whitaker-Brown et al., 2017). None of the interventionists were based in primary care.

Interventionists in reviewed studies appeared to occupy key network positions (i.e., bridge or central positions), which are important for connectivity and information flow. For studies in which triadic network structures were the core of the networks (Table 4), interventionists commonly served as a bridge between the hospital care networks and the PCP or cardiologist in the community during the transition (Valente, 2010). For studies with more complex network structures, the interventionist(s) occupied a central position having a higher-than-average number of ties with other nodes who conveyed information and resources and influenced others' behaviors (Valente, 2010).

A network model for transitional care. Based on the various nodes, ties, and structures possible for care coordination processes, we abstracted the care coordination processes in transitional care as a network model (Figure 4). During care transitions, patients and caregivers interact with various interdependent providers from the hospital- and community-based services. Various providers at different services interact within and across settings to coordinate care. The relational aspect of care coordination processes is visualized as networks. Viewed through an SNA lens, facilitating transitional care involves fostering the timely transfer of information and care relationships to ensure that an individual has sufficient support to cope with HF-related care needs and adapt to health behavior change as needed (Gittell et al., 2013; Turnbull et al., 2018; Valente & Fujimoto, 2010). Instead of focusing on care tasks, the focus of this model shifts to relationships and system structure.

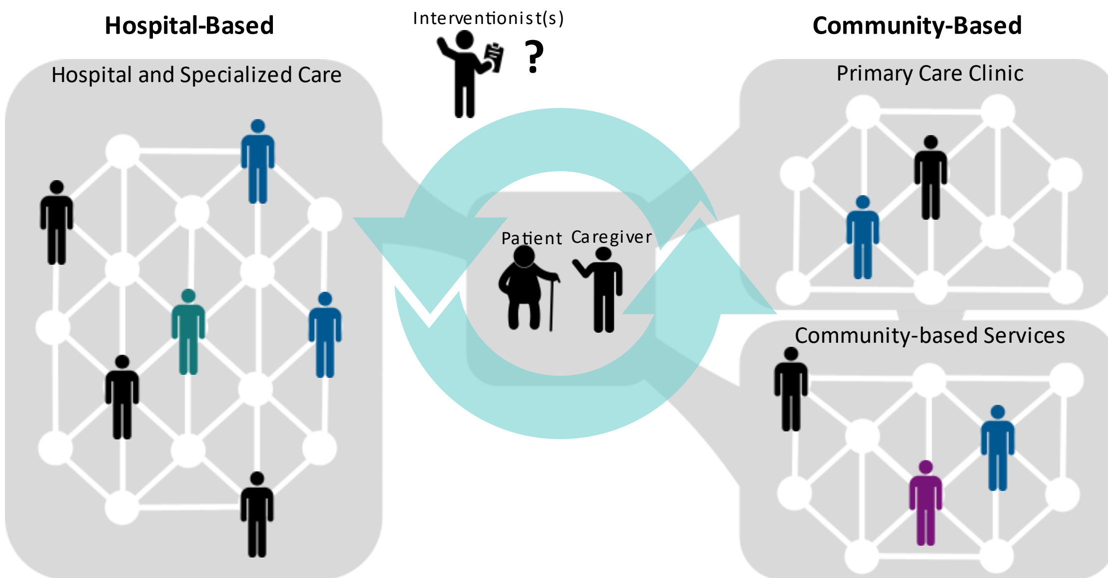


Figure 4: Care Coordination Processes in Transitional Care

2.4 Discussion

Consistent with previous literature reviews of transitional care interventions, we found inconsistent effects on reducing the 30-day readmission rate (Albert, 2016), and that a high degree of variability existed in models, interventionists, how components were combined, and settings of intervention activities (Albert et al., 2015; Naylor et al., 2018; Van Spall et al., 2017; Vedel & Khanassov, 2015). This review differs from previous reviews in that it examined the interdependent relationships among individuals essential for care coordination using an SNA framework. Our review identified a possible explanation for the high variability in interventions and outcomes: The key mechanism to ensure continuity of care during care transitions, care coordination is highly relational, dynamic, and dependent upon the individuals involved, their interdependent relationships, and the system environment (Gittell et al., 2013; Naylor et al., 2011; Naylor et al., 2018). Numerous permutations of provider types and components exist. As the efficacy of a given component set likely depends on existing relational processes and structures for information flow and collaboration, difficult to see consistent results without obtaining a full understanding of preconditions and how the interventions influenced the existing relational structures.

Integrating an SNA framework to review transitional care interventions shifts the focus from evaluating the independent effects of care components or tasks to relational processes that provide insights on individuals' roles and social structure in the care system (Barbara A Daveson et al., 2014; McDonald et al., 2014; Turnbull et al., 2018; Valente & Fujimoto, 2010). As an example, the common triadic structure found among the studies reviewed highlighted the relational processes among the interventionist(s), patient, and the next provider of care. Interventionists functioned as a bridge between the hospital-based and the community-based next-provider-of-care, and between the patient and the next-provider-of-care. The observed common process illustrates a concept known in SNA theory as triadic closure: When one person is connected with two people, those two people are likely to form a tie as well (Valente, 2010; Valente & Fujimoto, 2010). Triadic closure is the fundamental process for spanning network boundaries across disconnected subgroups within organizational networks by utilizing the power of weak ties (Granovetter, 1973; Tasselli & Caimo, 2019). Aligned with SNA theory, our review found that most interventions reviewed were likely weak-tie models because they focused on a single or short episode of care, and ties across settings were limited and primarily via virtual communication (Granovetter, 1973; Valente & Fujimoto, 2010). This is likely because networks of care teams involved in transitional care, like other social networks, tended to cluster by geographic boundaries, and as a result, strong ties were harder to achieve across clusters at different settings (Bae et al., 2015; Valente, 2010).

SNA not only supports a better understanding of relational processes and structures, it also provides a framework for future development of transitional care interventions. Triadic closure utilizing weak ties can be influential for information spread across independent or weakly connected networks but is less so for behavioral change or long-term care management (which are more influenced by strong ties) (Granovetter, 1973; Valente, 2010; Valente, 2012). Given the advancement of technologies (e.g., EHR) that have made information sharing across settings more accessible and timely, and the importance of behavioral changes and chronic care management, advancing the weak-tie model may be essential to the future success of transitional care. Two strategies may lead to novel intervention development: (1) add or strengthen ties, and (2) utilize key nodes to improve the network connectivity or accelerate behavior changes (Valente, 2012; Valente & Fujimoto, 2010).

Although we found that ties across settings were generally sparse and weak, a few studies with more complex network structures, particularly Daley's intervention, exhibited the potential of transitional care to increase network cohesion at a system level by creating or strengthening multiple ties between nodes across settings (Valente, 2012; Valente & Fujimoto, 2010). Multiple triadic closures can rewire a network, making significant system-level changes so that network clusters can become more connected. Such rewiring was demonstrated in Daley's intervention when both clinical providers and managerial leadership established multiple connections across hospital and community services facilitated by the interventionist (Bianconi et al., 2014; Daley, 2010; Valente, 2010). When multiple ties exist between network clusters at different settings, the network clusters are less likely to become disconnected because one bridging tie is lost (Valente, 2010); therefore, systems with a complex network structure are more cohesive than those with a triadic structure.

Strengthening ties with patients may be achieved by increasing the intensity of interventions (e.g., by increasing the duration of the intervention or by changing the mode from remote to in-person interactions). Meta-analyses found that interventions that focused on in-person interactions through nurse home visits or disease management clinics were more likely to be efficacious (Feltner et al., 2014; Van Spall et al., 2017; Vedel & Khanassov, 2015), and low-intensity interventions (i.e., telephone follow-ups alone or periodic outpatient clinic alone) or moderate-intensity interventions (i.e., home visits only, telecare only, or combination of telephone follow-up with clinic visits) of less than 6 months were not efficacious (Vedel & Khanassov, 2015). Our review found that the four studies with significant results all included in-person interactions with patients. Although most studies included both telephone and in-person interactions, only two studies lasted 6 months. Only a few transitional care interventionists traveled across care settings. While technology is becoming more widely used to assist care delivery across settings (Boonstra et al., 2018; Cipriano et al., 2013; Starnini et al., 2017), technologies may be more effective for information transfer but less so than in-person interactions for building strong and trusting care relationships or behavior changes. Future studies should examine differences in how modes of care interaction influence informational and relational continuity and how to best leverage technology to improve care transitions.

Utilization of key nodes was demonstrated by the finding that interventionists typically occupied bridge or central positions in transitional care networks. Key nodes (i.e., people who occupy bridge or central positions) are likely to influence network connectivity and behavior changes more often and to a greater extent than nodes in other positions (Valente & Fujimoto, 2010), and may require a specific skill set or competency in order to be effective. Consistent with previous reviews, the involvement of multidisciplinary teams may be essential (Albert, 2016; Coffey et al., 2017) due to the complexity of patients' medical and social needs (Gittell et al., 2013; Goldgrab et al., 2019). However, no consensus was found concerning who played the most critical role for care coordination in specific settings because three different provider types (i.e., nurses, pharmacists, and social workers) led similar care components, either independently or as part of a larger team comprising expertise from cardiology, nutrition, and physical therapy, and were implemented at different settings.

Transitional care may consider a better utilization of key nodes who normally have strong ties with patients for care management, such as primary care and informal caregivers. Primary care is considered by many to be crucial for care coordination in care transitions (Agency for Healthcare Research and Quality, 2014). Although a majority of reviewed studies involved nodes from primary care, none of the interventions were based in or partnered with primary care, which was primarily seen as a passive recipient in reviewed studies. The model of Patient-Centered Medical Homes combined with the Transitional Care Model is an example of a plausible community-based, patient-centered long-term solution (Hirschman et al., 2017). Additionally, reviewed interventions have focused primarily on processes within the formal care system. Only about one-third of studies have involved informal caregivers in the intervention (mainly as participants in education sessions, a largely passive role of receiving information). Informal care support is vital for care management in the community (Fivecoat et al., 2018; Graven & Grant, 2014; Lindsay Smith et al., 2017), but informal caregivers or care systems lack involvement in the reviewed transitional care interventions.

2.4.1 Limitations

Reviewed studies had inconsistent descriptions of intervention delivery (i.e., roles of health care providers involved and interactions among individuals during the intervention). Due to unstandardized reporting of intervention delivery, the care coordination processes extracted based on the intervention description may not be as comprehensive as the actual processes involved during intervention delivery, and not all studies systematically reported the frequency of contacts. Only studies conducted and published in the English language were included. Owing to differences in professional practice models and payment systems, findings on study and intervention characteristics may not be generalizable to health systems in other countries. However, our approach of extracting and synthesizing care coordination processes can be applied to review interventions that involve care coordination for other populations or in other countries.

2.5 Conclusions

The effectiveness and components of transitional care interventions published after 2010 are consistent with previous literature reviews. Reviewed interventions were highly variable regarding setting, timeframe, involved individuals, and mode and frequency of interactions among individuals. None of the studies were guided by SNA theory. Our review revealed that transitional care involves networks of individuals, and SNA provides a systematic approach to evaluate the complex relational processes and structure essential for care coordination. Mapping individuals and their interactions during care delivery into networks frequently revealed a triadic network structure in which interventionists bridged the information and care relationship transfer between hospital and community-based services. While in most studies, ties between individuals across settings were generally sparse and weak, a few with more complex network structures demonstrated the potential of transitional care interventions to increase the system's connectivity by fostering multiple ties among providers across settings. Future transitional care intervention development may be enhanced through systematic attention to the properties of relational processes and structure essential to care coordination in care transitions. Empirical knowledge learned from using SNA to evaluate multidisciplinary providers' network roles in the overall system comprehensively is needed to better determine key players and their functions in care coordination processes and inform future transitional care improvements.

3. Rethinking Re-hospitalization in Heart Failure Care Transitions: Heterogeneity in Utilization Typologies

3.1 Introduction

HF is one of the most common chronic illnesses affecting 6.2 million Americans (Virani et al., 2020). Despite financial incentives implemented by the Centers for Medicare and Medicaid Services and the use of various transitional care interventions (Goldgrab et al., 2019; Van Spall et al., 2017; Wadhera et al., 2019), high re-hospitalization, and its associated care and financial burden for patients with HF has been a persistent problem (Chamberlain et al., 2017; Jackson et al., 2018; Urbich et al., 2020; von Lueder & Agewall, 2018). Since 2012, the national 30-day readmission rate has plateaued around 22% (Blecker et al., 2019), suggesting the need to better understand the current underlying drivers of HF re-hospitalization.

A comprehensive understanding of patients' trajectories across inpatient and outpatient services over time is lacking. Since multiple re-hospitalizations are common for patients with HF (Bash et al., 2017; Wammes et al., 2019), a better understanding of patients' longitudinal patterns in acute care utilization may inform improvement strategies tailored to subgroups of patients who have different patterns of risk factors suboptimal utilization. Moreover, utilization of outpatient services is vital for care continuity and influences re-hospitalization; however, how outpatient utilization may be related to re-hospitalization is not clear (Bayliss et al., 2015; Morris et al., 2016; Safstrom et al., 2018; Sinha et al., 2017).

Risk factors for re-hospitalization among HF patients may affect subgroups of individuals differently. Group-based trajectory modeling, also called latent class trajectory analysis, focuses on associations among individuals (Jung & Wickrama, 2008), and identifies distinct latent groupings of individuals who follow similar patterns of trajectories (Jones & Nagin, 2007; Jones et al., 2001). This approach allows capturing latent heterogeneity within and between subgroups (Masyn, 2013; Woo et al., 2018). Understanding patients' heterogeneity in utilization trajectories may offer new perspectives for reducing re-hospitalization and promoting patient-centered care delivery, such as tailored care for different subgroups. Thus, this study aimed to evaluate how outpatient and acute care utilization are related among identified latent heterogeneous subgroups of patients. Specific research questions were 1) What are the distinct trajectories of acute and outpatient care services utilization one-year before and after the initial HF hospitalization; and 2) how is outpatient utilization associated with acute care utilization after controlling for sociodemographic, health behavior, and clinical factors?

3.2 Methods

We conducted a retrospective observational cohort study using data from EHR (Benchimol et al., 2015). The guidelines from the REporting of studies Conducted using Observational Routinely collected health Data (RECORD) were followed to guide this study's reporting (Benchimol et al., 2015). The study was approved by the Institutional

Review Board prior to the conduct of the study. Deidentified data supporting the findings of this study are available upon written request.

3.2.1 Data Source

Sociodemographic, diagnosis, and encounter data were extracted from the EHRs (i.e., a combination of the Epic Clarity database and the Legacy Clinical/Billing system) at Duke University Health System, a university-affiliated health system in the southeast of the United States. Data were extracted through the Duke Enterprise Data Unified Content Explorer (DEDUCE), a web-based environment that allows clinicians and researchers to extract patient data in the system without needing to use query language (Horvath et al., 2011).

3.2.1.1 Cohort Selection and Index Hospitalization Identification

A cohort (n=1269) of adult patients hospitalized with an initial, primary diagnosis of HF (the index hospitalization) between January 1, 2016, and December 31, 2018, at the health system, was identified. We included patients who (1) had a diagnosis of HF identified by having an International Classification of Diseases, Tenth Edition (ICD-10) diagnosis codes (i.e., I50) or International Classification of Diseases, Ninth Edition (ICD-9) diagnosis codes (i.e., 428); (2) had an initial hospitalization with a primary diagnosis of HF between January 1, 2016, to December 31, 2018; and (3) were 18 years and older at the index hospitalization admission. Patients were excluded from the study if they (1) did not use the health system for ambulatory care services to manage care, (2) died during the index hospitalization, or (3) were discharged to inpatient or home hospice. Selection processes and reasons for exclusion can be found in Figure 5. Because DEDUCE is a graphical user interface and the coding behind the interface is unavailable, to improve the reproducibility and ensure accurate cohort selection, data of the identified cohort were extracted and queried against inclusion and exclusion criteria again in R, a software environment for statistical computing (Version 3.6.3) (R Core Team, 2013). Discrepancies between results from DEDUCE and R were resolved by reviewing patients' medical records.

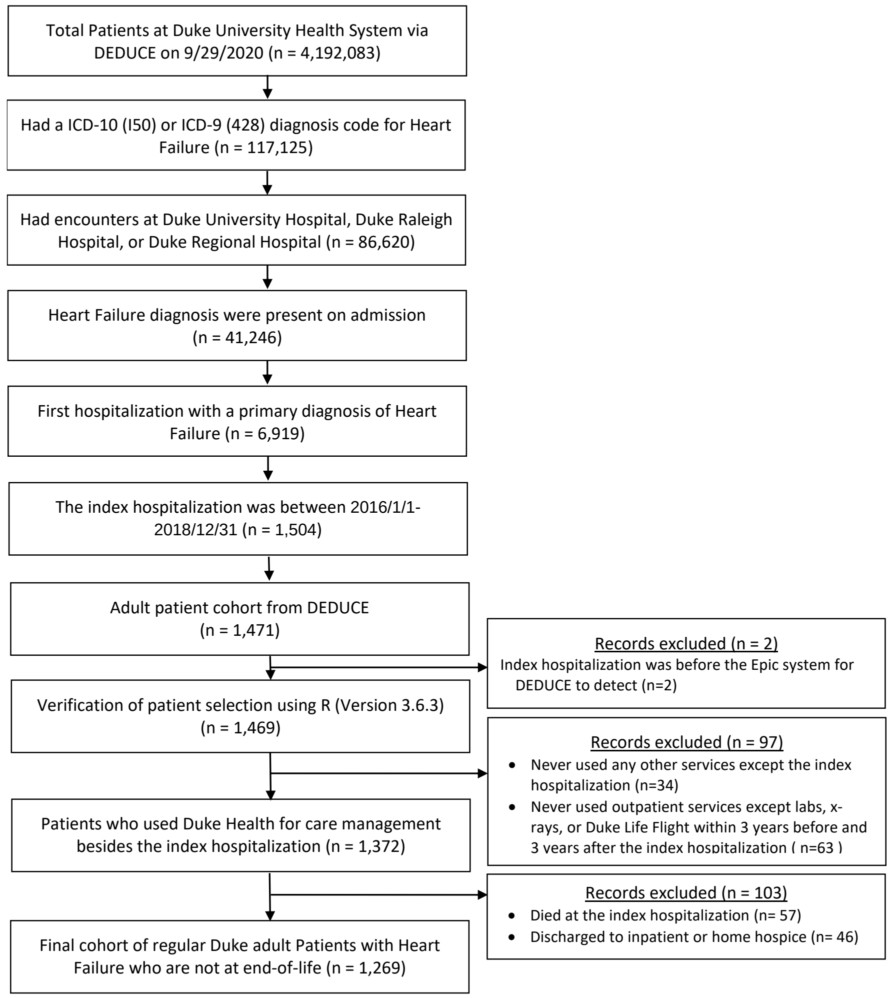


Figure 5: Cohort Selection and Index Hospitalization Identification Flow Chart

3.2.2 Variable Definition and Construction

3.2.2.1 Longitudinal Utilization Trajectories

Hospital and ambulatory care encounters 1-year before and 1-year after the index hospitalization were extracted from EHRs. The index hospitalizations were set to time 0 to standardize the timeline across patients. The admission time of different encounters was standardized as the negative or positive days to the index hospitalization's admission and discharge time, respectively. Because emergency department (ED) and inpatient visits are clinically different types of acute care utilization, they were both included but modeled separately. Whether a hospital service encounter was an inpatient stay or an ED visit was differentiated based on the patient classification for billing purposes and length of stay. All ambulatory encounters were considered outpatient utilization. The monthly frequency of patients using the three types of services one year before and one year after patients' index hospitalization was calculated for modeling their trajectories. The group-based trajectory modeling generated latent subgroups of patients according to their heterogeneous patterns of longitudinal inpatient, ED, and outpatient utilization trajectories.

