EXAMINING DISPARITIES IN CARE COORDINATION STRUCTURES FOR BARIATRIC SURGERY PATIENTS: A COMPARATIVE ANALYSIS ACROSS RACE, ETHNICITY, SURGERY TYPE, AND GENDER

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CHAPTER 1

Introduction

Obesity is a prevalent health condition, and bariatric surgery has proven to be an effective intervention for addressing obesity by limiting the total amount of calories absorbed by the patient. [Schauer et al. (2017); Adams et al. (2017); Puzziferri et al. (2014); Courcoulas et al. (2015)] In the United States, an average of 200,000 bariatric surgeries were performed annually between 2011 and 2020. Bariatric surgery, which includes procedures such as gastric bypass and banding, necessitates significant post-surgical lifestyle changes for patients. [Sarwer et al. (2017); Sjöström et al. (2004); King et al. (2017)] As a result, the treatment process involves pre-surgery, intra-surgery, and post-surgery phases, requiring a multidisciplinary healthcare team comprising surgeons, anesthesiologists, nurses, dietitians, medical specialists, physical therapists, psychiatrists, and others. [Apovian et al. (2009), Elder and Wolfe (2007)]

Care coordination, referring to the sharing of information between healthcare professionals treating the same patient, is a critical factor for the success of bariatric surgery. Effective care coordination, characterized by communication, adaptability, and role clarity, contributes to timely treatments, better patient outcomes, and optimal use of hospital resources. [Klitzner et al. (2010), Berry et al. (2013), Hofmarcher et al. (2007)] However, the literature currently lacks studies examining care coordination structures in bariatric surgery teams, despite their importance.

In this work, we propose to investigate care coordination patterns in bariatric surgeries using network analysis, where various aspects of care coordination are represented by network metrics. For instance, metrics such as degree (both indegree and outdegree), closeness centrality, diameter, density, reciprocity, and average shortest path length can serve as indicators for communication. Betweenness centrality, cluster coefficient of nodes, and network transitivity can serve as indicators for adaptability. The proportion of distributor, receiver, and balancer nodes, as well as edge connection homophily, can serve as indicators for role clarity.

Moreover, we examine disparities in care coordination patterns between different patient populations, categorized by gender, race/ethnicity, and surgery type. Our study fills a significant gap in the literature by highlighting the importance of care coordination structures in bariatric surgery and providing insights into potential disparities across diverse patient populations.

CHAPTER 2

Method

2.1 Data

We collected electronic health records (EHRs) for 1,799 patients who underwent bariatric surgery at Vanderbilt University Medical Center (VUMC) between January 1, 2018, and December 31, 2021. The involvement of healthcare professionals in each patient's care was extracted from seven different EHR sources, including diagnoses, procedures, orders, observations, notes, measurements, and drug exposures. Alongside each patient's demographic information, such as gender and race/ethnicity, we compiled a chronological sequence of healthcare professionals who provided services during the pre-surgery, intra-surgery, and post-surgery phases for each patient. This comprehensive dataset enables us to analyze care coordination patterns and investigate potential disparities in bariatric surgery care across diverse patient populations.

2.2 Network Construction and Definition of Pre-, Intra-, and Post-Surgery Phases

We defined the pre-, intra-, and post-surgery phases as [-31, -1), [-1, 1], and (1, 31], respectively, with the surgery date set as the index date (0). Days before the surgery are assigned negative numbers, while days after the surgery are assigned positive numbers (see panel a. on Figure 2.1). For each patient, we created three directed networks corresponding to the pre-, intra-, and post-surgery phases. We then combined all patients' networks into three overall networks representing coordination structures in pre-, intra-, and post-surgery phases.

In these networks, each healthcare professional is a node, and the connections between professionals are based on their adjacent positions in a chronological sequence. A directed connection is established from professional A to professional B if B provided a service to a patient immediately after A did. However, if the interval between the two services exceeds 24 hours, we do not create a connection, as we assume there may not be direct coordination between the two professionals with such a gap. Consecutive appearances of the same professional are compressed into a single appearance, and self-connections are disregarded. Additionally, there may be instances where multiple healthcare professionals provide services to the same patient simultaneously. In such cases, we will not establish connections between these professionals, as our focus lies in examining the chronological relationships that describe continuity of care for a patient. Connections are weighted by patient flow size, defined as the number of patients cared for by professionals A and B in succession.

