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Balancing bias and burden in personal network studies

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ABSTRACT

Personal network data is increasingly used to answer research questions about the interplay between individuals (i.e., egos) and their social environment (i.e., alters). Researchers designing such data collections face a trade-off: When eliciting a high number of alters, study participation can be particularly burdensome as all data is obtained by surveying the ego. Eliciting a low number of alters, however, may incur bias in network characteristics. In the present study we use a sample of 701 Dutch women and their personal networks of 25 alters to investigate two strategies reducing respondent burden in personal network data collections: (1) eliciting fewer alters and (2) selecting a random subsample from the original set of elicited alters for full assessment. We present the amount of bias in structural and compositional network characteristics connected to applying these strategies for every possible network size (2–24 alters) as well as the potential study time savings as a proxy for respondent burden reduction. Our results can aid researchers designing a personal network study to balance respondent burden and bias in estimates for a range of compositional and structural network characteristics.

The interplay between individuals and their social environment is becoming an increasingly important topic in behavioural science research (e.g. Kinderman et al., 2020). With rising interest in research questions about how characteristics of individuals' social environment influence their traits, cognitions and behaviour, or vice versa, social network data, particularly personal network data, is frequently collected (e.g. Aschbrenner et al., 2018; Rapp et al., 2019) and utilised in various contexts.

While whole social networks map out the ties in a well-defined closed social system (e.g. a school class), personal networks, also termed ego networks, contain information about one person's direct social connections (Perry et al., 2018). The central actor is termed the ego and the social connections are called alters. Rich data about the composition of the personal network (i.e. characteristics of alters and social relationships) as well as its structure (i.e. the ties between alters) is collected solely by surveying the ego (McCarty et al., 2019). A central concern in the literature regarding these data collections is the associated respondent burden (McCarty et al., 2007; Vehovar et al., 2008).

1. Respondent burden in personal network data collections

When providing social network data, an ego first has to list names of alters (see Marsden, 2014). Subsequently, information about the elicited alters is assessed by asking the ego so-called name interpreter questions. These questions refer to alter or tie attributes (e.g., gender, type of relationship with the alter, or closeness to the alter) as well as relations between the different alters, termed alter-to-alter ties (e.g., if alter X has contact with alter Y). Examples of such personal network survey questions can be found in Table 1.

Answering a large number of attribute and tie questions usually takes long and is repetitive. Therefore personal network data collections can be particularly burdensome for respondents (Vehovar et al., 2008). This can lead to compromised data quality (Hsieh, 2015; Manfreda et al., 2004; Matzat & Snijders, 2010). To lower respondent burden it is important to design an efficient and easily understandable survey (Manfreda et al., 2004; Vehovar et al., 2008).

An important development in the field is the use of graphical features (Hogan et al., 2007; McCarty & Govindaramanujam, 2005; McCarty, Molina, et al., 2007) and an interactive survey design (Eddens, Fagan & Collins, 2017; Stark & Krosnick, 2017; Tubaro et al., 2014, Stulp, 2021). Such modern designs make the data collection process more efficient and attractive, for example by asking respondents to draw the alter-to-alter ties into a network representation rather than assessing each tie with an individual question (McCarty & Govindaramanujam, 2005). Respondents find these interactive survey designs with graphical interfaces easily understandable and more enjoyable than traditional

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Table 1
Personal network survey.

Item		Response format[a]
Name generator	"Please list 25 names of individuals 18 years or older with whom you have had contact in the last year. This can be face-to-face contact, but also contact via phone, internet, or email. You know these people and these people also know you by your name or face (think of friends, family, acquaintances, etc.). You could reach out to these people if you would have to. Please name your partner in case you have one. The names do not have to match perfectly; you can also use nicknames. It is important that you would recognise these names in a future survey. For this research it is important that you actually name 25 individuals!"	Type names
Alter attributes		
gender	male or female	click on alter
age	18, 19,..., 49, 50, 50 +	radio button
type of relationship[b]	partner, parent, siblings, other relative, relative of partner, acquaintance/friend of partner, from primary school, from college/university, from work, from a social activity, through a mutual acquaintance/friend, from the neighbourhood, and other	checkboxes, multiple answers possible
closeness	very close (= 1), close, somewhat close, not close, really not close (= 5)	drag alters into boxes
education	Primary school or hasn't finished primary school (= 1), High-school diploma (or a similar diploma), Secondary vocational education (or a similar diploma), Higher vocational education (or a similar diploma), University degree or higher (or a similar diploma) (= 5)	drag alters into boxes
frequency of face-to-face contact	Daily (= 1), A couple of times per week, A couple of times per month, About once a month, A couple of times per month or less (= 5)	drag alters into boxes
frequency of other forms of contact	Daily (= 1), A couple of times per week, A couple of times per month, About once a month, A couple of times per month or less (= 5)	drag alters into boxes
which of these people do you consider a friend?	friend or not a friend	click on alter
does alter X have children?	yes or no	click on alter
Alter-to-alter ties	"With whom does alter X have contact? With contact we mean all forms of contact, including face-to face contact, contact via (mobile) phone, letters, emails, texts, and other forms of online and offline communication. Select the individuals that have contact with one another by clicking on the circle. A line will appear that indicates that those individuals have contact with each other. Press the circle again to remove the line, if the individuals do not have contact with one another."	click on alter pairs to connect

[a] A visual illustration of the items and response formats can be found in Stulp, 2021.
[b] We considered only the proportion of kin and friends in our analyses.

assessment methods and they also seem to improve data quality by reducing mechanical answering behaviours (Stark & Krosnick, 2017; Tubaro et al., 2014). However, these approaches do not seem to reduce the survey completion time.

Besides improving the overall survey design, there are two main factors that influence the length and burden of the survey (1) the number of elicited alters and (2) the number and format of alter attribute questions. We will elaborate on these points below.

