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Unlinked: Why alters reported in name generators cannot be used to estimate personal network size

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ABSTRACT

Personal network size is a versatile and fundamental structural network measure, capturing the total number of personal connections or specific subgroups within an individual's social environment. In standard sociological methods, such as surveys, personal network size is often indirectly inferred from name generators, which are used to list alters from the respondents' personal networks. Implicitly, a higher count of named alters is assumed to indicate a larger personal network. We explicitly test this common assumptionand address this imprecise association between network size and number of listed alters by comparing the results from two very distinct approaches to measuring personal network size: alter counts derived from name generators and size estimates obtained from the network scale-up method (NSUM). Using survey data from over 300 participants in Spain, we compute these two independent network measures for the same respondents and assess the strength, significance and robustness of their association, including potential question-order effects on personal network size. Our analyses conclude that the alter counts from name generators primarily reflect participants' response behaviour and task constraints rather than the underlying personal network size. Finally, our findings highlight critical limitations in the use of free name generators as proxies for personal network size.

1. Introduction

The use of personal network size as an independent variable to explain respondent-level outcomes has grown exponentially over the past forty years. A search of the Web of Science reveals that the annual number of articles including the term "personal network" increased from the single digits in the 1980s to 50–80 in recent years. It is widely accepted that for some outcomes, the characteristics of one's personal network, such as composition (Fernández-Peña et al., 2018; Drevon et al., 2021; Kumar et al., 2021; D'Adamo et al., 2025) and structure (Tracy et al., 2016; Park et al., 2012) can make a difference.

Personal network size is a different kind of variable. Here, we define personal network size as the number of people present in the ego's social environment whom the ego knowns personally and without being fully observable. Some studies describe personal network size as the total number of people someone is connected to Hill and Dunbar (2003), McCarty et al. (2001), whereas others report the number of alters listed with a cap on the total number, with the implication that those who list more alters have a larger network (Roberts et al., 2008, 2009). Additionally, personal network size is the number of alters listed from a specific type of relationship, such as alters who can provide some particular type of support (Marsden, 1990). In all these cases an implicit assumption is that those who list more alters have more total alters than those who list fewer.

There are multiple reasons why the reported number of alters may vary. By design, the participant's response to a name generator is an enumeration of their alters and this list is of variable length (Marsden, 2001). In many studies, the relationship of number of alters reflecting the actual personal network size is often assumed despite lacking empirical support (e.g., McCarty et al., 2001). At the same time, it is acknowledged that name generators solely capture a smaller subset of the network (Marsden, 1990). Further, Herz and Petermann (2017) found that differences in survey design (e.g., how a question is asked or answers are recorded) strongly affect the network size derived from alter lists. Consequently, variation in reported network size may

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not only depend on the personal environment, but also on the recall behaviour of the survey participant. Eagle and Proeschold-Bell (2015)'s work examines how the number of listed alters depends on where the name generator is placed in the survey (question-order effect). It shows that the list of names is getting shorter when placed at the end of the survey, likely due to respondent fatigue (see also Pustejovsky and Spillane, 2009; Yousefi-Nooraie et al., 2019). Survey design and behavioural adaptations can impact notably the network size estimated from the name generator.

This research was designed to test whether the number of listed alters can serve as a proxy for personal network size by indicating respondents' rank order in network size. Previous research has demonstrated very different structural properties of personal networks based on a fixed versus variable number of alters elicited (González-Casado et al., 2026). That study, as well as McCarty et al. (2019), raised the question whether the number of alters an ego lists is a proxy for size or whether egos stop listing alters for other reasons. These reasons include inability to remember more alters, respondent fatigue in listing more alters, and a limited cooperation in listing more alters. Following this, if response behaviour is driven by external factors rather than personal network size, alter counts cannot be utilised as comparative indicators of network size. It is important to understand that in a personal network study only the egos can know who is in their network and they must report this to the researcher. The question, then, is whether researchers should expect respondents to reliably report the number of alters they know. Here, we address the need, formulated in González-Casado et al. (2026), to uncover this perplexing relationship between network size and number of listed alters.

