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Influence networks among substance abuse treatment clinics: implications for the dissemination of innovations

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Abstract

Understanding influence networks among substance abuse treatment clinics may speed the diffusion of innovations. The purpose of this study was to describe influence networks in Massachusetts, Michigan, New York, Oregon, and Washington and test two expectations, using social network analysis: (1) Social network measures can identify influential clinics; and (2) Within a network, some weakly connected clinics access out-of-network sources of innovative evidence-based practices and can spread these innovations through the network. A survey of 201 clinics in a parent study on quality improvement provided the data. Network measures and sociograms were obtained from adjacency matrixes created by UCINet. We used regression analysis to determine whether network status relates to clinics' adopting innovations. Findings suggest that influential clinics can be identified and that loosely linked clinics were likely to join the study sooner than more influential clinics but were not more likely to have improved outcomes than other organizations. Findings identify the structure of influence networks for SUD treatment organizations and have mixed results on how those structures impacted diffusion of the intervention under study. Further study is necessary to test whether use of knowledge of the network structure will have an effect on the pace and breadth of dissemination of innovations.

Keywords

Sociometrics, Diffusion of innovations, Social networks, Network analysis, Addiction treatment

Implications

Practice: In the substance abuse specialty treatment system, purveyors of innovations may expect slow but steady diffusion of well-received innovations.

Policy: Policymakers who want to encourage the wide uptake of new practices should plan multiple introductions of a new practice over a long period of time as interest will spread slowly but surely through a provider network.

Research: Research should be conducted to study the deliberate use of network structure to seed and observe diffusion of innovation through SUD treatment networks.

INTRODUCTION

Social network analysis has been used for many purposes since Jacob Moreno first studied social connections at Sing Sing prison [1] and the Hudson School for Girls [2]. Contemporary uses of social network analysis include the mapping of terrorist networks [3], the effect of a government's science policy on communication between inter-disciplinary scientists [4], and information dissemination in commercial arenas [5] and public health [6–8]. Network analyses commonly address questions such as the following: Who influences whom? How connected are the members in a network? Do certain members in the network cluster into groups? Which members bring information about innovations into the network? The answers to these questions may explain individual and organizational decision-making about adopting innovations and allow innovators of policies or practices to predict how well their innovation may spread or plan dissemination activities. For example, an innovator external to a network could provide information, demonstrations, or training and technical assistance to influential individuals and organizations in hopes of speeding the adoption of the innovation throughout a network.

Studies from various industries and sectors indicate that people generally first learn of innovations relevant to them through mass or specialty media and then decide whether to try an innovation based on what their trusted colleagues are doing or communicating about the innovation(s) [9]. This means that dissemination must overcome sociological barriers between potential adopters [10], such as collegial or conflictual relationships, as well as psychological barriers within individuals based on perceptions of the innovation in question, such as general willingness to innovate. Whether an innovation is adopted may have less to do with the value of the idea than with the social relationships in a network and when an innovation is introduced [11–13]. In substance abuse treatment, Miller found that providers were most likely to learn about new treatments from other providers rather than from the media [14]. This marks a difference between substance abuse treatment and other fields, a difference that may make substance abuse treatment providers more susceptible to social influences in the adoption of innovations. However, substance abuse treatment provider networks have been described as decentralized, with many isolated addiction treatment centers [15], suggesting that interpersonal communications may not lead to the rapid dissemination of new ideas.

An organization adopting an innovation is a more complex process than an individual adopting an innovation [16–18], and a type of innovation may also influence the adoption process [19]. Many ways of differentiating types of innovations have been offered since Schumpeter's original classification [20]. This analysis will use the Edquist model of process and product innovation [21]. In this model, a process is more likely to be adopted in an organization via a top-down model than is a product innovation [17]. Process innovations–also called "administrative process innovations"–may spread through a network by "adaptive emulation," whereby organizational leaders look to their more successful peers or those they aspire to be like to identify ways to be more successful themselves [22]. The pace and process of this diffusion depend on the structure of the network. Network structure may be measured in terms of the number and multiplexity of connections between members, as well as the way in which members are linked (e.g., through a strong central member or via many looser connections) [23].

PURPOSE

The present study seeks to describe influence networks in substance abuse treatment clinics in five states. The goal of describing the networks is to assess the utility of social network analysis in understanding how process innovations disseminate in the networks. In addition to understanding the flow of new ideas through a network, we want to test two expectations: (1) that influential clinics can be identified with social network measures and (2) that weakly connected network agencies may be innovators who link sources of innovations to other providers in the network [24]. Understanding how networks of substance abuse treatment clinics function may make it possible to identify and work with key clinics in a network to improve the dissemination of innovations.

