

Primary Care Patient Social Networks and Tobacco Use: An Observational Study

Journal of Primary Care & Community Health
Volume 13: 1–10
© The Author(s) 2022
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/21501327211037894
journals.sagepub.com/home/jpc



Jaya Aysola^{1*} , Jeffrey Rewley^{1*}, Chang Xu¹, Marilyn Schapira¹, and Rebecca A. Hubbard¹

Abstract

Importance: Tobacco use remains the leading cause of preventable deaths and is susceptible to social influence. Yet, we know little about the characteristics of primary care social networks and how they influence tobacco use. **Objective:** To determine what primary care patient social network characteristics are associated with individual smoking behavior. **Design:** Cross-sectional. **Setting:** Two primary care practices in West Philadelphia, Pennsylvania (PA), USA. **Participants:** A random sample of 53 primary care patients and 155 of their nominated social ties. **Main Outcome and Measures:** We examined the association between social network characteristics (degree, communicated weighted social ties, and presence of social reinforcement) and tobacco use history (never smoker, successful quitter, or current smoker). Other covariates included age, race/ethnicity, sex, education, income, and employment status, self-efficacy, depression status, provider-patient relationship. **Results:** Of those enrolled in our study ($n=208$), 101 identified as never smokers, 59 as successfully quitters, and 48 as current smokers. Social reinforcements from connected alter pairs that never-smoked ($OR=1.20$, 95% CI: 1.08, 1.34) was significantly associated with a participant being a never smoker. Participants with stronger ties with successful quitters were significantly more likely to identify as successfully quitting ($OR=1.37$, 95% CI: 1.11, 1.69) and conversely had a negative association with stronger ties to unsuccessful quitters ($OR=0.59$, 95% CI: 0.44, 0.80) or current smokers who had not tried to quit in the last year ($OR=0.82$, 95% CI: 0.68, 0.98). Social reinforcement from connected pairs of alters that were unsuccessful quitters was significantly associated with the participant being a current smoker ($OR=1.26$, 95% CI: 1.10, 1.45). **Conclusions:** Our study suggests that smoking behaviors do not occur in isolation, nor because of 1 or 2 prominent social network members. Rather, our findings suggest that both strong ties and social reinforcement from clusters of similarly-behaving persons influence smoking behavior. Primary care practices have an opportunity to leverage these insights on patient networks to improve cancer prevention.

Keywords

smoking, primary care, prevention, health promotion, patient-centeredness, behavioral health

Dates received: 14 June 2021; revised: 17 July 2021; accepted: 20 July 2021.

Introduction

Tobacco use remains the leading cause of preventable cancer.^{1,2} With the call to invest in cancer prevention research, there remains a need to evaluate novel ways to curtail tobacco use.^{2,3} Tobacco use behaviors are contagious within social networks, which consist of a set of people and the connections between them.^{4,5} Social networks are the structural aspects of social relationships and social network studies seek to examine how the social structure or web of ties of individuals relate to outcomes of interest in them.^{6,7}

¹Perelman School of Medicine, University of Pennsylvania, Philadelphia, PA, USA

*Co-first authors.

Corresponding Author:

Jaya Aysola, Penn Medicine Center of Health Equity Advancement, Penn Medicine and Office of Inclusion, Diversity, and Equity, and Division of General Internal Medicine, Perelman School of Medicine, University of Pennsylvania, 1229 Blockley Hall, 423 Guardian Drive, Philadelphia, PA 19104-6201, USA.

Email: jaysola@upenn.edu



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons

Attribution-NonCommercial 4.0 License (<https://creativecommons.org/licenses/by-nc/4.0/>) which permits non-commercial use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (<https://us.sagepub.com/en-us/nam/open-access-at-sage>).

The type, strength, and structure of those social ties have been shown to influence tobacco use.⁸ Evidence suggests that tobacco use behaviors may require multiple, strong ties to spread or social reinforcement from interconnected ties that share the same behaviors.⁹⁻¹⁴ Leveraging such insights on how behaviors spread, primary care providers and practices have an unrealized opportunity to influence tobacco use and other cancer prevention behaviors that contribute to the burden of cancer in susceptible populations.¹⁵⁻¹⁹

Recent recommendations from the US Preventive Services Taskforce have called for primary care interventions to mitigate tobacco use.²⁰ Effectively addressing healthy behaviors in the primary care setting requires innovative approaches that build synergy between practices and the social networks of primary care patients. The objectives of this study were to understand the characteristics of primary care patient social networks and evaluate the associations between those network characteristics and tobacco use.

Methods

Data Collection

We identified a random sample of primary care patients to recruit from an electronic medical records (EMRs) query of 2 primary care practices serving West Philadelphia, located in the state of Pennsylvania, in the USA. We recruited eligible patients from study site waiting rooms (egos) if they were: (1) age 21 or older; (2) English speaking; and (3) seen at least once in the past 3 years (if patient has a designated PCP) or twice in the past 2 years (if no assigned PCP). We asked initial participants (egos) to name up to 6 social ties (alters), without further specification. Then we asked a series of questions about each nominated alter to determine their communication frequency, whether or not they attended the same primary care practice or discussed health related matters with their nominated ties. We reached out via telephone to recruit at least 2 of the 6 nominated alters, prioritizing those ties that they attended the same primary care practice as or discussed health matters with. Enrolled alters were then given the same survey as egos and this snowball sampling method was repeated 6 times, for a total of 208 participants, 55 egos (23 Non-Hispanic White and 32 Non-Hispanic Black patients) and 153 of their enrolled alters.^{21,22}

All participants received an incentive to complete a 60-min telephone survey that assessed individual attributes and behaviors as well as how they relate to and interact with each of their social ties. To determine the strength of the ties and the presence of social reinforcement, we asked each participant, whether or not their nominated alters know each other and if so, how frequently they communicate with one another. We assessed communication frequency using a scale from 0 to 6 (0=Never, 1=Less than every 2-3 weeks,

2=Every 2-3 weeks, 3=1-2 days a week, 4=3-5 days a week, 5>About once a day and 6=Several times a day; 99=Ties don't know each other; 98=Participant can't recall). Participants were able to assess the frequency of communication between their nominated social ties (alters) 98.3% of the time and, when those alters were themselves enrolled and nominated the original participant in turn, there was agreement between the ego's assessment and the alter's self-assessment 66.7% of the time. The institutional review board at the University of Pennsylvania approved this study protocol.