This research attempts to investigate this by having respondents provide two different measures of network size. One is a free list of network alters as described in the research above, and the other network size as measured through network scale-up (NSUM). NSUM was designed as a method to estimate the size of hard-to-count populations such as the homeless or those who are positive for HIV (Bernard et al., 2010). The method involves asking respondents to estimate the number of people they know in multiple known populations, then back estimate the size of their personal network, that aligns with their varied estimates. Respondents are asked to estimate the number of people they know in unknown populations, such as those with HIV. Accounting for the variability in personal network sizes enables the method to back estimate the size of the hidden subgroups in the more general population. For our purposes, NSUM provides a reliable estimate of personal network size that is independent of respondents' willingness or ability to list alters in a name generator.

The key aspect for this article is that personal network size as measured through NSUM is a very different approach to measuring personal network size than asking for respondents to list alters. Although applications in prior research suggest that both measures should be highly positively correlated, we examine how the personal network size derived from listing alters is linked to NSUM measure. We address the question of whether the length of the name generator can serve as a proxy for personal network size that allows for a ranking order of respondents.

We collect survey data from over 300 participants in Spain to compute two independent network measures and assess the strength, significance, functional form and robustness of their association. Our analysis also accounts for potential question-order effects on personal network size. A strong correlation would imply that the number of alters is a proxy for the personal network size, whereby individuals who list more alters should also have higher NSUM-based network size estimates. In contrast, a weak correlation would indicate that the number of alters captures a different aspect of the personal social environment and its variability is better explained by other factors than personal network size. Nonetheless, a weak correlation would not diminish the analytical value of variability in the number of alters listed, as it can still function as an independent or dependent variable. For the number of alters to be considered a valid proxy of network size, we would expect a strong rank-order association, which remains robust after removing capped values and is independent of question order.

Our paper is structured as follows. First, we describe the components of our survey, namely the name generator and the NSUM, which we utilise to examine their relation to the estimated personal network size. We, then, outline our data collection process and survey design that build the core of our empirical analysis. In the results section, we estimate personal network sizes through the name generator and the NSUM and determine the dependencies between these measures. Finally, the discussion section interprets the implications of our findings and sheds light on their limitations.

2. Methods

2.1. The Network Scale-Up Method

The Network Scale-Up Method (NSUM) utilises the composition of the personal networks to infer an unknown population size estimate from a subgroup. The underlying assumption is that an individual's personal environment inherits a similar distribution of smaller subpopulations as in the general population. To build a network size estimator, the NSUM relies on Aggregated Relational Data (ARD) that specifies the sizes of subpopulations that are present in the personal networks. For instance, respondents are typically asked questions such as, "How many teachers do you know?", which require a numerical response. Since the first introduction of NSUM by Killworth et al. (1990) to estimate the size of a hidden population, there have been several developments of the method to improve its accuracy and to counter sources of error (McCormick et al., 2010; Lubbers et al., 2025). A comprehensible, in-depth discussion on the developments of the NSUM method is addressed by work from Laga et al. (2021).

Here, we apply the NSUM to quantify the approximate size of the personal networks from our survey participants and to generate comparative data for our study. If a participant knows relatively more/less people of a subpopulation, then his/her network will be relatively larger/smaller. Each participant's personal network size ($\hat{d}_i$) is estimated by using a maximum likelihood estimator (Killworth et al., 1998; Laga et al., 2021). The network size estimator builds on a set of subpopulations $k = 1, \ldots, K$ with known prevalences $p_k = N_k/N$ in the general population N (here: Spain):

$$\hat{d}_i = \frac{\sum_k y_{ik}}{\sum_k p_k}, \tag{1}$$

where y_{ik} is the number of alters the participant i reported in the survey on subpopulations k (see Killworth et al., 1998). The ARD of the estimators are part of the survey design and are chosen by the research team (see Appendix D).

The drawbacks of the NSUM that affect its accuracy are widely known and depend heavily on the visibility of known subpopulations included in the ARD. Three main sources of error have been identified: transmission error, barrier effect and recall error.

