Piloting the Use of Artificial Intelligence to Enhance HIV Prevention Interventions for Youth Experiencing Homelessness

Eric Rice *University of Southern California*
Amanda Yoshioka-Maxwell *University of Southern California*
Robin Petering *University of Southern California*
Laura Onasch-Vera *University of Southern California*
Jaih Craddock *University of Southern California*
Milind Tambe *University of Southern California*
Amulya Yadav *University of Southern California*
Bryan Wilder *University of Southern California*
Darlene Woo *University of Southern California*
Hailey Winetrobe *University of Southern California*
Nicole Wilson *University of Southern California*

ABSTRACT ***Objective:*** Youth experiencing homelessness are at risk for HIV and need interventions to prevent risky sex behaviors. We tested the feasibility of using artificial intelligence (AI) to select peer change agents (PCAs) to deliver HIV prevention messages among youth experiencing homelessness. ***Method:*** We used a pretest–posttest quasi-experimental design. In the AI condition ($n = 62$), 11 PCAs were selected via AI algorithm; in the popularity comparison ($n = 55$), 11 PCAs were selected 6 months later based on maximum degree centrality (most ties to others in the network). All PCAs were trained to promote HIV testing and condom use among their peers. Participants were clients at a drop-in center in Los Angeles, CA. HIV testing and condom use were assessed via a self-administered, computer-based survey at baseline ($n = 117$), 1 month ($n = 86$, 74%), and 3 months ($n = 70$, 60%). ***Results:*** At 3 months, rates of HIV testing increased among participants in the AI condition relative to the comparison group (18.8% vs. 8.1%), as did condom use during anal sex (12.1% vs. 3.3%) and vaginal sex (29.2% vs. 23.7%). ***Conclusions:*** AI-enhanced PCA intervention is a feasible method for engaging youth experiencing homelessness in HIV prevention.

KEYWORDS: homeless youth, HIV/AIDS, artificial intelligence, preventive interventions, social networks

doi: 10.1086/701439

Journal of the Society for Social Work and Research, Volume 9, Number 4. 2334-2315/2018/0904-0004/$10.00.

Nearly 4.2 million youths experience homelessness in the United States each year (Morton et al., 2018), and these young people are at risk for contracting HIV/AIDS, with prevalence rates reported as high as 11.5% (Pfeifer & Oliver, 1997). Despite the heightened need for HIV prevention in this population, relatively few evidence-based interventions exist (Arnold & Rotheram-Borus, 2009). Given the central role that peers play in the HIV risk and protective behaviors of youth experiencing homelessness (e.g., Green, Haye, Tucker, & Golinelli, 2013; Rice, 2010; Rice, Barman-Adhikari, Milburn, & Monro, 2012; A. M. Valente & Auerswald, 2013), several commentators have suggested that a peer change agent (PCA) model for HIV prevention should be developed for youth experiencing homelessness (Arnold & Rotheram-Borus, 2009; Rice et al., 2012). PCA models identify a small number of individuals in a high-risk target population to become advocates in their community. These people are tasked with disseminating HIV prevention information and norm-changing messages to their peers (Kelly, et al., 1997; Latkin, Sherman, & Knowlton, 2003). This paper presents the results of a feasibility test to assess the impact of a PCA model developed for youth experiencing homelessness. We first adapted the PCA model to be appropriate for youth experiencing homelessness and then tested two versions of this model. In one study arm, we used artificial intelligence (AI) planning methods to strategically select peers who would, in theory, have the maximal capacity to spread influence in the network. In the comparison condition, we used the standard PCA selection technique, which is to pick the most popular individual in the network (which we defined as highest degree centrality, i.e., the people in the population with the greatest number of network ties to other individuals in the population). We believe that AI can provide novel solutions to complex intervention implementation issues, and in this context, we used AI to guide the selection of PCAs for peer-driven HIV prevention. The goal of this study was to determine if using AI to select PCAs would result in increased rates of HIV testing and condom use over time, relative to using the standard PCA selection method developed for other populations.

Peers and Sexual Health Among Youth Experiencing Homelessness

Promoting the healthy development of youth experiencing homelessness necessitates not only housing interventions, but also behavioral health interventions to promote healthy behavior and prevent diseases, such as HIV, that are fundamentally linked to the behavioral health of youth. There also is a need to identify new cases of HIV among youth experiencing homelessness to link youth to HIV treatment, not only for their own health but to also limit the spread of HIV. It is encouraging that 85% of youth experiencing homelessness in Los Angeles County, CA, reported lifetime HIV testing, but only 47% had an HIV test in the past 3 months (Ober, Martino, Ewing, & Tucker, 2012). The Centers for Disease Control and Prevention recommends at least annual testing for HIV, and testing should be more frequent (i.e., every 3–6 months) among higher risk groups, such as young men who have sex with men (Centers for Disease Control and Prevention, 2017).

Youth experiencing homelessness are not engaged in regular testing, in part, because they are often not well engaged in health care service use of any kind (Winetrobe, Rice, Rhoades, & Milburn, 2016). This arises due to factors such as feeling discriminated against, disrespected, and stigmatized because of their homeless state (Christiani, Hudson, Nyamathi, Mutere, & Sweat, 2008; Hudson et al., 2010; Martins, 2008; Wen, Hudak, & Hwang, 2007), and because they distrust health care and other social-service providers (Klein et al., 2000; Lindsey, Kurtz, Jarvis, Williams, & Nackerud, 2000). Youth experiencing homelessness instead rely on informal sources such as friends, relatives (Ensign & Gittelsohn, 1998), and the Internet for health care information (Barman-Adhikari & Rice, 2011).

Peers are an important part of adolescent life in general, and peer engagement may be even more important for risk and protective behaviors among youth experiencing homelessness. In developed Western nations, the normal developmental trajectory for adolescents has been well documented. From early to emerging adulthood, young people increasingly move toward independence and autonomy with the support and the relative influence of families, friends, and social institutions as socializing agents shifting over time (Arnett, 2000, 2001). By early adolescence, the role of family has changed, but the importance of peers and friends—as well as that of teachers and others in institutional settings—increases (Bauman, Carver, & Gleiter, 2001; Berndt, 1979). For youth experiencing homelessness, being kicked out of home or running away from home exaggerates the process of engagement with peers and disengagement with family, further disenfranchising youth from their connections to prosocial institutions such as school. The best developmentally focused models of this process are the *risk amplification model* (Whitbeck, Hoyt, & Yoder, 1999) and its augmentation, the *risk amplification and abatement model* (Milburn et al., 2009).

The risk amplification model asserted that the peer networks of youth experiencing homelessness are largely comprised of other homeless adolescents, many of whom come from problematic backgrounds and engage in risky and/or deviant behavior (Whitbeck et al., 1999). When social networks are comprised largely of other youth exhibiting deviant behaviors, the risks associated with living on the streets are magnified for individuals operating within those networks (McMorris, Tyler, Whitbeck, & Hoyt, 2002; Rice, Milburn, & Monro, 2011). Negative peer influences in the street-based networks of youth experiencing homelessness span a wide spectrum of risk-taking behaviors, including violence (Petering, Rice, & Rhoades, 2016), mental health (Fulginiti, Rice, Hsu, Rhoades, & Winetrobe, 2016), substance use (Barman-Adhikari, Rice, Winetrobe, & Petering, 2015; Yoshioka-Maxwell & Rice, 2017), and sexual risk-taking (Barman-Adhikari, Hsu, Begun, Portillo, & Rice, 2017).

