Social network fragmentation and community health

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Community health interventions often seek to intentionally destroy paths between individuals to prevent the spread of infectious diseases. Immunizing individuals through direct vaccination or the provision of health education prevents pathogen transmission and the propagation of misinformation concerning medical treatments. However, it remains an open question whether network-based strategies should be used in place of conventional field approaches to target individuals for medical treatment in low-income countries. We collected complete friendship and health advice networks in 17 rural villages of Mayuge District, Uganda. Here we show that acquaintance algorithms, i.e., selecting neighbors of randomly selected nodes, were systematically more efficient in fragmenting all networks than targeting well-established community roles, i.e., health workers, village government members, and schoolteachers. Additionally, community roles were not good proxy indicators of physical proximity to other households or connections to many sick people. We also show that acquaintance algorithms were effective in offsetting potential noncompliance with deworming treatments for 16,357 individuals during mass drug administration (MDA). Health advice networks were destroyed more easily than friendship networks. Only an average of 32% of nodes were removed from health advice networks to reduce the percentage of nodes at risk for refusing treatment in MDA to below 25%. Treatment compliance of at least 75% is needed in MDA to control human morbidity attributable to parasitic worms and progress toward elimination. Our findings point toward the potential use of network-based approaches as an alternative to role-based strategies for targeting individuals in rural health interventions.

community health | social networks | percolation | immunization | mass drug administration

The functioning of any complex system relies on its ability to respond to perturbations or failures (1–5). Whether high or low error tolerance of a complex system is desirable for public goods is dependent on the type of system studied. For example, high error tolerance is needed in Internet routing networks (1) and ecosystems (5), respectively, to protect against virus attacks and to ensure ecological stability after species loss. On the other hand, immunization campaigns seek to intentionally cause failures in social networks, i.e., stopping diffusion, by vaccinating a subset of individuals to quell the transmission of infectious diseases (4, 6–9).

Targeting nodes to induce fragmentation has thus far relied on the availability of information concerning network structure. The random removal of nodes requires no topological information and is a poor strategy for fragmenting complex networks (1). In contrast, targeted attacks are most detrimental to network connectivity (1, 2, 6, 7, 9). The removal of a small percentage of nodes in order of degree (1, 7, 9) or betweenness (10), particularly recalculated degree or betweenness (2), substantially damages complex networks. Although efficient, targeted attacks require full information about the global network structure. Complete network information usually is unavailable to policymakers (11). Network data can be costly to obtain, dependent on recollecting data as networks are dynamic and change over time, reliant on network type, contingent on available expertise to analyze graphs, and impractical to retrieve for time-constrained health interventions in low-income settings.

Efficient and practical network fragmentation has been achieved with acquaintance strategies (12). These algorithms target the neighbors of randomly selected nodes and use limited, local network information (12–14). However, it remains an open question whether acquaintance strategies should be used to fragment social networks in low-income settings. Acquaintance strategies need to be compared against conventional field-based approaches. In practice, individuals are targeted in rural villages using community roles (15) as opposed to network position (16). For example, lay health workers, local government members, and schoolteachers are provided health education to stop the spread of rumors or to address concerns during *en masse* deworming programs implemented in over 70 countries (17–19).

We compare the efficiency of acquaintance strategies to the efficiency of targeting community roles for damaging social networks in rural Uganda. There are studies of network diffusion (15) in low-income countries. However, whom to target to reach the most people differs from whom to target to efficiently destroy a social network (16, 20). Importantly, diffusion-based approaches that use a small set of seed nodes often do not reach everyone in the community (15, 21).

Two types of social networks were measured. Complete friendship and health advice networks were collected for nearly all households (3,491) in 17 villages bordering Lake Victoria in Mayuge

Significance

Fragmentation of social networks is needed in large-scale treatment campaigns. Direct vaccination of key individuals or the strategic provision of health education can prevent, respectively, the spread of viruses or misinformation. We present an easily implementable and generalizable network-based strategy for targeting households to induce fragmentation in social networks of low-income countries. Complete friendship and health advice networks were collected from 17 rural villages in Uganda. We discovered that acquaintance algorithms outperformed conventional field-based approaches for inducing social network fragmentation. Acquaintance algorithms targeted the neighbors of randomly selected nodes, whereas the latter method concerns targeting well-established community roles such as lay health workers, village government leaders, and schoolteachers. This algorithm also was effective in offsetting potential noncompliance to deworming treatments.