Dependent Variables

For participants, we examined the following smoking status binary outcomes (Yes vs No): (1) never smoker; (2) successful quitter; and (3) current smoker. We assessed participant smoking status using the following validated survey questions with yes or no response options: (1) Have you ever smoked (>100 cigarettes in your life); (2) Do you currently smoke; (3) Have you tried to quit in the past 12 months.²³ We characterized successful quitters as those who identified currently as non-smokers, but reported a prior history of smoking and unsuccessful quitters as those that identified as current smokers who reported trying to quit in the past 12 months.

Independent Variables

Our independent variables were social network measures reflecting the number, strength, and interconnectivity of ties. First, we examined degree—all alters connected to a given participant including their alters nominated alters, to adjust for network size of a given participant. To examine the joint associations of alter behavior and network structure, we then categorized alters' smoking into 1 of 4 mutually exclusive and exhaustive categories: (1) never smoker, (2) successful quitter, (3) unsuccessful quitter, and (4) current smoker who has not tried to quit in the last 12 months. These categories are distinct from our participant outcomes.

Strong Ties (Total Strength of Communication Weighted Network Dyads)

To examine the associations between the strength of social ties within a participant's network and their smoking status, we derived a set of network variables weighted by communication frequency (ordinal; ranging from 0=never to 6=more than once a day) and discussions of health matters (dichotomous; 1=yes vs 0=no). We examined the set of 0 to 6 participant-alter pairs (dyads), where the participant and alter discussed health and weighted those by

the frequency of communication, and segmented them according to the smoking status of the alters irrespective of the smoking status of the participant. We then summed all of these weighted communication frequencies to create 4 dyadic independent variables, 1 for each of the 4 possible smoking status characteristics.²⁴ For parsimony, hereafter we refer to these total strength of communication weighted networks ties simply as “strong ties.”

Social Reinforcement (Social Reinforcement Triad Counts)

Social reinforcement examines the intersection between transitivity, when 2 people who share a social tie are themselves connected, and homophily, when social ties share the same attribute. For each of the 4 smoking behaviors, we captured the number of social reinforcement triads, where the participant’s nominated social ties (alters) were also connected to each other (transitivity) and share a behavior (homophily) that served to reinforce that behavior with the ego.²⁵ For each participant, we took the subset of alters who all exhibited the smoking status in question. For each unique pair of alters in that subset, we counted those where the alters knew one another, as indicated by the participant. We normalized these counts by dividing by the number of unique pairs of alters sharing the smoking behavior.¹⁴ For example, if a participant had 4 alters who were never smokers, the count of never smoker social reinforcement triads would be divided by 6—the number of unique pairs that could be made from those 4 alters. We then scaled this normalized number from 0 to 10 rather than 0 to 1 to aid interpretability of results. We constructed a fifth social reinforcement triad count where the alters *did not share* a smoking behavior (heterophily) to isolate the effects of social reinforcement from that of merely having dense networks.²⁶ For a given participant, we counted the number of pairs of alters who had different smoking statuses and who knew one another. To normalize, we divided by the number of pairs that could be formed from *all* the participant’s alters, less the number of pairs that would form homophilous ties and rescaled this to have a range of 0 to 10.

Additional Covariates

We examined the following demographic and socioeconomic characteristics: age, race/ethnicity, sex, education, income, and employment status. We employed validated measures to assess participant self-efficacy,²⁷ whether or not they had depression²⁸ and their relationship with their primary care provider (provider-patient relationship).²⁹

Analysis

First, we compared the above demographic, socioeconomic, psychosocial, and network characteristics (density,

4 communication weighted tie counts, and 4 normalized social reinforcement triad counts) of participants by smoking status. We did so by conducting 2-sided *t*-tests for continuous variables and chi-square tests for categorical ones.

Second, to estimate the association between our independent variables and our binary smoking outcomes, we fit multivariable logistic regression models and used generalized estimating equations (GEE) with an exchangeable correlation structure to account for correlation among each participant’s ego-initiated network. Each ego-initiated network consisted of the ego, their nominated alters, and their enrolled alters’ nominated alters (second degree alters) and so forth. For each of our dependent variables, we fit a series of 3 models, adding additional covariates each time. For the successful quitter outcome, models were estimated in the subset of participants with a prior history of smoking ($n = 107$). Models for the never smoker and current smoker outcomes were estimated using the entire sample ($n = 208$). In Model 1, we included degree and our 4 communication weighted ties counts as measures of complex contagion. In Model 2, we added our social reinforcement variables, specifically the triad counts for each smoking status; as well as our control variable of the triad counts of those with heterophilous smoking behaviors. In Model 3 we further controlled for the additional covariates detailed above.

Network Visualizations

To visualize exactly how different network structures were associated with different smoking behaviors, we estimated the predicted probabilities from Model 3 for a series of arbitrarily chosen observed networks holding the demographic and socioeconomic characteristics at their mean if continuous and at their mode if categorical. Specifically, these networks were chosen such that they represented a wide range of predicted probabilities.

To isolate the network effects identified by our regression models, we calculated the predicted probabilities for a series of synthetic networks. We modified 1 network value at a time, holding other covariates constant, to isolate the effect of that change in the predicted probability for our 3 smoking status outcomes. The first set of synthetic networks comprise 2 homophilous alter pairs, with each pair having a distinct smoking behavior. Of these 2 pairs, 1 forms a social reinforcement triad, and the other does not, and we calculated all 6 possible configurations for each outcome.