3.2.2.2 Covariates

Based on previous studies (Chamberlain et al., 2017; Chamberlain et al., 2018; Eapen et al., 2015; Li et al., 2019; Patel et al., 2020; Su et al., 2019), factors associated with re-hospitalizations, patients' sociodemographic, health behavior, comorbidity, transitional care service access, and hospitalization were considered as potential covariates in this study. Patients' demographics and social history (e.g., age, gender, race, marital status, home address, history of smoking, alcohol, and illicit drug use) were accrued from the EHR but independent of encounters and thus were not time-varying. To account for patients' neighborhood deprivation context, we also included the Area Deprivation Index, an indicator for the average socioeconomic deprivation level of patients' residence, and were generated based on the 5-year (i.e., 2014-2018) average of the American Community Survey data. The Area Deprivation Index was linked with patients' 12-digit Census block group Federal Information Processing Standard codes associated with the address extracted from patient-level data (Knighton et al., 2016).

Other covariates (e.g., the total number of payor types, access to a same-day clinic, comorbidity, severity of illness, and characteristics of the index hospitalization) were constructed using encounter-level data, which were time-varying. Encounter-level data were nested within each patient and were time-stamped based on data collected at each encounter. Previous studies have shown that payor type may influence re-hospitalization for patients with HF (Panagiotou et al., 2019). Thus, we constructed the payer type and total numbers of payor types as an additional sociodemographic factor that may influence health care utilization (Andersen, 2008). Payor types for the index hospitalization were used to indicate the primary payor type for patient's care access and were categorized as Medicare, Managed Care, Medicaid, and others. Because a small number of people used Medicaid and other types, these two types of payers were combined. Based on the payor group entered at each encounter, we summated the total unique payor types used for hospital and ambulatory encounters during the 1-year before to 1-year after the index hospitalization.

The Charlson Comorbidity Index (CCI) was calculated based on patients' diagnoses history of chronic illnesses up to the index hospitalization (Quan et al., 2011; Quan et al., 2005). Patients' individual comorbidities before and at the index hospitalization were identified and extracted using ICD-9-CM, and ICD-10-CM diagnosis codes from the diagnosis dataset in EHRs (Quan et al., 2011; Quan et al., 2005). The diagnosis dataset contained lists of diagnoses entered by providers from each service encounter for billing purposes and was nested within encounter-level data and were time-varying.

Because the severity of illness influences patients' medical needs, the average severity of illness and change in the severity of illness over the two years were generated based on the 3M Clinical Risk Groups severity of illness measure that was nested in encounters and was time-varying. 3M-severity of illness score is a 4-level measure that indicates "the extent of physiologic decompensation or organ system loss of function" (Averill et al., 2003, p. 2). The 3M Clinical Risk Groups, a population classification software, assigns patients to one of the four severity levels, minor (0), moderate (1), major (2), and extreme (3) based on patients' longitudinal data, including but not limited to primary and secondary diagnoses, procedures, pharmaceutical data, and functional health status (Averill et al., 2003). Increased severity reflects that the individual has multiple serious chronic conditions and greater difficulty in treatment, requiring increased use of health resources (Averill et al., 2003). We constructed the mean of all severity of illness scores and the change in the severity of illness scores during the 2-year encounters to reflect the average level and change of severity of illness for each patient.

Heart Failure Same Day Access Clinic provides streamlined access and intensive services by a team of cardiologists and nurse practitioners (2018). This clinic is a part of the care pathway which aims to help people prevent unnecessary hospitalizations (2018). A binary variable indicating whether patients used the Same Day Access Clinic was created based on if a patient had at least one encounter sometime during the 2-year study period. Previous studies have shown that characteristics of index hospitalization influence re-hospitalization (Haneuse & Lee, 2016; Li et al., 2019). Thus, characteristics of the index hospitalization, including admission source (whether admitted from the emergency department or not), discharge disposition, and length of stay, were also extracted and were included in the analysis. All data cleaning and variable construction were conducted in R (R Core Team, 2013).

3.2.3 Statistical Analysis

Monthly frequencies of inpatient, ED, and outpatient utilization one year before and one year after the index hospitalization were used in group-based trajectory models to identify patient's longitudinal inpatient, ED, and outpatient utilization trajectories. The PROC TRAJ procedure in SAS v9.4 was used to identify latent groups of 2-year utilization trajectories based on the highest predicted probability calculated from a multinomial logit function (Jones & Nagin, 2007; Jones et al., 2001). Missing monthly utilization frequency before death was considered as the monthly frequency of 0, and missing monthly utilization frequency after death remained missing. Thus, patients contributed utilization only until death, allowing the model to fit patients to a trajectory that best fit their pre-death utilization. The final model was selected based on the following criteria: if the number of groups is meaningful for clinical interpretation, having at least 5% of the total sample, changes in Bayesian Information Criterion between models, visual inspection of trajectory plots, and groupings' average posterior probability greater than 70% (Jones & Nagin, 2007; Jones et al., 2001; Nagin, 2005).

We initially attempted to identify latent heterogeneous subgroups of patients using group-based multi-trajectory modeling to take into account heterogeneity of ED, inpatient, and outpatient utilization at the same time. However, the model poorly discerned inpatient and ED utilization patterns from outpatient utilization patterns because the frequency of outpatient utilization was more than ten times that of inpatient or ED utilization and had a poor model fit and low convergence. So we decided to use group-based trajectory modeling instead of group-based multi-trajectory modeling to model trajectories of utilization in each setting of care separately. To comprehensively consider both ED and inpatient visits for acute care utilization, we cross-classified the identified ED and inpatient utilization groupings to identify acute care utilization typologies.

Utilization typologies, sociodemographic, health behavior, comorbidity, the average and change in the severity of illness, transitional care service access, and index hospitalization factors were assessed for missingness. The amount of missing data ranged from 0 to12.4%. Little's missing data analysis was performed, and missingness was found to be completely at random (MCAR) ($\chi2$=23.68, df=21, p=0.309) (Little, 1988), thus, missing data imputation may be unnecessary. Nevertheless, to preserve the maximum number of observations and hence the maximum power, missing values were imputed using the expectation-maximization (EM) algorithm. After all missing values were imputed, the means and standard deviations and frequency and proportion were assessed for continuous and categorical variables. Multinomial logistic regression was used to evaluate the relationship between outpatient and acute care utilization, controlling for sociodemographic, health behavior, comorbidity, the severity of illness, transitional care service access, and index hospitalization factors. Stepwise backward-selection was used to identify the final parsimonious model based on p-values which were set at 0.05. Missing data analysis and multinomial logistic regression modeling were completed in IBM SPSS Statistics for Windows, Version 27.0 (IBM Corp, 2020).

3.3 Results

3.3.1 Cohort Characteristics

Among patients meeting eligibility criteria (n=1269), most were White (56.6%), unmarried (55.2%), and male (53.4%), with a mean age of 65.5 years (SD=16.3) at the index hospitalization (Table 5). Ninety-one percent of the patients lived in the same state as the studied health system. Patients' Area Deprivation Index ranged from 2% to 100% of the national ranking with a mean score of 52.7% (SD=25.1%). Medicare or Medicare

Advantage was the most common payor type used for the index hospitalization. Patients had an average of two different types of payors and ranged from 1 to 6 types of payors used during the study period. Most of the people were nonsmokers (88.7%) and did not drink (77.3%) or use illicit drugs (96.6%). Most patients had multiple chronic illnesses with a mean Charlson Comorbidity Index score of 4.2 (SD=2.4), came from home (71.7%), were admitted to the ED (66.0%) for the index hospitalization, and were discharged to home with (27.3%) or without (58.3%) home health care. The average length of stay for the index hospitalization was 8.73 days (SD=13.1). On average, patients' severity of illness was rated as "major" (mean=1.9, SD=0.6), and their illness worsened in severity by an average of almost 1 level (mean=0.8, SD=0.8) during the 2-year study period.

Table 5: Baseline Characteristics of Patient Cohort

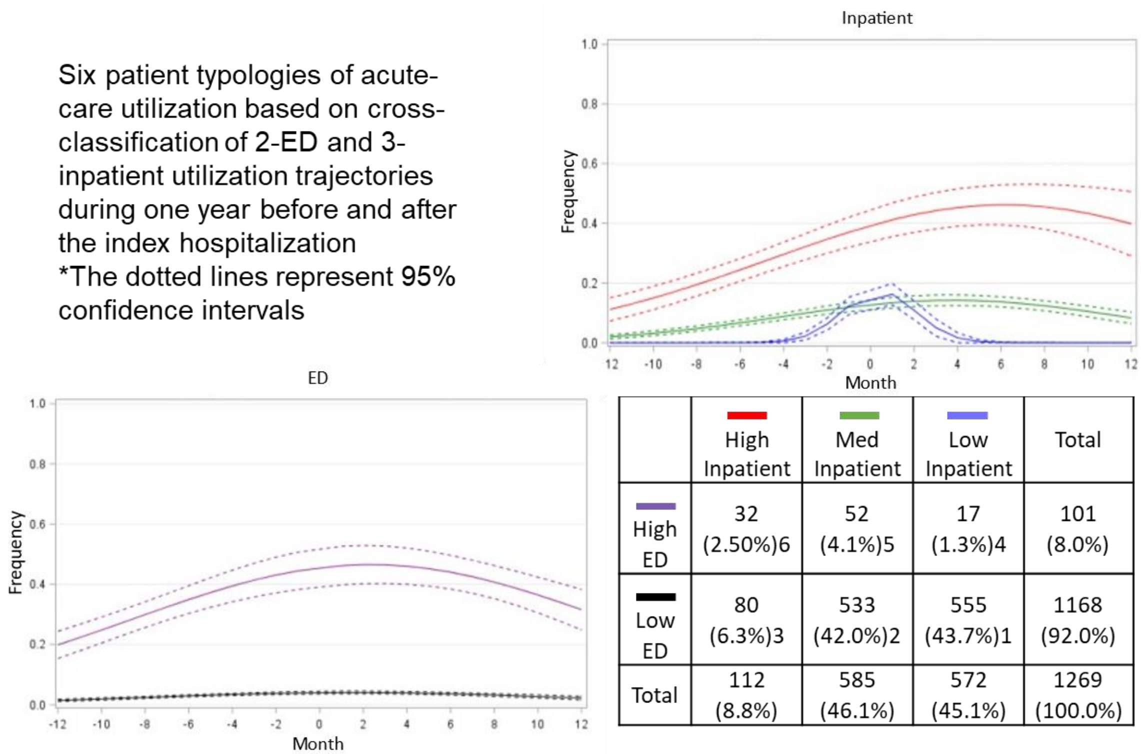
	Mean±SD/Max-Min	**Freq (Percentage)**
Patient-level sociodemographic factors		
Female		591 (46.6%)
Non-White		551 (43.4%)
Married		568 (44.8%)
Live in Durham		369 (29.1%)
Live in North Carolina		1154 (90.9%)
Area Deprivation Index	52.7±25.1/ 2-100	
Smoking		144 (11.3%)
Alcohol use		288 (22.7%)
Illicit drug use		68 (5.4%)
Characteristics at the Index hospitalization		
Age at Admission	65.52±6.3/ 19-100	
Charlson Comorbidity Index	4.16±2.4/ 0-15	
Insurance used at index hospitalization		

Medicare or Medicare Advantage		859 (67.7%)
Managed Care		233 (18.4%)
Medicaid		126 (9.9%)
Others		51 (4.0%)
Admission source		369 (29.1%)
From home		910 (71.7%)
From physician office		129 (10.2%)
From another institution*		230 (18.1%)
Discharge disposition		
To home		740 (58.3%)
To home health care		346 (27.3%)
To others[3]		183 (14.4%)
Length of stay	13.08±8.73/ 0.53-232.02	
Factors over the 2-year period		
3M Severity of Illness(SOI) Score		
Mean SOI	1.9±0.6/ 0-3	
Change of SOI	0.8±0.8/ 0-3	
Used Same Day Access Clinic or not†		110 (8.7%)
Total types of insurances ‡	1.9±1.0/ 1-6	

*Institutions include long-term acute care, rehab facility, skilled nursing facility, psych facilities, and other acute hospitals or healthcare institutions.
†If the patient has ever used the Same Day Access Clinic at least once during the study period
‡The total numbers of insurance types used by patients over the study period at inpatient and outpatient services

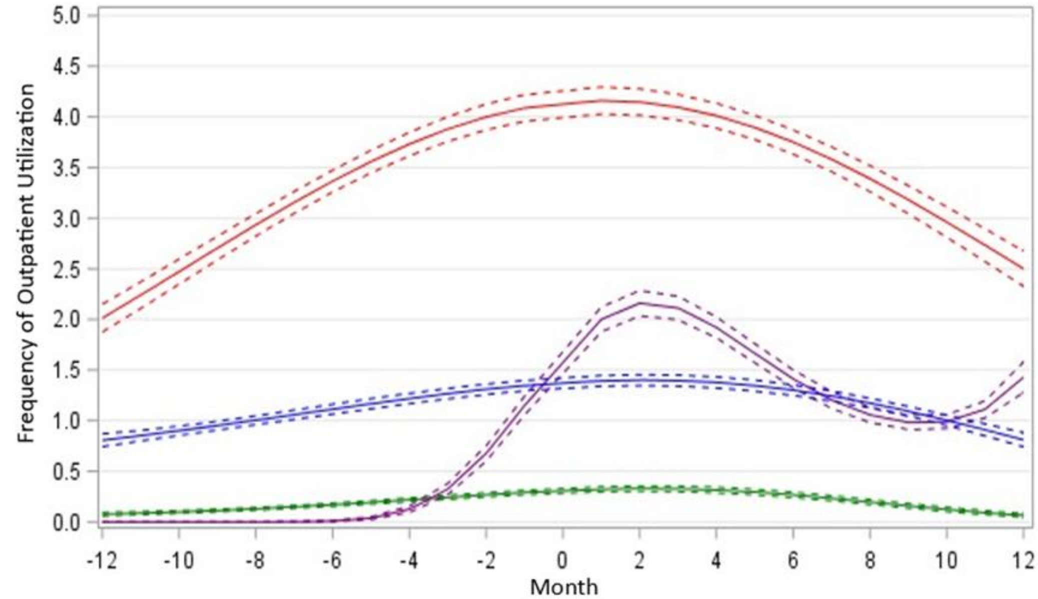
3.3.2 Distinct Trajectories across Services

Patients' utilization of acute and outpatient care services demonstrated considerable heterogeneity. The 1269 patients had 1770 ED, 2573 inpatient, and 27690 outpatient encounters in one year before and after the index hospitalization. Group-based trajectory modeling identified two latent heterogeneous ED utilization subgroups (i.e., low and high users), three latent heterogeneous inpatient utilization subgroups (i.e., low, medium, and high users), and four latent heterogeneous outpatient utilization subgroups (i.e., low, fluctuate, medium, and high users), as the best groupings based on distinct trajectory patterns (Figures 6 and 7). Posterior average probability and fit statistics showed strong grouping convergence (Table 6).



	High Inpatient	Med Inpatient	Low Inpatient	Total
High ED	32 (2.50%)6	52 (4.1%)5	17 (1.3%)4	101 (8.0%)
Low ED	80 (6.3%)3	533 (42.0%)2	555 (43.7%)1	1168 (92.0%)
Total	112 (8.8%)	585 (46.1%)	572 (45.1%)	1269 (100.0%)

Figure 6: Six Acute Care Utilization Typologies



Utilization	Number (%) of Patients	Total Encounters (%)
High	138 (10.9)	10274 (37.1)
Medium	431 (34.0)	11003 (39.8)
Fluctuate	221 (17.4)	4328 (15.6)
Low	479 (37.7)	2085 (7.5)

Figure 7: Trajectories of Outpatient Utilization before and after the Index Hospitalization

Table 6: Grouping Statistics from Group-based Latent Class Growth Analysis

	Trajectory	**n (%)**	**Parameter**	**SE**	***t*-value**	***p*-value**	**BIC**
ED	Low	168 (92.0)	Quadratic	1.11	81.54	0.000	-6159.90
	High	101 (8.0)	Quadratic	1.11	8.27	0.000	
Inpatient	Low	585 (46.1)	Quadratic	2.65	20.09	0.000	
	Near Index	572 (45.1)	Quadratic	2.57	14.10	0.000	-8236.47
	High	112 (8.8)	Quadratic	1.73	6.15	0.000	

Outpatient	Low	479 (37.7)	Cubic	1.53	24.69	0.000	-35769.80
	Fluctuate	221 (17.4)	Cubic	1.14	15.21	0.000	
	Medium	432 (34.0)	Cubic	1.42	23.71	0.000	
	High	138 (10.9)	Quadratic	0.92	11.97	0.000	

Subgroups of patients with high ED and inpatient trajectories were consistently high users, having a higher frequency of using ED and inpatient services than those with lower ED and inpatient trajectories since before the index hospitalization. They tended to increase their utilization faster than others. Patients belonging to the low ED trajectory group tended to have a stable low usage throughout the two years. Patients with a low inpatient utilization trajectory showed increased usage around the index hospitalization while remaining zero in other months.

The crosstabulation of the ED and inpatient utilization groupings revealed that patients could be grouped into six distinct typologies of acute-care utilization (Figure 6). The four *high* acute-care utilization typologies are those with high utilization trajectories in ED or inpatient or both: 32 (2.5%) high inpatient and ED users, 52 (4.2%) medium inpatient and high ED users, 17 (1.3%) low inpatient but high ED users, 80 (6.3%) high inpatient but low ED users. Subgroups of patients belonging to the four high acute care typologies (n = 181, 14.3%) accounted for 52% (n=922) and 33.0% (n=851) of the total ED and inpatient encounters. Five hundred eighty-five patients (45.1%) had low ED and medium inpatient utilization trajectories and were considered *medium* acute care users. Five hundred seventy-two patients (43.7%) used both inpatient and ED in a *low* amount.

