Published in final edited form as:

Med Care. 2019 June ; 57(6): 460–467. doi:10.1097/MLR.0000000000001123.

Association between Degrees of Separation in Physician Networks and Surgeons' Use of Perioperative Breast Magnetic Resonance Imaging

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Abstract

Background: Perioperative magnetic resonance imaging (MRI) is frequently used in breast cancer despite unproven benefits. It is unclear whether surgeons' use of breast MRI is associated with the practices of other surgeons to whom they are connected through shared patients.

Methods: We conducted a retrospective study using Medicare data to identify physicians providing breast cancer care during 2007-09 and grouped them into patient-sharing networks. Physician pairs were classified according to their "degree of separation" based on patient-sharing (e.g., physician pairs that care for the same patients were separated by 1 degree; pairs that both

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Disclosures: Dr. Gross and Ms. Soulos receive research funding from 21st Century Oncology LLC. Dr. Gross has also received funding from Medtronic and Johnson & Johnson. Dr. Pollack reports stock ownership in Gilead Pharmaceuticals; the authors report no other relationships or activities that could appear to have influenced the submitted work.

Authorship: All authors fulfill the International Committee of Medical Journal Editors criteria for authorship.

share patients with another physician but not with each other were separated by 2 degrees). We assessed the association between the MRI use of a surgeon and the practice patterns of surgical colleagues by comparing MRI use in the observed networks with networks with randomly shuffled rates of MRI utilization.

Results: Of the 15,273 patients who underwent surgery during the study period, 28.8% received perioperative MRI. These patients received care from 1,806 surgeons in 60 patient-sharing networks; 55.1% of surgeons used MRI. A surgeon was 24.5% more likely to use MRI if they were directly connected to a surgeon who used MRI. This effect decreased to 16.3% for pairs of surgeons separated by two degrees, and 0.8% at the third degree of separation.

Conclusions: Surgeons' use of perioperative breast MRI is associated with the practice of surgeons connected to them through patient-sharing; the strength of this association attenuates as the degree of separation increases.

Keywords

Breast Neoplasms; Surgeons; Magnetic Resonance Imaging; Medicare

Introduction.

Although the diffusion of new technologies into routine cancer care offers the potential for clinical benefit, the actual effect of new technologies may not always live up to the initial promise. For instance, perioperative Magnetic Resonance Imaging (MRI) is widely used in breast cancer practice, since it can identify more lesions than traditional imaging. However, randomized trials have not demonstrated survival benefit.^{1,2} Further, MRI is costly and has been associated with overdiagnosis and more aggressive surgical care, leading to recommendations against its routine use.^{3–5}

The uptake of a new technology such as MRI into clinical care is thought to depend primarily on clinical risks and benefits, economic considerations, and personal preferences of patients and physicians.^{6–11} Because MRI in this setting is a relatively new technology without clear benefit, its use might also be explained by social contagion, whereby the decisions and behaviors of colleagues regarding MRI – might have an impact on a surgeon's MRI use.

The application of social contagion theory to medical innovations can be traced back to the classic work by sociologist James Coleman and colleagues, who found that the diffusion of tetracycline use could be attributed to direct contact between physicians.¹² However, social influence might have an impact beyond direct contact between a pair of individuals, as the use of a new technology could cause a ripple effect such that once the innovation is adopted by a set of physicians, other physicians who are only indirectly connected may also be affected. This indirect social influence, in contrast to analysis of individuals in pairs, is associated with clustering of behavior within a network, which can cause widespread prevalence of adoption or non-adoption of medical practices irrespective of their benefits.

Within a network, these indirect connections can be quantified by the idea of “degrees of separation”.^{13,14} Simply put, if persons A and B are directly connected to each other, they

are connected by one degree of separation (Figure 1). If A and C are not directly connected to each other, but if they are both connected to person B, then A and C are connected by 2 degrees of separation. Investigators have demonstrated that behaviors and ideas can be associated not only across directly connected individuals (1st degree connections), but also across indirectly connected pairs.¹⁵ Prior observational and experimental research has shown this effect across a range of behaviors, including obesity¹⁶, happiness and depression¹⁷, and smoking and drug use¹⁸.