1.1. *The number of alters*

Increasing the number of elicited alters increases respondent burden in three ways. First, additional alter names need to be generated. This may become particularly burdensome when asking for large(r) networks (e.g., > 5 alters), as the time it takes to list an individual alter is longer for later alters (Stulp, 2021). Second, for each alter, all alter attributes need to be assessed. Therefore, the total number of questions increases linearly with the number of alters. Third, the potential ties between the different alters need to be indicated. The number of these alter pair evaluations increases quadratically with the number of alters.

Previous studies (Golinelli et al., 2010; Stulp, 2021) indicate that the name generation phase can be completed for a large number of alters (e.g. 25) relatively fast (in ~3.5 min). The increasingly large number and repetitiveness of alter attribute and alter-to-alter tie questions can, however, impose an additional burden besides mere time investment and may also lead to motivational loss (Hsieh, 2015). This can significantly decrease data quality (Manfreda et al., 2004). The number of assessed alters is also associated with study drop-out rates (Vehovar et al., 2008). Therefore, different authors advise to limit the number of alters included in the network (e.g., Gerich & Lehner, 2006; Manfreda et al., 2004).

1.2. *Alter attribute questions*

The way in which attribute questions are asked, matters: Assessing alter attributes question-wise rather than alter-wise reduces cognitive effort as well as study duration. In other words, respondents should be asked to rate all alters on one alter attribute rather than measuring all alter attributes for one alter at a time (Coromina & Coenders, 2006; Lackaff, 2012; Vehovar et al., 2008). Due to the lowered burden, this approach also increases data quality (Vehovar et al., 2008).

The number and response format of alter attribute questions evidently also impact respondent burden. For each additional alter attribute question, the question has to be answered as many times as there are number of alters. There are also great differences in the time needed to respond to the questions based on the format of questions. A recent study assessing personal networks with 25 alters by Stulp, 2021 indicates that with an interactive and user-friendly survey design, assessing 16 alter attributes is on average considerably more time consuming than the alter elicitation and the alter-to-alter tie assessment combined (15.2 versus 7.1 min). Simple questions, for example 'indicate alters that are friends', which only required clicking on respective alters, could be completed reasonably fast (~30 s for 25 alters). Other questions, such as how close the ego is to each of the alters, which required dragging each alter into a box, needed double the time to be completed (~1–1.5 min for 25 alters). Questions which required either the use of a radio button to indicate alter age or the evaluation of multiple check-boxes to indicate the type of relationship with the alter, took even longer (~2–3 min for 25 alters). Thus, in order to minimise respondent burden, the number of alter attribute questions in general, and of more demanding question types (e.g., how old is alter X?) and response formats (e.g., evaluating multiple check-boxes) in particular, should be kept to a minimum (McCarty, Killworth, et al., 2007).

2. The trade-off between respondent burden and bias in estimates

When considering only respondent burden, it is evident that the number of attribute questions and the number of alters in a personal network data collection should be limited. Besides burden, a researcher, however, also has to consider the potential for bias: While choosing a high number of alters to elicit may decrease data quality due to respondent burden, a number too low may lead to biased network estimates, although this depends on what type of network the researcher has in mind when eliciting names. Small personal networks certainly do not contain so-called weak ties (Granovetter, 1973) and potentially even some stronger social contacts are not included (Marin & Hampton, 2007). Therefore, the extent to which the assessed network represents the social environment of the ego can be distorted.

Hence, eliciting fewer alters can lead to biased estimates of both, structural (Costenbader & Valente, 2003; McCarty, Killworth, et al., 2007) and compositional network characteristics (Marin & Hampton, 2007). Structural measures hereby refer to statistics that are derived from the ties between alters, such as density, and compositional measures refer to statistics derived from attributes of alters such as the average age of alters. How strongly and in which direction these measures are biased, however, varies considerably, not only between compositional and structural measures, but also between measures within one category (Marin & Hampton, 2007; McCarty et al., 2007). Given that no reliable inferences can be drawn when using biased measures of network structure and composition, a balance needs to be found between the respondent burden, i.e., the study duration and repetitiveness mainly influenced by the number of alters in the study, and the bias incurred in estimates of network characteristics.

3. Overcoming the trade-off

A proposed strategy to reduce respondent burden without compromising estimates is to initially elicit a large number of alters in the name generation phase, but only assess alter attributes and alter-to-alter ties for a random subset of those alters (Manfreda et al., 2004; Marin & Hampton, 2007). Marin and Hampton (2007) termed this strategy multiple generator random interpreter (MGRI) and found first evidence for its effectiveness in obtaining precise estimates of network measures while assessing fewer alters (6 instead of around 13 alters).

McCarty and colleagues (2007) further tested four ways of reducing respondent burden in personal network studies: (1) eliciting fewer alters, (2) MGRI, (3) randomly selecting a subset of specific alter-to-alter ties for evaluation and (4) predicting alter-to-alter ties based on transitivity. Eliciting fewer alters (25 instead of 45) appeared to be a feasible strategy since 25 alters still sufficiently captured the structural network characteristics of their data. MGRI appeared to be an even more promising strategy, as it provided reasonable estimates of almost all measures with 45 generated names of alters but as few as 10 fully assessed alters. The remaining two strategies that McCarty and colleagues tested biased estimates severely and are therefore not recommended.

Golinelli and colleagues (2010) further investigated MGRI using a synthetic network with 20 alters to specifically quantify the bias of simulated structural measures (i.e. density, percentage of isolates, maximum degree and degree centralization) in terms of Root Mean Squared Error (RMSE) when assessing different network sizes (5–19 alters). From their simulation they concluded that the estimation error increases slower after at least half of all alters (i.e., 10–12) are sampled.