Most patients (n=479, 37.7%) had a *low* outpatient utilization trajectory and accounted for 7.5% of the total cumulative outpatient encounters, about 4-5 total encounters per person during the two-year study period. *Medium* users (n=431, 34%) had outpatient encounters about once per month. The smallest group of patients (n =138, 10.9%) were *high* outpatient users who used 37.1% of the total outpatient encounters. They used outpatient services two to four times per month, and their utilization peaked around the index hospitalization. *Fluctuating* outpatient users (n=221, 17.4%) had few to no outpatient encounters until 4-months before the index hospitalization, when their outpatient use increased until around 2-months after the index hospitalization, and then fluctuated downward and then upward around 9-months after the index hospitalization.

3.3.3 Relationship between Outpatient and Acute Care Utilization

Multinomial logistic regression modeling (Table 7) showed that, when holding all covariates constant, two of the four outpatient utilization typologies were associated with acute care utilization. People classified as high outpatient utilizers compared to low outpatient utilizers were associated with all four high acute care utilization typologies. The odds ratios for these significant associations ranged from 5.12 (p=0.0175, 95% CI 1.33-19.71) to 7.59 (p=0.0002, 95% CI 2.65-21.79). People with medium outpatient utilization only had significantly increased odds of being in the low ED and medium inpatient user typology (OR=1.96, p=0.0001, 95% CI 1.39-2.76), and 3.88 times higher odds of being the low ED and high inpatient user typology (OR=4.88, p<0.0001, 95% CI 2.31-10.34) than those with low outpatient utilization. However, the association between outpatient and higher acute-care utilization typologies was not significant among people with fluctuating outpatient utilization.

Table 7: Association Between Outpatient and Acute Care Utilization Typologies, Low ED and Low Inpatient (n = 555; 43.7%) as the Reference*

	Med Acute Care Typology		Four High Acute Care Typologies (n = 181; 14.3%)							
	Low ED & Med Inpatient (n = 533; 42.0%)		Low ED & High Inpatient (n = 80; 6.3%)		High ED & Low Inpatient (n = 17; 1.3%)		High ED & Med Inpatient (n = 52; 4.1%)		High ED & High Inpatient (n = 32; 2.5%)	
	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.	OR	Sig.
Outpatient Utilization										
Low	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Medium	1.957	0.0001	4.883	<0.0001	1.450	0.5853	2.131	0.0775	2.419	0.1175
Fluctuate	1.494	0.0527	1.543	0.3984	1.368	0.7227	1.047	0.9428	0.577	0.6350
High	1.605	0.1026	5.130	0.0013	6.061	0.0249	7.592	0.0002	5.122	0.0175
Clinical factors										
Change in severity of illness	4.106	<0.0001	8.737	<0.0001	2.593	0.0078	6.748	<0.0001	10.922	<0.0001
Mean severity of illness	1.796	<0.0001	4.659	<0.0001	1.389	0.5048	0.848	0.6064	2.025	0.1277
Charlson Comorbidity Index	1.134	0.0002	1.247	0.0001	1.265	0.0219	1.117	0.1407	1.456	<0.0001
Sociodemographics										
Age	1.000	0.9788	0.992	0.4565	0.970	0.0790	0.979	0.0873	0.965	0.0268
Non-White	1.009	0.9580	1.931	0.0319	1.508	0.5032	2.926	0.0066	1.980	0.1785
Married	0.966	0.8167	0.845	0.5699	0.078	0.0174	0.903	0.7810	0.719	0.5095
Total types of insurances†	1.299	0.0035	1.504	0.0052	1.107	0.7423	1.584	0.0070	1.624	0.0331
Insurance used at index										
Medicare	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
Managed Care	0.559	0.0128	0.668	0.3537	0.393	0.2915	0.317	0.0407	0.076	0.0246
Medicaid and others	1.012	0.9623	1.091	0.8483	0.392	0.3057	0.780	0.6267	0.634	0.4565
Live in Durham county	0.979	0.9027	1.359	0.3345	2.231	0.1583	2.306	0.0200	2.403	0.0645
Health behaviors										
Smoking	1.090	0.7234	1.239	0.6488	1.730	0.4146	1.573	0.3330	4.581	0.0033

Alcohol use	0.531	0.0003	0.434	0.0215	1.183	0.7762	0.906	0.7961	0.630	0.3654
Hospitalization factors										
ED admitted	1.124	0.4840	1.291	0.4347	5.021	0.1320	2.769	0.0543	5.237	0.0226
Discharge disposition										
To home	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref	Ref
To home health care	1.184	0.3315	1.642	0.1390	1.633	0.5026	4.080	0.0006	1.328	0.5985
To others‡	1.252	0.3207	2.357	0.0295	0.984	0.9848	2.648	0.0541	0.745	0.6815
Length of stay	0.996	0.5207	0.996	0.6379	0.819	0.0917	0.840	0.0028	0.996	0.8613

*This table only contains results from the final parsimonious model. Other factors used but were excluded from the final parsimonious model include gender, area deprivation index, illicit drug use, index hospitalization sites, admission source, and access to the same day access clinic.

†The total numbers of insurance types used by patients over the study period at inpatient and outpatient services

‡Institutions include long-term acute care, rehab facility, skilled nursing facility, psych facilities, and other acute hospitals or healthcare institutions.

Additionally, the final parsimonious model also showed that some covariates (i.e., both mean severity of illness and change in the severity of illness, Charlson Comorbidity Index, age, race, marital status, insurance, living in Durham county, smoking, alcohol use, and a few index hospitalization characters) were significantly associated with the four high acute care utilization typologies (Table 7). In particular, the rate of change or the incremental increase in severity of illness during the study period had a higher level of significance (p-value) and stronger magnitude of effect (odds ratio) than any other variables in the model. While the average severity of illness was only significantly associated with medium (OR=1.80, p<0.0001, 95% CI 1.40-2.31) and one typology (low ED and high inpatient utilization) of high acute care utilization (OR=4.66, p<0.0001, 95% CI 2.52-8.61), change of severity of illness over time was significantly associated with medium (OR=4.11, p<0.0001, 95% CI 3.31-5.10) and all four typologies of high acute care utilization having an odds ratio of 8. Using the high ED and high inpatient type of high acute care utilization typologies as an example, for each unit of increase in severity of illness, patients were ten times more likely to be in the high ED and inpatient trajectory group (OR=10.92, p<0.0001, 95% CI 6.11-19.53).

3.4 Discussion

The findings in this study explicate an important gap in the relationship between outpatient care and acute care utilization. We identified six subgroups of patients with distinct longitudinal acute care utilization typologies, using group-based trajectory modeling. While controlling for other factors known to influence acute care utilization such as sociodemographic, behavioral, and clinical factors, including the severity of illness (Chamberlain et al., 2017; Chamberlain et al., 2018; Eapen et al., 2015; Li et al., 2019; Patel et al., 2020; Su et al., 2019), patients with high outpatient utilization had more than four times the likelihood of also having high acute care utilization. Similar to findings in previous studies, these high utilizers comprise a relatively small (14.3%) proportion of the overall population (Ng et al., 2019; Rao et al., 2018; Wammes et al., 2019), and they had a higher frequency of utilization both prior to and following the initial HF hospitalization, as well as a higher increase in the frequency of acute care utilization compared to patients in other utilization groups.

High outpatient utilization is commonly found to prevent high acute care utilization (Bayliss et al., 2015; Cainzos-Achirica et al., 2019). However, we found that consistently high outpatient utilization was closely related to consistently high acute care use during the 2-year study period, similar to a previous finding that patients who saw more prescribing providers were associated with higher ED and inpatient visits (Maciejewski et al., 2014). The association between high outpatient utilization with high acute care utilization may suggest potential unmeasured confounders, such as the extent to which care was coordinated and opportunities for improved recognition or management of HF exacerbations. Although increased access to outpatient care has been advocated as a strategy for reducing acute care, when patients visit many outpatient providers, their care may become fragmented because of the lack of coordination among providers from different subspecialty clinics. Patients may experience challenges deciding which provider to contact in the event of deterioration, receive conflicting advice regarding priorities in care, or be negatively impacted by sides effects of polypharmacy (Maciejewski et al., 2014; Safstrom et al., 2018). Additionally, the encounters themselves may not have provided the necessary support to avoid acute care. Patients with consistently high outpatient utilization may have more support and better access to healthcare resources. However, more care does not necessarily lead to lower acute care utilization, or better outcomes (Maciejewski et al., 2014; McWilliams, 2016). Frequent episodes of poorly coordinated care could lead to equally poor outcomes. Future studies should identify care coordination measures that can be used or collected during care transitions in routine care and investigate factors associated with high outpatient utilization and confounding the relationship between outpatient care and inpatient care utilization.

Another common thread across this and previously reported studies was the relationship between higher severity of illness as measured by the 3M-severity of illness scale and higher acute care utilization. While consistent with other studies that higher average severity of illness was significantly associated with higher acute care utilization (Fang et al., 2015; Wong et al., 2016), this study identified that the rate of change over time was an even stronger predictor and explained more variance than the average severity of illness in acute care utilization after accounting for other significant factors including outpatient utilization. The rate of change in the severity of illness over time was the strongest contributor to acute care utilization among all accounted factors, in part because patients may have been more likely to recognize symptom exacerbation and seek support. The severity of illness has long been considered an important factor in care management strategies for this reason, as patients with higher severity of illness are more likely to have increased frailty and care needs and be at higher risk for adverse events (Fang et al., 2015; Parikh et al., 2019; Wong et al., 2016). While previous studies focus on the average severity of illness (Fang et al., 2015), greater attention should also be paid to the rate of change in the severity of illness.

In addition to demonstrating the heterogeneity in inpatient utilization among the HF population found by other studies (Corrao et al., 2015; Dupre et al., 2017; Rao et al., 2018), this study comprehensively evaluated utilization heterogeneity and identified subgroups based on heterogeneity in ED and inpatient utilization before and after the initial HF hospitalization. The acute care utilization typology identified complements the cross-sectional 30-day re-hospitalization metric by providing a new approach to consider how individual patients vary with respect to both outpatient and inpatient service utilization. The 30-day re-hospitalization rate for this cohort was 19.7% (n = 250), and only 26.8% of them were classified as one of the four typologies of high acute care utilizer. Considered through the lens of different utilization patterns among these 250 patients, the use of 30-day re-hospitalization rates alone as a quality indicator may obscure the experience of patients who have much higher utilization outside the 30-day readmission mark. For example, a patient who was re-hospitalized on the 20th day after discharge compared with a patient who was re-hospitalized on the 40th day may not differ significantly in terms of patient experience, cognitive burden, daily function, and cost, but the patient who was readmitted on the 20th day is considered a worse outcome. However, being someone who only needs one hospitalization around the time of index hospitalization over two years versus needing 7 to 9 inpatient or ED visits over the two years may have a widely disparate experience in terms of cost, distress, and disruption to daily life. An important direction for future research is to understand how various models of outpatient care and care coordination might influence both 30-day rehospitalization rates and the utilization trajectory of inpatient services after controlling for severity of illness.

Using the group-based trajectory modeling approach not only provided a longitudinal view of patient hospitalization use (including rehospitalization), but also demonstrated a new potential approach to identify high-need and high-cost patients. Consistent with previous findings that a small proportion of the population were high utilizers (Ng et al., 2019; Rao et al., 2018; Wammes et al., 2019), the 14.3% of patients who had high use in ED, inpatient or both, accounted for most of the total acute care encounters. These patients tended to have higher acute care use even prior to the initial

HF hospitalization and had a higher increase of usage over time than patients in other groups. Various sociodemographic factors were associated with different high acute care utilization typologies, demonstrating the potential complex social determinants of health that affect how patients use health care services to manage care (White-Williams et al., 2020). Based on these findings, future studies should further investigate factors associated with high outpatient utilization. Intervention studies should address strategies for mitigating the small proportion of consistently high acute and outpatient service users, particularly focusing on the care coordination mechanisms for these high utilizers as a means of identifying the underlying drivers of care fragmentation. Targeting the small subgroups of constantly high users and then developing and testing tailored interventions to meet their care needs in the outpatient setting are warranted. Interventions that help to dentify and overcome social barriers to care management and coordination, monitoring, and timely adjustment of care plans for patients undergoing deterioration facilitate care that is more patient-centered to reduce avoidable rehospitalization and care fragmentation.

3.4.1 Limitations

The majority of EHR data are unstructured, which limited patient-level and system-level factors available to be used for research. Variables such as the New York Heart Association Class and the guideline-directed medical therapy quality metric, that would have been informative but were not easily extractable were not accounted for in this study. Because EHR currently only capture information when patients used services within the system, this study did not account for services outside of the health system where EHR data was extracted. Therefore, there might be an underestimation of patients' utilization when they also used other systems to manage care.

3.5 Conclusion

This study provided new knowledge regarding how outpatient utilization was associated with patients' acute care utilization and revealed a possible approach to examine high heterogeneity in patients' care utilization. Identifying heterogeneous subgroups may help develop and implement interventions suitable for the needs of subgroups to promote more patient-centered care delivery. Furthermore, identifying subgroups of high users who are likely high-need and high-cost patients and helping them better coordinate care to be more effective and efficient in outpatient settings may improve the overall 30-day readmission rate and the financial burden associated with high acute care utilization. Outpatient utilization and various sociodemographic, health behavioral, clinical, and service utilization factors were associated with high acute care utilization. Future studies should attempt to improve understanding of the influence of social context on care transitions and care coordination mechanisms among providers across settings, and may consider developing patient-centered interventions in the outpatient setting tailored towards the needs of the small subgroup of patients with consistently high utilization, particularly those negatively influenced by social determinants of health during change of severity of illness, to improve HF re-hospitalization rates.

4. A Novel Use of Social Network Analysis to Explore Barriers to Care Coordination for Patients with Heart Failure

4.1 Introduction

Care fragmentation in care transitions for people with HF has been a persistent problem, particularly for those adversely affected by social determinants of health (Albert et al., 2015; Blecker et al., 2019; White-Williams et al., 2020). Despite years of research, results across transitional care intervention studies are inconsistent (Albert et al., 2015; Heidenreich et al., 2013); patients with HF remain the group with the highest 30-day readmission rate, and the national HF 30-day readmission rate has stopped improving in recent years (Blecker et al., 2019).

Care coordination "involves deliberately organizing patient care activities and sharing information among all participants concerned with a patient's care to achieve safer and more effective care" (AHRQ, 2018), and it is a crucial mechanism to improve care fragmentation and achieve the Quadruple Aim (improving patient experience, provider work experience, and care outcomes, and reducing costs) (Chen & Miller, 2016; Craig et al., 2011; B. A. Daveson et al., 2014; Peterson et al., 2019; Sikka et al., 2015). Successful care coordination requires that various providers at different services work together over time, yet current understanding of care coordination processes is often focussed on a single setting (e.g., hospital or primary care) or discipline of providers (e.g., physicians) (McDonald et al., 2014; Peterson et al., 2019; Schultz et al., 2013). A systematic and comprehensive understanding of how all participants, especially outpatient providers, are connected in coordinating patient care during HF care transitions is urgently needed for informing improvement in HF transitional care.

With the wide adoption of EHRs for routine care, the use of EHR data combined with social network analysis (SNA) is an emerging and promising approach to systematically evaluate patterns of relationships across settings and disciplines for care coordination (Begun & Thygeson, 2014; DuGoff et al., 2018; Durojaiye et al., 2019; McDonald et al., 2014). An EHR can offer a longitudinal record of a patient's service utilization and medical history with rich contextual data and notes from the multidisciplinary providers from different services who have been involved in care delivery (Lanzer et al., 2020; McDonald et al., 2014). Clinical notes contain qualitative data that are similar to transcribed field notes but not biased by recall or the subjectivity of observers (Casey et al., 2015; Perry et al., 2018; Voirin et al., 2015). SNA is a systematic approach to modeling interdependent relationships or interactions among people or entities as networks that may help to improve understanding of the relational processes and structures essential for care coordination (DuGoff et al., 2018; McDonald et al., 2014; Valente, 2010). A few studies have evaluated outpatient service networks or inpatient provider networks in the context of cardiovascular disease (Carson et al., 2016; Merrill et al., 2015); however, no studies have evaluated the interdependent relationships among multidisciplinary providers across settings in the context of HF care transitions.

Using SNA to understand the interdependent and relational processes of care coordination may provide new perspectives on the roles of individuals and patterns of relationships involved in care transitions that can be used to improve transitional care (Begun & Thygeson, 2014; Valente, 2010). Clinical notes from EHRs provide information about when and why various multidisciplinary providers have been involved in the patient's care, and they offer rich longitudinal information regarding clinical context that can facilitate an in-depth understanding of care coordination processes in care transitions. The purpose of this mixed-methods study is to understand the social context and structure of care coordination processes 1-year before, during, and 1-year after patients' index hospitalization for primary diagnosis of acute decompensated HF. Specific aims are to

1. Test the feasibility of combining 2-mode (patient-sharing) SNA with EHR clinical notes to construct provider networks and characterize individual patient's provider networks (e.g., size, density, and centrality) during HF care transitions.
2. Examine the quantitative and qualitative characteristics of the social and clinical contexts comprising care coordination during HF care transitions for patients with similar severity of illness but diverse social indicators.

4.2 Methods

4.2.1 Study Design

We conducted a mixed-method sequential explanatory design study using existing EHR data (Ivankova et al., 2006). First, we constructed the entire provider networks for the identified cohort in Chapter 3 (n = 1269) using 2-mode (i.e., patient-sharing) SNA; individual's provider networks were then extracted and visualized for a purposively sampled subgroup of patients (n

= 11) (Casalino et al., 2015; DuGoff et al., 2018). Because we were interested in understanding provider positions within the system as well as the characteristics of patients' provider networks, the quantitative indicators characterizing providers' network positional characteristics within the entire network as well as the structural characteristics of selected individuals' provider networks were generated. The qualitative indicators characterizing clinical and social contexts were generated from the contents of clinical notes during the study period; then network maps and quantitative network characteristics were integrated with qualitative analysis results to provide an understanding of patients' social and clinical context and the meaning of the SNA measures, and to identify patterns of social relationships for care coordination.

A mixed-method sequential explanatory design was chosen because numbers from quantitative SNA are only meaningful and useful when they are embedded and explained in narratives about the context and meaning of social networks (White, 2012). Additionally, because this is the first study to use clinical notes data to generate individual patients' provider networks across settings and over time for patients with HF, rich qualitative information can be useful for examining the face validity of network graphs and measures.

4.2.2 Setting and Sample

The Duke University Health System is a major university-associated research hospital system in North Carolina. This study used the same cohort of adult patients (18 years or older) who had had a first hospitalization with a primary diagnosis of HF (the index hospitalization) between January 1, 2016 and December 31, 2018 at Duke University Health System (as identified in Chapter 3). A subgroup of patients (n = 11) was selected from the whole cohort using stratified purposive sampling for this mixed-methods study. Three strata, based on race (White or non-White), insurance (Medicaid used or not used), and Area Deprivation Index (living in a high or low deprived area), were used to capture cases representing a full spectrum of experience of socioeconomic disadvantages. Additionally, all 11 patients had close to identical levels of comorbid illness (as measured by the Charlson Comorbidity Index) and average severity of illness as well as the same levels of change in the severity of illness, thus reducing variance in medical needs. The case stratification is shown in Table 8.

