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# Sampling Methods and the Precision of Data Estimates: A Systematic Review of Recent Methodological Developments, 2000–2026

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Abstract

Sampling is an area of empirical research since it defines to what extent the chosen cases can be used to provide valid estimates of a target population. The recent methodological studies indicate that the precision cannot be deteriorated down to the level of the sample size only. The sampling frame, selection process, allocation plan, response pattern, data collection mode, nonresponse adjustment, data imputation, weighting plan, process of variance estimation, and transparency in reporting are all aspects that shape precision. This systematic review brings together the recent literature on the sampling methods and the accuracy of the data estimates within the timeframe of 2000 to 2026. The review is based on a PRISMA-based screening framework and a review log of 250 records initially identified, then 212 records screened based on title and abstract, 161 papers that have been assessed based on the full-text, and 68 records contained in the final synthesis. The findings reveal that probability sampling is the most robust ground on which population inferences can be drawn but its accuracy is subject to the quality of the sampling frame as well as the adequate consideration of the design effects, the nonresponse bias, missing data and the ratio. Nonprobability sampling is growing in both digital and applied spaces, but it demands direct modification using auxiliary information, pseudo-weighting, calibration, data integration, or model assisted inferencing. More recent developments around the estimation of small areas, Bayesian models, geospatial sampling constructs, mixed-method surveys, and margin of total error have shifted focus of the field to a broader conception of precision as a composite product of design quality and error control. It is concluded that in future sampling studies, the authors should be more open about their use of selection methods, frame building, including rules of eligibility, response procedures, weighting choices, missing data practices and uncertainty estimation.

**Keywords**: sampling methods, data estimates, precision, probability sampling, nonprobability sampling, sample size, nonresponse bias, weighting, variance estimation, small area estimation, PRISMA, total survey error.

## 1. Introduction

Sampling is defined as the method by which a researcher chooses some units out of a given population in the name of generating empirical evidence. The chosen entities can be an individual, family, company, health service, an institution, a geographic area, a business transaction, or an online record. The question of whether the chosen sample is large is not the main methodological question but rather a subset of the larger question. In applied research there are a lot of poor estimates due to the fact that sampling is considered as a practical action and not a root of validity. Even a large sample size can still yield a biased conclusion when the selection is incomplete, the selection process is uncontrolled, the eligible units are systematically missed or the non respondents are not similar to respondents based on variables related to the estimate (Biemer, 2010; Groves, Fowler, couper, Lewkowski, Singer and Tournamentau, 2009; Lohr, 2021).

The recent studies have invited a fresh focus on how sampling design and precision relate to each other. According to Zrineh, Al-Usta, and Alwawi (2026), probability sampling methods like simple random sampling, systematic sampling, stratified sampling and cluster sampling are helpful in supporting stronger inference when they are aligned to the research design and target population. But the choice of probabilities may not assuredly be good estimations. The sampling frame will be made to address the target population, clusters shall be handled through proper design-based analysis and sample size shall be planned keeping in mind the variance, power and expected nonresponse (Ahmed, 2024; Ranganathan, Deo, and Pramesh, 2024; Thompson, 2012). Nonprobability sampling also has the same rationale since a purposive, snowball, and convenience design may be useful in challenging settings, but it increases the difficulty of drawing conclusions on the asymptotic aspects of sampling error as well as results generalisation (Baker, Brick, Bates, Battaglia, Couper, Dever, Gile, and Tournament, 2013; Cornesse, Blom, Dutwin, Krosnick, de Leeuw, Legleye, Pasek, Pennay, Phillips, Sakshaug, Struminskaya, and Wenz, 2020; Elliott and Valliant, 2017). The issue of the accuracy of the data estimates has also become more intricate due to an inability to restrict survey designs to traditional methods of data collection using a face-to-face method. Now there are common web surveys, mobile surveys, mail push-to-web designs, QR code recruitment, administrative data linkage, digital panels, and geospatial sampling frames. Marlar and Schreiner (2024) reviewed the use of QR codes to encourage participation in web-first sequential mixed-mode longitudinal surveys, whereas Cabrera-Álvarez and Lynn (2024) reviewed the use of text-messages in support of participant participation in web-first sequential mixed-mode longitudinal surveys. Asimov and Blohm (2024) also demonstrated the applicability of sequential and concurrent mixed-mode designs to current survey practice. These studies suggest that participation, respondent burden, breakoff and response quality could be influenced by digital recruitment and survey mode. This consequently means that sampling precision now depends not only on with whom it is in contact so as to be sampled but also with how the surroundings in which it is sampled influences response behavior.

