RDS has focussed primarily on estimating population means and proportions (Yauck et al., 2022).

Bootstrapping Methods

Sampling procedure

We selected our first wave of participants nonrandomly by convenience sampling. Mobile phone numbers were used both to identify seed participants and to act as a unique identifier for those whom they referred.

We used the publicly available ‘Neighboot’ bookstrapping procedure to estimate confidence limits from our sample (Yauck and Moodie, 2020). Bootstrapping contributes to overcoming the high degree of uncertainty surrounding estimates from samples generated through respondent-driven sampling and allows better statistical inference, especially related to sampling variability (Baraff et al., 2016). These authors develop a multi-level tree bootstrapping procedure based on resampling recruitment trees that depends solely upon the structure of the sampled recruitment trees rather than the attributes being measured on the respondents. This allows estimation of variability and correlations between attributes. Their tree bootstrap method can produce interval estimates that are able to account for the high variability of the RDS process, even when the design effects are very large, producing estimates that are slightly conservative – which is preferable in this situation. The process involves a sample, without replacement from initial seed participants, followed by resampling from each of the selected seeds recruits and further resampling form second-level recruits’ recruits and continues until there are no recruits remaining (Baraff et al., 2016; Yauck et al., 2022).More recently, however, Yauck et al. (2022) have raised concerns that the tree bootstrapping method proposed by Baraff et al., 2016) severely over estimates uncertainty and, instead, propose a neighborhood bootstrap method to quantify uncertainty in RDS. This is designed to capture the ‘local’ neighborhood depdendence by including the selected recruiters’ recruits. Yauck et al., (2022) argue that this approach improves upon previously advocated approaches because the ‘local’ neighbors’ ties are present in any full, unobserved network of the target population. This method is particularly suitable for our study, since it offers computational efficiencies which yield confidence intervals with conservative coverages for small sample sizes and is based on resampling recruited individuals and their observed neighbors -defined as those individuals with whom they are directly connected within the RDS tree. Yauck et al.’s method relies on the following assumptions: i) social connections are reciprocal and ii) an individual within the network can reach another individual through a finite set of connections. Their bootstrap method is based upon sequentially resampling recruiters and their recruits and can be described in two main steps: step 1 involved the random selection, with replacement of the number of recruiters within the RDS sample. Step 2 then includes the selected recruiters and their corresponding recruits in the bootstrap sample.

The method allows the construction of calibrated interval estimates. Unlike other methods, the advantages of this approach include its ability to derive estimates from a single bootstrap sample for any number of attributes.

Limitations

Baraff et al. (2016)'s approach relies on a series of simplifying assumptions, namely: i) the social network is finite and connected ii) network connections are reciprocal, not directed [I believe this to be true of the respondents in our study] iii) recruits accurately report their network degree [this is facilitated by the concrete request to provide a count of domestic workers contacts within their mobile phone – thereby minimising recall error[iv) recruitment coupons are distributed uniformly at random to neighbours in the network [in our study, the research team managed the distribution of the survey link to those suggested by our seeds and respondents from earlier waves] v) that individuals may be recruited into the sample more than once. Baraff et al., note that this latter assumption particularly does not relate to the reality of RDS in practice.

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