Title: Using social networks to understand and overcome implementation barriers in the global HIV response

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Abstract

Despite the development of several efficacious HIV prevention and treatment methods in the past decades, HIV continues to spread globally. Uptake of interventions is non-randomly distributed across populations, and such inequality is socially patterned both statically (due to homophily) and dynamically (due to social selection and influence). Social network analysis (SNA) methods, including egocentric, sociocentric, and respondent-driven sampling, provide tools to measure most-at-risk populations, to understand how epidemics spread, and to evaluate intervention take-up. SNA-informed designs can improve intervention effectiveness by reaching otherwise inaccessible populations and improve efficiency by maximizing spillovers to at-risk but susceptible individuals through social ties; they thus have the potential to be both more effective and less unequal in their effects than SNA-naïve approaches. While SNA-informed designs are often resource-intensive, they are uniquely able to help reach those most in need of HIV prevention and treatment interventions. Increased collection of social network data during both research and implementation work would provide important information to improve the roll-out of existing studies in the present and to inform the design of more data-efficient, SNA-informed interventions in the future.

Introduction

The global HIV response has been transformed by new discoveries during the past two decades, including the preventive efficacy of antiretroviral therapy, pre-exposure prophylaxis (PrEP), insertable microbicides, and medical male circumcision (1-5). However, the field has had less success translating these efficacious interventions into effective implementation at scale. Quantifying this gap between evidence and practice, understanding why it exists, and developing strategies to overcome it is a core goal of HIV implementation science (6). One of the most challenging aspects of successful implementation of HIV prevention programs has been motivating participants to initiate, adhere to, or maintain use of these interventions (7-9). In the setting of sub-optimal utilization, one approach to maximizing HIV prevention, as illustrated by the DREAMS partnership (10), involves providing an intensive package of multiple evidence-based interventions to those at greatest risk.

However, insofar as uptake and adherence are correlated across interventions, such user-dependent approaches to public health intervention at scale might risk iatrogenically increasing inequalities in HIV risk within populations, often leaving the most vulnerable at risk of both HIV acquisition and HIV-associated stigma (11-13) – a phenomenon variously described as the “inverse care law” (14), the “inverse equity hypothesis” (15), and the “inequality paradox” (16). Furthermore, when intervention uptake is non-randomly distributed within the population, risks for all are increased, as illustrated in the recent U.S. measles outbreak (17, 18). While structural interventions (that are not user-dependent, and which might benefit everyone within the population) can potentially mitigate such disparities (13, 19, 20), intervention approaches that can deliver proven methods effectively and efficiently to at-risk groups within populations will continue to remain a valuable part of the HIV prevention toolkit.

Innovative ideas, and corresponding behaviors, typically diffuse to populations via communication channels (21-23). While mass media campaigns might have broad capacity for achieving saturated

awareness, changing (or maintaining) behaviors typically requires deeper engagement and interaction. Social support, the communication of social norms, and other forms of social influence that can generate such sustained engagement flow through social network ties (24). Adoption of a social network approach therefore seems natural and likely to be fruitful in helping us understanding how intervention uptake and adherence are patterned across communities, how this patterning is generated, and maintained, and how barriers to uptake and adherence might most efficiently be overcome.

Social network data collection

Three social network data collection methods are commonly used. They can be roughly categorized by the extent to which the data can be linked and the extent to which the sampling frame is *a priori* known (25). ‘Egocentric’ network data are defined as those in which it is not possible to directly link the information provided by each respondent. These data are typically elicited through surveys, in which respondents (‘egos’) are asked to identify social network ties who occupy specific or general roles of social importance in their lives (‘alters’). Following the administration of these ‘name generators’ (26, 27), further information is sought from the ego through ‘name interpreters,’ which are questions that elicit information about characteristics of the named alters, and about characteristics of the ties between the ego and their alters. One extension of egocentric data collection is to elicit from the ego perceived properties of ties between each pair of alters, sometimes called “ego-centered cognitive social structures” (28, 29). This design results in the ability to better typify the immediate social network of each ego, but requires many additional questions (e.g., for five alters, there are 10 undirected alter-alter ties, for six alters this number rises to 15), often leading to interview fatigue and reduced data quality (30). Nevertheless, the collection of egocentric data is a relatively straightforward process, since they differ little from standard survey questions and can be captured from a sample of the entire network. However, these data rarely allow for network-wide

processes or outcomes to be directly evaluated, because typically no one ego reports on every ego in the network, and because egos' responses cannot be linked to one another.