The second change in the recent literature is the expanded coverage of error. Precision is not supposed to be handed out in a manner such that it is only presented by the formula of standard error. Instead, preciseness has to be obtained in the context of total survey error, in which sampling error, coverage error, nonresponse error, measurement error, processing error, and model error all play roles in determining the quality of an estimate (Biemer, 2010; Biemer and Lyberg, 2003; Groves, Fowler, Couper, Lepkowski, Singer, and Tourciteau, 2009). Recent research also indicates that nonresponse and measurement error could interact to cause an increase in the total bias, particularly when the response behavior is somehow related to the outcome being estimated (Neri and Porreca, 2024; Schroeder and West, 2025; Stefan and Hidiroglou, 2024). In this review article, the recent methodological literature is discussed on sampling methods as well as accuracy of the estimated data. It is predominantly non-randomized with emphasis placed on the publications published in 2024 to 2026 due to the significant amount of work on nonresponse, mixed-mode design, small area estimation, model-assisted Inference, geospatial sampling frames, and data integration. Nevertheless, some groundwork articles are also selected since the sampling theory, survey error, weighting, and the estimation of the variance require a certain methodological background (Lohr, 2021; Searndal and Lundstrom, 2005; Valliant, Dever, and Kreuter, 2018; Wolter, 2007). The review is not confined to a single discipline since sampling precision is applicable to social sciences, health research, official statistics, market research, education and public policy. The primary value of the paper is that it summarizes recent advances in methodologies and demonstrates how the decisions taken in sampling design have an impact on the reliability of estimates.

## 2. Objectives and Review Questions

Overall, the aim of this review is to investigate how the sampling techniques can affect the accuracy of data estimates in recent methodological literature. The types that the review covers are probability sampling, nonprobability sampling, constructions of sampling frame, planning of sample size, procedures of responses, missing data, weighting, estimation of the variances, and model assisted estimation. These spheres are in the focus of survey quality as the precision of estimators is determined by the system of sample design and methods of post-data-collection adjustments.(Kalton & Flores-Cervantes, 2003; Little & Rubin, 2019; Lohr, 2021; Valliant, Dever, & Kreuter, 2018).

### 2.1 Specific Objectives

1) To review recent developments in probability and nonprobability sampling methods.
2) To examine how sampling frame quality, stratification, clustering, and allocation affect estimator precision.
3) To analyze the role of sample size, power, and confidence interval width in estimating precision.

4) To evaluate how nonresponse, missing data, and survey mode affect data quality.
5) To synthesize recent approaches to weighting, imputation, variance estimation, and small area estimation.
6) To identify methodological gaps and future research directions in sampling research.

### 2.2 Review Questions

1) How do recent studies define and operationalize precision in sampling-based estimation?
2) Which sampling methods are presented as most defensible for population-level inference?
3) How do recent studies handle nonresponse, missing data, and selection bias?
4) How are weighting, imputation, and model-assisted methods used to improve data estimates?
5) What methodological gaps remain in reporting sampling procedures and uncertainty?

## 3. Methodology

This review was in the form of a systematic literature review under the logic of transparent reporting. The identification, screening, eligibility evaluation and inclusion were made clear through this approach. The systematic review is particularly applicable to a methodological review as it will ensure that the literature search will be not a selective narrative but a process that focuses on elucidating how the subjects of interest were incorporated into the review process and how many of the records included in the review process were retained to become a synthesis.

### 3.1 Search Strategy

The search strategy was developed to include literature published recently on sampling and precision. These primary search terms were supplemented with those ones concerned with the quality of survey, accuracy of estimators, and control of errors. The databases that will be included in the review are the following: Scopus, Web of Science, PubMed, Google Scholar and the publisher-level search in Oxford Academic and Wiley. The search expression model was searched with the following search string:

sampling method OR survey sampling OR sample size OR probability sampling OR nonprobability sampling OR sampling frame OR nonresponse bias OR weighting adjustment OR variance estimation OR small area estimation AND precision OR data estimates OR estimation quality OR survey error.

The search strategy was informed by key areas in sampling and survey methodology, such as sample design, nonresponse, weighting, imputation, small area estimation, and total survey error (Biemer, 2010; Lohr, 2021; Rao and Molina, 2015; Sarno and Lundstram, 2005; Valliant, Dever, and Kreuter, 2018).

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### 3.2 Inclusion and Exclusion Criteria

The selection of studies occurred based on being published between 2024 and 2026, addressing sampling methods or other statistical considerations and having direct relevance to the terms precision, representativeness, the quality of estimations or survey error. research that mentioned sampling, did not discuss estimates quality, was not given methodological detail, were out of review period, or were reported a second time. To ensure a narrow inclusion criteria, it was aimed at methodological relevance, as opposed to disciplinary location. By making this decision, the review was able to include studies based on survey methodology, official statistics, clinical research, social research, and applied data collection.

Published before 2024, the foundational methodological works were retained when they offered necessary theoretical support which gathers sampling design, survey error, weighting, missing data, nonresponse, or variance estimation. This was required as recent studies tend to be based on established methods in the field of probability sampling, complex survey analysis and total survey error (Biemer and Lyberg, 2003, Groves, Fowler, Couper, Lepkowski, Singer and Tourciteau, 2009, Little and Rubin, 2019, Wolter, 2007).

