

Referrals Among Cancer Services Organizations Serving Underserved Cancer Patients in an Urban Area

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Significant racial, socioeconomic, and geographic disparities exist nationwide in cancer screenings, treatments, and outcomes. Differences in health and social service provision and utilization may contribute to or exacerbate these disparities. We evaluated the composition and structure of a referral network of organizations providing services to underserved cancer patients in an urban area in 2007. We observed a need for increased awareness building among provider organizations, broader geographic coverage among organizations, and increased utilization of tobacco cessation and financial assistance services. (*Am J Public Health*. 2011;101:1248–1252. doi:10.2105/AJPH.2010.300017)

Racial disparities exist in screening, treatment, and outcomes for breast,^{1–6} colon,⁷ lung,^{8,9} and prostate cancers.^{10–12} These disparities are often partially attributed to socioeconomic status^{1,7,13–17} and to geographic factors such as the proximity of and access to quality health care facilities.^{14,17–21} Disparities are manifested in a higher number of unmet needs,^{22–24} along with differences in access to care,^{4,13,18,25} utilization of health services,^{14,18,19} and types of treatment.^{11,19} Providing comprehensive and accessible services to cancer patients without resources requires understanding of cancer service referral networks for the underserved.^{26–28} We used novel statistical network modeling techniques to examine the cancer services

network for underserved patients in St Louis, Missouri.^{7,29–33}

METHODS

During the summer of 2007, we obtained a list of organizations providing cancer services for underserved persons in St Louis compiled by the Program for Elimination of Cancer Disparities and the National Cancer Institute Cancer Information Service. We identified additional organizations through an online and phone book search, for a total of 38. We invited an individual from each organization to complete an online survey. The response rate was 87%, and we collected the survey data in October and November 2007.

Measures

The survey asked about cancers addressed, services provided, geographic areas served, and barriers to working with other organizations. We assessed relationships among organizations through questions adapted from previous studies.^{26,34,35} Respondents were asked, “Are you aware of the following agencies’ work in cancer services?” to assess awareness and to select a subset of organizations (those who answered yes) on which to focus subsequent network questions.

We assessed contact frequency by asking, “On average, how often has your agency had direct contact (e.g., meetings, phone calls, faxes, letters, or emails) with each of the following agencies within the past year? (Do not count listservs or mass emails.)” Responses were no contact, yearly, quarterly, monthly, weekly, and daily. To measure referrals, we asked, “Does your agency send or receive referrals with the following agencies? (sends referrals to, receives referrals from, both sends and receives, neither).” We also used Google Maps to determine travel time between pairs of organizations on public transportation.

Analysis

In addition to describing network composition by frequencies and percentages, we examined basic network structure. In-degree and out-degree measured the number of links received by or sent from a node, respectively. Density was the proportion of

observed links in a network to the total number of possible links.

We used exponential random graph modeling to examine the pattern of referrals in the network. This method predicts the likelihood of a tie between 2 network constituents on the basis of constituent characteristics and network structures.^{36,37} Although the method was developed specifically to handle nonindependent network data, models are interpreted similarly to logistic regression models.^{35,37,38}

We began with a null model (no predictors), added structural predictors,^{39,40} and then incorporated network and attribute predictors. Our model had 4 structural predictors:

1. Geometrically weighted dyadwise shared partner: tendency for organizations (linked or not) to have shared partners^{39,41};
2. Geometrically weighted edgewise shared partner: tendency for directly linked organizations to have multiple shared partners;
3. Geometrically weighted in-degree: tendency for organizations with higher in-degree to form additional partnerships; and
4. Geometrically weighted out-degree: tendency for organizations with higher out-degree to form additional partnerships.

Network and organizational attribute predictors were contact frequency, travel time, and service provided. We did not include awareness because it was a screening variable. An organization not aware of another cannot send it referrals, resulting in redundant values for awareness and referrals when organizations are unaware of each other. Likewise, values would be redundant for organizations that made a referral.

We measured goodness of fit with the Akaike information criterion and a comparison of model-based simulations with observed network properties. We conducted analyses in SPSS 17.0 (SPSS Inc, Chicago, IL), Pajek 1.13,⁴² and *R*-statnet.⁴³

RESULTS

The network was complex, with most organizations providing multiple services to patients from multiple regions who had various cancers. On average, organizations received and sent referrals with 10.9 partners. The most common

barrier identified to working with others was lack of awareness of other organizations (64%; n=33; Table 1).