METHODS

Parent study

Data for this study come from a parent study called NIATx 200, which was a cluster-randomized trial funded by the National Institute on Drug Abuse [25, 26]. NIATx stands for the Network for the Improvement of Addiction Treatment (NIATx), which is a program within the Center for Health Enhancement System Studies at the University of Wisconsin–Madison. NIATx espouses a quality improvement model built on five principles of successful organizational change identified in a meta-analysis of both successful and failed change efforts in many industries: (1) understand the customer, (2) select a powerful change leader, (3) solve key problems, (4) get ideas from outside the field, and (5) use rapid-cycle change processes [27].

NIATx 200 sought to identify the most cost-effective method of disseminating quality improvement (QI) in addiction treatment by randomizing 201 addiction treatment clinics from five states to four interventions: a web-based learning kit plus monthly group phone calls, individual organizational coaching, face-to-face meetings, or the combination of all three. All four interventions taught the same content, which included such innovations as eliminating appointments, increasing referral sources, and streamlining paperwork. The study had three outcomes: waiting time (days between the first contact and the first treatment), number of annual program admissions, and length of patient continuation in treatment.

The addiction treatment clinics in NIATx 200 came from Massachusetts, Michigan, New York, Oregon, and Washington. To be eligible, clinics needed to provide an outpatient addiction treatment and have at least 60 admissions per year to their outpatient program, receive some levels of public funding, and have had no previous experience with NIATx. We excluded clinics from the New York City metropolitan area (the five boroughs and Long Island) because another NIATx QI initiative was taking place there at the same time. We also excluded clinics from the Upper Peninsula of Michigan because they are so physically distant from other Michigan clinics.

At each participating clinic in NIATx 200, the executive director or CEO was asked to complete a baseline organizational survey consisting of 10 questions, including information on organization type (e.g., private non-profit, county governmental agency, etc.) and organizational characteristics (e.g., number of employees, approximate annual revenues, etc.). One question on the survey also asked: "Besides your own clinic, which do you consider to be the five most influential clinics in your state?" Our goal in asking the question was to identify opinion leaders among clinics in each state–clinics that can influence other clinics. The question relates to Rogers' definitions of opinion leadership and influence, though Rogers applied the terms to individuals rather than organizations. He said [9]: "Opinion leadership is the degree to which an individual is able to influence other individuals' attitudes or overt behavior in a desired way." Our assumption was that executive directors or CEOs would, by virtue of their position, come into contact with many individuals from other clinics and also be familiar with the performance of other clinics in their states. Respondents were not restricted to naming clinics involved in NIATx 200 but were restricted to clinics within their state.

Data sources

Answers to the question about the five most influential clinics in each state were used to analyze a network structure in this paper. Previous research has shown that, for process innovation, executive leadership is the appropriate level of organizational influence to investigate [21]. Any nominated clinic within the state became part of this analysis.

We also examined data for three proxies for a clinic's willingness to adopt an innovation: the length of time it took a clinic to join the study, which was obtained from NIATx 200 administrative records, and two of the three parent study outcome measures, waiting time and annual program admissions, which were obtained from patient records. Time to join the study served as a proximal measure of a clinic's willingness to adopt an innovation (defined as the NIATx model of quality improvement as a whole) and reflected executive decision-making more than the outcome measures in the parent study. But we also examined the relationship between a clinic's influence and the two outcomes, waiting time and annual program admissions, because these two variables represented the level of improvement achieved by each clinic. The third outcome, continuation in treatment, was not examined because there was no effect found in the parent study for this outcome. Information for these outcomes was collected from individual patient data reported by the clinic. Among the 201 participating clinics in the parent study, more than 70,000 patient records were analyzed to compute the average change in average patient waiting time per clinic. A change in the annualized number of new patients treated by a clinic was collected in annual surveys.

Analysis

Survey data on clinics named as influential were cleaned by spelling out acronyms, correcting misspelled clinic names, and removing clinics not within one of the five states. UCINet was used to calculate individual clinic and network properties; sociograms were created using NetDraw (www.analytictech.com/ucinet/). UCINet organizes responses into an adjacency matrix with the names of surveyed and nominated clinics in each state. The adjacency matrix provides a mathematical description of the links for all clinics mentioned in the survey in each state. Analyzing the adjacency matrix provides metrics about the properties of each network and the individual clinics in each network. All clinics that participated in the parent study and all clinics named by study participants as influential are identified as points in the resulting sociograms, one sociogram per state. When one clinic mentioned another clinic, a link appears as a line between the two clinics on the sociogram. The sociogram is not a map in the geographical sense but a representation of relationships, with the most influential clinics (calculations described further) in the center and the least influential clinics at the periphery.