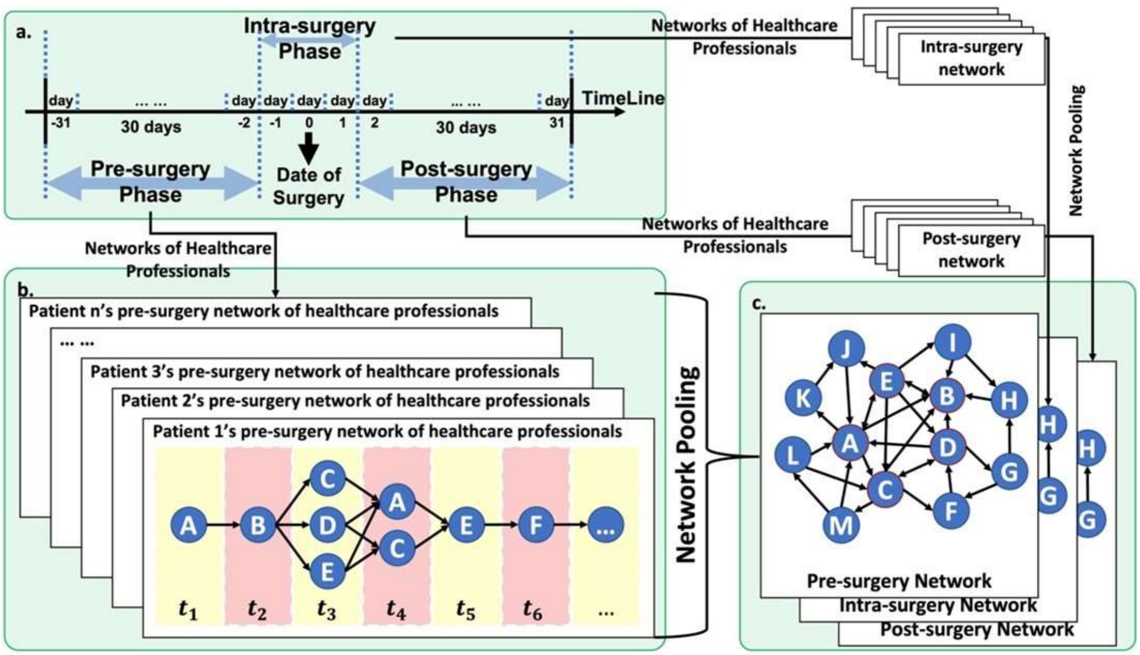

Figure 2.1: Building process for care coordination networks.

In addition to the pre-, intra-, and post-surgery networks, we also created subnetworks for patient populations divided by race/ethnicity, gender, and surgery type, including Roux-en-Y Gastric Bypass (RYGB) and Vertical Sleeve Gastrectomy (VSG).

2.3 Develop Metrics to Quantify Coordination Structures

We assess care coordination by analyzing communication, adaptability, and role clarity within healthcare teams. These metrics create a comprehensive framework for evaluating care coordination networks. These metrics provide a quantitative framework for assessing care coordination networks, focusing on effective communication, adaptability, and role clarity among healthcare professionals. To more effectively assess connection characteristics, we introduce the concept of Strongly Connected Components (SCC). An SCC is a subset of nodes in the network where every node is mutually reachable. Analyzing the number and size of SCCs offers valuable insights into the network's overall connectivity and structure. The largest SCC in a network, containing the highest number of nodes, is referred to as the network's largest SCC. Both diameter and average shortest path length are calculated based on the largest SCC within each network.

2.3.1 Communication Metrics

Communication metrics measure the extent to which team members exchange information related to patient care. Effective communication ensures timely updates of patient information and care plans. In a coordination network, communication is represented by the connections between nodes. Network metrics used to quantify communication are as follows.

2.3.1.1 Indegree

Indegree quantifies incoming information to a professional, defined as the number of incoming connections (edges) to a node (professional) in the network.

2.3.1.2 Outdegree

Outdegree measures information dissemination by a professional, defined as the number of outgoing connections (edges) from a node (professional) in the network.

2.3.1.3 Degree

Degree indicates a professional's importance in information exchange, defined as the sum of indegree and outdegree for a node (professional) in the network.

2.3.1.4 Diameter

Diameter reflects care network efficiency and robustness, defined as the maximum shortest path length between any two nodes in the network.

2.3.1.5 Average Shortest Path Length

Average shortest path length reveals network efficiency and navigability, defined as the mean of the shortest path lengths between all pairs of nodes in the network.

2.3.1.6 Density

Density measures connection prevalence in the network, defined as the ratio of the actual number of connections (edges) in the network to the maximum possible number of connections.

