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

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Draft Date: 6/06/18
Accepted for Publication at Journal of the Society for Social Work Research

ABSTRACT

Objectives. Promoting healthy youth development continues to be a major focus of social work science. Youth experiencing homelessness are at extreme risk for contracting HIV and in great need of interventions which prevent risky sex behaviors. The feasibility of using Artificial Intelligence (AI) to select peer change agents (PCA) to deliver HIV prevention messages among youth experiencing homelessness was tested, compared to PCAs selected via popularity (operationalized as highest degree centrality or most ties to others in the network).

Methods. A pre-test, post-test quasi-experimental design was used: 62 youth were recruited in the AI condition, six months later 55 youth were recruited for testing the popularity/degree centrality condition at one drop in center in Los Angeles, CA, in 2016. In the AI condition, 11 PCA were selected via HEALER, in the comparison condition 11 youth were selected based on maximum degree centrality and trained to promote HIV testing and condom use among their peers. All participants completed a computer-based self-administered survey at baseline (n = 117), 1 month (n = 86, 74%), and 3 months (n = 70, 60%). HIV testing and condom use were assessed via self-report.

Results. The two conditions enrolled youth with similar demographic and baseline behaviors. At three months, overall rates of HIV testing increased more youth 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% increase) and vaginal sex (29.2% vs 23.7% increase). PCA youth reported higher rates of HIV testing but lower rates of condom use compared to non-PCA.

Conclusions. An AI-enhanced PCA intervention appears to be a feasible method for engaging youth experiencing homelessness in HIV prevention, with promising effect sizes. We see this as a “proof of concept” for using AI to enhance intervention implementation and design.

Recent national estimates show that there are nearly 4.2 million youth experiencing homelessness in the United States each year (Morton et al., 2018), and these youth are at great 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 important role peers play in the HIV-risk and protective behaviors of youth experiencing homelessness (e.g. Green et al., 2013; Rice, 2010; Rice et al., 2012; 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). In general PCA models, identify a small set of persons in a high-risk target population to become advocates in their community. These persons are tasked with disseminating HIV prevention information and HIV prevention norm changing messages to their peers (e.g. Kelly, et al 1997; Latkin et al., 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. Two versions of this model were tested. In one study arm, we used planning methods from Artificial Intelligence (AI) 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" youth in the network (which was defined as highest degree centrality – that is the persons 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. In this context we utilize AI to guide the selection of PCAs in the context of peer-driven HIV prevention. The specific goal of the study was to determine if using AI to select PCA 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. These interventions promote healthy behavior and prevent diseases such as HIV that are fundamentally linked to the behavioral health of youth. There is a need to identify new cases of HIV among youth experiencing homelessness. The overall purpose being 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 reported lifetime HIV testing, but only 47% had a HIV test in the past 3 months (Ober et al., 2012). The Centers for Disease Control and Prevention recommend at least annual testing for HIV, and this recommendation should be more frequent (i.e., every 3-6 months) among higher risk groups, such as YMSM (Centers for Disease Control and Prevention, 2017).

Youth experiencing homelessness are not engaged in regular testing, in part because they are oftentimes not well engaged in healthcare service utilization 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 et al., 2008; Hudson et al., 2010; Martins, 2008; Wen, Hudak, & Hwang, 2007), and distrust with healthcare and other social service providers (Klein et al., 2000; Kurtz, Lindsey, Jarvis, & Nackerud, 2000). Youth experiencing homelessness instead rely on informal sources such as friends or relatives (Ensign

& Gittelsohn, 1998), and the internet to receive healthcare information (Barman-Adhikari & Rice, 2011).

Peers are an important part of adolescent life in general and peer engagement can be potentially even more important for risk and protective behaviors among youth experiencing homelessness. In Western developed 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 while 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, and further disenfranchises youth from their connections to pro-social institutions, like school. The best developmentally-focused models of this process are the Risk Amplification Model (RAM) (Whitbeck, Hoyt, & Yoder, 1999) and its augmentation, the Risk Amplification and Abatement Model (RAAM) (Milburn et al., 2009).

RAM asserted that the peer networks of youth experiencing homelessness on the streets 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 (e.g., McMorris et al. 2002; Rice, Milburn, and Monro 2011). Negative peer influences in the street-based networks of youth experiencing homelessness can be seen cutting across a wide spectrum of risk-taking behaviors, including violence (Petering et al., 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 et al., 2017).