In contrast to egocentric data, 'sociocentric' data arise when all egos in a population are sampled, and the alters that egos enumerate are identified, i.e., entity resolution. Entity resolution can be done either by having egos select their alters from a closed list (e.g., school register, employee list, population census) or by eliciting sufficient information about each alter such that they can be later linked as egos themselves by the data analyst. The latter approach typically leaves a substantial proportion of alters unidentified; on the other hand, having an *a priori* population census may be infeasible due to economic or practical considerations, especially when the population of interest is not well known. Sociocentric data can be extremely powerful and, when captured longitudinally, can allow us to identify how infections and interventions spread through communities. However, the collection of sociocentric data is substantially more resource-intensive compared with egocentric approaches because of the need to obtain information from and about the entire population of egos, which necessarily requires a population census. Examples of sociocentric studies conducted in resource-limited settings are rare (31) and require careful consideration of ethical issues such as consent for data collection and processing (32). One way to circumvent the resource requirements of sociocentric network data collection is by using existing network datasets, such as online social networks or phone records (33, 34). While such methods can be extremely powerful, they rarely provide the specific kinds of detail required to evaluate HIV treatment and prevention programs.

Both egocentric and sociocentric methods are based on interviewing a pre-defined population of egos. Some populations, however, are hidden insofar as their membership is not *a priori* known. In such situations, 'respondent driven sampling' (RDS) plays an important role (35, 36). RDS begins by interviewing a sample – often visible members – of the population. After completing the initial round of interviews, first-round egos ('seeds') are provided with a mechanism to invite alters to participate

in the survey (e.g., a voucher that can be redeemed with the study team). In this way, subsequent egos ‘self-refer’ to the study. These referral chains help the study team to survey individuals who might otherwise not have been identified, but since the overall population of interest is usually not well characterized, it can be difficult to derive population-representative estimates from RDS designs. Several methods have been proposed for assessing and adjusting for such potential biases (36, 37). However, RDS estimation remains an active field of enquiry, with no agreed-upon “gold standard,” and there remains concern about the tenability of the strong assumptions required to move from RDS sample-specific to population-level prevalence measures (38-41).

Using social networks to understand HIV treatment and prevention

In this article, we focus on three comparative advantages of the social network approach, namely the kinds of information it can provide where other methods cannot, and its relevance for three important aspects of the HIV epidemic: risk population definition, infection spread, and behavior patterns.

First, social network analysis (SNA), particularly using RDS methods, is uniquely able to help us understand the characteristics and risk behaviors of hard-to-reach, at-risk populations. Such knowledge allows us to see who is unable or unwilling to take up interventions and, potentially, why. The power of SNA in this context arises from the principle of homophily: an ego’s alters tend to be more similar to the ego than to other egos in the population (42). As a result, studies that elicit information from egos about their alters yield additional information about the risk groups to which the egos belong, including information about seroprevalence. This exercise is particularly important in the context of HIV since many of those most at risk are members of stigmatized or criminalized populations. In the case of RDS, egos are asked to refer alters who fit a particular profile, allowing detection and identification of specific high-risk populations (43), including people who use injection drugs (44-46), men who have sex with men (MSM) (47-51) and people who engage in sex work (52-55). Similarly, qualitative descriptions of the social networks of at-risk populations can provide vital

insights into the activities of at-risk groups, notably of the interactions between members, which can provide unique understanding about barriers and facilitators of intervention delivery (56, 57).

Second, SNA that captures sexual and other risk interactions is uniquely able to help us understand how HIV spreads through populations. Since the 1990s, researchers have used social network data (e.g., partner notification and contact tracing) to understand sexual behavior (58) and epidemic change for both HIV (59, 60) and other sexually transmitted infections (61). More recently, two approaches have been used to capture sexual networks *de novo*: (i) focusing on quasi-closed communities, such as those confined to islands (62) or those with well-defined social networks where boundary specification is relatively straightforward (63, 64); and (ii) attempting to gain saturated coverage of behaviorally or geographically defined groups (65-68). One powerful emerging use of social networks for understanding HIV transmission is its combination with phylogenetic data, thereby attempting to minimize the limitations of both data types (69-71), although there remain important ethical issues to consider in such detailed inference (72).