In addition, Golinelli and colleagues (2010) used data from a personal network survey of homeless women (see Ryan et al., 2009) to quantify the estimation error as well as the respondent burden in terms of study duration in 28 different networks. To obtain these 28 networks 20 alters were elicited, but 14 alter attribute questions and the alter-to-alter ties were only assessed for a random sample of 12 alters. Their results indicated that including alter-to-alter tie information of 12–19 alters led to up to 10% error of structural network characteristics, while the error sharply increased when including fewer than 12 alters.

4. This study

The current study adds to previous work by (1) using a representative sample, (2) investigating the burden (i.e., study time) connected to assessing alter attributes, the part of personal network data collection that is often the lengthiest, and (3) quantifying the amount of bias in compositional measures (in addition to structural measures), which are often key variables used in personal network studies.

Specifically, we use representative data from a sample of Dutch women of ages 18–41 and their personal networks (of 25 alters) to show the trade-off between the bias in structural and compositional network estimates and the number of alters that are assessed (Buijs and Stulp, 2021; Stulp, 2021; Stulp and Barrett, 2021). The two most successful strategies to reduce respondent burden identified by McCarty and colleagues (2007) are applied: (1) eliciting fewer alters and (2) MGRI, i.e. generating a larger number of alters (i.e. 25) but only assessing a random subset of them.

Additionally, estimated study time savings for slow, fast and average respondents connected to applying these two methods are presented. This information enables researchers to make informed decisions about minimizing the respondent burden of their personal network data collection while still obtaining sufficiently reliable estimates of structural and compositional network characteristics. We also present an interactive web-application, that can aid researchers in deciding on the number of alters to elicit and assess in their personal network survey.

5. Methods

5.1. Data

The current study uses data of a representative sample of Dutch women ($N = 758$; age range 18–41) and their personal networks with 25 alters obtained via the LISS (Longitudinal Internet Studies for the Social Sciences) panel (Scherpenzeel, 2011; Stulp, 2021). All women of the LISS panel between the ages 18 and 40 were invited to participate ($N =$ 1332), of which 758 filled-in the survey, 66 clicked on the invitation link, but did not complete the survey and 501 did not respond to the invitation. Respondents received a compensation of €12.50 for completion of the survey.

The personal network data was collected with a modified version of GENSI (Stark & Krosnick, 2017), a recently developed tool for assessing personal network data using interactive graphical elements. In addition to the elicitation of 25 alters, respondents were asked to answer 16 attribute questions about these alters, as well as evaluate the presence of all 300 alter-to-alter ties (i.e., each possible pairing of alters). For the present study only 9 attribute questions were considered, as these questions were deemed generalisable across different study contexts (see Table 1). A full description of the data collection procedure, the representative sampling of the LISS panel and the complete survey can be found in Stulp, 2021. Data will become available on https://www.lissdata.nl/.

5.1.1. Personal network data

For the present study participants were only included if they (1) filled in exactly 25 alters, (2) had no more than 10 missing responses on alter attribute questions, (3) completed the survey on a computer as instructed rather than on a phone or tablet (GENSI was optimised for use on computer), (4) listed alter-to-alter ties for at least three alters. These inclusion criteria resulted in a final dataset containing 701 personal networks.

5.1.2. Study duration data

Respondents who took breaks while filling out the survey can still provide valid network data, they, however, should not be considered when determining a representative study duration. Therefore, only respondents who completed the survey in one run were included for the duration calculations. According to analyses by Stulp (2021) this includes only participants who took less than 10 min per question (N = 646). Based on this subsample, we determined study durations of all parts for the average respondent, the 10th percentile (i.e., the 10% fastest respondents) and the 90th percentile (i.e., the 10% slowest respondents). The total study duration is composed of the time that it takes respondents to (1) generate all alter names, (2) answer the nine alter attribute questions, and (3) evaluate all alter-to-alter ties.

For the name generation, precise data indicating how long each ego took to name each alter was available. We averaged the duration for naming each separate alter across the 646 egos and added these durations to determine how long it took the respondents on average to name 1–25 alters. For example, to determine the duration for naming 2 alters the average time it took our respondents to name the first alter was added to the average time it took them to name the second one. The same procedure was followed for the 10% fastest and slowest respondents to give some sense of how the different strategies impact respondent burden for different groups of respondents.

For all name interpreter questions, only the total time that it took each ego to answer the respective question for all 25 alters was available (e.g., the time it took an ego to indicate the gender of all alters). In case of name interpreter questions for which respondents had to necessarily evaluate each alter separately (i.e., *gender*, *age*, *relationship type*, *closeness*, *education*, *contact frequency*, *alter children*, *alter-to-alter tie evaluation)* we determined the time for assessing one alter by averaging the duration of the given question across the 646 egos and divided it by 25. Therefore, we assume that answering the question took equally long for each alter. This time is then multiplied by the number of alters to determine the duration of this question for each sample size. For example, on average it took respondents about 28 s to indicate the gender of all 25 alters. From this we calculated that indicating the gender of one alter took about 1.12 s, for two alters 2.24 s and so on.

One name interpreter question (i.e., *indicate friends*) did not necessarily require separate actions for each alter. Therefore, assuming that it would take equally long to answer the question with respect to each alter is less realistic. For this question, the mean duration across egos for assessing 25 alters (i.e., 34 s) is taken regardless of the number of alters. This most likely results in an overestimation of the study duration when selecting fewer alters. Again, the same procedure was repeated for the 10% fastest and slowest respondents.

5.2. Network measures

The structural measures that we investigated are the most common measures used in the literature: network density, the proportion of isolates, maximum degree centrality, mean and maximum closeness centrality, mean and maximum betweenness centrality as well as degree, closeness and betweenness centralisation. Measures that are sensitive to the number of alters in the network were normalised according to Wassermann and colleagues (1994).