The awareness network had a density of 0.48, demonstrating that many of the organizations were aware of one another. The contact frequency network had a density of 0.41, an average density compared with similar

networks, indicating a moderate level of contact among organizations.³⁴ The referral network had a density of 0.29. Few studies of referral networks have been conducted, so we do not know whether the referral density was typical.

We identified model 3 (Table 2) as the best fit. Figure 1 (available as a supplement to

the online version of this article at <http://www.ajph.org>) shows a comparison of 10 000 simulated model-based predictions to the corresponding observed network parameters for shared partners, in-degree, and out-degree.^{35,36}

Three structural measures (geometrically weighted dyadwise and edgewise shared partners and out-degree) and contact frequency were significant predictors of a referral tie between organizations (Table 2). Organizations providing advocacy, financial assistance, health education, information and referrals, and support were significantly more likely than were other organizations to provide referrals. Organizations providing advocacy, health care, health education, housing, medical equipment, and prostheses were significantly more likely than were other organizations to receive referrals. Organizations providing medical equipment and prostheses were significantly less likely than were other organizations to provide referrals. Organizations providing financial assistance, smoking cessation, and support were significantly less likely than were other organizations to receive referrals.

DISCUSSION

The network of cancer service providers was well connected overall, with moderate levels of awareness and contact among organizations. Although we know little about typical referral patterns in similar systems, the organizations appeared to be actively referring patients to each other. We detected a strong positive relationship between contact frequency and referrals among organizations: the more often 2 organizations had contact, the more likely they were to have a referral tie between them. Organizations providing informational services (e.g., health education) were more likely to refer patients to other organizations. This relationship is logical because organizations providing health education and information are likely to be a first stop after diagnosis for individuals gathering information about their new disease status. Organizations providing more specialized services (e.g., prostheses) were more likely to receive referrals from other organizations.

Few organizations in the network (n=4) provided housing services, and these organizations

TABLE 1—Characteristics of Cancer Service Providers: St Louis, MO, 2007

Characteristics	Providers, No. (%)	Referrals Received, Referrals Sent, Mean Referrals		
		Mean (SD)	Mean (SD)	Received/Sent
Type of cancer patient served				
Breast	29 (87.9)	11.7 (7.9)	12.0 (7.6)	0.98
Colorectal	23 (69.7)	11.7 (7.9)	12.7 (7.8)	0.92
Lung	23 (69.7)	10.7 (6.9)	11.7 (7.3)	0.91
Prostate	24 (72.7)	11.5 (7.8)	12.4 (8.1)	0.93
Other ^a	20 (60.6)	12.4 (8.3)	14.1 (8.0)	0.88
Service provided				
Health education ^a	22 (66.7)	13.0 (8.2)	14.2 (7.2)	0.92
Prostheses and accessories	11 (33.3)	13.2 (8.7)	10.2 (8.2)	1.29
Advocacy ^a	10 (30.3)	13.4 (7.2)	16.7 (5.2)	0.80
Housing ^b	4 (12.1)	18.5 (7.1)	16.3 (9.8)	1.13
Smoking and tobacco cessation	11 (33.3)	10.7 (7.4)	14.1 (6.8)	0.76
Financial assistance	9 (27.3)	11.6 (6.7)	14.6 (6.7)	0.79
Information and referrals ^a	23 (69.7)	12.0 (8.5)	13.4 (7.9)	0.90
Support groups and support services ^a	21 (63.6)	12.0 (8.4)	14.1 (7.3)	0.85
Health care	12 (36.4)	11.0 (6.0)	12.2 (6.1)	0.90
Medical equipment and supplies	7 (21.2)	13.4 (5.4)	10.1 (6.3)	1.33
Transportation	12 (36.4)	11.8 (6.4)	13.9 (7.3)	0.85
Geographic area covered				
North St Louis City	27 (81.8)	12.5 (7.9)	12.6 (7.6)	0.99
South St Louis City ^b	23 (69.7)	13.3 (8.0)	13.3 (7.8)	1.00
St Louis County	29 (87.9)	11.9 (7.9)	12.0 (8.0)	0.99
Metro East	13 (39.4)	12.6 (9.3)	14.8 (7.8)	0.85
Outlying counties	20 (60.6)	12.1 (7.7)	12.9 (7.7)	0.94
Barriers to working with other organizations				
Lack of awareness of other organizations	21 (63.6)			
Lack of time	12 (36.4)			
Unable to identify appropriate partner	12 (36.4)			
Organizational structure/bureaucracy	11 (33.3)			
Past experiences	7 (21.2)			
Incompatible agency goals or strategies	7 (21.2)			
Benefits of collaborating do not outweigh costs	7 (21.2)			
Interagency politics	6 (18.2)			
Other	8 (24.2)			

Note. Sample size=33.
^aSent significantly more referrals than did other organizations, P<.05.
^bReceived significantly more referrals than did other organizations, P<.05.