Transmission error occurs when participants lack information about the alters, which interferes with the assumption of perfect awareness. Barrier effects addresses the issue of non-random mixing in the personal network, indicating that people are more likely to know others similar to themselves (e.g., age, profession, economic status). Recall error corresponds to the participants' performance in responding to the survey, where participants tend to overestimate small groups and underestimate large ones. The sources of error demonstrate the limitations of the underlying assumptions for indirect network size estimation (McCarty et al., 2001; Laga et al., 2021; Killworth et al., 2006).

Nevertheless, with an appropriate selection of the ARD, the NSUM method provides a reliable estimate of personal network size. Even when variations in the ARD or network sizes are present, the method consistently reproduces the ranking of the participants' network sizes (Lubbers et al., 2025).

2.2. Free name generator

Name generators (NG), where participants are asked to recall a subset of people from their personal social network and list their names, are commonly used descriptors of egocentric network in surveys (McCarty et al., 2019). This survey tool is designed to capture the names or identifiers of people (alters) to whom a respondent (ego) is socially connected through a specified type of relationship that is determined by explicit prompting (Marsden, 1990). Name generators request that respondents list alters who meet predefined response requirements, which may constrain the number of names either by setting variable limits (i.e., upper bound, lower bound, or free) or by specifying a fixed number of names (see Marsden and Hollstein, 2023; González-Casado et al., 2026). The *free* name generator allows the respondents to provide as many alters as they wish and, therefore, allows also a variation in the number of names. In our data collection, we will make use of a free name generator with an upper bound of 50 names. The intention is to uncover a vast subset of the personal networks from the participants.

3. Data

3.1. Collection procedure

The survey design and collection were conducted using Qualtrics, an online survey instrument. We invited 1581 people from subject pools at two Spanish universities, the University Carlos III of Madrid and the Universidad Loyola Andalucía. Participants were recruited by sharing a survey invitation via email. To motivate the participation, we offered an incentive of five Euros for their participation and the possibility to receive, in a random draw under all participants, additional 50 Euros. Participation was voluntary, and respondents could withdraw at any time without consequences.

3.2. Survey design

In the introduction to the survey, we provide a common definition of a close contact (alter) from the participant's personal environment that applies to all sections of the survey. An alter is someone with whom the ego shares mutual first-name recognition and has had contact in the last two years, provided the ego could reach out to them if necessary. Before advancing to our study questions, the participants must accept the informed content and share their contact details, such as their Name, their ID Number and an email address that is linked to PayPal account.[1]

After this first part, we ask the participant about their age group they belong to, their gender, their place of residence and their professional status during the last three months. Additionally, if employed, we requested information on the economic sector they work in, or, if studying, their field of study.

The main part of the study consists of two components administered in counterbalanced order to control for question-order effects:

1. **Free name generator task:** We ask the respondents to list names of people they know personally and could, in principle, contact if necessary. The response option for this item is an interface with 50 name fields. In a follow-up question, the participants are asked a multiple choice question about their reasons for stopping providing names in the previous question.
2. **NSUM items:** The set of questions for NSUM are divided into two categories. In the first category, we asked the participants how many people they know in 17 specific population subgroups (e.g., "people working for the police force", "with a Columbian nationality", or "teachers"; see Appendix D). In the second category, the questions addressed common first names from the Spanish population with a known distribution. We selected twelve first names (six male and six female), provided by a Spanish NSUM study from Lubbers et al. (2019). Further, in the questions about the population subgroups, we integrated four quality checks by requesting all first names of the people they know from a specific group. These tests are only activated when the participants knows three or more people and they provide a form of validation to ensure high data quality.

The order of these two components was randomised so that approximately half of the participants completed the free name generator task first, followed by the network size estimation questions, and vice versa. This approach helps to identify potential systematic collection errors as discussed above. Hence, the participants were divided into one of two experimental conditions:

- *Condition A:* Name generator first, followed by NSUM items.
- *Condition B:* NSUM items first, followed by the name generator.

An additional question captured the respondents' reasons for stopping before reaching the maximum number of names. Additional details regarding the survey instrument are provided in Appendix D.