**Table 1: Search Terms and Screening Logic**

| Search Component | Terms Used | Purpose |
|---|---|---|
| Sampling design | probability sampling, nonprobability sampling, stratified sampling, cluster sampling, systematic sampling | To capture studies on selection procedures and representativeness |
| Precision and error | precision, sampling error, standard error, margin of error, total survey error | To capture studies linking sampling with estimate quality |
| Adjustment methods | weighting, calibration, imputation, nonresponse adjustment, pseudo-weighting | To capture methods used to reduce bias or improve inference |
| Advanced estimation | small area estimation, Bayesian estimation, model-assisted survey sampling, variance estimation | To capture recent model-based and model-assisted developments |
| Survey mode | web survey, mobile survey, mixed-mode survey, push-to-web, QR codes | To capture mode effects on response and precision |

### 3.3 PRISMA Flow Diagram

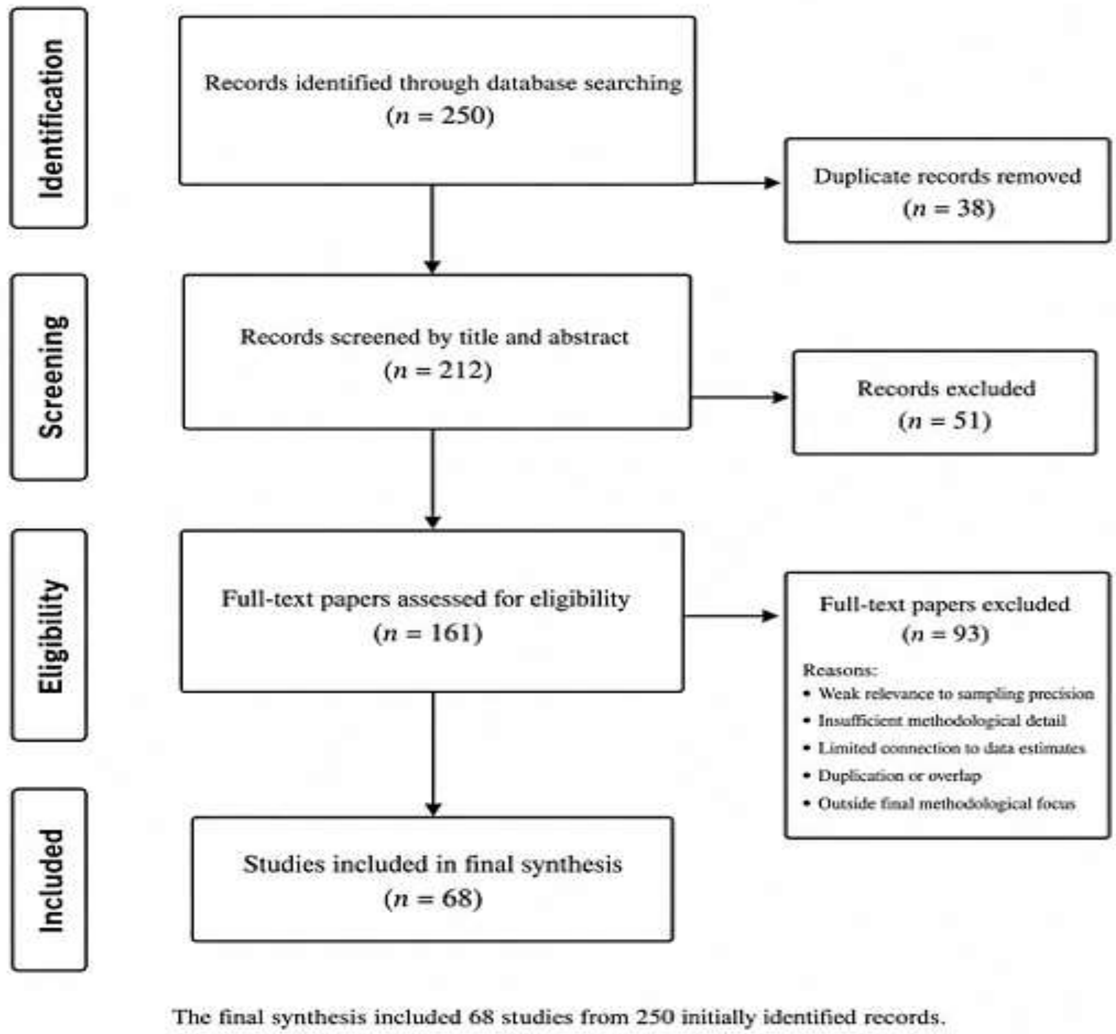


**Figure 1. PRISMA flow diagram for the systematic review. The final synthesis included 68 studies from 250 initially identified records.**

The log described in PRISMA style was used in this review with the initial amount of 250 records. 212 records were then filtered using the title and abstract after the removal of 38 duplicate records. At the screening level, 51 records were dropped due to lack of a direct link to sampling method, data estimates precision, survey error, sampling size determination, nonresponse, weighting or the advanced estimation procedures. The assessment cases then were 161 papers in which full text was assessed. Out of them, 93 full-text papers were excluded due to weak relevance to sampling precision, lack of sufficient methodological description, inadequate connection with data estimates, duplication with another report, or did not sufficiently focus its final approach to methodology, which was the primary subject of the review. The last synthesis thus comprised 68 studies.

**4. Conceptual Foundation: Sampling, Precision, and Error**

Precision is the variation and an approximate range of an estimate about the anticipated value or figure. Survey and sampling type of research have precision that can be expressed in form of standard errors, confidence limits, design effects and margins of error. Nevertheless, even an accurate estimate can be in error provided it is an accurate mistake. That is why when analyzing literature, precision is distinguished and contrasted with accuracy. Precision relates to how different estimates vary instead of the contrary, whereas accuracy related to the similarity of an estimate to the actual population value. The most successful sampling designs are trying to control both (Biemer, 2010; Kowalewski, Chizinski, Powell, Pope, and Pegg, 2015; Lohr, 2021).