We investigated the compositional network measures summarizing the assessed alter attributes. The resulting measures fall into two categories: demographic composition and role relationships/tie characteristics. We used averages and standard deviations to summarise (approximately) continuous alter attributes and proportions for categorical alter attributes. In order to be able to compare characteristics measured on a different scale to each other, continuous characteristics were normalised to a scale from 0 to 1.

5.3. Simulating burden reduction strategies

All data preparations, simulations, analyses and visualizations were done using R (R Core Team, 2018). We used the following packages: broom (Robinson, 2014), ggraph (Pedersen, 2017), ggplot2 (Wickham, 2016), Hmisc (Harrell Jr, 2019), igraph (Csardi, 2013), knitr (Xie, 2014), lme4 (Bates et al., 2015), patchwork (Pedersen, 2019), tidygraph (Pedersen, 2018), tidyverse (Wickham, 2017) and skimr (Waring et al., 2020). All analysis scripts be found on DataVerseNL (https://doi.org/10.34894/JNVWNH).

We calculated all network measures using the full 25 alter networks. These estimates are considered the 'true' compositional and structural measures for the purpose of this study. We calculated descriptive statistics of these measures across the 701 personal networks.

5.3.1. Eliciting fewer alters

To investigate the strategy of eliciting fewer alters, all compositional and structural network characteristics were calculated for each sample size (2–24 alters) for each ego by selecting the respective alters from the top of each generated alter list and dropping all other alters. For example, to simulate the assessment of only 10 alters, we only considered the data connected to the first 10 alters that an ego generated. Based on this sample, all structural and compositional measures were calculated. This procedure was completed for each ego for each sample size (2−24).[1] In our results, we refer to this strategy as 'dropping alters' since this is essentially how we simulated 'eliciting fewer alters' based on our data.

5.3.1.1. Determining bias. We then determined the incurred bias by subtracting the true value of the network measure from the sample estimate. Thus, a positive bias value indicates overestimating the measure in the sample while negative errors signify underestimating. Besides these raw errors (i.e., bias), we also determined absolute error values.

5.3.1.2. Determining burden. We operationalised respondent burden reduction as the total study time saving connected to eliciting fewer alters. We calculated the study time saving for the average respondent by subtracting the average study duration of the reduced network assessment (e.g., when dropping the last 15 alters) from the total average study duration (i.e., when generating 25 alters and also assessing all questions for all 25 alters). When for example dropping the last 15 alters (i.e., only eliciting the first 10 alters), the average duration of generating 10 alter names was added to the average durations of answering each name interpreter question for 10 alters. We repeated this procedure for the 10% fastest and slowest respondents.

5.3.2. MGRI

We, again, considered all network sizes, ranging from 2–24 alters, with the number of alters denoted by n. Similar to Golinelli and colleagues (2010), we drew 1000 samples[2] of n alters from each of the full personal networks. For network sizes of 2, 23 and 24 alters, we differed from this number of samples, since there are fewer than 1000 combinations of alters possible. Thus, for these three network sizes, we considered every possible combination of alters, which leads to 300, 300 and 25 simulations for these network sizes, respectively. For each simulated sample, all network characteristics were estimated. Due to high computation time, simulations and error computations were run on the Peregrine HP Cluster (Peregrine Documentation, 2020).

5.3.2.1. Determining bias. In accordance with the work of Golinelli and colleagues (2010) we calculated bias by taking the difference between the true network measure and the average of the simulated network measures of the same sample size. Following methods of these authors

[1] Closeness and betweenness centralisation, as well as betweenness centrality are not defined for less than 3 alters, thus for those measures simulated network sizes only range from 3 to 24 alters.

[2] Simulating 10.000 instead of 1000 samples had minimal effects on estimates.

further, we calculated the root mean squared error (RMSE) by summarizing the squared errors across the different simulations per sample size and then taking the root in order to obtain values on the original scale of the measure.

5.3.2.2. Determining burden. We operationalised respondent burden reduction as the total study time saving connected to assessing fewer alters fully. Again, we calculated this study time saving by subtracting the average study duration of the reduced network assessment (e.g., when randomly sampling 10 alters) from the total average study duration. For example, when randomly sampling 10 alters from a generated list of 25 alters, the average duration of eliciting 25 alters was added to the average duration of answering each name interpreter question for 10 alters. Also for this burden reduction strategy we calculated time savings not just for the average respondent, but also the 10% fastest and slowest respondents.

5.3.3. Shiny app

Because of the multitude of simulation results, using two different strategies of reducing burden, varying network size, and applying those to 23 different outcomes, presentation and elaborate discussion of each of these outcomes would be beyond the scope of this article. Instead, we focus on patterns that hold across outcomes, and provide a more detailed walk-through on density (which is a frequent measure of interest). However, different researchers may be interested in different outcomes, which is why we also provide an accompanying Shiny app (https://socialsciencemethods.shinyapps.io/BalancingBiasAndBurden) that allows readers to access the full results relevant to their research.

6. Results

6.1. Descriptives of the personal network characteristics

Descriptive statistics of all ‘true’ network measures across the 701 personal networks containing all 25 alters can be found in Table 2. As can be seen, there is considerable variation in the investigated structural and compositional network characteristics. Further interpretation of the descriptive statistics is not the aim of the current paper.

6.2. Simulation results

In the following, we will give a general overview of patterns in the results for all network measures.

Table 3 shows bias for each network characteristic across the 701 personal networks when applying each burden reduction method including 5, 10, 15 and 20 alters. Several observations can be made from this table. First, as expected, lowering the number of alters increases median bias for both methods. While median bias is comparatively low when considering 20 alters, including only 5 alters in a personal network data collection leads to less precise estimates of network measures regardless of the applied strategy.