The risk amplification and abatement model extended this thinking by recognizing that the networks of youth experiencing homelessness are also a major source of resilience (Milburn et al., 2009; Rice, Milburn, & Rotheram-Borus, 2007). Several studies point to peers from home and family members as the major source of these prosocial influence behaviors (Rice et al., 2007; Rice, 2010; Rice et al., 2011). Fortunately for our interests in PCA prevention interventions, this work also uncovered subtle, previously ignored positive impacts of homeless peers, particularly with respect to sexual health. Whereas youth who were more deeply embedded in social networks of other street youth were less likely to use condoms (Rice et al., 2012), being connected to condom-using peers who were also experiencing homelessness was associated with increased condom use (Rice, 2010).

Developing a New PCA Intervention for Youth Experiencing Homelessness

In general, PCA is a network-based intervention modality. These models are typically used when populations are hard to reach, such as injection drug users (Latkin et al., 2003) or men who have sex with men (Kelly et al., 1997). Often the populations being targeted for PCA-based HIV prevention experience social stigma and are thus distrustful of outsiders. Alternatively, these targeted populations are commonly trusting of members of their own community. The two seminal HIV prevention PCA models are Kelly's POL (Popular Opinion Leader; Kelly et al., 1997) and Latkin's SHIELD (Self-Help in Eliminating Life-Threatening Diseases; Latkin et al., 2003) interventions. The general method used selects a small number of people from the target population and trains them to become agents for positive change in health behaviors in their communities. The models are predicated on the notion that positive norm-changing messages and accurate information about health can be taught to the PCA, who will then share this information with her or his peers; this information will thus diffuse throughout the larger network of the population (Rogers, 2010).

At present, there are few PCA interventions to improve health behaviors among youth experiencing homelessness, and the interventions and evaluations that have been conducted have had mixed results. One study found that peer-based models increased substance use knowledge and preventive behaviors among youth experiencing homelessness (Fors & Jarvis, 1995). However, another study found that although a peer-led intervention increased HIV-related knowledge, it did not reduce sex risk and substance use behaviors among youth experiencing homelessness (Booth, Zhang, & Kwiatkowski, 1999). Another program, YouthCare, included youth experiencing homelessness as staff in outreach and HIV prevention education efforts, and as a whole program, there was an increase in HIV testing among youth experiencing homelessness (Tenner, Trevithick, Wagner, & Burch, 1998). These interventions not only showed mixed results, but they are also at least 20 years old. A new PCA model that is specific to youth experiencing homelessness is needed.

The Importance of How Change Agents are Selected in PCA Models

PCA models such as POL (Kelly et al., 1997) and SHIELD (Latkin et al., 2003) have been found to be effective for HIV prevention in many contexts (Medley, Kennedy, O'Reilly, & Sweat, 2009), but there have been some notable failures (NIMH Collaborative HIV/STD Prevention Trial Group, 2010). Some early discourse about failures suggested that programs that were overly focused on HIV education were less effective than those focusing more explicitly on norm-changing messaging (Kelly, 2004). However, Kelly oversaw a large National Institute of Mental Health HIV/STD prevention trial (NIMH Collaborative HIV/STD Prevention Trial Group, 2010) that addressed this limitation but still yielded unimpressive results.

Schneider, Zhou, and Laumann (2015) suggested that PCA model failures may be due to how PCAs are selected to participate in the intervention. They argued that the change agents who are selected to do the PCA work can often be as important, if not more important, than the messages they convey (Schneider et al., 2015). As developed by Kelly, the standard method for selecting PCAs is to use ethnographic methods to identify the most popular individuals in the social network. This can be operationalized more formally as selecting PCAs who have the greatest number of network connections to others in a population, a concept known as *highest degree centrality in social network*. Several authors—but particularly Valente (T. W. Valente & Pumpuang, 2007)—have described how network-driven prevention programs can benefit from explicitly modeling social networks and leveraging network methods such as degree centrality in the context of intervention delivery (Rice et al., 2012; Schneider et al., 2015).

Improving the Implementation of PCA Models With AI

Recent computational experiments in the AI field suggest that dynamic influence-maximization algorithms outperform more static network-based solutions proposed in prevention science (Kempe, Kleinberg, & Tardos, 2003; Yadav et al., 2015; Yadav et al., 2016). Thus, we focused our work on developing and testing the feasibility of using AI to select a set of PCAs who will have maximal impact based on an influence-maximization algorithm and comparing these PCAs to those selected by maximal degree centrality (i.e., most popular youth).

For most researchers in the field of social work and in related applied social sciences, exposure to AI is limited to what is discussed in the popular media. These discussions tend to focus on fanciful fears of killer robots, more realistic fears of job loss due to the automation of cognitive tasks, or on the recent advances in machine learning. As a field, however, AI is much broader and has the potential for varied impact. AI explores the creation of computer software capable of "intelligent behavior," such as complicated decision-making. Our work was based on influence-maximization research in computer science (Kempe et al., 2003; Yadav et al., 2015; Yadav et al., 2016), which is a subset of planning research applied to social networks. In general, planning algorithms solve complex problems, recommend specific actions, and account for the uncertainty of data available at any point in time and how data may change. The most common example of a planning algorithm that is used by most people is Google Maps, which automatically recommends specific travel routes and accounts for the uncertain and changing nature of traffic at any given point in time.

Much like traffic networks in busy cities, the social networks of youth are not only complex, but the dynamic nature of social ties necessitates that we also consider the uncertainty present in these networks (Rice et al., 2013). In general, adolescents and young adult relationships change rapidly as new connections form, dissolve, and grow closer over short periods of time (Arnett, 2000, 2001). The lives of homeless and unstably housed youth are transient, further complicating networks that also are developmentally fluctuating (Whitbeck et al., 1999; Milburn et al., 2009). Youth experiencing homelessness may leave the population for a variety of reasons, such as returning to their city of origin, entering into a stable housing situation, or becoming incarcerated (Milburn et al., 2009). In our prior work, we attempted to interview the entire population of youth who accessed drop-in services over a 1-month period at two partner drop-in centers: My Friend's Place in Hollywood, CA, and Safe Place for Youth in Venice, CA. We repeated these population panel surveys every 6 months for a year. In Hollywood, we found that on average, 43% of the population remained stable over a 6-month period (44% of participants in Panel 1 were also included in Panel 2; 42% of participants who were included in Panel 3 had participated in Panel 2). In Venice Beach, only 16% of the population remained stable over 6 months (18% persisted from Panel 1 to Panel 2, and 14% persisted from Panel 2 to Panel 3; Rice et al., 2013).