Probability sampling also gives a formal basis to estimate the sampling error as the selection probabilities are known. Conversely, nonprobability sampling typically does not have known probabilities of selection, and thus it is hard to perform standard design-based inferences. It does not imply that it is impossible to use any nonprobability sample. It implies that researchers have to report about the limits of the inference and, where possible, use adjustment procedures such as calibration, propensity score weighting, pseudo-weighting, data integration or model-based estimation (Baker, Brick, Bates, Battiglia, Couper, Dever, Gile, and Tourãio, 2013; Elliott and Valliant, 2017; Mercer, Lau, and Kennedy, 2018). Jäckle, Burton, Couper, and Lessof (2024) demonstrate how the comparison of probability-based and nonprobability panels can indicate the differences in measurements and the quality of estimates. Such comparisons are useful in that they go beyond mere statements of the type of sample and analysis how the estimates in fact behave.

The larger error system is a necessity. The presence of reported uncertainty should not be restricted to sampling variability should other sources of error exist. Total survey error offers a more comprehensive framework since it also takes into consideration sampling error, coverage error, nonresponse error, measurement error, processing error, and other related sources of bias (Biemer, 2010; Biemer and Lyberg, 2003; Groves, Fowler, Couper, Lepkowski, Singer, and Tourciteau, 2009). This, in particular, is crucial in modern survey settings where response rates might decrease, web response might vary with population subset, and measurement may differ across devices or modes (Bethlehem, 2010; Couper, 2000; Dillman, Smyth, and Christian, 2014). The overall implication is that researchers ought not to represent statistical precision in a manner that implies that sample formula by itself is entirely sufficient to describe the quality of estimates.

## 5. Probability Sampling and Frame Quality

The best justifiable point to make when it comes to generating generalizable estimates is on probability sampling. The value of it is that all units within the target population have known and non-zero probability of selection. This enables the researcher to estimate the sampling variability and form confidence intervals. But probability sampling requires the sampling frame to be very important. A sampling frame is not a lengthy list. It describes the feasible section of the entire population on which the sample may really be taken. Unless the frame represents important subgroups, resulting estimates can be biased even when the procedure of frame selection is formally random (Lohr, 2021; Thompson, 2012; Valliant, Dever, and Kreuter, 2018).

In the recent paper on geospatial sampling frames, how the quality of frames is coming to dominate official and humanitarian statistics. With the help of geospatial techniques, Qader, Darin, Dicko, Galal, Park, Moreno Jimenez, Harfoot and Tatem (2026) constructed an enumeration area based sampling frame tailored to a particular population subgroup. The reason their study is significant is that it helps address the issue of outdated or incomplete sampling frames (in particular, those that are not effectively represented in traditional census-based frames). The accuracy of estimates in such situations is hooked up to whether the chosen units are capable of reaching the target population. Sample size efficiency is also determined by frame quality. When a nominal sample looks large on paper, there is also a risk that the effective sample size will greatly decrease, and high field costs will be incurred. The implication is that the calculation of the sample size should be viewed together with frame coverage. As illustrated by Qader, Darin, Dicko, Galal, Park, Moreno Jimenez, Harfoot, and Tatem (2026), geospatial frame development may help eliminate ineffectiveness by balancing the sampling units with actual geographic and population distributions. This is a methodological improvement since it links the construction of a sampling frame to the field and estimator practices.

Another way of enhancing precision has to deal with stratification. Stratified sampling can help minimize variance when some significant subgroups can be identified, and the sampling variance within a subgroup decreases as the population within the subpopulation increases.<|human|>It is when the population can be divided into internally similar groups that stratified sampling can help reduce the variance. That is, as the population within a subpopulation increases, the stratified sampling can be used to reduce the variance. The stratification should however be meaningful. Strata that are poorly selected can only increase the complexity without enhancing the precision. In comparison, cluster sampling can be considered more cost-effective, but can also lead to an increase in variance when individuals inside of clusters are alike. This generates a cost/precision trade-off. There are however methodological studies that lay emphasis on design effects and a determination of variance instead of merely indicating the name of the sampling method (Heeringa, West, and Berglund, 2017; Lehtonen and Pahkinen, 2004; Wolter, 2007).

**6. Nonprobability Sampling and Adjustment-Based Inference**

The nonprobability sampling has grown due to limited sample size (budget) by many researcher, limited accessibility of sampling frame, online sample recruitment environments and inaccessible populations. Applied studies utilize convenience, purposive, quota, snowball and online panel sampling. These approaches are nice, yet cause severe inferential constraints since it is not known how likely it is that the selection occurs. The ordinary design-based standard errors are not sufficient and lack specific selection probabilities without considering possible selection bias (Baker, Brick, Bates, Battaglia, Couper, Dever, Gile, and Touranteau, 2013; Cornesse, Blom, Dutwin, Krosnick, de Leeuw, Legleye, Pasek, Pennay, Phillips, Sakshaug, Struminskaya, and Wenz, 2020; Elliott and Valliant, 2017).