Third, SNA can allow us to observe how behavior is patterned and how novel ideas and behaviors spread through populations. Studies of MSM have demonstrated that there is homophily in behavior between egos and alters (73, 74) and that social network characteristics are correlated with use of PrEP (75). Studies of the spread of interventions through networks are rare and often limited to egocentric designs due to the larger budgets typically required for longitudinal sociocentric data collection (76), although RDS methods can also be appropriate (77). However, in the context of vaccine uptake, there is evidence that social norms are central to the generation and maintenance of vaccine hesitancy norms on online social networks (78).

Increasing interest in HIV self-testing provides an opportunity to understand how self-test kits are distributed and used by sexual partners (79) and by friends and family (80). Any attempt to infer causal processes in uptake must account for the strong dependencies between connected individuals,

while also disentangling the effects of homophily (being friends with similar people), social selection (becoming friends with similar people) and social influence (becoming similar to friends) (81-84). Several approaches have been proposed for conducting causal inference around peer effects, including stochastic actor-oriented models (85, 86), peer effects models (87), instrumental variables estimation (88), and dynamic matched sample estimation (89), but there remain ongoing debates about the extent to which causal inference is possible in these settings (82, 90). One important subset of behaviour change is that which is initiated intentionally, i.e., through intervention deployment. SNA can therefore also provide important information on where and why non-network informed interventions fail. Qualitative investigation of several past implementation trials has shown non-uptake or non-adherence to protocols (7); SNA in such situations could provide information about how non-adherence is patterned or even spread through the trial communities – information that could help with subsequent roll-out of the same or similar interventions.

Social network-informed interventions for HIV treatment and prevention

The above three SNA uses can help improve understanding of the HIV epidemic and barriers to its implementation. Beyond this, several social network-informed intervention (SNI) methods can be deployed to help overcome implementation barriers encountered with other approaches (91-93). Valente (76) has proposed four types of network interventions: individual; segmentation, or group change; inducted interaction; and network tie alteration. Randomized trials of such interventions to improve a range of health outcomes have often been successful (33).

Individual interventions are by far the most common SNI in HIV prevention. Examples include seeding behavior change messages (with the expectation that these messages will be passed on to social ties) and using network information to inform intervention targeting. Past experience has shown that carefully selected individuals can shift HIV risk behavior within populations (e.g. community popular opinion leaders [CPOs] (94)), but only when the CPOs selected were truly

influential (95, 96). Diffusion approaches that rely on random seeding are unlikely to reach everyone in the population, much less those at highest risk who are often hardest to reach (97), since by definition previous messaging has already failed to reach them. Careful planning and evaluation of individual SNIs is thus vital.

Induced interventions can be seen in the example of treatment supporters for HIV treatment and care. Such supporters may be either identified from existing contacts who are asked to assume new roles (98, 99) or created *de novo* (100, 101); both approaches appear to increase treatment adherence (102-104). Examples of network tie alteration strategies are rarer, not least because SNIs that eliminate ties or otherwise attempt to fragment/damage social networks pose obvious ethical problems. SNIs that use SNA to guide tie formation may hold more promise, but compelling studies in the field of HIV are yet to be done (105).

SNA highlights the importance of initial conditions for intervention targeting in two ways. First, when identifying initial seeds for behavior change, it is vital to choose those who are influential within their communities (106). Randomly selected seeds will be less efficient at inducing behavior change, since they will exert weaker spillover effects on others (107), while the earliest adopters of innovations are rarely the most influential since they are usually by definition not deeply embedded in local networks (108). Second, SNIs that select people who are already interested in behavior change will likely miss key high-risk populations (109). It is therefore important for an SNI to ensure broad coverage of the social space of interest (e.g., a school, a village, young MSM living in a city) and, potentially, to selectively enroll most-at-risk individuals.

Another lesson from SNA is the importance of complex contagion (110), where uptake or infection requires exposure to multiple sources. The threshold level of exposure required for complex contagion may be an absolute number or a proportion (e.g., of social ties who exert influence on one's behavior). In the context of HIV prevention, there is a close analogy to the importance of

social norms, both descriptive and injunctive: behavior change becomes much more likely once the behavior is adopted or endorsed by a sufficiently large part of one's social referent group (111, 112). In practical terms, ideas of complex contagion reinforce the importance of sufficiently dense seeding of the most at-risk parts of any social network, suggesting that random targeting will do even worse than one might expect.

