What Happened After the Great Resignation?

An Observational Study of a Health Research Center using Social Network Analysis as Part of a Community Outreach and Engagement Program Evaluation

Dian Hu[1], Manisha Salinas[2,3], Daniel W. Lee[2,3], Sandra K Bisbee[2], Folakemi T. Odedina[2,3], Hongfang Liu[1,2]

1. Department of Artificial Intelligence and Informatics, Mayo Clinic, 200 First St. SW, Rochester, Minnesota, 55905, U.S.
2. Mayo Clinic Comprehensive Cancer Center, Mayo Clinic, 4500 San Pablo Road, Jacksonville, Florida, 32224, U.S.
3. Center for Health Equity and Community Engagement Research, Mayo Clinic, 4500 San Pablo Road, Jacksonville, Florida, 32224, U.S.

{hu.dian,salinas.manisha,lee.daniel2,bisbee.sandra, odedina.folakemi,liu.hongfang}@mayo.edu

Abstract. "The Great Resignation" has become a concern for many in healthcare since the pandemic. Inspired by the literature on social network analysis, we applied SNA techniques to analyze the impact of the Great Resignation on a large health research center. We found that although the great resignation has caused evident turbulence among inter-program and inter-scholar collaborations, most of those who did not resign were able to adjust and establish new connections within the center. This study has reaffirmed the strength of SNA in understanding organizational structures in health institutions and has demonstrated SNA's potential in real-time and interactive program evaluation.

Keywords: Community Outreach, Community Engagement, Social Network Analysis, Program Evaluation, Great Resignation

1 Introduction

COVID-19 caused a sudden shift towards remote or hybrid work for many research institutions worldwide. Several pilot studies have suggested that although remote work will not negatively affect the productivity of the workforce [1], prolonged remote work is still likely to negatively impact employees' job satisfaction and psychological well-being [2]. Concurrently, an ongoing trend in which employees voluntarily and collectively resigned from their positions, namely "The Great Resignation," has become a major concern for many, particularly those in healthcare and health research [3]. Thus, the question of how to remediate after the great resignation has become an active research topic [4]. Some argue that this problem existed long ago in many places and that the pandemic is only the last straw [5]. Some observe this trend is toxic and self-perpetuating [6], and institutions should actively combat it with strategies and additional resources [7]. In contrast, others claim that "Great Resignation" is an unprecedented opportunity for institutions to reform and reorganize for future opportunities if handled correctly [8]. Nevertheless, most scholars agree that leadership should carefully examine the scale of "Great Resignation" of their institutions respectively before formulating any strategy.

However, traditional surveys and questionaries used for exploratory analysis of this type are often tedious and distracting for health researchers, especially for those already overwhelmed by the pandemic and impacted by their colleagues' departure. Furthermore, survey-based evaluations within health institutions are often prone to the Hawthorne effect [9] and recall bias [10]. Meanwhile, social network analysis (SNA) has been proven effective in many studies at unraveling large organizations' structure and information flow [11, 12, 13]. SNA has also been widely used in studying scientific collaboration [14], scholarly communications [15], and co-citation relationships [16] without direct communication with the studied stakeholders.

In this paper, we report the result of a center-wide social network analysis to assess the impact of "The Great Resignation" as part of the Mayo Clinic Comprehensive Cancer Center (MCCCC) Community Outreach and Engagement program evaluation. In this study, we define the "Great Resignation" period as the entire year of 2021, post COVID-19. During this period MCCCC witnessed a 61.53% increase in members' departure when compared to the mean value of the departure pre-COVID-19 (2018, 2019, and 2020). This analysis was part of the MCCCC institutional-wide Community Outreach and Engagement program evaluation. Although initially motivated by an operational requirement to identify bottlenecks hindering potential collaborations among investigators relative to community outreach and engagement, we want this pilot study to reaffirm the strength of SNA in understanding organizational structures in health institutions and to demonstrate SNA's potential in real-time and interactive program evaluation. This study is approved and monitored by the Mayo Clinic Office of Human Research Protection as an internal investigation. All authors are employees of Mayo Clinic and trained and registered in Mayo Clinic IRB eSystem.