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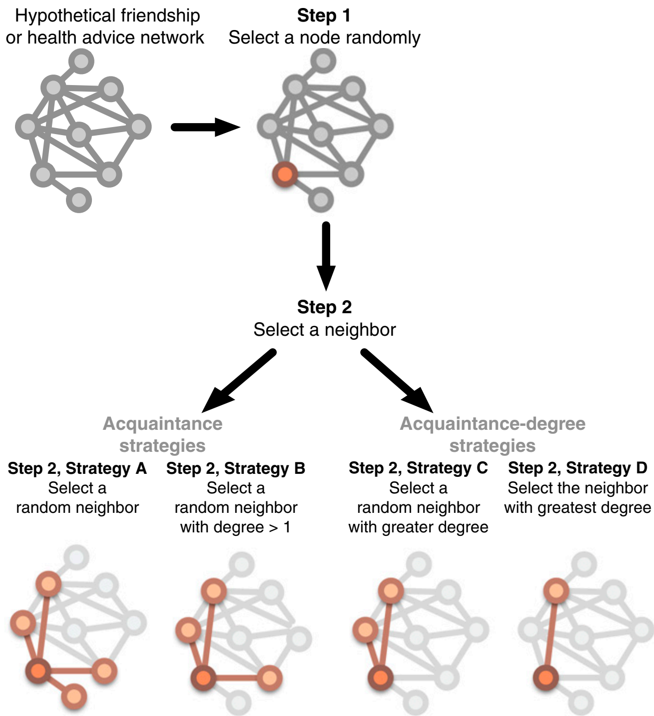

Fig. 1. Schematic illustrating network-based fragmentation algorithms. All four strategies begin with the random choice of a node (step 1), before proceeding to step 2, at which one of four strategies can be chosen. Strategies A and B are acquaintance strategies, which entail choosing a random neighbor or a random neighbor with degree ≥2 of the node chosen in step 1. Strategies C and D are acquaintance-degree strategies. A random neighbor with degree greater than the original node (C) or the neighbor with highest degree (D) is chosen. A random choice is made between two nodes of equal highest degree.

District, Uganda. Undirected networks were graphed between households. Nodes were removed using two sets of algorithms as shown in Fig. 1. All strategies first selected a node randomly. The acquaintance strategies then entailed removing either a random neighbor or a neighbor with degree ≥2 of the randomly selected node. For the acquaintance-degree strategies, a neighbor of higher degree or the highest-degree neighbor was removed. By contrast, the formal position strategy directly targeted households in order of village position; the order was first current health workers, then village government members, and lastly schoolteachers. When no formal positions remained, an acquaintance or acquaintance-degree strategy was used. Efficiency was defined as the percentage of nodes required for achieving a specified level of damage to the network. Fragmentation was measured using the normalized Borgatti F (20, 22) indicator to capture the number and size of components remaining in the network. A completely undamaged network had $F = 0$, whereas a destroyed network had $F = 1$ (22). Importantly, we tested the algorithms with data from a round of mass drug administration (MDA) for intestinal schistosomiasis and hookworm that we tracked at the time the social networks were surveyed (21). The percentage of nodes at risk for receiving misinformation about bad drug side effects was examined. We identified connected components that included a household with someone who refused deworming treatment due to previously experiencing an adverse drug reaction. The total number of nodes in a component with a noncompliant household was divided by the total number of nodes in the original network. Here we show that acquaintance-degree algorithms were systematically more efficient than targeting well-established community roles for fragmentation. Acquaintance-degree algorithms also were effective in reducing the percentage of nodes at risk for noncompliance in MDA.

Results

Acquaintance Strategies Outperform Targeting Formal Positions. Figs. 2 and 3 present the fragmentation outcomes for a sample of four villages; 13 villages are presented in *SI Appendix*, Figs. S1 and S2. The removal of the number of nodes that equaled the number of formal positions was examined (*SI Appendix*, Table S1). Only 8–26 nodes were removed per village, which was an average of 8.70% (SD 3.31%) and 8.96% (SD 3.47%) of the total nodes in friendship and health advice networks, respectively. Acquaintance-degree strategies, e.g., selecting the highest-degree neighbor of a random node, achieved greater fragmentation than the formal position strategy in 94.12% of all friendship (16/17) and health advice (16/17) networks. In all 17 friendship networks, removal of highest-degree neighbors ($F = 0.204$, SD 0.083) induced more damage than the formal position strategy ($F = 0.185$, SD 0.067, paired t statistic 3.395, P value = 0.004). This difference was stark for health advice