RAAM extended this thinking by recognizing that the networks of these youth 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 pro-social influence behaviors (Rice, 2010; Rice et al., 2011; Rice et al., 2007). 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. While youth who were more deeply embedded in social networks of other street youth were less likely to be using condoms (Rice, Barman-Adhikari, Milburn, & Monro, 2012), being connected to condom-using peers who were also experiencing homelessness was found to be associated with increased condom use (Rice, 2010).

Developing a New PCA Intervention Specifically for Youth experiencing homelessness

In general PCA is a network-based intervention modality. Typically these models are 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 suffer from a great deal of 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 (Kelly et al., 1997) and Latkin's SHIELD (Latkin et al., 2003). The general method used selects a small number of persons 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 their peers and this information will diffuse throughout the larger network of the population (e.g. Rogers, 1994).

At present, there is a dearth of PCA interventions to improve health behaviors among youth experiencing homelessness. Of the limited interventions and evaluations that have been conducted, there were mixed results. One study found that peer-based models were effective in increasing youth experiencing homelessness' substance use knowledge and preventive behaviors (Fors & Jarvis, 1995), while another study found that although a peer-led intervention was effective in increasing HIV-related knowledge, it was ineffective in reducing sex risk and substance use behaviors among youth experiencing homelessness (Booth, Zhang, & Kwiatkowski, 1999). Another program, YouthCare included youth experiencing homelessness as staff in their 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, however, not only showed mixed results but are also 20 years old or more. A new PCA model, specific to youth experiencing homelessness is needed.

PCA Models and the Importance of How to Select Change Agents

PCA models, such as Kelly's POL (Kelly et al., 1997) and Latkin's SHIELD (Latkin et al., 2003) have been found to be effective for HIV prevention in many contexts (Medley et al., 2009), but there have been some notable failures (e.g., NIMH Collaborative, 2010). Some early discourse about failures suggested that programs which were overly focused on HIV education were less effective than those which focused more explicitly on norm-changing messaging

(Kelly et al., 2004). However, the large NIMH (NIMH, 2010) was overseen by Kelly and addressed this limitation, yet still yielded unimpressive results.

In recent years, Schneider and colleagues have suggested that PCA model failures may be due to how the PCA are selected to participate in the intervention. As they argue, the change agents themselves 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). The standard method for selecting PCA as developed by Kelly is to use ethnographic methods to identify the most popular persons in the social network. This can be operationalized more formally as selecting PCAs who have greatest number of network connections to others in a population, a concept known as highest degree centrality in social network science. Several authors, but particularly Valente, have described on how network-driven prevention programs can benefit from explicitly modelling social networks and leveraging network methods such as degree centrality in the context of intervention delivery (Valente & Pumpuang, 2007; Schneider et al., 2015; Rice et al., 2012).

AI and Improving the Implementation of PCA Models

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

Many in the field of social work and related applied social sciences have little exposure to artificial intelligence outside of 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 that is capable of making "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 these data may change. The most common example of a planning algorithm which 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 consider the uncertainty present in these networks (Rice, 2013). In general, adolescents and young adult relationships change rapidly – new connections form, dissolve, and grow closer over short periods of time, (Arnett, 2000; Arnett, 2001). Homeless and unstably housed youth lives are by definition transient, further complicating already developmentally fluctuating networks (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 one-month period of time 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 12 months. We found in Hollywood, that on average, 43% of the population remained stable over a six month period of time (44% were included in panel 2 who were seen in panel 1, 42% who were included in panel 3 were seen in panel 2) and in Venice Beach, only 16% of the population remained stable over six months (18% stability to panel 2, 14% stability to panel 3) (Rice, 2013).

To make matters even more complicated, the collection of network data is difficult in any context and even more so from youth experiencing homelessness in community settings (Petering et al., 2016; Rice et al., 2014; Yoshioka-Maxwell & Rice, 2017). Most social network data collection relies on "free recall" (i.e. persons list out their social connections) or from responding to rosters of a population (e.g. persons are shown classroom roster and asked to nominate important persons). Rosters are more accurate, but 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 (e.g. Brewer (2000) for a review of these methodological issues). The AI work which informs this intervention explicitly models the uncertainty within these networks, allowing for social network data to be treated as probabilistic in nature not deterministic. We believe any "real world" network data should not be treated as "ground truth" but rather a best guess, much as Google maps treats traffic predictions not as truth but as well-informed predictions based on prior data collection.

As a final note in introducing AI planning algorithms into the world of social work science, we feel it is important to point out that the computer science work which undergirds this intervention implementation has been rigorously vetted by the peer review process in computer science. Two of the three most competitive and rigorous publication outlets in the field of artificial intelligence are the published conference proceedings of the American Association for Artificial Intelligence (AAAI) and the International Conference on Autonomous Agents & Multiagent Systems (AMAS). The computational experiments that utilized 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 computational experiments. The aim of this pilot study was to see if 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 PCA and other youth in the population.