The recent literature has moved past this probability versus nonprobability discussion to a more cautious discussion about adjustment-based inference. Probability-based, nonprobability panels were compared in the study by Jäckle, Burton, Couper, and Lessof (2024), who demonstrated that the probability-based and nonprobability panels can influence the quality of estimates, depending on the source of panel and the mode of data collection. According to their investigation, it does not necessarily answer the question of whether a sample is probability-based, but rather how various aspects of selection, mode, measurement and adjustment affect estimates. Ballerini and Liseo (2025) take nonignorable nonresponse by taking information on other sources to conclude on the population composition. This kind of work is critical in nonprobability and weak-response establishment since external knowledge may partially lessen bias in nonprobability establishment where the sample being observed is not identical to the targeted population. Nonetheless, there are very powerful assumptions underlying such methods. In case, the auxiliary variables fail to describe the selection or response mechanisms, then there is an adjustment which causes an appearance of correction but the important bias is not removed. Estimates may be more accurate when there is some useful auxiliary information available, even though they cannot correct possible unknown selection mechanisms fully without something to defend their assumptions (Kalton and Flores-Cervantes, 2003; Mercer, Lau, and Kennedy, 2018; Valliant, Dever, and Kreuter, 2018).

One such critical implication to writing a review paper is that nonprobability sampling cannot be said to be weak and invalid. Should be evaluated based on the objective of the research. In cases of exploratory research, qualitative research, underrepresented groups, or initial pilot development of a measure, nonprobability methods might be tolerable. More justification and correction are required where we have to estimate prevalence using population total, policy indicator or subgroup comparison. The paper must then make the distinction between descriptive use, exploratory use and inferential use of nonprobability samples (Heckathorn, 2002; Magnani, Sabin, Saidel, & Heckathorn, 2005; Salganik and Heckathorn, 2004).

### 7. Sample Size, Power, and Precision

One of the most actively discussed aspects of sampling, sample size is often approached without going into details. Increasingly large samples tend to decrease sampling variability, but necessarily not decrease bias. A biased sample of 5,000 respondents might not be as accurate as a probability sample of respondents of 500 respondents that was carefully selected. Thus, the methodological literature focuses on the fact that sample size must be planned along with the sampling design, anticipated variance, anticipated response rate, anticipated effect size, anticipated power, anticipated design effect, and anticipated analysis plan (Ahmed, 2024; Lohr, 2021; Thompson, 2012).

The current demonstration of education through the article authored by Zrineh, Al-Usta and Alwawi (2026) is a recent review of educational research on sampling methods and determination of sample size in clinical research. The utility of their work lies in connecting sampling methods to the sample size needs in the study design. Simple guide to selecting sampling techniques, determining sample size is also provided by Ahmed (2024), and Bujang (2024) discusses the determination of sample size used in correlation analysis using effect sizes and the width of the confidence interval. Ranganathan, Deo, and Pramesh (2024) also discuss the calculation of the sample size in a clinical study. A combination of these studies indicates that sample size is not a unique figure. It is based on the outcome, hypothesis, the variability of the population, the expected effect, and acceptable level of uncertainty. Sampling precision discussed in a review article must be explicit regarding the use of the sample size to conduct an approximation of the study as well as testing of the hypothesis. Estimation In estimation, there is often an object of interest which is the desired level of the margin of error or confidence interval width. When testing hypotheses the statistical power, effect size and effect level have been of interest. The design effect should also be taken into account when working with complex surveys since clustering and unequal weights may decrease the effective sample size. Because of this, sample size should be reported not only in terms of given number of respondents but also in terms of effective sample size in case complex designs or weights are used (Heeringa, West, and Berglund, 2017; Lumley, 2010; Wolter, 2007).

One of the weaknesses commonly found in applied research is the application of a general table or rule but offers no explanation of the assumptions made behind the table or rule. Indicatively, a sample size table might be appropriate in simple random sampling but not on a clustered design involving high levels of intraclass correlation. On the same note, a justified sample size used in correlation would not be suitable in regression, subgroup analysis, testing mediation, or testing small area estimation. Recent literature thus supports a design specific and not formula alone approach to sample size planning (Ahmed, 2024; Bujang, 2024; Ranganathan, Deo, and Pramesh, 2024; Zrineh, Al-Usta, and Alwawi, 2026).

**8. Nonresponse, Missing Data, and Follow-Up**

One of the most significant threats to accuracy and precision also is nonresponse. Unit nonrespondent is when the selected units are not involved at all. Item nonresponse is where respondents have attended, but have not responded to a particular question. Both types of missingness have the ability to bias the estimates in case nonrespondents differ with regard to respondents. Low response rates do not necessarily mean drastic bias, but they heighten the necessity of nonresponse analysis since the bias depends upon how the response propensity correlates with the variables of study (Biemer, 2010; Särndal and Lundström, 2005; Schroeder and West, 2025).

In an off-wave mail survey done in a long-term panel study, Schroeder and West (2025) explore potential non-ignorable selection bias. In their study, Collins and Kern (2025) investigate the research subject of longitudinal nonresponse prediction using time series machine learning. These studies indicate that recent nonresponse researches emphasize predictive and longitudinal methods more and not just use the final rate of response. The aim is to determine which units are unlikely to reply and whether their non-representation may have any impact on the estimates. Direct method of dealing with nonresponse is follow-up. Stefan and Hidiroglou (2024a) discuss the estimation of a population total under nonresponse using follow-up. The significance of follow-up is that it can provide some relief to bias by recalling data in hard-to-access units or by picking up adjustment models. Nevertheless, make-up adds cost to the field and must be allocated very carefully. Mendelson and Elliott (2024) discuss the optimal allocation presupposing nonresponse, demonstrating that the allocation decisions may be considered as a part of the precision strategy, rather than as an entirely operational issue.