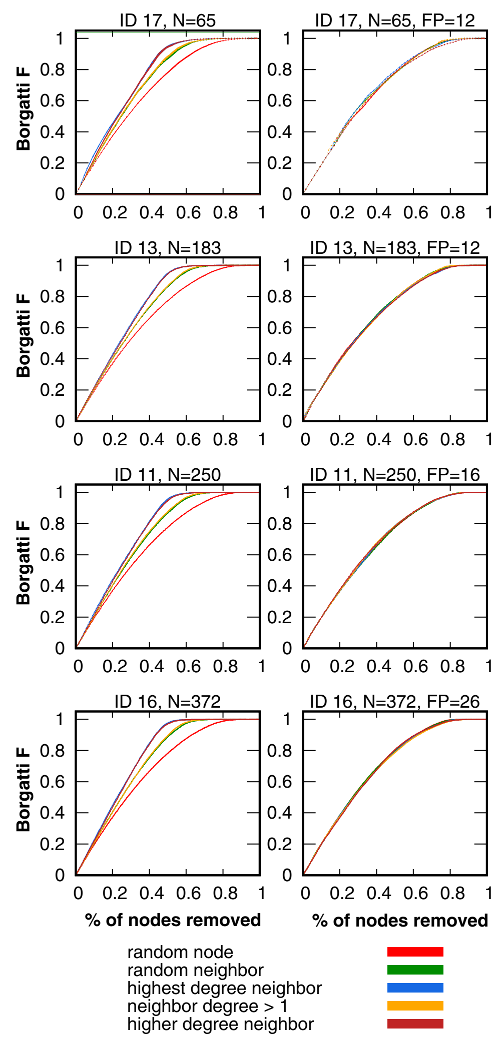

Fig. 2. Fragmentation outcomes for friendship networks. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S1. IDs correspond to project-assigned village IDs. N is the total number of nodes in the original network and FP is the total number of formal positions in the village. If FP is noted then the FP strategy was used; otherwise, acquaintance and acquaintance-degree strategies were used. Line widths represent 95% confidence intervals.

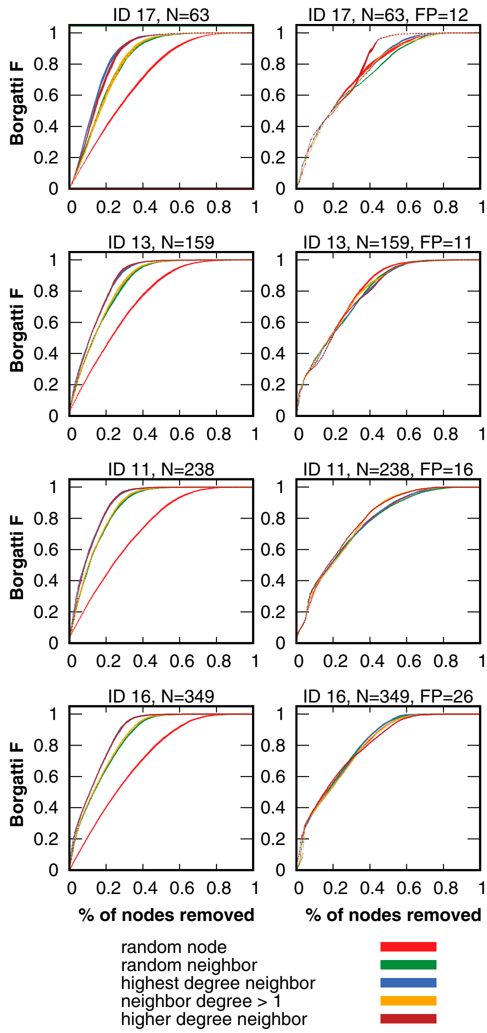

Fig. 3. Fragmentation outcomes for health advice networks. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S2. IDs correspond to project-assigned village IDs. N is the total number of nodes in the original network and FP is the total number of FPs in the village. If FP is noted then the FP strategy was used; otherwise, acquaintance and acquaintance-degree strategies were used. Line widths represent 95% confidence intervals.

networks. An average 0.412 (F SD 0.207) fragmentation was achieved by removing highest-degree neighbors compared with an average 0.300 (F SD 0.136) damage caused from targeting households with formal positions (observed 17, paired t statistic 5.303, P value < 0.001).

Notably, pure acquaintance strategies outperformed targeting community roles. Removing random neighbors of randomly selected nodes caused more fragmentation than targeting formal positions in 88.24% (15/17) and 76.47% (13/17), respectively, of friendship and health advice networks. There was no discernible difference between formal position types with respect to the damage caused to friendship networks; targeting any position linearly increased fragmentation. Surprisingly, removing lay health workers only caused a nonlinear change in fragmentation in 23.53% (4/17) of health advice networks.