Recent studies have applied network concepts to physician practices, finding, for example, that patient-sharing networks are linked with the uptake of MRI for breast cancer¹⁹, costs of medical care^{20,21}, and treatment for prostate cancer²². We have demonstrated that breast cancer patients treated by surgeons who had not used MRI during 2004–2006 were more likely to receive MRI during 2007–2009 if their surgeon was in a patient-sharing group with higher use of MRI in 2004–2006.²¹ While this study suggests a temporal peer influence, it does not tell us whether the influence is limited to surgeons who were directly connected to early adopters of MRI.

Unlike the prior analysis which explored how networks vary in their adoption of MRI over time, in this study we employ a cross-sectional design to better understand how distance between surgeons, measured by degrees of separation, is associated with peer influence within networks. To our knowledge, this concept has not been applied to physician practice in the literature. Information about whether there is an association between degrees of separation and surgeon behavior would support the hypothesis that physician practice may be affected by social influence and could inform future interventions promoting effective medical care and inhibiting less valuable interventions.

Methods.

Overview

We conducted a cross-sectional study in which we constructed physician patient-sharing networks using Medicare data for beneficiaries undergoing breast cancer surgery during 2007–2009, when MRI was diffusing into clinical practice. We classified each surgeon as an MRI user or non-user and calculated the degree of separation between each pair of surgeons. For surgeons who were directly connected (one degree of separation), we compared the likelihood that they shared the same MRI utilization behavior with the likelihood of sharing behavior between the same pairs of surgeons in a network where structure was preserved, but MRI utilization behavior was randomly shuffled^{16,23}. We then repeated the analysis for increasing degrees of separation between pairs of surgeons.

Key Terminology

Nodes in the patient-sharing networks are physicians (surgeons or non-surgeons); the “weight” of a tie connecting two physicians is the number of shared patients (eFigure 1, Supplemental Digital Content 1, <http://links.lww.com/MLR/B776>). The “ego” is the focal node, meaning the surgeon who is of interest for a given analysis; his/her connected nodes are the “alters”. The identity of the ego and alters are dynamic and are defined with respect

to each other; every surgeon can be considered both an ego (with respect to him/herself) and an alter (with respect to his/her connected peers). Degree of separation is the length of the shortest path on the network (in terms of the number of intervening alters) connecting two nodes. k -degree alters ($k=2,3,\dots$) are the physicians who are not directly connected to the ego, but are connected by $k-1$ intervening physicians on the shortest path.

Data Source and Study Sample

We used the Surveillance, Epidemiology, and End Results (SEER)-Medicare database, which includes Medicare claims, patient demographics, and cancer registry data. We included patients with a first diagnosis of in situ or localized breast cancer during 2007–2009, as well as a 5% random sample of female Medicare beneficiaries without cancer in order to more fully capture patient-sharing ties. We excluded women with breast cancer who met any of the following criteria: breast cancer not the first or only primary cancer, stage IV disease, histology not consistent with epithelial origin, unknown month of diagnosis or diagnosis reported on autopsy or death certificate, not 66–94 years at diagnosis, or not continuously enrolled in Medicare Parts A and B from one year prior to diagnosis through either one year after diagnosis or death (if they died within one year). Women from the 5% random sample of Medicare beneficiaries without cancer were required to fulfill the same age and Medicare enrollment criteria as the cancer patients and were randomly assigned an index date, which was used analogously to the date of diagnosis. The Yale Human Investigations Committee determined this inquiry was not human subjects research.

