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Identifying emerging research collaborations and networks: Method development

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Abstract

Clinical and translational research is a multidisciplinary, collaborative team process. To evaluate this process, we developed a method to document emerging research networks and collaborations in our medical center to describe their productivity and viability over time. Using an email survey, sent to 1,620 clinical and basic science full-and part-time faculty members, respondents identified their research collaborators. Initial analyses, using Pajek software, assessed the feasibility of using social network analysis (SNA) methods with these data. Nearly 400 respondents identified 1,594 collaborators across 28 medical center departments resulting in 309 networks with 5 or more collaborators. This low-burden approach yielded a rich dataset useful for evaluation using SNA to: a) assess networks at several levels of the organization, including intrapersonal (individuals), interpersonal (social), organizational/institutional leadership (tenure and promotion), and physical/environmental (spatial proximity) and b) link with other data to assess the evolution of these networks.

Keywords

Research collaboration; social network analysis

Introduction

Clinical and translational research is a collaborative, multidisciplinary team process and a key component of the NIH roadmap that served as the framework of the initial Clinical and Translational Science Awards (CTSAs) (Zerhouni). One key role of CTSAs is promoting multidisciplinary research by preparing investigators to serve on and lead multidisciplinary research teams. In 2010, the CTSA *Evaluation Key Function Committee* recommended that awardees use Social Network Analysis (SNA) to understand the collaborative process, in light of the onset of cross-disciplinary opportunities made available by the National Institutes of Health and the National Science Foundation. Similarly private foundations are increasingly interested in supporting team-science approaches (see definitions, Table 1) in biomedical research (e.g. MacArthur, Robert Wood Johnson, W.T. Grant and The National Academies' KECK Futures). To understand and evaluate the development and successes of these teams, many evaluators have incorporated the use of SNA, a multi-level systems approach, or both to characterize the collaborations within institutions and groups and to describe linkages amongst individuals that identify networks of investigators, their size, density and connectedness to other research networks (Table 1).

Previous attempts to use SNA to assess research collaborations primarily drew on archival data sources such as co-authorship on research studies and grant proposals (Masse, et al, 2008; Stokols, Gress, Fuqua & Phillips, 2005). While useful, these data may not represent the full extent of research collaborations and do not fully exploit the ability of SNA to reveal how collaborations are generated (Albert & Barábasi, 2002; Newman, 2010; Newman, Barábasi, & Watts, 2006), how they are structured (Newman, 2001), and how they evolve over time (Nagarajan, Lowery & Hogan, 2011). SNA can also identify the most influential members in a team and power dynamics among team members (Nagarajan et al.; Watts & Strogatz, 1998) including concepts of centrality, betweenness, and tight and weak connections among team members (Table 1). SNA has also been used to identify contextual factors of team effectiveness. Such analyses reveal those contextual factors that may be modifiable vs. those that are beyond direct control of the institutional environment.

The 2006 CTSA application submitted by the University of Rochester identified the importance of nurturing cross-disciplinary collaborations, including the establishment of a clinical and translational science (CTS) building to co-locate key departments and services. At the time, the University of Rochester School of Medicine and Dentistry and the School of Nursing were geographically dispersed across the main campus and two off-campus sites within a mile of the main campus. Our evaluation data collection endeavor coincided with the establishment of a new CTS building in April 2011. Research departments and divisions (biostatistics, public health sciences, pediatric outcomes, emergency medicine), centers (e.g. National Center for Deaf Health Research) and the administrative offices of the Clinical and Translational Science Institute (CTSI) including research support services (e.g. IRB,

Regulatory Support) moved into the building. Our primary aim was to analyze research collaborations before and after these various groups moved.