To further complicate matters, the collection of network data is difficult in any context, and more so when collecting data in community settings from youth experiencing homelessness (Petering et al., 2016; Rice et al., 2013; Yoshioka-Maxwell & Rice, 2017). Most social network data collection relies on free recall (i.e., people list out their social connections) or from responding to population rosters (e.g., people are shown a classroom roster and asked to nominate important individuals). Rosters are more accurate but are impossible to generate in the context of youth experiencing homelessness. Recall error from free recall is not unique to youth experiencing homelessness, and the methods for reducing this error have been extensively studied by social network researchers (see, e.g., Brewer, 2000, for a review of these methodological issues). The AI work that informs this intervention explicitly models the uncertainty within these networks, allowing for social network data to be treated as probabilistic in nature rather than deterministic. We believe that real-world network data should not be treated as "ground truth" but rather as a best guess, much as Google Maps treats traffic predictions not as truth but as well-informed predictions based on prior data collection.

Finally, we feel it is important to point out that the computer science work undergirding this intervention implementation has been rigorously vetted by the peer-review process in computer science. Two of the three most competitive and rigorous publications in the AI field are the published conference proceedings of the American Association for Artificial Intelligence and the International Conference on Autonomous Agents and Multiagent Systems. The computational experiments that used existing social network data on youth experiencing homelessness were all published in these venues and have undergone the most exacting peer review computer science has to offer.

What remains to be seen is if these algorithmic solutions indeed improve the performance of HIV prevention efforts in community settings, not just in computational experiments. The aim of this pilot study was to determine whether AI-based PCA selection relative to popularity-based PCA selection (i.e., degree centrality) would lead to higher rates of (a) recent HIV testing, (b) condom use during vaginal sex, and (c) condom use during anal sex over time among PCAs and other youths in the population.

Method

Research Design, Sampling, and Recruitment

All study procedures were approved by the University of Southern California Institutional Review Board. This is a quasi-experimental, two-group, pretest/posttest design, drawn from two unique networks of youth experiencing homelessness. The two networks of youths (ages 16–24) were collected from one Los Angeles, CA, drop-in center where they were seeking basic services (e.g., food, clothing, case management, mobile HIV testing). The first network was recruited in February 2016, and the second network was recruited in September 2016. The recruitment was separated by a 6-month interval to allow for sufficient numbers of new youths to replace prior clients. Earlier work at this drop-in center had shown an 85% turnover in clients every 6 months, making it an ideal environment from which to collect two unique networks with similar populations and the same service environment (Rice et al., 2013). First, 62 participants were recruited for testing the AI PCA selection method; 6 months later 55 participants were recruited for testing the comparison group using the standard PCA selection method of the most popular individuals. Specifics of PCA selection follow the description of the intervention delivery model. All youths receiving services were eligible to participate and were informed of the study as they entered the drop-in center. The same two study staff members recruited participants in both conditions to ensure that no participants were included in both study arms. The small number of youths who accessed the drop-in center during both the first and second recruitment periods were only included in the first study condition.

Intervention Design and Delivery

Our intervention design was based on previous literature, community collaborations, youth input, and research team members' long-term experience working with youth experiencing homelessness in both research and service delivery contexts. The intervention design was also informed by multiple theories, including the risk amplification and abatement model, which combines elements of ecological theory (Bronfenbrenner, 1977) and social learning (Bandura, 1986) but is specific to the context of youth experiencing homelessness (Milburn et al., 2009). We also relied on diffusion of innovations (Rogers, 2010) and a positive youth development model (Catalano, Berglund, Ryan, Lonczak, & Hawkins, 2004).

It was critical that the intervention be crafted for the service environment and the context and capacity of youths in that environment. We intentionally developed an intervention for youth experiencing homelessness who access drop-in service centers—safe havens where they can access food, clothing, and case management services. Such programs have been shown to be better suited to engaging homeless emerging adults in services than emergency shelters (Slesnick et al., 2016).

In the context of drop-in center service delivery to youth experiencing homelessness, the most important contextual consideration was the need to develop a short and flexible intervention delivery model. Youths visit drop-in centers intermittently as they perceive a need for services. Drop-in center attendance can vary widely (Rice et al., 2013) and is subject to the transience and instability of the lives of youth experiencing homelessness, who have unpredictable and constantly changing schedules, especially due to housing and employment instability (Slesnick et al., 2016). Relatively short-duration interventions have been shown to be effective with homeless teens (Milburn et al., 2012), and recent research on interventions for at-risk populations has suggested that brief adaptations of longer interventions are just as effective in changing behavior (Morrison, Goolsarran, Rogers, & Jha, 2014). We designed the primary intervention training to be implemented for approximately 4 hours (one half-day). The training had two goals: educating PCAs about sexual health risk reduction and promoting personal development. The initial training was supported by 7 weeks of 30-minute follow-up check-in sessions, which focused on positive reinforcement of PCAs' successes in engaging peers in HIV prevention conversations, problem-solving strategies to improve future conversations, and setting goals for the week with respect to peer-to-peer conversations about HIV prevention. Because of the difficulty in scheduling and the transience of this youth population, the check-in schedule was flexible, and PCAs could check in individually with the facilitator via phone or text. All PCAs checked in at least once; modal attendance was five sessions.

In both conditions, PCAs were recruited over a 3-week period. Each training session was limited to a maximum of 5 participants. To achieve the desired total number of PCAs in the network, researchers conducted three subsequent weekly trainings with a small group of participants. In each condition, 11 PCAs were trained. Training was delivered by two or three facilitators who were PhD students with MSWs or who were MSW student interns. Training was interactive and broken into six 45-minute modules on the mission of PCAs, sexual health, HIV prevention, communication skills, leadership skills, and self-care. PCAs were asked to focus their communications on their social ties, particularly other youths at the drop-in center, and to promote regular HIV testing and condom use. PCAs were encouraged to focus on face-to-face interactions if possible but to use social media as well. The training minimized lecture-based learning and was designed to be engaging by including a variety of learning activities: group discussion, games, journaling and reflection, experiential learning, and role-playing. The small-group setting was crucial for maintaining a safe and manageable space for youths to learn and reflect. Further, the training was developed to be an empowering experience for PCAs. Consistent language was used throughout to reiterate PCAs' role as leaders within their community. PCAs received $60 for the training and $20 for each check-in session.

PCA Selection Methods

Regardless of PCA selection method, social network data were used as the basis for selecting participants. A Facebook app collected network data regarding which participants were connected to one another, (i.e., friends). The app collected only information about individuals who were study participants, and it did not appear on their Facebook profiles. These data were augmented by field observations collected by the research team during the 2 weeks of recruitment, based on which participants study staff observed regularly interacting with one another. The network data collected from Facebook and from field observations were compiled into a network data set that was used in one of two different PCA selection approaches.

AI-based PCA selection. In the first network, we used the AI algorithm called HEALER to select 20% of the recruited network to be trained as PCAs. Papers detailing the development and computational experiments of this AI selection procedure are available (Yadav et al., 2016). The algorithm treats two aspects of the network as uncertain and hence probabilistic: the state of each node (a youth) and the existence of each tie between nodes. Once PCAs are trained, we cannot monitor them on a moment-by-moment basis; thus, we cannot be certain which of their network connections will be approached for attempted influence (uncertain state of nodes). We also know that networks change rapidly over time and are difficult to capture perfectly in this setting (uncertain state of the ties). Moreover, we treat the influence action itself as probabilistic; that is, if a tie exists between two people, there is some chance (but not certainty) that a message will be disseminated and accepted. These conditions leave an enormous action space that the program must learn. To find a specific solution, the algorithm parses the large network of youths into subnetworks of highly interconnected individuals and selects a specific set of PCAs from within each subnetwork. These PCAs are individuals who can theoretically maximize influence in the subnetworks. The final peer selection within the subnetworks is achieved by using what is referred to as *partially observable Markov decision processes*.