Measures

We report on two types of network measures: three measures related to each state's network as a whole and one measure related to the influence of individual clinics.

Overall network measures—The following three measures characterize the structure of a state's network. *Distance* [28] measures the average of the shortest path between all possible combinations of two clinics in a sociogram. The lowest possible average distance is 1, when all clinics are connected directly to one another. Higher numbers mean greater distance, e.g., longer paths between clinics, and consequently slower diffusion of innovations. *Degree* measures the likelihood that any two clinics in a network are directly linked to each other, calculated as the average of the number of links per clinic in the network. The *clustering coefficient* is the ratio of the number of links that actually exist between clinics to the number of all potential links. It identifies the level of cliquishness within the network. Cliques are clusters of organizations within a network that are more closely tied to one another than to the rest of the network.

A measure of individual clinic influence—A clinic's influence within a network is measured by eigenvector *centrality* [29]. This measure characterizes a clinic's influence through (1) the number of other clinics to which it is linked and (2) the number of connections that the clinic to which it is linked has. Having influential connections (connections with many other connections) raises the centrality score of a clinic more than having connections with non-influential clinics. Eigenvector centrality is particularly useful in measuring influence networks because it identifies clinics that may be influential via a single relationship with a well-linked clinic as well as clinics with many links. To put it in another way, high-centrality clinic A raises the centrality score of clinic B even if clinic B only has one connection. High-centrality clinics (or *influential* clinics, the term we use in this paper) are defined in this study as those with centrality scores within the top 10 %. Low-centrality (non-influential but linked) clinics are those with centrality scores within the bottom 10 % of non-zero scores (excluding isolates with no connections).

After identifying clinics with the highest and lowest influence scores, we created indicator variables for three categories—influential, non-influential, and bridging (clinics that are poorly linked except to one or two influential clinics)—and performed a series of regression analyses using SAS 9.2 to identify whether being influential or being a bridging organization was associated with a difference in pace of joining the study or in the two outcome measures. For the first two linear regression analyses, the dependent variables were the two outcome measures, improvement in waiting time and an increase in annual program admissions [25, 26]. Because the parent study had data from 18 months, we assumed better outcomes related to earlier or fuller adoption of the innovation. The independent variables were whether a clinic was

Table 1 | Network characteristics of substance abuse treatment clinic networks, by state

State	MA	MI	NY	OR	WA
Number of agencies	76.00	81.00	102.00	54.00	86.00
Number of links	179.00	172.00	127.00	229.00	124.00
Clustering coefficient	0.06	0.11	0.08	0.19	0.04
Number of cliques	1.00	1.00	3.00	1.00	1.00
Average degree	2.36	2.12	1.25	4.24	1.44
Average distance	2.01	2.09	1.99	2.23	1.62

identified as a bridge, whether the clinic was in the highest or lowest influence category, and clinic demographics that may have confounded the outcome. These potential confounders were the size of the organization based on number of employees, defined in full-time equivalents (FTEs); whether the clinic was in a metro area; the proportion of male patients, criminal-justice-referred patients, or minority patients served; and whether there were multiple clinics from the same organization participating in the study. We clustered the effects by state. We also ran a regression using a negative binomial distribution with a dependent variable of number of days to join the study and the same independent variables as above.

RESULTS

Description of networks and identification of influential clinics

From the 201 clinics that participated in the parent study, 176 center directors responded to the survey. A total of 399 clinics were nominated as influential. Each state network is loosely connected, with a moderately high distance (most communications would require approximately two clinics between the originator and the intended receiver). The degree (the likelihood that any two clinics in a network are directly linked to each other, using an average of the number of links per clinic) varied widely, averaging from 1.4 in Washington to 4.2 in Oregon (Table 1).

The sociograms that follow show the reported influence among clinics by state. In each sociogram, a square represents one substance abuse treatment clinic (either one participating in the parent study or named by a study clinic as influential). Each larger, darker square represents one of the three most influential clinics in the state. Each line represents a link between clinics. Arrows point from nominating clinics to clinics named as influential. The three most influential clinics based on eigenvector centrality are highlighted. The average of the centrality scores of all the participating and nominated clinics in the state (possible scores of 0 to 1) is also given as a means of comparison for the most influential clinics (Figs. 1, 2, 3, 4, and 5).