Table 8: Sample Stratification and Case Profiles Based on Three Indicators of Socioeconomic Inequalities

<table>
<tr><th></th><th colspan="2">White</th><th colspan="2">NonWhite</th></tr>
<tr><th></th><th>Low ADI</th><th>High ADI</th><th>Low ADI</th><th>High ADI</th></tr>
<tr><td rowspan="2">Medicaid</td><td rowspan="2">Case #5 (ADI=14)</td><td rowspan="2">Case #8 (ADI=95)</td><td rowspan="2">Case #9 (ADI=21)</td><td>Case #10 (ADI=98)</td></tr>
<tr><td>Case #11 (ADI=90)</td></tr>
<tr><td rowspan="2">Not Medicaid</td><td>Case #1 (ADI=8)</td><td>Case #4 (ADI=95)</td><td rowspan="2">Case #6 (ADI=33)</td><td>Case #7 (ADI=90)</td></tr>
<tr><td>Case #2 (ADI=23)</td><td>Case #3 (ADI=91)</td><td></td></tr>
</table>

4.2.3 Quantitative Phase

4.2.3.1 Quantitative Data Collection

Structured clinical notes data for the identified cohort in Chapter 3 were extracted from the EHR through Epic Clarity by the Duke Heart Center data team. These structured data included timestamp, author of the notes, provider’s clinical role and credentials, department, note type, encounter type, and encounter ID 1-year before, during, and after the index hospitalization. All types of notes created by providers about patients during care encounters were extracted, including but not limited to progress, procedure, patient instruction, assessment, and telephone notes.

4.2.3.2 Quantitative Data Analysis

Provider networks before, during, and after the index hospitalization were generated through 2-mode network analysis by assuming and inferring connections between pairs of providers based on a shared degree of having written clinical notes for the same patient during the delivery of routine care (Casalino et al., 2015; DuGoff et al., 2018). All quantitative data cleaning, curation, and analysis were conducted in R, a software environment for statistical computing (Version 3.6.3) (R Core Team, 2013).

Network Construction. Provider networks were constructed based on how all involved providers shared patients for the identified cohort. A provider who had written clinical notes for a patient was considered a *node* in the care networks. Relationships between providers (i.e., *ties*, also called *links* or *edges* in SNA) were implied if both providers had written notes for the same patient. Because providers may write different amounts of notation for a given patient, we followed the tie-weighting approach used by Casalino et al. and coded the minimum frequency of notes that two providers had written for a patient as the tie weight between the two providers (e.g., were a nurse to write six notes for patient A, and a physician were to write two notes for patient A, the tie weight between the nurse and physician would be 2). The sum of shared tie weights between each pair of providers was used as the ties' total strength (Casalino et al., 2015).

Over estimation of connections is a commonly known method limitation of the 2-mode network analysis approach. Because all providers shared at least one patient in our sample, providers who shared only one or two patients, especially in different settings, were likely to have weak to no relationships. Previous studies have commonly used a fixed threshold or counted the top 20% of the strongest ties as a connection between two providers to reduce overestimation (Casalino et al., 2015; DuGoff et al., 2018). We followed the methods used by previous studies and kept ties only if the tie strength between two providers was equal or more than 3. After the non-directional provider networks for the cohort before, during, and after the index hospitalization were constructed, we separated out the selected 11 patients' provider networks for individual analysis.

Network Analysis. After the whole provider networks (socio-centric) and the individual provider networks (ego-centric) for each case were constructed, two types of indicators of network characteristics were generated for each of the 11 cases. The first set of network measures indicated the providers' network positions (i.e., weighted degree centrality, betweenness centrality, and Eigenvector centrality) in the overall system (i.e., the whole provider network caring for the identified cohort). The second set of network measures indicated individual case network structure (i.e., size, density, and components). Table 9 provides definitions and interpretations of the positional and structural measures used. All measures were generated by analyzing the generated provider networks using functions in *igragh,* a software package for network research (Csardi & Nepusz, 2006), in R.

Positional SNA indicators. Positional measures focused on how central each provider was in the overall system. All provider centrality measures were calculated first; then, the measures for the providers who had provided care for each of the 11 cases were selected for review and comparison. Degree centrality measures how many connections a provider has: A high degree of centrality indicates that the provider is central in the local network (Valente, 2010). Betweenness centrality measures the degree at which a provider lies between other providers in the network. High betweenness indicates that the person functions as a bridge between provider teams (network clusters) (Valente, 2010). Eigenvector centrality measures centrality based on the connectedness of the node and the node's neighbors (connected providers) and is commonly used to indicate a node's importance, influence, or popularity (Valente, 2010). A provider with a high eigenvector centrality is connected with well-connected providers in the network and thus is likely to have a greater influence on network behaviors, such as information spread, than those with low eigenvector centrality (Valente, 2010).

Structural SNA indicators. Structural measures focused on evaluating characteristics of individual cases in their provider network structure. Network size indicates how big a network is; it is determined by counting the total number of involved providers. Density among the providers involved in caring for each case indicates the degree to which they are closely connected. Finally, the components measure calculates the number of connected teams in the whole network.

Table 9: Quantitative Measures for Network Characteristics

Domain	Concept	Meaning
Measures of Providers' Positions in the Whole Network (Positional Characteristics)	Adjusted Valued Degree Centrality (whole number)	Number of connections; How central is the provider locally
	Betweenness Centrality (whole number)	The degree a provider lies between other providers in the network; the extent to which a provider bridges network clusters
	Eigenvector Centrality (normalized range 0–1)	The importance or influence of a provider while considering the importance or influence of the providers' neighbors (connected providers)

Measures of Individuals' Provider Network Structure (Structural Characteristics)	Size (whole number)	Number of participants/nodes
	Density (normalized range 0–1)	The extent to which providers are closely connected overall. The degree an individual's set of providers know one another
	Components (whole number)	The number of connected teams in the whole network.

4.2.4 Qualitative Phrase

4.2.4.1 Qualitative Data Collection

Contents of clinical notes were reviewed within the Epic Maestro Care system. First, I read through encounters and understood the patient's journey during the identified study period; then, the contents of the notes during the identified period were reviewed and manually recorded into matrixes in Microsoft Excel.

4.2.4.2 Qualitative Analysis

The content of clinical notes was reviewed and analyzed to obtain an understanding of the participants and the formation of their provider networks and to identify significant relational and clinical contexts meaningful for the provider networks based on a set of a priori questions and codes (Table 10) (Polit & Beck, 2012). Because the text fields of clinical notes were not structured and could not easily be extracted and imported into qualitative analysis tools like NVivo, the content of notes was reviewed within Epic through Maestro Care. Detailed logs of identified text and codes were recorded in Microsoft Excel sheets in matrixes during data analysis to adjust for the limitation due to the extraction limitation. Data related to prior questions and codes were manually recorded into an excel sheet.

Due to the extensive length and frequency of notes recorded in the EHR, review efforts were focused primarily on the telephone, Mychart messenger, progress, psychological, social work, case management, transitional care follow-up, and history and physical examination notes. For progress, hospital, and discharge notes, more attention was paid to the sections on history and current complaints, reasons for visits or communication, care plans, and instructions for the patient. Particular attention was paid to note content related to social background, family or informal caregiver involvement, and key provider(s) with whom the patient more frequently and consistently visited or communicated over time because these people were likely to have a stronger relationship with the patient and more influence on their care. Content closely related to care transitions, such as care plans in discharge plan, post-discharge telephone follow-up notes, and case management notes, was also closely considered to enhance understanding of the care transition processes and continuation of care planning and management. Additionally, to help enrich our understanding of the formation or deformation of the networks and provider positions in the network identified in the SNA analyses and to validate network construction, we paid attention to (a) involvement by providers from outside services (e.g., home health care) who did not chart in the Duke EHR system; (b) notes regarding new providers (e.g., referrals, reasons for referrals, ED visits and reasons for ED visits); and (c) discontinuation or changes in communication or visit patterns with key providers (Hollstein, 2014).

Table 10: Research Questions and A Priori Coding Manual

Open Code	Operationalization
What are the additional social and clinical contexts not captured by the available quantitative data?	Identify HF classifications; diagnosis; change in conditions and symptoms; elements of social history, such as living situation, social support, or other social characteristics identifiable from provider notes.
How, when, with whom, and for what reasons did interactions occur between participants. Have care plans for the patient been consistent from hospital discharge to post-discharge ambulatory care? Who helps most with the patient's care plans and adaptation to new conditions or changes?	Identify consistent and most common interactions with the patient to find the key person who helped the patient coordinate and adjust to care plans. Identify whether providers across different departments were referred or in communication about similar care issues or plans. Identify the main reasons for interaction or communication among participants, particularly when transitioning across settings or adjusting to changes in care plans. Compare and contrast care plans in time sequence.
How did patient care flow from one department to another or between ambulatory and acute care settings?	Identify the time, frequency, reasons for hospitalizations, or involvement of new departments. If the visit was referred or recommended through communication with an ambulatory provider, record that provider's role and name.
Were providers from outside the Duke system involved in the patient's care, and with whom did they communicate? What was the reason for the communication? With whom did they most frequently communicate to coordinate care?	Identify involvement of providers from systems not linked with the Duke EHR system.

Two levels of analysis were performed: (1) within cases, and (2) across cases. First, I read and coded notes from each case to (a) understand the patient's social context and care trajectory, and the participants involved; and (b) develop an impression of their care management within the community as well as their care transitions in the hospital and after discharge. Second, the nodes and recorded matrixes were reviewed again to identify key themes across cases related to common barriers to care management, participants' involvement and interactions during care delivery, common patient behaviors in health service utilization and interactions with providers, and key persons for patients' care coordination. To increase the rigor of the qualitative analysis, the strategies listed in Table 11 were used to ensure credibility, dependability, confirmability, and transferability.

Table 11: Strategies to Increase Rigor

Domain	Credibility	Dependability	Confirmability	Transferability
Defination	Truth of the data	Consistency of the data	Objectivity of the data	Generalizability of findings
Strategy	• Cross-validate stories of patient health care utilization and provider networks with clinical notes; • Verify with providers	• Describe and record data extraction, coding, and analysis clearly; • Code based on a priori coding manual and questions	• Record coding and analysis steps into audit trails for each patient	• Provide sufficient information about each subject and their social and clinical context using data from clinical notes

4.2.5 Integration of the Quantitative and Qualitative Results

After quantitative and qualitative analyses were conducted, results from the different approaches were integrated, and joint display matrixes were constructed to help integrate findings from the quantitative and qualitative data analyses. The qualitative data were integrated with the network graphs and characteristics to understand (a) the context and reasons for the evolution of network structures before, during, and after the index hospitalization, (b) differences in network characteristics across inpatient and outpatient providers within cases, and (c) the similarities and differences in network characteristics among cases considering their clinical and social context and care outcomes assessed by the number of hospitalizations, unplanned 30-day readmissions, and mortality.

The integration of qualitative and quantitative approaches to investigate data from clinical notes was designed to reach three goals: to (1) converge relationships among participants observed from clinical notes with provider network graphs and measures of network characteristics generated from SNA to assess the validity and meaning of such quantitative abstraction, (2) identify possible events or interactions that shaped changes in network structure and care outcomes, and (3) enhance understanding of the clinical context and processes, especially for significant care plan changes such as the addition of home health care or transition to palliative care. Given that the phenomenon of care coordination in care transition is dynamic and variable depending on the context, a fuller understanding of the context of care coordination is needed to appreciate its importance to the formation of or change in provider networks and a patient's utilization trajectory. Abstraction of text data was integrated with visualizations of patients' social network characteristics to help understand features of provider networks and how these networks and patient utilization evolved over time.

4.3 Results

4.3.1 Demographic and Clinical Characteristics

We ensured that the sample was diverse in social and economic status by using the predetermined factors of social strata, race, use of Medicaid, and area deprivation index. Among the 11 selected cases, 6 used Medicaid as their insurance, and 6 were African American. Although we aimed to select 6 patients living in highly deprived neighborhoods (i.e., a home address associated with an area deprivation index greater than 90), our sample included 8 patients who lived in a more deprived environment. The addresses recorded in the system for Cases 5 and 9 were associated with a low area deprivation index (14 and 21 respectively); however, based on qualitative content in clinical notes, it seems likely that these patients lived in a deprived environment: Case 5 lived in a trailer home, and Case 9 was homeless and gave an address of a shopping center. Their unstable living situations indicated that their low area deprivation indexes likely reflected their actual living environment inaccurately and needed correction, thus 6 of the 11 cases (cases 5, 7, 8, 9, 10, 11) had intersections of 2 or more negative social strata as shown in Table 12.

Table 12: Case Profiles Based on Three Socioeconomic Indicators

	White		**Black**	
	Low ADI	**High ADI**	**Low ADI**	**High ADI**
Medicaid	None	Case #5	None	Case #9
		Case #8		Case #10
				Case #11
Not Medicaid	Case #1	Case #4	Case #6	Case #7
	Case #2	Case #3		

Because this study focused on the social and relational factors for care coordination, we reduced variance in medical needs by controlling the variability in the Charlson Comorbidity Index and 3M severity of illness score to reduce the variability in medical needs. The 11 cases had Charlson Comorbidity Index ranged from 2 to 4 with a mode of 3 (n = 5) and a mean of 2.8 (SD = 0.8). All cases had a 2-level change in the severity of illness score during the study period.

At the index hospitalization, most cases (n = 6) had major, 3 had moderate, and 2 had extreme severity of illness, and the variability in the severity of illness at the index hospitalization was balanced between those cases with intersections of 2 or more negative social indicators and those with 1 or no negative social strata.

Table 13 summarizes the demographic and clinical characteristics of the 11 selected cases. The mean age of the 11 patients was 64.2 (SD = 15.2) years. Most were male (n = 7), unmarried (n = 8), not a current smoker (n = 8), did not drink regularly (n = 7), and did not use illicit drugs (n = 8). Those who had more intersections of strata tended to have more acute care encounters (i.e., ED visits and inpatient stays) and unplanned 30-day readmissions. During the study period, those who had 1 or no negative social stratum had no emergency department visits and tended to have fewer inpatient stays than those who had intersections of 2 or more negative social indicators, who visited emergency departments ranging from 2 to 13 times (Figure 8).

Table 13: Demographic and Clinical Characteristics of Study Cases (n = 11)

Case	ADI	Race[a]	Medicaid	Age	Gender	Marital Status	Cocaine Use	CCI	SOI[c]	Diagnosis	# of Outpatient[b]	# of ED[b]	# of Inpatient[b]	30-day Readmit	Days to Death[e]
1	8	White	No	80	Male	Married	No	3	Major	Diastolic CHF, NYHA class 2, paroxysmal atrial fibrillation, mitral valve replacement with bioprosthetic valve, tricuspid valve repair, maze operation for atrial fibrillation, chronic anticoagulation, allergic rhinitis, asthma, gastroesophageal reflux disease, mixed hyperlipidemia	47	0	2	No	Alive
2	23	White	No	>85	Female	Widowed	No	2	Extreme	Systolic CHF, aortic stenosis, cardiac asthma, hypertension, depression, pleural effusion	14	0	2	No	421
3	91	White	No	69	Female	Widowed	No	3	Moderate	Systolic HF class 3, severe mitral regurgitation, left ventricular systolic dysfunction, COPD, pleural effusion, chronic pulmonary hypertension, anorexia	20	0	3	Planned	Alive
4	95	White	No	47	Male	Married	No	2	Major	HFrEF, CHF, acquired hypothyroidism, ischemic cardiomyopathy, acute kidney injury, history of amiodarone therapy	17	0	7	Planned	Alive
5	NA[d]	White	Yes	61	Female	Single	No	4	Major	Diastolic CHF, coronary artery disease involving coronary bypass graft of native heart, anemia of chronic disease, pulmonary hypertension, chronic kidney disease stage 3, hypertension, type 2 diabetes with nephropathy	38	3	9	No	310
6	33	Black	No	61	Female	Single	No	4	Major	Systolic and diastolic CHF, NYHA class 4, left ventricular hypertrophy, atrial fibrillation with rapid ventricular response, acute respiratory failure with hypoxia, pulmonary artery hypertension associated with connective tissue disease, anorexia, scleroderma, moderate to severe pulmonary hypertension, anemia of chronic disease, acute on chronic combined major depression	7	0	5	No	1185
7	90	Black	No	66	Male	Divorced	Yes	3	Extreme	CHF, hypertension, noncompliance with diet and medication regimen, mixed hyperlipidemia, tobacco use disorder, alcohol abuse, uncontrolled type 2 diabetes	6	11	2	Unplanned	Alive

8	NA[d]	White	Yes	57	Male	Widowed	No	2	Moderate	HfrEF, acute on chronic congestive HF, AV nodal re-entry tachycardia, 2-vessel coronary artery disease, coronary atherosclerosis of native coronary artery, thrombocytopenia, hypertension, chronic hepatitis C, major depressive disorder	0	8	9	Unplanned	183
9	NA[d]	Black	Yes	61	Male	Single	Yes	2	Major	Systolic and diastolic CHF, acute respiratory failure with hypoxia, elevated brain natriuretic peptide(BNP) level, acute Cocaine use	0	2	2	No	Alive
10	98	Black	Yes	58	Female	Single	Yes	3	Major	Diastolic CHF, hypertension, acute on chronic respiratory failure with hypoxia, COPD, cocaine abuse, neuropathic pain of hand	13	13	10	Unplanned	206
11	90	Black	Yes	46	Female	Married	No	3	Moderate	Diastolic CHF, mitral valve disease, hypertension, combined hyperlipidemia, Uncontrolled type 2 diabetes	48	7	5	Unplanned	681

Note: ADI = Area Deprivation Index, CCI = Charlson Comorbidity Index, ED = Emergency Department, SOI = Severity of Illness; CHF = congestive heart failure, COPD = chronic obstructive pulmonary disease, NA = Not applicable

[a] Ethnicity: all participants were non-Hispanic

[b] Severity of illness 3M score at the time of the index hospitalization

[c] Number of outpatient, ED stay, and inpatient stay visits

[d] Not applicable because these cases were homeless or living in a trailer home, and area deprivation index may not most be acurate, but they were considered as having high area deprivation index

[e] Number of days to the date of death after the index hospitalization

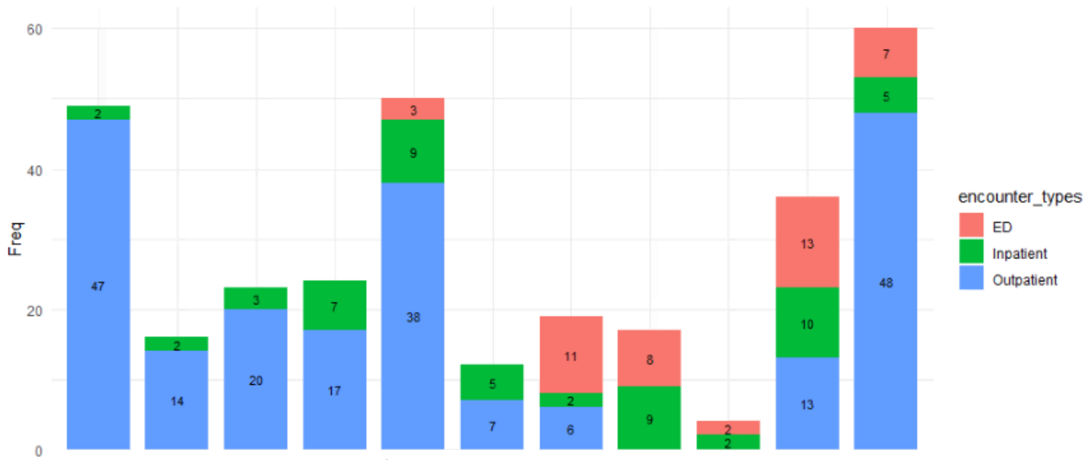


Figure 8: Frequency of Encounters by Encounter Types during Study Period

4.3.2 Provider Networks for Care Coordination in Care Transitions

The use of quantitative data from the EHR combined with SNA was found to be feasible and fruitful for obtaining a systematic and comprehensive view of positional and structural characteristics of the selected 11 cases during their HF care transitions, their providers' positional characteristics in the system, and structural characteristics of their provider networks.