Comparison group PCA selection. In the second network, we used popularity as defined by degree centrality to select PCAs—that is, the 20% of youths who have the greatest number of ties to other youths were recruited (T. W. Valente & Pumpuang, 2007). This is the most straightforward operationalization of selecting the "most popular" youths, which is the recommended implementation strategy in the PCA literature (e.g., Kelly et al., 1997).

Assessments

All participants were assessed at three time points: a baseline interview; a 1-month follow-up interview that was conducted immediately after the PCAs were trained and initially deployed; and a follow-up interview 3 months after baseline, which was conducted after the 7 weeks of follow-up sessions provided to PCAs. The assessments were computer-based self-administered surveys: baseline ($n = 117$), 1 month ($n = 86$, 72%; 74% in AI, 69% in comparison), and 3 months ($n = 70$, 59%; 62% in AI, 55% in comparison). Participants received $20, $25, and $30 for each respective assessment. All baseline surveys were administered at the drop-in center. At 1 month and 3 months after the baseline assessment, most participants were surveyed again at the drop-in center. Approximately 10% of follow-up surveys were conducted online, as some participants left the area or discontinued using drop-in services. For these participants, a link to an online survey was sent via text or e-mail, and incentives were provided in the form of downloadable gift cards.

Specific survey items focused on demographic issues and HIV-prevention behaviors. For this analysis, basic demographic variables were included, such as age, race, gender, and sexual orientation. Additionally, questions pertaining to HIV-testing behaviors and condom use with anal and vaginal sex were asked. Stem questions that captured lifetime testing preceded recent testing for HIV. Likert scales were used to assess how recently participants were tested, including "*less than a month ago*," "*2–3 months ago*," "*3–6 months ago*," and "*more than 6 months ago*." For the outcome analysis, these variables were dichotomized to include those participants who were tested recently (i.e., in the last 6 months), and those who were not. For condom use, Likert scales were used to assess how frequently condoms were used with anal and vaginal sex in the past month. Options included, "*never (0% of the time)*," "*almost never (1%–10% of the time)*," "*sometimes (11%–36% of the time)*," "*half the time (36%–65% of the time)*," "*most of the time (66%–90% of the time)*," "*almost always (91%–100%)*," or "*no anal/vaginal sex in the past month*." For the outcome analyses, these questions were dichotomized into ever/never categories.

Statistical Analysis

Descriptive statistics were first conducted to examine the age, race, gender, and sexual orientation of the two treatment conditions and to visually examine differences in demographic characteristics between PCA and non-PCA roles. Frequency distribution in outcomes by condition and PCA status follow.

Results

Results from the descriptive statistics in Table 1 indicate that although the two networks were collected at two different times from the same drop-in center, the demographic and behavioral profiles of the two samples are very similar.

Because of the small sample size, statistical analyses are not relevant, but visual inspection of the data is useful. The average participant age was 23; across conditions, the majority of youth identified as White, with the second largest group being Black/African American. The majority of participants for both groups identified as male. Nearly half of participants identified as heterosexual, followed by bisexual. PCAs show similar demographic profiles as non-PCA participants. The one notable exception is that in the comparison group, 45% of PCAs were Latino, relative to only 14% of non-PCA participants.

Baseline levels of HIV testing and condom use were similar across the two treatment conditions. For non-PCA participants in the AI condition, 43.1% had not been tested in the past 6 months, compared to 55.8% of non-PCA participants in the comparison group. In the AI group, 36.2% of PCAs had not tested in the past 6 months, whereas only 18.2 % of PCAs in the comparison group had not tested. Among non-PCA participants in the AI arm, 19.2% never used condoms during anal sex, relative to 29.3% of non-PCA participants in the comparison group. Among PCAs in the AI arm, 33.3% never used condoms during anal sex, relative to 20.0% of PCAs in the comparison group. Among non-PCA participants in the AI condition, 36.2% never used condoms during vaginal sex, relative to 23.8% of non-PCA participants in the comparison condition. Among PCAs in the AI condition, 20.0% never used condoms, relative to 10.0% of PCAs in the comparison condition.

Table 2 presents the frequency distributions of outcome behaviors, separating PCA and non-PCA results. There was more HIV testing in the AI condition. Among non-PCA participants in the AI condition, 74.3% had a recent HIV test by 1 month, relative to 63.0% of non-PCA participants in the comparison condition. At 3 months, 71.4% of non-PCA participants in the AI condition reported a recent HIV test, relative to 50.0% of non-PCA participants in the comparison condition. The trend is similar for PCAs, but the rates of testing are higher overall among PCAs in both conditions. Condom use during both anal and vaginal sex shows a similar pattern over time. At 1 month, PCA and non-PCA participants in the comparison condition reported more condom use, but at 3 months this trend reverses, and participants in the AI

Table 1

Demographic and Baseline Behavioral Profiles of Youth by Treatment Condition and PCA and non-PCA Roles

	Non-PCA				PCA			
	AI Condition		Comparison		AI Condition		Comparison	
Variables	*n*	%	*n*	%	*n*	%	*n*	%
Race								
American Indian or Alaska Native	3	6.0	2	4.6	0	0.0	1	9.1
Asian	0	0.0	1	2.3	0	0.0	0	0.0
Black or African American	10	20.0	6	13.6	2	20.0	1	9.1
Latino/Hispanic	5	10.0	6	13.6	3	30.0	5	45.5
Mixed race	7	14.0	10	22.7	3	30.0	1	9.1
Native Hawaiian or Other Pacific Islander	2	4.0	1	2.3	0	0.0	0	0.0
White	23	46.0	18	40.9	2	20.0	3	27.3
Gender								
Female	11	21.6	8	18.2	3	27.3	1	9.1
Male	39	76.5	33	75.0	8	72.7	10	90.9
Transgender	1	2.0	3	6.8	0	0.0	0	0.0
Sexual orientation								
Bisexual	9	18.0	3	7.0	1	9.1	0	0.0
Heterosexual (straight)	38	76.0	37	86.1	10	90.9	10	90.9
Homosexual (gay or lesbian)	2	4.0	2	4.7	0	0.0	0	0.0
Questioning/unsure	1	2.0	1	2.3	0	0.0	1	9.1

