Mobile Phone Assessment in Egocentric Networks: A Pilot Study on Gay Men and Their Peers

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Abstract
Mobile phone-based data collection encompasses the richness of social network research. Both individual-level and network-level measures can be recorded. For example, health-related behaviors can be reported via mobile assessment. Social interactions can be assessed by phone-log data. Yet the potential of mobile phone data collection has largely been untapped. This is especially true of egocentric studies in public health settings where mobile phones can enhance both data collection and intervention delivery, e.g. mobile users can video chat with counselors. This is due in part to privacy issues and other barriers that are more difficult to address outside of academic settings where most mobile research to date has taken place. In this article, we aim to inform a broader discussion on mobile research. In particular, benefits and challenges to mobile phone-based data collection are highlighted through our mobile phone-based pilot study that was conducted on egocentric networks of 12 gay men (n = 44 total participants). HIV-transmission and general health behaviors were reported through a mobile phone-based daily assessment that was administered through study participants' own mobile phones. Phone log information was collected from gay men with Android phones. Benefits and challenges to mobile implementation are discussed, along with the application of multi-level models to the type of longitudinal egocentric data that we collected.

Keywords: Gay men, HIV risk behaviors, mobile phone log, ecological momentary assessment, ohmage

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1. Introduction

Mobile phones are by nature social devices as highlighted by numerous studies on the structure of mobile communication networks (e.g., Onnela et al., 2007; Ye et al., 2008) and individual tie strengths (Zhang & Dantu, 2010). Most studies have analyzed sociometric data where large and bounded networks are observed. In contrast, egocentric networks of individuals, i.e. *egos*, and their peers, i.e. *alters*, have received less attention. In part, the focus on sociometric data may be due to the availability of "safe" data sets that are collected in laboratory settings, often on faculty and students where privacy issues are less critical and participants are technologically savvy. A good example is the MIT Reality Mining data set (Zhang & Dantu, 2010).

Egocentric networks are often assessed in public health settings on marginalized populations, e.g. drug-using networks (Yang, Latkin, Muth, & Rudolph, 2013). Privacy is critical and "tech-savvy" assumptions may be unrealistic. Yet mobile assessment has been successfully carried out in cocaine-addicted homeless patients (Freedman et al., 2006) and other marginalized populations. Furthermore, mobile technologies can enhance data collection and intervention delivery in public health settings, e.g. ecological momentary interventions (Heron & Smyth, 2010). As we have found in our own transition from more traditional modes of data collection to mobile-based studies, an important part of the implementation process is a clear understanding of what mobile technologies can and cannot do. As noted by Lazer et al. (2009), researchers and institutional review boards (IRBs) alike need to be up to speed on the latest technologies in order to design and evaluate proper privacy and encryption protocols, respectively.

In this article, we highlight the benefits and limitations of mobile data collection through egocentric data that was collected to test the implementation of a mobile phone-based health assessment in a sample of 12 gay men, i.e. *egos*, and their peers, i.e. *alters*. Both egos and alters used their own phones to fill out a health assessment and enter sensitive information on HIV-transmission behaviors. We collected phone-log data from a subset of the egos with Android phones in order to compare mobile communications with alters in the study and with individuals who did not enroll in the study. Therefore, our study provides a good opportunity to discuss privacy and ethical issues that are central to public health settings.

We also give examples of research questions and analytic strategies that are afforded by the collection of mobile data in an egocentric study. A key feature of our data is the three levels of hierarchy. Egocentric data normally contains two levels where individuals (both egos and alters) are nested within egocentric networks. Multi-level models are applied and contain random effects for each network to allow mean levels of the outcome to differ across networks (e.g., Hall, 2010; Rice et al., 2009; Snijders, Spreen, & Zwaagstra, 1995; Valente, 2010). In our study, participants filled out an end-of-the-day mobile assessment over a month; repeated observations are nested within individuals. We discuss extensions to the basic multi-level model to analyze longitudinal egocentric data. It is important to note that longitudinal data in our study resulted from daily reporting which is a course version of ecological momentary assessment (EMA) where events are recorded as they occur in situ. EMA also involves a large number of repeated measurements and depends on careful timing, e.g. several times a day, to capture variations in behavior within days (See Shiffman, Stone, & Hufford, 2008, and Stone and Shiffman, 1994, for overviews). In contrast, standard assessment methods rely on retrospective recall where study participants are asked to report on behaviors over a period of time and are often interviewed in a clinical setting. EMA minimizes recall biases that are intensified as individuals reconstruct and retrieve events from their memory over longer periods of time. By self-administering assessments, EMA may also reduce interview bias, e.g. in giving socially desirable responses to sexual behavior questions (Kissinger et al., 1999).