2 Background

2.1 Mayo Clinic Comprehensive Cancer Center

MCCCC is the only National Cancer Institute (NCI)-designated comprehensive cancer center in the nation with three geographic sites and three distinct catchment areas in Arizona (AZ), Florida (FL) and the Midwest. MCCCC facilitates collaboration across these three campuses among more than 350 cancer-focused investigators, aligned in one of our nine basic or disease-associated programs, representing 44 Mayo departments that impact highly diverse regional and national communities. At MCCCC, a culture of innovation and collaboration is driving research breakthroughs that are changing approaches to cancer prevention, screening, detection, treatment and survivorship. The primary drive is to improve the lives of cancer survivors focusing on patient-centered care, developing novel treatments, training future generations of cancer experts, and bringing cancer research to communities.

2.2 Community Outreach and Engagement

Cancer Centers such as MCCCC are guided by The National Cancer Institute's (NCI) Cancer Center Support Grants (CCSGs) specifically to reduce cancer burden in specified, self-defined geographic areas ("catchment areas") in order to reduce the burden of cancer, and improve health equity through a structural approach in Community Outreach and Engagement [17]. *NIH states "Cancer Centers – working with community stakeholders – should identify community needs, communicate those needs across the Center's leadership and research programs and catalyze activities of special relevance to the Cancer Center's self-defined geographic catchment area population."* [18] COE and participatory approaches involve bidirectional relationships with community members and leaders and are beneficial to reduce existing health disparities among marginalized groups [19]. In cancer prevention, care and control, COE efforts have been shown to be effective in increasing participation rates in clinical trials, direct involvement in research and academic training, and improving inclusiveness of minorities in scientific studies [20]. MCCCC has initiated a wide array of COE activities to encourage and integrate investigators and research programs to collaborate and co-lead cancer-focused studies directly with impacted communities. In the Cancer Center, COE activities are embedded in translational, clinical, and basic research, along with population science, education & training, clinical practice and Diversity, Equity and Inclusion offices. SNA falls under a major aim in COE, which is to track, monitor and evaluate the impact of MCCCC COE activities for continuous quality improvement, and demonstrate the impact of COE activities in the catchment area communities. In this paper, we assessed current interactions among MCCCC members in order to measure the effect of COE activities on scholarly collaborations and publications of various efforts implemented over the next year. Our long-term goal is to understand the patterns of relationships amongst investigators, programs, and departments and how to integrate COE into practice in order to improve the Center's community engagement efforts, reduce health disparities, and decrease cancer burden in marginalized groups through collaborative research stemming from MCCCC.

3 Methods

3.1 Data Collection and Annotation

As part of the Cancer Center Support Grant requirements of an NCI-designated Cancer Center, the fourth author (SB) collected data on all MCCCC Members throughout the year. For the purposes of this project, data was reviewed beginning in early 2022. We first identified all the researchers with active MCCCC program membership who have published at least one paper during either the year 2021 or 2022, regardless of the sequence of the authorship. The personnel list has the following research-related information: person UUID, MCCCC program affiliation (annotated manually, including researchers involved in dual programs). We then formulated a list of all PubMed-indexed papers with at least one author from the MCCCC personnel list. The publication list contains the following research-related information: PubMed ID, title, author's person UUID, the sequence of the authorship, and abstract. To protect the stakeholders' privacy, researchers, physicians, and departments will be de-identified in this paper, even though re-identifying them was essential for internal operational management.

In this process, we identified 388 researchers in 2021 and 392 researchers in 2022. 66 of them left or became inactive in 2022, while 70 new researchers joined the center or became active in 2022. As a result, 322 researchers are active in both 2021 and 2022. Most of the researchers on this list have been assigned to one of nine MCCCC programs, while a few new or temporal researchers have been labeled as "Non-Aligned." On the publication side, we identified 2615 publications in 2021 and 2597 publications in 2022.