Construction of Variables

MRI use was ascertained during the perioperative period (3 months before diagnosis through 3 months after surgery) using Medicare claims. Age at diagnosis, race, and marital status were obtained from the SEER-Medicare data. Patients were assigned to area level median household income (census tract if available, otherwise zip code). Using Medicare claims from the 12 months through one month before diagnosis, we identified comorbid conditions by searching for International Classification of Diseases, 9th revision, diagnosis codes using a modified list of the conditions suggested by Elixhauser et al^{24,25}. Stage was identified using the derived AJCC stage categorization (6th edition) provided by SEER.

Construction of Networks

For each of the 100 Hospital Referral Regions (HRRs) in our sample, we constructed patient-sharing networks among physicians, where two physicians were considered connected if they billed for care for ≥ 3 of the same patients during the observation period.^{26–28} We tested tie weights of 4 and 5 in sensitivity analyses²⁶. We only included physician specialties likely to be involved in breast cancer care: surgeons, medical oncologists, radiation oncologists, radiologists, and primary care providers including obstetrician-gynecologists. Specialty was determined using the Medicare specialty code. We also classified physicians as surgeons, medical oncologists, or radiation oncologists based on the provision of relevant procedures for ≥ 2 patients, regardless of specialty code. Use of administrative billing claims has been validated as an effective method for identifying patient-sharing ties among physicians.²⁷

Because our focus was on MRI use in the perioperative period, and our prior work demonstrated that surgeons exert a strong influence on whether patients receive MRI, we restricted our analysis to surgeons' MRI use patterns. However, recognizing that information and ideas flow across physicians of different specialties, our measurement of the path connecting two surgeons included all specialties listed above. Each surgeon was classified as an MRI user or non-user based on whether they had any patient who received MRI. Within each HRR, we restricted our analyses to the largest group of interconnected physicians (termed largest component). To facilitate the analysis of pairwise similarity of MRI utilization, we restricted to networks with ≥ 2 surgeons. Of the 2,031 surgeons who were included in our groups, 1,806 surgeons were retained for the final analysis.

Degrees of Separation analysis

For each degree of separation k we calculated a 'risk ratio' as the average of network specific risk ratios. The numerator of the network specific risk ratio was the likelihood that a surgeon in the network would use MRI if their k -degree alters also used MRI; the denominator was the same likelihood calculated using a randomly shuffled pattern of MRI use. This approach eliminates the probability of behavioral associations due to non-network mechanisms. For example, surgeons may adopt a new technology because of exposure to a network-wide common environment or policy. Hence, each network had an "observed" version in which each surgeon's MRI use was derived from the actual Medicare claims, and a "null" version in which MRI utilization was randomly assigned, while keeping the network-wide MRI utilization constant between the observed and the randomized groups.^{15,16,18} To facilitate the interpretation of the risk ratio, we calculated the increase in relative risk. For further details, see eMethods, Supplemental Digital Content1, <http://links.lww.com/MLR/B776>.

We calculated the overall risk ratio separately for pairs of physicians stratified by $k=1, 2, 3$ and 4 degrees of separation to determine whether the effect of social contagion was present beyond directly connected peers. In a sensitivity analysis, we increased the minimum number of shared patients used to define a patient-sharing tie from 3 to either 4 or 5. By increasing the minimum shared patients, we replicated the analysis on networks that have stronger ties and a higher degree of separation between a pair of surgeons, as other shorter paths between them could be eliminated because the shared patients fail to meet the minimal requirement for a network tie. We also calculated the relative increase in likelihood of MRI use within each HRR, with 95% confidence intervals calculated from 1000 randomized permutations of MRI use for each HRR.

Analyses were performed using SAS 9.4, Stata 14.2, R 3.2.1, and igraph 0.9.

Results.

Our final sample included 21,031 physicians and 15,273 patients. Of the 1,806 surgeons, 995 (55.1%) had a patient who received MRI during the study period. The median number of physicians per network was 284 (IQR=168–452) and the median number of surgeons was 20 (IQR=14–32). Surgeons were directly connected to, on average, 1.1 (IQR=1.0–1.2) other surgeons. The median number of breast cancer patients per surgeon was 5 (IQR=3–10). In

the final sample, 60 networks had 2 surgeons in the largest connected component. When the patient-sharing tie weight was 4 and 5, there were 35 and 30 networks having 2 surgeons in the largest connected components.