Second, when dropping alters, median bias rises more steeply than when randomly sampling alters. Dropping the last 5 alters and randomly sampling 20 from 25 elicited alters leads to a similar average degree of error for most measures. Dropping the last 20 alters, however, can lead to considerably larger average errors than randomly sampling 5 from 25 elicited alters.

Third, median bias when randomly sampling alters shows logically less variability (i.e., a lower median absolute deviation) between the 701 different personal networks than median bias when dropping alters completely. It is important to note, that this is also due to the fact that bias when randomly sampling indicates the centre of the distribution of 1000 values and does not reflect a single raw error calculation (as is the case when dropping alters).

Last, median bias differs largely between different network measures, with structural measures being more difficult to estimate than compositional ones. Maximum degree and degree centralisation are particularly problematic. In order to accurately estimate these two characteristics, randomly sampling alters is clearly the better choice than dropping alters. For other structural measures (i.e., the proportion of isolates and maximum betweenness centrality) dropping alters delivers lower median bias than randomly sampling alters at all network sizes. For all compositional measures, randomly sampling 20 alters provides less biased estimates than dropping the last 5 alters completely. Particularly for the proportion of kin in the network, average closeness to alters and average contact frequency with alters, dropping alters completely biases estimates considerably more than random sampling.

Table 2
Descriptive Statistics of Network Measures Across All Personal Networks.

	Minimum	*Mean*	*Median*	*Maximum*	*Standard Deviation*
Density	0.02	0.24	0.23	0.81	0.11
Proportion of Isolates	0	0.07	0.04	0.72	0.10
Maximum Degree	0.02	0.33	0.30	0.82	0.16
Degree Centralisation	0.12	0.57	0.54	1	0.21
Betweenness Centralisation	0	0.26	0.21	0.90	0.20
Mean Betweenness Centrality	0	0.02	0.02	0.16	0.02
Maximum Betweenness Centrality	0	0.27	0.23	0.90	0.20
Closeness Centralisation	0	0.16	0.07	0.94	0.21
Mean Closeness Centrality	0.04	0.20	0.12	0.86	0.18
Maximum Closeness Centrality	0.05	0.28	0.15	1	0.27
Average Alter Age	18.57	30.84	31.32	45.14	5.56
SD Alter Age	0.53	6.06	5.99	14.20	2.69
Proportion of Female Alters	0	0.64	0.64	1	0.13
Average Education	1.40	3.43	3.40	5	0.62
SD Education	0	0.89	0.88	1.70	0.26
Proportion of Friends	0	0.42	0.40	1	0.21
Proportion of Kin	0	0.38	0.36	0.92	0.18
Average Closeness	1	2.52	2.48	4.48	0.47
SD Closeness	0	1.06	1.05	1.86	0.24
Average In-Person Contact	1.20	3.14	3.12	4.72	0.60
SD In-Person Contact	0	1.16	1.17	1.88	0.25
Average Not In-Person Contact	1	3.16	3.20	4.68	0.58
SD Not In-Person Contact	0	1.19	1.21	1.95	0.26

Note. $N = 701$. Compositional network estimates are not yet normalised, but on their original scales as described in Table 1.

6.2.1. Detailed example ‘density’ and study time savings

Fig. 1a and b show the absolute error and bias incurred in network density when dropping alters completely. Fig. 1c and d display the RMSE and bias incurred in network density when applying MGRI (i.e., eliciting a large number of alters and then randomly sampling a subset for further assessment). The y-axis of each graph represents the amount of error or bias incurred in the network measure. The main x-axis on the bottom of

Table 3
Median bias (median absolute deviation) in network characteristics across all personal networks.

