From hidden populations to social structure:
Evolution of the Network Scale-Up Method, Aggregated Relational Data, and their applications

Introduction to the Special Issue on the Network Scale-Up Method and Aggregated Relational Data in the journal Social Networks

Miranda J. Lubbers
Department of Social and Cultural Anthropology, Universitat Autònoma de Barcelona, Spain. Corresponding author. ORCID: https://orcid.org/0000-0001-8398-6044

Beate Völker
Department of Sociology, VU Amsterdam, The Netherlands. ORCID: https://orcid.org/0000-0002-9823-474X

Michał Bojanowski
Department of Quantitative Methods & Information Technology, Kozminski University, Poland, & Department of Social and Cultural Anthropology, Autonomous University of Barcelona, Spain. ORCID: https://orcid.org/0000-0001-7503-852X

Abstract: To situate the sixteen articles included in this Special issue on the Network Scale-Up Method (NSUM) and Aggregated Relational Data (ARD), we synthesise nearly four decades of research in the field. Drawing on 301 studies, we introduce key concepts and trace major trends, including the shift from hidden population estimation to the analysis of extended personal networks. We also reassess claims of NSUM's unsatisfactory performance in public health, showing that many evaluations rely on earlier implementations rather than more advanced estimation models. In addition, we identified major surveys and software supporting NSUM and ARD, including recent large-scale datasets, to compare how these methods have been implemented across studies. Throughout the review, we offer practical guidance, including new suggestions regarding the need to select coherent sets of probe groups. Because design issues are not always well documented, we also propose a reporting checklist to enhance transparency and comparability. Finally, we show that the sixteen articles included in this Special Issue engage directly with the issues raised in this review, addressing biases, refining estimation models, analysing acquaintanceship networks, and demonstrating how NSUM outputs can inform agent-based models.

Keywords: Network Scale-Up Method; Aggregated Relational Data; Acquaintanceship Networks; Personal Networks; Hard-to-count Populations; Survey Design

Introduction

Accurate estimates of hard-to-count, often vulnerable subpopulations are essential for effective policymaking, including resource allocation, monitoring, and advocacy. Examples of such groups are unhoused or trafficked people, women undergoing unsafe abortions, people who inject drugs, and people at risk of HIV. Despite the need for reliable estimates, researchers typically lack suitable sampling frames for these groups, who are less likely to participate in standard surveys because of housing instability, limited internet access, distrust of researchers, or anonymity concerns (e.g., Verdery et al. 2019). This raises the challenge of how to estimate the size of these groups.

Nearly four decades ago, a team of researchers invented the *Network Scale-Up Method* (NSUM) to address this challenge (Bernard et al. 1989, 1991; Killworth et al. 1990). Their ground-breaking idea was that, under certain assumptions, the share of a subpopulation in society can be inferred from its share within the extended personal networks of a representative sample of the national population. To calculate this fraction, survey respondents are asked how many people they know who belong to the target population. To estimate each respondent's acquaintanceship network size needed to scale up these counts, researchers also ask how many people they know in a set of subpopulations of *known* sizes (e.g., people with common first names). Responses to these "How many people do you know who [belong to a certain subpopulation]?" questions are now known as *Aggregated Relational Data* (ARD; McCormick & Zheng 2012).

While *Social Networks* provided comprehensive coverage of NSUM's origins (Johnsen et al. 1995; Killworth et al. 1990, 2003; Killworth, Johnsen et al. 1998; Shelley et al. 1995), the method has since gained international acceptance across health sciences, sociology, demography, criminology, and statistics. This broad disciplinary uptake has dispersed the literature across numerous fields, making it difficult to follow developments comprehensively. Over the past six years alone, publications on NSUM and ARD have nearly doubled, with some appearing in top-tier journals such as *Social Forces*, *European Sociological Review*, *Sociological Methodology*, *Journal of the American Statistical Association*, *Annals of Applied Statistics*, *PNAS*, *Econometrica*, *American Economic Review*, *American Journal of Public Health*, and the *American Journal of Epidemiology*. At the same time, the method's utility has expanded to the broader study of extended personal networks, transforming NSUM from a specialised estimation technique into a powerful framework for investigating social structure.

Given NSUM's roots in social network research and the growing use of NSUM and ARD to investigate extended personal networks and broader social structures, we believe this is an opportune moment for *Social Networks* to reflect on this rapidly expanding global literature. This Special Issue features sixteen articles selected from an open call for contributions, offering both methodological advances and innovative empirical applications. To contextualise these contributions, this introduction synthesises the NSUM and ARD literature. Drawing on 301 publications, we introduce key concepts, classify biases into network-structural and perceptual biases, and highlight major methodological and substantive developments. We also review the surveys and software accompanying these studies to compare how NSUM and ARD are implemented in practice. This analysis motivated us to propose a reporting checklist for NSUM and ARD studies to enhance transparency and comparability. Against the backdrop of this review, we then introduce the papers in this Special Issue. The synthesis offered here and the Special Issue papers show the current state of the field and point to promising directions for future research.

Methodology

To map the literature on NSUM and ARD, we constructed a database of publications employing or explicitly describing the Network Scale-Up Method or Aggregated Relational Data. We began by searching the Web of Science and Google Scholar using the terms: "Network Scale-Up Method" OR "Network Scale Up Method" OR "Aggregated Relational Data" OR "Aggregate Relational Data" (Google Scholar returned 1,190 results on 01/01/2026, our last update). To capture early and terminologically more heterogeneous contributions, we also included works listed on NSUM inventor H. Russell Bernard's website[1], as well as publications cited in previous literature reviews (Bernard et al. 2010; Feehan and Salganik 2016; Laga et al. 2021).

From this corpus, we excluded materials that were not substantive academic publications, such as conference abstracts, Master's Theses, grant applications, unsupported citations, and our own call for papers. We also excluded papers that mentioned NSUM or ARD only tangentially (e.g., in reference lists or in summaries of prior studies). We retained journal articles, book chapters, full conference proceedings papers, scientific reports, PhD theses, and online preprints deposited on platforms such as *arXiv, medRxiv,* or *SSRN* that engaged with NSUM and/or ARD. Where a preprint had been formally published as a journal article or book chapter, we retained only the published version and excluded the preprint. Because our searches were conducted in English, we only included non-English publications if they used the English NSUM or ARD terms in the main text or in an English-language abstract.

We also examined the surveys used in the identified papers as well as the software developed alongside them, to map how NSUM and ARD have been implemented in practice. This enabled us to identify additional papers analysing ARD items, even when they did not use the terms ARD or NSUM to describe them.

Using this approach, we identified 301 original contributions published between 1989 and 2025 (see Supplementary Materials). Of these, sixteen were PhD theses, and twenty-two were scientific reports. Eleven papers appeared online in 2025 but were assigned to print issues in early 2026; these were excluded from Figure 1 to avoid distortions caused by publication timing[2]. Three contributions to this Special Issue were published in 2025; these are included in Figure 1 but excluded from the review below, as they are discussed in a later section.

[1] https://hrussellbernard.com/scale-up/

[2] Unpublished preprints (15) and publications published online first (2) may also have later publication dates after we finished our analyses (the first trimester of 2026), but we decided to keep them in our dataset as they reveal the latest tendencies.