2.3.1.7 Reciprocity

Reciprocity indicates collaboration and mutual information exchange levels, defined as the proportion of connections (edges) in the network that are mutual, meaning both nodes are connected to each other in opposite directions. [Garlaschelli and Loffredo (2004)]

2.3.1.8 Median Closeness Centrality

Median closeness centrality represents efficient communication across the network, defined as the median of the inverse sum of the shortest path lengths from a node to all other nodes in the network. [Freeman et al. (2002); Wasserman and Faust (1994)]

2.3.2 Adaptability Metrics

Adaptability metrics measure a cooperative team's ability to adapt to changing situations and manage emergencies and uncertainties. A adaptive team can operate efficiently even with some members absent and still ensure great patient outcomes. In a coordination network, adaptability can be reflected by healthcare professionals with broad skill sets for handling emergencies and uncertainties. To measure adaptability, we use betweenness centrality and clustering coefficient of nodes, as well as network transitivity.

2.3.2.1 Maximum Betweenness Centrality

Maximum Betweenness Centrality highlights professionals crucial for information flow and emergency response coordination, defined as the highest value of the number of shortest paths between all pairs of nodes in the network that pass through a particular node. [Brandes (2001, 2008)]

2.3.2.2 Median Clustering Coefficient

Median Clustering Coefficient measures the network's collaborative nature, defined as the median of the ratio of the number of connections (edges) between a node's neighbors to the maximum possible number of connections between them. [Saramäki et al. (2007); Onnela et al. (2005)]

2.3.2.3 Transitivity

Transitivity reveals the extent of support among professionals during emergencies and uncertainties, defined as the ratio of the number of triangles (three connected nodes) in the network to the number of connected triples (three nodes with at least two connections). [Luce and Perry (1949)]

2.3.3 Role Clarity

Role clarity is a measure of how well-defined responsibilities are among team members. It is crucial for fostering specialized and efficient treatment procedures. In a care coordination network, the proportion of distributor, receiver, and balancer nodes, along with the homophily of edge connections, can serve as indicators of role clarity.

2.3.3.1 Node Classification (Receivers, Distributors, Balancers)

The role of professionals in information exchange are categorized based on their indegree (incoming connections) and outdegree (outgoing connections). Specifically, professionals can be classified as:

- **Receivers:** Individuals with a higher indegree than outdegree, indicating they primarily receive information.
- **Distributors:** Individuals with a higher outdegree than indegree, suggesting they primarily disseminate information.
- **Balancers:** Individuals with equal indegree and outdegree, indicating they both receive and distribute information equally.

To evaluate the degree of information exchange asymmetry or imbalance in a network, we examine the proportions of receivers, distributors, and balancers. A higher proportion of balancers signifies a lower degree of information exchange asymmetry, as individuals tend to both equally receive and share information. Conversely, higher proportions of distributors and receivers indicate a higher degree of information exchange asymmetry or imbalance, as individuals predominantly focus on either disseminating or receiving information within the network, which may result to higher role clarity.

2.3.3.2 Normalized Homophily Score

Homophily measures the tendency of professionals with similar roles to connect (0 for perfectly heterophily, 1 for perfectly homophily) [Karimi et al. (2018)], calculated as follows:

$$\text{Homophily Score} = \frac{\text{Number of connected homophily pairs}}{\text{Total connected pairs}} - \frac{\text{Number of disconnected homophily pairs}}{\text{Total disconnected pairs}}$$

$$\text{Normalized Homophily Score} = 0.5 * \text{Homophily Score} + 0.5$$

2.4 Disparity Analysis

We evaluate differences in care coordination structures among patients grouped by race/ethnicity, gender, and surgery types using network metrics across three themes. Additionally, we compare coordination structures between patients who experienced the most favorable and least favorable BMI changes three months after surgery. BMI, or body mass index, is calculated as the body weight divided by the square of the body height and is expressed in units of kg/m2, with body weight in kilograms and body height in meters. [Keys et al. (1972)] The BMI change for a patient is determined by calculating the difference between the BMI measured three months after the surgery date and the BMI measured on the surgery date itself.

2.5 Visualizing coordination structures through radar graph

To visualize coordination structures across three themes encompassing 12 metrics, we normalize each metric's values to a range between 0 and 1. Radar graphs are employed to display pre-, intra-, and post-surgery networks, as well as subnetworks for subpopulations divided by race/ethnicity, gender, and surgery type.