HIV testing								
Within the past month	13	25.5	8	18.6	4	36.4	2	18.2
2–3 months ago	10	19.6	9	20.9	2	18.2	4	36.4
3–6 months ago	6	11.8	2	4.7	1	9.1	3	27.3
More than 6 months ago	12	23.5	10	23.3	2	18.2	0	0.0
Never	10	19.6	14	32.6	2	18.2	2	18.2
In the past month, how often did you use a condom when you had anal sex?								
Never (0% of the time)	9	19.2	12	29.3	3	33.3	2	20.0
Almost never (1%–10% of the time)	1	2.1	5	12.2	1	11.1	1	10.0
Sometimes (11%–35% of the time)	3	6.4	3	7.3	1	11.1	0	0.0
Half the time (36%–65% of the time)	2	4.3	1	2.4	0	0.0	0	0.0
Most of the time (66%–90% of the time)	0	0.0	1	2.4	0	0.0	1	10.0
Almost always (91%–100% of the time)	8	17.0	4	9.8	0	0.0	0	0.0
No anal sex in the past month	24	51.1	15	36.6	4	44.4	6	60.0
In the past month, how often did you use a condom when you had vaginal sex?								
Never (0% of the time)	17	36.2	10	23.8	2	20.0	1	10.0
Almost never (1%–10% of the time)	5	10.6	3	7.1	1	10.0	2	20.0
Sometimes (11%–35% of the time)	0	0.0	4	9.5	3	30.0	0	0.0
Half the time (36%–65% of the time)	3	6.4	3	7.1	0	0.0	0	0.0
Most of the time (66%–90% of the time)	3	6.4	3	7.1	1	10.0	1	1.0
Almost always (91%–100% of the time)	12	25.5	8	19.1	2	20.0	3	30.0
No vaginal sex in the past month	7	14.9	11	26.2	1	10.0	3	30.0

Note. PCA = peer change agent; AI = artificial intelligence.

Table 2
Outcomes at 1-Month and 3-Month Follow-Up

	AI Condition		Comparison	
	n	%	*n*	%
All youth (PCA and non-PCA)				
Recent HIV testing at 1 month	36	78.30	25	68.40
Recent HIV testing at 3 months	30	76.90	18	60.00
Condom use anal sex at 1 month	11	42.30	12	63.20
Condom use anal sex at 3 months	11	55.00	7	50.00
Condom use vaginal sex at 1 month	22	56.40	18	69.20
Condom use vaginal sex at 3 months	19	67.90	10	52.60
Non-PCA				
Recent HIV testing at 1 month	26	74.29	17	62.96
Recent HIV testing at 3 months	20	71.43	10	50.00
Condom use anal sex at 1 month	9	50.00	8	57.14
Condom use anal sex at 3 months	8	72.73	6	60.00
Condom use vaginal sex at 1 month	17	56.67	13	68.42
Condom use vaginal sex at 3 months	15	71.43	8	61.54
PCA				
Recent HIV testing at 1 month	10	90.91	9	81.82
Recent HIV testing at 3 months	10	90.91	8	80.00
Condom use anal sex at 1 month	2	25.00	4	80.00
Condom use anal sex at 3 months	3	33.33	1	25.00
Condom use vaginal sex at 1 month	5	55.56	5	71.43
Condom use vaginal sex at 3 months	4	57.14	2	33.33

Note. PCA = peer change agent; AI = artificial intelligence.

condition reported more condom use. Among non-PCA participants in the AI condition, 50.0% reported using condoms during anal sex at 1 month, relative to 57.1% of non-PCA participants in the comparison condition. At 3 months, 72.7% of participants in the AI condition reported condom use, relative to 60.0% of participants in the comparison conditions. Among non-PCA youth in the AI condition, 56.7% reported condom use during vaginal sex at 1 month, relative to 68.4% in the comparison group. At 3 months, 71.4% of non-PCA participants in the AI condition reported condom use, relative to 61.5% in the comparison group. The direction of this effect is the same among PCAs, yet PCAs in both conditions reported less condom use than non-PCAs.

Because patterns for PCA and non-PCA participants are similar, it is useful to simplify these results and compare the overall increase in HIV testing and condom use during anal and vaginal sex. In the AI arm at 3 months, there was a 18.82% increase relative to baseline in recent HIV testing, compared to an 8.1% increase in the comparison group. Three months after baseline, there was a 12.1% increase in using condoms during anal sex among participants in the AI condition, relative to a 3.3% increase in the comparison group. In addition, 3 months after baseline, there was a 29.2% increase in condom use during vaginal sex among participants in the AI condition, relative to a 23.7% increase in the comparison group.

Discussion

In both conditions, there was an increase in recent HIV testing and condom use, demonstrating that a PCA model is feasible for HIV prevention targeting youth experiencing homelessness. This pilot study also demonstrates that the method of PCA selection may influence the efficacy of PCA-based prevention. Using AI to select PCAs is feasible, and it outperforms more traditional network-based metrics, specifically individual popularity. We observed a greater percentage increase in recent HIV testing and condom use during anal and vaginal sex in the AI condition relative to the comparison condition. Results from this study demonstrate the possibility of implementing AI-enhanced PCA models to increase efficiency and to reduce resource burden and redundancies in targeted information dissemination.

Our findings should be interpreted with caution as the purpose of this study was to assess feasibility of the PCA intervention model, the use of an AI algorithm for PCA selection, and the combination of both of these strategies. This study also was a pilot in terms of determining effect size of change on desired outcomes. As a result, the sample size was small, and there was no purely observational control. Our findings support previous research demonstrating that PCA models are an effective HIV prevention strategy for many at-risk populations (e.g., Medley et al., 2009). The observed differences in changes between the AI and comparison conditions suggest that PCA selection methods are a critical component of overall intervention success. We are encouraged by these findings and by the fact that using AI in the context of social services appeared to be both feasible and acceptable by study participants and the agencies that serve them.

We believe that the observed differences in outcomes occurred for several reasons. First, AI intelligently selected individuals from different social pockets of the overall network, which increased the optimal reach of our information dissemination efforts. The AI algorithm selected participants in dyads, triads, or cliques that may have been disconnected from the larger social network, and their inclusion allowed for information to spread within those smaller network components. Second, the AI program prevented redundancies in information dissemination. For example, using the popularity metric for selection, PCAs who were invited to participate in the intervention were connected to each other and to similar—if not the same—people in the network. Furthermore, facilitators noticed a marked difference in the training sessions between the two groups. When PCAs were selected using AI versus popularity, training sessions included diverse sets of youths from different social circles. Many of those who were selected did not interact with one another before the training, and this allowed for more successful bonding with training facilitators, focus on work, and community building among PCAs.

We illustrate these results with the metaphor of the "Breakfast Club" versus the "high school football team." In the case of the popularity/degree-centrality condition, we observed a phenomenon akin to selecting most PCAs from the football team in a typical high school. These PCAs were individuals who were connected by many other individuals, but most of these individuals are from a limited number of other social circles, and many of their ties were with one another. This limited both their reach into social space; for example, the "nerds" of the network would get left out of conversations. PCAs' existing interpersonal status dynamics were also at play during intervention sessions, which reduced their capacity to bond with facilitators and become motivated to engage in health advocacy work.

In the case of the AI algorithm, which explicitly parses the social space into subnetworks and then looks for PCAs in each of those communities, we experienced something akin to the 1985 film *The Breakfast Club*. In that film, five teens from different social circles—the nerd, the stoner, the jock, the princess, and the Goth—come together for a daylong detention. They bond with one another outside of the context of their typical social relationships and then return to their respective social circles at the end of the movie. In the context of the AI-selected PCAs, we observed the same dynamic. Youths who did not know one another came together, bonded with one another, bonded with the facilitation team, became energized about the PCA work, and then returned to their own distinct social circles, where they conducted their PCA advocacy efforts.