All acquaintance and formal position strategies are attempts to heuristically approximate targeted attacks by degree (7, 9). Targeted attacks by degree, as widely shown elsewhere (1, 2), were more efficient than any acquaintance or formal position strategy for destroying all networks (*SI Appendix*, Fig. S3). Formal positions were a good proxy indicator for nodes with high degree; individuals with community roles as health workers, government members, and schoolteachers had on average higher degree than other households in the same village (*SI Appendix*, Table S2). However, acquaintance-degree strategies more reliably selected higher-degree nodes in all 34 networks than the formal position strategy (Fig. 4 and *SI Appendix*, Fig. S4). This result is remarkable considering that formal positions targeted intuitively predefined network hubs, e.g., health workers in health advice networks or community-elected village government leaders in friendship networks. Moreover, in 76.47% (13/17) of friendship networks, every node selected by the highest-degree neighbor algorithm had degree greater than or equal to any node removed with a community role. In 58.82% (10/17) of health advice networks, the degree of the first node selected with the highest-degree neighbor strategy was greater than or equal to the degree of the most connected node with a formal position (here, health workers). These results suggest that limited topological information may be used in place of sociodemographic data when selecting households to reduce social network connectivity.

Physical Proximity and Connectivity to Sick People. A role-based strategy may be used during disease outbreaks as a potential proxy indicator of physical proximity and connections to sick people—two factors pertinent to the spread of pathogens that are directly transmitted from human to human. We measured how well the formal position strategy approximated physical proximity and connectivity to sick people. Physical proximity was measured as the average distance in meters from the household of interest to every other household in the village. The average distance between any two households in each village was small; households were only separated by an average of 130.61–638.67 m (SD 86.02–450.41). This result suggests that physical distance is unlikely to be a barrier to personal contact within a village. In 94.12% (16/17) of villages, households with formal positions were not significantly (P value > 0.05) closer in physical proximity to other households compared with the average physical proximity of all households without formal positions (*SI Appendix*, Table S3). We also compared the physical proximity of households with formal positions to the households selected through acquaintance-based strategies or simple random selection. Neither acquaintance-based nor formal position strategies consistently selected households with close physical proximity compared with the selection of households at random (*SI Appendix*, Fig. S5). None of the proposed fragmentation strategies, including targeting formal positions, selected households that were good indicators of physical proximity to a large number of households or people.

We collected data on the number of all individuals within each home that were reported by the household head and/or wife to have diarrhea within the 3 mo preceding the sociometric survey. In our 17 study villages, 12.44% (2,035/16,357) of individuals reported diarrhea. We calculated the number of people with diarrhea in the neighborhood of a node (in households directly connected to the node of interest) and divided this number by the degree of the node of interest, henceforth referred to as sickness connectivity. Diarrheal cases are of interest here because of the direct transmission of pathogens from human to human via the fecal-oral route, the low coverage of improved sanitation among all study households [12.58% (439/3491)]; see https://www.wssinfo.org for definition of improved sanitation), and recent large-scale cholera outbreaks in the study area (23). If physical proximity is irrelevant for contact within the study villages, we might assume that close friendships and whom individuals turn to when they are sick are proxy indicators for village contact. Accordingly, we examined how well acquaintance-based versus formal position strategies selected households with high sickness connectivity in the friendship and health advice networks. We found that an acquaintance-based strategy, here the highest-degree neighbor of a random node, more often selected households with higher sickness connectivity in friendship and health advice networks than targeting formal positions (Fig. 5 and *SI Appendix*, Fig. S6). This result is surprising considering that community health workers had high sickness connectivity, as expected, in health advice networks.

Combined Formal Position and Acquaintance Strategies. There is a practical constraint to completely destroying network connectivity ($F \sim 1$) by targeting formal positions. As previously discussed, only a small proportion of households in each village had community roles. The maximum fragmentation achieved by targeting formal positions was $F = 0.608$ in a health advice network (ID 6). Supplementing the removal of formal positions with acquaintance or acquaintance-degree strategies resulted in these network-based approaches becoming equivalent to the random removal of nodes (Figs. 2 and 3 and *SI Appendix*, Figs. S1 and S2). Nearly all nodes were removed to completely fragment the networks. Selecting nodes first by formal position then using the highest degree neighbor strategy required on average 82.79% (SD 5.25%)