Among women with breast cancer, 28.8% received perioperative MRI. MRI use decreased with patient age, from 40.6% among patients aged 66–69 to 11.5% among those aged 85–94 (Table 1). Among white patients, 29.7% received MRI compared to 19.0% for black patients. Area-level household income was positively associated with the likelihood of MRI receipt, while increasing comorbidity was negatively associated with MRI receipt. Cancer stage was not associated with MRI use.

Figure 2 illustrates the largest network, which contains 137 surgeons (denoted by squares), of whom 82 were MRI users (yellow squares) and 55 were non-users (red squares). Clustering of MRI users, or the extent to which they are connected to one another more often than to non-users, is visible. When a surgeon has alters at one degree of separation who used MRI, the likelihood of MRI use in the observed network for this HRR increases by 29.6% compared with those in a randomized network.

Across all the networks, the increase in the relative risk of using MRI if a first-degree alter used MRI was 24.5% higher in the actual versus randomized networks (Figure 3, orange bar). The relative increase declined to 16.3% at 2 degrees of separation and 0.8% at 3 degrees of separation. The relative increase became negative at 4 degrees of separation (−3.8%). Similar patterns of MRI clustering were evident in the sensitivity analyses, in which networks were constructed with minimum tie strength of 4 or 5 patients. Consistent with our primary analysis, we observed a positive network effect between surgeons out to three degrees of separation in the networks for both weighting schemes (Figure 3, yellow and green bars).

The relation between first-degree alter MRI use and surgeon's use of MRI varied across HRRs/networks (Figure 4). For instance, of the HRRs with 2 first-degree surgeons, the highest increase in the likelihood of a given surgeon (i.e. the ego) using MRI if his/her connected peer (i.e. alter) uses MRI was 248.5% and the largest drop was 32.4%. Two-thirds of the networks across HRRs exhibited a positive, statistically significant change in the likelihood of use, and 16.0% exhibited a negative, statistically significant change in the likelihood of use. Similarly, using tie strength of 4 patients, 77.1% of networks had a significantly positive association between first degree connections and MRI use, while 14.3% had a negative association. The findings were consistent using minimum tie strength of 5 patients (eFigure 2, Supplemental Digital Content1, <http://links.lww.com/MLR/B776>).

Conclusions.

We found that surgeons' use of MRI was associated with the practice style of surgeons connected to them through patient-sharing, and the strength of this association was inversely associated with degree of separation. These results suggest that surgeons' use of perioperative MRI may be affected by proximity to other surgeons in their network, although we cannot infer a causal relationship. While this finding is consistent with the pattern of

social influence observed in other social systems,^{15–18,29} this is the first study investigating degrees of separation in the setting of medical care, to our knowledge. Our study contributes to the research on social facets of medical practices in important ways.¹² Prior literature has explored how medical practices are similar between a pair of physicians connected by a relationship^{12,22,30,31} or among members in small cohesive groups^{26,28}. While these studies suggest that social influence might play a role in pairwise association of behavior, they did not explore the association between degrees of separation in provider networks and physician behavior, which has profound implications for how surgical behaviors are distributed in global networks of physicians. A unique contribution of our study is that we demonstrated that the behavior of physicians is associated with that of other physicians in the network, and this association diminishes with increasing distance between physician pairs. If a behavior is clustered on networks, it can create a cascading phenomenon in which surgeons are influenced by peers to adopt the behavior, particularly in the setting of uncertainty about clinical effectiveness. The findings of our study suggest a potential mechanism explaining why MRI has become a practice of choice by cancer care surgeons despite its benefit remaining uncertain.