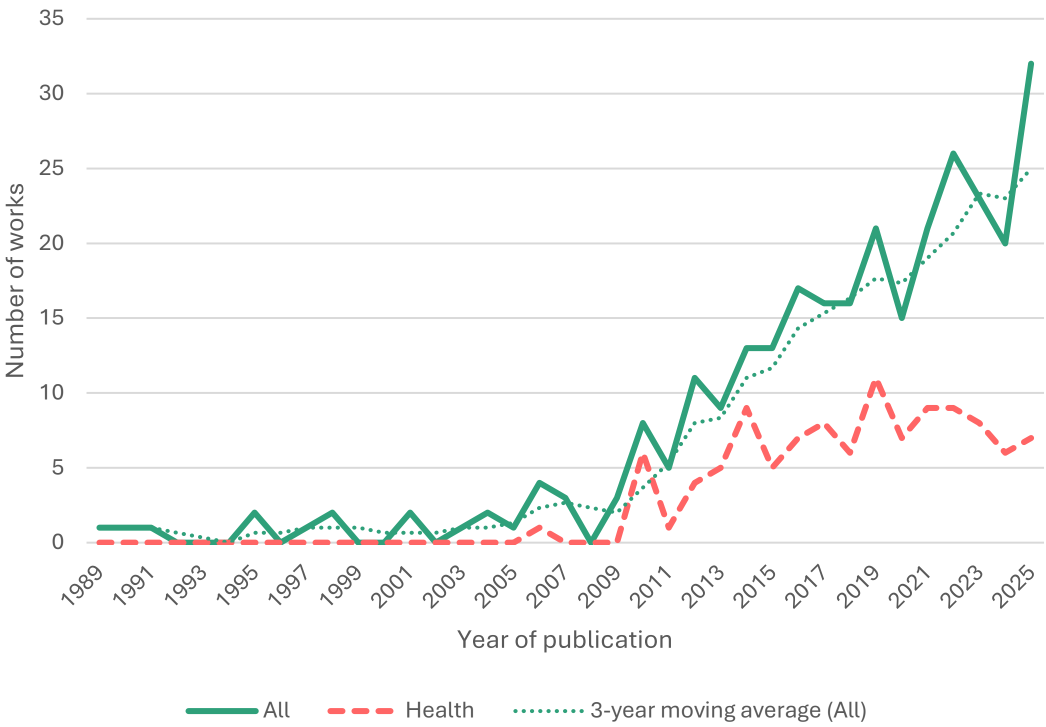

Figure 1. Yearly evolution of the NSUM and ARD literature between 1989 and 2025 (*N*=290), overall (green) and within health sciences (red). *Note:* Discipline is categorised based on the venue (journal or book); for other formats (e.g., reports), it is derived from the topic. To capture the state of the art, the dataset includes 15 preprints and 2 "online-first" works available as of December 2025; they are indexed by their date of first appearance, regardless of whether they eventually carry later official publication dates or remain as preprints. Conversely, 11 papers available online in 2025 were excluded because they have been assigned an official 2026 publication date during the first trimester of 2026. Source: Own elaboration.

Figure 1 describes how the NSUM and ARD literature has developed over time. Based on the figure, we distinguish four periods. The first, extending to 2005, consists primarily of publications by the original research team. A second, transitional period (2006–2013) shows growing engagement by other scholars and application in other countries, particularly in public health. The third period (2014–2019) represents a phase of substantial extension beyond health. Finally, the most recent period (2020–2025) is characterised by continued overall growth and relative stagnation in public health applications. In each period, the literature expanded substantially. Below, we outline the key developments in each period, as summarised in Table 1.

Period:	1989 – 2005	2006 – 2013	2014 – 2019	2020 – 2026
Methodological developments:	First formulation of NSUM Known population method Summation method Identification of biases ML estimation	Bayesian NSUM Game of contacts (visibility) Generalised NSUM designs	Network survival method (mortality) Latent space and latent surface models for ARD Degree ratio bias adjustment	Sample size guidelines Binary ARD formats Small area estimation
Assumptions and biases addressed:	Barrier, transmission, recall (conceptualised)	Quantifying and adjusting for barrier and transmission effects	Tie definition sensitivity: joint modelling of barrier / transmission / recall biases Identification of degree-ratio bias	Integrated treatments of barrier / transmission /recall / degree ratio bias Subnational heterogeneity Practical diagnostics
Target populations:	Seroprevalence Victimisation (earthquake, 9/11 terrorist attacks) Rape Drug use Homelessness Imprisonment	Groups at risk of HIV Drug use Injuries / choking in children Doping	Groups at risk of HIV Drug use Abortion Illnesses and disabilities Deaths and suicides International migrants Religious populations Imprisonment Earthquake victims	Groups at risk of HIV Drug use Trafficking and forced labour COVID-19 Abortion (Cyber)crime LGBTQ Ukraine invasion Scientific misconduct International migrants
Network applications:	Network size	Network size and composition (as explanans and explanandum) Visibility of target groups	Network size and composition Network exposure	Network size / composition Network exposure Network structure
Software developed:			NSUM, *no longer maintained* networkreporting	networkscaleup stansum

Table 1. Overview of developments in NSUM and ARD research

The Development of the ARD and NSUM Literature

Origins and Early Development (1989–2005)

In 1989, anthropologist H. Russell Bernard and his colleagues Eugene Johnsen, Peter Killworth and Scott Robinson introduced what would later become known as the Network Scale-Up Method (NSUM). Their central idea was that, under certain assumptions, the size of a hidden population could be inferred from the fraction it represents in the extended personal networks of a representative sample of the overall population. In their initial application, estimating deaths from the 1985 Mexico City earthquake, respondents were asked if they knew any people who died in the earthquake. Dividing these counts by respondents' personal network sizes and averaging across the sample yields an estimate of the subpopulation's prevalence. Because personal network size is itself unknown, this early work suggested borrowing average network sizes from previous research but already warned that "personal network size is not a constant" (p. 161).

Between 1989 and 2006, the method was refined primarily by its inventors, joined by Christopher McCarty and Gene Shelley. Fourteen academic papers appeared during this period, eleven led by the team, six of which published in *Social Networks*. A central concern was how to estimate respondents' "*active network*" size (e.g., Killworth, Johnsen et al. 1998), defined as all the people they know and with whom they have had some contact in the past two years. Active networks are much larger than support or core discussion networks, which were considered too small and homogeneous for estimation purposes (Bernard et al. 2010; related terms are *weak-tie networks, extended networks*, and *acquaintanceship networks*).

Two strategies for estimating active network size emerged (McCarty et al. 2001). The first, the *summation method*, asks respondents how many people they know across an exhaustive set of mutually exclusive social contexts (e.g., family, neighbourhood, work) and then sums the responses. The second, and ultimately more influential, approach formalised the logic outlined in the introduction. In addition to being asked about populations of unknown size, later called *target groups* (e.g., Paniotto et al. 2009), or also *key* populations (e.g., Guo et al. 2013), respondents reported how many people they knew in multiple subpopulations of known size. These latter groups were referred to as *probe groups* (e.g., Laga 2025), *reference groups* (Bernard et al. 1991), or *bridge populations* (e.g., Kovtun et al. 2024). Bernard et al. (2010) recommended using at least 20 probe populations. Dividing responses by the known population fractions yields estimates of personal network size. This approach became known as the "*known population method*" (Killworth, McCarty, et al. 1998)[3]. Together, these methods offered a cost-effective means of estimating quantities that were otherwise hard to measure.

Early work articulated three main assumptions underlying NSUM (e.g., McCarty et al. 2001; see Panels 1, 3, and 4 of Figure 2). First, individuals are assumed to mix randomly with respect to the subpopulations under study, such that the probability of knowing

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[3] The group also described the known population method as "back estimation" (Killworth, McCarty, et al. 1998; Bernard et al. 2001). Since this term is now commonly used to mean the diagnostic step of estimating known-size groups to assess data quality (e.g., Habecker et al. 2015), we recommend reserving "back estimation" for this later use to avoid ambiguity.

someone in the target group depends only on personal network size and subpopulation size. Violations of this assumption, called "*barrier effects*", arise from social segregation and/or homophily. A second assumption concerns awareness. NSUM requires respondents to know which of their acquaintances belong to the target group. Violations of this assumption, referred to as "*transmission bias*" (masking), occur when membership is stigmatised, private, or simply rarely discussed in informal conversations, as is the case of drug use, income, or certain health conditions (McCarty et al. 2001). The third concerns reporting. Respondents are assumed to accurately report how many of their network members belong to each subpopulation. A notable violation of this assumption, labelled "*recall bias*", is the systematic underreporting of members of larger subpopulations (Killworth et al. 2003). Additional cognitive errors arise from inconsistent understandings of the subpopulation's boundaries or the meaning of "knowing someone," heaping, and social desirability. The early literature already warns that the validity of NSUM estimates hinges on minimising these biases and on using survey samples that are sufficiently large and representative of the general population (e.g., Bernard et al. 1989).