		5 alters		*10 alters*		*15 alters*		*20 alters*	
	Median True Value	*Dropping alters (one simulation)*	*MGRI (1000 simulations)*	*Dropping alters (one simulation)*	*MGRI (1000 simulations)*	*Dropping alters (one simulation)*	*MGRI (1000 simulations)*	*Dropping alters (one simulation)*	*MGRI (1000 simulations)*
Density	0.23	0.44 (0.31)	0 (0)	0.18 (0.15)	0 (0)	0.08 (0.09)	0 (0)	0.03 (0)	0 (0)
Proportion of Isolates	0.04	0 (0.06)	0.33 (0.12)	0 (0.06)	0.13 (0.07)	0 (0.04)	0.05 (0.04)	0 (0.01)	0.02 (0.02)
Maximum Degree	0.30	0.54 (0.22)	-0.14 (0.13)	0.39 (0.20)	-0.08 (0.09)	0.30 (0.17)	-0.04 (0.05)	0.26 (0.12)	-0.02 (0.03)
Degree Centralisation	0.54	-0.40 (0.27)	-0.14 (0.13)	-0.27 (0.20)	-0.07 (0.08)	-0.25 (0.16)	-0.04 (0.05)	-0.24 (0.13)	-0.02 (0.03)
Betweenness Centralisation	0.21	0.45 (0.34)	-0.12 (0.16)	0.15 (0.16)	-0.08 (0.12)	0.06 (0.07)	-0.04 (0.09)	0.02 (0.02)	-0.01 (0.04)
Mean Betweenness Centrality	0.02	0.45 (0.44)	0 (0.01)	0.17 (0.21)	0 (0.01)	0.07 (0.10)	0 (0.01)	0.02 (0.03)	0 (0)
Maximum Betweenness Centrality	0.23	0.08 (0.23)	-0.13 (0.18)	0.07 (0.14)	-0.08 (0.13)	0.03 (0.06)	-0.04 (0.09)	0.01 (0.02)	-0.01 (0.05)
Closeness Centralisation	0.07	0 (0.04)	0.06 (0.05)	0.01 (0.03)	0.02 (0.03)	0.01 (0.01)	0.01 (0.02)	0 (0.01)	0 (0.01)
Mean Closeness Centrality	0.12	-0.11 (0.21)	0.17 (0.06)	-0.03 (0.15)	0.06 (0.04)	0 (0.10)	0.03 (0.02)	0 (0.06)	0.01 (0.01)
Maximum Closeness Centrality	0.15	-0.10 (0.20)	0.18 (0.08)	-0.03 (0.14)	0.07 (0.05)	0 (0.10)	0.03 (0.03)	0 (0.05)	0.01 (0.01)
Average Alter Age	31.32	-0.01 (0.09)	0 (0)	-0.01 (0.06)	0 (0)	0 (0.04)	0 (0)	0 (0.03)	0(0)
SD Alter Age	5.99	-0.04 (0.08)	-0.01 (0.01)	-0.02 (0.06)	-0.01 (0)	-0.01 (0.04)	0 (0)	0 (0.02)	0 (0)
Proportion of Female Alters	0.64	-0.08 (0.18)	0 (0.01)	-0.02 (0.12)	0 (0)	0 (0.10)	0 (0)	0 (0.06)	0 (0)
Average Education	3.40	-0.01 (0.12)	0 (0)	-0.01 (0.07)	0 (0)	0 (0.04)	0 (0)	0 (0.03)	0 (0)
SD Education	0.88	-0.01 (0.08)	-0.01 (0.01)	0 (0.05)	0 (0)	0 (0.03)	0 (0)	0 (0.01)	0 (0)
Proportion of Friends	0.40	0.04 (0.36)	0 (0.01)	0.08 (0.21)	0 (0)	0.07 (0.10)	0 (0)	0.04 (0.06)	0 (0)
Proportion of Kin	0.36	0.36 (0.30)	0 (0.01)	0.18 (0.21)	0 (0)	0.09 (0.12)	0 (0)	0.04 (0.06)	0 (0)
Average Closeness	2.48	-0.28 (0.12)	0 (0)	-0.18 (0.09)	0 (0)	-0.10 (0.06)	0 (0)	-0.04 (0.03)	0 (0)
SD Closeness	1.05	-0.13 (0.11)	-0.01 (0)	-0.06 (0.08)	0 (0)	-0.03 (0.05)	0 (0)	-0.01 (0.02)	0 (0)
Average In-Person Contact	3.12	-0.24 (0.15)	0 (0)	-0.12 (0.11)	0 (0)	-0.07 (0.07)	0 (0)	-0.03 (0.04)	0 (0)
SD In-Person Contact	1.17	-0.06 (0.12)	-0.01 (0)	-0.02 (0.07)	0 (0)	-0.01 (0.05)	0 (0)	0 (0.02)	0 (0)
Average Not In-Person Contact	3.20	-0.28 (0.16)	0 (0)	-0.17 (0.10)	0 (0)	-0.10 (0.06)	0 (0)	-0.04 (0.04)	0 (0)
SD Not In-Person Contact	1.21	-0.08 (0.13)	-0.01 (0)	-0.03 (0.08)	0 (0)	-0.01 (0.05)	0 (0)	0 (0.02)	0 (0)

Note. $N = 701$; Bias when dropping alters reflects the difference between the true network measure and one simulated value, bias in connection to MGRI reflects the difference between the true network measure and the average of 1000 simulated values; The scales of compositional characteristics can be found in Table 1.