2. Data and Methods

2.1 Participants

Recruitment was conducted online (Figure 1). From April to August, 2013, 455 egos were recruited through pop-up messages on *Grindr*, a dating website for gay men, and postings on *Craigslist* that directed them to a study webpage. *Craigslist* is an online forum for classified ads.

The study webpage directed egos to online screening and consent forms that were hosted by *SurveyMonkey* (http://www.surveymonkey.com/). Study eligibility required egos to 1) self-identify as a gay or bisexual man; 2) be at least 18 years old; 3) live in Los Angeles County; 4) use a web-enabled Android phone, version 2.3 or higher (issued after November 2010), or an iPhone; 5) use their mobile phone to participate in the study; and 6) recruit at least 3 alters who had an Android or iPhone they could use to participate in the study.

Out of 455 egos who started the online forms, 19% were not eligible (n = 85) and 37% did not finish filling out the forms (n = 167). It is hard to know why

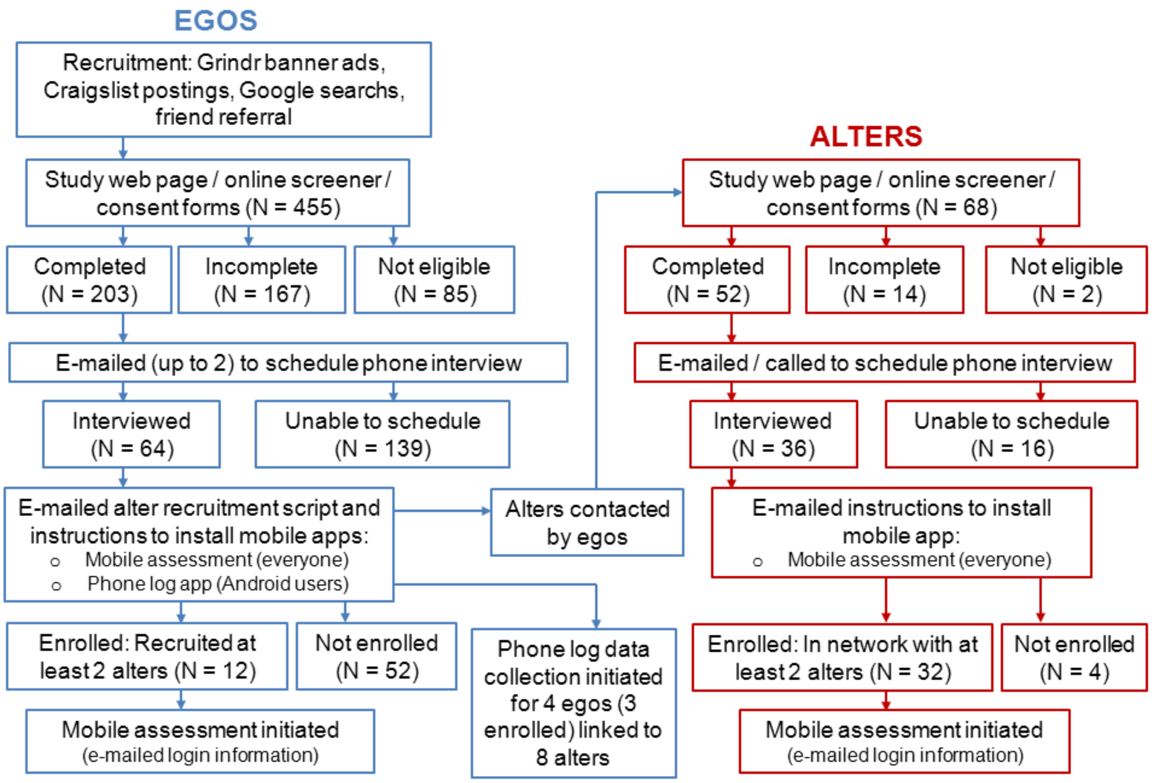

Figure 1: Recruitment and enrollment of egos (gay men) and alters and initiation of mobile phone-based data collection.

so many individuals did not finish filling out forms. In at least one instance, a peer started to fill out the forms on their mobile phone, lost internet connection, and did not attempt to re-initiate the forms.