Methods of missing data are also crucial. Robbins (2024) explains the general concept of the joint imputation of general data, whereas Little and Rubin (2019) present a more comprehensive methodological background of statistical analysis using missing values. These works demonstrate that the absence of data treatment is to be mentioned as a key component of the sampling methodology. Estimates can be misleading because they might seem accurate but represent the response rate of the subset that responded. In the case of imputation, the assumptions of the missing data model should be well defined.

**9. Weighting, Imputation, and Variance Estimation**

Weighting is applied to compensate for unequal choices of probability of selection, nonresponse, and unmatched sample and population distributions. Biases and future of weighting can be reduced by proper weighting, but at the same time, higher variance of weight can be caused by proper weighting. The implication of this is that weighting is not mechanical corrective. It is a trade-off between reduction in bias and loss of precise. Kalton and Flores-Cervantes (2003) offer an essential ground upon which one can base their weighting methods, whereas Valliant, Dever, and Kreuter (2018) prescribe practical tools that one can use to design and weight survey samples. Medous (2025) adds to this field of work by undertaking the task of creating optimal weights in the generalized method of weight sharing.

Stefan and Hidiroglou (2024b) present a jackknife bias-corrected generalized regression estimator of a survey sampling, emphasizing the role of variance and bias adjustment in a survey estimator. Estimation of variance is necessary as it decides the form of reporting on uncertainty. Basic formulae are frequently inapplicable to even basic survey data due to stratification, clustering, uneven weights and imputation influencing standard errors. Wolter (2007), Lumley (2010), and Heeringa, West, and Berglund (2017) demonstrate that estimating variance has to be based on the actual survey design, but it cannot be a routine calculation. Tillé and Panahbehagh (2024) study maximum entropy design by a Markov chain process, research that leads to the designing aspect of survey sampling. With informative sampling of complex survey data, Nascimento and Goncalves (2024) deal with Bayesian quantile regression models of complex survey data. The following studies demonstrate that the more modern can be the precision research carried on based no longer upon the classical formulas. It involves simulation, Bayesian approaches, design-based correction and model-assisted procedures. But there are more sophisticated techniques that do not eliminate the necessity of transparency in reporting. The more complicated the approach is the better the assumptions and diagnostics are supposed to be presented.

One extremely important aspect of weighting and imputation to researchers is that it should not be buried in a short method note. They are supposed to be explained to be in sufficient details so that it can be interpreted. The paper is supposed to report which variables were imputed, how extreme weights are treated, whether post-stratification is used or calibration, the imputation model that was chosen and how the uncertainty of imputation are accommodated. In the absence of such information, readers are not able to assess the fact that the final estimates are also credible (Little and Rubin, 2019; Robbins, 2024; Valliant, Dever, and Kreuter, 2018).

## 10. Small Area Estimation and Model-Assisted Precision

Small area estimation is getting more and more important since researchers and policymakers need to have a small area estimation of sub groups or geographic areas where direct survey sample sizes are small. Direct estimates can also be erratic on small scales, generating large confidence intervals or not reliably estimating the rate. Model-assisted and model-based methods apply the aid of auxiliary information to enhance precision. Such techniques may be useful but they require model assumptions and the quality of any additional data (Rao & Molina, 2015; Valliant, 2024).

Recent research demonstrates that there has been major progress in this field. A suggestion by McGovern, Wilson, and Wakefield (2026) is direct-assisted Bayesian unit-level modeling of small area estimation of rare events prevalence. Dong, Wu, Li, and Wakefield (2026) seem to propose a principled workflow to achieve prevalence mapping, based on data of household surveys. Angkunsit and Suntornchost (2026) generalizes the multivariate Fay-Herriot model of data containing outliers. These studies indicate that small area estimation is being shifted toward flexible models that may accept rare instances, spatially structured data and non standard forms of data. Mori and Ferrante (2025) approximate the household economic information within the generalized additive models of location, scale, and shape with their assumption. In Das and Chambers (2024), the estimation of small areas poverty is investigated in the light of heteroskedasticity. Bersson and Hoff (2024) focus on the best way to conformal predict using small areas. The problem of these studies is unanimous: when the model is complex, the precision of the small areas is impossible to guarantee. It also involves critical consideration of the sampling design, informative sampling, auxiliary variables, domain definitions, and model validation.

The contribution of Valliant (2024) is the overview of how the use of models in survey sampling has changed over time. The important point here is that with a careful use of models, the improved estimates can be obtained, but the improved estimates should not be regarded as the automatically better estimates as compared to the earlier design-based estimates. They come in handy when the assumptions made are defendable, the auxiliary information is strong and uncertainty is reported with integrity. It is especially relevant to policy utilization where estimates of small areas may affect funding of planning or intervention targeting.