4.3.2.1 Description of Frequency and Types of Providers Involved

A large number and many types of providers were involved in caring for the patient cohort during their HF care transitions. A total of 14593 providers wrote 530,944 notes while caring for the patient cohort during the study period: 10724 unique providers cared for the patient cohort during the year before the index hospitalization, 5671 during the index hospitalization, and 11802 during the year after the index hospitalization. During the year before and the year after their index hospitalization, patients in the study cohort had a combined 4343 inpatient encounters (1770 ED encounters and 2573 inpatient stays) and 27690 outpatient encounters. More providers were involved in the inpatient encounters than the outpatient encounters for care delivery. Inpatient encounters involved 7538 and 8391 providers; outpatient encounters involved 4529 and 4939 providers during the year before and the year after the index hospitalization.

Across the reviewed 11 cases, a total of 393 and 1446 providers were involved in inpatient encounters during the year before and after the index hospitalization, respectively. Sixty-three providers were involved in outpatient encounters one year before and 214 providers one year after the index hospitalization, respectively. One hundred sixty-four providers were involved during the index hospitalizations. The number of providers involved in care for reviewed cases tended to increase after the index hospitalization, as shown in Figure 9. Medical doctors (MD) and registered nurses (RN) comprised the majority of the providers. Cases with intersections of 2 or more negative social strata had a larger number of providers involved in care than those with intersections of 1 or less negative social strata, especially after the index hospitalization.

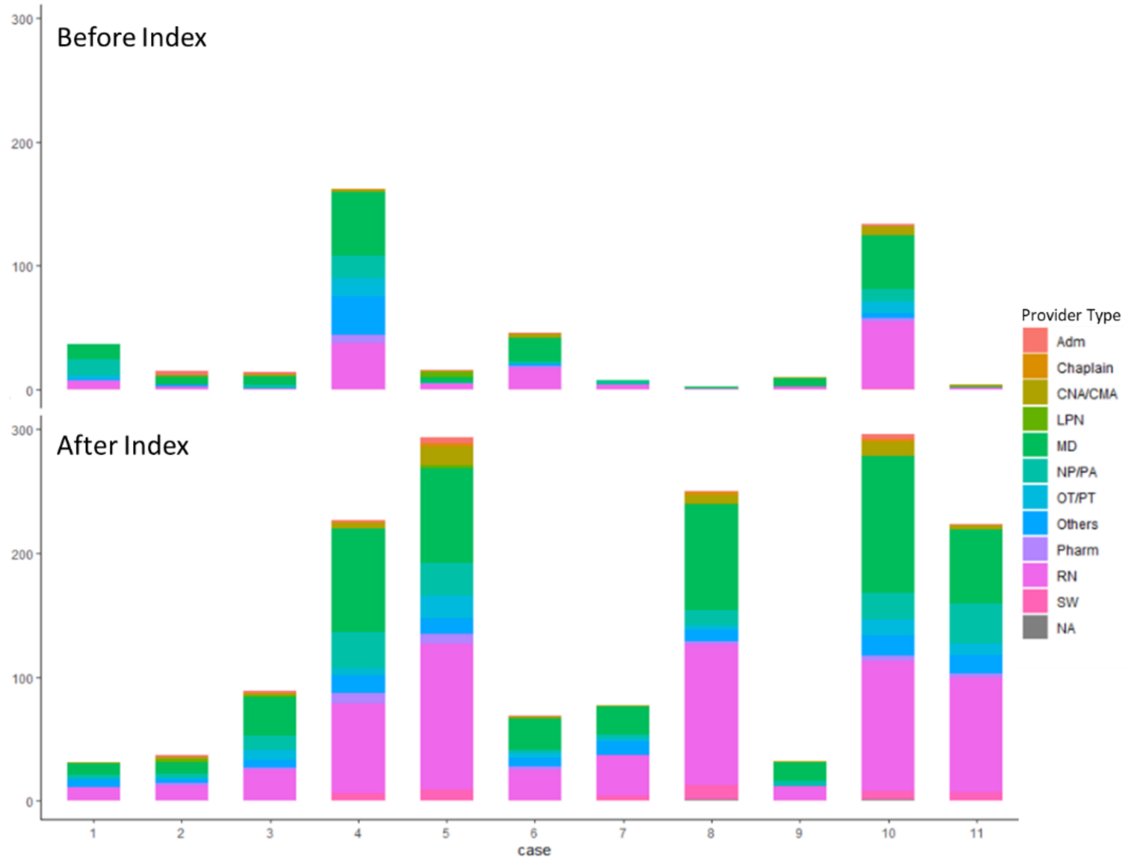


Figure 9: Number of Providers by Type for Each Case

4.3.2.2 Providers' Positional Characteristics in the System for Reviewed Cases

Tables 14, 15, and 16 show the distribution of positional network measures (i.e., degree centrality, betweenness centrality, eigenvector centrality) of individual providers involved in caring for each of the 11 cases before, during, and after the index hospitalization, respectively. Before the index hospitalization, provider positional characteristics did not have obvious differences in the mean, 75%, and 95% confidence interval of degree and betweenness centrality, but those who had 1 or no negative social stratum tended to have higher average eigenvector centrality for outpatient providers.

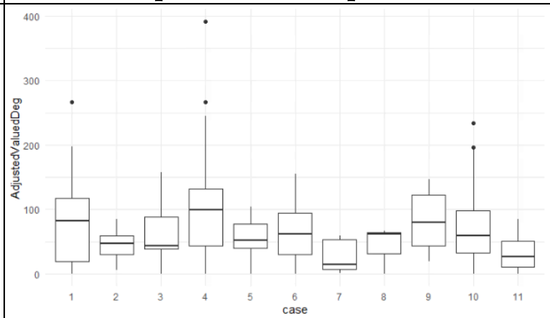
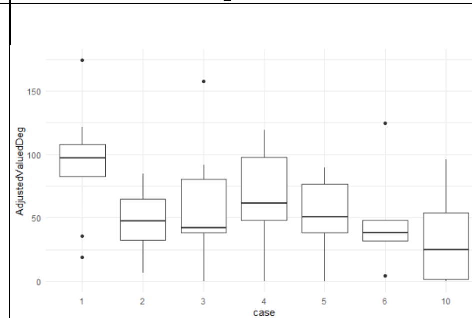
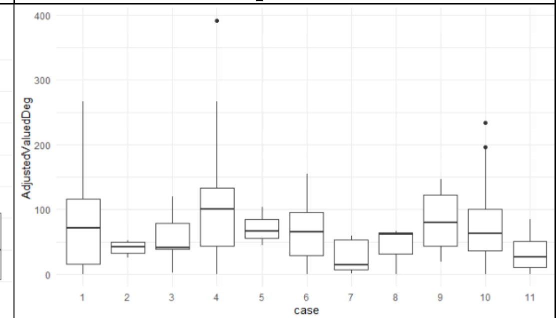
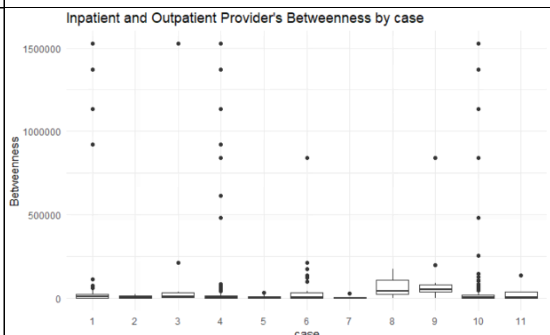
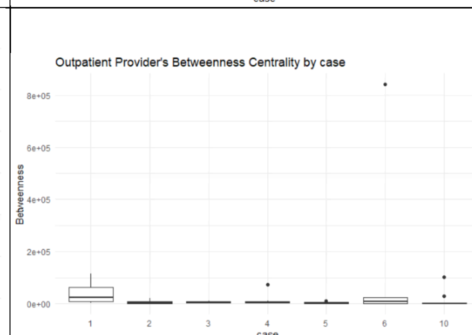
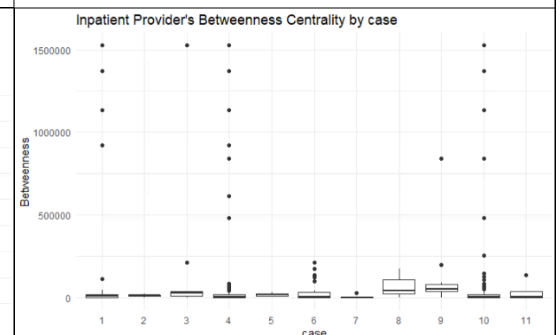
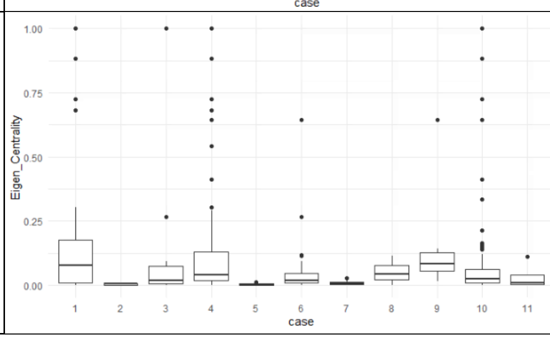
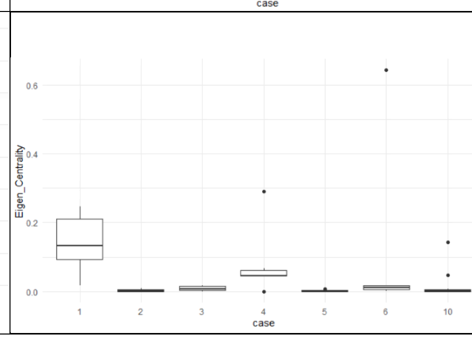
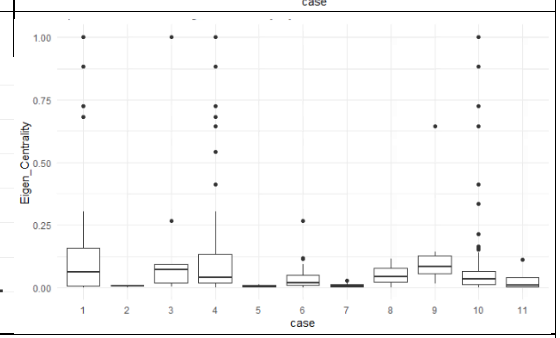
The difference in provider positional network measures was more obvious during and after the index hospitalization. Three of the 5 cases that had 1 or no negative social stratum (Cases 1, 3, and 4) had a higher distribution of degree, betweenness, and eigenvector centrality than the other cases. After the index hospitalization, although these 3 cases did not have significantly higher distribution in providers' degree and betweenness centrality, their inpatient and outpatient providers' eigenvector centrality was significantly higher than that of the other cases.

4.3.2.3 Network Structural Characteristics for Reviewed Cases

Table 17 shows the structural characteristics of the provider networks for the 11 cases. High variance exists in the structural characteristics of individuals' provider networks. Although all of the 5 cases who had one or no negative social stratum had outpatient encounters and outpatient providers involved in care management, 4 of the 6 cases with intersections of 2 or more negative social indicators (Cases 7, 8, 9, 11) did not have any outpatient providers involved before the index hospitalization. The size of the cases' inpatient provider networks (number of providers) ranged from 3 to 153, and 7 to 266, before and after the index hospitalization, respectively. The size of the outpatient provider networks was smaller than that of the inpatient networks, ranging from 0 to 19, and 1 to 64, before and after the index hospitalization, respectively. The density of inpatient and outpatient providers tended to remain about the same or increase after the index hospitalization. Those with 1 or no negative social stratum tended to have fewer providers who were unconnected with other providers (isolates in SNA) than those with intersections of 2 or more negative social indicators.

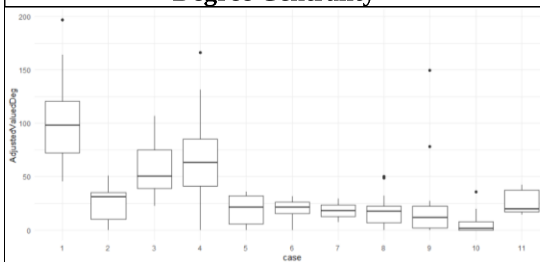
The network size during the index hospitalization ranged from 3 to 33, the network density ranged from 0.056 to 0.944, and the components ranged from 1 to 10. Three of the 5 cases with 1 or no negative social stratum had density on the higher end, and 2 of the 7 cases with intersections of 2 or more negative social stratum had density on the higher end. At the index hospitalization, those with 1 or no negative social stratum also tended to have fewer components than those with intersections of 2 or more negative social indicators.

Table 14: Distribution of Providers' Positional Measures for Each Case before the Index Hospitalization

	Inpatient and Outpatient	Outpatient[a]	Inpatient
Degree Centrality			
Betweenness Centrality			
Eigenvector Centrality			

[a] Cases 7, 8, 9, 11 did not have any outpatient encounters before the index hospitalization

Table 15: Distribution of Providers' Positional Measures for Each Case during the Index Hospitalization

<table>
<tr><th>Degree Centrality</th><th>Betweenness Centrality</th><th>Eigenvector Centrality</th></tr>
<tr>
<td>
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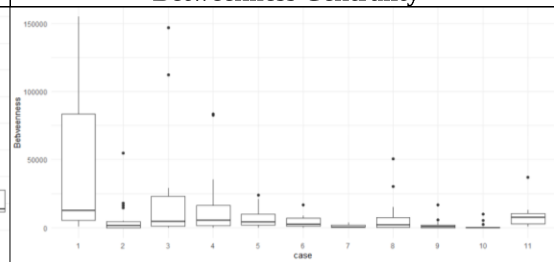
<td>
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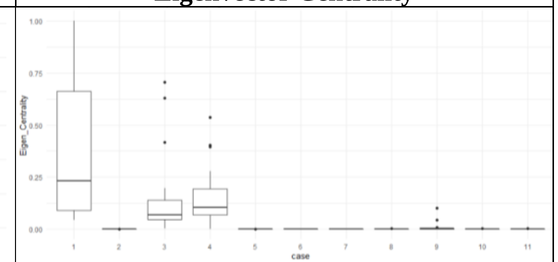
<td>
</td>
</tr>
</table>

Table 16: Distribution of Providers' Positional Measures for Each Case after the Index Hospitalization

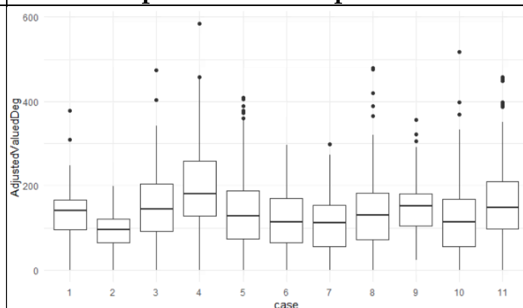
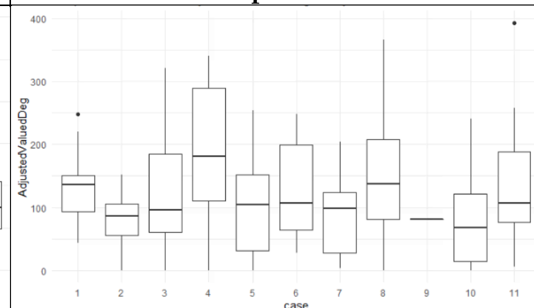
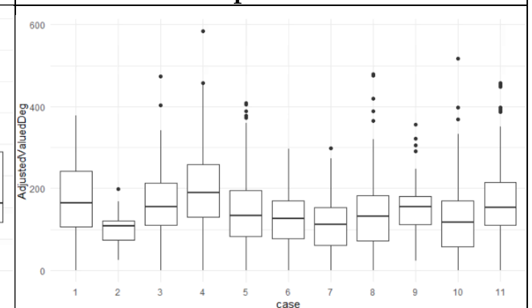
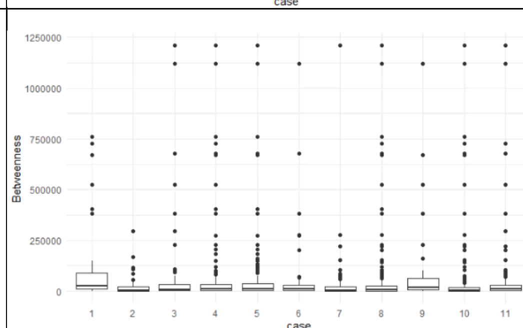
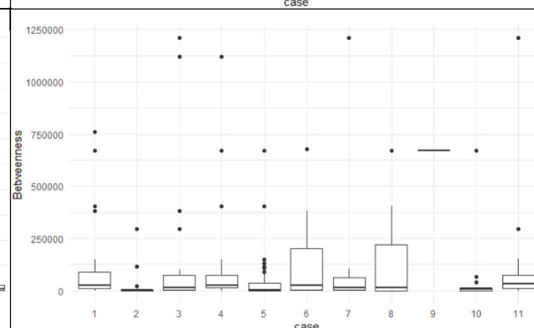
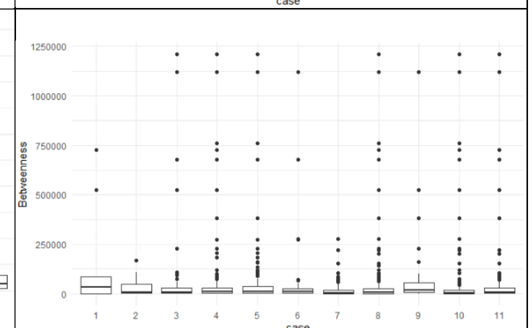
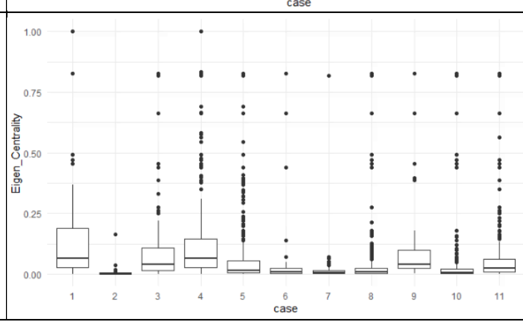
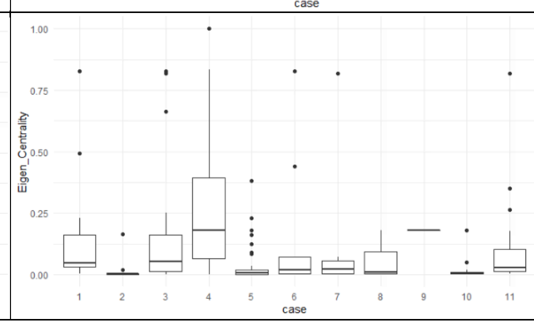
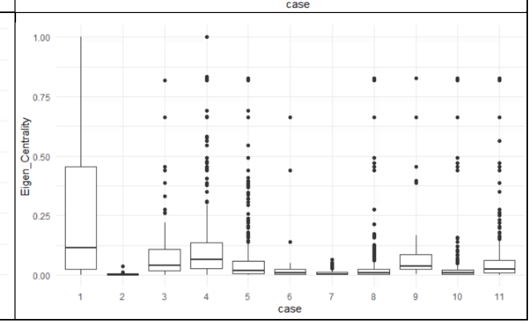
	Inpatient and Outpatient	Outpatient	Inpatient
Degree Centrality			
Betweenness Centrality			
Eigenvector Centrality			