3.2 Constructing the Collaboration Network.

In this analysis, we built two networks for each year's data: one co-author network and another program collaboration network. *In the co-author network of each year*, we define the node to be each author affiliated with the center in that year, and we define the weighted undirected edge between two nodes to be the frequency of two authors' co-appearance in one paper. Thus, the 2021 network has 388 nodes (including nodes with 0 degree) and 2141 edges. Similarly, the 2022 network has 392 nodes (including nodes with 0 degree) and 2282 edges. Note that if one paper is published by only one MCCCC member and all other authors of that paper are not affiliated with MCCCC, that paper will be excluded in our co-author network (caused by no MCCCC co-authorship). But it will still be included in the total publication of the center, which resulted it the discrepancy between the total edges presented here and the total publications mentioned in section 3.1. *In the program collaboration network*, we define the node to be nine programs within the center plus the "Non-Aligned" (thus, 10 nodes in both 2021 and 2022). We then define the weighted undirected edge between two nodes to be the frequency of collaboration between two authors affiliated with each program; authors with dual program membership will earn half the value (0.5) for either of their programs in each collaboration. The network data was prepared and aggregated via Python and the network visualization was constructed via Gephi.

3.3 Network Metrics and Study Design

In this analysis, we retained the following network metrics in Table 1. We decided to use the one-shot design as our primary design. We also performed several paired sample t-tests on the node and edge levels to assess whether the collaboration network changed between 2021 and 2022.

Table 1. Network Metrics

Level of Analysis	Features
Node	Degree, Weighted degree, Betweenness Centrality [21], Closeness Centrality [21], Eigenvector Centrality [22], number of triangles centered at the node [23]
Edge	Weighted Degree

Whole Graph	Clustering Coefficient [23], Density

4 Results

Figure 1 is the visualization of the inter-program level networks. The de-identified nodes (programs) are arranged clockwise manually based on alphabetical order. The color of the edge represents whether the cooperation level has increased (green) or dropped (red). The scaling of the color is determined by the magnitude of the change.

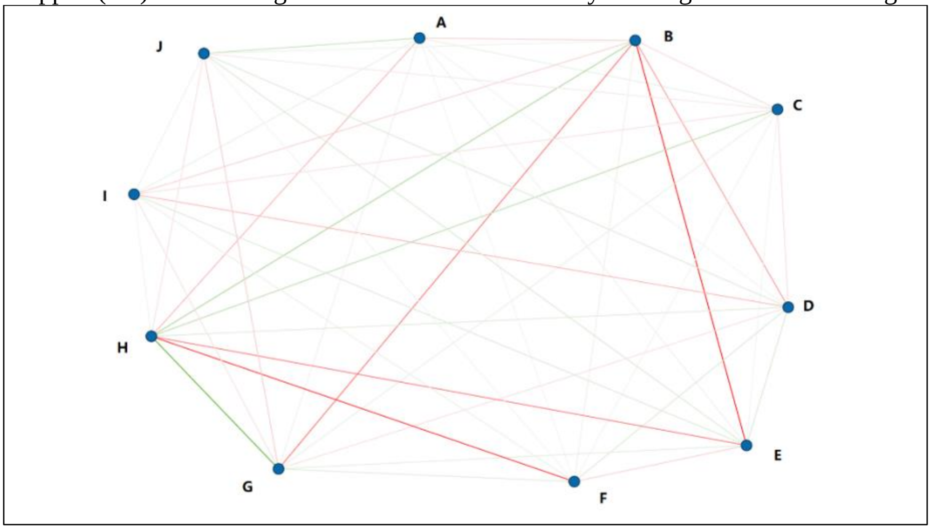

Fig. 1. Visualization of Inter-Department Cooperation 2021-2022

The rank of the total weighted degree of 10 nodes (A-J) is the same between 2021 and 2022. We also performed paired sample t-test of the 45 weighted edges, and the result (P=0.408) indicates the mean value of inter-department collaboration did not significantly change between 2021 to 2022. Therefore, we conclude that there is no effect on the department level networks between these two years. However, our analysis pinpointed three program pairs that dropped over 40 percent, which is vital for the management team to identify potential bottlenecks causing the problem. We also identified three program pairs that increased by over 40 percent, who might be served as exemplars and role models for others. Even though the center looks stable overall, we saw a trend of divergent performance among program pairs.