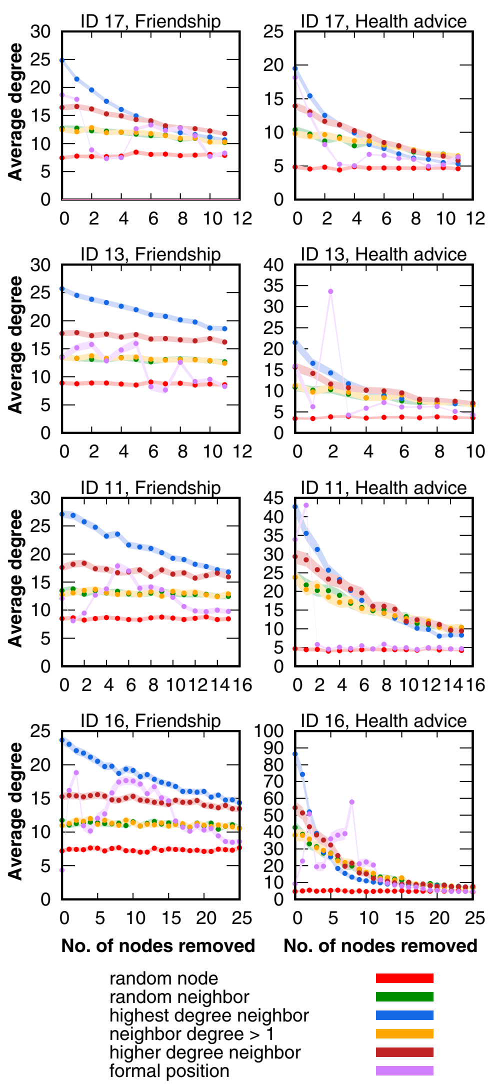

Fig. 4. Average degree of node removed by acquaintance and FP strategies. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S4. The average degree for each node removed is shown up to the number of FPs. IDs correspond to project-assigned village IDs. The type of network is labeled accordingly. One thousand iterations were run and line widths represent 95% confidence intervals.

and 74.06% (SD 7.08%) of nodes to be removed, respectively, before friendship and health advice networks were destroyed. Comparatively, using just the highest-degree neighbor algorithm, all networks were more efficiently destroyed (observed 17, paired t statistic friendship = 19.515, health = 17.910, P values < 0.001). Only an average of 62.33% (SD 4.01%) and 50.35% (SD 5.84%) of nodes in friendship and health advice networks, respectively, were selected to induce complete fragmentation. If a higher-degree neighbor was not found then the initially selected random node was removed. This approach was not only more straightforward, but also more efficient than conventional methods (14) that ignore nodes that do not meet, for example, degree cutoffs (*SI Appendix*, Fig. S7). These results suggest that the inclusion of individuals with established community roles may be limited to only a probabilistic selection with acquaintance or acquaintance-degree algorithms as opposed to directly targeting formal positions.

The efficiency of acquaintance-based strategies depended on a widely noted phenomenon in social networks, the "friendship paradox" (24). On average, the friends of a node are more connected than the node of interest (24). This disassortativity, i.e., negative degree–degree correlations, can exist because of structural constraints (25). Hubs have many connections and the number of edges that are possible between hubs is limited. As most nodes have low degree in real-world networks (26), hubs are the acquaintances of many poorly connected nodes. Thus, with a uniform probability of selection, initially nodes with a few connections will be chosen. It is then likely a hub will be sampled from the neighborhood of this peripheral node. Targeting nodes with formal positions removed significant (P value < 0.05) negative correlations of degree with average neighbor connectivity in 58.82% (10/17) of friendship and 94.12% (16/17) of health advice networks (*SI Appendix*, Figs. S8 and S9).

Resilience by Social Network Type. All networks displayed heavy-tailed degree distributions compared with random networks with the same number of nodes and edges (*SI Appendix*, Table S4), although friendship networks were more resilient than health advice networks. Within every village, removing the same percentage of nodes achieved less fragmentation in the friendship network than the health advice network (rightward shift of Borgatti F curves, Figs. 2 and 3 and *SI Appendix*, Figs. S1 and S2). The maximum number of connected components produced by fragmenting friendship networks (average 12.674, SD 5.022) also was less than the number (average 15.484, SD 6.419) observed in health advice networks (paired t statistic −5.544, P value < 0.001).

Differences in fragmentation were due to variations in global network topology. Friendship networks (average $N = 202.118$, SD 85.761) were slightly larger than health advice networks (average $N = 193.059$, SD 83.069, paired t statistic 5.306, P value < 0.001). Network transitivity, i.e., global clustering, was greater in friendship (average 0.113, SD 0.050) than in health advice networks (average 0.076, SD 0.033, paired t statistic 4.834, P value < 0.001). Targeting formal positions caused little damage to friendship networks because of their almost onion-like structure (27). The core numbers of nodes with formal positions were largest (P value < 0.05) in friendship networks for 94.12% (16/17) of villages (*SI Appendix*, Table S5). Hence, nodes with formal positions belonged to densely connected nuclei (16, 28) of friendship networks that remained connected after the removal of a few nodes. Acquaintance-based strategies also initially produced little damage to friendship networks due to the existence of paths between nodes of the same or lower degree. Such paths form layers around the core of the network and are onion-like in that each degree layer must be targeted (27). The removal of the core leaves the network relatively intact, as many nodes do not rely on paths through hubs to remain connected. Friendship networks (average 0.491, SD 0.102) had a greater index (29) of onion-likeness than health advice networks (average 0.240, SD 0.099, paired t statistic 8.565, P value < 0.001).