METHODS

Research Design, Sampling and Recruitment

All study procedures were approved by the [blinded for review] institutional review board. This is a quasi-experimental, two-group, pre-test/post-test design, drawn from two unique networks of youth experiencing homelessness. The two networks of youth (aged 16–24) were collected from the same drop-in center where youth were seeking basic services (e.g., food, clothing, case management, mobile HIV testing site). The first network was recruited in February of 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 youth to replace prior clients. Prior work at this space has 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 exact same service environment (Rice, 2013). First, 62 youth were recruited for testing the AI PCA selection method; 6 months later 55 youth were recruited for testing the comparison group, using the standard PCA selection method of "the most popular" youth. Specifics of PCA selection follow the description of the intervention delivery model. All youth receiving services were eligible to participate and were informed of the study as they entered the drop-in center. In both conditions, the youth were recruited by a set of two consistent study staff. This insured that no youth were included in both study arms. The small number of youth still accessing the drop in center at the time of the second recruitment period 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 the long-term experience of many members of our team in working with youth experiencing homelessness, both in the context of research and service delivery. The intervention design was also informed by multiple theories including RAAM, which combines elements of ecological theory (e.g. Brofenbrenner, 1977) and social learning (Bandura, 1986) but which is specific to the context youth experiencing homelessness (Milburn et al., 2009). We also relied on diffusion of innovations (e.g Rogers, 1994) and a positive youth development model (Catalano, Berglund, Ryan, Lonczak, & Hawkins, 2004).

It was critical that the intervention be crafted to meet service environment and the context and capacity of youth in that environment. We intentionally developed an intervention for youth experiencing homelessness who access drop-in services. Drop-in service centers, are safe havens for youth experiencing homelessness 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, by far the most important contextual consideration was the need to develop a short and flexible intervention delivery model. Drop-in centers are spaces where youth visit intermittently as they perceive a need for those services. Attendance at drop-in centers can vary widely (Rice, 2013) and is subject to the transience and instability of the lives of youth experiencing homelessness. Youth experiencing homelessness have unpredictable and constantly changing schedules, especially due to instabilities of housing and employment (Fest, 2013). 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 suggested that brief adaptations of longer interventions are just as effective in changing behavior (Morrison, Goolsarran, Rogers, & Jha, 2014). The primary intervention training was designed to be implemented for approximately 4 hours, during one half day. The training has two goals: educating PCA about and sexual health risk reduction and promoting personal development. The initial training was supported by 7 weeks of follow-up "check-in" sessions. These sessions lasted approximately 30 minutes and focused on positive reinforcement of the PCA for their 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 population of youth, the "check in" schedule was flexible and PCA could check in individually with the facilitator at a different time via phone or text. All PCA attended at least one "check in", modal attendance was 5 sessions.

In both conditions, PCA were recruited over a three week period. Each training session was limited to 4-5 youth. To achieve the desired total number of PCA in the network, three subsequent weekly training with a small group of youth were conducted. In both conditions, 11 total peer leaders were trained. Training was delivered by 2-3 facilitators who were PhD students with MSWs or MSW interns. Training was interactive and broken into six 45-minute-long modules on: The mission of PCA, sexual health, HIV prevention, communication skills, leadership skills, and self-care. PCA were asked to focus their communications on their social ties, particularly other youth at the drop-in center, and to promote regular HIV testing, and condom use. Youth were encouraged to focus on face-to-face interactions if possible, but to use social media as well. The training was designed to be engaging and include a variety of learning activities including group discussion, games, journaling and reflection, experiential learning, and role-playing. The training minimized lecture based learning. The small group setting was critical for maintaining a safe and manageable space for youth to learn and reflect. Further, the training was developed to be an empowering experience for the PCA. Consistent language was used throughout to reiterate the participant's role as a leader within their community. PCAs received $60 for the training and $20 for each "check-in" session.

<u>Two Methods of PCA Selection</u>

Regardless of PCA selection method, social network data is used as the basis for selecting youth. A Facebook app collected network data regarding which participants were connected to one another, i.e., friends. Only information about individuals who were study participants was collected by the app, which did not appear on their Facebook profiles in any way. These data were augmented by field observations collected by the research team during the 2 weeks of recruitment, based on which participants who were observed by study staff to regularly interact with one another. The network data collected from Facebook and from field observations by the team was compiled into a network data set which was used as input into 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 PCA. 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 a PCA is 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 persons, 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. Thus, to find a specific solution, the algorithm works by parsing the large network of youth into subnetworks of highly interconnected youth and selects a specific set of PCA from within each sub-network who can theoretically maximize influence in these sub-networks. The final peer selection within the sub-communities is achieve by using what is referred to as Partially Observable Markov Decision Processes.