In terms of modelling, this period saw the introduction of a maximum likelihood estimator for NSUM (Killworth, McCarty et al. 1998), laying the groundwork for later statistical developments. Empirical applications in this period were primarily conducted in Mexico (e.g., Bernard et al. 1991) and the United States (e.g., Killworth, McCarty et al. 1998; McCarty et al. 2001). The US General Social Survey (GSS) included several ARD questions between 1988 and 1993 (Johnsen et al. 1995), before introducing a 30-item ARD battery in 2006 (e.g., DiPrete et al. 2011).

This early work emerged within a period of rapid innovation in social network methodology, spanning the mid-1980s to the early 2000s. Researchers experimented with new measures of core and extended networks, including name generators, position and resource generators, the reverse small world method, and telephone book experiments. They also developed exponential random graph models and other statistical approaches, network-based sampling methods such as respondent-driven sampling (Heckathorn & Cameron 2017), and epidemiological network models. NSUM emerged from, and contributed to, this fertile methodological landscape by offering a novel way to infer population properties from personal network data without directly observing ties.

Diffusion and Methodological Scrutiny (2006–2013)

Between 2006 and 2013, a more diverse body of scholarship began to emerge. During these years, 43 academic publications appeared (see Figure 1), only four of which were authored by the original team. Researchers, often working closely with the method's inventors, began applying NSUM to estimate the size of hidden and hard-to-count populations across the world. Early applications remained concentrated in public health (40% of all papers), particularly focusing on subpopulations at heightened risk of HIV or drug use. Large-scale surveys were conducted in China (Guo et al. 2013; Huan et al. 2013; Wang et al. 2015), Iran (Rastegari et al. 2013), Japan (Ezoe et al. 2012), Moldova (Bernard et al. 2010; Feehan and Salganik 2016), Rwanda (Rwanda Biomedical Center et al. 2012), and Ukraine (Paniotto et al. 2009; Berleva et al. 2010). International organisations such as UNAIDS (UNAIDS 2012; UNAIDS & WHO 2010) also began incorporating NSUM into their data collections, often with guidance from the inventors. Beyond infectious disease and drug use, researchers applied NSUM to study choking among children in Italy (Snidero et al. 2007) while ARD items were included in a survey on doping among athletes in England (James et al. 2013). These applications marked an early step toward the broader use of ARD to estimate rare or stigmatised behaviours in general populations.

At the same time, researchers continued to scrutinise the assumptions underlying NSUM and developed survey recommendations and statistical techniques to correct its biases. Much of this work was led by Matthew Salganik, Tian Zheng, and Tyler McCormick. Three papers were particularly influential. First, Zheng et al. (2006) introduced a multilevel overdispersed Poisson regression model that identified barrier effects through overdispersion in ARD and adjusted for them. In doing so, they provided the first Bayesian model for NSUM. Second, through statistical modelling and simulation, McCormick et al. (2010) demonstrated that careful selection of probe subpopulations substantially improves estimation accuracy. They recommended using sets of relatively rare first names (e.g., "How many men do you know whose name is Bas?"), because this reduces all three biases: a) names are among the earliest things people know about one another, which reduces transmission bias, b) although individual names may exhibit barrier effects due to their gender, age, ethnic, and sometimes class profiles, these effects can offset on another in a well-selected set, and c) selecting low prevalence names (0.1–0.2%) helps to mitigate recall bias. Third, Salganik et al. (2011) developed the "*game of contacts*", a survey-based method for estimating a target population's social visibility and thereby quantifying transmission bias directly (cf. Shelley et al. 1995), using reports from the target population itself. In a study in Brazil, the authors showed that people disclose their drug use far more often to other drug users than to non-users. The game of contacts has since been adopted in NSUM studies and in studies using other network-based methods such as "the confidante method" for estimating abortion prevalence (e.g., Giorgio et al. 2024).

These methodological advances also led to a conceptual shift: biases were no longer merely viewed as statistical nuisances, but as indicators of substantively meaningful social processes. A landmark paper in this regard was DiPrete et al. (2011), who used the ARD battery in the 2006 GSS to estimate extended network size and social segregation, measured through the overdispersion of ARD counts, and associated variation in network position to sociodemographic attributes. Their findings suggested that social segregation in weak-tie (acquaintanceship) networks was as strong as in strong-tie (trust) networks. Later research built on this insight by using ARD not only to estimate subpopulation sizes but also to examine the structure of social networks themselves.

Methodological Maturation (2014–2019)

Between 2014 and 2019, work on NSUM and ARD expanded further, with at least 13 papers published yearly (96 in total), bringing the cumulative total to 153, nearly triple the number of earlier publications (*N*=57; see Figure 1). Almost half of the publications from this period (*N*=46) appeared in the health sciences.

A notable development was the rapid uptake of NSUM in Iran following early publications in the second period (Shokoohi et al. 2010, 2012; Rastegari et al. 2013). There, NSUM became a central tool for estimating the prevalence of stigmatised or illicit behaviours, such as sex work and the purchase of sexual services (Jafari-Khounig et al. 2014; Maghsoudi et al. 2014), extramarital sex (Zahedi et al. 2019), abortions (Rastegari et al. 2014), and drug use (Jafari-Khounig et al. 2014; Maghsoudi et al. 2014). By relying on indirect reports about network members rather than self-reports ("*anonymous third-party reporting*"; e.g. Rossier et al. 2022), NSUM helped researchers mitigate severe underreporting in direct surveys conducted in institutionally restrictive contexts (Sheikhzadeh et al. 2014). The method's usefulness in these contexts contributed to its prominence: in the third period, Iranian publications accounted for 36% (*N*=35) of all NSUM/ARD studies, before declining to 22% (*N*=32) in the fourth period.

Beyond this regional pattern, trends in this period are methodological maturation and a growing recognition of ARD's value for studying social networks rather than solely for estimating population size. On the methodological front, researchers continued to refine NSUM by addressing its key biases (cf. Laga et al. 2021). Building on Zheng et al. (2006), Maltiel et al. (2015) developed a Bayesian framework that jointly accounts for recall bias, barrier effects, and transmission bias, although the accuracy of the transmission-bias correction depends on reliable external data on the size of this bias, something the game of contacts could supply. Feehan and Salganik (2016) identified *degree ratio bias*, a fourth type of bias that arises when target or probe populations differ from the general population in average network size, which distorts subpopulation and network size estimates (see Figure 2, panel 2). Like barrier effects, we consider this a network bias because it arises from the structure of the underlying networks. Recall and transmission biases, by contrast, result from respondents' memory and knowledge of their networks (perceptual biases, see Figure 2). To address different biases jointly, Feehan and Salganik proposed a generalised NSUM design that collects data from both the general population and the target subpopulation(s). Habecker et al. (2015) proposed techniques such as sample weighting and recursive trimming to improve robustness by identifying poorly performing probe populations.

A closely related line of work focused on the definition of social ties. Feehan, Umubyeyi et al. (2016) demonstrated that NSUM estimates depend strongly on how "knowing someone" is defined. Their findings show that stronger tie definition, such as having "shared meals or drinks in the past 12 months", can yield more accurate estimates. We believe this is particularly useful when the target and probe populations are larger: when strong tie definitions are applied to very rare populations, responses are typically dominated by zeroes, resulting in imprecise estimation. Stronger tie definitions, therefore, appear most beneficial for larger subpopulations or for groups whose membership is primarily known through close relationships.

A major advance during this period was the introduction of latent geometry and other more complex models for ARD to investigate underlying patterns of network segregation (McCormick & Zheng 2015; Sahai et al. 2019; Smith et al. 2019). Rather than assuming random mixing or merely correcting barrier effects, latent space and latent-surface models assume that people mix according to their social positions in an unobserved social space, where distance governs contact probabilities. McCormick and Zheng

(2015)'s latent surface model embeds both respondents and subpopulations on a continuous surface, modelling expected ARD counts as a function of distance and degree (see Park 2021 for a later application). This approach handled much of the heterogeneity previously attributed to barrier effects. Smith et al. (2019) extended this approach to non-Euclidean, curved spaces with flexible link functions, improving fit where clustering and multiple similarity dimensions are present. Their model can be used to infer dyadic network ties from distance. Other complex models include Sahai et al. (2019)'s application, which introduced latent kernel formulations to improve personal network size estimation under non-random mixing. These more complex ARD models integrate within a single framework what earlier approaches treated separately: estimating respondents' mixing patterns, visibility, and sometimes network sizes. Their adoption has nevertheless remained limited, perhaps because of their computational complexity.