Methods

We developed a survey to obtain data that could be analyzed in the context of SNA to define team-based structures at our institution. The design of the questionnaire was informed by the multi-level systems approach (Borner et al, 2010) (Table 1). In May 2011, we emailed an online survey invitation to *all* full- and part-time faculty with primary University of Rochester Medical Center (URMC) appointments, including tenure and non-tenure track. There was no presumption about who was involved in research, and therefore no attempt was made to exclude individuals based on their appointment titles (e.g. clinical, instructor or research associate) or primary department or status (full/part time). This resulted in a distribution list of 1,620 individuals.

The link to the survey was embedded in an email distributed under the auspices of the Director of the CTSI and included the purpose of the survey. While respondents were identifiable, their responses would remain confidential. Follow-up reminders to non-responders were sent three times over a period of eight weeks.

Survey Instrument

The first question of the survey asked if the respondent was involved in research at all. Those responding “yes,” were then asked to identify up to 10 individual research collaborators from a drop-down list pre-populated with the names of investigators from within the institution, although write-ins were also allowed and more than 10 collaborators could be named. As this work was exploratory we did not attempt to impose a definition of collaboration or collaborator. We were able to link data about faculty rank, full- and part-time status, and departmental affiliation to all the individuals in the drop-down list. Because we limited our assessment of research collaborations to those within our medical center we did not capture details about collaborations with other UR or outside investigators.

Analysis

We first computed frequencies of respondent demographics and the identified collaborations. We then conducted several representative preliminary analyses to identify individual- and department-level collaborations and research networks, and to explore how networks differed by collaborator characteristics. Only those with at least 5 members were counted as networks. All analyses were done with Pajek (<http://pajek.imfm.si/doku.php?id=pajek>).

Results

Feasibility and Representativeness

Of the initial set of 1,620 faculty members, 395 (24.4%) individuals responded and 90 (0.6%) were found to be no longer employed by the university. Respondents were similar to those in the original faculty distribution list in terms of faculty rank and full- or part-time

status. Individuals from basic science departments were over-represented (18.4% of those invited vs. 24.8% of respondents). A total of 55 (13.9%) reported not participating in research. Among the remaining 340 individuals, 11.2% reported no research collaborators and 6.5% reported only collaborators from outside the medical center. The remaining 280 (82.4%) identified at least one collaboration from within our medical center. Of these, 26.4% were Full Professors, 27.5% were Associate Professors, 26.4% were Assistant Professors, and 10.3% were Research Assistant Professors. Respondents represented 28 of the 29 departments. Most (97.1%) were full time and 73.2% were from clinical departments.

Respondents identified a mean of 5.7 collaborators (range 1-16), and reported a total of 1,594 collaboration dyads involving 730 individuals. In some cases, two respondents reported the same dyadic relationship (i.e., respondent 1 reported a collaboration with respondent 2, and respondent 2 reported a collaboration with respondent 1). This situation occurred 111 times, so the dataset includes a total of 1,483 unique collaborations (1,372 collaborations were reported by only one collaborator; 111 collaborations were reported by both). For the purposes of our analyses bidirectionality was not required so, both reports of the relationship were counted. Among all identified collaborators, 32.0% were Full Professors, 29.7% were Associate Professors, 21.1% were Assistant Professors and 6.0% were Research Assistant Professors (data not shown).

Collaborations occurred across a mix of faculty ranks, as depicted in Table 2. Among all reported collaborations, Full Professors were reported or were identified in 1,032 (64.7%). Nearly half of all collaborations involved Associate Professors (785; 49.2%), 429 (26.9%) involved Assistant Professors and 262 (16.4%) involved Research Assistant Professors.

Among the reported collaboration dyads, 403 (25.3%) involved at least one off-site collaborator. Within this group, 311 (77.2%) included on- and off-campus collaborators, while the remainder included off-campus collaborators only (data not shown).