3.3. Data description

From a subject pool at the Universidad Carlos III de Madrid and Universidad Loyola Andalucía, 308 people participated successfully in our survey.[2] This dataset contains participants from Spain and the majority falls within the 18–34 age group (about 38% are between 25–34 and around 35% between 18–24 years old). The gender distribution is skewed towards female participants (over 64%). The male participants are at over 35% whereas a small fraction is not covered by these two categories. Nearly half of the participants are employed and over a quarter of the participants are students. The other participants are distributed over the remaining categories (working part-time, unemployed, retired, staying at home and others).

For controlling the question-order effect, the block orders are evenly distributed among the participants (i.e., Condition A or Condition B). Hence, approximately half of the participants saw the NSUM questions first and the name generator last, and the remaining part in the reverse order. Further details are summarised in the Appendix A.

4. Results

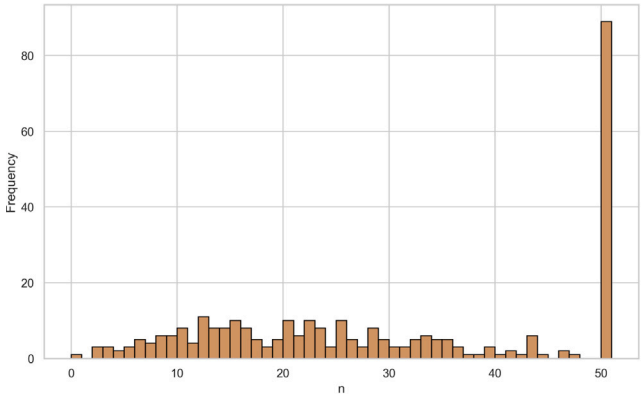
4.1. Distribution of free name generator sizes

With regard to the responses obtained from the free name generator, we focus primarily on the number of listed alters that varies but is limited by the maximum list length ($n = 50$). On average, participants name approximately 29 alters each, with a wide spread distribution (mean=29.4; sd=16.0; see Fig. 1(b)). The minimum number of names provided was as low as two, reported by only one participant. In contrast, about 29% of the participants reached the maximum of 50 names (see Fig. 1(a)). This indicates that the upper limit was a substantial constrain in the length of the names list.

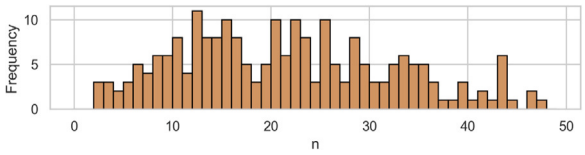
The participants responded to 29 network size estimation items regarding specific subpopulations with a known share in the population: (1) 17 items from the first category and (2) 12 items from the second category (see response distributions in Appendix B, Fig. 10).

[1] This was necessary as a proof of participation and to issue the compensation via PayPal.

[2] In total, 337 people took part of which 22 did not finish our survey and seven people filled it out twice.



(a) Length of name generator list including capped values.



(b) Length of name generator list excluding capped values at 50.

Fig. 1. Comparison of capped (a) and uncapped (b) histograms for number of listed people in the name generator task to provide close contacts.

The median values vary across subpopulations and show substantial heterogeneity. Despite the distinction between male and female first names, there are no obvious gender-specific differences in provided numbers in their personal networks.

Our sample data is demographically less diverse and is not representative for the Spanish population. Nevertheless, it captures a high variation in recall performance for the name generator question as well in the numbers of network size estimation items. In the following, we will present the results of the network size estimation as well as the link between the estimated network size and the number of names in the name generator.

4.2. Distribution of estimated personal network sizes

We estimate the personal network sizes by using the NSUM, described in Section 2.1. For each participant, we evaluate the network size by inferring it from the known subpopulations and the number of people present in their social environment. To reduce the barrier effects, known subpopulations that align exactly with the participant's characteristics were excluded from the calculation. For instance, if the participant was a teacher, we excluded the item NSUM6 ("How many people do you know who are professors or teachers at any educational level?"). More than a quarter of all participants had at least one subpopulation excluded due to this criterion. The most frequent exclusions occurred for the items *NSUM5* (31 cases), *NSUM1* (21 cases), and *NSUM6* (18 cases). The estimated personal network sizes ($\hat{d}_i$) from all respondents ($n = 308$) show a distribution with a mean of 125.88 (SD = 92.57) and a median of 105.94 (see Fig. 2).