Eligible egos (45%; n = 203 of 455) were e-mailed to set up a one-time telephone interview and also received instructions on how to install and use the study mobile apps; calls were scheduled with 64 egos. During the call, we administered a demographic and social network assessment. *Grindr* banner ads were the primary recruitment source (n = 53 of 64 telephone interviews).

After the telephone interview, egos were sent an e-mail template they could send to alters they wished to invite into the study. The e-mail template contained a link that directed interested alters to a separate study webpage and in turn, online screener and consent forms. The online form asked alters to enter the first name and phone number of the ego who recruited them so we could construct ego-alter links. Eligible alters fulfilling 2), 4), and 5) were contacted and administered a demographic assessment. We relaxed the requirement for egos to recruit 3 alters and allowed egos and alters to participate if at least 2 alters per egocentric network were recruited. Out of 64 egos who completed a telephone interview, roughly 1 in 5 recruited at least 2 alters and enrolled in the study (n = 12 of 64; Figure 1). We did not follow-up with unenrolled egos to find out the reason. One ego let us know that his friends did not want to join and "share private information".

Out of 68 alters who started the online screener, 75% (n=51) completed the screener and provided contact information to schedule an interview. Thirty two of 36 alters who were interviewed by telephone enrolled in the study.

Egos and alters were e-mailed Amazon gift card activation codes worth \$60 and \$50, respectively, at the end of the study as incentives. Egos and alters who were the most compliant in filling out the daily health assessment were entered into a drawing to also receive an Amazon gift card activation code worth \$100. All study procedures were approved by the Institutional Review Board at the University of California, Los Angeles.

2.2 Data collection

Telephone interviews were conducted at the beginning of the study prior to the start of the mobile phone health assessment. Egos were queried on where they heard about the study, the model of the mobile phone they would be using during the study, age, and ethnicity. Alters were queried on their relationship to the ego who recruited them, gender, age, ethnicity, whether or not they lived in Los Angeles County, and their sexual orientation. During the telephone interview, egos were also administered a 9-item adapted version of the Arizona Social Support Inventory (Barrera & Gottlieb, 1981) to elicit names of people with whom the respondent socializes, lives, eats meals, has sex, does alcohol and drugs, receives health advice, calls upon for material and emotional support, or any other people who were important to them that had not been prompted by the prior name-generator questions. After the 9-item inventory, we asked for names of alters the ego was planning to ask to join them in the study. Almost all of the egos who enrolled in the study recruited at least one alter who had not been prompted by the 9-item inventory (n = 10 of 12). We calculated the size of each egocentric network based on the number of names generated by the 9-item inventory. Seven of the 64 egos gave "other" responses that encompassed multiple people, e.g. "family", and were excluded from the network-size calculation.

Phone logs were recorded through *SystemSens* (http://systemsens.ohmage.org), an Android application that was designed to collect passive system data and developed through the UCLA Center for Embedded Networked Sensing. Egos with Android phones were asked to download *SystemSens* to their mobile phone through an e-mail link. Once installed, *SystemSens* automatically encrypted and uploaded phone-log data (including phone numbers, the duration, and date / time stamp of incoming and outgoing calls and text messages) to servers at UCLA whenever the user charged their phone. To protect the identity of phone numbers belonging to individuals who were not enrolled in the study, all phone numbers in the phone log were scrambled using SHA-256, a cryptographic hash function published by the National Institute of Standards and Technology. There are several notable features of SHA-256. Hashed numbers appear as unique 256-bit values, e.g. "b8475260a8bdd4af2984d7d7d8eb9b5a". As a result, one is able to identify if two hashed numbers are of the same phone number. However, it is nearly impossible to recover the original phone number from a hashed number alone. The original phone number is necessary to act as a key that unscrambles the hashed number and verifies the original number.