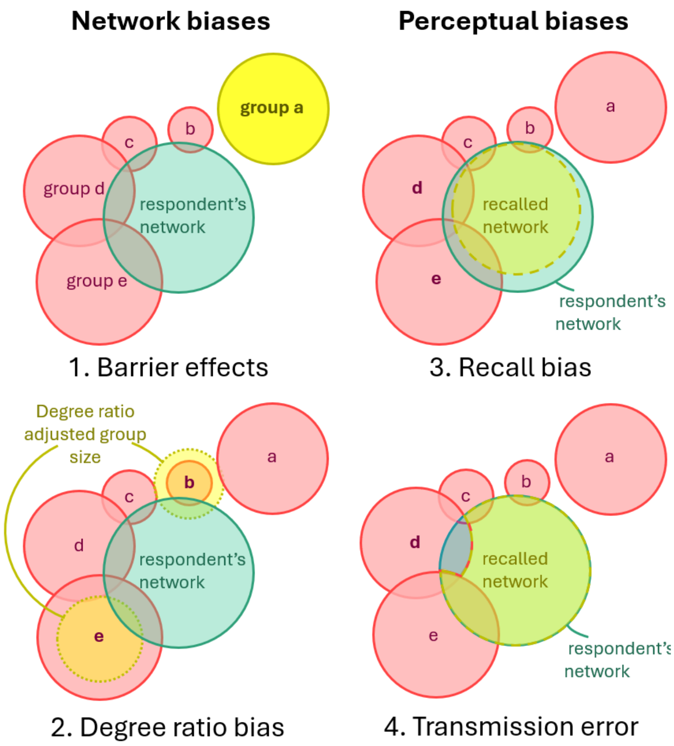

Figure 2. Stylised representation of four types of biases affecting NSUM estimates. Note: Inspired by McCormick's (2020) visualisation of recall bias, the figures depict a typical respondent's acquaintanceship network (in green) and the relative (downsized) sizes of different probe and target groups (in red). Yellow highlights the source of bias. We distinguish between network structural biases and perceptual biases. *Network biases* reflect actual differences in social network structure. Barrier effects (1) occur when contact with a group is lower than expected given its population size (here, this affects group a). Degree ratio biases (2) arise when groups have systematically larger (group b) or smaller (group e) average network sizes than the general population, affecting the likelihood that respondents know someone in those groups. *Perceptual biases* reflect differences in how respondents' perceptions, recall, or knowledge of their networks. Therefore, we project the recalled network onto the actual one. Recall biases (3) lead respondents to underestimate the number of network members in larger groups (here, strongest for the largest group e, followed by group d). Transmission errors (4) occur when respondents know members of a group (group d), but do not know their group membership. Source: Own elaboration.

This period also saw the emergence of methods related to, or inspired by, NSUM. Feehan et al. (2017) developed the "*network survival method*" as a variation on the Network Scale-Up Method (cf. Breen et al. 2025). This method estimates general and subgroup-specific mortality rates in countries lacking reliable registration data. By asking respondents how many people they know who died during a given period, the method leverages the high visibility and social relevance of deaths relative to other subgroup statuses, making it more robust to barrier effects, transmission bias, and recall error. Other extensions included the venue-based generalised network scale-up method (Verdery et al. 2019), designed to circumvent the need for a representative general-population sample.

Empirically, NSUM's use for estimating population sizes remained largely concentrated in studies of drug use and populations at risk of HIV in this period (e.g., Teo et al. 2019), although some studies examined abortion prevalence (Zamanian et al. 2016, 2019) or less typical targets such as religious populations (Yang & Yang 2017). However, following DiPrete et al. (2011), sociologists increasingly employed NSUM and ARD to study features of networks themselves, rather than solely as tools for estimating population size. ARD directly measure the acquaintanceship layer of social life, dominated by weak ties, which, according to long-standing network theory, are central to information diffusion (e.g., Granovetter 1973), social opportunity (Lin et al. 2001), and societal cohesion (e.g., Blau 1977). Some studies estimated extended network size and treated it as the *explanandum,* examining its antecedents, such as sociodemographic characteristics or personality (e.g., Shati et al. 2014; Ishiguro 2016; Lubbers et al. 2019). Others used ARD-derived network measures as *explanans,* to explain outcomes such as perceived social support (e.g., Lu & Hampton 2017; Lubbers et al. 2019). These developments reflected a broader reconceptualisation of ARD from merely an input for estimating subpopulation size to a resource for analysing extended personal networks.

Another interesting development was the growing use of single ARD questions to measure network exposure to specific life events and social phenomena. Such exposure has sometimes been conceptualised as *spillover* (Lee et al. 2015) or *ripple effects* (Bernard et al. 2001), in the sense that events that individuals experience affect others through their wider networks. Using ARD from the 2006 GSS, Lee et al. (2015) revealed stark racial inequalities in US citizens' connectedness to prisoners: on average, Black men knew six times as many prisoners as White women, and Black women had 20 times as many incarcerated family members as White men. Mondak et al. (2017) showed that "vicarious" encounters with the police or justice system –encounters experienced by respondents' network members rather than by themselves– affect respondents' perceptions of the police and courts. Because social networks are relatively homogeneous by race and encounters with the justice system are unevenly distributed across racial groups, these indirect experiences widen racial and ethnic differences in perceptions. Feigelman et al. (2018) used a single ARD question, together with follow-up data from the 2016 GSS, to study network exposure to suicide. From a social contact theoretical perspective, DellaPosta (2018) used longitudinal data to show that having gay or lesbian acquaintances increased support for same-sex marriage and acceptance of homosexuality over time. These studies illustrate that even single ARD items can be useful to reveal unequal patterns of social exposure to disadvantage and trauma, as well as to social diversity.

Reorientation toward Social Network Analysis (2020–2026)

The period reviewed by Laga et al. (2021), covering publications through 2019, comprised 153 entries in our database. In the subsequent six years, the literature nearly doubled: we identified a further 148 papers on NSUM and ARD published between 2020 and 2025, including eleven published online in 2025 with print dates in 2026. This near duplication underscores the need for an updated review of the literature. This most recent wave is characterised by continued improvement in modelling and a more decisive shift toward using ARD as a tool for social network analysis.

Methodologically, two types of developments define this period. The first concerns improvements of data quality. Josephs et al. (2022) proposed guidelines for the minimum sample sizes required to achieve the desired levels of statistical precision in NSUM estimation. Baum and Marsden (2023) evaluated binary response formats[4] as an alternative to counts. Binary response formats are cognitively less demanding and particularly advantageous in long ARD batteries involving relatively sparse probe populations. A hybrid design, first asking respondents *whether* they know anyone in each subpopulation and requesting counts only when they do, offers a promising middle ground (Völker et al. 2025, this Special Issue). Lubbers et al. (2025) demonstrated high test-retest reliability of ARD questions over a two-week interval and showed that response cards reminding respondents what it means to "know someone" and displaying typical social foci (e.g., family, neighbourhood, work) help recall and consistency in extensive ARD batteries. Finally, Fenoy et al. (2023) contributed a method for the principled selection of probe subpopulations, opening a line of work that subsequent research can elaborate and formalise.

The second set of developments addresses statistical modelling. Parsons et al. (2022) proposed Bayesian hierarchical approaches that combine multiple methods for population size estimation, while Lubold et al. (2025) developed goodness-of-fit tests for ARD. Kunke et al. (2024) compare the performance of various simple NSUM estimators across various conditions, clarifying when classical estimators remain stable and when more complex models are preferable. Laga et al. (2023) addressed the degree ratio bias identified by Feehan & Salganik (2016; see previous period, and panel 2 of Figure 2). They proposed estimators that account for it *without* requiring additional data from the target subpopulations themselves. Laga (2025) further proposed to estimate the size of probe groups directly from survey data, making NSUM easier to apply when official statistics on suitable probe groups are unavailable or poorly aligned with survey years. This work also extends NSUM/ARD beyond national averages to subnational inference (see also Datta et al. 2025; Jin et al. under revision): Using a nationally representative survey of Jordan, Laga estimated the number of migrant domestic workers at the governorate level, hence showing a practical pathway for small-area estimation.