Comparison Group PCA Selection

In the second network, popularity as defined by degree centrality was used to select PCA -- that is, the 20% of youth who have the greatest number of ties to other youth were recruited

(Valente & Pumpuang, 2007). This is the most straight forward operationalization of selecting the "most popular" youth, 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 one month follow up interview which was conducted immediately after the PCA were trained and initially deployed, and a follow up 3 months post baseline which was conducted after the 7 weeks of "follow up" sessions provided to the PCA. 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 youth were surveyed again at the drop in center. Approximately 10% of follow up surveys were conducted online, as some youth left the area or discontinued using drop in services. For these youth a link to an online survey was sent via text or email 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 sex 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, in the last 6 months, and those who have 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 in order to examine the age, race, gender, and sexual orientation of the 2 treatment conditions, and to visually examine differences in demographic characteristics between the 2 conditions, separated by PCA and non-PCA youth. Frequency distribution in outcomes by condition and PCA status are presented.

RESULTS

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

[INSERT TABLE 1]

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, the majority of youth identified as White with the second largest group being Black/African American, across conditions. The majority of participants for both groups identified as male. Nearly half of participants identified as heterosexual, followed by bisexual. PCA, likewise, show similar demographic profiles as the non-PCA youth. The one exception worth noting is that in the comparison group 45% of PCA were Latino relative to only 14% of the target youth.

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

[INSERT TABLE 2]

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, 74.3% in the AI condition had a recent HIV test by 1 month relative to 63.0% in the comparison condition. At three months, 71.4% of non-PCA in the AI condition reported a recent HIV test relative to 50.0% of youth in the comparison condition. For PCA the trend is similar but the rates are higher among PCA in both conditions. Condom use during both anal sex and vaginal sex show a similar pattern over time. At one month, the comparison condition youth show reported more condom use, but at three months this trend reverses and youth in the AI condition report more condom use. Among non-PCA youth, 50.0% of youth report using condoms during anal sex at one month relative to 57.1% in the comparison condition. At three months 72.7% relative to

60.0% of youth in the AI versus comparison conditions reported condom use. Among non-PCA youth, 56.7% reported condom use during vaginal sex at one month in the AI condition relative to 68.4% in the comparison group. At three months, 71.4% of non-PCA youth reported condom use relative to 61.5% in the comparison group. The direction of this effect is the same among PCA, yet PCA in both conditions reported less condom use than non-PCA youth.

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

DISCUSSION

A PCA model is a feasible means for HIV prevention targeting youth experiencing homelessness. In both conditions, there was an increase in recent HIV testing and condom use. This pilot study also demonstrates that the method of selecting PCAs appears to be a critical factor in the likely efficacy of PCA-based prevention. Utilizing Artificial Intelligence in selecting PCAs is not only feasible but 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 popularity condition. Results from this pilot study demonstrate the possibility of implementing AI–enhanced PCA models to increase efficiency, reduce resource burden, and resource redundancies in targeted information dissemination.

Our findings should be interpreted with caution as the purpose of this study was both 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. Findings support previous research on PCA models as an effective strategy for HIV prevention for many at risk populations (e.g. Medley et al., 2009). We believe that the observed differences in the changes between the AI arm and the comparison arm suggest that selection methods for PCA was a critical component of overall intervention success. We are encouraged by these findings and by the fact that the using Artificial Intelligence 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 that were invited to participate in the intervention were connected to each other and to similar if not the same persons in the network. Further, facilitators noticed a marked difference in the training sessions between the two groups. When PCAs were selected using AI, versus their popularity, training sessions included diverse sets of young persons from different social circles. Many of those that were selected did not interact with one another before the training which allowed for more successful bonding with training facilitators, focus on work, and community building amongst the PCAs.

We have come to explain these results with the metaphor of the “Breakfast Club” versus the “high school football team.” In the case of the popularity/degree centrality condition, what we observed was something akin to if we had selected most of our PCAs from the football team in a typical high school. These 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. It also made it such that their existing interpersonal status dynamics were at play during the intervention sessions, which reduced their capacity to bond with facilitators and become less motivated to engage in health advocacy work.