Table 2. Pairwise Comparison of Collaboration Between MCCCC Programs, 2021-2022

Difference and Direction			Difference and Direction			Difference and Direction		
A-B	-14.89%	-	B-I	-15.12%	-	E-F	-15.20%	-
A-C	15.79%	+	B-J	6.67%	+	E-G	22.22%	+
A-D	0.82%	+	C-D	-11.36%	-	E-H	-42.86%	-
A-E	6.47%	+	C-E	0.77%	+	E-I	35.00%	+
A-F	-0.66%	-	C-F	0.87%	+	E-J	37.78%	+
A-G	-5.50%	-	C-G	13.70%	+	F-G	29.17%	+

A-H	-24.24%	-	C-H	84.62%	+	F-H	-66.67%	-
A-I	15.43%	+	C-I	-10.08%	-	F-I	13.30%	+
A-J	67.61%	+	C-J	-7.79%	-	F-J	0.00%	=
B-C	-11.96%	-	D-E	38.81%	+	G-H	158.33%	+
B-D	-33.33%	-	D-F	34.04%	+	G-I	-9.46%	-
B-E	-77.27%	-	D-G	-10.26%	-	G-J	-15.91%	-
B-F	9.09%	+	D-H	30.77%	+	H-I	3.08%	+
B-G	-45.90%	-	D-I	-22.76%	-	H-J	-9.52%	-
B-H	N/A (over 0)	+	D-J	34.78%	+	I-J	6.51%	+

Figure 2-4 of the nodes of the co-author network are arranged by the Noverlap algorithms at Gephi in the default setting, where the color of the node (from yellow to dark cyan) illustrates the weighted degree of each node, and the width of the link illustrates the frequency of collaboration between two authors. Figures 2 and 4 are the real-world network captured at the end of 2021 and 2022, respectively. While Figure 3 represents how the 322 nodes transitioned from 2021 to 2022. Figure 3 demonstrates an extensive rewiring process where the veteran researchers actively search for new partners and co-authors when their prior collaborators are left. As a result, they established a much denser inter-center network in 2022, and most of them have obtained higher weighted degrees.