[4] It is a question, though, whether binary responses still fall under the term "Aggregated Relational Data," as this would imply that responses to Lin's position generators (Lin et al. 2001) or Van Der Gaag and Snijders' (2005) resource generators are also ARD. In this overview, we have not included responses to traditional position and resource generators (e.g., "Do you know a doctor? Do you know someone who can repair a car?").

Substantively, while NSUM remains a cost-efficient and flexible approach to estimating hard-to-count populations, public health applications show signs of stagnation after 2019 (see Figure 1). Exceptions persist in areas where direct surveys face severe underreporting, such as abortion (e.g., Farrokhi et al. 2025; Giorgio et al. 2023; Rossier et al. 2022; Santana Paiva et al. 2020; Sully et al. 2020). Increasingly, public health researchers turn to alternative methods such as capture-recapture and multiplier methods, which may yield greater precision or rely on fewer behavioural assumptions (e.g., Abdul-Quader et al. 2014). Yet many critical evaluations of NSUM fail to take implementation quality into account. As Ocagli and colleagues (2021) note, many empirical applications still use the classical estimators that reflect earlier stages of NSUM development rather than the current state of the art. Much of the scepticism in public health (e.g., Kovtun et al. 2024; Sully et al. 2020) may therefore reflect how NSUM was implemented in the past rather than in how it performs when survey design and statistical estimation control properly for biases. In a different vein, Ocagli et al. (2021) report bias when simulating Maltiel et al.'s (2015) Bayesian model, but estimate network size using only one known population, which is analogous to measuring social capital with a single position generator (e.g., "How many doctors do you know?"). In addition, Xu et al. (2022) classify social media-based estimates as NSUM, complicating a comparison between NSUM and alternative methods. For a fair assessment of NSUM's reliability, future research should compare state-of-the-art implementations of NSUM, including Bayesian modelling, bias adjustment and carefully designed probe sets, with alternative methods. Only then can we assess whether NSUM has been discounted too quickly or whether the concerns about it are well-founded.

Beyond health research, NSUM has been taken up to estimate populations affected by rapidly emerging social issues, particularly when traditional data collection is infeasible or too slow. In publications from 2020 to 2025, NSUM provided timely estimates of COVID-19 incidence and mortality (e.g., Baquero et al. 2021; Boisclair et al. 2022; Ocagli et al. 2021; Ramírez et al. 2023) as well as the number of victims and forcibly displaced persons due to Russia's war on Ukraine (Schroeder et al. 2020). The method has also been incorporated in the literature on trafficking and modern slavery (e.g., Shelton 2015; Barrick & Pfeffer 2021). Recent studies estimate child trafficking in West Africa (Okech et al. 2022a, 2022b; Yi et al. 2025), human trafficking in Fiji (UNODC 2023), forced labour in the Philippine fishing industry (Nyarko-Agyei et al. 2026), and even kidney trafficking in Bangladesh (Li et al. 2023). Other recent NSUM applications addressed the prevalence of violence against women (Gohari et al. 2023), the size of transgender populations (Suriya et al. 2024), cybercrime (Breen et al. 2022), and scientific misconduct (Fox et al. 2022).

One of the most exciting developments in this period is the further consolidation of ARD as a tool for studying large-scale patterns of social interaction. After decades of research into strong-tie core networks, researchers increasingly recognise that weaker acquaintanceship networks are also critical for understanding individual outcomes and societal cohesion (e.g., Sandstrom & Dunn 2014; Sprecher 2022). ARD capture this layer of sociality uniquely well. Building on DiPrete et al. (2011) and developments such as latent-space and latent-surface models (see previous period), scholars increasingly treat ARD as partially observed network data that can be collected at a fraction of the cost of complete network data, with one study reporting savings of 70–80% (Breza et al. 2020).

Within this broader turn toward analysing extended personal networks, NSUM and ARD serve several functions. First, like in the previous period, they enable the estimation of individuals' *extended network sizes* through the summation and known population methods (e.g., Feehan et al. 2022; Hofstra et al. 2021). These size estimates have become both outcomes (for instance, of social media use or personality) and explanatory variables in sociological analyses.

Second, ARD capture properties of extended network composition, revealing patterns of *homophily* or social segregation across dimensions such as social class (e.g., Otero et al. 2021; Park 2021), ethnicity (Jeroense et al. 2025), religion (Djupe et al. 2025), and political orientation (Baldassarri & De Jong, 2022). In this sense, ARD operationalise *network exposure*, that is, the share of one's acquaintances in particular social groups or circumstances. Following the social contact hypothesis, this exposure is expected to affect attitudes and beliefs (e.g., Djupe et al. 2025). Echoing this idea, Gelman and Margalit (2021) introduced the notion of a group's "*penumbra*": the set of people who have personal ties to that group. ARD effectively quantify such penumbras, allowing researchers to study the effects of network exposure. For example, exposure to economic hardship in one's network predicts institutional trust, net of income, education, and other individual covariates (Lubbers 2025); exposure to crime is associated with voter preferences (Ventura et al. 2024); and acquaintanceship with politically diverse others is linked to partisan animosity (Baldassarri & De Jong, 2022). Because acquaintance relationships are conduits of information and social support, ARD methods have also been used in research on social capital, complementing position generators by emphasising the breadth of resource-bearing acquaintances (e.g., Baalbergen & Jaspers 2023; Otero et al. 2021). Figure 3 summarises the investigated associations between extended network size and composition and other variables.

Third, ARD are increasingly being used to recover features of the *structure* of societal networks, despite not measuring those networks directly (Breza et al. 2020, 2023; Tian 2025). Although ARD do not reveal the precise edges between individuals (Breza et al. 2020), they can identify structural features consistent with the data (cf. Smith et al. 2019). This work opens a promising frontier: using ARD to infer aspects of societal connectivity, such as clustering or mixing patterns, traditionally accessible only through expensive or impractical whole-network studies.

Finally, factors once treated purely as sources of bias, such as visibility, degree ratios, transmission bias, and recall bias, are increasingly understood as substantive properties of personal networks. They describe who is visible to whom and which relationships are remembered or forgotten, with implications for how people access information and other resources (Jing et al. 2024). Rather than nuisance, these patterns signal how people inhabit and perceive their social worlds, which relates to a broader literature on the cognitive representation of social networks (for a review, see Smith et al. 2020).