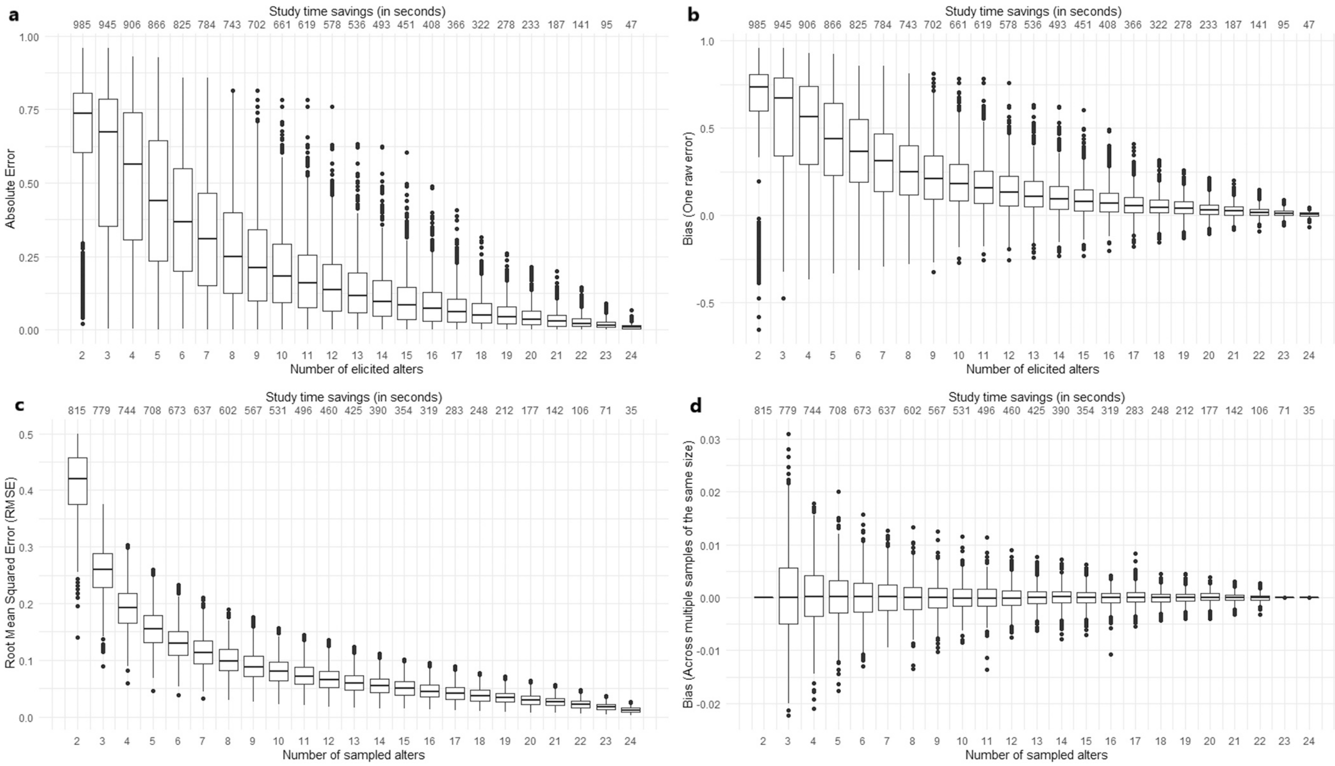

Fig. 1. Boxplots of Error (left panels) and Bias (right panels) Incurred in Density When Dropping Alters Completely (Top) And When Applying MGRI (Bottom). *Note.* $N = 701$; Burden reductions are displayed for the average respondent of our reduced sample ($N = 646$).

the graph displays the number of alters included in the network (i.e., 2–24). The secondary x-axis on the top displays the potential time savings for average respondents connected to the two burden reduction methods (e.g., when only including 10 instead of 25 alters in the network data collection). Readers can access all plots for their measure of interest in our Shiny app and use this example to guide their interpretations. The app also provides the option to change the secondary x-axis to view time savings for the 10% fastest and slowest respondents from our dataset.

In Fig. 1a it can be seen that when including fewer alters in the network the median error rises steeply, with 8 alters already delivering error rates of 0.25, which is a quarter of the total range of the measure. Fig. 1b shows that density is overestimated (i.e., biased in the positive direction) for most of the 701 personal networks when dropping alters completely. Note for both of these plots, that the variability between the different personal networks is also increasing when fewer alters are included (as is indicated by the size/length/height of the box). This means that when fewer alters are sampled, it is more difficult to give general recommendations since bias varies more between different networks.

The variability between networks is smaller when using MGRI (Fig. 1c and d) due to the inherent methodological difference in testing the two burden reduction strategies (i.e., obtaining one versus multiple error values; see methods). Fig. 1c further shows that the RMSE connected to MGRI rises slowly when decreasing the number of alters, with less than 0.1 median RMSE until about 9 alters, thus allowing to collect fewer alters when applying this strategy compared to the strategy of dropping alters completely. Fig. 1d additionally shows, that on average MGRI does not bias density in a particular direction.

The secondary x-axis of each plot displays the potential study time saving when including 2–24 instead of 25 alters in the data collection. These time savings differ between the two methods since when dropping an alter completely, the name does not need to be generated and subsequently no further questions about this alter are asked. When using MGRI, only the assessments of alter attribute questions and alter-to-alter ties are omitted, but still all alter names need to be generated. Therefore, time savings are larger when dropping alters completely. When for example dropping the last 5 alters, 233 s (i.e., nearly 4 min) of study time can be saved. When eliciting 25 alters but only fully assessing a random sample of 20 alters, only 177 s (i.e., nearly 3 min) can be saved. With a network size of 15 alters, dropping alters saves approximately 7 ½ minutes while using MGRI saves 6 min (i.e., a difference of 1 ½ minutes). With 10 alters, the time difference between the two methods rises to about 2 min. The additionally invested time, however, also on average leads to less biased estimates of the network density.

These estimates on saving time are based on the average respondent. Researchers might consider samples that are faster (e.g., young, internet-savvy respondents) or slower (e.g., older respondents or patient populations), which is why we also present estimates for the 10% fastest and slowest respondents of our sample. When completely dropping the last 5 alters, 112 s (i.e., about 2 min) of study time can be saved for the fastest respondent, whereas the slowest respondent experience a considerably higher time reduction of 384 s (i.e., almost 6 ½ minutes). When eliciting 25 alters but only fully assessing a random sample of 20 alters the differences between the groups are less pronounced: 104 s (i.e., nearly 2 min) can be saved for the fast group, and 264 s (i.e., 4 ½ minutes) for the slow group. With a network size of 15 alters, dropping alters saves approximately 4 min (fast) or 12 min (slow) while randomly sampling alters saves 3 ½ (fast) or 9 min (slow). Considering 10 alters, the slowest group can even save almost 18 min of study time when dropping alters completely and 13 min when randomly sampling alters. For the fast group the study time savings are at 5 ½ and 5 min, respectively. These results indicate that alter name generation required a substantial amount of time, especially for slow respondents.

7. Discussion

In the present study we used two strategies to evaluate reductions in respondent burden in personal network studies connected to the number of alters that are included in the network: (1) eliciting and assessing fewer alters altogether and (2) eliciting a larger number of alters (i.e., 25) but only selecting a random subsample for answering name interpreter questions, referred to as Multiple Generator Random Interpreter (MGRI). We presented the amount of bias in structural and compositional network characteristics when applying these strategies as well as the respondent burden reduction (i.e., study time savings) for every possible network size (2–24 alters).

Our results show that there are considerable differences in how well different network characteristics can be estimated with the two methods for respondent burden reduction. Most measures that we investigated seem to be estimated better when eliciting 25 alters and then randomly sampling a subsample of those for full assessment rather than when dropping the last alters completely. This makes sense, since it can be assumed that respondents start with generating alter names of alters closer to them and with whom they have more contact. Thus, dropping the last alters, rather than using MGRI should bias the network towards more close social contacts. This assumption is confirmed by the sharp distinction between the two methods when considering some of the compositional characteristics of the networks (e.g., the proportion of kin and average closeness). According to our results, when a researcher is interested in estimating compositional network measures, eliciting 25 alters and then randomly sampling as few as 10 of those to assess alter attribute questions can be sufficient. This is especially useful since alter attribute questions take up most of the data collection time.