Table 17: Structural Characteristics of Inpatient and Outpatient Provider Networks by Case

	1-year before the Index			Index Hospitalization			1-year after the Index		
Inpatient Provider Network-Level Characteristics									
Case	Size	Density	Components	Size	Density	Components	Size	Density	Components
1	26	0.434	5	9	0.944	1	7	0.810	1
2	4	0.333	2	18	0.386	4	21	0.771	1
3	9	0.639	1	17	0.640	2	66	0.578	3
4	153	0.412	13	33	0.725	2	197	0.677	4
5	3	1.000	1	8	0.357	3	236	0.432	6
6	38	0.447	3	9	0.361	2	59	0.419	3
7	8	0.214	3	3	0.667	1	65	0.617	3
8	3	0.333	2	31	0.318	4	243	0.395	11
9	10	0.756	1	14	0.066	9	31	0.723	1
10	119	0.327	5	15	0.048	10	266	0.316	21
11	4	0.333	2	7	0.619	1	198	0.435	3
Outpatient Provider Network-Level Characteristics									
1	14	0.758	1				24	0.830	2
2	11	0.855	1				16	0.475	2
3	6	0.200	3				28	0.606	4
4	12	0.439	2				49	0.794	2
5	13	0.551	3				64	0.327	7
6	8	0.250	3	Not Applicable			11	0.545	1
7	0	0.000	0				14	0.560	1
8	0	0.000	0				10	0.467	2
9	0	0.000	0				1	0.000	0
10	19	0.246	5				33	0.212	5
11	0	0.000	0				35	0.647	1

4.3.3 Social Context and Structure for Care Coordination in Care Transitions

Integrating the qualitative and quantitative data revealed that combining social network analysis with EHR data was informative for understanding the social context and structures essential for care coordination in care transitions. Those patients with more socioeconomic disadvantages were less likely to have visited outpatient providers before the index hospitalization and tended to interact with a higher proportion of providers during acute care encounters overall. Turbulence in care transition can result from sources other than transitioning between settings. Three themes emerged as main barriers or facilitators to coordinated care and well-managed symptoms: social stability, lost in the maze, and the strength of the triangle.

4.3.3.1 Social Instability

Social instability was a common theme for patients with intersections of 2 or more negative social strata. Those 6 patients (Cases 5, 7, 8, 9, 10, 11) tended to have more frequent acute care utilization, particularly ED visits; were less likely to attend follow-up appointments scheduled at discharge planning; and were harder for case managers to reach via telephone.

The primary reason for acute care utilization was unmanaged or worsening symptoms. However, all of the patients with intersections of 2 or more negative social strata were noted as being noncompliant with medications (Cases 5, 8, 9, 10, and 11) or diagnosed with "total self-care deficit" (Cases 7). They were much more likely to have no caregiver support (Cases 5, 7, 8, 9) and have difficulty going to appointments or pharmacies due to lack of transportation (Cases 5, 7, 8) or paying for medications (Cases 5, 8, 9, 10, 11). In addition, they often experienced instability in their living environment, such as being homeless (Cases 8 and 9), living in a trailer home (Case 5), living in a sibling's home (Case 10), or being incarcerated (Case 9). Additionally, 3 (Cases 7, 9, 10) of these 6 patients struggled with cocaine addiction, although only 5.8% of the cohort reported using illicit drugs. All of these 6 patients lived in deprived environments, 5 (Cases 5, 8, 9, 10, and 11) were on Medicaid, and 5 (Cases 6, 8, 9, 10, and 11) were African American.

Although noted as having difficulties complying with medication and care plans, these 6 patients showed initiative or intent to manage care, as observed by their behaviors: They regularly communicated with PCPs to manage care and regularly visited the ED to seek help and medicine; however, their lack of social stability and support likely hindered their care management. For example, 3 (Cases 5, 7, 8) of the 4 patients with no caregiver support (Cases 5, 7, 8, 9) told providers that their reason for missing appointments or medicine was lack of transportation. It is particularly difficult for patients experiencing homelessness to follow care plans. For example, one patient (Case 8) told a provider that it was hard for him to follow dietary recommendations because "[I] can't get to the grocery and can't walk far, no one to help," and another patient (Case 9) had a note that said, “He reports being homeless at this time, making diet compliance difficult. His diet consists of fast food meals.” Although these patients had multiple encounters with case management and follow-up appointments with a PCP and cardiologist set up at discharge planning, both missed almost all their scheduled ambulatory appointments.

Poorly or unmanaged HF symptoms also contribute to a vicious cycle of social instability and increased difficulty managing care. For example, as shown in telephone notes, one patient (Case 5) canceled appointments because she was unable to travel far due to shortness of breath; although using oxygen helped with her shortness of breath, carrying an oxygen tank outside of the home without assistance made her short of breath and unable to attend her appointment. Other patients (Cases 7 and 11) complained of an inability to continue working due to symptom burdens, which increased their economic instability further.

Those patients with poor social stability seemed to rely more heavily on formal systems (e.g., the hospital) for social support and resources. Due to the financial inability to buy medications, all of the Medicaid users used the ED to obtain better access to medications or care support (Cases 5, 8, 9, 10, 11). For example, one patient’s (Case 9) providers noted, “Patient presents requesting medication refills. Denies any acute complaints today . . . states that he was d/c'ed from the hospital and they prescribed him all of his medications, and he is now out of them." Although clinical notes showed that his symptoms were stable, one patient (Case 8) had 7 ED visits or inpatient stays in June and spent most nights in the hospital (with the exception of June 1-3 and June 10).

4.3.3.2 Lost in the Maze

Notes showed that even patients with low socioeconomic disadvantages and good family support, and without care access issues, (e.g., Cases 2 and 3) could find their journey to manage care and symptoms was not always smooth. Both patients had periods of time during which they experienced an increasing burden of symptoms that led to a hospital admission through the ED for exacerbation of HF, despite their having visited outpatient providers from different clinics or departments during these periods. They did not seem to have established a reliable and consistent working relationship with one care team; although their conditions were declining, no telephone conversations with their providers were noted related to care or symptom management between visits. Both patients had received adequate discharge planning during hospitalization. Their turbulence in care did not seem to have been caused by changes in care settings, but rather by changes in or lack of care relationships with provider teams who could guide care management and coordination in the community setting during times of change in needs.

One patient (Case 2) had regular communication with her PCP during the first half of the year before her index hospitalization, calling or visiting the PCP first whenever acute events like falls or changes in symptoms occurred. However, her PCP left the system, and she seemed to experience a period of loss and difficulty finding someone with whom to consult when experiencing a change in her condition or symptoms. Notes and encounters suddenly ceased for 5 months, until a newly designated PCP was listed in the system around 2 months before the index hospitalization. The patient seemed to struggle to establish the same regular and timely communicative relationship with the new PCP as with her first PCP. Although she established care with the new PCP two months before the index hospitalization, she also visited 3 other physicians from the same primary care clinic (one of whom referred her for the index hospitalization), skipped her scheduled Medicare annual wellness check, had little to no telephone communication with the new PCP between visits, and requested that the clinic to change her PCP after her second hospitalization for HF exacerbation 1 year after the index hospitalization.

Although this patient's outpatient provider network became bigger and more diverse after her index hospitalization because specialists from wound care and cardiology joined her care team, the density of her outpatient provider team dropped from 0.86 to 0.48, and all her other network characteristics were about average to lower compared with other patient cases. Her first PCP had held the primary provider care team together as a tight cluster, operating at the central position in the network to direct care management and connect the patient with health care services like home health care as needed. Loss of the central provider with whom the patient had worked closely, and her inability to establish a similar relationship with another PCP or specialist, could have contributed to her more frequent outpatient utilization with different physicians from the same clinic, an unmanaged and nonhealing ulcer before the index hospitalization, and more symptom burden reported in notes after the index hospitalization. Her experience of an unhealed ulcer, noticeable change of communication and utilization patterns with her PCP, and telephone notes showing a caregiver's report of a wrong medication dosage sent to the pharmacy indicate that she likely struggled to find proper care after her first PCP left the system.

Similarly, another patient (Case 3) had consistent and regular visits with her PCP but experienced a period of uncertainty and difficulty finding key teams for guidance and support while experiencing worsening cardiovascular symptoms before her index hospitalization. Despite established consultations with a cardiologist and other specialists such as endocrinologists at Duke following referrals by her PCP before her index hospitalization, she did not seem to have established a close working relationship with the cardiologist similar to the supportive relationship indicated by regular communications with her cardiologist-surgeon team for symptom management and medication titration later in her care trajectory. Her index hospitalization was unplanned due to HF exacerbation. At the index hospitalization, she was connected with a surgeon who coordinated a subsequent hospitalization for a scheduled surgery for mitral valve replacement. After her surgery, the surgeon's team helped her transition back into the hospital as an inpatient due to post-surgery complications. The surgeon also connected her with a cardiologist who had a strong working relationship with the surgeon's team. Afterwards, she regularly called and visited the cardiologist team to optimize medications and symptom management, and she occasionally consulted the surgeon according to her most recent notes. Becoming connected and establishing a trusted working relationship with the strongly connected cardiologist and surgeon care teams seemed to be a turning point for this patient, from a period of not knowing whom to ask to manage her care to a later period of coordinated and continuous planned care in the outpatient setting. Her outpatient provider network density increased from 0.20 to 0.61.

Similar to the above patient, two other patients (Cases 6 and 10) had family caregivers and a consistent PCP before and after the index hospitalization. Their PCPs ordered home health care to support their care management and referred them to various specialists before the index hospitalization. Although both visited various specialists referred by their PCPs, each patient had more than one rehospitalization after the index hospitalization and did not initiate or establish bidirectional communication with a cardiovascular provider team to optimize medicine and manage HF-related symptoms. One of the patients in particular (Case 10) struggled to manage her symptoms and had 13 ED visits and 10 inpatient stays. Although her case involved 19 outpatient providers before and 33 outpatient providers after the index hospitalization, her provider network density was 0.25 and 0.21.

The patient in Case 11 had the most outpatient encounters but also higher ED stays (n = 7) and inpatient stays (n = 5). She seemed to struggle to establish bidirectional communication patterns for care or symptom management with an outpatient care team overall. She did not have a PCP before the index hospitalization or a consistent PCP after the index hospitalization, and had no outpatient care providers before the index hospitalization. This patient had a mitral valve replacement after her index hospitalization, similar to the patient in Case 3; however, she struggled to manage her symptoms despite the involvement of outpatient specialists, and she frequented the ED with complaints of symptoms such as nausea, vomiting, GI issues, and shortness of breath. She had regular ambulatory anticoagulation visits after her surgery with a densely connected team (density = 0.65), but these visits seemed to be highly specialized for anticoagulant monitoring only and did not address symptom management. She did not communicate consistently with an outpatient provider team to obtain help to manage her symptoms.

4.3.3.3 The Strength of the Triangle

While reviewing the cases of two patients (Cases 1 and 4) who experienced the smoothest transitions and comparing other patients' access and communication behaviors for care management, I found that the presence of three key roles/teams (the patient and caregiver[s], primary care, and cardiovascular specialty team) were part of smooth care coordination in care transitions. More important, reciprocal communication or bidirectional interactions among these three teams to coordinate care over time emerged as crucial for dealing with changes in conditions or symptoms over time. Regarding the patients with the smoothest transitions (Cases 1 and 4), their hospitalizations were advised or referred by providers, and their inpatient notes mentioned care plans from outpatient notes or links with provider-patient/family conversations during outpatient encounters. These patients had low or average acute care utilization frequency and are still alive, and one (Case 4) underwent a successful heart transplant.

Both patients had strong care support from their wives and showed self-care efforts by continuously engaging in care conversations with their providers. Before the index hospitalization, both had existing and consistent PCPs and actively communicated with their cardiovascular team to obtain refills, express questions or concerns, or discuss changes in symptoms via telephone and Mychart messages. They had regular in-person and remote encounters with their primary care and cardiovascular teams, and both of their index hospitalizations were referred or suggested by cardiologists.

Although the patient in Case 1 was the second oldest patient in the cohort and had a similar or worse comorbidity burden and severity of illness than most of the other patients, he seemed to be the best at managing his care and had the fewest number of hospitalizations among the reviewed cases. This patient lived in an affluent area and used provided resources such as cardiac rehab and social work consultations effectively.

He was compliant with diet, exercise, and medication recommendations according to notes. His wife was a registered nurse who helped with him when needed, and he had a Master's degree and seemed to have high health literacy. Although his PCP was at a different health system, he informed his Duke cardiologist through Mychart when he saw his non-Duke providers and informed his providers about medication changes or any errors he noticed in his medical records.

Strong reciprocal interactions among patient/family, PCPs, and cardiology teams before the index hospitalization not only helped with smooth transitions before and after the index hospitalization but also with subsequent hospitalizations. Two patients' (Cases 1 and 4) network characteristics seemed to reflect smoother and more coordinated care transitions than those of the other patients. Their providers were in more central positions in the whole system network, as shown by more centralized positions in the whole network (higher adjusted valued degree), were more likely to bridge provider teams (higher betweenness centrality), and were connected with more highly connected providers (higher eigenvector centrality) on average before, during, and after their index hospitalizations (Tables 14, 15, and 16). Their provider networks during the index hospitalization had the highest in density at the index hospitalization and were more densely connected for both inpatient and outpatient encounters before and after the index hospitalization; this was particularly apparent for outpatient encounters and after the index hospitalization compared with the other patients' cases (Table 17).

4.3.4 Network Matters: Inequalities in Provider Network Characteristics

People with more socioeconomic disadvantages were less likely to have providers in central positions in the system network, and their provider teams were less densely connected. Four cases were at polar ends of the range of socioeconomic disadvantages: patients in Cases 1 and 3 had intersections of 1 or less negative social strata, and patients in Cases 5 and 10 had intersections of 2 or more negative social strata. These patients had a similar presence of types of providers involved in their care throughout the study period (consistent PCP teams and regularly accessed cardiovascular and/or pulmonary outpatient services and other specialists), but they showed very different network characteristics and care outcomes. Patient cases 1 and 3 had no ED visits, and low and mostly planned hospitalizations during the study period, and they are still alive today (more than 3 years after their index hospitalization); in comparison, both patients in cases 5 and 10 had frequent inpatient and ED encounters, and patient case 10 had an unplanned 30-day readmission after the index hospitalization. Both of these patients died within a year of the index hospitalization (Table 18).

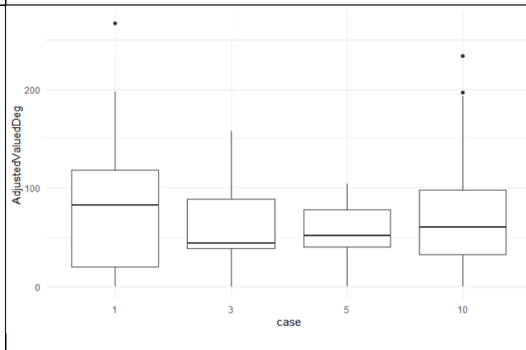
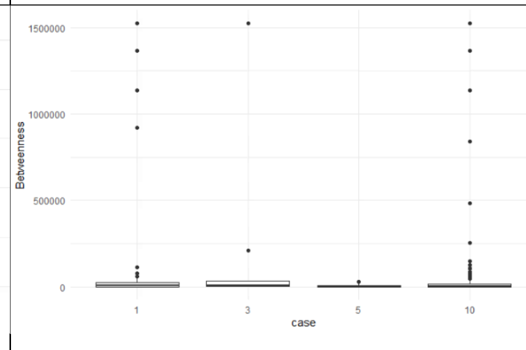
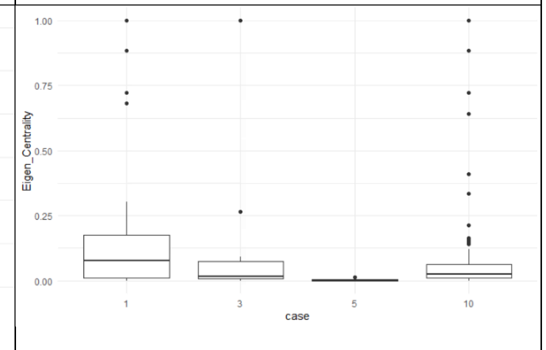
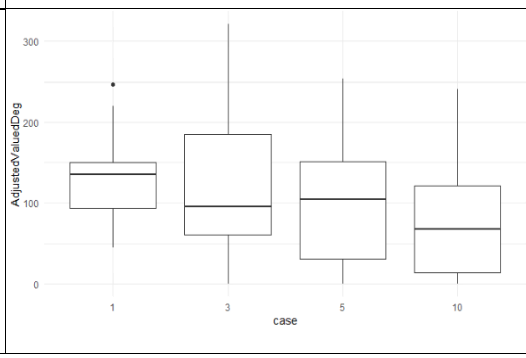
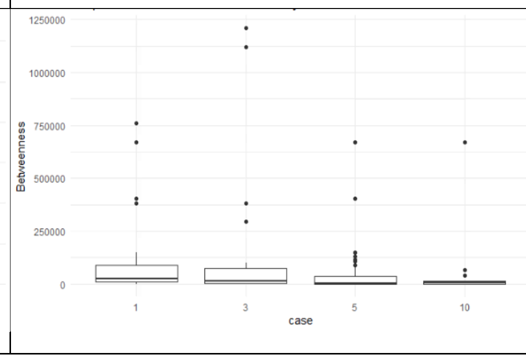
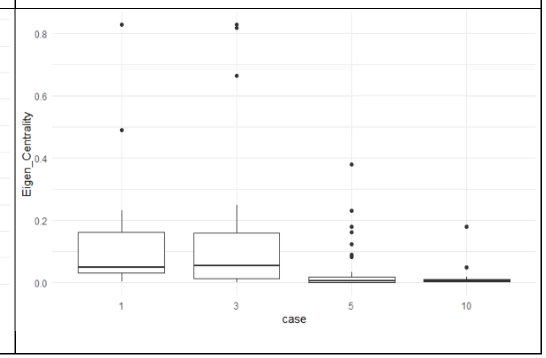
Table 18: Inequalities Shown in Care Access and Outcomes among Four Cases