The second set of synthetic networks likewise comprise the participant and 2 homophilous alter pairs, with each pair sharing 1 of the 2 behaviors that had the strongest associations with the relevant outcome in Model 3. In these networks, we held the smoking status of all alters constant, and altered the connections between them: (1) absence of all transitive ties; (2) presence of a transitive tie connecting

Table 1. Participant Characteristics by Smoking Status.

Characteristics	Never smoker (N = 101)	Successful quitter (N = 59)	Current smoker (N = 48)	
			Unsuccessful quitter (N = 36)	Never tried to quit (N = 12)
Degree—Mean (SD)	8.0 (5.1)	8.5 (4.9)	9.1 (4.3)	8.8 (6.2)
Communication weighted Dyads—Mean (SD)				
Never smokers	4.4 (5.1)	2.1 (3.2)	2.0 (3.9)	4.0 (3.6)
Successful quitters	1.5 (3.0)	3.0 (3.8)	1.2 (2.3)	1.9 (3.7)
Unsuccessful quitters	0.8 (2.1)	0.8 (2.2)	3.0 (4.6)	2.6 (3.3)
Current smokers that have not tried to quit in the last 12 months	0.3 (1.3)	0.5 (1.6)	0.6 (1.8)	2.3 (2.8)
Social reinforcement triads—Mean (SD)				
Never smokers	0.5 (0.5)	0.1 (0.3)	0.1 (0.2)	0.3 (0.4)
Successful quitters	0.0 (0.2)	0.2 (0.4)	0.0 (0.2)	0.1 (0.3)
Unsuccessful quitters	0.0 (0.1)	0.2 (0.2)	0.4 (0.5)	0.1 (0.3)
Current smokers that have not tried to quit in the last 12 months ^a	0.0 (0.0)	0.0 (0.2)	0.1 (0.2)	0.3 (0.5)
Heterophilous alters	0.4 (0.4)	0.5 (0.4)	0.6 (0.4)	0.5 (0.4)
Age—Mean (SD)	44.4 (17.7)	55.9 (15.7)	49.2 (16.6)	53.5 (10.4)
Race (Non-White)—N (%)	81 (80.2)	42 (71.2)	31 (86.1%)	10 (83.3)
Education-level—N (%)				
Less than a Bachelor degree	59 (58.4)	38 (64.4)	34 (94.4)	9 (75.0)
Bachelor or Graduate degree	42 (41.6)	21 (35.6)	2 (5.6)	3 (25.0)
Sex (male)—N (%)	34 (33.7)	24 (40.7)	14 (38.9)	2 (16.7)
Income—N (%)				
Less than \$24999 or Unknown	28 (27.7)	29 (49.2)	23 (63.9)	7 (58.3)
\$25 000–\$49 999	35 (34.7)	11 (18.6)	6 (16.7)	2 (16.7)
\$50 000 or more	38 (37.6)	19 (32.2)	7 (19.4)	3 (25.0)
Employment—N (%)				
Unemployed ^b	16 (15.8)	5 (8.5)	6 (16.7)	1 (8.3)
Unable to work	18 (17.8)	16 (27.1)	12 (33.3)	2 (16.7)
Retired	10 (9.9)	15 (25.4)	6 (16.7)	2 (16.7)
Employed	57 (56.4)	23 (39.0)	12 (33.3)	7 (58.3)
Depression (PHQ-2)—N (%)	20 (19.8)	6 (10.2)	18 (50.0)	0 (0.0)
Self-efficacy—Mean (SD)	31.0 (6.1)	31.1 (6.9)	30.1 (6.6)	29.2 (7.7)
Provider-patient relationship (PDRQ-9)—Mean (SD)	28.7 (6.0)	29.9 (6.0)	29.5 (6.6)	32.6 (4.6)

^aThere were no homophilous closed triads for alters who were current smokers who have not tried to quit. This variable was therefore not included in the regressions.

^bUnemployed = Student, Homemaker, Out of work for less than 1 year, Out of work for 1 year or more.

alters with the same smoking status (homophily); and (3) presence of a transitive tie connecting alters with different smoking status (heterophily).

All models were fit using SAS v 9.4.

Results

Of the 208 participants, 101 identified as never smokers, 59 were successful quitters, and 48 were current smokers (Table 1). Of the 48 current smokers, 36 (75%) reported trying to quit and 12 (25%) reported not trying to quit. We found significant differences in smoking status by age, income, employment status, and depression status. We also

found significant differences in smoking status by social network characteristics. Degree did not vary by smoking status ($P = .48$), but the communication-weighted ties to alters did ($P = .002$ for ties to never smokers, $P = .01$ for ties to successful quitter, and $P < .001$ for ties to unsuccessful quitters). Social reinforcement triads also differed across smoking behaviors ($P < .001$ among never smokers, $P = .002$ among successful quitters, and $P = .004$ among current smokers who had not tried to quit). Table 1 details the full list of covariates by smoking status.

We found several significant associations between “strong ties” (total strength of communication weighted ties), social reinforcement (homophilous triads) and the

odds of identifying as a never smoker, successful quitter, and current smoker. Table 2 summarizes the results of all 4 sequential models for our 3 smoking outcomes and includes the adjusted odds ratios, 95% confidence intervals, and *P* values without adjustment for multiple comparisons.

Never Smoker

After adjusting for demographic, socioeconomic and psychosocial variables (Model 3), we found that participants with stronger ties to never smokers (OR=1.20, 95% CI: 1.07-1.34) and weaker ties to unsuccessful quitters (OR=0.77, 95% CI: 0.63-0.95) had significantly increased odds of being a never smoker. Connecting 1 unconnected alter pair in a network with 5 alters (10 possible pairs) who all identify as never smokers, would increase the total fraction of reinforcing triads by 10%, thus increasing the odds that the participant was a never smoker by 20%. Conversely, connecting 1 alter pair in a network with 5 individuals identifying as unsuccessful quitters, would decrease the odds that the participant was a never smoker by 23%.