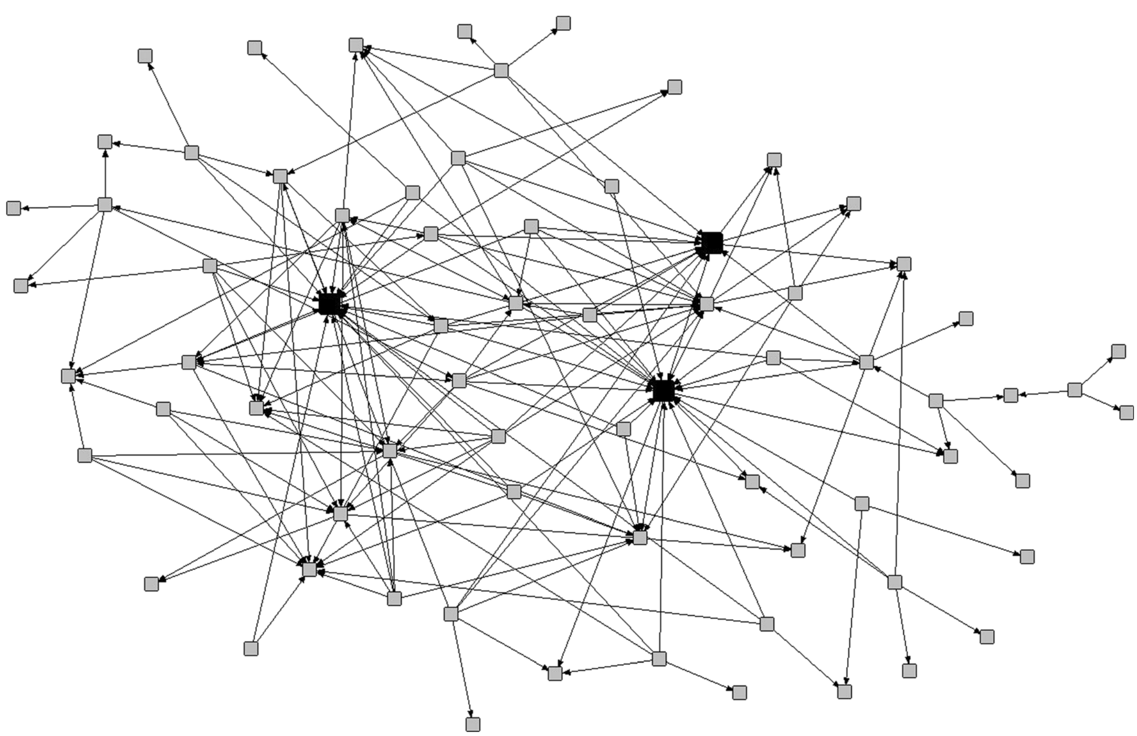

Fig 1 | **Massachusetts network map. Eigenvector centrality scores of the three most influential clinics were 0.38, 0.30, and 0.25, with an average of 0.09 for all surveyed and nominated clinics**