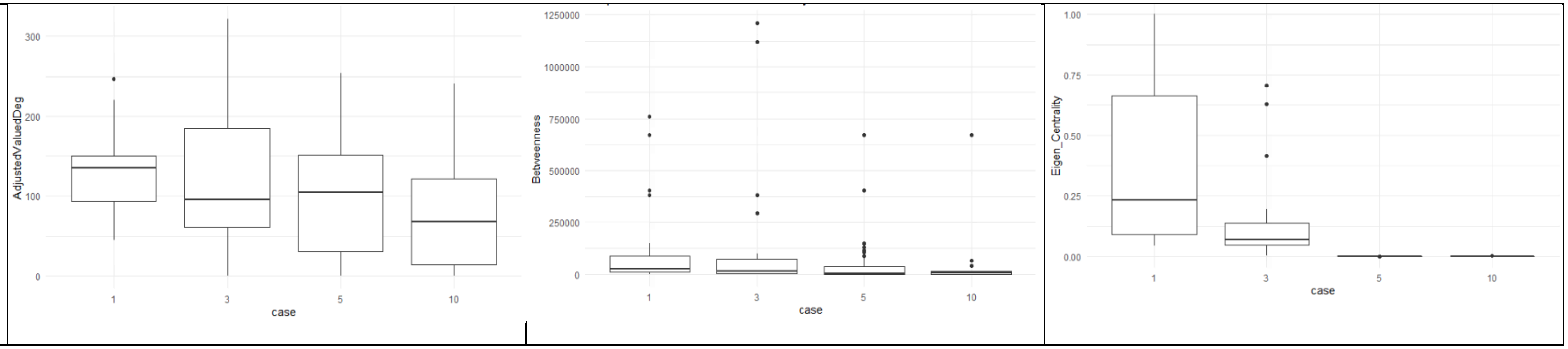
	Utilization			Outcomes	
Case	**Outpatient Frequency**	**ED Frequency**	**Inpatient Frequency**	**30-day Readmit**	**Days to Death**
1	47	0	2	No	Alive
3	20	0	3	Planned	Alive
5	38	3	9	No	310
10	13	13	10	Yes	206

The patients with intersections of 1 or less negative social strata tended to have better care coordination than those in the other two cases, as demonstrated by their having more consistent and bidirectional interactions or conversations with ambulatory providers after the index hospitalization. The patients in Cases 1 and 3 were much more likely to have outpatient providers in key network positions; their providers had a higher average degree centrality, betweenness centrality, and eigenvector centrality as well as more outliers who were high in these three centrality measures (Tables 14, 15, and 16). The inequalities in providers' positional measures among the 4 cases were especially obvious for outpatient providers before and after the index hospitalization and inpatient providers at the index hospitalization, and for the eigenvector centrality measure (Table 19). The patients in Cases 1 and 3 also had a higher density provider network overall—in particular, their inpatient provider team at the index hospitalization and their outpatient provider team after the index hospitalization (Tables 20 and 21). Their providers had stronger connections measured by tie weights shown as tie thickness and much higher eigenvector centrality (shown as node size in Tables 20 and

21). The provider network for Cases 1 and 3 were high in centrality and densely connected.

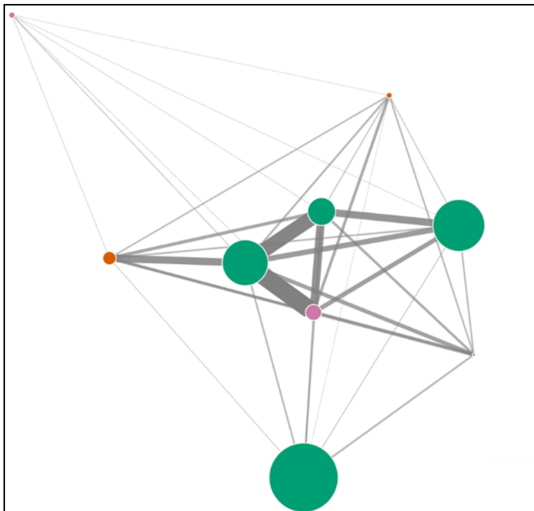
Table 19: Distribution Positional Network Characteristics for Outpatient Providers

	Degree Centrality	Betweenness Centrality	Eigenvector Centrality
Before			
After			

Index	

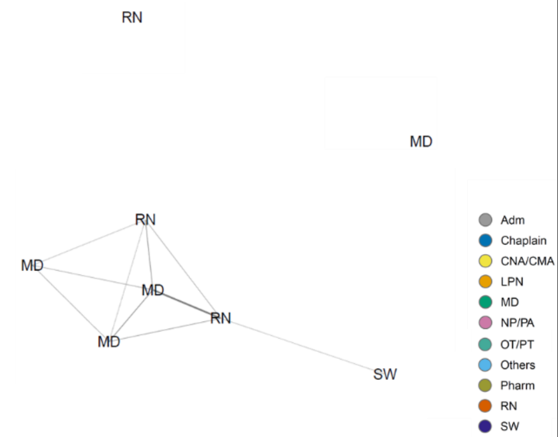
AdjustedValuedDeg
300
200
100
0
case
1
3
5
10
Betweenness
1250000
1000000
750000
500000
250000
0
Eigen_Centrality
1.00
0.75
0.50
0.25
0.00

Table 20: Individuals' Provider Networks at Index Hospitalization



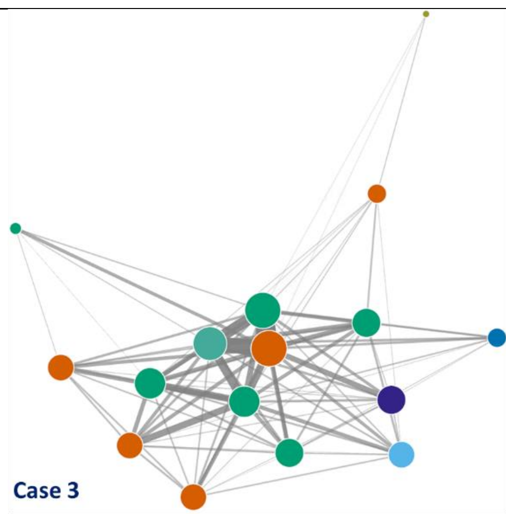
Case 1

Length of Stay = 3.01 days; Severity of Illness = 2;
Network Size = 9; Density = 0.944; Components = 1



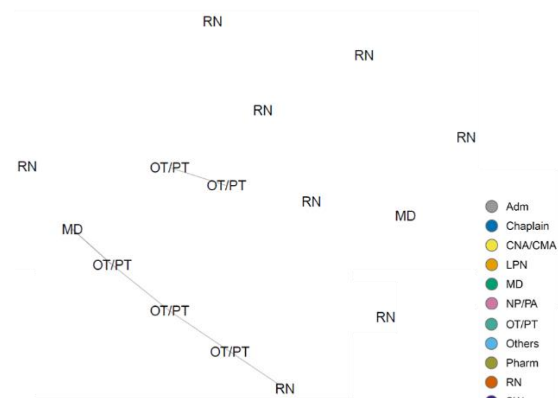
Case 5

Length of Stay = 2.24 days; Severity of Illness = 2;
Network Size = 8; Density = 0.357; Components = 3



Case 3

Length of Stay = 3.23 days; Severity of Illness = Moderate;
Network Size = 17; Density = 0.640; Components = 2



Case 10

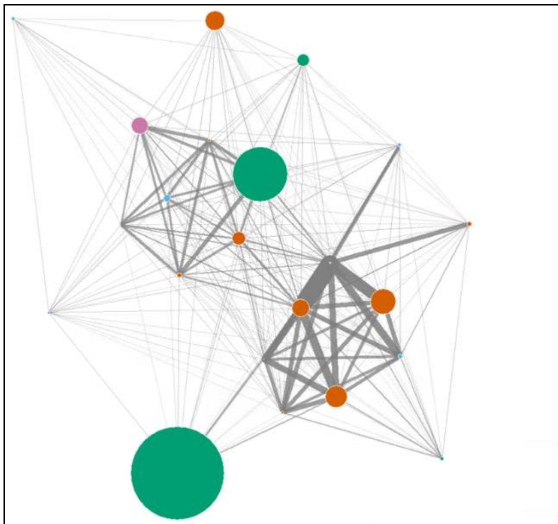
Length of Stay = 5.21 days; Severity of Illness = Major;
Network Size = 15; Density = 0.0952; Components = 10

*Thickness of the ties was based on tie weight, indicating the strength of ties.
Size of the nodes were based on providers' eigenvector centrality.
The acronyms indicate provider role or credential.

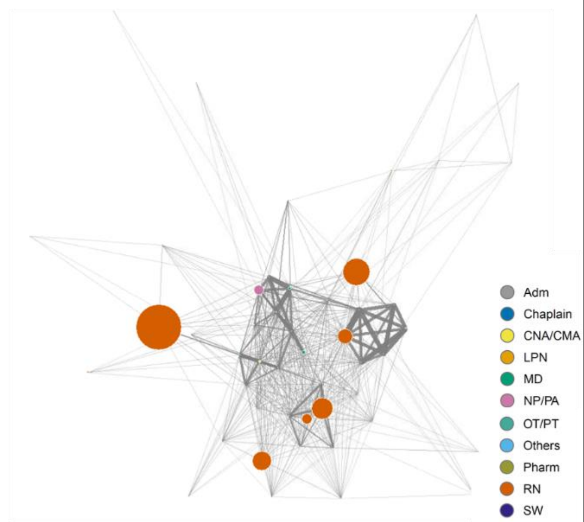
- Adm = Administrative Staff
- Chaplain = Chaplain
- CNA/CMA= Certified Nursing Assistant/Certified Medical Assistant
- LPN = Licensed Practical Nurses
- MD = Doctor of Medicine or Doctor of Osteopathic Medicine

NP/PA = Nursing Practitioner or Physician Assistant
OT/PT = Occupational Therapist or Physical Therapist
Others = Others
Pharm = Pharmacist
RN = Registered Nurse
SW = Social Worker

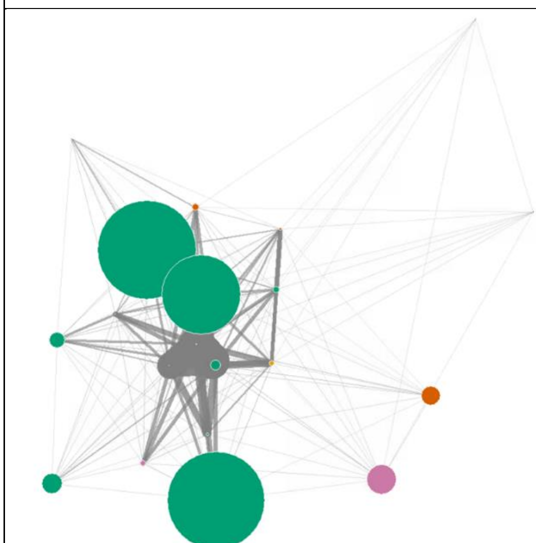
Table 21: Individuals' Outpatient Provider Networks after the Index Hospitalization



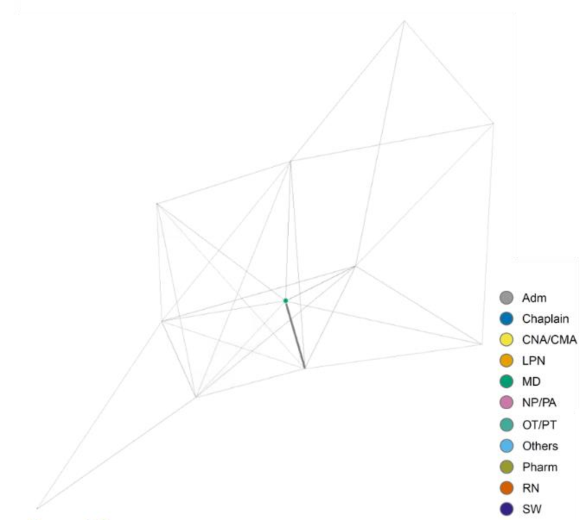
Case 1
Network Size = 27; Density = 0.830; Components = 2



Case 5
Network Size = 64; Density = 0.327; Components = 7



Case 3
Network Size = 28; Density = 0.606; Components = 4



Case 10
Network Size = 33; Density = 0.212; Components = 5

*Thickness of the ties was based on tie weight, indicating the strength of ties.
Size of the nodes were based on providers' eigenvector centrality.
The acronyms indicate provider role or credential.

Adm = Administrative Staff
Chaplain = Chaplain
CNA/CMA= Certified Nursing Assistant/Certified Medical Assistant
LPN = Licensed Practical Nurses

MD = Doctor of Medicine or Doctor of Osteopathic Medicine
NP/PA = Nursing Practitioner or Physician Assistant
OT/PT = Occupational Therapist or Physical Therapist
Others = Others
Pharm = Pharmacist
RN = Registered Nurse
SW = Social Worker

4.4 Discussion

This study demonstrates the feasibility of combining SNA and clinical notes from EHRs to uncover the social context and structures involved in care coordination for patients who have undergone HF transitions in routine care as well as their possible relationships with inequities in care outcomes. The three indicators of socioeconomic disadvantages used in purposive sampling did capture people with a wide range of social conditions. Those who were less socially disadvantaged were more likely to have more coordinated care and better health outcomes, such as less acute care hospitalization, no ED stays, more planned inpatient stays, and a longer life. Adding to existing knowledge on factors such as the severity of illness, health behaviors, and comorbidities that influence care outcomes of patients with HF (Chamberlain et al., 2017; Chamberlain et al., 2018; Eapen et al., 2015; Li et al., 2019; Patel et al., 2020; Su et al., 2019), results from our study suggest that socioeconomic inequalities are related to care coordination, manifested as inequalities in network characteristics, and consequently related to care outcomes.

Two critically important network features that advance the science of care coordination were identified in this study. First, the presence of bidirectional communication or interaction patterns among three key roles (patient and family, primary care, and cardiology teams) is important for longitudinal care management and coordination, especially when a patient is adapting to changes in symptoms and conditions. The reciprocal communication patterns observed from qualitative analysis of clinical notes probably indicated strong relationships among these key roles (Tasselli & Caimo, 2019; Valente, 2010). Patients who exhibited reciprocal communication patterns likely had providers with strong ties demonstrated their providers had high tie weights and dense networks indicated by high density and low components in their network structure. More densely connected provider networks may indicate closer working relationships for care coordination and more efficient teams, and less likelihood of medical errors (Song, 2013; Turnbull et al., 2018; Valente, 2012). Although patients' communications and visits with provider teams can fluctuate widely depending on symptom exacerbation, the establishment of a bidirectional relationship with a provider team, and continuous telephone and progress notes with the same primary and heart care teams over time were common features among the patients who had fewer unplanned ED or inpatient stays. Lack of consistency in communication with ambulatory providers for symptom management over time may suggest that patients struggle with ambiguity about whom to contact with questions or in the event of deterioration or exacerbation (Safstrom et al., 2018).

The second important feature is the placement of well-connected providers in central positions within the system as indicated by centrality measures. People in more central positions (indicated by degree centrality) or bridge positions (indicated by betweenness centrality) in the network can have a greater influence on system function, connectivity, and information consistency, so patients working with providers in more central network positions may have an advantage toward receiving a high quality of care (Granovetter, 1973; Song, 2013; Turnbull et al., 2018; Valente, 2012).

In this study, patients less socioeconomic disadvantaged were more likely to exhibit a connection to the two important network features and had better care outcomes. They had providers with a higher degree centrality, especially at the index hospitalization, meaning that they had providers who were in more central positions in the system, and were connected with more important providers than average (Valente, 2010). These patients also had a higher average of and more outliers in betweenness centrality, meaning that their provider team consisted of providers who could reach other providers more quickly and bridge clusters of provider teams (Valente, 2010); thus they would have the ability to connect patients quickly with new care teams for increased support such as home health care or rehabilitation, or with providers with specialized expertise such as cardiologists or surgeons. These patients also had average and more outliers in eigenvector centrality, meaning that their providers were connected to more influential or resourceful providers. Providers with high eigenvector centrality may more easily exercise their social capital (i.e., social relationships that can provide resources to help achieve desired outcomes) and accelerate patients' access to a better quality of care, especially for care continuity during a time of change, such as rapidly declining conditions.

Furthermore, although most transitional care is focused on processes during hospitalization and post-discharge, we found that differences in relationship structure for care coordination between the patient cases with better or worse coordinated care were apparent during the year before the index hospitalization. Patients who were less influenced by socioeconomic disadvantages were more likely to have social support, stability, and connection with more influential providers in the network before discharge from their initial HF hospitalization. Among the reviewed cases, although well-recognized transitional care processes such as comprehensive discharge planning, post-discharge follow-up calls, and scheduling of PCP and cardiologist follow-up appointments were in place, these care components did not address the main drivers of care turbulence: lack of consistent and reciprocal working relationships with an ambulatory care team to maintain longitudinal care management and coordination during changes in condition or symptoms. Future studies of care coordination in care transitions should focus attention on shifts in care relationships rather than directing attention solely to care settings or tasks across the care continuum.

Examination of patients' social context and structure before and after the index hospitalization showed that the intersection of different socioeconomic disadvantages contributes to two main concepts previously shown to influence health outcomes: social stability and social capital (German & Latkin, 2012; Song, 2013). Similar to previous findings, patients who experienced less or no socioeconomic disadvantage had better social stability and were more likely to have partners or families for care support (social capital from an informal care system) (German & Latkin, 2012; Uphoff et al., 2013). Experiencing social instability and low informal care support created barriers to care management and coordination. For example, difficulty purchasing medication or attending scheduled follow-up appointments was common across all cases with intersections of 2 or more negative social strata. Social instability can negatively influence people's ability to retain or gain social capital from the informal care system and vice versa (German & Latkin, 2012; Song, 2013). Although influencing social stability and social capital from informal care systems may be difficult, providers can help improve health inequity by leveraging social capital from the formal care system to buffer the negative effects of social instability and lack of social capital from the informal care system on health outcomes.