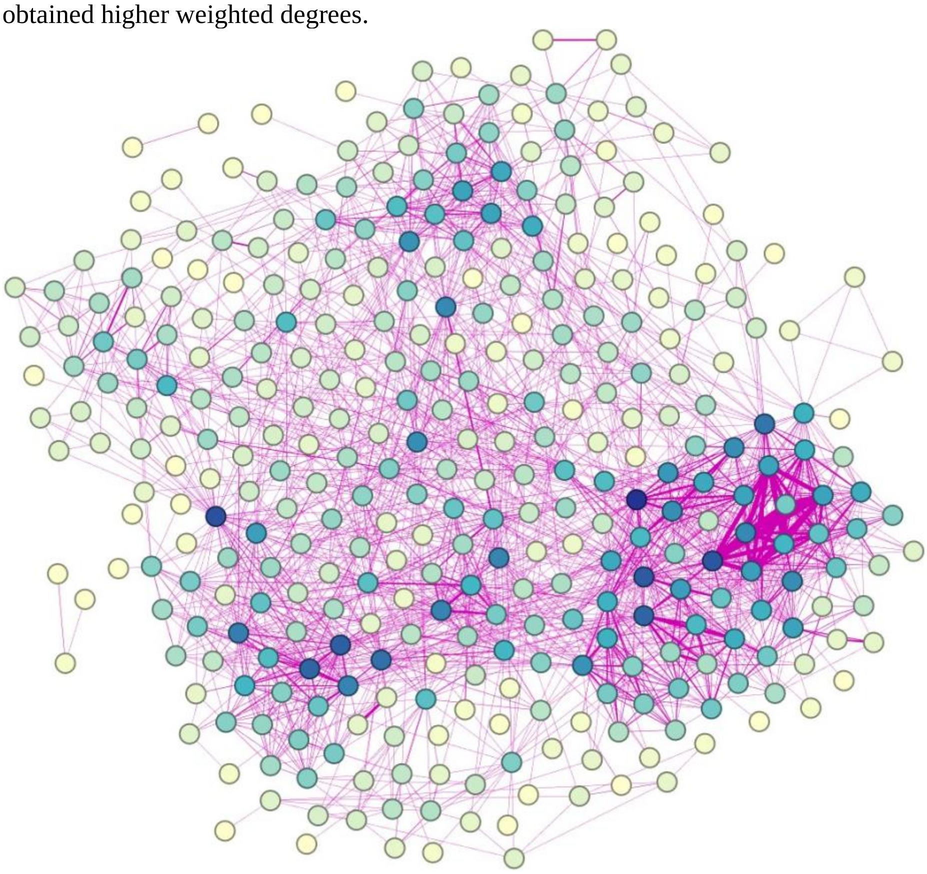

Fig. 2. 2021 Co-Author Network, Full

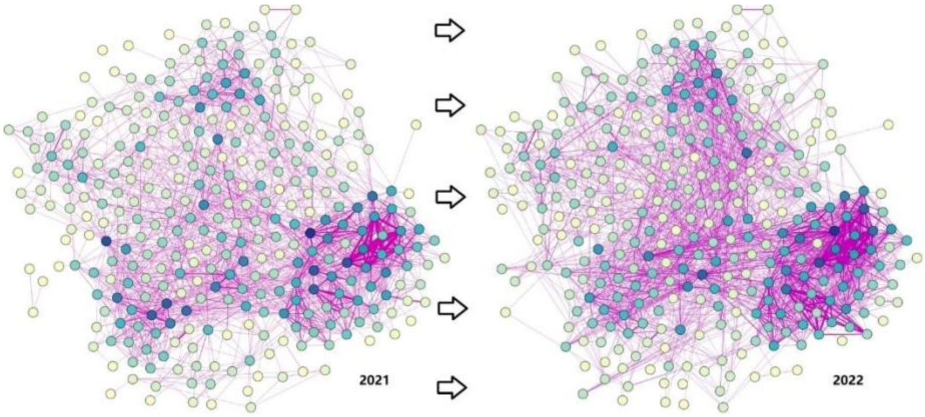

Fig. 3. Co-Author Network in transition, 322 mutually present nodes in both years.