Social Network Analyses

To assess the feasibility of using these data for future social network analyses, and consistent with the levels described by Borner et al. (2010), we first examined the entire network (macro-level), and next, at the meso level, we examined collaborations across departments. Our preliminary analyses identified different patterns of inter- and intradepartmental collaborations. Among all respondents, when viewed by clinical vs. basic department, 17.3% of the respondents from clinical departments and 18.5% from the basic sciences departments had either no research collaborators or only had collaborations with non-URMC investigators. These respondents were not concentrated in any particular department.

Across the 28 departments representing the respondents, 205 were from clinical departments reporting 1,115 within-URMC collaborations (69.9%) (Table 2). Of these 50.9% (567) were *interdepartmental* and ranged from a high of 78.6% to a low of 36.3%. *Intradepartmental* collaborations represented the balance (n=548) and showed a similar pattern ranging from 78.6% to 36.3%. Respondents from the 10 basic science departments represented 479

collaborations (n=75 respondents) with 79.3% of these being interdepartmental ranging from 50.0% to 90.4% across departments.

These department-level data illustrate differences that can be explored further with SNA. For instance, Figure 1 depicts networks from two different departments. The diagrams on the right (A and C) depict department level collaborations. Each circle represents a department, with the department in the upper left being the one of primary interest. The size of the each circle is proportional to the number of interdepartmental collaborations involving that department. The diagrams on the right (B and D) portray individual-level networks representing first-degree connections involving members of the chosen department. The diagrams reveal substantial differences between the two departments, with Department Z having more collaborations, and a greater proportion of intradepartmental collaborations, as compared to Department S.

Beyond departmental analyses, these data may provide sufficient detail for SNA at the individual investigator level (micro-level). For example, Figure 2 illustrates reported first- and second-degree collaborations for two different investigators (represented by the circle in the center of each panel). The size of the circles is proportional to the number of first-level collaborations. The shading is indicative of the department. The differences between these two investigators, in terms of the number of first-degree connections and the density of second-degree connections are apparent. This sort of diagram (alone or in combination with other investigators' networks) can be analyzed in further detail by applying SNA metrics (e.g. betweenness, centrality) to reveal the nature and extent of these investigator's research networks (See Table 1).

Discussion

Using this methodology, 280 respondents with research collaborations identified 1483 unduplicated collaborations across multiple clinical and basic science departments within one medical center. This approach yielded a representative group of investigators across faculty rank, type of department and part/full time status. The number of individuals who did not identify any research collaborators was somewhat unexpected. Given that they represent a variety of departments, further analysis of these individuals' characteristics would likely provide important information to guide departmental or institutional initiatives. Further exploration of collaborations outside the medical center is also warranted as this is an important area of future growth.

Our results suggest that this method yielded data with granularity sufficient to be useful for application of SNA methods, including characterization of these networks using measures of centrality and power and analyses from multiple perspectives (e.g. individual, department, and other factors). Furthermore, linkage of these data with other data sources would create opportunities for additional network analyses to determine how many collaborations are emerging (i.e., how many have not yet produced tangible products) that are not identifiable through other means (e.g. publications analysis).

This data set would allow for SNA to assess team effectiveness at several levels of organization, including intrapersonal (individuals), interpersonal (social) organizational/institutional leadership (tenure and promotion), and physical/environmental (spatial proximity). For example, the geographic distribution of collaborators both within and outside of the institution would help to explore how spatial proximity influences the establishment of collaborations. The data can also be analyzed using the perspective of a multi-level systems approach. At the macro level, the data provide an institutional view of these research networks (Borner, et al). The distribution of collaborations across faculty ranks provides information on the extent to which senior faculty are involved in research collaborations. Findings from our preliminary analyses suggest that Professors and Associate Professors collaborate with individuals from a wider variety of faculty ranks than was true for more junior faculty, an indirect assessment of the degree to which senior faculty serve as mentors. As demonstrated, each individual network can also be analyzed by the extent of senior faculty involvement, often a key factor in successful research initiatives from grantsmanship to publication.