These insights into network dynamics may not necessitate the use of AI in all contexts. What the AI algorithm may have uncovered is the need to disaggregate a larger social space into smaller subnetworks and then select PCAs from across these smaller social spaces. This approach "spreads the wealth" of where PCAs are located in social space and also allows for more productive intervention dynamics when working with high-risk youths, who are often difficult to manage in small-group settings—particularly if their existing relationships with one another interfere in bonding with interventionists. The success of Valente's peer-driven model for smoking prevention (T. W. Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003) and Amirkhanian's model for HIV prevention (Amirkhanian et al., 2003) was likely due to researchers having accessed smaller subnetworks. AI was particularly beneficial to us in the planning process because the initial computational experiments showed that the segmentation approach would yield higher expected returns to intervention deployment. Once the team was in the field testing this approach, we were able to observe the interpersonal dynamics between youths—dynamics that were activated and successfully exploited by this set of decision rules.

Anecdotally, study participants and agency staff felt that the selection process was unbiased, acknowledging that the selection was made by "the computer" and not a person. Because we were also able to select "popular youth" with a very simple degree-centrality procedure, we were able to have "the computer" always be the agent that selected participants, regardless of condition. We believe this contributed to overall acceptability of this new social-network-based intervention. We intend to make this software freely available to agencies and are also working to reduce the network data collection burden by experimenting with algorithms that do not rely on complete network data (Wilder, Yadav, Immorlica, Rice, & Tambe, 2017).

Limitations

This study has some limitations that must be acknowledged. Our participants represented a small, convenience-based sample of two networks of service-seeking youth experiencing homelessness in Los Angeles. This was a quasi-experimental, nonrandomized design, which is typical in PCA models (e.g., Kelly et al., 1997). We cannot rule out the possibility that there may have been changes unrelated to the intervention that contributed to increase in HIV-testing rates (although we know of no changes in service delivery or ease of accessing HIV testing at the partner agency). Our study retention rate was somewhat lower than what has been reported in other studies involving longitudinal follow-up of youth experiencing homelessness (Milburn et al., 2009; Rotheram-Borus et al., 2003). However, this past research was conducted within slightly more stable populations of new runaways, most all of whom returned home (Milburn et al., 2009), or youths recruited from shelter services (Rotheram-Borus et al., 2003). Youths with chronic experiences of homelessness who are attending a drop-in center are far more difficult to track and retain. Indeed, Bender and colleagues (2016) worked with a similar drop-in-based population and had similar follow-up rates. Attrition in the comparison arm was 6% higher than in the AI condition. Fortunately, there were no significant differences in baseline risk behaviors among those lost to follow-up (e.g., baseline HIV testing was 67% for those retained vs. 64% among those lost).

Conclusion

These initial findings demonstrate the value of using AI to augment intervention design. Traditional methods of intervention design are costly with respect both to financial resources and time. Using AI and computational experiments allows one to test various hypothetical intervention implementation decisions quickly and at low cost. For example, the computational experiments that preceded our fieldwork suggested that degree centrality would outperform random assignment but underperform relative to greedy algorithmic approaches, which would underperform relative to HEALER (Yadav et al., 2015). Thus, we were able to discard two possible selection mechanisms in favor of a test between the standard in public health (i.e., degree centrality) and our new algorithm.

We have begun to refer to this style of research as algorithmic intervention science (AIS). In general, we believe that many intervention implementation issues can be modeled with computer simulations that take advantage of novel algorithmic techniques from AI, specifically with respect to planning algorithms. Some features of AIS are worth noting from the perspective of both computer science and social work science. First, this work is typically focused on communities that are marginalized and lack resources, making intervention mistakes costlier. Second, unlike many machine-learning contexts, AIS usually operates in conditions in which there is little data and much uncertainty that must be modeled. In this study, that uncertainty focused primarily on what the actual network structure might be and who exactly would be reached at any given point in time. Third, human decisions in the context of interventions are not perfectly rational, and we need to rely on complex behavioral models based on the best possible social theories available in a particular context. Simplistic rational-choice models from economics are unlikely to be helpful. In these computational models, we must strive to capture simulations of people's behaviors, considering the complexity of what social work science knows to be motivations for action in that specific context, and accounting for typically observed decisions and outcomes in the context of interventions in that social setting. Fourth, in most intervention contexts in community settings, people are influenced by the behavior of others in their social networks as well as by the interests of the interventionists. Modeling social influence in many of these contexts is critical. We hope that our preliminary work on AIS will inspire others to attempt similar intervention implementation strategies that use AI and computational experiments to improve the speed of implementing the most effective interventions for high-risk, marginalized populations.

Author Notes

Eric Rice, PhD, is an associate professor at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Amanda Yoshioka-Maxwell, MSW, is a PhD candidate at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Robin Petering, PhD, is a postdoctoral scholar at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Laura Onasch-Vera, MSW, is a project director at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Jaih Craddock, MSW, is a PhD candidate at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Milind Tambe, PhD, is a professor at the University of Southern California Viterbi School of Engineering.

Amulya Yadav, MS, is a PhD candidate at the University of Southern California Viterbi School of Engineering.

Bryan Wilder, MS, is a PhD candidate at the University of Southern California Viterbi School of Engineering.

Darlene Woo, MSW, is a clinical associate professor at the University of Southern California Suzanne Dworack-Peck School of Social Work.

Hailey Winetrobe, MPH, is head of center operations at the University of Southern California Center for Artificial Intelligence in Society.

Nicole Wilson, MSW, is a project specialist at University of Southern California Suzanne Dworack-Peck School of Social Work.

Correspondence regarding this article should be directed to Eric Rice, 1150 S. Olive St., Suite 1400, Los Angeles, CA 90036 or via e-mail to ericr@usc.edu

References

Amirkhanian, Y. A., Kelly, J. A., Kabakchieva, E., McAuliffe, T. L., & Vassileva, S. (2003). Evaluation of a social network HIV prevention intervention program for young men who have sex with men in Russia and Bulgaria. *AIDS Education and Prevention*, *15*(3), 205–220. doi:10.1521/aeap.15.4.205.23832

Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist*, *55*(5), 469–480. doi:10.1037/0003-066X.55.5.469

Arnett, J. J. (2001). Conceptions of the transition to adulthood: Perspectives from adolescence through midlife. *Journal of Adult Development*, *8*(2), 133–143. doi:10.1023/a:1026450103225

Arnold, E. M., & Rotheram-Borus, M. J. (2009). Comparisons of prevention programs for homeless youth. *Prevention Science*, *10*(1), 76–86. doi:10.1007/s11121-008-0119-4

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Barman-Adhikari, A., Hsu, H.-T., Begun, S., Portillo, A. P., & Rice, E. (2017). Condomless sex among homeless youth: The role of multidimensional social norms and gender. *AIDS and Behavior*, *21*(3), 688–702. doi:10.1007/s10461-016-1624-2

Barman-Adhikari, A., & Rice, E. (2011). Sexual health information seeking online among runaway and homeless youth. *Journal of the Society for Social Work and Research*, *2*(2), 89–103. doi:10.5243/jsswr.2011.5

Barman-Adhikari, A., Rice, E., Winetrobe, H., & Petering, R. (2015). Social network correlates of methamphetamine, heroin, and cocaine use in a sociometric network of homeless youth. *Journal of the Society for Social Work and Research*, *6*(3), 433–457. doi:10.1086/682709