Compared with previous, larger acquaintanceship-network estimates (e.g., Lubbers et al., 2019), our lower network size estimates may partly reflect the narrower definition of an alter used in our survey (see survey summary in Appendix D).

4.3. Association between free name generator sizes and the estimated personal network sizes

If the free name generator were a valid approximation of network size, we would expect an obvious association between the estimated

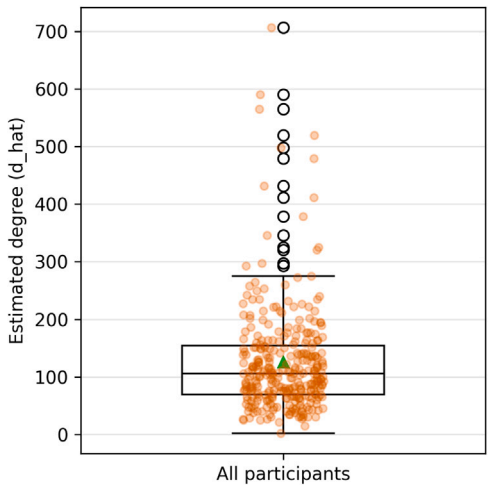


Fig. 2. Distribution of estimated personal network sizes ($\hat{d}_i$) across all respondents. The mean (green triangle) is 125.88 (SD = 92.57) and a median (black line) is 105.94. The values of $\hat{d}_i$ range from 2.52 to 706.29.

personal network size and the number of names reported in the name generator. First, we quantify this association by using the Pearson correlation on the full data set as well as without the people who reached the maximum value in the free name generator survey. However, the results from the name generator are capped at 50 (maximum list length) and, therefore, cannot show a continuous, linear relation. Further, we assess whether both measures align in their rank ordering of respondents. Hence, we also apply Spearman's rank correlation as a non-parametric statistical measure to evaluate this rank-order association.

In Table 1, we show the outcomes and their statistical significance of three tested associations between estimated personal network size and free-name generator:

1. Pearson correlation on the full data set ($n = 308$) shows a small but statistically significant positive correlation ($r = 0.278$, $p < 0.001$, 90% CI [0.189, 0.363]).
2. After excluding participants with maximum values for the name generator ($n = 219$, the correlation is negligible ($r = 0.039$, $p = 0.563$) and does not show any relationship between the two distributions.
3. The Spearman's rank correlation for the full data set ($n = 308$) draws a similar picture by estimating a weak but positive association ($\rho_s = 0.271$, $p < 0.001$) (see Fig. 3).
4. The Spearman's rank correlation is repeated for the dataset without capped values ($n = 219$). It does not show any relationship between the two distributions. ($\rho_s = 0.054$, $p = 0.424$) (see Fig. 3).

We implement further robustness tests to detect certain patterns and to control for characteristics of the respondents. First, using equivalence testing, we assess whether the association differs practically from zero. In line with the results above, after excluding capped values, the results indicate equivalence to zero, while the full dataset shows a small association. Second, we estimate several OLS regression models explaining estimated network size while controlling for age, gender, occupation and block order. We additionally introduce a simple non-linear, quadratic model. All in all, the estimated effect remains limited in size and does not support using the free-name generator count as a reliable proxy for network size; this association again disappears when capped values are excluded (detailed results in Appendix C).

The results underline that capped values contribute substantially to the observed association between the two estimates of network size, as the association vanishes when excluding the capped values in both Pearson and Spearman correlations.

Table 1
Relation between estimated personal network size and free-name generator.