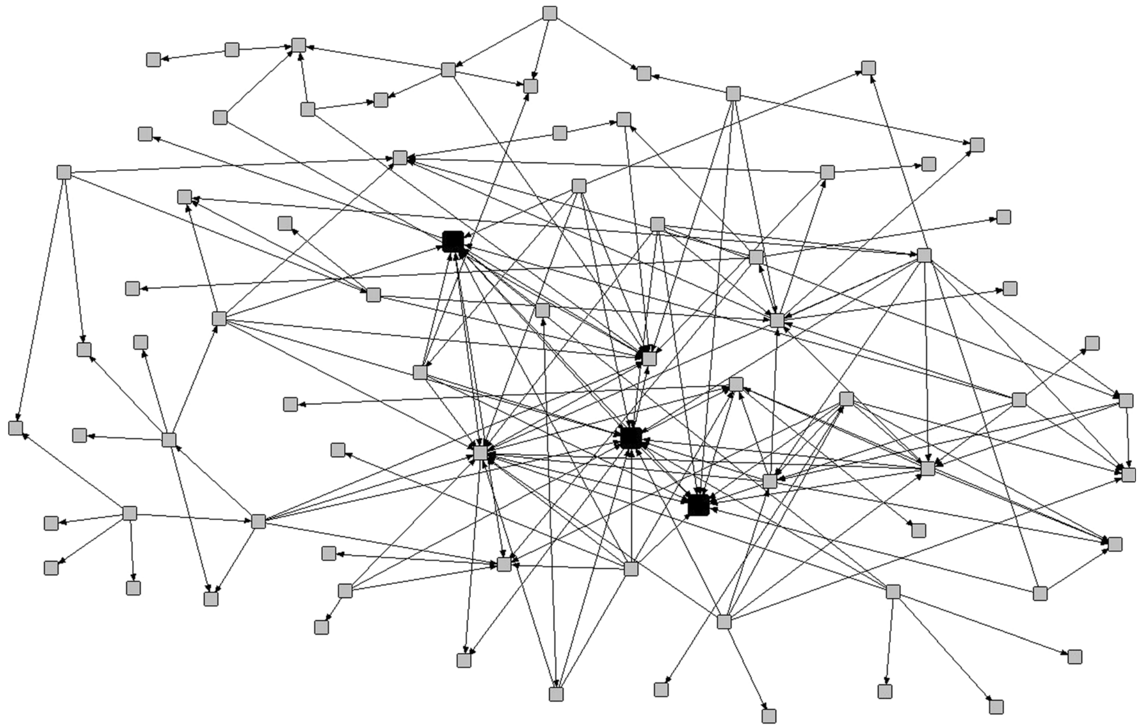

Fig 2 | Michigan network map. Eigenvector centrality scores of the three most influential clinics were 0.36, 0.28, and 0.26, with an average of 0.07 for all surveyed and nominated clinics

After removing isolates, all states except New York have one connected group of organizations, with no cliques. New York has three cliques. Generally, networks have substructures that can be studied using a clique analysis. Overall, these five states have very few cliques and generally low clustering coefficients.

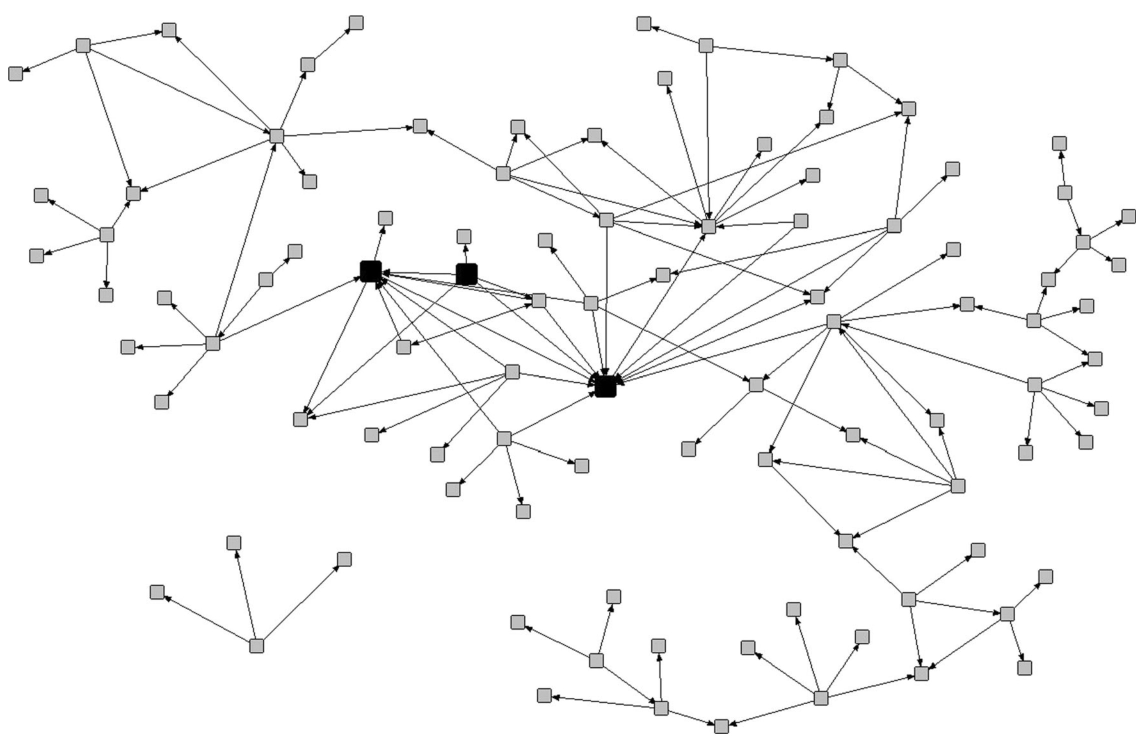

Fig 3 | New York network map. Eigenvector centrality scores of the three most influential clinics were 0.50, 0.39, and 0.26, with an average of 0.05 for all surveyed and nominated clinics