Bauman, K. E., Carver, K., & Gleiter, K. (2001). Trends in parent and friend influence during adolescence: The case of adolescent cigarette smoking. *Addictive Behaviors*, *26*(3), 349–361. https://doi.org/10.1016/S0306-4603(00)00110-6

Bender, K. A., DePrince, A., Begun, S., Hathaway, J., Haffejee, B., & Schau, N. (2016). Enhancing risk detection among homeless youth: A randomized clinical trial of a promising pilot intervention. *Journal of Interpersonal Violence*, *33*(19) 2945–2967. doi:107.171/0778/806882620650156166333208

Berndt, T. J. (1979). Developmental changes in conformity to peers and parents. *Developmental Psychology*, *15*(6), 608–616. doi:10.1037/0012-1649.15.6.608

Booth, R. E., Zhang, Y., & Kwiatkowski, C. F. (1999). The challenge of changing drug and sex risk behaviors of runaway and homeless adolescents. *Child Abuse & Neglect*, *23*(12), 1295–1306. http://dx.doi.org/10.1016/S0145-2134(99)00090-3

Brewer, D. D. (2000). Forgetting in the recall-based elicitation of personal and social networks. *Social Networks*, *22*(1), 29–43. http://dx.doi.org/10.1016/S0378-8733(99)00017-9

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32*(7), 513–531. doi:10.1037/0003-066X.32.7.513

Catalano, R. F., Berglund, M. L., Ryan, J. A., Lonczak, H. S., & Hawkins, J. D. (2004). Positive youth development in the United States: Research findings on evaluations of positive youth development programs. *The Annals of the American Academy of Political and Social Science*, *591*(1), 98–124. doi:10.1177/0002716203260102

Centers for Disease Control and Prevention. (2017). *HIV testing*. Retrieved from https://www.cdc.gov/hiv/testing/index.html

Christiani, A., Hudson, A. L., Nyamathi, A., Mutere, M., & Sweat, J. (2008). Attitudes of homeless and drug-using youth regarding barriers and facilitators in delivery of quality and culturally sensitive health care. *Journal of Child and Adolescent Psychiatric Nursing*, *21*(3), 154–163. doi:10.1111/j.1744-6171.2008.00139.x

Ensign, J., & Gittelsohn, J. (1998). Health and access to care: Perspectives of homeless youth in Baltimore City, USA. *Social Science & Medicine*, *47*(12), 2087–2099. http://dx.doi.org/10.1016/S0277-9536(98)00273-1

Fors, S. W., & Jarvis, S. (1995). Evaluation of a peer-led drug abuse risk reduction project for runaway/homeless youths. *Journal of Drug Education*, *25*(4), 321–333. doi:10.2190/TU92-LX8W-G7FD-9LEM

Fulginiti, A., Rice, E., Hsu, H.-T., Rhoades, H., & Winetrobe, H. (2016). Risky integration. *Crisis: The Journal of Crisis Intervention and Suicide Prevention*, *37*(3), 184–193. doi:10.1027/0227-5910/a000374

Green, H. D., Haye, K., Tucker, J. S., & Golinelli, D. (2013). Shared risk: Who engages in substance use with American homeless youth? *Addiction*, *108*(9), 1618–1624. doi:10.1111/add.12177

Hudson, A. L., Nyamathi, A., Greengold, B., Slagle, A., Koniak-Griffin, D., Khalilifard, F., & Getzoff, D. (2010). Health-seeking challenges among homeless youth. *Nursing Research*, *59*(3), 212–218. doi:10.1097/NNR.0b013e3181d1a8a9

Kelly, J. A. (2004). Popular opinion leaders and HIV prevention peer education: Resolving discrepant findings, and implications for the development of effective community programmes. *AIDS Care*, *16*(2), 139–150. doi:10.1080/09540120410001640986

Kelly, J. A., Murphy, D. A., Sikkema, K. J., McAuliffe, T. L., Roffman, R. A., Solomon, L. J., . . . Kalichman, S. C. (1997). Randomised, controlled, community-level HIV-prevention intervention for sexual-risk behaviour among homosexual men in U.S. cities. *The Lancet*, *350*(9090), 1500–1505. http://dx.doi.org/10.1016/S0140-6736(97)07439-4

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. *Proceedings of the ninth ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 137–146). Retrieved from http://www.theoryofcomputing.org/articles/v011a004/v011a004.pdf

Klein, J. D., Woods, A. H., Wilson, K. M., Prospero, M., Greene, J., & Ringwalt, C. (2000). Homeless and runaway youths' access to health care. *Journal of Adolescent Health*, *27*(5), 331–339. http://dx.doi.org/10.1016/S1054-139X(00)00146-4

Latkin, C. A., Sherman, S., & Knowlton, A. (2003). HIV prevention among drug users: Outcome of a network-oriented peer outreach intervention. *Health Psychology*, *22*(4), 332–339. http://dx.doi.org/10.1037/0278-6133.22.4.332

Lindsey, E. W., Kurtz, P. D., Jarvis, S., Williams, N. R., & Nackerud, L. (2000). How runaway and homeless youth navigate troubled waters: Personal strengths and resources. *Child and Adolescent Social Work Journal*, *17*(2), 115–140. doi:10.1023/A:1007558323191

Martins, D. C. (2008). Experiences of homeless people in the health care delivery system: A descriptive phenomenological study. *Public Health Nursing*, *25*(5), 420–430. doi:10.1111/j.1525-1446.2008.00726.x

McMorris, B. J., Tyler, K. A., Whitbeck, L. B., & Hoyt, D. R. (2002). Familial and "on-the-street" risk factors associated with alcohol use among homeless and runaway adolescents. *Journal of Studies on Alcohol*, *63*(1), 34–43. doi:10.15288/jsa.2002.63.34

Medley, A., Kennedy, C., O'Reilly, K., & Sweat, M. (2009). Effectiveness of peer education interventions for HIV prevention in developing countries: A systematic review and meta-analysis. *AIDS Education and Prevention*, *21*(3), 181–206. doi:10.1521/aeap.2009.21.3.181

Milburn, N. G., Iribarren, F. J., Rice, E., Lightfoot, M., Solorio, R., Rotheram-Borus, M. J., . . . Eastmen, K. (2012). A family intervention to reduce sexual risk behavior, substance use, and delinquency among newly homeless youth. *Journal of Adolescent Health*, *50*(4), 358–364. doi:10.1016/j.jadohealth.2011.08.009

Milburn, N. G., Rice, E., Rotheram-Borus, M. J., Mallett, S., Rosenthal, D., Batterham, P., . . . Duan, N. (2009). Adolescents exiting homelessness over two years: The risk amplification and abatement model. *Journal of Research on Adolescence*, *19*(4), 762–785. doi:10.1111/j.1532-7795.2009.00610.x

Morrison, A. B., Goolsarran, M., Rogers, S. L., & Jha, A. P. (2014). Taming a wandering attention: Short-form mindfulness training in student cohorts. *Frontiers in Human Neuroscience*, *7*(897), 1–7. doi:10.3389/fnhum.2013.00897

Morton, M. H., Dworsky, A., Matjasko, J. L., Curry, S. R., Schlueter, D., Chávez, R., & Farrell, A. F. (2018). Prevalence and correlates of youth homelessness in the United States. *Journal of Adolescent Health*, *62*(1), 14–21. https://doi.org/10.1016/j.jadohealth.2017.10.006