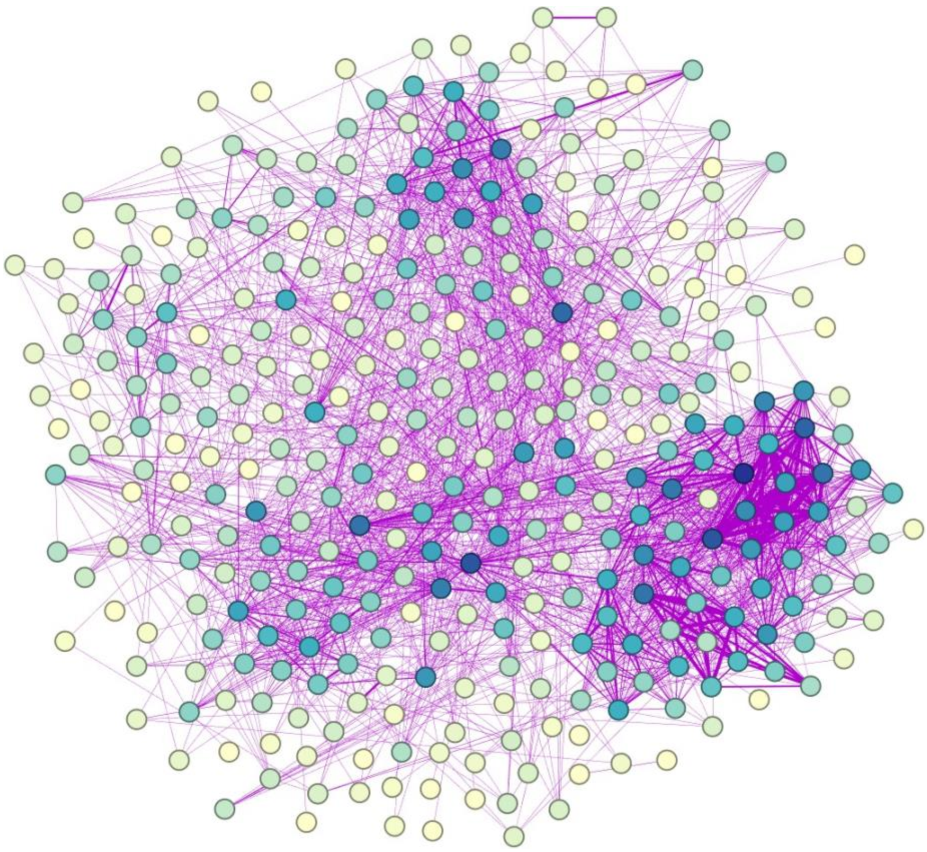

Fig. 4. 2022 Co-Author Network, Full

When numerically comparing the graphs: the weighted degree of all edges between the 2021 co-author network (2141) and 2022 co-author network (2282) directly using all data, the unpaired t-test indicates that the mean of the weighted degree of the edges of the 2022 network (2.52) is significantly higher than the 2021 value (2.22), (mean diff=0.3, P=0.0055). Furthermore, to make it a fair comparison of the 322 authors presented in both 2021 and 2022 in Figure 3, we performed another paired t-test of the node metrics of these authors who went through great resignation but decided to stay on. The result is presented in Table 3.

Table 3. Paired T-Test of Nodes Level SNA Metrics of 322 Authors Presented in Both Years

Node Level Metrics	**2021 Mean of**	**2022 Mean of**	**Mean Diff**	**Paired sample t-test, p-value**	**Significant**
Degree	12.913	13.528	0.615	0.577	NO
Weighted Degree	29.224	34.873	5.649	**0.000**	**YES**
Closeness Centrality	0.343	0.336	-0.007	0.254	NO
Betweenness Centrality	385.917	403.723	17.805	0.601	NO
EigenCentrality	0.165	0.159	-0.006	0.439	NO
Triangles	53.683	62.898	9.214	**0.004**	**YES**

We have witnessed a significant increase (*mean diff*=5.649, P=0.000) in the mean of the weighted degree and a significant increase (*mean diff*=9.214, P=0.004) in the number of affiliated triangles of the nodes, which is consistent with the information observed from Figure 3. The fact that the total publication in 2022 (2597) is slightly less than the 2021 data (2615) suggest no evidence to support the claim that the increment on the weighted degree is caused by "the center has published more papers in 2022"; On the contrary, the center has published slightly less in 2022. Furthermore, these two paired t-tests on the node level also corroborate the analysis of the weighted degree of the edges. Therefore, we conclude that those veteran researchers in the center have built stronger inter-center ties after the 2021 great resignation trend.

5 Discussions, Limitation and Future Works

In this pilot study, we developed two series of center-wide collaboration networks, one on the program level and another on the author level. We used these networks to explore the impact of the Great Resignation on the center. We found that collaborations between several programs have been impacted heavily from 2021 to 2022, while a few thrived against the odds. Meanwhile, we have seen a visible trend of collaboration rewiring on the author level, which results in a denser co-author network with significantly higher numbers of triangles and weighted degrees. The finding is also hinted by the theory originated from the small-world networks literature [23, 24]. The results have also shown that scholars with a high level of connectiveness are more likely to become connected when others are searching for opportunities for collaboration. On the operational side, this analysis has provided the Center's leadership with precise information on authors' collaborations, thus enabling new data-driven initiatives to engage under-connected researchers. Furthermore, our pilot analysis has provided an up-to-date baseline of the Center's collaboration relationships, which can be used for historical (pre-pandemic) and future (post-pandemic) research.

This study is certainly not a replacement for traditional program evaluation methods of survey and questionnaire. We cannot use the network alone to determine the psychological and emotional part of the researcher's decision when seeking cooperation, nor can we assess their job satisfaction and mental well-being during this difficult time. Nevertheless, using this method, we can identify those struggling and conduct further qualitative investigations with higher precision.

Lastly, this study has shown that although the impact of Great Resignation is vivid, it is not necessarily detrimental to the entire organization or institution. Each organization can benefit from a data-driven analysis to better prepare for the post-pandemic era. In the future, we plan to use SNA to explore the Center's external impact on academia and the local community along with citation analysis and patient demographic analysis.

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