At the meso level, department leadership could use these diagrams of collaboration to assess patterns of their faculty's research activities. For example they could identify gaps and potential opportunities for supporting emerging networks by promoting the addition of senior faculty or inclusion of both basic and clinical investigators. At both the meso and micro levels, these findings can also inform CTSI initiatives, supporting the identification of developing networks and individuals who may not be fully using research-support services. Additionally, individual investigators could undertake a similar review (micro level), identifying their collaborators who have connections to other investigators who might be useful to the network.

As noted, these data can be linked with other data, further enhancing their utility for evaluation of research networks. For example, dimensions such as geography, funding and types of publications (translational, clinical or basic sciences) could be added to assess the ongoing development of networks and the growth of clinical and translational research. Lastly, by identifying department-level characteristics, such data can provide a context to understand the development and growth of these networks. Ultimately, findings from these analyses can provide some important guides to emerging networks, including macro-, meso- and micro-level factors for their ongoing success. Interventions could include providing additional support to emerging networks such as encouraging senior faculty participation, assuring that networks are connected to other networks (e.g. weak linkages), recommending expansion to include other disciplines or expertise, or providing training or support for moving the network toward seeking new or different types of funding.

Our methodology has several strengths. Gathering these data required a relatively low respondent burden. The methodology resulted in network data sufficiently granular to detect individual and departmental differences. Further, as with other social network data, networks can be depicted despite missing data, in that only one participant in a collaboration needs to provide data in order for the analysis to be conducted. In our case we learned about investigators involved in research collaborations even though they did not respond or report the collaboration. Emerging networks can be identified because the analysis does not depend

on the existence of products (publications or grant awards). Networks can be analyzed concurrently and over time (with additional data collections). Analyses could occur at multiple levels (macro, meso and micro), from the perspective of multiple dimensions (e.g. department, faculty rank), and based on team-effectiveness characteristics. The methods described can be useful for other institutions seeking to identify emerging research collaborations or networks.

Limitations

Despite the amount of data we gathered, they do not fully depict all of the research networks or collaborations, as we did not include collaborations with non-URMC investigators. Furthermore, our promotion of survey participation was not extensive, which likely contributed to our respondents representing only a quarter of the faculty. This weakness is counterbalanced somewhat by a strength of social network analysis: despite missing data, many relationships were identified by one member of a dyad. In our case, respondents provided some data on approximately half of all faculty members at the medical center. Nevertheless, it is probable that we have not captured all existing networks. Another limitation is that, due to confidentiality of responses, we were unable to share individual investigator names with department chairs. In subsequent survey administrations, we anticipate requesting permission to share names. Additionally, as this is a description of methods, we have not yet assessed the context, quality or longevity of the identified collaborations or networks. It is also possible that the collaborations and networks we find represent an underlying or latent dimension that we have not assessed. Finally, as noted, not all of the identified collaborations were mutually identified. This potential bias will need to be considered when interpreting future analyses.

Conclusions

Our method provides a novel way to analyze the evolution of research collaborations and networks. These data could be useful to organizational leaders and evaluators who wish to identify opportunities for programs to provide support and resources for such research collaborations. With future analyses, we will also be able to evaluate the breadth of research networks and describe their productivity and viability over time.

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Figure 1.

Interdepartmental collaborations of two departments (Z and S).

NOTE: Size of circles is proportional to the number of first-degree investigators identified as collaborators in the various departments. For diagrams B and D shading represents different departments

Diagram A: Department Z's interdepartmental collaborations

Diagram B: Department Z's investigators' networks

Diagram C: Department S's interdepartmental collaborations

Diagram D: Department S's investigators' networks

Figure 2.
First and second degree connection for two investigators from different departments
NOTE: Size of circles is proportional to the number of collaborators

Table 1

Definition of Terms

Team-science: is “a collaborative effort to address a scientific challenge that leverages the strengths and expertise of professionals trained in different fields...coordinated teams of investigators with diverse skills and knowledge may be especially helpful for studies of complex social problems with multiple causes.”
<https://www.teamsciencetoolkit.cancer.gov/public/WhatIsTS.aspx>