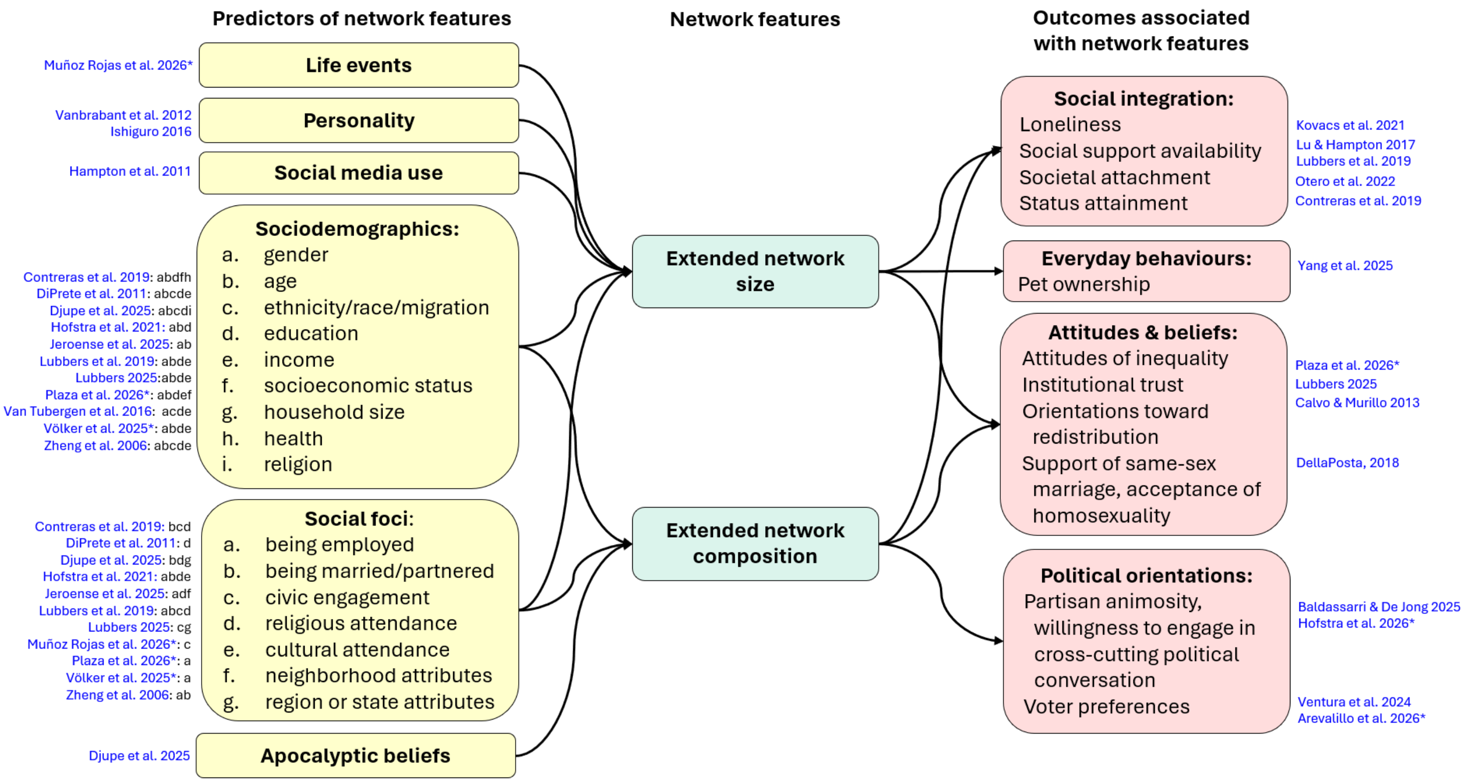

Figure 3. Extended network features as explanans and explanandum. *Note:* Arrows indicate hypothesised or empirically observed associations (not necessarily causal). *Publications in this Special Issue. Source: Own elaboration.

Surveys and Software

Another way to trace the development of the field is to examine the dozens of surveys on which these studies rely, as well as the software created to support analysis and replication. The reviewed publications draw on a wide array of face-to-face, telephone, and online surveys conducted across the world that include ARD items or item batteries (see Figure 3). Figure 3 also presents two recent large-scale data sets: the cross-national PATCHWORK project in Hungary, the Netherlands, Poland, and Sweden (*N*=6,000)[5] and the Civic Health and Institutions project (CHIP50) in the United States[6]. Both collected ARD data in 2025 and are currently being analysed.

[5] https://patchwork-erc.eu/en; PI Miranda Lubbers
[6] https://www.chip50.org/; PIs David Lazer, Matthew Baum, Katherine Ognyanova, Roy H. Perlis, Mauricio Santillana, James Druckman. See https://www.chip50.org/proposals/social-network-competition

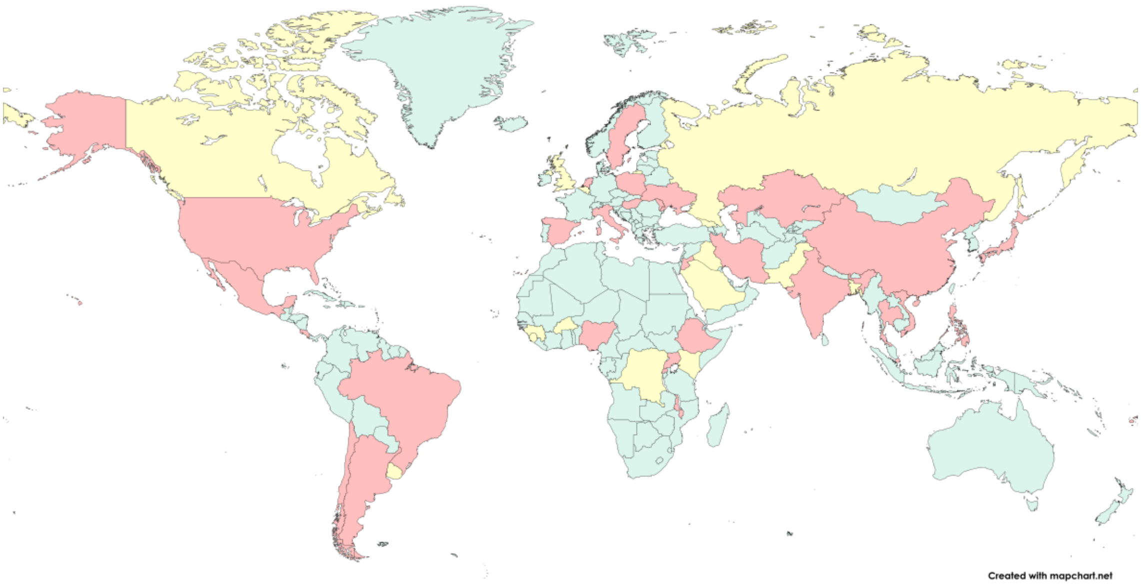

Figure 4. Countries where ARD or NSUM surveys have been held, according to the literature. *Note:* Red indicates that at least one national population survey has been conducted or multiple regional ones, and yellow indicates more limited coverage, based on one to three subnational surveys conducted in a specific city or region. Source: Own elaboration.

The surveys mapped in Figure 4 range from one-time surveys to longstanding national infrastructures and newer longitudinal and cross-national projects (see Table 2). Sample sizes typically fall between 1,000 and 4,000 respondents, allowing reasonably robust estimation of network size and subpopulation size. However, a non-trivial share of studies relies on small or non-representative samples, warranting caution, especially when these data are used to estimate target subpopulation sizes.

Across the surveys we reviewed, more than 800 target and probe populations have been used. First names and occupations are the most common probe items, reflecting both their relatively low susceptibility to bias and the availability of population statistics on names in many countries. If surveys have sufficiently large samples relative to subpopulation size, such items can also be used to infer subpopulation sizes directly from the sample (cf. Laga et al. 2025). The literature also draws on many other types of ARD items, including occupational statuses, life events, religions, resources owned, health conditions, or crime victimisation and offending (see Annex 1). Importantly, rigorous studies adapt ARD batteries to their social and cultural contexts, yielding items as diverse as having co-wives or owning camels or exotic cows in some regions, and cohabiting as a couple or owning electric cars or guns in others.

Surveys vary widely in the number of ARD items on probe and target subpopulations, reflecting only in part differences in the substantive aims of data collection, such as estimating subpopulation sizes, network sizes, or network exposure. A considerable number of surveys include fewer than the 20 probe populations recommended by Bernard et al. (2010). While ARD items on probe groups are typically justified based on the availability of external statistics, the overall coherence of ARD batteries is hardly ever reported, leaving it unclear how the set was selected and whether it provides comparable reporting opportunities across respondent groups. For example, a battery dominated by occupational probes may decrease counts for retirees, students, and unemployed respondents, even if their networks are not in fact smaller, while name sets consisting primarily of native names may suppress counts among migrants. Furthermore, subpopulations may be mutually exclusive (e.g., first names), overlapping (e.g., when combining names and occupations), or hierarchically nested (e.g., people who used opium at least once in the past 12 months and people who use opium 2–3 times a week), which need different treatments. Not all studies report the prevalence levels of probe groups, making it difficult to assess variation in subpopulation size and therefore the risks of underreporting (see McCormick et al. 2010, who recommended prevalence levels of 0.1–0.2% for names) or excess zeroes (see Laga 2025, who recommended 1.0–2.5% prevalence).