2.6 Homophily Test

To determine if patients received consecutive services from the same type of healthcare professionals (e.g., two adjacent professionals are both physicians or non-physicians), we performed a homophily test. This test helps assess whether the network exhibits homophily or heterophily, indicating whether connections appear between professionals of the same type or different types.

	Connected	Not Connected
Homophily (physician-physician pair or non-physician-non-physician pair)	a_{11}	a_{12}
Heterophily (physician-non-physician pair)	a_{21}	a_{22}

Table 2.1: Two by two contingency table describing the relationship between connection and roles of two adjacent healthcare professionals in the networks.

We created a contingency table (Table 2.1) for the network, where a_{11} and a_{21} represent the number of connected pairs of professionals that exhibit homophily (same type) and heterophily (different types), respectively. Meanwhile, a_{12} and a_{22} represent the number of disconnected pairs of professionals that exhibit homophily and heterophily, respectively.

We performed a Chi-square test to examine the null hypothesis that homophily and connection of healthcare professionals are independently related, based on the contingency table we created. This test was conducted in pre-, intra-, and post-surgery networks.

For each network, if the p-value is larger than 0.05, we considered that the homophily of the network cannot be accurately determined. If the p-value for the homophily test is less than 0.05 and the normalized homophily score is less than 0.5, we considered the network to exhibit heterophily, i.e., physician-non-physician connections. If the normalized homophily score is greater than 0.5 and the p-value for the homophily test is less than 0.05, we then consider the network to exhibit homophily, i.e., physician-physician or non-physician-non-physician connections. We performed the homophily test in pre-, intra-, and post-surgery networks.

CHAPTER 3

Results

3.1 Pre-, Intra-, and Post-surgery Coordination Networks

Based on the data in Table 3.1, the intra-surgery phase has the highest number of patients (1,799), healthcare professionals (3,559), and connections between healthcare professionals (83,597). In comparison, the pre-surgery phase has the lowest number of patients (1,138) and professionals (1,187), but has 3,478 connections. The post-surgery phase has a slightly higher number of patients (1,304) and professionals (3,615), with 23,419 connections between healthcare professionals. The comparison of the 12 metrics across the pre-, intra-, and post-surgery networks in terms of communication, adaptability, and role clarity metrics is shown in Figure 2.

3.1.1 Communication Metrics

The intra-surgery network has the best communication strength, with the highest density (0.0066), efficiency (med closeness: 0.3748), and reciprocity (0.5968). The intra-surgery network has the lowest overall difficulty for information transmission, with the lowest diameter (10) and average shortest path length (2.71). The pre-surgery network coordination is more one-way and costly, with density (0.0025), med closeness (0.1772), and reciprocity (0.3997). The post-surgery network lies in between the other two networks, with a density of 0.0018, med closeness of 0.2703, and reciprocity of 0.4750, and is the most sparsely connected.

Phase	# of Patients	# of Professionals	# of Connections	Homophily Test (p-value)
Pre-	1138	1187	3478	0.0001
Intra-	1799	3559	83597	0.0000
Post-	1304	3615	23419	0.4217

Table 3.1: Comparison of patients, healthcare professionals, and connections among healthcare professionals across pre-, intra-, and post-surgery networks.

3.1.2 Adaptability Metrics

All networks have similarly low maximum betweenness centrality: pre-surgery (0.2167), intra-surgery (0.1918), and post-surgery (0.1941). In emergency situations, surgery teams can organize effective coordination to complete the surgery. The intra-surgery network has the best local connectivity, with the highest transitivity (0.1006) and median clustering coefficient (0.3526), ensuring a variety of alternative coordination plans. The pre-surgery network has the lowest prevalence of local cliques, with transitivity (0.0670) and median clustering coefficient (0.1000), while the post-surgery network lies in between, with transitivity (0.0444) and median clustering coefficient (0.2222).

3.1.3 Role Clarity Metrics

All networks have a balanced portion of distributors and receivers, with the following ratios: pre-surgery (distributors: 0.2890, receivers: 0.2671), intra-surgery (distributors: 0.3622, receivers: 0.3287), and post-surgery (distributors: 0.2730, receivers: 0.2744). The intra-surgery network has a significantly smaller portion of balancers, with a balancers ratio of 0.3091, compared to pre-surgery (0.4440) and post-surgery (0.4526) networks. This suggests more specialization in information dissemination and reception in the intra-surgery network. Both the pre-surgery and intra-surgery networks show a significant tendency for heterophily (patients tend to transit to professionals with different specialties), with normalized homophily scores and p-values as follows: pre-surgery (0.4645, p=0.0001), intra-surgery (0.4903, p=0.0000). The post-surgery network does not demonstrate a significant tendency, with a normalized homophily score of 0.4963 and a p-value of 0.4217.