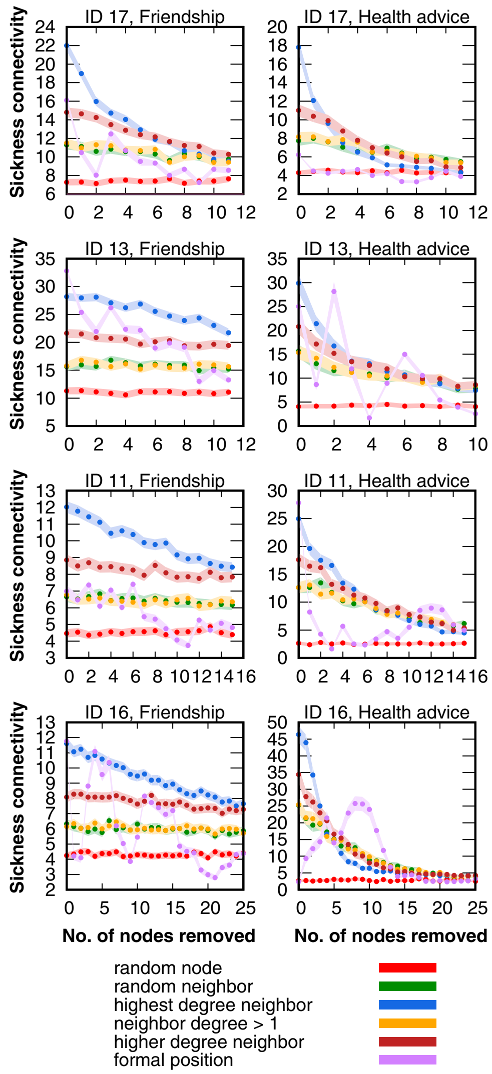

Fig. 5. Average connectivity to sick people. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S6. IDs correspond to project-assigned village IDs. The type of network is labeled accordingly. Sickness connectivity was defined as follows. The number of people in the neighborhood of a node who reported diarrhea within the 3 mo preceding the sociometric survey was divided by the degree of the node of interest. The average sickness connectivity for each node removed is shown up to the number of FPs. One thousand iterations were run and line widths represent 95% confidence intervals.

Fragmentation Efficiency for MDA. The effect of fragmentation on health outcomes is shown in Figs. 6 and 7 and *SI Appendix*, Figs. S10 and S11. There were 1–28 households per village (14/17) with individuals who refused deworming treatment due to previously experiencing an adverse drug reaction (*SI Appendix*, Table S6). We examined the percentage of nodes in a connected component with a household that refused deworming treatment, herein referred to as being "at risk." This outcome was similar to the standard percolation measure of the percentage of nodes remaining in the largest component (*SI Appendix*, Fig. S12). Nodes were at risk because they were reachable for the spread of misinformation or negative health influences from noncompliant households (30). Hence, we investigated how the strategic "removal" of households, for example by potentially providing health education before MDA, may prevent the flow of information from noncompliant households to other households.

When the same number of nodes was removed as there were formal positions, acquaintance-degree algorithms outperformed the formal position strategy in 78.57% (11/14) of friendship and 100% (14/14) of health advice networks with noncompliant households. In friendship networks, only a nominal difference in the percentage of nodes remaining at risk was found when the highest-degree neighbor algorithm (average 89.68%, SD 4.88%) and the formal position strategy (average 90.61%, SD 4.40%) were compared (observed 14, paired t statistic −2.572, P value = 0.023). In health advice networks, selecting highest-degree neighbors of random nodes left only an average of 77.46% (SD 16.76%) of nodes at risk compared with an average of 85.12% (SD 7.85%) of nodes remaining at risk after targeting formal positions (observed 14, paired t statistic −2.725, P value = 0.017).

Treatment compliance of 75% is needed in MDA to control human morbidity attributable to parasitic worms and progress toward elimination (31). Accordingly, we examined what percentage of nodes must be removed for 25% or less of all nodes to remain at risk for refusing treatment. With the highest-degree neighbor algorithm, only an average of 47.30% (SD 5.37%) of nodes in friendship networks needed to be removed for 25% or less of nodes to be at risk. In contrast, an average 61.91% (SD 17.18%) of nodes in friendship networks were removed using a combined formal position and highest-degree neighbor strategy (observed 14, paired t statistic −3.351, P value = 0.005). Remarkably, by selecting highest-degree neighbors in health advice networks, only an average of 32.08% (SD 9.48%) of nodes were removed to reduce the percentage of nodes at risk to 25%. In comparison, an average 54.54% (SD 14.08%) of nodes had to be targeted by formal positions (observed 14, paired t statistic –6.606, P value < 0.001). Thus, by selecting only 32–47% of households with the highest-degree neighbor algorithm in health and friendship networks, respectively, an additional 28–43% of households might be deterred from refusing treatment despite receiving no direct public intervention.