As opposed to findings in the existing literature, this study found that quality rather than quantity of social capital from formal care systems across the care continuum affects health outcomes. Patients who experienced more socioeconomic disadvantages in this study had a similar or greater number of providers involved in their care than other patients, especially at and after the index hospitalization. Among patients with a similar outpatient care access and types of provider roles involved, those who were more socioeconomically disadvantaged had higher acute care access and equal if not more access to case managers and discharge planning, yet they were less likely to (a) have consulted with and established reciprocal relationships with a cardiovascular team before the index hospitalization, (b) have densely connected provider networks, and (c) have providers who were central or influential positions in the cardiovascular care system. More does not necessarily mean better care coordination or quality of care (McWilliams, 2016). Characteristics of provider networks (i.e., social capital from formal care system) can be potential indicators to infer the quality of care coordination. Current transitional care interventions have focused on additive effects, assuming that more care components or encounters result in better outcomes. Future studies should evaluate and focus more on quality of care coordination than on quantity or components of care coordination in influencing care outcomes.

4.5 Conclusion

To our knowledge, this is the first study combining clinical notes and social network analysis to improve understanding of the quantitative and qualitative characteristics of care coordination in care transitions for patients with HF. Social network analysis deepened our understanding of the social context and mechanisms for care coordination. The qualitative data in clinical notes showed providers' realistic views of patients' care trajectories and patterns of care interactions that have not been previously well studied. Socioeconomic disadvantages can be manifested as intensity or quantity of social instability and lack of family care support, and moreover, was shown to be related to characteristics of patients' provider networks. More socially advantaged patients tended to be connected with more central and well-connected providers in the system and to have denser networks. This feasibility study shows that a larger future study with more samples is warranted to evaluate and identify provider network types and the evolution of networks more comprehensively as well as how they are related to health outcomes.

5. Conclusion

5.1 Key Findings

Care coordination has been well recognized as the key to ensuring that care is integrated rather than fragmented. Extensive research exists related to care coordination and transitional care (Albert et al., 2015; Coffey et al., 2017; Kilbourne et al., 2018; McDonald et al., 2014); however, studies of implementation and care coordination processes and complex relationships among services and providers are often focused on a single setting, discipline, or care episode. To address this gap, this dissertation aimed to gain a more comprehensive understanding of care coordination processes in HF care transitions by evaluating the longitudinal and relational processes among services and providers in inpatient and outpatient settings. To achieve this overall goal, this dissertation used novel approaches to identify previously unexplored patterns important for care coordination. Chapter 2 revealed the complex and relational processes and structures involved during transitional care intervention delivery by integrating SNA theories and techniques into a review of published transitional care interventions. Chapter 3 identified outpatient and acute care utilization patterns and factors associated with consistently high acute care utilization by using group-based trajectory modeling. Chapter 4 demonstrated the feasibility of using clinical notes and SNA to assess providers' networks for patients with HF in care transitions and showed the potential to capture structural inequalities that exist in care delivery and may influence the efficiency of care coordination and health outcomes for patients with HF.

5.1.1 Network Lens to Review Transitional Care interventions

Care coordination processes are highly relational and variable. SNA is a feasible and promising approach to obtain a systematic understanding of relational processes essential for care coordination. Our integrative review of transitional care interventions published after 2010 systematically evaluated the care coordination processes involved in delivering transitional care interventions for older adults with HF through a social network lens.

Findings regarding the effectiveness and components of transitional care interventions were consistent with those of previous literature reviews. Reviewed interventions were highly variable regarding setting, timeframe, involved individuals, and mode and frequency of interactions among individuals. Despite the high variability in how transitional care interventions were delivered across studies, a majority of the interventions demonstrated a triadic network structure in which interventionists occupied bridge positions; more complex network structures occurred when interventionists occupied the most central positions in the network. Ties between individuals across settings were generally sparse and weak in most studies; however, a few with more complex network structures demonstrated the potential of transitional care interventions to increase the system's connectivity by fostering multiple ties among providers across settings.

While none of the reviewed studies were guided by SNA theory, SNA provides a systematic approach to evaluate the complex relational processes and structure essential for care coordination. Viewed through a social network lens, transitional care is a special set of tasks supported through a pattern of processes necessary to foster a timely transfer of information, and processes are dependent on relationships across hospital and community settings. Future transitional care intervention development may be enhanced through systematic attention to the properties of relational processes and structure essential to care coordination in care transitions. Empirical knowledge obtained from using SNA to evaluate multidisciplinary provider network roles in the overall system comprehensively is needed to better determine key players and their functions in care coordination processes and inform future transitional care improvements.

5.1.2 Relationship between Outpatient and Acute Care Utilization

Chapter 3 demonstrated that outpatient care influences acute care utilization and provided a longitudinal perspective on outpatient and acute utilization that expanded our perspective on readmission for patients with HF. There is significant heterogeneity in patients' outpatient and acute care utilization. This study enhanced our understanding of how outpatient utilization was associated with patients' acute care utilization and revealed a possible approach to identify patients with high needs and high costs. The relationship of high-intensity outpatient care with high acute care utilization may be an essential and actionable indicator of fragmented care. Characterizing heterogeneity in utilization and its relationship to outpatient care patterns may be useful to tailor future interventions in the outpatient setting, improve the overall 30-day readmission rate, and promote the delivery of more patient-centered care.

5.1.3 Inequalities in Social Context and Structure

Inequalities exist in patients' provider-network position and structure, and these inequalities influence care outcomes. Chapter 4 supported existing evidence that social barriers influence care coordination and outcomes. Patients who were more socioeconomically advantaged were more likely to have smoother care transitions and better health outcomes. More importantly, this chapter found new knowledge that patients who were more socioeconomically advantaged were more likely to have providers whose teams were more closely connected and who were more central and influential in the system network. Lack of consistent and reciprocal relationships with outpatient provider teams, especially PCP and cardiology, was precedent to poor care management and coordination, not change in care settings.

This dissertation not only included traditional individual-level social determinants of health but also demonstrated characteristics of social structures in the system that may contribute to health outcomes and health inequity (Southwell, 2013). Poor care transitions commonly happen when patients have unstable care relationships with providers, despite care management and discharge planning efforts consequent to hospitalization. Additionally, differences in provider network characteristics, as well as differences in utilization and outcomes between patients who were socioeconomically advantaged or disadvantaged, indicated inequalities in the social structure that may underlie some of the variability and inequalities in care outcomes. Well-connected care teams who work with patients and families in outpatient settings are key to effective care transitions and may mediate inequalities in health outcomes.

5.2 Implications for Research

This dissertation provided evidence regarding the processes and structure that form the backbone of care coordination. Recognizing and understanding the inherent mechanisms of care integration offers a high potential for improving how researchers and providers view, investigate, and implement transitional care, and for improving health outcomes for people with HF.

5.2.1 Theoretical Perspective

Current transitional care research has been dedicated to evaluating the independent effects of a single care component or activity or combination of care components or activities. High variability and inconsistent transitional care study results, and lack of improvement in HF rehospitalizations suggested the importance of a better understanding of the dynamic and relational processes needed to deliver these components in order to achieve suitable and sustainable solutions in real-world settings

(Anderson et al., 2015; Anderson & McDaniel, 2008; Thompson et al., 2016). This dissertation attempted a shift from traditional reductionism to a view of transitional care as a complex system (Begun & Thygeson, 2014; Heng, 2008; McDaniel & Driebe, 2001): A view of transitional care not as a special set of care tasks but as an interconnected and dynamic system that involves networks of services and providers who are adaptive to patients' context and needs over time (Anderson & McDaniel, 2000; Bar-Yam et al., 2013; Begun & Thygeson, 2014; Braithwaite et al., 2018; McDonald, 2007). Outcomes of complex systems do not depend on one person or care activity but on patterns of interactions or interdependencies among social entities and with the environment (Anderson et al., 2015; Anderson & McDaniel, 2008; Ladyman et al., 2013; Thompson et al., 2016).

Findings from this dissertation support the view that transitional care is a complex dynamic system, and that care coordination processes are relational, which contributes to our understanding of the complexity and variability of transitional care. This dissertation found that although existing transitional care interventions possessed similar care components, their relational processes and structure varied greatly, and high heterogeneity existed in patients' longitudinal patterns of outpatient and acute care utilization. Embracing the heterogeneities and conceptualizing care coordination processes as networks can help to describe this complex system and illuminate complex and intertwined patterns of relationships. The new perspectives and knowledge gained from applying data analytics that fit the complex systems framework also demonstrated methodological innovations that might be gained from embracing the complex systems framework.

5.2.2 Methodology

The dissertation demonstrated that SNA has the advantage of uncovering the interdependent relationships essential for care delivery but has not been well measured or understood. To our knowledge, this dissertation was the first to use EHR notes/data and SNA to measure multidisciplinary provider networks across settings involved in care transitions for patients with HF. Methods used in this dissertation can be applied to review interventions and understand utilization heterogeneity patterns and provider networks for other populations or in other countries. The approach used in this dissertation demonstrated the potential to provide a better understanding of both patient-level and system-level network characteristics for transitional care and could be applied to future studies to broaden perspectives concerning (1) social capital (i.e., how people obtain, use, and share resources embedded in social connections); (2) social embeddedness (i.e., how individuals obtain certain network positions inside a system structure; (3) social selection and influence (i.e., how relationships are formed, and subsequently, how these connections influence health behaviors and care outcomes); and (4) diffusion (i.e., how characteristics of network structures hinder or improve information flow, resource utilization, and behavior changes) (Kreager et al., 2016).

Because of the rich qualitative information available in clinical notes, this dissertation helped enhance our understanding of why and how social context and structures may matter for care coordination and inequalities in health outcomes. Provider networks play a critical role in ensuring the quality of care; they can contribute to chronic illness management, prevent the decline in physical and cognitive function, and enhance the effective use of health care resources (Cornwell & Laumann, 2015; Litwin & Stoeckel, 2014). Social networks influence health via social support, social influence, social engagement, interpersonal interactions, and access to social resources (Smith & Christakis, 2008; Song, 2013). The surge and spread of COVID-19 have increased awareness of the social determinants of health and enhanced research interest in the influence of social networks on health outcomes (Abrams & Szefler, 2020; Holmes et al., 2020). Because positive relationships that are established and maintained through social networks can be a critical source of support for people with HF, especially those who are negatively impacted by social determinants of health, there is increased interest in leveraging provider networks in order to develop novel interventions to improve their health-related and psychosocial outcomes. This dissertation demonstrated the feasibility and utility of using SNA to gain a deeper understanding of the social mechanisms and structures that contribute to health inequalities. The challenges imposed by COVID-19 serve to remind researchers and clinicians that care coordination is a complex social and health issue requiring innovative approaches to understanding the complex social determinants of health and improving health system efficiency. Future research using a larger sample size with better generalizability and an improved approach to better utilize structured and unstructured data available from routine care is warranted.

Studying care coordination processes in the form of provider networks allows us to assume that services and providers are interdependent in health care delivery and uncover the relational structures in the system, which traditional methods cannot achieve. However, a few limitations may exist in the 2-mode SNA. First, over-estimation of ties between providers is a well-known limitation of 2-mode SNA (DuGoff et al., 2018). Although Chapter 4 applied strategies to reduce this limitation, the approach used in Chapter 4 to construct provider networks may not provide the best inference for providers' network positions and relationships, especially for PCPs. Additionally, although weighting ties based on the minimum frequency of notes written for shared patients helped account for tie strengths (Casalino et al., 2015), improvements in analyzing provider networks are needed, such as better identification and consideration of the providers who had consistent and frequent contact with patients.

The use of EHR data for research is difficult, complex, and currently in an early phase. Although operational and analytical challenges exist (Muller et al., 2013; Rebola et al., 2013; Vayena et al., 2015; Yu et al., 2015), EHR provided rich, objective, and realistic data to provide a better understanding of the relational processes and structure across the care continuum. Unstructured data in clinical notes provided rich qualitative data to illuminate the clinical and social context important for patients' care coordination and should be better utilized for research in the future. Advanced data analytics such as natural language processing may be promising for automating some qualitative analysis processes used in Chapter 4 to evaluate patients' social and clinical context of provider networks on a greater scale (Feder, 2018; Ridgway et al., 2021).

5.2.3 Intervention Development

This dissertation identified evidence that transitional care development should move toward strong-tie models to support long-term care relationships in outpatient settings for the management of chronic HF and comorbidities. Chapter 2 identified the triadic closure as the common intervention strategy among existing transitional care interventions. Triadic closure utilizing weak ties can be influential for information spread across independent or weakly connected networks but is less so for behavioral change or long-term care management, which are more influenced by strong ties (Granovetter, 1973; Valente, 2010; Valente, 2012). Future transitional care innovations should consider strategies to improve network connectivity or accelerate behavior changes by leveraging key nodes in the system and patients' strong ties.

An in-depth understanding of the inpatient and outpatient provider networks and social and clinical context of patients with HF 1 year before, during, and 1 year after their initial HF hospitalization further demonstrated the importance of outpatient care relationships for patient care transitions and outcomes. Chapter 4 supports the findings in Chapter 2 that (a) relational processes and structure varied greatly but are essential for care coordination, (b) SNA is a feasible and promising approach to systematically understand relational processes and structure essential for care coordination, and (c) consistent, and densely connected provider networks are vital for care coordination in care transitions. Chapter 4 also supports the finding in Chapter 3 that outpatient care influences rehospitalization and is crucial for managing chronic HF, especially during a change in prognosis and symptoms. While current transitional care interventions have focused primarily on care activities for care management and coordination at or shortly after discharge, transitional care interventions should shift focus from care tasks toward care relationships, especially care relationships with outpatient care providers.

5.3 Implications for Practice

Coordination of health care utilization and provider networks remains an aspect of the health care delivery system that should be made more effective. This dissertation provided a longitudinal and comprehensive perspective on the relational aspects of care coordination in care transition using real-world data generated from routine care. Care coordination is an intrinsic part of care delivery. Findings from this study have a wide range of clinical implications, such as optimizing staffing, developing evidence-based guidelines for care coordination, helping providers better understand their roles in patients’ care teams, developing EHR-based tools to provide real-time mapping of patients' service and provider networks, identifying real-time social and structural barriers, and prioritizing strategies that may accelerate care coordination and improve health outcomes (Valente, 2010).

The use of SNA to understand the patterns of interdependent relationships has proved important for improving communication and collaboration patterns among providers in health care (Bae et al., 2015; Braithwaite et al., 2018). A cross-sectional comparative study of email communication networks among multidisciplinary care units caring for children with complex conditions showed that individual participants have distinct patterns and that teams have distinct network structures with varying leadership styles and productivity (Palazzolo et al., 2011). A better understanding of the relationships that lead to distinct leadership styles and communication structures with health and care outcomes could be helpful for building more effective care teams, making successful leadership style changes, and increasing productivity (Bae et al., 2015; Palazzolo et al., 2011). An understanding of information and communication network structures may illuminate inefficiencies in existing system networks and suggest structural changes for improving the current episodic and siloed practice patterns.

Establishing more robust system structures and procedures to improve handover processes, as in the event of provider turnover, is a critical but understudied aspect of health care delivery. Previous studies have shown that PCP turnover is associated with decreased use of primary care, increased use of acute or specialist services, and increases in medical costs, with these effects lasting over 2 years (Reddy et al., 2015; Sabety et al., 2020). Provider turnover is often unavoidable due to factors such as retirement and change of practice location for personal or professional reasons (Reddy et al., 2015), but much can be learned from examples of standardized hand-off protocols that have improved care quality and reduced costs, such as those in perioperative settings (Bloomstone et al., 2019). Establishing processes prior to changes or shifts in care relationships, particularly involving providers who have worked closely with patients and been patients' gatekeepers, to facilitate the development of a trusting relationship with their new providers may improve care transitions and relational continuity (Birkhäuer et al., 2017; Mitchell et al., 2018; Östman et al., 2020).

5.4 Implications for Policy

This dissertation provided evidence that supports a health system shift from the current task-oriented episodic care model to a relationship-focused value-based care model (Begun & Thygeson, 2014; Clancy et al., 2008). A relationship-driven view considers people's concerns a higher priority than accomplishing clinical tasks (Anderson et al., 2015; Parish & Yellowlees, 2014). The relationship-centered view matches the principles of the person-centered approach and may encourage practices that are more patient-centered rather than task-centered (2016; Hirschman et al., 2017). More efficient, equitable, and higher quality of care, especially in outpatient settings, may be possible by improving relational processes and structures for care coordination through evaluation of care coordination processes across settings in routine care (Gardiner et al., 2018).

Challenges exist in generating evidence to accelerate the shift towards a relationship-focused value-based care model. Firstly, data are often only available in isolated settings (Granger et al., 2013). For instance, while the qualitative review of notes content revealed some aspects of out-of-Duke care (e.g., whether home health care involvement was involved), we could not accurately evaluate provider networks from non-Duke health services utilized for care coordination. Secondly, routinely collected data from EHR lack direct measures of care processes such as communication among providers across services. The 2-mode network analysis based on patient-sharing only provided indirect inferences to collaborative relationships. Research and implementation efforts to advance value-based models for HF are limited by the connectivity of information systems and health care systems.

Importantly, the current fee-for-service reimbursement system does not incentivize care that focuses on addressing patients' longitudinal chronic disease needs (Joynt Maddox et al., 2020). Process improvement initiatives that seek to bridge communication gaps and improve collaboration and connectivity across settings are prevalent. Most fail, however, due to financial barriers or the persistent, siloed nature and structure of U.S. health care (Kilbourne et al., 2018). A care communication vacuum still exists between hospitals and community-based care services. Departing from episodic payment models and building infrastructure and workforce with the capacity for furthering value-based care models is the next step toward enabling implementation efforts that leverage relational processes and structures to improve care continuity and system efficiency (Joynt Maddox et al., 2020).

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Biography

Sijia Wei was born in China and earned her BA, RN from St. Olaf College, MN in 2014 and was a geriatric nurse who worked in hospice, long-term care, and home health care before starting her PhD journey at Duke University School of Nursing. During her time at Duke, she was inducted to Sigma Theta Tau International honor society of nursing in 2016 and has received Duke University Tuition and Fee Scholarship for 5 years, Duke University School of Nursing PhD Pilot Fund for 3 times, Duke Summer Research Fellowship for 3 times, 6th Year Tuition Scholarship with COVID-19 Funding Extension, GSA Emerging Scholar and Professional Organization- Carol Schutz Registration Award, American Heart Association Scientific Sessions 2021 Travel Grant, Edith Anderson Leadership Education Grant from Sigma Theta Tau International, Hartford Small Grant Research Fund, and New England Complex Systems Institute Student Scholarship. To date, Sijia has published 8 articles and has 3 manuscripts under review.

Outside of her PhD program, Sijia has been a competitive ballroom dancer and has won titles at numerous local and national competitions. To share her love and passion for ballroom dancing, she founded and taught at the Duke Ballroom Dance Club. Duke Ballroom Dance Club has been recognized as a sport club at Duke University and was nationally ranked 8th at the National Collegiate DanceSport Championships in 2019.