**11. Web, Mobile, and Mixed-Mode Survey Designs**

Sampling products and services via the web, mobile, and mixed-mode sampling are increasing. These modes are able to decrease cost and enhance speed, and they also present coverage and measurement difficulties. Individuals vary in access to the internet, type of device, digital literacy and willingness to respond online. Consequently, the sample obtained via a digital mode could be different than the sample obtained via the design. This may impact both estimates and response rates (Bethlehem, 2010; Couper, 2000; Couper, 2008).

Asimov and Blohm (2024) address sequential and concurrent mixed-mode design and underline the necessity to customize the strategies of mode. Cabrera-Alvarez and Lynn (2024) discuss the use of text messages to facilitate a transition towards web-first sequential mixed-mode designs of longitudinal surveys. Coffey and Elliott (2024) consider the ability of data collection interventions to balance cost and quality within sequential multimode surveys. These works indicate that mode strategy has become a component of sampling methodology. The sampling plan should also incorporate contact designing, the mode series, reminder, and measure effects of the mode. Digital data collection has the potential to impact respondent burden and measurement quality as well. Engstrom and Sinibaldi (2024) experiment with dependent interviewing as a means of eliminating burden in web surveys. Caporaso and Presser (2024) consider cognitive interviewing as a questionnaire-based method of evaluation. Hoellerbauer (2024) uses a mixture model approach to assess measurement error using reinterviews. These studies indicate that precision of sampling and quality of measures are related. The valid estimates that a well-selected sample will give, should there be a systematic measurement error in the instrument used, will be invalid.

New design problems are also created in the digital environment. Marlar and Schreiner (2024) determine the use of the QR code in experiments of the mail in the form of a push to web survey. Cabrera-Alvarez and Lynn (2024) also demonstrate that communication tools, including text messages, have the ability to influence the participation in web-first mixed-mode designs. These writings point to the idea that digital means are able to enhance the participation of some respondents but can also lead to inequality in participation and quality of responses. As such, the digital sampling should involve usability testing, optimization of the devices, and paradata monitoring.

**12. Synthesis of Findings**

The literature survey helps to justify a wide meaning of the concept of precision. Precision starts off with the sampling design, but it is filled in through response management, missing data treatment, weighting, variance estimation and reporting. The greatest fact to come out is that sample size is not enough to provide an idea of quality. A large nonresponse, weak frame coverage, unchecked nonresponse, unstable weights and invalid standard errors. Such a research might look statistically powerful but produce weak estimates (Biemer, 2010; Groves, Fowler, Couper, Lepkowski, Singer, and Touranteau, 2009; Lohr, 2021).

The second conclusion is the fact that the probability sampling is the most powerful general method of population inference. Nonetheless, recent research indicates that probability sampling needs to be conducted effectively. The sampling frames may either be obsolete or incomplete particularly in a situation involving the displaced, mobile population, informal settlements or those existing online. Frame construction itself is shown by Qader, Darin, Dicko, Galal, Park, Moreno Jimenez, Harfoot, and Tatem (2026) to potentially be a methodological innovation when the traditional census-based frames are not sufficiently representative of the population.

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The third prediction is that nonprobability sampling is not going away. Due to online panels, low cost online recruitment, hard to reach population, and limitations of applied research, this is increasingly becoming common. The greatest challenge is that nonprobability samples need special readjustment and slight assertion. A combination of Jäckle, Burton, Couper and Lessof (2024), Ballerini and Liseo (2025), Baker, Brick, Bates, Battaglia, couper, Dever, Gile and Touramineau (2013) and Elliott and Valliant (2017) demonstrates that the quality of an estimate should be judged through error sources and adjustment quality, rather than through the label attached to the sample.

The fourth observation is that the industry is being shifted towards more unified error models. No longer are side issues nonresponse, missingness, measurement error, and mode effects. They contribute to the estimate production process. Schroder and West (2025), Collins and Kern (2025), Neri and Porreca (2024) and Hoellerbauer (2024) demonstrate that nonresponse and measurement issues can inform final estimates. This favors the proposal that the discussion of the total survey error in a review paper ought to be done alone and should not be mixed with the discussion concerning the sampling error.

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**Table 2: Thematic Synthesis of Recent Literature**

| Theme | Recent studies | Main contribution | Implication for precision |
|---|---|---|---|
| Sampling frame quality | Qader, Darin, Dicko, Galal, Park, Moreno Jimenez, Harfoot, and Tatem (2026) | Geospatial frame construction for specific population subgroups | Frame coverage determines whether selected units can represent the target population |
| Total survey error | Biemer (2010); Biemer and Lyberg (2003); Groves, Fowler, Couper, Lepkowski, Singer, and Tourangeau (2009) | Broader treatment of sampling and nonsampling error | Precision reporting should move beyond sampling error alone |
| Sample size planning | Ahmed (2024); Bujang (2024); Ranganathan, Deo, and Pramesh (2024); Zrineh, Al-Usta, and Alwawi (2026) | Design-specific sample size guidance | Sample size must match design, effect size, variance, and analysis |
| Nonresponse adjustment | Schroeder and West (2025); Collins and Kern (2025); Stefan and Hidiroglou (2024a); Mendelson and Elliott (2024) | Prediction and correction of nonresponse | Response behavior can influence both bias and uncertainty |
| Small area estimation | McGovern, Wilson, and Wakefield (2026); Dong, Wu, Li, and Wakefield (2026); Mori and Ferrante (2025); Das and Chambers (2024) | Bayesian, flexible, and model-assisted estimation for small domains | Model-assisted methods can improve domain-level precision when assumptions are defensible |
| Mixed-mode survey design | Asimov and Blohm (2024); Cabrera-Álvarez and Lynn (2024); Coffey and Elliott (2024) | Mode sequencing and intervention strategies | Survey mode affects response rates, cost, burden, and estimate quality |
| Variance estimation | Wolter (2007); Lumley (2010); Stefan and Hidiroglou (2024b); Tillé and Panahbehagh (2024) | Improved treatment of complex design uncertainty | Valid standard errors require methods suited to complex designs |