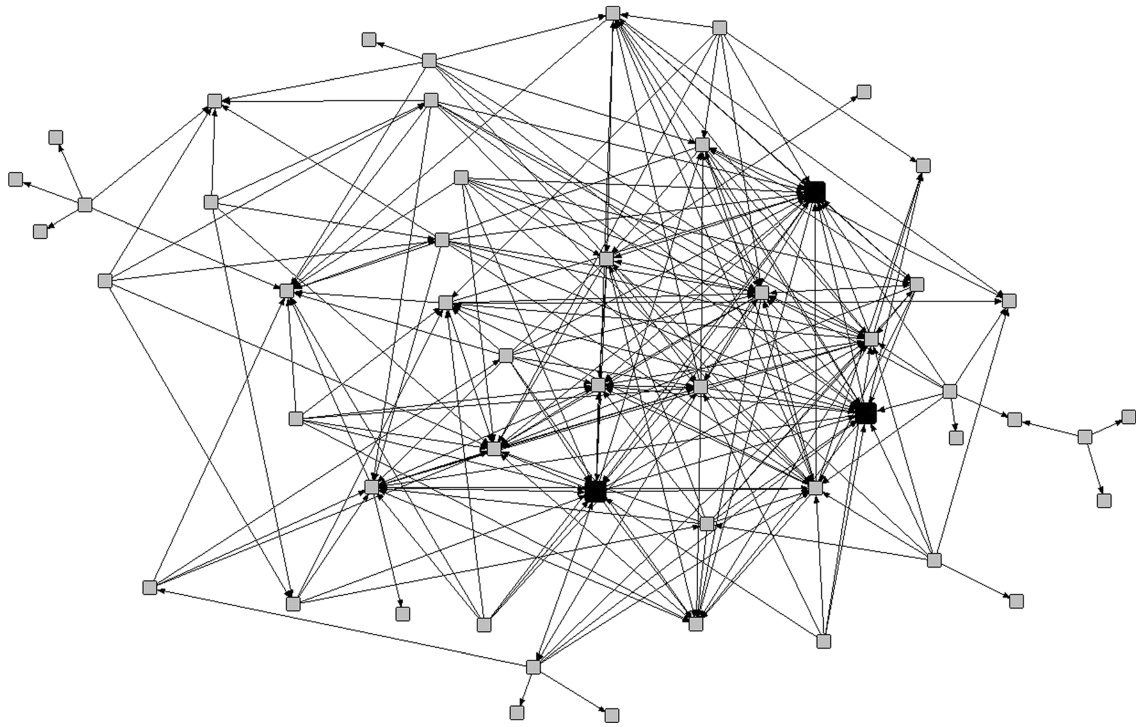

Fig 4 | Oregon network map. Eigenvector centrality scores of the three most influential clinics were 0.27, 0.26, and 0.25, with an average of 0.10 for all surveyed and nominated clinics

Relationship between influence and (a) willingness to adopt innovation and (b) parent study outcomes

Low-influence clinics took about a day less to sign up for the study than other clinics. While this may not seem significant, in most cases, it is the difference between making a decision to participate on the day the information about the study was presented during a recruitment meeting or waiting to enroll for some