Moreover, the definition of a tie also varies substantially across surveys. Most studies adopt a version of the inventors' definition of "knowing someone by sight or by name"[7], but differ on additional criteria, such as whether recognition must be mutual, how recent the last contact should have been (past 2–3 months, e.g., Yang & Yang 2017; past year, e.g., Teo et al. 2019; past two years, e.g., Ocagli et al. 2021), whether the person can be contacted again (e.g., Kovacs et al. 2021), or whether respondents are willing to talk to these contacts if encountered by chance (e.g., Hofstra et al. 2021). Some surveys impose further restrictions on network members' age (e.g., adults, e.g., Breen et al. 2022; people aged 10 years and over, e.g., Kovtun et al. 2024), location (e.g., within the country, Ezoe et al. 2012; within the same municipality; Guo et al. 2013), duration of residence (Guo et al. 2013), or relationship type (e.g., relatives only, e.g., Vardanjani et al. 2015; including disliked others, Paniotto et al. 2009). These discrepancies affect degree and visibility estimates, which should be considered when comparing ARD studies.

Response formats also vary, ranging from unrestricted counts to top-coded counts, bins, and binary responses. Studies using top coding differ in the threshold they adopt (cf. Clay-Warner et al. 2025, this issue), while those using bins differ in how these responses are analysed. These and other design choices directly affect degree estimation, visibility, and recall, reinforcing the need for standardised documentation and sensitivity analyses. To address these gaps, Table 3 proposes a checklist to improve transparency and comparability in reporting NSUM studies.

Alongside survey development, methodological consolidation has been supported by the creation of dedicated software packages for R and Stan and the release of open code. Maltiel and Baraff (2015) implemented classical and Bayesian NSUM models in the now discontinued R package *NSUM*. Feehan and Salganik (2014) implemented the generalised NSUM, along with earlier estimators, in the R package *networkreporting*. R packages *networkscaleup* (Laga et al. 2025) and *stansum* (Bojanowski & Baum 2024) provide interfaces to several Bayesian models, including those described in Zheng et al. (2006), Maltiel et al. (2015), Laga et al. (2023), and Baum and Marsden (2023), which are internally implemented in the Bayesian modelling language Stan (Stan Development Team 2025).

[7] For instance, Killworth et al. (1998:291) specified that "*"knowing" someone meant that a respondent knew that person and vice versa, by sight or by name, that the person could be contacted, that contact (either in person, by telephone or by mail) had occurred during the last two years, and that the person lived within the United States.*"

These tools have helped to standardise practice and broaden uptake, while also facilitating replication and encouraging more principled and transparent modelling choices in recent NSUM and ARD research.

Data set or survey name	**Country**	**Field-work Year**	**Sample size**	***n* sub-populations**	**Key reference(s)**
Florida phone interviews	US	1993–1994	1,524	40	Killworth, McCarty et al. 1998; Killworth, Johnsen et al. 1998
Estimation of the number of populations with high risk for HIV	Ukraine	2009	10,866	40	Paniotto et al. 2009
Internet & American Life Social Network Site survey	US	2010	2,255	34	Hampton et al. 2011
ESPHS study	Rwanda	2011	4,669	26	Rwanda Biomedical Center et al. 2012
–	China (Taiyuan)	2012	8,262	48	Jing et al. 2018
Special *National Barometer*	Spain	2014	2,468	24	Lubbers et al. 2019; Lubbers 2025
–	Iran	2016	15,124	14	Rastegari et al. 2023
Estudio Longitudinal Social (ELSOC)	Chile	2016 2018 2021	2,927 3,748 2,740	25 25 26	Contreras et al. 2019
PMA survey	Uganda Ethiopia	2018	2,161 3,755	15	Sully et al. 2020
-	Singapore	2019	2,802	15	Quaye et al. 2023
Estimating the size of key populations, bridge populations and other categories	Ukraine	2020	10,000	55	Kovtun et al. 2024
Child Trafficking Survey	Sierra Leone	2020	3,070	15	Yi et al. 2023; Okech et al. 2022
INCIDENT study	Italy	2020	1,963	19	Ocagli et al. 2021
Hungarosurvey	Hungary	2021	7,000	16	Kisfalusi et al. 2022
Dutch Network Size Survey	The Netherlands	2021	1,325	42	Völker et al. 2025*
BRIDGES survey	Spain	2021	1,500	41	Jin et al. in preparation
Scale of Harm project	Philippines	2022	3,600	19	Nyarko-Agyei et al. 2026
Transparency, Trust, and Social Media	Mexico	2024	2,401	16	Ventura et al. 2024
Jordan Migrant Domestic Worker survey	Jordan	2024	NA	37	Laga 2025

Table 2. Twenty example datasets, chosen among those with more than 1,000 respondents and more than ten subpopulations, with temporal and geographical variation. *Publications in this Special Issue.

Item	What to report	References
General survey design	Target population; Sampling frame / design; Minimum sample size calculation, if used; Survey mode; Fieldwork dates; Sample size; Response rate; Design weights; Coverage limitations; Missing data handling	General survey literature / reporting guidelines. For minimal sample size calculation: Josephs et al. (2022)
Tie definition	Verbatim wording of the tie definition shown to respondents or in interviewer scripts, including reference periods for ties or events (e.g., "the past 2 years" or "12 months")	Relevance of tie definition: Feehan, Umubyeyi et al. (2016)
Subpopulations (target, probe)	Complete list of probe and target subpopulations; Prevalence or size statistics of probe subpopulations and their sources and dates; Rationale for selecting the set of probe subpopulations (e.g., prevalence, diversity) and potential risks of bias; Order of subpopulations in questionnaire (e.g., randomised)	*N* subpopulations: Bernard et al. (2010); Prevalence levels: Laga (2025); McCormick et al. (2010); External data: Feehan et al. (2022)
Response format	Format of ARD items: counts, top-coded counts (e.g., 0, 1, ..., 10, >10), bins (e.g., 0, 1, 2–5, 6–10, 11–20, 21–50, >50), binary items. If using bins, specify whether midpoints or interval models were used to handle grouped responses	Binary ARD: Baum & Marsden (2023); Binary & counts: Völker et al. (2025)*; Top coding: Clay-Warner et al. (2025)*
Instrument development & pre-fieldwork	Pretests, pilot-tests, cognitive tests, debriefing (if used); Any probe screening (e.g., removal of items with persistent error or high sparsity)	Habecker (2017); Lubbers et al. (2025); McCarty et al. (2001)
Fieldwork procedures & aids	Any response aid used (e.g., show cards; cell phone); Interviewer training for consistency of ARD administration; Any fieldwork quality control	Lubbers et al. (2025)
Estimator / model specification	Estimator and model specification; Software package & version; Covariates / post-stratifiers; If Bayesian: priors, computation, convergence diagnostics; Sources of visibility parameters, if used; Handling of outliers (e.g., removing respondents with extremely high network sizes)	e.g., Baum (2025)*; Laga et al. (2021, 2023); Maltiel et al. (2015); Rastegari et al. (2022); Vogel et al. (2026)*
Model diagnostics	Goodness-of-fit; Posterior predictive checks (Bayesian); If used: Probe back estimation accuracy; Proportion of zero responses per ARD item; Distribution of responses (for heaping)	Laga et al. (2026); Lubold et al. (2025); McCormick et al. (2010); Ward et al. (2026)*; Zheng et al. (2006)
Estimation results (network size and / or subgroup size)	Network size: Central tendency (mean, median), dispersion (SD, IQR), uncertainty (SE, confidence interval); Subgroup size: Point estimates, uncertainty (e.g., SE, confidence interval); Subgroup and small-area estimates (if used) with post-stratification details (if MRP)	Feehan & Salganik (2016); Laga (2025); Maltiel et al. (2015); Zheng et al. (2006)
Sensitivity analyses	For each sensitivity analysis (if conducted): aspect varied (e.g., tie definition, probe set, visibility priors, estimator, outlier handling), alternatives or parameter ranges tested and impact on estimates	Feehan, Umubyeyi et al. (2016); Kunke et al. (2024); McCormick et al. (2010)
Reproducibility	Availability of data (ARD responses and external statistics), code, and documentation (questionnaire, codebook).	General survey literature, e.g., Krähmer et al., 2026

Table 3. Checklist for reporting of NSUM studies where network size/composition or subpopulation size is estimated. *Publications in this Special Issue.

This Special Issue

This Special Issue brings together sixteen methodological and empirical articles that advance the state of the field. It opens with an invited commentary by NSUM inventors McCarty and Bernard (2026), who reflect on the method's origins, the ideas that shaped its early development, and the evolution of the literature.