NIMH Collaborative HIV/STD Prevention Trial Group. (2010). Results of the NIMH collaborative HIV/STD prevention trial of a community popular opinion leader intervention. *Journal of Acquired Immune Deficiency Syndromes*, *54*(2), 204–214. doi:10.1097/QAI.0b013e3181d61def

Ober, A. J., Martino, S. C., Ewing, B., & Tucker, J. S. (2012). If you provide the test, they will take it: Factors associated with HIV/STI testing in a representative sample of homeless youth in Los Angeles. *AIDS Education and Prevention*, *24*(4), 350–362. doi:10.1521/aeap.2012.24.4.350

Petering, R., Rice, E., & Rhoades, H. (2016). Violence in the social networks of homeless youths. *Journal of Adolescent Research*, *31*(5), 582–605. doi:10.1177/0743558415600073

Pfeifer, R. W., & Oliver, J. (1997). A study of HIV seroprevalence in a group of homeless youth in Hollywood, California. *Journal of Adolescent Health*, *20*(5), 339–342. doi:10.1016/S1054-139X(97)00038-4

Rice, E. (2010). The positive role of social networks and social networking technology in the condom-using behaviors of homeless young people. *Public Health Reports*, *125*(4), 588–595. doi:10.1177/003335491012500414

Rice, E., Barman-Adhikari, A., Milburn, N. G., & Monro, W. (2012). Position-specific HIV risk in a large network of homeless youths. *American Journal of Public Health*, *102*(1), 141–147. doi:10.2105/ajph.2011.300295

Rice, E., Milburn, N. G., & Monro, W. (2011). Social networking technology, social network composition, and reductions in substance use among homeless adolescents. *Prevention Science*, *12*(1), 80–88. doi:10.1007/s11121-010-0191-4

Rice, E., Milburn, N. G., & Rotheram-Borus, M. J. (2007). Pro-social and problematic social network influences on HIV/AIDS risk behaviours among newly homeless youth in Los Angeles. *AIDS Care*, *19*(5), 697–704. doi:10.1080/09540120601087038

Rice, E., Winetrobe, H., Rhoades, H., Petering, R., Carranza, A., Dent, D., . . . Milburn, N. G. (2013, November). *Substantial differences in risk behaviors of homeless youth in two large networks* *of homeless youth in Los Angeles*. Paper presented at the American Public Health Association Annual Meeting, Boston, MA.

Rogers, E. M. (2010). *Diffusion of innovations* (4th ed.). New York, NY: The Free Press, Simon & Schuster.

Rotheram-Borus, M. J., Song, J., Gwadz, M., Lee, M., Van Rossem, R., & Koopman, C. (2003). Reductions in HIV risk among runaway youth. *Prevention Science*, *4*(3), 173–187. https://doi.org/10.1023/A:1024697706033

Schneider, J. A., Zhou, A. N., & Laumann, E. O. (2015). A new HIV prevention network approach: Sociometric peer change agent selection. *Social Science & Medicine*, *125*, 192–202. http://dx.doi.org/10.1016/j.socscimed.2013.12.034

Slesnick, N., Feng, X., Guo, X., Brakenhoff, B., Carmona, J., Murnan, A., . . . McRee, A.-L. (2016). A test of outreach and drop-in linkage versus shelter linkage for connecting homeless youth to services. *Prevention Science*, *17*(4), 450–460. doi:10.1007/s11121-015-0630-3

Tenner, A. D., Trevithick, L. A., Wagner, V., & Burch, R. (1998). Seattle YouthCare's prevention, intervention, and education program. *Journal of Adolescent Health*, *23*(2), 96–106. http://dx.doi.org/10.1016/S1054-139X(98)00057-3

Valente, A. M., & Auerswald, C. L. (2013). Gender differences in sexual risk and sexually transmitted infections correlate with gender differences in social networks among San Francisco homeless youth. *Journal of Adolescent Health*, *53*(4), 486–491. https://doi.org/10.1016/j.jadohealth.2013.05.016

Valente, T. W., Hoffman, B. R., Ritt-Olson, A., Lichtman, K., & Johnson, C. A. (2003). Effects of a social-network method for group assignment strategies on peer-led tobacco prevention programs in schools. *American Journal of Public Health*, *93*(11), 1837–1843. doi:10.2105/AJPH.93.11.1837

Valente, T. W., & Pumpuang, P. (2007). Identifying opinion leaders to promote behavior change. *Health Education & Behavior*, *34*(6), 881–896. doi:10.1177/1090198106297855

Wen, C. K., Hudak, P. L., & Hwang, S. W. (2007). Homeless people's perceptions of welcomeness and unwelcomeness in healthcare encounters. *Journal of General Internal Medicine*, *22*(7), 1011–1017. doi:10.1007/s11606-007-0183-7

Whitbeck, L. B., Hoyt, D. R., & Yoder, K. A. (1999). A risk-amplification model of victimization and depressive symptoms among runaway and homeless adolescents. *American Journal of Community Psychology*, *27*(2), 273–296. doi:10.1023/A:1022891802943

Wilder, B., Yadav, A., Immorlica, N., Rice, E., & Tambe, M. (2017). Uncharted but not uninfluenced: Influence maximization with an uncertain network. In S. Das, E. Durfee, K. Larson, & M. Winikoff (Eds.), *Proceedings of the 16th Conference on Autonomous Agents and Multiagent Systems* (pp. 1305–1313). International Foundation for Autonomous Agents and Multiagent Systems. Retrieved from http://www.aamas2017.org/proceedings/pdfs/p1305.pdf

Winetrobe, H., Rice, E., Rhoades, H., & Milburn, N. (2016). Health insurance coverage and healthcare utilization among homeless young adults in Venice, CA. *Journal of Public Health*, *38*(1), 147–155. doi:10.1093/pubmed/fdv001

Yadav, A., Chan, H., Xin Jiang, A., Xu, H., Rice, E., & Tambe, M. (2016) Using social networks to aid homeless shelters: Dynamic influence maximization under uncertainty. In J. Thangarajah, K. Tuyls, C. Jonker, & S. Marsella (Eds.), *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems* (pp. 740–748). Retrieved from http://www.ifaamas.org/Proceedings/aamas2016/pdfs/p740.pdf

Yadav, A., Marcolino, L. S., Rice, E., Petering, R., Winetrobe, H., Rhoades, H., . . . Carmichael, H. (2015). Preventing HIV spread in homeless populations using PSINET. In *Planning, Search and Optimization: Papers from the 2015 AAAI Workshop* (pp. 92–99). Association for the Advancement of Artificial Intelligence. Retrieved from http://www.aaai.org/ocs/index.php/WS/AAAIW15/paper/download/10069/10239

Yoshioka-Maxwell, A., & Rice, E. (2017). Exploring the impact of network characteristics on substance use outcomes among homeless former foster youth. *International Journal of Public Health*, *62*(3), 371–378. doi:10.1007/s00038-016-0845-5

Manuscript submitted: March 30, 2018
Revision submitted: June 6, 2018
Accepted: June 11, 2018
Electronically published: November 29, 2018