3.1.4 Summary

The intra-surgery network exhibits the strongest communication and adaptability metrics, while role clarity metrics are relatively balanced across all networks, with the intra-surgery network showing more specialization in information dissemination and reception.

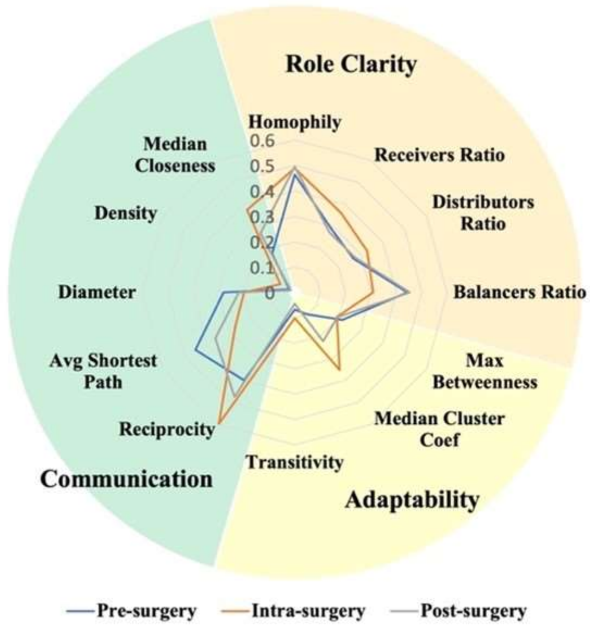

Figure 3.1: Radar graph comparing 12 metrics across pre-, intra-, and post-surgery networks. The graph illustrates the differences in communication, adaptability, and role clarity metrics among the three networks. Communication metrics include density, med closeness, reciprocity, diameter, and average shortest path length. Adaptability metrics encompass maximum betweenness centrality, transitivity, and median clustering coefficient. Role clarity metrics consist of distributors ratio, receivers ratio, balancers ratio, and normalized homophily scores. The intra-surgery network generally exhibits the strongest communication and adaptability metrics, while role clarity metrics remain relatively balanced across all networks.

3.2 Coordination Subnetworks Categorized by Patient Subgroups, Segmented Based on Gender, Surgery Type, and Race/Ethnicity.

Table 3.2 provides a summary of pre-, intra-, and post-surgery networks, broken down by different patient subgroups such as gender, surgery type, and race/ethnicity. The table includes the number of patients, professionals, connections, and the average 3-month BMI change for each subgroup.

3.2.1 Pre-surgery Network

3.2.1.1 Gender

Males have fewer patients, professionals, and connections than females, with a slightly higher average 3-month BMI change (-7.94 vs. -7.37).

3.2.1.2 Surgery Type

RYGB has more patients, professionals, and connections than VSG, with a slightly higher average 3-month BMI change (-7.81 vs. -7.00).

3.2.1.3 Race/Ethnicity

Non-Hispanic White patients have the highest number of patients, professionals, and connections, followed by Non-Hispanic Black, Hispanic, and Other. The average 3-month BMI change is highest for the Other category (-7.75) and lowest for Non-Hispanic Black (-6.91).

3.2.2 Intra-surgery Network

3.2.2.1 Gender

Males have fewer patients, professionals, and connections than females, with a higher average 3-month BMI change (-8.23 vs. -7.38).

3.2.2.2 Surgery Type

RYGB has more patients, professionals, and connections than VSG, with a slightly higher average 3-month BMI change (-7.81 vs. -7.00).

3.2.2.3 Race/Ethnicity

Non-Hispanic White patients have the highest number of patients, professionals, and connections, followed by Non-Hispanic Black, Hispanic, and Other. The average 3-month BMI change is highest for the Other category (-7.75) and lowest for Non-Hispanic Black (-6.91).

3.2.3 Post-surgery Network

3.2.3.1 Gender

Males have fewer patients, professionals, and connections than females, with a higher average 3-month BMI change (-8.23 vs. -7.38).

3.2.3.2 Surgery Type

RYGB has more patients, professionals, and connections than VSG, with a higher average 3-month BMI change (-7.90 vs. -7.07).