TABLE 2—Statistical Models Predicting the Probability of a Referral Among Cancer Service Providers: St Louis, MO, 2007

	Model 1, ^a OR (95% CI)	Model 2, ^b OR (95% CI)	Model 3, ^c OR (95% CI)
Coefficient			
Arcs (links)	1.70 (0.13, 0.50)	0.11 (0.05, 0.25)	0.02 (0.01, 0.03)
GWESP ^d (clustering)	0.42 (0.94, 3.06)	1.67 (0.82, 3.37)	1.21 (1.14, 1.28)
GWODegree ^e	0.88 (0.002, 2.52)	0.07 (0.002, 34.61)	0.03 (0.01, 0.06)
GWIDegree ^f	1.70 (0.001, 109.55)	3.29 (0.02, 477.42)	0.73 (0.08, 6.46)
GDWSP ^g	0.04 (0.84, 0.91)	1.00 (0.93, 1.08)	1.05 (1.01, 1.09)
Network predictors			
Frequency of contact		2.39 (2.16, 2.63)	2.72 (2.42, 3.06)
Travel time, min		1.00 (0.99, 1.00)	1.00 (1.00, 1.01)
Service provided by referring organization			
Advocacy			1.92 (1.70, 2.15)
Financial assistance			1.27 (1.11, 1.46)
Health care			0.96 (0.85, 1.08)
Health education			2.16 (1.96, 2.38)
Housing			1.02 (0.65, 1.60)
Information and referrals			1.34 (1.24, 1.45)
Medical equipment			0.55 (0.47, 0.65)
Prostheses			0.41 (0.35, 0.47)
Smoking cessation			0.98 (0.87, 1.10)
Support groups			1.58 (1.46, 1.71)
Transportation			1.26 (0.94, 1.69)
Service provided by referred organization			
Advocacy			1.27 (1.11, 1.46)
Financial assistance			0.66 (0.57, 0.75)
Health care			1.22 (1.09, 1.37)
Health education			3.16 (2.92, 3.42)
Housing			3.42 (2.22, 5.27)
Information and referrals			1.04 (0.96, 1.13)
Medical equipment			1.65 (1.44, 1.89)
Prostheses			1.60 (1.39, 1.84)
Smoking cessation			0.40 (0.35, 0.46)
Support groups			0.62 (0.56, 0.68)
Transportation			0.74 (0.53, 1.03)
Model fit			
AIC	1646.4	1374.1	1178.5
Df	5	7	29

Note. AIC = Akaike information criterion; CI = confidence interval; GDWSP = geometrically weighted dyad-wise shared partners; GWESP = geometrically weighted edgewise shared partners; GWIDegree = geometrically weighted in-degree; GWODegree = geometrically weighted out-degree; OR = odds ratio.

^aStructural predictors only.

^bModel 1 plus network predictors.

^cModel 2 plus attribute predictors.

^dTendency for directly linked organizations to have multiple shared partners.

^eTendency for organizations with higher out-degree to form additional partnerships.

^fTendency for organizations with higher in-degree to form additional partnerships.

^gTendency for organizations (linked or not) to have shared partners.

received referrals from significantly more partners. Weaknesses in the network also included a lack of organizations serving East St Louis, lack of referrals to organizations providing smoking cessation or financial assistance, and a perceived lack of awareness among organizations. Other barriers related to limited resources (e.g., lack of time) and difficult relationships (e.g., interagency politics) might also influence network structures (Table 1).

Limitations

We collected data at the organizational level, and they might not translate directly to individuals' use of referrals. In addition, data were cross-sectional, so causal relationships could not be explored. Finally, although our list of service providers comprised a wide variety of organizations, we may have missed some.

Conclusions

Significant racial, socioeconomic, and geographic disparities exist in cancer screenings, treatments, and outcomes. Our analyses provide a first look at the composition and structure of a cancer services network in an urban area. We used an innovative network approach to identify 3 gaps that could be addressed to strengthen the network.

First, few partners provided housing services. Although we did not obtain utilization data, we observed that the few organizations that provided housing services received referrals from significantly more partners than did other organizations. This finding might indicate a greater need for housing services among underserved cancer patients or a need for additional housing service providers in the area.