Social Network Analysis (SNA): “allows researchers to describe, integrate, and analyze spatial, mathematical, and substantive dimensions of the social structures formed as a result of ties formed between persons, organizations, or other types of nodes. Researchers can represent networks graphically, locate them spatially, and describe and analyze their properties mathematically. These spatial and mathematical relations (i.e., “networks”) can then be related to the content and quality of interpersonal ties, individual or group phenotypes and behaviors, and the well-being and dynamics of groups and communities.”
<http://grants.nih.gov/grants/guide/pa-files/PA-10-145.html>

Centrality: relates the way that individuals are connected to other individuals the network (Hawe, Webster, Shiell, 2004). There are three common measures of centrality, each reflecting different concepts of connectedness. The simplest is degree *centrality*, which is a count of the number of connections that an individual has to other individuals in the network. For any individual, this can be computed by simple inspection. By contrast, computation of the other 2 measures of *centrality* (closeness and betweenness) requires specialized software.

a) *Closeness* is a measure of the average distance from any given individual to all other individuals in the network, and thus relates to the speed with which information arising from anywhere in the network is likely to reach the individual.

b) *Betweenness* measures how often the individual lies on the shortest path between every possible pair of other individuals in the network. Betweenness is closely related to ideas of brokerage and power within networks; an individual with high betweenness can function as a gatekeeper of information or resources (Hawe et al, 2004.). If an individual with high betweenness leaves an organization or network, then the remaining members may have less access to information arising elsewhere in the network.

Gatekeepers also connect across different networks for information sharing and coordination

Tight and weak linkages: are relational ties between individuals within a network. (In practice, individuals have varying degrees of ties to one another, and thus the binary distinction between a “tight” and “weak” linkage always involves some operational criterion, such as frequency of contact.) Within a larger social network, smaller sub-networks may be defined as those comprising individuals who all have tight ties to one another. Novel information is more likely to move across weak rather than strong links. (Hawe et al., 2004; Granovetter, 1973), leading to the counterintuitive notion of the “strength of weak ties.” A sub-network made up only tight linkages may well be insular and disconnected from the remainder of the organization.

Multi-level systems approach: as described by Borner et al (2010) this includes three levels of team structure: (a) the macro level, which involves the larger cultural context in which teams are embedded; (b) the meso level, including group dynamics, training and education, and; (c) the micro level, which describes specific individuals within teams.

Table 2

Number of Collaborations by Respondents' and Collaborators' Faculty Rank

Respondent Rank	Collaborator Rank	#	% of total collaborations
Full Professor	Full Professor	244	15.3
	Associate Professor	149	9.4
	Assistant Professor	67	4.2
	Research Asst. Professor	31	1.9
	Other ^a	37	2.3
Associate Professor	Full Professor	238	14.9
	Associate Professor	150	9.4
	Assistant Professor	55	3.5
	Research Asst. Professor	15	<1
	Other ^a	20	1.3
Assistant Professor	Full Professor	118	7.4
	Associate Professor	78	4.9
	Assistant Professor	45	2.8
	Research Asst. Professor	15	<1
	Other ^a	11	<1
Research Assistant Professor	Full Professor	77	4.8
	Associate Professor	51	3.2
	Assistant Professor	27	1.7
	Research Asst. Professor	32	2.0
	Other ^a	8	<1
Other^a	Full Professor	71	4.5

Respondent Rank	Collaborator Rank	#	% of total collaborations
	Associate Professor	29	1.8
	Assistant Professor	13	<1

^aIncludes Associates, Senior Associates, Instructors, Senior Instructors, Nurse leader, Professors Emeritus

NOTE: Collaborations are organized by respondent so some collaborations are duplicated if the collaborator also responded (n=111)