Metric	n	r/ρ_s	90% CI	Two-sided p
Pearson (full data set)	308	0.278	[0.189, 0.363]	$p < 0.001$
Pearson (excluded capped values)	219	0.039	[−0.072, 0.150]	0.563
Spearman ρ_s (full data set)	308	0.271	[0.181, 0.355]	$p < 0.001$
Spearman ρ_s (excluded capped values)	219	0.054	[−0.057, 0.165]	0.424

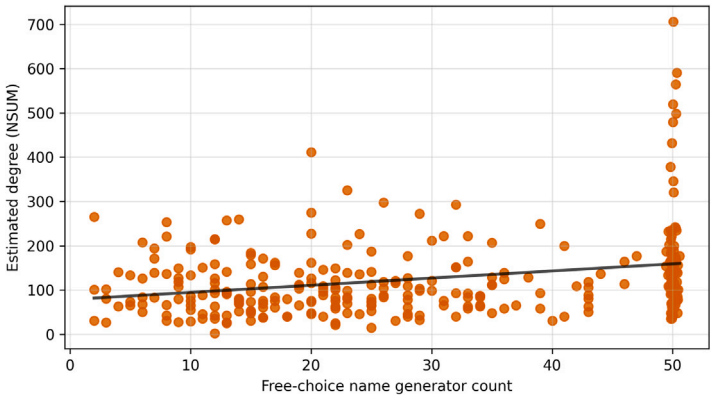


Fig. 3. Rank correlation between estimated personal network size (NSUM) and the free-name generator (n = 308). Spearman's $\rho_s = 0.271$ with $p < 0.001$.

Table 2
Correlation between estimated personal network size (NSUM) and the free-name generator across experimental conditions A (*List of alters first*) and B (*NSUM first*).

Condition	Metric	n	r/ρ_s	90% CI	Two-sided p
A: *NG first*	Pearson	157	0.375	[0.256, 0.483]	$p < 0.001$
A: *NG first*	Pearson (excl. capped values)	117	0.244	[0.095, 0.383]	0.008
A: *NG first*	Spearman ρ_s	157	0.393	[0.275, 0.499]	$p < 0.001$
A: *NG first*	Spearman ρ_s (excl. capped values)	117	0.226	[0.076, 0.366]	0.014
B: *NSUM first*	Pearson	151	0.173	[0.040, 0.301]	0.033
B: *NSUM first*	Pearson (excl. capped values)	102	−0.141	[−0.298, 0.023]	0.156
B: *NSUM first*	Spearman ρ_s	151	0.148	[0.014, 0.277]	0.070
B: *NSUM first*	Pearson (excl. capped values)	102	−0.115	[−0.273, 0.050]	0.922

4.4. Question-order effects in our two experimental conditions

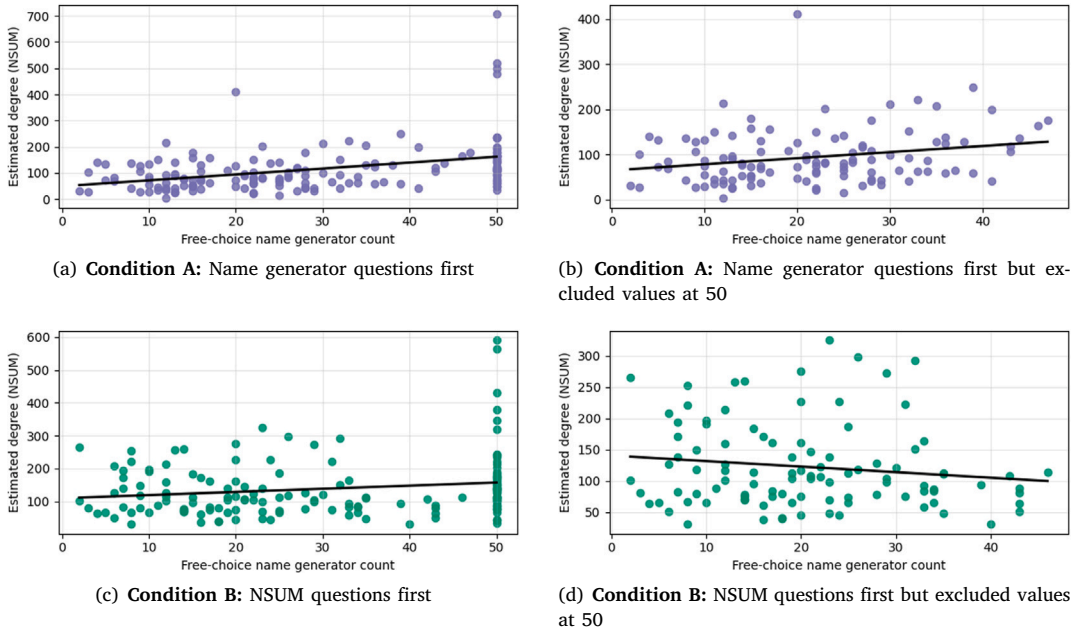
Previous literature (e.g., Eagle and Proeschold-Bell, 2015) indicates the presence of a systematic question-order effect when collecting data through name generator tasks. We account for this by randomising the order of the two survey blocks. Therefore, approximately half of the participants ($n = 157$) filled out the survey in Condition A (Order: 1. NG; 2. NSUM) whereas the other half ($n = 151$) completed the survey Condition B (Order: 1. NSUM; 2. NG). Here, we examine how the order affects the link between the length of the name generators and the estimated personal network size.