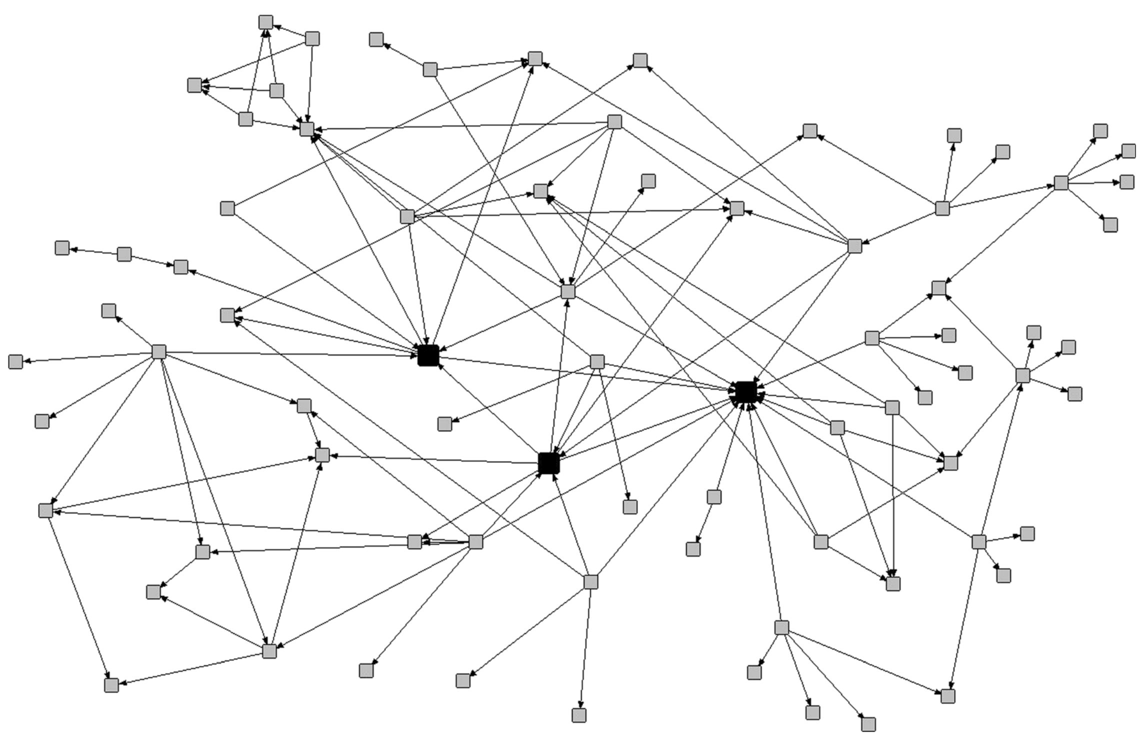

Fig 5 | Washington network map. Eigenvector centrality scores of the three most influential clinics were 0.42, 0.38, and 0.34, with an average of 0.07 for all surveyed and nominated clinics

Table 2 | Relationship between clinic characteristics and innovation adoption, as measured by time to join the study and study outcomes

Agency level characteristics	Days to agree to participate	*p*	Change in treatment waiting time (days)	*p*	Increase in number of people treated	*p*
High-centrality agency	0.40	0.14	2.34	0.49	1.20	0.06
Low-centrality agency	**−0.90**	**0.036**	−6.10	0.06	0.98	0.81
Bridging	N/A		N/A		N/A	

Values were adjusted for size, urbanicity, the number of sites a clinic organization had participating in the parent study, and whether the clinic was hospital based

Boldface items are significant at 95 %

period of time after the meeting (0 or 1+). Once a clinic was in the study, its influence had no impact on outcomes. Only one clinic identified as a bridging clinic participated in the study, providing too little data to analyze whether being a bridging clinic related to time to join the study or to study outcomes, though it may be that being a bridging clinic related to non-participation in the study (Table 2).

DISCUSSION

We sought to examine the structure of influence networks among substance abuse treatment clinics in Massachusetts, Michigan, New York, Oregon, and Washington to: (1) describe the networks in order to understand the flow of innovations within them, (2) test whether we could identify influential clinics, and (3) learn whether weakly linked clinics acted as sources of innovation for the network.

Our study affirms previous studies using different methods, suggesting that the substance abuse treatment field is somewhat decentralized [15], or at least not tightly integrated via influence networks between senior executives. Informally, most clinics are at least somewhat integrated in a single statewide network, loosely linked, with few if any subgroups or cliques. This structure in other industries causes innovations to flow slowly through the network, but because most substance abuse treatment clinics are linked in a single network, diffusion may proceed more quickly when influential clinics react positively to an innovation. While most innovations in substance abuse treatment can be expected to spread gradually in all five networks, research in other industries indicates that innovations actively seeded with influential clinics or clinics linked to influential clinics could speed diffusion.

We found evidence of more highly influential clinics in New York and Washington, but in the other three states, at least three clinics had about equally moderate levels of influence. This finding suggests that intervention in New York and Washington with leaders of substance abuse treatment clinics could be efficient if an innovator external to the network knew this information and spent extra time with those few highly influential clinic leaders. In the other states, influence was more evenly spread among a number of clinics; thus, an innovator would have to attend to more clinics, with less time devoted to each. On the other hand, having just one or two influential clinics in a statewide network poses a greater risk for the interventionist: If the influential clinic leaders form negative opinions of the innovation, they can more effectively block diffusion within the network. This is commonly observed in a substance abuse treatment, as it is for innovations generally [30]. The study from which our data are drawn did not actively attempt to use any of this knowledge in conducting the study, so we cannot assert that either prediction–rapid or blocked dissemination–took place; we can only point out the network structure and how those types of structures have behaved in previous diffusion studies.

The 10 % of clinics with the highest influence scores did not perform differently from other clinics on reducing waiting time to treatment and increasing annual program admissions. After adjusting for the size, treatment population served, and urbanicity of clinics, no statistical difference existed between outcomes for non-influential and other clinics either. We expected that improved outcomes would indicate faster or more complete adoption of the QI innovation (the NIATx 200 model) and would relate to a clinic's influence in the network. It may be that the outcomes were too distally related to innovation adoption to be used in this manner, or that the active dissemination process used in the NIATx 200 study masked the effect of the network's influence, or that influential clinics formed ambivalent or negative attitudes about the NIATx 200 model. It could also be that our assumption that the social network of the CEO was the most important factor in adoption is not true in these organizations. Because we did not collect network data from other staff members of a clinic, we cannot test this assumption.