Mobile phone assessment. All participants (both egos and alters) were asked to fill out the same daily assessment on their mobile phone for a month. Assessments were launched using the *ohmage* application (http://www.ohmage.org), an open-source application that is compatible with Android and iPhones. *Ohmage* allows for assessments to be rapidly authored using the Extensible Markup Language (XML), and allows data to flow from participants' mobile phones to a centralized database. In this study, *ohmage* was launched with an HTML5 application implemented using the Mobile Web Framework (MWF). The application runs on both Android and iPhones and is available for download from the Google Play and Apple app stores, respectively. A version of *ohmage* that is native to Android phones has been implemented in prior studies (Swendeman et al., 2014); feedback from focus groups on prior mobile studies informed the design of the mobile assessment (Ramanathan et al., 2012). Once installed, participants accessed the mobile asssessment through the *ohmage* dashboard shown in Figure 2A. At the end of each assessment, responses were encrypted, uploaded to servers at UCLA, and removed from the user's mobile phone, as long as there was network connectivity and the phone battery was not low. Responses could also be manually uploaded at a later time.

Mobile phone assessment consisted of 14 questions that participants were asked to fill out at the end of the day for a month. Questions encompassed the

Table 1: Frequency of communication with alters based on ego reports (includes face-to-face, telephone, and social media contact) and based on the number of days between phone log calls/ text messages between egos and alters

				Call logs	
Ego	Alter	Alter relation	Self-report	Median days	Range
1	1	Partner	Daily	1	1-3
	2	Friend	Once a week	2.5	1-13
	3	Friend	Once a week	7	2-9
2	1	Boyfriend	Daily	1	1-5
	2	Friend	Daily	1	1-2
3	1	Partner	Daily	8.5	7-10
4	1	Ex-boyfriend	3.5 times a week	1	1-7
	2	Sister	Daily	1	1-5

following domains in the following order: (a) An adapted version of the Healthy Days Symptoms Module from the Health-Related Quality of Life instrument (HRQOL; Centers for Disease Control and Prevention, 1995), including 5 questions on mood, worry, sleep, energy level, and impairment; (b) Daily minutes of exercise and type of exercise, e.g. "Jogging"; (c) Rating of one's daily eating, e.g. "Less healthy than usual"; (d) A food inventory that was constructed from multiple food inventories (e.g., Fulkerson et al., 2008; Kaiser et al., 2003; Sisk, Sharkey, McIntosh, & Anding, 2010) and designed to fit across two cell phone screens; (e) Sexual behavior, including the number of sexual encounters involving anal or vaginal sex, the number of encounters with "casual (including one-time and first-time) partners", and condom usage; and (g) Alcohol and substance use.

All questions included a "Refuse to answer" response option so that participants were not forced to answer any questions they did not want to. However, we did not want participants to repetitively select refusal responses in order to get through the daily assessment more quickly. We placed additional "speed bump" questions that required participants to specify why they refused to answer the prior question in two places. The first speed-bump question was placed after minutes of exercise were queried, and the second was placed after the number of sexual encounters was queried at approximately the halfway point and end of the assessment. No refusals were entered, except for the impairment question (1 refusal) and substance use (3 refusals).

3. Analytic Strategies and Results

3.1. Sample characteristics

Among egos who were interviewed over the telephone (n = 64), the average age was 30.8 years old (range = 18 to 58). Ethnicity was reported as African American (12.5%), Latino (34.4%), White (37.5%), or Other (15.6%). Egos reported a network size of 8.4 members, on average (range = 2 to 30). Networks were fairly homogenous with respect to age and ethnicity. For example, most of the White egos (n = 5 of 6) only recruited White alters. Half of the Latino egos (n = 2 of 4) only recruited Latino alters.