Successful Quitter

After adjustment (Model 3), we found that, among ever smokers, participants with strong ties with successful quitters were significantly more likely to identify as successfully quitting (OR=1.37, 95% CI: 1.11, 1.69). So, adding one social tie that identifies as a successful quitter, with whom the participant communicates with less frequently than every 2 to 3 weeks, would increase the odds of the participant being a successful quitter by 37%. Conversely, participants with strong ties to unsuccessful quitters (OR=0.59, 95% CI: 0.44, 0.80) and current smokers who had not tried to quit (OR=0.82, 95% CI: 0.68-0.98) were significantly less likely to identify as a successful quitter. Participants with social reinforcement from successful quitters were significantly more likely to be successful quitters themselves (OR=1.33, 95% CI: 1.07-1.66).

Current Smoker

After adjustment (Model 3), participants with strong ties to never smokers were significantly less likely to identify as a current smoker (OR=0.83, 95% CI: 0.73-0.85), and participants with social reinforcements from unsuccessful quitters (OR=1.26, 95% CI: 1.10-1.45) remained significantly more likely to identify as a current smoker. Conversely, participants with social reinforcement from successful quitters remained significantly less likely to identify as a current smoker (OR=0.86, 95% CI: 0.76-0.98).

Network Visualizations

Based on observed relationships in Model 3, Figure 1 illustrates how the number of ties to alters of a given smoking behavior, the weight of those ties, and the number of ties between them change the predicted probability of a given smoking behavior. In our first set of synthetic networks (Figure 2) the predicted probability dramatically changed when a transitive tie was switched from 1 pair to the other. For example, the predicted probability of never smoking increases from 6% to 94% when changing the transitive tie from unsuccessful quitters (second network) to never smokers (sixth network). Figure 3 illustrates the predicted probabilities for our synthetic networks that change the connections between alters when holding the smoking behavior of the 4 alters constant. Given the associations between social reinforcement triads among alters who had *different* smoking statuses (heterophily) were non-significant and had small effect sizes in all models, the predicted probabilities are similar between the networks without social reinforcement triads and with 2 social reinforcement triads among heterophilous alters.

Discussion

Our study of the social network characteristics of 53 primary care patients and 153 of their social ties revealed 2 key insights. First, we found that primary care patients were significantly more likely to share the same smoking behaviors as their strong social ties, defined as those with whom they had more frequent communication and discussed health matters.^{11,30} Strong ties appeared to be more consistently associated with successful quitting than smoking initiation. Second, we found that primary care patients with social reinforcement from their social ties (ie, the social ties are connected to each other—transitivity—and share a smoking behavior—homophily), were significantly more likely to also share the same smoking behavior. These network characteristics were associated with primary care patient smoking status even after adjusting for demographic, socioeconomic, and psychosocial characteristics.

Our findings strengthen the evidence that social reinforcement rather than only the number of connections to network members with a certain behavior (homophily) or having a dense network (transitivity) drives smoking behavior.^{12,20} Social reinforcement maximizes social influence through multiple ties sharing a behavior who are themselves are connected. The presence of social reinforcement has been shown to accelerate the spread of acute behaviors such as registering for a forum in simulated studies.^{12,13} This study, however, is the first to our knowledge, to simultaneously examine the independent effects of these network conditions in a real-world setting, using methods to

Table 2. Adjusted Associations Between Network Characteristics and Smoking Status.

	Model 1: Network characteristics (degree, communication weighted dyads)		Model 2: Model 1 + social reinforcement triads		Model 3: Model 2 + additional covariates ^a	
	OR (95% CI); P-value ^b		OR (95% CI); P-value		OR (95% CI); P-value	
Outcome: Never smoker (Y/N) (n = 208)						
Degree	0.96 (0.90, 1.02); .21		0.91 (0.86, 0.97); .004		0.92 (0.85, 1.00); .057	
Communication weighted dyads						
Never smokers	1.13 (1.05, 1.22); <.001		1.06 (0.96, 1.17); .28		1.01 (0.92, 1.12); .93	
Successful quitters	0.97 (0.88, 1.06); .48		1.01 (0.92, 1.11); .80		0.99 (0.88, 1.11); .90	
Unsuccessful quitters	0.92 (0.83, 1.03); .14		1.04 (0.89, 1.22); .62		1.07 (0.89, 1.28); .46	
Current smokers that have not tried to quit in the last 12 months	0.85 (0.66, 1.10); .21		0.89 (0.64, 1.25); .50		0.90 (0.67, 1.21); .49	
Social reinforcement triads						
Never smokers			1.17 (1.08, 1.26); <.0001		1.20 (1.08, 1.34); .001	
Successful quitters			1.00 (0.91, 1.10); .96		0.98 (0.88, 1.10); .76	
Unsuccessful quitters			0.77 (0.63, 0.95); .01		0.78 (0.66, 0.92); .002	
Heterophilous alters			0.96 (0.89, 1.04); .35		0.98 (0.89, 1.07); .60	
Outcome: Successful quitter (Y/N) (n = 107)						
Degree	1.01 (0.93, 1.09); .89		0.99 (0.89, 1.11); .88		1.00 (0.87, 1.14); .97	
Communication weighted dyads						
Never smokers	0.97 (0.88, 1.07); .49		1.04 (0.92, 1.17); .53		1.02 (0.84, 1.23); .87	
Successful quitters	1.26 (1.03, 1.55); .03		1.33 (1.11, 1.60); .003		1.37 (1.11, 1.69); .003	
Unsuccessful quitters	0.69 (0.56, 0.85); <.001		0.64 (0.55, 0.76); <.0001		0.59 (0.44, 0.80); <.001	
Current smokers that have not tried to quit in the last 12 months	0.87 (0.76, 1.00); .06		0.78 (0.69, 0.87); <.0001		0.82 (0.68, 0.98); .03	
Social reinforcement triads						
Never smokers			1.06 (0.92, 1.22); .41		1.05 (0.90, 1.23); .54	
Successful quitters			1.26 (1.06, 1.52); .009		1.33 (1.07, 1.66); .01	
Unsuccessful quitters			0.82 (0.69, 0.99); .04		0.88 (0.74, 1.04); .14	
Heterophilous alters			0.92 (0.81, 1.04); .17		0.97 (0.86, 1.10); .66	
Outcome: Current smoker (Y/N) (n = 208)						
Degree	1.06 (0.97, 1.14); .19		1.07 (0.98, 1.17); .12		1.08 (0.97, 1.20); .15	
Communication weighted dyads						
Never smokers	0.83 (0.78, 0.89); <.0001		0.89 (0.84, 0.94); <.0001		0.93 (0.86, 1.00); .048	
Successful quitters	0.89 (0.80, 1.00); .050		0.87 (0.78, 0.96); .007		0.83 (0.73, 0.95); .007	
Unsuccessful quitters	1.27 (1.13, 1.43); <.0001		1.18 (1.04, 1.32); .008		1.17 (0.98, 1.40); .09	
Current smokers that have not tried to quit in the last 12 months	1.20 (1.03, 1.39); .02		1.19 (0.97, 1.47); .09		1.17 (0.97, 1.41); .10	
Social reinforcement triads						
Never smokers			0.93 (0.84, 1.04); .21		0.91 (0.83, 1.01); .07	
Successful quitters			0.89 (0.78, 1.01); .07		0.86 (0.76, 0.98); .02	
Unsuccessful quitters			1.29 (1.14, 1.45); <.0001		1.26 (1.10, 1.45); .001	
Heterophilous alters			1.06 (0.98, 1.15); .12		1.02 (0.92, 1.13); .68	