The influence of surgeons through a social mechanism is plausible, given that social contagion has been demonstrated in several other domains of human behavior^{16,17,29,32,33}. Further, prior work by our group has suggested that surgeons who are members of a peer group with higher MRI use in one time period are more likely to subsequently adopt MRI²⁶. Similarly, surgeons who had a first-degree connection with an alter who used brachytherapy in the care of their breast cancer patients were more likely to subsequently adopt brachytherapy³⁰. These studies suggest a longitudinal effect of social influence. In both studies, we limited the sample to patients treated by physicians who did not use the treatment of interest during the early time period to assess the effect of social influence on new adoption. The current study is consistent with these earlier studies, showing that social influence may play an important role in the spread of clinical practice. We further expand on these findings by demonstrating a cross-sectional influence of peers, illustrating that medical practice may be able to spread across indirectly connected peers in a relatively short period of time. By using cross-sectional data, we isolate the association between physician distance and use of MRI, separate from the temporal social influence.

Nevertheless, there are two other potential reasons for this network effect. First, there may be confounding caused by common environments or patient characteristics that are shared by one group of physicians (e.g., in the same hospital) but not others. However, prior work found that the association between peer groups and physician behavior remained after controlling for hospital assignment and accounting for a range of patient characteristics²⁶. This suggests that physician social networks may exert an independent impact on physician behaviors beyond such contextual environment. A second reason is homophily, a selective choice made by surgeons to collaborate with other surgeons who engage in a similar practice style. While it is unlikely surgeons would seek each other out for collaboration or participate in referral networks based on propensity to use MRI, it is not possible to rule out homophily, since use of MRI may be a marker of a more general common practice style that motivates surgeons to collaborate with each other. Similarly, while some patient characteristics may be

associated with selection of surgeons, our use of a control group helps to account for potential patient selection of surgeons.

Our study suggests the importance of the clustering of surgical practices up to three degrees of separation. The sensitivity analysis also confirmed similar patterns of declined but positive network association with increasing degrees of separation when the networks were constructed by more stringent conditions, potentially indicating a stronger likelihood of a true advice-seeking or referral relationship between pairs of colleagues.²⁷ The observed clustering at one degree of separation seems the most intuitive as it is possible, by sharing in the care of the same patient, surgeons may directly receive information about one another's practice style. Two and three degrees of separation represent indirect connections and communication between pairs of physicians. If confirmed in future research, it may be possible to leverage the role of social contagion to encourage the spread of beneficial behavior, for example through opinion leaders. An educational campaign with limited resources might seek to educate only those physicians within a group of connected physicians with the most number of first degree connections, understanding that this has the potential to effect behavioral change beyond those who are directly subject to the intervention.

This study has several limitations. First, there was no clear threshold for the appropriate tie weight that indicates a 'true' connection between a pair of physicians representing knowledge of one another's practice styles, referral relationships, and advice-seeking.²⁷ However, we varied the threshold and observed similar findings. Second, our analysis included only Medicare data, so our findings may not be generalizable to younger patients. It will be important to test the findings in other populations and with respect to other medical technologies. Third, we did not consider structural features of the networks and the types of physicians that are most likely to induce behavioral adoption on the network. For instance, the specialty of the "connecting" physicians that lay between two surgeons connected by >1 degree of separation could influence the degree to which they are concordant regarding MRI use. Fourth, we were not able to capture complete patient-sharing information for the physicians in our networks, since we were limited to including Medicare patients with breast cancer in the SEER regions and non-cancer patients from the Medicare 5% random sample. Fifth, our analysis was based on observational data using a cross-sectional design; future research should continue to explore the effects of social influence using other study designs—including prospective data—and in other clinical areas. Sixth, we cannot assert definitively the network mechanisms driving the observed associations; future work involving longitudinal study designs and different clinical settings are warranted.