Discussion

We discovered that local network strategies outperformed conventional field-based approaches in damaging rural friendship and health advice networks in Uganda. Performance was measured not only in terms of general fragmentation efficiency, but also with respect to a community health intervention required for over 1.9 billion people worldwide, i.e., MDA (32). The latter outcome concerned how best to isolate nodes from households with members that refuse medicines to limit the reach of noncompliance with deworming treatments (31). In 17 villages, the selection of highest-degree neighbors of randomly selected nodes damaged social networks more than the targeting of households with established community roles. In practice, implementation costs (33) limit the number of households that can be approached in a village; here we showed that, even with a few nodes, more fragmentation was achieved using network-based strategies than targeting formal positions. Moreover, combining acquaintance-based algorithms with targeting formal positions resulted in a loss of fragmentation efficiency and consistency. To achieve the same outcome, more nodes were removed with combined strategies than with only acquaintance algorithms. With combined approaches, acquaintance algorithms also became inconsistently ordered, degenerating to efficiencies equivalent to the random selection of nodes. This finding is striking as it indicates that important village positions, in contrast to published literature (4, 15, 16, 30, 34), might be best left untargeted for any interventions seeking to stop the spread of information, behaviors, or pathogens through a rural social network.

Acquaintance-degree algorithms are easily implementable in low-income settings. Local network information, including neighbor degree (35), can be elicited through a simple survey prompt. The number of nodes that can be selected and, in turn, the fragmentation that can be achieved with acquaintance algorithms, is not constrained by the number of households with community roles. There is frequent turnover of individuals with community roles (36). Formal position approaches require the recollecting of sociodemographic data during each intervention to accurately target current village health workers, government leaders, and schoolteachers. In contrast, acquaintance algorithms (12–14) do not need to be reformulated with changes in the community or network structure over time.

Our results are the product of one study in one geographical location. Additional research is needed to replicate our results in other low-income countries. Although beyond the scope of this study, we encourage future research to calibrate our findings for disease-specific transmission models. Here we assume that the network structure is an accurate description over which transmission of information, behaviors, or pathogens occurs. Our data lend support to this assumption. Physical distance is an unlikely barrier to transmission within a village because of the short average

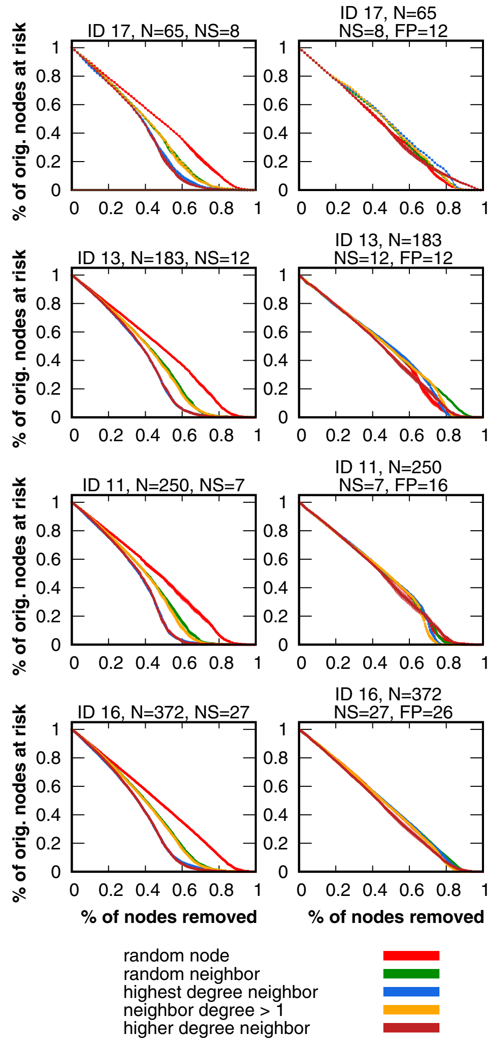

Fig. 6. Health outcomes for friendship networks. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S10. IDs correspond to project-assigned village IDs. N is the total number of nodes in the original network and FP is the total number of FPs in the village. NS is the number of noncompliant seeds; these nodes represent households with someone who refused deworming treatment due to a previous adverse drug reaction. If FP is noted then the FP strategy was used; otherwise, acquaintance and acquaintance-degree strategies were used. Line widths represent 95% confidence intervals.