^aAge, race/ethnicity, sex, education, income, and employment status, self-efficacy, depression status, provider-patient relationship.

^bp < .05 considered statistically significant and are shown in bold.

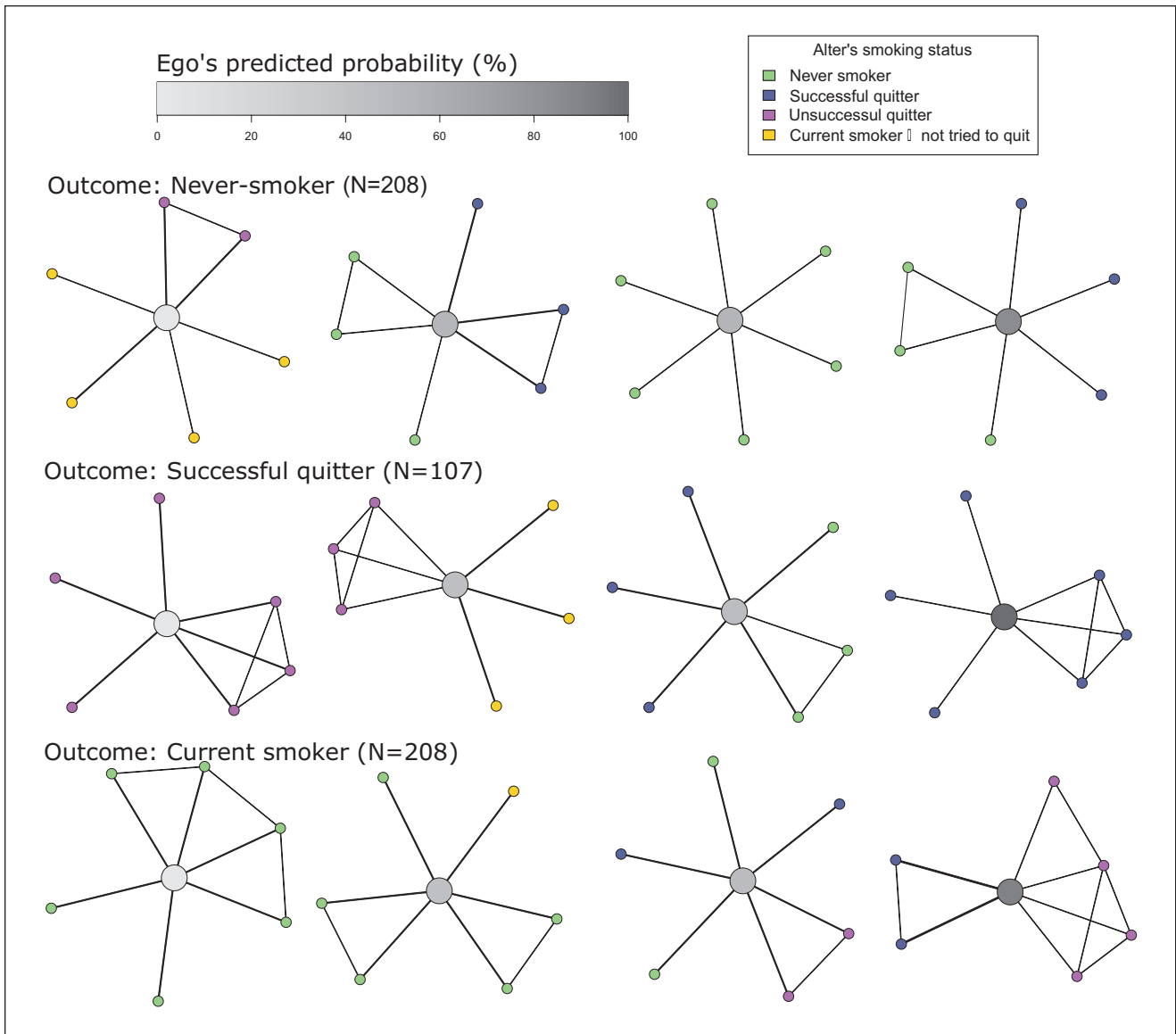


Figure 1. Ego's predicted probability of smoking outcome by network characteristics. For each outcome, 4 networks were arbitrarily chosen to represent a wide variety of predicted probabilities. We then visualized the network, color-coding alter nodes by their smoking status and the ego's nodes by their predicted probability. For a given outcome, left to right, the predicted probability for the ego increases and is reflected by increasing darkness on the gray scale. For example, for predicting "never-smokers" the left-most network comprises 4 unconnected current smokers and a reinforcing triad of unsuccessful quitters, which all have negative associations in the corresponding regression, leading to a low predicted probability. On the right, the network has 3 unconnected successful quitters and 3 never smokers, 2 of whom form a reinforcing triad, leading to a high predicted probability.

determine the exact number of social reinforcement triads only recently developed.²⁵ That our variables measuring homophily and dense networks were generally less predictive than the social reinforcement triad counts suggests that among social network effects, social reinforcement is the primary driver of smoking behavior. Thus, interventions leveraging social networks to alter smoking behavior should account for social reinforcement rather than less complex measures of strong ties, homophily or network density.