3.2.3.3 Race/Ethnicity

Non-Hispanic White patients have the highest number of patients, professionals, and connections, followed by Non-Hispanic Black, Hispanic, and Other. The average 3-month BMI change is highest for the Other category (-7.87) and lowest for Hispanic (-7.10).

3.3 Comparison of 12 Metrics across Coordination Subnetworks Differentiated by Patient Gender Groups

Figure 3.2 presents the structural metrics of networks for different genders. All three male networks exhibit stronger bottleneck effects (male max betweenness/female max betweenness: pre = 0.3204/0.1719, intra = 0.2627/0.1846, post = 0.4415/0.2048), making healthcare teams more vulnerable, particularly when bottleneck nodes are unavailable. No significant differences are observed in the other metrics between male and female networks.

3.4 Comparison of 12 Metrics across Coordination Subnetworks Differentiated by Patient Race/Ethnicity Groups

Figure 3.3 displays the structural metrics of networks for different race/ethnicity subgroups. Network metrics for Non-Hispanic White and Non-Hispanic Black patients are calculated, as the population sizes of Hispanic and Other race/ethnicity patients are too small for meaningful comparisons. The overall efficiency of information flow in the pre-surgery Non-Hispanic Black network is notably lower (pre-surgery diameter: White/Black = 15/18, pre-surgery average shortest path length: White/Black = 4.32/5.72). There is no difference in the metrics between Non-Hispanic White and Non-Hispanic Black patients in the intra- and post-surgery.

Phase	Category	Type	# of Patients	# of Professionals	# of Connections	Average 3 Month BMI change
Pre-	Gender	Male	207	398	1011	**-7.94**
		Female	**931**	**951**	**2637**	-7.37
	Surgery Type	RYGB	**639**	**747**	**2138**	**-7.81**
		VSG	499	637	1562	-7.00
	Race/Ethnicity	Hispanic	19	71	116	-7.10
		Non-Hispanic Black	258	505	1227	-6.91
		Non-Hispanic White	**851**	**827**	**2315**	-7.64
		Other	10	19	24	**-7.75**
Pre-	Gender	Male	326	1914	20559	**-8.23**
		Female	**1473**	**3313**	**70850**	-7.38
	Surgery Type	RYGB	**980**	**2892**	**50431**	**-7.90**
		VSG	819	2697	44957	-7.07
	Race/Ethnicity	Hispanic	27	453	1838	-7.10
		Non-Hispanic Black	402	2144	25721	-7.06
		Non-Hispanic White	**1354**	**3190**	**65265**	-7.68
		Other	16	299	1134	**-7.87**
Post-	Gender	Male	233	1039	4344	**-8.24**
		Female	**1071**	**3273**	**19756**	-7.35
	Surgery Type	RYGB	**699**	**2558**	**14206**	**-7.88**
		VSG	605	2124	10376	-7.03
	Race/Ethnicity	Hispanic	17	146	399	-7.02
		Non-Hispanic Black	327	1698	7990	-7.05
		Non-Hispanic White	**947**	**2903**	**16160**	-7.67
		Other	13	45	93	**-7.76**

Table 3.2: Summary of patient subgroups in pre-, intra-, and post-surgery networks. The table presents the number of patients, healthcare professionals, connections, and average 3-month BMI change for each subgroup, categorized by gender, surgery type (RYGB and VSG), and race/ethnicity (Hispanic, Non-Hispanic Black, Non-Hispanic White, and Other). The data highlights the differences in network characteristics and postoperative outcomes among various patient subgroups across the three surgical phases.

3.5 Comparison of 12 Metrics across Coordination Subnetworks Differentiated by Patient Surgery Groups

Figure 3.4 presents the structural metrics of networks for different surgery types. The RYGB network exhibits stronger local connectivity than the VSG network in the pre-surgery phase (pre-surgery median clustering coefficient: RYGB/VSG = 0.1186/0.0000), indicating that the RYGB network is more adaptable to changing situations. The bottleneck effect of professionals in the RYGB network is more pronounced than in the VSG network (RYGB max betweenness/VSG max betweenness: pre = 0.2370/0.1722, intra = 0.2288/0.1720, post = 0.2530/0.2182).