Some ways forward

SNA provides a range of insights into how HIV interventions can be changed and improved. However, implementing many of these insights will require better data than are currently available. While social network descriptions exist, notably for school-aged children and some specific well-defined populations (e.g., people who use injection drugs or MSM in higher-income settings), we know still little about the social networks of those at greatest risk. In particular, the continued high incidence of HIV among young persons in sub-Saharan Africa (113) is not reflected in an understanding of their social networks. It is unclear to what extent the social realities of young persons in sub-Saharan Africa are similar to those of previously studied populations. There is therefore an urgent need to study the patterning of attitudes and behaviors across social space, how such factors change over time, and indeed how social networks evolve, in the context of young adults throughout sub-Saharan Africa. Much of these data will need to be longitudinal, which adds standard cohort design issues (e.g., entry/exit conditions, loss to follow-up) to social network design issues (e.g., defining boundaries, missing tie information). As we implement SNIs in these populations (often without considering them to be SNIs), it will be vital to collect sufficient social network data to enable evaluation of how social networks pattern intervention effects as well as how interventions pattern social networks – we should expect social networks to evolve under the pressure of new ideas spreading across them (114).

Despite this need for better data in order to understand social processes, it is not often feasible to collect sociocentric or even egocentric data routinely. Developing scalable HIV interventions that draw on social network insights will therefore require ways to quickly identify key individuals for SNIs. While occasional examples of low-cost social network data collection processes exist, such as downloading contacts from cellphones (66), there may be other settings in which they cannot be implemented without ethical problems or substantial refusals. Sociocentric datasets that measure social influence can be used to test whether algorithms based on non-network properties can identify influential individuals within populations. Such algorithms can then be tested in randomized studies to determine whether such non-network-identified seeds are more effective than randomly- or network-selected seeds at reducing HIV risk within the network. More evaluations of SNIs are also required, although such studies can be prohibitively expensive as they require the collection of sociocentric social network data from many independent networks that can then be randomized to different SNIs (115, 116).

Even without social network data, however, social network theory highlights that there are low-cost ways to improve on random selection for intervention targeting. For example, the “friendship paradox” highlights that, on average, the friends of individuals have more friends than the individuals who nominated them (117). Other evidence suggests that people tend to identify as friends people who are of higher social status than themselves (118). A theoretical prediction thusly emerges: asking a random sample of individuals to identify their friends and then enrolling a random friend should improve the reach and effectiveness of interventions (119). This prediction was borne out in a recent SNI trial of multivitamins in Honduras (120); the same research group also showed that this theoretical prediction could be leveraged to predict an outbreak of H1N1 influenza 6 weeks in advance even in the absence of having full network data (121). A SNI that randomly selects the most-connected alter (rather than a random alter) may be even more effective (122).

Our review has focused on individual-level intervention uptake, in the context of community networks. However, social networks are also likely to play key roles in determining which evidence-based interventions are embraced by policymakers, providers, organizations, and communities. In particular, the choice of which interventions to roll out will depend on who is championing them and how they can influence those with the power to make funding decisions. Delayed roll-out of antiretroviral therapy in South Africa after the turn of the millennium (123, 124), or of PrEP in the National Health Service in England in recent years (125), might well be understood through a social network lens where those with decision-making power were influenced by individuals not convinced of the interventions' effectiveness. SNA can also be applied to organizational networks to identify isolated organizations (that may not be in a position to take up an intervention), central organizations (that might serve as either positive or negative influences on other organizations within the network), or disconnected subgroups of organizations (that could potentially be brought together by organizational brokers for the purposes of consolidating intervention efforts) (126-128). A meaningful understanding of the existing network structure of potential implementing organizations can potentially facilitate the deployment and maintenance of the implementation process. Consistent with this idea, Gesell et al. (129) have proposed a method by which social networks can be monitored during the process of intervention implementation, with the aim of using "social network diagnostics" to guide program activities.

Conclusion

The history of HIV contains many examples of proven interventions being deployed to the benefit of communities at risk. It also contains several examples where these interventions have left behind some groups – often those who are most vulnerable and least visible. Social network analysis can help us to identify who is being missed and why, and what barriers limit their capacity to use the interventions being offered. Social network-informed interventions can work with the grain of

society to improve the reach of interventions, especially to most-at-risk populations, and to maximize intervention impact once delivered. To achieve these objectives, it is vital that we collect more social network data now, and strategically study how to minimize our need of such resource-intensive data in the future. Achieving these goals will help curtail the HIV epidemic while not iatrogenically worsening health disparities.

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