Second, organizations perceived a lack of awareness of other providers. Awareness might increase with the dissemination of a comprehensive directory of all providers in St Louis. This increased awareness would help ensure that patients are referred to all services they need that are available in their area. For example, organizations providing financial assistance were significantly less likely than were other organizations to receive referrals. A large proportion of urban cancer patients have been found to need such assistance,²⁴ so our findings may indicate a lack of awareness of these services.

Third, partners were less likely to refer patients to organizations providing smoking cessation than to other types of organizations. Although we did not have data on the smoking rates of patients who used this network, smoking rates, with their related health outcomes, are high in Missouri and higher among individuals with low socioeconomic status, so this finding is troubling. Although some studies have shown lower smoking rates among cancer survivors than among the general population,^{44,45} others have shown a lack of cessation counseling after cancer diagnosis and continued smoking among cancer patients and survivors.^{45–47} We recommend providing cancer service providers with detailed information regarding cessation services in their area.

Although cancer patients of any socioeconomic status may have unmet needs related to social and health services as they undergo treatment,^{23,24,48,49} understanding the health and social services system available to underserved cancer patients is especially important because of the particular barriers^{3,13,14,17–22,24} and outcomes^{1–12} these patients face. Future studies should collect data from cancer patients as well as organizations. Health and social service systems serving underserved patients facing other chronic diseases may also benefit from similar assessments.

Examining organizational characteristics and relationships along with individual utilization, demographic, and geographic characteristics may help us better understand the complex patterns of service provision and utilization. This understanding would allow system improvements to more effectively meet patient needs and address chronic disease-related disparities. ■

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This article was accepted September 5, 2010.

Contributors

J.K. Harris and N.B. Mueller conceptualized, designed, and implemented the study. J.K. Harris conducted analyses and led the writing of the article. J. Cyr helped collect data. B.J. Carothers analyzed data. All authors participated in writing and editing the article.

Acknowledgments

Funding for this project was provided by the Program for the Elimination of Cancer Disparities (U01CA114594) and the Alvin J. Siteman Cancer Center (P30CA91842).

We extend our sincere gratitude to all the cancer services providers who participated in this important project.

Human Participant Protection

The Saint Louis University institutional review board approved this study.

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Racial and Ethnic Disparities in Uptake and Location of Vaccination for 2009-H1N1 and Seasonal Influenza

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To learn more about racial and ethnic disparities in influenza vaccination during the 2009-H1N1 pandemic, we examined nationally representative survey data of US adults. We found disparities in 2009-H1N1 vaccine uptake between Blacks and Whites (13.8% vs 20.4%); Whites and Hispanics had similar 2009-H1N1 vaccination rates. Physician offices were the dominant location for 2009-H1N1 and seasonal influenza vaccinations, especially among minorities. Our results highlight the need for a better understanding of how communication methods and vaccine distribution strategies affect vaccine uptake within minority communities. (*Am J Public Health.* 2011;101:1252–1255. doi:10.2105/AJPH.2011.300133)

Epidemiological data collected over the past century suggest that racial and ethnic minorities are at greater risk of contracting seasonal and pandemic influenza—and of experiencing more negative consequences as a result—compared with Whites.^{1–3} Despite this heightened risk, minorities in the United States have historically been vaccinated for influenza at rates as much as 15 to 18 percentage points lower than the rates for Whites, reflecting access barriers, negative attitudes toward vaccination, distrust of the medical system, and perceived risk of side effects.^{3–7}

To minimize disparities in vaccine uptake during the 2009-H1N1 pandemic, local public health authorities adopted specifically targeted outreach efforts to encourage 2009-H1N1 vaccination among minorities. These outreach efforts included the use of alternative vaccination sites, such as retail clinics and school-located clinics; engagement of faith-based organizations; and communication in multiple languages and through ethnic media.^{8–10} Furthermore, the federal government made 2009-H1N1 vaccine available free of charge, to remove cost-related barriers to uptake. However, local public health officials reported disparities in uptake of 2009-H1N1 vaccine.¹¹ To our knowledge, the only comparable, published national data on this topic measured uptake through the first few weeks of the vaccination campaign.¹² To assess whether targeted outreach to minority populations during the 2009-H1N1 pandemic succeeded in narrowing historical disparities in influenza vaccination, we used national, cross-sectional survey data measuring influenza vaccination of adults to estimate uptake of seasonal and 2009-H1N1 influenza vaccination, vaccination location, and attitudes toward influenza vaccination by race and ethnicity.

METHODS

From March 5 to March 24, 2010, we used an online research panel operated by Knowledge Networks to field a nationally representative survey of US adults aged 18 years and older (n=4040). Knowledge Networks recruits panelists through a probability-based sampling method that includes both online and offline