The division of the participants into the two conditions has a clear effect on the strength of the association between our two measures (see Table 2 and Fig. 4). In the full sample, the association is weak but significant ($r = 0.278$, $\rho_s = 0.271$, $p < 0.001$). In comparison, Condition A notably augments the strength of this correlation ($r = 0.375$, $\rho_s = 0.393$) whereas Condition B lowers it ($r = 0.173$, $\rho_s = 0.148$). It is striking that in Condition B without the capped values at 50 the correlation disappears entirely and might suggest a negative association; however, this effect is not significant (see Fig. 4(d)). The substantial difference between the strengths of alignment indicates a shift in the participants performance, e.g., lower capacity of recalling names or declining motivation for the name generator in a later stage of the survey.

5. Discussion

Our analyses reject the free name generator as a reliable proxy for the personal network size. The findings suggest merely a weak relation between the estimated personal network size using NSUM and the size derived from the free name generator, — a correlation that declines even further when leaving out the capped values. To ensure robustness, we examined both Pearson and Spearman correlations. Additionally, as expected by the experimental setup, the question-order affects the strength of correlation, further underlining the lack of a direct relation between the two measures. Hence, our results are nuanced: the association is sensitive to experimental setup and does not robustly support significant, positive relationship, despite small positive correlations for parts of the data. In short, the name generator length is an inadequate proxy for the personal network size.

The name generator length may to be influenced by several other factors, e.g. motivation and recall capacity, in addition to actual personal network size More than 60% percent of the participants answered that they were not able to recall more people from their close network at the time of the survey. Despite that, over a quarter of the participants hit the 50-names limit of the task. This could suggest that, instead of proving an estimate for the network size, we may better distinguish the participants by their level of engagement, sort them into groups of motivated and unmotivated participants. Highly motivated participants might be willing to invest more time and effort to fill in all available spaces (up to 50 names), whereas less motivated participants might respond with minimal effort. Hence, the length of the name generator may partly reflect participants' task and survey performance more than their actual personal network size. The two distinct order conditions of our survey have a clear impact on the task performance of the participants. In Condition A, the correlation between the two measures is small but consistent, whereas in the reversed order (Condition B),



(a) **Condition A:** Name generator questions first

(b) **Condition A:** Name generator questions first but excluded values at 50

(c) **Condition B:** NSUM questions first

(d) **Condition B:** NSUM questions first but excluded values at 50

Fig. 4. Scatter plots of the correlation between estimated personal network size (NSUM) and the free-name generator across experimental conditions A (1. NG; 2. NSUM) and B (1. NSUM; 2. NG) with and without capped values in the name generator task.

the strength of the correlation drops significantly. When the capped responses were excluded, there was no more correlation visible. This simple order swap may indicate a decline in cognitive or motivational factors of the participants in recalling social contexts when the name generator comes later in the survey, similar to the response fatigue (Eagle and Proeschold-Bell, 2015). These observations link back to previous literature where question-order effects have been recognised as an interference factor for collecting data via name generators (Yousefi-Nooraie et al., 2019; Marsden and Hollstein, 2023).