In the case of the AI algorithm, which explicitly parses the social space into sub-communities and then looks for PCA in each of those communities, we experienced something akin to the 1985 film “The Breakfast Club.” In that film five youth from different social circles, the nerd, the stoner, the jock, the princess, and the goth come together for a day long detention. They bond with one another outside the context of their typical social relationships and then at the end of the movie return to their respective social circles. In the context of the AI selected PCAs, we observed this very same dynamic. Youth 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 unearthed is the need to disaggregate a larger social space into smaller sub-networks and then select PCAs from across these smaller social spaces. This approach both "spreads the wealth" of where PCA are located in social space and also allows for more productive intervention dynamics when working with high risk youth who are often difficult to manage in small group settings, particularly if their existing relationships with one another can interfere with bonding with interventionists. We believe that the success of Valente's peer-driven model for smoking prevention (Valente et al., 2003) or Amirkhanian's model for HIV prevention (Amirkhanian et al, 2003) are likely due to having stumbled upon similar solutions in each of those cases. AI, however, was particularly beneficial to us in the planning process because we were able to see that this segmentation approach yielded higher expected returns to intervention deployment in the initial computational experiments. Then, once the team was out in the field testing this approach, we were able to observe the interpersonal dynamics between youth which were activated and successfully exploited by this set of decision rules.

Lastly, anecdotally, participants enrolled in the study as well as 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 which selected youth, 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. We are also working to try to reduce the network data collection burden by experimenting with algorithms which do not rely upon complete network data (Wilder et al., 2017)

This study has a few limitations which 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, non-randomized design, which is typical in PCA models (e.g. Kelley 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). Retention rate was somewhat lower that what has been reported in other studies involving longitudinal follow up of youth experiencing homelessness (Rotheram-Borus et al., 2003; Milburn et al., 2009). 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 youth recruited from shelter services (Rotheram-Borus et al., 2003). Drop-in center attending, youth with chronic experiences of homelessness are far more difficult to track and retain. Indeed, Bender and colleagues (Bender et al., 2016) who worked with a similar drop-in based population had similar follow-up rates. We had a 6% higher attrition rate in the comparison arm. 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 versus 64% among those lost).

Conclusion

We believe that these initial findings serve as a “proof of concept” in 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, our computational experiments which preceded our fieldwork suggested that degree centrality would outperform random assignment, but underperform relative to greedy approaches, which would underperform relative to HEALER (Yadav et al., 2015). Thus we were able to discard two possible selection mechanisms, favoring a test between the standard in public health (e.g. 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. We believe that there are some features of AIS that are worth noting, from the perspective of both computer science and social work science. First, we believe that this work is typically focused on communities who are marginalized and lack resources, making intervention mistakes all the more costly. Second, unlike many machine learning contexts, AIS usually operates in conditions wherein there is a dearth of data and there is much uncertainty that must be modeled. In this study, that uncertainty focused primarily on what the actual structure of the network might be and who exactly is being reached at any given point in time. Third, the decisions of persons 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. We must work diligently to capture in these computational models, simulations of people's behaviors that take into consideration the complexity of what is known by social work science to be motivations for action in that specific context and what are 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 not merely the interests of the interventionists. Modelling 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, utilizing AI and computational experiments so as to improve the speed of implementing the most effective interventions for high-risk, marginalized populations.

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Table 1: Demographic and baseline behavioral profiles of youth, by PCA and non-PCA, by treatment condition

	Non-PCA				PCA			
	AI Condition		Comparison		AI Condition		Comparison	
Race	n	%	n	%	n	%	n	%
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 to 3 months ago	10	19.6	9	20.9	2	18.2	4	36.4
3 to 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

Table 2: Outcomes at one-month and three-month follow up,

	AI Condition		Comparison	
All Youth (PCA and Non-PCA)	n	%	n	%
Recent HIV Testing at 1 month	36	78.3	25	68.4
Recent HIV Testing at 3 month	30	76.9	18	60
Condom use anal sex at 1 month	11	42.3	12	63.2
Condom use anal sex at 3 month	11	55	7	50
Condom use vaginal sex at 1 month	22	56.4	18	69.2
Condom use vaginal sex at 3 months	19	67.9	10	52.6
Non-PCA				
Recent HIV Testing at 1 month	26	74.29	17	62.96
Recent HIV Testing at 3 month	20	71.43	10	50
Condom use anal sex at 1 month	9	50	8	57.14
Condom use anal sex at 3 month	8	72.73	6	60
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 month	10	90.91	8	80
Condom use anal sex at 1 month	2	25	4	80
Condom use anal sex at 3 month	3	33.33	1	25
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