## 13. Methodological Gaps and Future Research Directions

Recent sampling research and implemented reporting still have some gaps. The initial gap is the incomplete reporting of sampling frames. Most of these studies will identify what the sampling method is, but leave out what the frame is, what is limited in its coverage may be excluded by the sampler, what the eligibility rules are, and the procedures used to update or verify the frame. In the absence of this information, readers will not be able to verdict representativeness. The source, date, coverage, limitations and cleaning procedures of the sampled frame should be reported in future studies (Lohr, 2021; Qader, Darin, Dicko, Galal, Park, Moreno Jimenez, Harfoot, and Tatem, 2026; Valliant, Dever, and Kreuter, 2018).

The second is a poor justification of sample size. The sample size can be used as a finished figure rather than a decision to be taken. Future research needs to provide assumptions on sample size planning including the expected effect size, confidence level, power, variance, design effect, response rate and subgroup requirements. In the event of complex sampling, the effective sample size should be considered as well (Ahmed, 2024; Bujang, 2024; Ranganathan, Deo, and Pramesh, 2024; Zrineh, Al-Usta, and Alwawi, 2026).

The third gap is a small reporting of nonresponse analysis. The response rates are reported without necessarily looking into the question of whether the respondents and the nonrespondents are different. In future research, frame variables, paradata, or follow-up data available should be used to assess nonresponse bias. In the case of weighting or imputation, the variables and assumptions are to be explained in an understandable manner (Collins and Kern, 2025; Sarndal and Lundstorm, 2005; Schroeder and West, 2025; Stefan and Hidiroglou, 2024a).

The fourth gap is the lack of sufficient incorporation of the measurement error into the sampling error. A research can have a powerful sampling design and yet yield weak predictions in the event the measurement tool was not well designed or mode effects were in play to corrupt responses. The connection between questionnaire testing, cognitive interviewing, reinterview approaches and devices usability with the final interpretation of the precision should be established in future work (Caporaso and Presser, 2024; Hoellerbauer, 2024; Presser, Rothgeb, Couper, Lessler, Martin, Martin, and Singer, 2004).

The fifth gap relates to the transparency of model-assisted estimation. It can be possible to use the estimation of small areas, Bayesian integration, and machine learning, which will improve estimates but can also cause model-dependent results. Future work ought to provide a report of model diagnostics, sensitivity analysis, auxiliary data quality and uncertainty measures. This becomes particularly critical when it comes to policy decisions that are made using estimates (Dong, Wu, Li, and Wakefield, 2026; McGovern, Wilson, and Wakefield, 2026; Rao and Molina, 2015; Valliant, 2024).

**13.1 Proposed Reporting Checklist**

- Identify the target population, and the practical sampling frame separately.
- State the source, date, coverage, and known restrictions of the sampling frame.
- Describe selection probabilities or give the reason why these are not available.
- Defend sample size based on design specific assumptions.
- Report response rates and investigate nonresponse bias where data are available.
- Explain weighting factors, calibration, and managing extreme weights.
- Report a treatment and imputation assumptions in missing data.
- Procedures to estimate variance of reports that is appropriate to the design.
- Elaborate on these measurement error and mode effects when appropriate.
- State the limits of generalizability with regard to the sampling design.

## 14. Conclusion

The modes of sampling directly affect the accuracy and reliability of the estimates of data. Recent literature (2000-2026) demonstrates that sample size alone is not necessary to create precision. It is created by the interplay of the sampling frame quality, the selection procedure, allocation, the response behavior, the missing data treatment, the weighting, the estimation of the variance, the measurement quality, and the assumptions of the model. Probability sampling is the best position to infer the population, but it needs to be based on a current and comprehensive frame to serve as a basis to infer the population. In applications, nonprobability sampling is still useful, although it must be explicitly constrained with strategies to address such constraints. A synthesis of 68 covered in PRISMA reveals that the discipline is evolving to converged exactness models. These paradigms consider sampling error, nonresponse error, measurement error and model uncertainty as correlated elements of the quality of estimates. Recent work on margin of total error, geospatial sampling frames, mixed-mode design, nonresponse prediction, imputation, variance estimation, and small area estimation has a greater basis on which a review paper on sampling methods can be grounded. Empirical research in future ought to underscore design quality and nonsampling error and display the sampling procedures more carefully. The number with the confidence interval, is not the credible estimate only. It is the product of an unobstructed design, defensible sample, explicit adjustment plan, and candid reporting of uncertainty.

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