Although this research is novel in many ways, it is not without limitations. While our outcomes, such as successful quitter may contain some information about *past* behavior, given the cross-sectional network design, we cannot infer causality.³¹ Future work should include longitudinal assessments of these associations. Future inquiry may also benefit from recruiting unconnected participants, while recognizing the tradeoff would be the loss of richness this interconnected data provides.

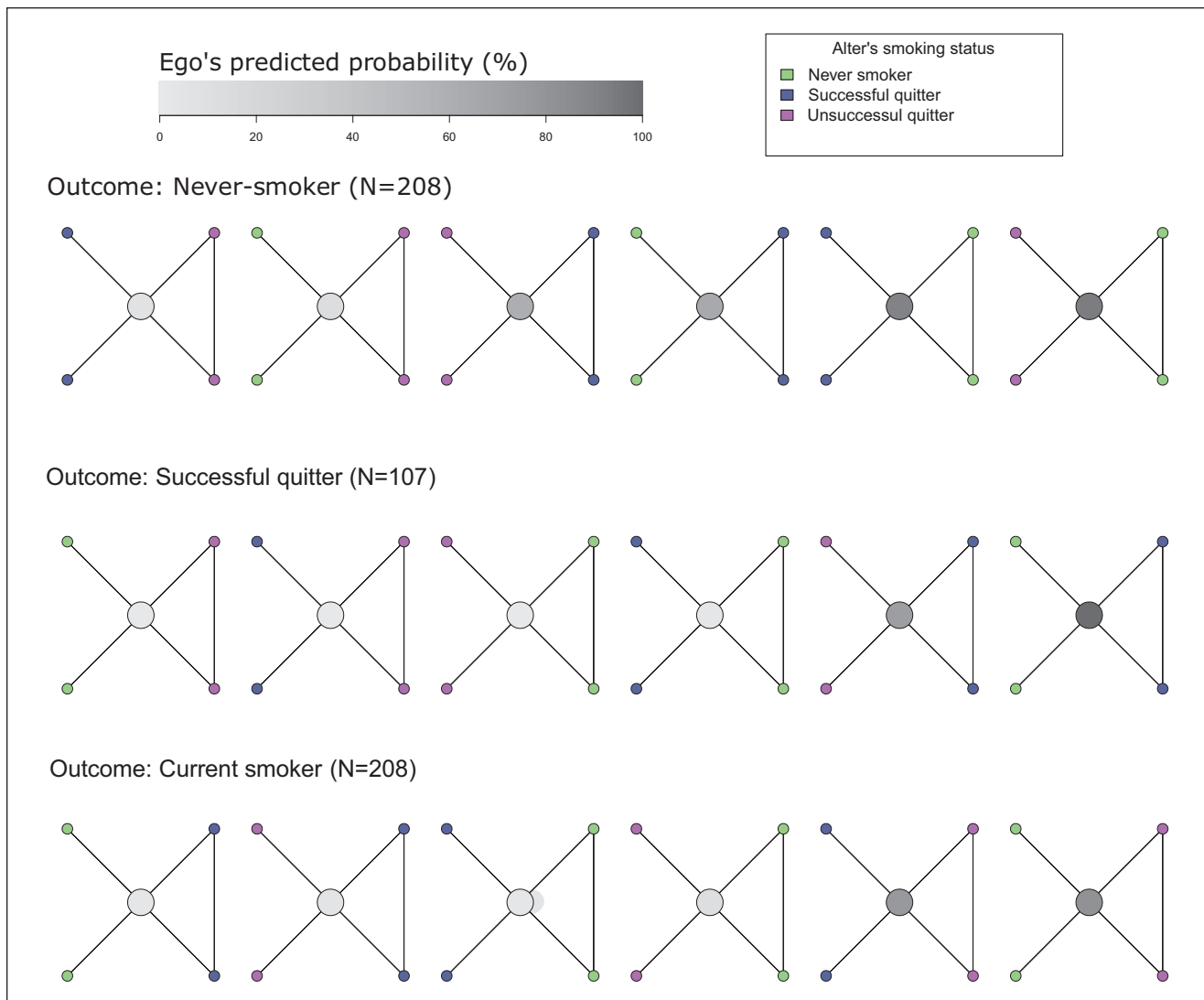


Figure 2. Ego's predicted probability of smoking outcome by Alter's smoking status. For each outcome, we constructed 6 synthetic networks comprising 2 pairs of alters, 1 pair forming a reinforcing triad and the other not. The 6 networks cover all permutations of pairing alters by smoking status. We then visualized the network, color-coding alter nodes by their smoking status and the ego's nodes by their predicted probability. For a given outcome, left to right, the predicted probability for the ego increases and is reflected by increasing darkness on the gray scale.

Early work revealed that smoking behaviors are contagious, but it is not merely who you know that drives whether or not you successfully quit smoking or never smoke. What appears to matter is the way you are connected to your social ties and how they are connected to each other. Our study suggests that smoking behaviors do not occur in isolation, nor because of 1 or 2 prominent social network members. Rather, our findings point toward the potential role of clusters of similarly-behaving persons in influencing smoking behavior. There is an opportunity for primary care practices to design interventions that consider these insights. Leveraging connections between

people within the primary care setting is not necessarily a new concept. Group visits have effectively leveraged connections between patients within primary care settings to meet desired outcomes.³²⁻³⁵ The capacity to connect people online opens the possibility to conduct group visits for cancer prevention virtually and recent events have illustrated the promise of virtual care.³⁶⁻³⁸ Such models could be applied to facilitating tobacco cessation discussions within peer-to-peer networks that includes a physician and their panel of patients or the spread by patients of smoking prevention interventions within their natural-occurring social networks.