A similar, but less pronounced difference between the methods can be seen for structural characteristics such as network density, although structural measures generally seem to be more difficult to estimate than compositional ones. McCarty and colleagues (2007) conclude that when initially eliciting 45 alters, randomly selecting 10 alters is sufficient to estimate many structural characteristics. Based on our results, when eliciting only 25 alters initially, sampling fewer than 15 alters is not recommended when structural network measures are the main focus of a study.

Particularly maximum degree and degree centralisation seem to be challenging to reliably estimate, corroborating earlier research by Golinelli and colleagues (2010). Results of McCarty and colleagues (2007) show similar issues, but only when estimating maximum degree based on a sample of fewer than 30 of their 45 elicited alters. This indicates that estimating this network measure without substantial bias requires researchers to elicit larger numbers of alters than 25. The same seems to apply to degree centralisation, as it, contrary to our and Golinelli and colleagues' results, appeared quite stable in McCarty and colleagues' analyses when they estimated it based on a random alter sample drawn from 45 elicited alters.

Based on the distinction between compositional and structural measures, a possible respondent burden reduction strategy could be to use a stepwise MGRI approach. A researcher could, for example, elicit 25 alter names, then assess alter-to-alter ties for a random sample of 20 alters and then further randomly sample 10 alters of those 20 to assess alter attribute questions. Applying this strategy to the current network data collection would lead on average to a study duration of 11 ½ instead of 19 min.

A somewhat surprising result of our study is that in order to estimate the proportion of isolates, betweenness centralisation and maximum betweenness centrality eliciting fewer alters (i.e., 15–20) seems to perform better than MGRI. The results of McCarty and colleagues (2007) do only partially corroborate these findings: While maximum betweenness was also better estimated when simply dropping alters, their findings indicate that the proportion of isolates as well as betweenness centralisation is estimated better when using MGRI rather than dropping alters completely. This difference may, again, be due to their larger initially elicited alter list.

The results of this paper can aid researchers to strike a balance between burdening the respondent and obtaining reliable estimates for their particular compositional and structural network characteristics of interest (e.g., the proportion of kin in the network or network density). All results can be interactively explored in our accompanying shiny app (https://socialsciencemethods.shinyapps.io/BalancingBiasAndBurden/).

8. Limitations and future research

There are several aspects to keep in mind when using the results of this study. First, the present study is based on the assumption that researchers want their collected personal network to be representative of the wider social environment of the ego. This may not always be the case and it is important to match the data collection strategy to the underlying research questions: If only networks of confidants or frequent interaction partners are of interest, a small number of alters may be sufficient. If a network representative of the wider social environment (also including weak ties) is desired, the current results can be of help. However, some authors (e.g. Hogan et al., 2007) argue that not even 60 alters can provide such estimations since true personal networks contain multiple hundreds of social contacts.

Second, our data was obtained via an online survey and can therefore not be compared to other data collection modes such as interviews or pen-and-pencil surveys, which are still prevalent in the field. In a similar vein, our survey used a particular name generator question which may lead to different estimates of network characteristics and study duration than different name generation questions. It is known that such design choices do matter and likely influence participant experience and study completion time. Therefore, our exact study time savings should be interpreted with caution.

Third, when comparing our results with the study by McCarty and colleagues (2007) it becomes apparent that the number of initially elicited alters matters. It would be useful for future research to obtain a network dataset with a larger list of initially elicited alters (e.g., 45 instead of 25) and then also investigate how long the list of generated alter names from which the random alter samples are drawn ideally should be. This could be done by gradually decreasing the generated alter list by dropping the last alter and at each step sampling random subsamples of all sizes in which network characteristics are determined. For example, first consider all 45 generated alters and then determine network measures in random samples of 2–44 of those 45 alters, then consider only the first 44 generated alters and determine network measures in random samples of 2–43 of those alters and so on.

Fourth, while our sample is representative for Dutch women of reproductive age, it is unclear how far our results generalise beyond that. Particularly personal networks of older individuals differ from those of younger ones (Suanet et al., 2013). Older individuals might similarly take longer coming up with names and filling out the survey. Thus, when using our results, researchers should consider how well their target population matches our sample.

Lastly, structural and compositional network characteristic are seldom the final product of personal network research. They are often used as predictors in regression or multilevel models. From these results it is unclear how much error would be incurred in regression coefficients. Future studies should investigate the impact of respondent burden reduction strategies on conclusions regarding precise personal network research questions by performing full analyses with complete data as well as smaller alter samples.

9. Conclusion

The present study provides information on how to reduce respondent burden during a personal network data collection while minimising bias in the network characteristics that a researcher would like to determine. In most cases eliciting 25 alters and then randomly sampling 15–20 of those for a full network assessment is a feasible strategy providing sufficiently precise estimates of network characteristics. However, there are considerable differences in how well different network measures can be estimated with this respondent burden reduction method: For some compositional measures even fewer alters may be sufficient, but for other structural measures simply eliciting fewer alters (i.e., 15–20) may perform just as well or even better.

Thus, researchers with an applicable target population should carefully consider the measures they are interested in and can consult our results when deciding on the number of alters to elicit and assess. Our online tool (https://socialsciencemethods.shinyapps.io/BalancingBiasAndBurden/) can aid this process. A particularly useful strategy to minimise respondent burden while minimising bias in estimates for researchers interested in both structural and compositional network characteristics could be to elicit a large number of alters, assess alter-to-alter ties for a random sample of those alters and then assess alter attributes for an even smaller subsample. In addition to limiting the number of alters, researchers should also consider to keep the number of particularly demanding attribute questions to a minimum in order to reduce study time and therefore respondent burden.

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Declaration of Competing Interest

None.

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