The limited association between the two measures may also reveal that they focus on partly different layers of personal networks. NSUM-based estimates are designed to approximate a broader acquaintance network (Laga et al., 2021). In contrast, a free-name generator may be more specific and capture closer parts of personal networks, while it is also a flexible instrument depending on the wording of the name generator (McCarty et al., 2019). These two perspectives on broader and closer layers of personal networks could open new avenues for future studies. For example, instead of being alternative indicators, the two measures may complement each other and help to evaluate the relation between different layers for each respondent. However, we focus here on the use of the free-name generator count in personal network studies and leave this interpretation for future studies.

Limitations and future directions

The survey results play a key role in our argument and therefore we discuss here briefly their limitations. Our pool of participants exhibits less variation in characteristics compared to the general population, and may include certain biases. While comparing results from a more homogeneous group reduces the chances of confounding effect from other characteristics, our results are not generalisable to the Spanish population. Further, the sample size is large enough to support a statistically solid argument but not large enough to represent a whole population. Future work could make use of a more age-diverse sample or different contexts. In the survey design, we ensured that the participants have the same understanding of what a *close contact* is by providing a common definition. Nonetheless, the interpretation of this definition can vary from participant to participant. This could include a more narrow definition where only strong ties are included or a wider definition with more weak ties. On the other hand, the network estimation by NSUM suffers from its known limitations we presented above. A potential bias may arise from the interplay between the two measures. Both methods rely on recall (McCarty et al., 2001; Marin, 2004), which may affect how consistently participants respond across the two tasks. Shared recall bias may therefore affect both measures and partly shape the observed association between them. At the same time, the recall performance of people in the subpopulations might also be affected by the question-order effects, such as response fatigue. Another limitation concerns potential self-selection bias from the recruitment strategy via email and incentive structure (see, e.g. Bethlehem, 2010; Ball, 2019). A demanding network survey may attract respondents who are more motivated, available, or comfortable with detailed survey tasks. These limitations do not reduce the result validity but highlight potential sources of bias that should be considered.

The name generator in our survey is the most basic form and estimates the network size by only one response. However, as shown previously (see, e.g., Marin and Hampton, 2007), using several name generators improves the data quality and reliability of the results and leads to a more nuanced understanding of the personal environment. A possible extension of this study could be breaking down the name generator question into multiple items. This recommendation is also consistent with the free-listing elicitation literature, which shows that the number and diversity of elicited items can increase when researchers use successive lists, domain decomposition, or light follow-up prompting rather than relying on a single broad prompt (Quinlan, 2005; Brewer, 2002; Ryan et al., 2000). For instance, we could employ several questions to uncover different social groups, such as family or work-related friends, or to address distinct social circles (Dunbar, 2018), such as support clique or sympathy group.

Our results offer several implications for future research on personal networks. From a methodological standpoint, the analysis of personal networks could be simplified by eliciting a fixed number of alters. This standardisation can be implemented through a fixed name generator, which makes many network metrics more comparable across respondents (González-Casado et al., 2026). Network size should not be treated as a by-product of name elicitation. Ranking participants by network size based on the name generator should be avoided.

If network size plays a role in the analysis, we recommend using a dedicated instrument, such as the NSUM.

Despite these limitations, we conclude that, under the conditions of our study, the single free-name generator is a very limited proxy for NSUM-based network size. The weak correlations suggest that the two methods capture different characteristics of a personal network. The correlation is not robust and vanishes even further when capped values are excluded or the survey order is taken into account. If estimating personal network size is relevant for a study, we advise to rely on established methods, such as the NSUM. The length of the free name generator mainly appears to reflect participants' response behaviour and task constraints rather than a reflection of personal network size.

CRediT authorship contribution statement

Alejandro Dinkelberg: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Christopher McCarty:** Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Miguel A. González-Casado:** Writing – review & editing, Conceptualization. **Miroslav Pulgar:** Writing – review & editing, Methodology, Conceptualization. **Angel Sánchez:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **José Luis Molina:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT and Gemini in order to improve the clarity and readability of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.socnet.2026.08.001.

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