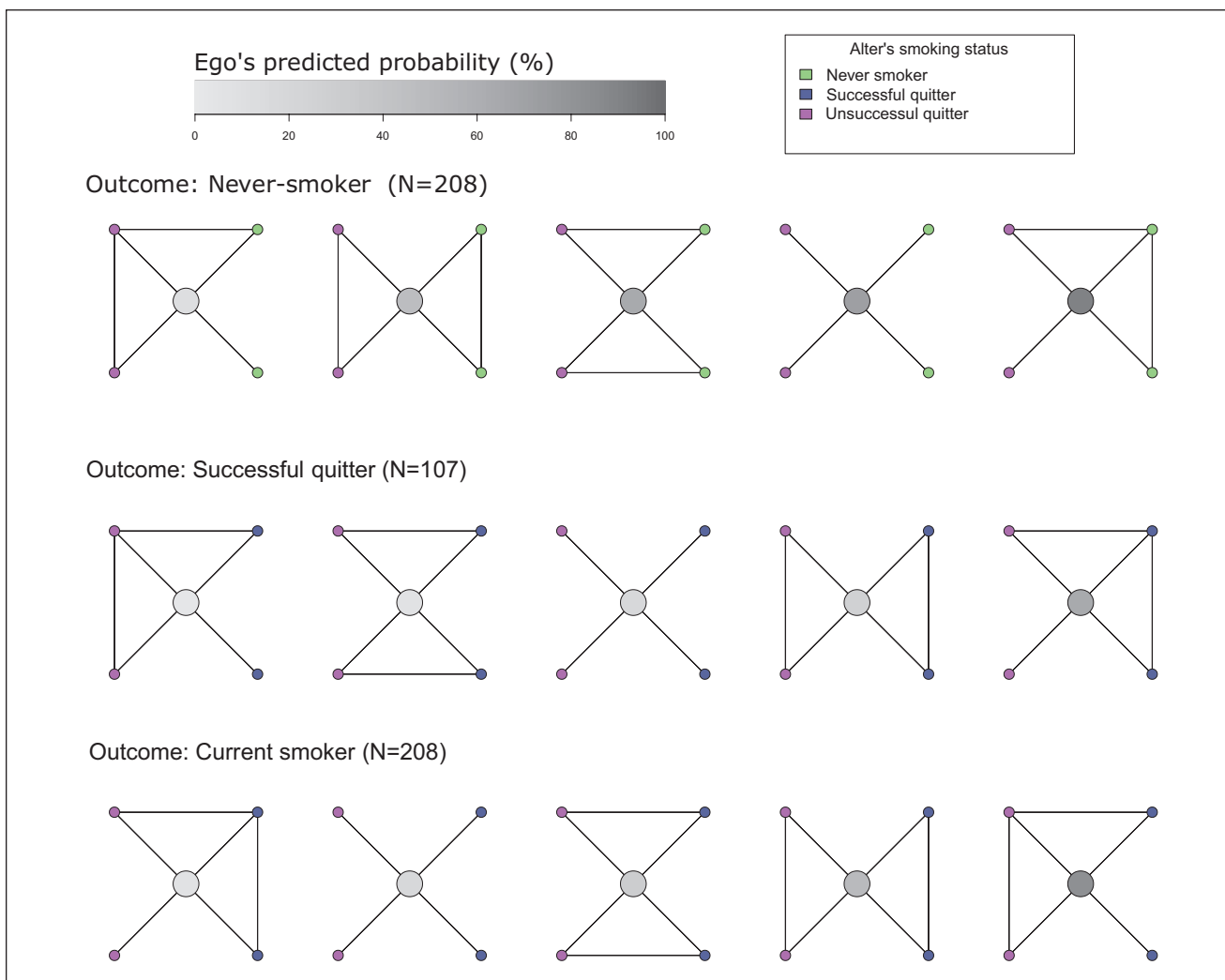


Figure 3. Ego's predicted probability of smoking outcome by network structure. For each outcome, we constructed 5 synthetic networks comprising 2 pairs of alters, each pair sharing a smoking behavior. The networks included (1) no alter-alter ties, (2) both possible reinforcing triads, (3) both possible heterogeneous triads, and (4-5) One reinforcing triad and one heterogeneous triad. We then visualized the network, color-coding alter nodes by their smoking status and the ego's nodes by their predicted probability. For a given outcome, left to right, the predicted probability for the ego increases and is reflected by increasing darkness on the gray scale.

Author's Note

An abstract of this study a virtual oral presentation at the American Public Health Association Annual Meeting on October 28, 2020, and acknowledged poster abstract at the AcademyHealth Annual Research Meeting in July 2020.

Acknowledgments

I would like to thank Dr. Damon Centola and members of the Network Dynamics Group for their input in the design of this study.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Jaya Aysola, MD, MPH, was supported by an American Cancer Society—Tri-State CEO's Against Cancer Mentored Research Scholar Grant, MRS-G-17-155-01-CPPB. In addition, this study was supported in part by the Abramson Cancer Center's American Cancer Society Institutional Research Grant (129784-IRG-16-188-38-IRG).

ORCID iD

Jaya Aysola  <https://orcid.org/0000-0002-8474-3682>

References

- Gallaway MS, Henley SJ, Steele CB, et al. Surveillance for cancers associated with tobacco use—United States, 2010–2014. *MMWR Surveill Summ.* 2018;67(12):1-42.