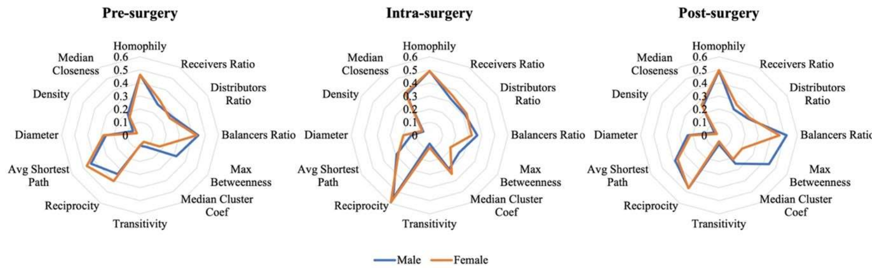

Figure 3.2: Visualization of structural metrics for networks by gender subgroups. The figure compares male and female networks across three surgical phases (pre-, intra-, and post-surgery) based on their structural metrics.

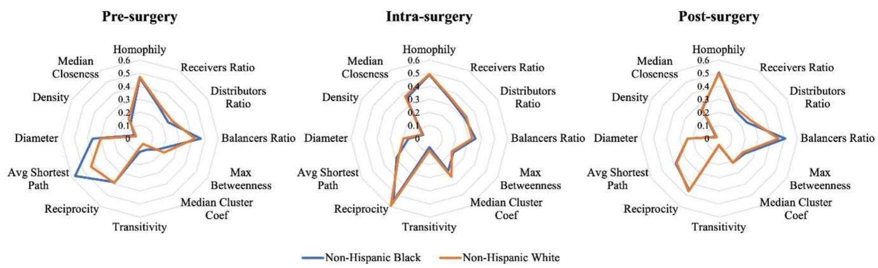

Figure 3.3: Visualization of structural metrics for networks by race/ethnicity subgroups. The figure compares Non-Hispanic White and Non-Hispanic Black networks across the pre-, intra-, and post-surgery phases, as the population sizes of Hispanic and Other race/ethnicity patients are too small for meaningful comparisons. The overall efficiency of information flow in the pre-surgery Non-Hispanic Black network is notably lower, as evidenced by a larger diameter and longer average shortest path length compared to the Non-Hispanic White network.

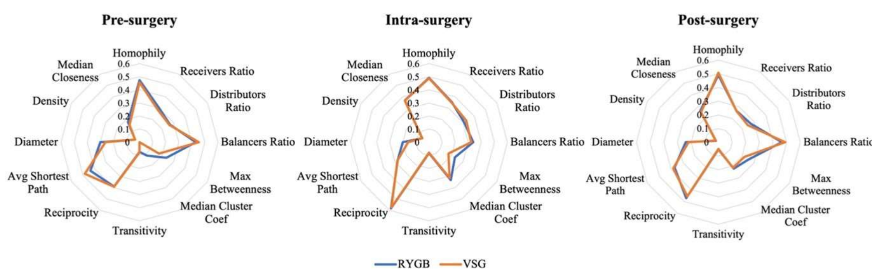

Figure 3.4: Visualization of structural metrics for networks by surgery type subgroups. The figure compares RYGB and VSG networks across the pre-, intra-, and post-surgery phases.

Phase	Category	Metrics	Male RYGB		Male VSG		Female RYGB		Female VSG	
			Black	White	Black	White	Black	White	Black	White
Pre-	Patients Outcome	Average 3 Month BMI Change	-7.41	**-8.46**	-7.02	**-7.66**	-7.19	**-7.80**	-6.57	**-7.01**
Intra-			-8.25	**-8.76**	-7.54	**-7.68**	-7.29	**-7.79**	-6.68	**-7.06**
Post-			-7.89	**-8.83**	-7.57	**-7.71**	-7.30	**-7.76**	-6.67	**-7.01**
Pre-	Adaptability	Transitivity	**0.1233**	0.0981	**0.1244**	0.0584	**0.1243**	0.0819	**0.1285**	0.0940
Intra-	Adaptability	Max Betweenness	**0.4084**	0.2517	**0.4091**	0.2479	**0.2622**	0.2339	**0.2368**	0.2044
	Role Clarity	Balancers Ratio	0.4939	**0.4115**	0.4335	**0.4088**	0.4040	**0.3530**	0.3833	**0.3715**
		Distributors Ratio	0.2378	**0.2922**	0.2719	**0.3012**	0.2723	**0.312**2	0.2988	**0.3123**
	Communication	Avg Shortest Path	3.8168	**3.1139**	3.5431	**3.1876**	3.1636	**2.8188**	3.0730	**2.8993**
		Reciprocity	0.4787	**0.5517**	0.4895	**0.5418**	0.5279	**0.5745**	0.5463	**0.5608**
		Median Closeness	0.2608	**0.3373**	0.2829	**0.3270**	0.3273	**0.3630**	0.3377	**0.3544**

Table 3.3: Summary of patient subgroups in pre-, intra-, and post-surgery networks. The table presents the number of patients, healthcare professionals, connections, and average 3-month BMI change for each subgroup, categorized by gender, surgery type (RYGB and VSG), and race/ethnicity (Hispanic, Non-Hispanic Black, Non-Hispanic White, and Other). The data highlights the differences in network characteristics and postoperative outcomes among various patient subgroups across the three surgical phases.