Two papers further revisit well-known sources of bias in NSUM applications. Kmetty and Kisfalusi (2026) investigate recall bias by comparing respondents' remembered numbers of Facebook friends with specific first names to the actual numbers of their Facebook friends with these names. They find that recall is better among individuals with smaller networks and for same-gender names and names more prevalent within respondents' age cohorts. The findings also nuance earlier recommendations regarding the optimal prevalence range of first names (McCormick et al. 2010), although memorising names in general and names of Facebook friends may involve partly distinct cognitive processes. Addressing a different but common survey practice, Clay-Warner et al. (2025) compare three strategies of top-coding counts using two empirical datasets. Their analysis provides practical guidance for handling extreme values when estimating hard-to-count subpopulations.

Five papers advance NSUM estimation. Díaz-Aranda et al. (2026) assess the robustness of classical maximum-likelihood estimators (see also Kunke et al. 2024) and propose more robust alternatives based on location estimators, demonstrating their performance on empirical NSUM data. Ward et al. (2026) compare several Bayesian NSUM models (Zheng et al. 2006; McCormick et al. 2010; McCormick & Zheng 2015; Sahai et al. 2019) on synthetic data, introducing a within-iteration rescaling procedure that removes the need for post-hoc adjustments. Vogel et al. (2026) extend Bayesian NSUM models by jointly accounting for degree correlations and top-coding, proposing a censored, degree-correlated Bayesian NSUM model. Baum (2025) introduces a covariate-based NSUM model that incorporates correlations between individual covariates, such as gender or ethnicity, and network sizes and barriers. Finally, Feld and McGail (2026) draw on NSUM and capture-recapture approaches, developing a method that estimates the size of hard-to-count populations with unknown visibility without requiring information from the target group.

One methodological contribution stands out conceptually by connecting ARD-based measurement to computational modelling. Lee and Xu (2026) use ARD-estimated degree distributions as inputs to classic agent-based models of diffusion and cultural dynamics (e.g., Axelrod 1997). The diffusion processes that such models address are theoretically associated with weak ties, but models tend to rely on synthetic networks with unrealistically small degrees for such ties. Lee and Xu show that incorporating empirically grounded degree distributions from ARD estimations yields substantially different results, highlighting the importance of realistic network assumptions in simulation research.

The Special Issue also features seven empirical applications of NSUM and ARD aimed at better understanding social networks. Völker et al. (2025) document the size and composition of extended networks in the Netherlands, including gender and educational homophily, as well as various sociodemographic correlates of network size. Espinosa-Rada et al. (2026) demonstrate that extended networks display homogeneity in occupational prestige and show that the level of homogeneity is related to education but not with social mobility. Two studies use ARD to explain political outcomes, contributing to the growing use of NSUM and ARD in political science (e.g., Ratliff Santoro & Sokhey 2024; Baldassarri & De Jong 2022; Djupe et al. 2025; Ventura et al. 2024). Specifically, Arevalillo et al. (2026) propose using NSUM to predict electoral outcomes, illustrating the approach with a pre-selection sample of 200 respondents in Spain. This strategy may be particularly useful in countries with relatively few parties and clearly differentiated ideological positions. Hofstra et al. (2026) examine whether the willingness to engage in political conversation depends on extended network size and composition. They find that ethnic composition, but not size or gender composition, predicts openness to cross-cutting political conversation.

Two contributions adopt a longitudinal perspective on extended networks by examining network change. Muñoz Rojas et al. (2026) show that civic participation increases extended network size over time, while disruptive life events have little effect. Plaza et al. (2026) investigate whether changes in network heterogeneity over time affect attitudes toward inequality, finding that increasing heterogeneity is associated with heightened perceptions of inequality and stronger egalitarian preferences. Longitudinal studies offer stronger grounds for establishing causal inference (cf. DellaPosta 2018).

Finally, Almquist et al. (2026) combine an ARD question with other network measures to study the personal networks of people experiencing homelessness. Their work demonstrates the value of ARD for capturing aspects of network structure in highly marginalised populations.

Conclusion

Our review of 301 publications synthesised four decades of NSUM and ARD research and traced how the literature has evolved over time. Methodologically, NSUM has expanded from a single estimation technique into a family of survey methods, including the network scale-up method, network survival method, summation method, known population method, and game of contacts. In addition, it has developed increasingly sophisticated estimators to address well-known biases. Yet these more complex models have been slow to diffuse into applied research. Substantively, the literature has developed in two directions. First, applications were initially concentrated in public health research but have broadened to a wide range of hard-to-count populations, including concerning abortion, human trafficking, cybercrime, displaced persons, and transgender populations. Across these domains, NSUM and ARD have yielded important insights into the size and characteristics of the world's most vulnerable populations. While the use of NSUM has stagnated in public health research following several critical reviews comparing NSUM unfavourably to alternative methods, these reviews often evaluate NSUM based on older implementations that do not account for well-known biases, thereby potentially underestimating the performance of current models. A second substantive development is a shift from population size estimation towards the use of ARD to study social networks themselves, including the size and composition of individuals' acquaintanceship networks, the structure of wider societal networks, and individuals' perceptions of them. This work contributes to understanding how weak ties are organised in society and how they relate to social segregation and cohesion.

We also reviewed major surveys on which NSUM and ARD research relies and compared how they implement ARD questions. This analysis revealed wide heterogeneity in the number and types of probe populations, definitions of "knowing someone", and response formats, and showed that these design choices are not always well documented despite their influence on estimates of population and network size. To support more transparent and comparable practice, we proposed a reporting checklist. We also recommended stronger justification of the coherence of sets of probe populations to ensure that respondents in all social groups have similar opportunities to report acquaintances.

The sixteen articles included in this Special Issue speak directly to the different issues raised in this review. They advance methodology (e.g., through new estimators and diagnostics) and extend substantive applications by contributing, for instance, to an emerging body of work that uses NSUM and ARD to explain political attitudes and behaviours, and by taking longitudinal measures that provide stronger bases for testing causal inference. Taken together, the articles help consolidate the literature and demonstrate its continued relevance.

Looking ahead, we anticipate several developments. First, because NSUM and ARD depend on both careful survey design and appropriate statistical models, future progress will require advances on both fronts. Among other developments, we expect more cognitive studies examining how respondents process ARD questions, expanding a line of work by McCarty et al. (2001), Habecker (2017), and Lubbers et al. (2025). Future studies could also examine whether respondent characteristics (e.g., gender, age) and interview(er) effects introduce systematic variation in responses. Second, as more sophisticated estimation models remain underused in applied research, closer collaboration between statisticians and applied researchers is essential. Third, and relatedly, future comparisons between NSUM and alternative methods for population size estimation should incorporate the most recent modelling advances in NSUM to enable fairer assessments of NSUM's performance. Fourth, we have shown that studies using ARD to infer features of network structure (e.g., Breza et al. 2023; McCormick & Zheng 2015) and network perceptions are still in their infancy. We expect these to become major areas of future research, ideally by combining ARD with survey questions specifically designed to capture structural or perceptual dimensions of wider acquaintanceship networks. Such work can help us understand how society-wide networks are organised in comparison to core networks. Taken together, these developments could transform ARD and NSUM from a niche methodology to indispensable tools for mapping the structure of society-wide networks, including the ways in which individuals perceive and remember them. This can deepen our understanding of the network foundations of societal cohesion.

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Annex.

ARD item type (category)	Example ARD item "How many ... do you know?"
First names	Women named Sarah
Surnames	People with the surname Zhu
Occupational statuses	Taxi drivers
Civic and household arrangements	Households with more than 5 children
Gender-age groups	Women over 70
Life events	Men who officially divorced in [year]
Gender identities	People who identify as transgender
Religions	Muslims
Ethnicities, races, nationalities	American Indians
Political orientations	Members of the communist party
Properties	People who drive an electric car
Health conditions	People who are deaf
Crime victimisation and offending	People who are currently incarcerated
Educational levels	University students
Geographic mobility	People who moved from the Autonomous Republic of Crimea to other regions of Ukraine in the past 5 years
Sports and leisure	People who go fishing
Consumption	Vegans

Table A1. Common types of ARD items and example items