2. Meza R, Jimenez-Mendoza E, Levy DT. Trends in tobacco use among adolescents by grade, sex, and race, 1991-2019. *JAMA Netw Open*. 2020;3(12):e2027465.
3. Neugut AI, Gross CP. Targeting the cancer moonshot. *JAMA Oncol*. 2016;2(4):421-422.
4. Christakis NA, Fowler JH. Quitting in droves: collective dynamics of smoking behavior in a large social network. *New Engl J Med*. 2008;358(21):2249-2258.
5. Seo DC, Huang Y. Systematic review of social network analysis in adolescent cigarette smoking behavior. *J Sch Health*. 2012;82(1):21-27.
6. Perkins JM, Subramanian SV, Christakis NA. Social networks and health: a systematic review of sociocentric network studies in low- and middle-income countries. *Soc Sci Med*. 2015;125:60-78.
7. Gallant MP, Dorn GP. Gender and race differences in the predictors of daily health practices among older adults. *Health Educ Res*. 2001;16(1):21-31.
8. Maddox R, Davey R, Lovett R, van der Sterren A, Corbett J, Cochrane T. A systematic review protocol: social network analysis of tobacco use. *Syst Rev*. 2014;3(1):85.
9. Centola D, Macy M. Complex contagions and the weakness of long ties. *Am J Sociol*. 2007;113:702-734.
10. Centola D. The social origins of networks and diffusion. *Am J Sociol*. 2015;120(5):1295-1338.
11. Green HD, Horta M, Haye KDL, Tucker JS, Kennedy DR, Pollard M. Peer influence and selection processes in adolescent smoking behavior: a comparative study. *Nicotine Tob Res*. 2013;15(2):534-541.
12. Centola D. The spread of behavior in an online social network experiment. *Science*. 2010;329(5996):1194-1197.
13. Lü L, Chen D-B, Zhou T. The small world yields the most effective information spreading. *New J Phys*. 2011;13(12):123005.
14. O'Malley AJ, Arbesman S, Steiger DM, Fowler JH, Christakis NA. Egocentric social network structure, health, and prosocial behaviors in a national panel study of Americans. *PLoS One*. 2012;7(5):e36250.
15. Smedley BD, Stith AY, Nelson AR. *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care (With CD)*. National Academies Press; 2009.
16. Freeman HP. Poverty, culture, and social injustice: determinants of cancer disparities. *CA Cancer J Clin*. 2004;54(2):72-77.
17. Aysola J, Bitton A, Zaslavsky AM, Ayanian JZ. Quality and equity of primary care with patient-centered medical homes: results from a national survey. *Med Care*. 2013;51(1):68-77.
18. Bach PB, Pham HH, Schrag D, Tate RC, Hargraves JL. Primary care physicians who treat blacks and whites. *New Engl J Med*. 2004;351(6):575-584.
19. Katz SJ. Socioeconomic disparities in preventive care persist despite universal coverage: breast and cervical cancer screening in Ontario and the united states. *J AMA*. 1994;272(7):530-534.
20. Desai AN. Preventing tobacco use in children and adolescents. *JAMA*. 2020;323(16):1626-1626.
21. Goodman LA. Snowball sampling. *Ann Math Stat*. 1961;32:148-170.
22. Goodman LA. Comment: On respondent-driven sampling and snowball sampling in hard-to-reach populations and snowball sampling not in hard-to-reach populations. *Sociol Methodol*. 2011;41(1):347-353.
23. Centers for Disease Control and Prevention (CDC). Behavioral risk factor surveillance system survey questionnaire, 2014. Accessed August 3, 2021. <http://www.cdc.gov/brfss/questionnaires/>
24. Hall JA, Valente TW. Adolescent smoking networks: the effects of influence and selection on future smoking. *Addict Behav*. 2007;32(12):3054-3059.
25. Lienert J, Koehly L, Reed-Tsochas F, Marcum CS. *An Efficient Counting Method for the Colored Triad Census [doi:10.1016/j.socnet.2019.04.003]*. Elsevier Science; 2019.
26. Cobb NK, Graham AL, Abrams DB. Social network structure of a large online community for smoking cessation. *Am J Public Health*. 2010;100(7):1282-1289.
27. Schwarzer R, Jerusalem M. Optimistic self-beliefs as a resource factor in coping with stress. In: *Extreme Stress and Communities: Impact and Intervention*. Springer; 1995; 159-177.
28. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med*. 2001;16(9):606-613.
29. Porcerelli JH, Murdoch W, Morris P, Fowler S. The patient-doctor relationship questionnaire (PDRQ-9) in primary care: a validity study. *J Clin Psychol Med Settings*. 2014;21(3):291-296.
30. Mercken L, Snijders TA, Steglich C, Vartiainen E, de Vries H. Dynamics of adolescent friendship networks and smoking behavior. *Soc Netw*. 2010;32(1):72-81.
31. Shalizi CR, Thomas AC. Homophily and contagion are generically confounded in observational social network studies. *Sociol Methods Res*. 2011;40(2):211-239.
32. Yancy WS Jr, Crowley MJ, Dar MS, et al. Comparison of group medical visits combined with intensive weight management vs group medical visits alone for glycemia in patients with type 2 Diabetes: a noninferiority randomized clinical trial. *JAMA Intern Med*. 2020;180(1):70-79.
33. Wadsworth KH, Archibald TG, Payne AE, Cleary AK, Haney BL, Hoverman AS. Shared medical appointments and patient-centered experience: a mixed-methods systematic review. *BMC Fam Pract*. 2019;20(1):97.
34. Thompson-Lastad A. Group medical visits as participatory care in community health centers. *Qual Health Res*. 2018;28(7):1065-1076.
35. Heyworth L, Rozenblum R, Burgess JF, et al. Influence of shared medical appointments on patient satisfaction: a retrospective 3-year study. *Ann Fam Med*. 2014;12(4):324-330.
36. Centola D. Social media and the science of health behavior. *Circulation*. 2013;127(21):2135-2144.
37. Wosik J, Fudim M, Cameron B, et al. Telehealth transformation: COVID-19 and the rise of virtual care. *J Am Med Inform Assoc*. 2020;27(6):957-962.
38. Rodin D, Lovas M, Berlin A. The reality of virtual care: implications for cancer care beyond the pandemic. *Healthcare*. 2020;8(4):100480.