3.2. Call logs

Phone logs were recorded for four egos with Android phones. Logs began recording as soon as SystemSens was installed and continued until the end of the study that included the 30-day health assessment time period

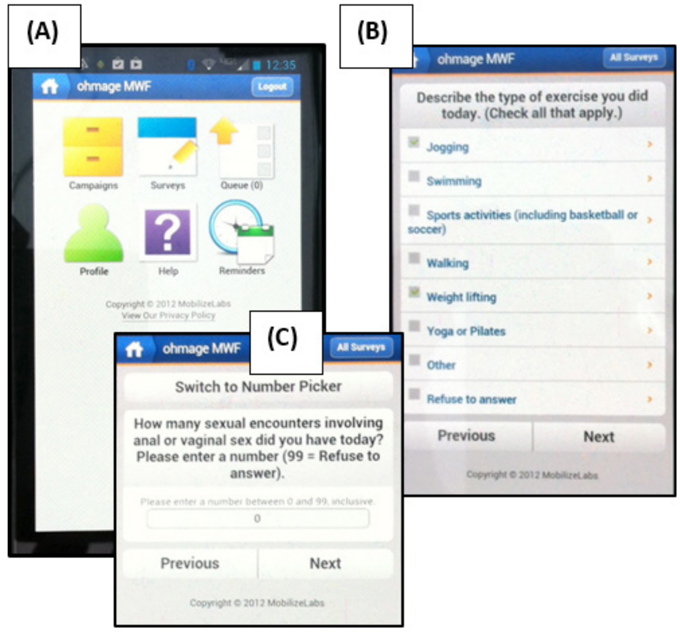

Figure 2: ohmage MWF screenshots showing (A) dashboard for accessing daily health survey and sample questions from the daily health survey, including a (B) multiple-response item and (C) an item requiring numeric entry.

(range = 20 to 45 days). One ego was only able to recruit one peer and dropped out of the study after 20 days. Similar to Onnela et al. (2007), we excluded one-way communications where calls or text from an ego to a phone number occurred, or vice versa, but were not reciprocated. By focusing on reciprocated communications, we eliminated communications related to single events where egos did not personally know individuals they were communicating with. Two phone log analyses are discussed.

Agreement between self-reported contact and phone logs. The frequency of contact with network members is typically self-reported by egos. Given the additional contact information provided by mobile communication (both calls and text messages), a natural question arises. Do phone logs provide overlapping information to self-reported contact or do phone logs provide additional information? Table 1 demonstrates a way to address this question by showing egos' self-reported frequency of contact with alters that was reported during the telephone interview and the median number of days between mobile communications with alters. Phone logs corroborate the self-reported frequencies fairly well. For example, four of five "daily" reports matched up with call logs where half of the communications occurred within a day of each other.

Alter closeness. There is a general understanding in social network research that observed networks in a study are incomplete. Social ties with individuals outside

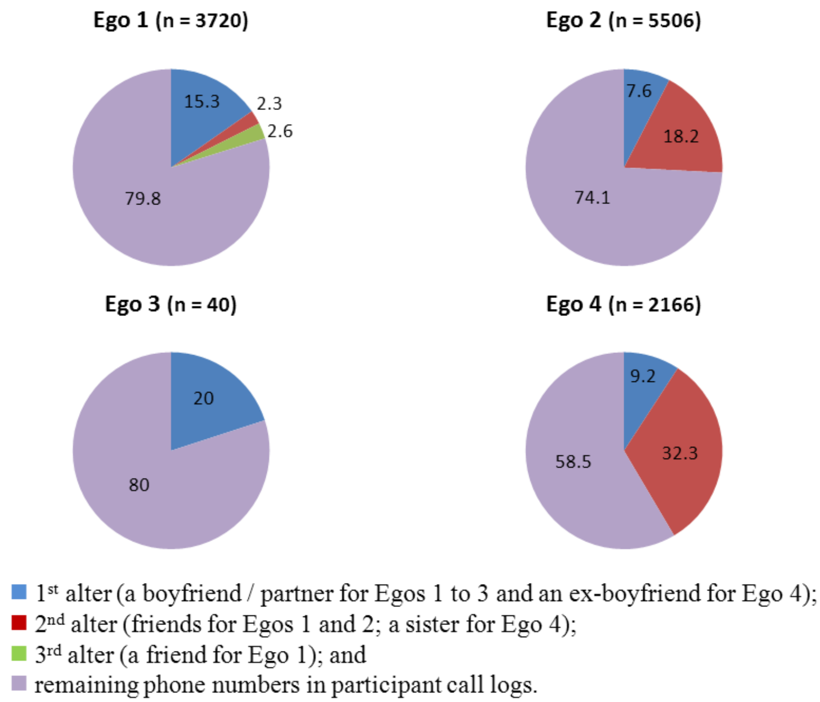

Figure 3: Percentage of (n) reciprocated calls or text messages:

the study network can sometimes be constructed by self-report (e.g., Fowler & Christakis, 2008), though this is typically not the case. Therefore, phone log communication data can fill in gaps on self-reported network compositions. In particular, we focus on the frequency of egos' mobile communications with recruited alters and individuals outside the study as a proxy for ego-alter closeness. Information on closeness with alters who are likely to be recruited into a study has the potential to inform the design of both social network-based interventions (see Valente, 2012 for a review) and recruitment strategies (e.g., respondent-driven sampling; Heckathorn, 1997, 2002). Figure 3 shows the percentage of communications with each alter and with the remaining telephone numbers in the phone logs. Among these four egos, we note that they recruited at least one alter they were in fairly frequent contact with, e.g. partners for Egos 1 and 3 (15.3% and 20.0% of the total communications, respectively).

3.3. Mobile health assessment

We discuss two types of multi-level regression models that address research questions specific to each level of hierarchy in a longitudinal egocentric data set.

Network-level questions. Holistic health approaches often track multiple and disparate measures of health. For example, le Roux et al. (2013) examined mental health, general health, and HIV-transmission behaviors. In this vein, we examined how multiple health behaviors and HRQOL cluster within networks. Due to the small sample size, an ad hoc approach was used. Responses for each individual were aggregated over their 30-day study period. We then fit separate multi-level models to each HRQOL or behavioral measure. Pearson product-moment correlations were then examined within the 12 pairs of network-level random effects between all possible pairs of HRQOL and behavioral outcomes. Correlations were in expected directions. For example, at the network level, there were negative correlations between numbers of alcoholic beverages and both mean levels of healthy feelings ($r = -.42$) and days of exercise ($r = -.50$).

A more formal modeling approach uses a bivariate-outcome multi-level model similar to Comulada et al. (2010, 2012). Here we consider longitudinal egocentric data with two continuous outcome measures, e.g. levels of mood and sleep. For individual i in network n at time point *t* and outcome *k* (= 1,2), a bivariate random-intercept linear model on continuous outcome y_{nitk} is expressed as

$$y_{nitk} = x_{nitk}'\beta_k + \lambda_{nk} + \eta_{nik} + \varepsilon_{nitk}, \qquad (1)$$

where β_k is a vector of regression coefficients for covariate vector x_{nitk} on outcome *k*. Correlations for each outcome within networks and across repeated observations within individuals are accounted for by random effects λ_{nk} and η_{nik}, respectively. Residual error term ε_{nitk} accounts for variance that is unexplained by the random effects. A key feature of the model is that correlations between outcomes are modeled through a variance-covariance matrix that is shared by random effects and residual terms across outcomes. In particular, cross-correlations can be examined between outcomes at different time points, e.g. the relationship between drug use and trust between egos and alters over several time points (Comulada et al., 2012).

Individual-level questions. Longitudinal studies typically entail a few time points. Analyses focus on mean changes over time, e.g. decreases in drug use. EMA in our study resulted in numerous time points (intensive longitudinal data; Walls & Shafer, 2006). In larger samples, changes in variability, as well as mean levels, can be examined using location scale models (Hedeker, Mermelstein, & Demirtas, 2008; Hedeker, Demirtas, & Mermelstein, 2009). For example, Hedeker, Demirtas, & Mermelstein (2009) examined mood fluctuations in smokers over time.

4. Discussion

Our mobile phone-based pilot study on egocentric networks of gay men and their peers highlights a number of benefits that are scalable to larger studies and other populations.