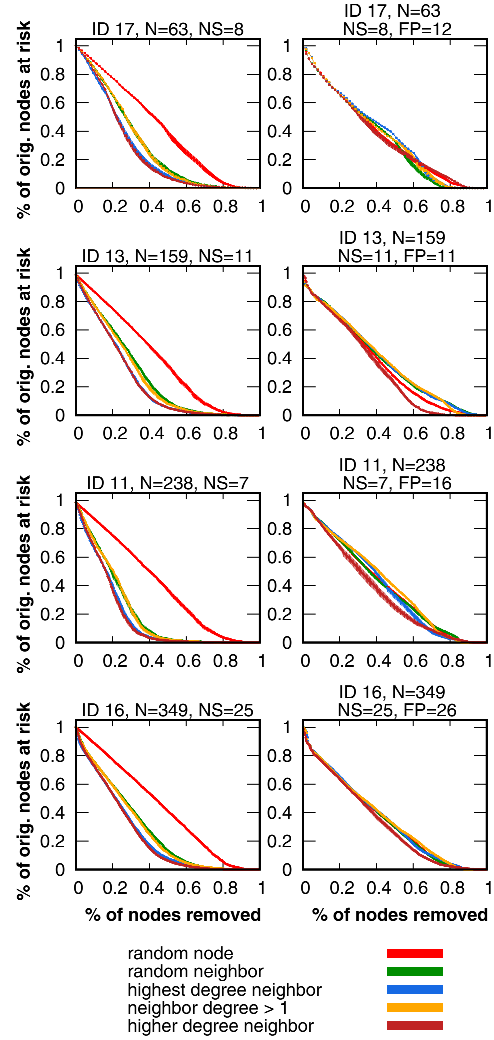

Fig. 7. Health outcomes for health advice networks. Four villages are shown that had the fewest, median, 75th percentile, and greatest number of nodes. The remaining villages are shown in *SI Appendix*, Fig. S11. IDs correspond to project-assigned village IDs. N is the total number of nodes in the original network and FP is the total number of FPs in the village. NS is the number of noncompliant seeds; these nodes represent households with someone who refused deworming treatment due to a previous adverse drug reaction. If FP is noted then the FP strategy was used; otherwise, acquaintance and acquaintance-degree strategies were used. Line widths represent 95% confidence intervals.

distance in meters between any two households. We approximated direct contact between village members by measuring close friendships and whom individuals approach when they are sick. Concerning pathogen transmission, acquaintance strategies selected households that were highly connected to other households with potentially contagious individuals. These individuals reported diarrheal illness within the past 3 mo. We also assume transmission proceeds as a simple epidemic. This general approach provides a starting point where the probability of transmission can be calibrated to reflect the type of contagion germane to different health interventions of interest.

Our findings are promising for public interventions in rural poor settings. If our results are replicated in other contexts, health policymakers may implement the acquaintance-degree algorithms to select individuals to vaccinate or to increase drug uptake in large-scale treatment campaigns. Importantly, if these strategies were implemented in the field, special attention would need to be given to the exact nature of the sociometric item, i.e., it must conform as closely as possible to a measure that predicts dyadic transmission of the pathogen (or misinformation) of interest. Network data collection also would need to include any actors who have important transmission roles, e.g., schoolteachers, but may not be formally part of the system studied. Here, we showed that health advice networks were destroyed more easily than friendship networks. Only an average of 32% of nodes were removed to reduce the percentage of nodes at risk for refusing treatment in MDA to below 25%. Health education may be provided to a subset of individuals, who are chosen by the acquaintance-degree strategy before MDA, to strategically and preemptively prevent the spread of rumors. A number of MDA programs are progressing toward globally or regionally eliminating infections, e.g., lymphatic filariasis and schistosomiasis (18). However, elimination efforts can be halted due to discontent with lay health workers or other individuals with village positions who are formally involved in MDA implementation (30). We showed that acquaintance-degree strategies identify alternative individuals to target for resolving negative events during MDA. Future empirical studies in low-income countries should further investigate the use of network-based approaches in place of targeting established community roles to damage social networks and, in turn, to quell the transmission of information, behaviors, or pathogens.

Materials and Methods

Python v2.7 with the NetworkX library (37) and Stata v13.1 were used to analyze and fragment the networks. All fragmentation algorithms removed each node sequentially until only one node remained in the network and began with only connected components (no isolates). All friendship networks began with one connected component. Health advice networks for village ID 5 and IDs 11–13 had more than one connected component. We ran 100 iterations of each algorithm on 34 undirected friendship and health advice networks. If any criteria were unmet, i.e., for the acquaintance and acquaintance-degree strategies, then the initially selected node was removed. Similarly, if the initially selected node was an isolate then that node was removed. Degree was calculated as the sum of incoming and outgoing edges with reciprocated or multiedges treated as one edge. Detailed methods are provided in the *SI Appendix*.

Ethics. This study was reviewed and approved by the Uganda National Council of Science and Technology and the Cambridge University Human Biological Research Ethics Committee. Informed consent was obtained from all respondents. Project-assigned village IDs were used to preclude the identification of individuals.

Data Availability. All relevant data are available in the paper, *SI Appendix*, and upon request from the corresponding author.

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