Because scoring in the lowest 10 % of non-zero influencers (organizations that had at least one link were not considered isolates) correlated with taking less time to join the study, we believe that the first explanation above–that the outcome measures were too distally related to the decision to adopt–is probably the best interpretation of the results. Although the decision to adopt can be directly related to the decision to participate in the study, successfully adopting and achieving study outcomes are affected by multiple factors more related to execution than decision-making. The finding that organizations with weak ties to the network were more eager to adopt the innovation indicates that substance abuse clinics behave like organizations in other industries [9, 31, 32]. More central clinics in a network have comfortable positions that may be disrupted by change. They tend not to be the first to adopt potentially risky innovations but to wait and see the results obtained when outliers adopt the innovations. Less influential clinics have less to lose and more to gain by trying new things.

It also may be that because the networks are generally loose, with few highly central actors, weakly linked clinics are the organizations most able to bring innovations to the network rather than bridging clinics (which, by our definition, had to have a direct link to at least one influential clinic). With an average distance of about two in all of the states, knowledge of an innovation needs to go through only one additional clinic before it reaches a potentially influential organization.

Loosely structured networks like those described here, with few cliques and few highly influential organizations, lend themselves to the deliberate use of social network theory to disseminate innovation [32], according to experience in other industries and research on individuals. Identifying influential network members and seeding them with an innovation can speed diffusion. With a lack of powerful members to act as naysayers and low levels of clustering and clique formation, these networks have few barriers to spread. While the parent study focused on the implementation process rather than the adoption process, results from this secondary analysis suggest that deliberately focusing on dissemination and adoption via social network models could be fruitful in future studies.

Limitations

Approximately 40 clinics in each state participated in the parent study. Surveys were conducted with a maximum of 38 clinics, although states had up to 102 eligible clinics. While surveying all clinics in each state might have produced different sociograms, it has been estimated that the most central 10 % of clinics can be identified with 64 % accuracy using eigenvector centrality measures with even 50 % of data missing [33].

Participating clinics were not a random sample of clinics overall in the five states [21]. Clinics that participated in the study were larger than clinics that did not participate and served a less racially diverse population than those that chose not to participate. Only non-methadone outpatient treatment programs were eligible for the parent study. Results may have been different with a random sample.

Another limitation is that we assumed that clinic influence and clinic leadership influence were interchangeable. The surveys were conducted with executive directors and CEOs. The results may have been different if we surveyed clinical directors or counselors. We assumed that the influence networks of the executive director/CEO were the most likely to affect decision-making in terms of process innovations in the clinic. Though theoretically driven, these assumptions have not been tested in substance abuse treatment clinics.

By asking clinics to name influential clinics from only within the state, we set an artificial constraint. Data from an earlier, unpublished national survey we conducted indicated that most relationships between clinics were with other in-state clinics, which is why we set the limit. But network links that cross state lines could be even more interesting, given the importance of bridging clinics in introducing new ideas to networks and the difficulty we had identifying those clinics [24]. Examining relationships across state lines may identify bridging clinics in a way that we were unable to accomplish within the states.

CONCLUSIONS

Substance abuse treatment clinics are embedded within loosely knit influence networks in the five states studied. Centrality scores and the visual inspection of sociograms make it easy to identify influential clinics in all five states. For process innovations in substance abuse treatment, these statewide networks have no single highly influential organization but up to five moderately influential members who might be considered opinion-leading clinics. Bridging clinics (those with only one or two links to the network but whose links included an influential network member) were unlikely to participate in the study, but other poorly linked clinics were more likely to join in the parent study quickly (one of our proxies for clinic willingness to adopt an innovation). This result suggests that innovators in a network (those willing to take risks and try innovations) may not always be clearly linked to opinion leaders (who act as both facilitators and barriers to the diffusion of innovations within a network) [34]. However, with low clustering and a few moderately strong influencers, the networks have few internal barriers to the diffusion of innovations. In such networks, innovators from outside the network may have difficulty introducing an innovation but then experience steady uptake once the innovation has been demonstrated. The mixed results of this study suggest that more research is warranted to understand how network structure can be used to disseminate innovation in substance abuse treatment programs.

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Authors' statement of conflict of interest and adherence to ethical standards: All authors claim no conflict of interest. The research was conducted with the approval of the University of Wisconsin—Madison, Institutional Review Board and included informed verbal consent from the participants.

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