First, recruitment and implementation of the study was carried out without in-person visits with study participants. Second, participants used their own mobile phones, which alleviated the need to carry another electronic data-entry device. Both features served to reduce participant burden and study costs that are associated with traditional studies, e.g. interviewers were not needed. A degree of anonymity was also provided for participants, which may be an important issue for marginalized populations.

Past EMA studies have typically relied on paper diaries that are prone to backfilling (Stone et al., 2002, 2003). Palm top computers address this issue, but still introduce a degree of user burden that can be attenuated by making use of an individual's own mobile phone. An important feature of our study, in terms of data quality, was the ability to visualize uploaded mobile assessment data through a website portal in near real time. Research staff checked the data every few days. In one instance, no data was observed for an alter after initial study enrollment. Telephone contact with the study participant revealed that they were accidentally preventing their assessment data from being uploaded to the study team. The problem was easily corrected, and only a few days of data were lost.

The strength of our technologically-driven study design is also an obvious limitation for implementation in other populations. In studying egocentric networks of gay men who use *Grindr* and live in Los Angeles, we focused on a fairly tech-savvy population. Furthermore, gay men in Los Angeles are often targeted for HIV-related studies, especially through *Grindr* (e.g., Rendina et al., 2014). At enrollment, a number of our study participants were already familiar with standard study protocols. These characteristics facilitated the use of online recruitment and mobile assessment. Using these tools would be more difficult in other populations where study details are better explained in person and where study participants may be more reluctant to enter sensitive information during a survey, especially on an electronic device. Few concerns were voiced by participants in our study. Online recruitment may be unethical in populations were a language barrier is present, and online consent forms may be easy to click through without understanding the content.

Despite the technological savvy of our population, three main limitations remained with our study design. Approximately half of the eligible gay men who clicked through our *Grindr* banner ad and initiated the online forms, completed the study participation forms (55%; n = 203 / 370; Figure 1). This percentage is similar to initial participation rates that were found in another study that recruited gay men through *Grindr* and asked them to fill out a one-time online survey (43%; n = 2175 / 5026; Rendina et al., 2014). A big difference between Rendina et al. (2014) and our study is that they retained 27% of the initial gay men in their analysis sample. We retained 12 egos (3%) in our study. Increasing rates of online recruitment offers potential participants a smorgasbord of studies to select from. Moreover, there is less buy-in when shopping amongst online studies.

For example, rapport may be established with a recruiter during recruitment in a clinic. Online recruitment may be best suited for studies offering instant participation. Recruitment through Grindr reached gay men with risky sexual behavior profiles as intended; Nineteen percent of interviewed gay men reported anonymous / one-time sex partners in their network during the telephone interview (n = 12 of 64). Yet only one of the 12 (8%) enrolled gay men had reported anonymous partners. Though not statistically significant, this percentage drop suggests that an online forum that attracts users with a targeted behavior is not necessarily a good recruitment source.

Another limitation was our restriction of phone-log data collection to Android users. In our study, the majority of participants were iPhone users, e.g. 64% of egos and 70% of alters who filled out online forms. iPhone users tend to have other iPhone users as friends (Canright, 2013). Android and iPhone users also tend to have different demographic and social characteristics (Albanesius, 2011). Phone log-based inference that is based on one type of mobile phone is likely to miss a segment of the population and be biased. Text message-based assessment that that does not require a smartphone may be a better option in other populations.

Lastly, lengthy assessments may call for larger computer screens and human interaction to encourage compliance. Our mobile assessment could be taken in a few minutes. Questions contained a few response categories and mostly fit on one screen. This may partly explain high compliance in our study (a median of 24 days of reporting).

The benefits and challenges in our study support a marriage of traditional and new data collection methods that is likely to remain in social network research. Visual web interfaces that allow participants to construct their own personal networks through a self-administered social network inventory have met with limited success; an interviewer may still be necessary (Matzat & Snijders, 2013). Moreover, one mode of electronic communication may not adequately capture social interaction (Quintane & Kleinbaum, 2011). That is why we assessed the frequency of ego-alter contacts through self-report and mobile communication. Despite the challenges of incorporating new technologies into research, the social dynamics of mobile devices and social media are difficult to ignore. It is hard to fully understand the dynamics of health-related behaviors without them.

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