In conclusion, our novel analysis revealed an understudied yet important facet in the shared use of a new medical technology among physicians. The network effect that drives behavioral similarity among surgeons suggests that surgeons' decision-making may not be independent of their peers' behaviors. Rather, their surgical practices tend to be similar not only with directly connected peers, but also with peers of peers, a finding of three degrees of influence that has been confirmed in other social systems. Our research contributes to the nascent study of social effects in medical practice.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements:

The collection of the California cancer incidence data used in this study was supported by the California Department of Public Health as part of the statewide cancer reporting program mandated by California Health and Safety Code Section 103885; the National Cancer Institute's Surveillance, Epidemiology and End Results Program under contract N01-PC-35136 awarded to the Northern California Cancer Center, contract N01-PC-35139 awarded to the University of Southern California, and contract N02-PC-15105 awarded to the Public Health Institute; and the Centers for Disease Control and Prevention's National Program of Cancer Registries, under agreement #U55/CCR921930-02 awarded to the Public Health Institute. The ideas and opinions expressed herein are those of the author(s) and endorsement by the State of California, Department of Public Health the National Cancer Institute, and the Centers for Disease Control and Prevention or their Contractors and Subcontractors is not intended nor should be inferred. The authors acknowledge the efforts of the Applied Research Program, NCI; the Office of Research, Development and Information, CMS; Information Management Services (IMS), Inc.; and the Surveillance, Epidemiology, and End Results (SEER) Program tumor registries in the creation of the SEER-Medicare database. The interpretation and reporting of the SEER-Medicare data are the sole responsibility of the authors.

Funding: This work was supported by the National Cancer Institute of the National Institutes of Health (R01CA190017). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The funders had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; and preparation, review, or approval of the manuscript.

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Hypothetical physician network, where circles represent physicians and lines represent patient-sharing connections. Surgeon A has a first degree connection to alter B, a second degree connection to alter C, and a third degree connection to alter D.

Figure 1.
Illustration of Degrees of Separation

The network contains 137 surgeons, of whom 82 were MRI user and 55 were non-users. The network layout is based on a force-directed algorithm in igraph. Clustering of surgeons according to their MRI-use is notable in the network, in that the colored squares tend to be proximal to one another. When a surgeon has 1-degree use alters, the risk of MRI use in the observed network is 29.6% higher compared with those in a network in which MRI use is randomly assigned across surgeons in the network.

Figure 2.
Diagram of the Largest Patient-Sharing Network

The vertical axis represents the risk ratio by comparing the conditional probability of use if a k -degree alter also adopted in the observed networks with the same conditional probability in the randomized networks. The colors of the bars indicate the minimum required number of shared patients for projecting a tie between two physicians. The larger the tie weight, the stronger the network ties are.

Figure 3.
Effect of Social Distance from Adopter Alters on the Probability of an Ego's MRI Adoption

Figure 4.
Probability of an Ego's MRI Adoption In Networks With Tie Weight 3 if 1-Degree Alter Adopts

Table 1.

Patient Characteristics

	# patients	% patients	% received MRI	P-value ^a
Total	15273	100		
Age (years)				<.001
66-69	3467	22.7	40.6	
70-74	3885	25.4	34.6	
75-79	3449	22.6	26.7	
80-84	2650	17.5	19.5	
85-94	1822	11.9	11.5	
Race				.31
White	13522	88.5	29.7	
Black	1024	6.7	19.0	
Other	727	4.8	26.1	
Marital status				.41
Married	6786	44.4	34.0	
Unmarried	7876	51.6	24.4	
Unknown	611	4.0	26.5	
Median household income				.05
<\$33K	2629	17.2	18.5	
\$33K - \$39,999	1964	12.9	21.0	
\$40K - \$49,999	3184	20.9	27.0	
\$50K - \$62,999	3247	21.3	31.0	
\$63K	4247	27.8	38.4	
Comorbid conditions				.03
0	8204	53.7	33.8	
1-2	5443	35.6	25.3	
3	1626	10.7	15.1	
Stage				.75
I	8965	58.7	29.5	
II	4915	32.2	28.7	
III	1393	9.1	24.3	

^aP-values calculated from chi-square tests of the association between categorical variables and % received MRI