3.6 Comparative Analysis of Network Metrics and 3-Month BMI Change Across Patient Subgroups in Pre-, Intra-, and Post-Surgery Periods

Table 3.3 presents a comparison of various metrics across different patient subgroups based on gender, surgery type, and race/ethnicity in pre-, intra-, and post-surgery periods.

For the average 3-month BMI change, White patients generally showed a greater decrease compared to Black patients in all three periods. Males undergoing RYGB surgery had the most significant change in both pre- and post-surgery periods, while White male RYGB patients experienced the largest decrease during the intra-surgery period.

In terms of adaptability, transitivity was generally higher for Black patients in the pre-surgery phase. The max betweenness for intra-surgery adaptability was highest among Black males undergoing RYGB and VSG surgery.

Regarding role clarity in the intra-surgery phase, the balancers ratio was highest among Black male RYGB patients, while the distributors ratio was relatively similar across subgroups, with a slight increase for White patients.

For communication metrics during the intra-surgery phase, the average shortest path was the lowest for White female patients. Reciprocity was generally higher for White patients, and the median closeness was highest for White female RYGB patients.

CHAPTER 4

Discussion

This study provides an in-depth analysis of the coordination networks of healthcare teams involved in bariatric surgery, focusing on different phases of the surgical process and patient subgroups. Our findings have several implications for improving patient outcomes and optimizing the allocation of healthcare resources.

The most complex and coordinative network was the intra-surgery network, with better communication, adaptability, and role clarity among professionals. This highlights the importance of strong team coordination during the surgical process. In contrast, the pre-surgery network was the weakest in terms of communication and adaptability. This suggests that efforts to improve pre-surgery coordination, particularly in terms of strengthening communication and adaptability, could positively impact patient outcomes.

Our results also revealed differences in coordination structures for different patient subgroups. Male patients had more adaptable care teams, which may contribute to their higher BMI changes compared to females, although further research is needed to explore this relationship. In terms of surgery type, the VSG network demonstrated weaker local connectivity, which could be attributed to differences in pre-surgical treatment procedures.

Significant disparities were observed in the coordination networks of white and black patients, particularly in the intra-surgery phase. White patients' care teams demonstrated better communication, adaptability, and role clarity, which may contribute to their better surgical outcomes. This highlights the need to address systemic issues in healthcare that disproportionately affect black patients and to optimize care coordination for all patient populations.

Our study has several limitations that should be considered when interpreting the results. First, the distribution of gender and race among patients is unbalanced, which may impact metrics such as density. Additionally, the population size for Hispanic and other ethnicities was insufficient for analysis. Second, our data was not well-aligned across the pre-, intra-, and post-surgical populations, with some missing visit records. This may cause some instability in the results.

Furthermore, there are limitations in the generalizability of our findings. Our study focused on bariatric surgery, and the coordination structures and patterns we observed may not be directly applicable to other types of surgeries or healthcare procedures. Future research should explore the applicability of our network analysis approach to other healthcare contexts to better understand the broader implications of our findings.

Another limitation is the interpretation of network metrics in terms of care coordination. While we utilized several network metrics to describe communication, adaptability, and role clarity, these metrics may not fully capture the complexities of care coordination in healthcare teams. For example, certain network metrics may not directly translate into improved patient outcomes or better resource allocation. Additional research is needed to establish more concrete links between network metrics and care coordination outcomes and to identify other relevant metrics that could enhance our understanding of healthcare team coordination.

CHAPTER 5

Conclusion

Our analysis of bariatric surgery healthcare team coordination networks reveals the importance of strong coordination, particularly during the intra-surgery phase. Differences in coordination structures were observed across patient subgroups, with potential implications for surgical outcomes. Future research should further explore these relationships and seek to improve care coordination for all patients, addressing disparities that may contribute to differing outcomes. Despite the limitations of our study, our findings contribute valuable insights to the ongoing effort to enhance the quality of bariatric surgery and optimize healthcare resources.

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