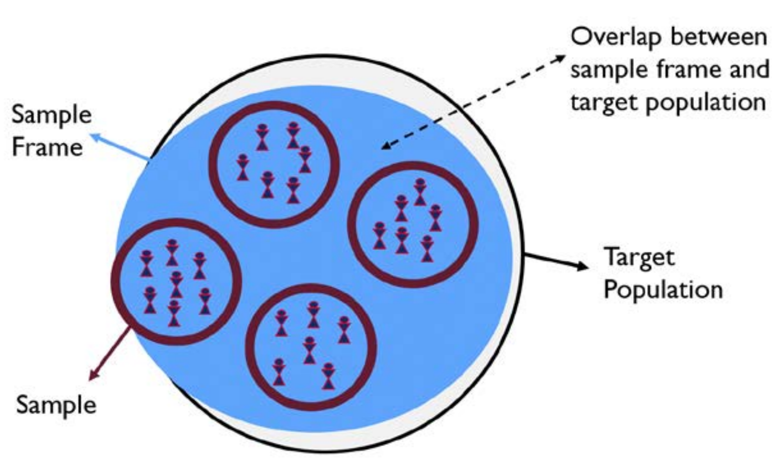
A COMMISSIONER'S GUIDE TO PROBABILITY SAMPLING FOR SURVEYS AT USAID

by: Julie Uwimana and Jennifer Kuzara



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By: Julie Uwimana and Jennifer Kuzara

Submitted to:

Virginia Lamprecht, Contracting Officer’s Representative (COR)

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Document Purpose and Audience

Sampling is the process of studying a subset of a population for the purposes of describing or testing questions about a whole population. At USAID, sampling may be used to collect data for baselines, evaluations (both impact evaluations and performance evaluations), assessments that require survey data, and in some cases in indicator reporting.

This document includes answers to common questions that the authors have been asked by USAID staff and is based on experience, best practice, and existing agency guidance. Some USAID bureaus have specific guidance for population-based surveys, like the Feed the Future's Population Based-Survey Sampling Guide, which is guidance targeted at practitioners. This guide reviews similar content at a simplified level to support commissioners of surveys.

The purpose of this document is to provide a foundational understanding of probability sampling to USAID staff to equip them as well-informed commissioners and consumers of surveys, evaluations, and other products (hereafter referred to as studies) that require probability sampling. We hope that it will serve as a resource for commissioners to make informed decisions about surveys and to use monitoring, evaluation, and learning (MEL) resources effectively. The main audience for this document includes monitoring, evaluation, and learning specialists, Contracting Officer's Representative (CORs), and Agreement Officer's Representative (AORs).

This document is intended to provide a general overview of sampling and related concepts of representative survey design. It is not official guidance. Rather, it represents good practices in the survey design field. It is not specific to any USAID initiative or requirement, nor is it exhaustive. When pursuing a representative survey for USAID or in collaboration with other organizations, remember that there are guidelines and requirements associated with the purpose of the survey, which depends heavily on the stakeholders involved. The first step to a successful survey is to understand the data needs, existing requirements, and policies of all stakeholders. As the commissioner, if you are unsure about the information provided by the external survey team, or the team is unable to answer your questions directly or transparently, seek the assistance of a survey design expert.

Survey design is a specialized skill set, even among monitoring and evaluation experts. As a commissioner of a survey, consider the composition of an evaluation or assessment team conducting a survey to ensure the team has the right mix of skills and equipped to identify potential issues in a survey you are overseeing.

Surveys at USAID

Surveys provide information for decision-making throughout the Program Cycle, answering USAID's information needs in annual reporting, assessments, impact evaluations, and performance evaluations. Surveys can be administered specifically to program participants or the general population of the communities being served. They can be administered internally by implementing partners as part of their regular monitoring and evaluation, or they can be administered by USAID or by a party contracted by USAID specifically for that purpose, such as a monitoring, evaluation, and learning (MEL) platform.

Reporting might include surveys of participants. For example, indicator performance levels are frequently collected through participant-based surveys and included in annual reports. This kind of survey is typically administered by implementing partners and reviewed by USAID as part of the regular Data Quality Assessments conducted on indicator data as required by ADS 201.

Surveys might also be included in assessments. Assessments are forward-looking and may be designed to examine a country or sector context or to characterize the specific set of problems to be addressed by an activity, project, or strategy. Assessments may be used to inform strategic planning and both activity and project design. An assessment is distinct from an evaluation. Assessments, like gender assessments or household economic analyses (HEAs), are often conducted in advance of or as part of the design process. Not all assessments use surveys, but when they do, it is because the findings are intended to be representative of a certain geographic area. Assessments may be used to provide baseline values for key indicators, and in these cases, it is critical that they represent the intended geographic programming area and population.

Impact evaluations usually include surveys to provide quantitative data for an outcome of interest. Impact evaluations measure the change in a development outcome for program beneficiaries that is attributable to a defined intervention. Impact evaluations are based on models of cause and effect and require a credible and rigorously defined counterfactual to control for factors other than the intervention that might account for the observed change. In these studies, the measurable change attributed to the intervention is called the "effect size." Impact evaluations can have either experimental or quasi-experimental designs. In experimental designs, conditions are randomly assigned to participants; one condition is the intervention being tested, and the control group may receive no interventions, or they may receive the current standard of care or some variant of it. Quasi-experimental designs also use comparison groups, but they are not randomly assigned, which means they require specialized statistical techniques to address the potential for bias in their comparison groups. These designs include propensity score matching, regression discontinuity, and using before and after measures from a non-equivalent comparison group.

Surveys are also frequently used in performance evaluations. Performance evaluations encompass a broad range of evaluation purposes and approaches. They may incorporate before-after comparisons but lack a rigorously defined counterfactual. More often, performance evaluations provide cross-sectional data (a snapshot of a single point in time) at mid-term or end-line. When surveys are used in performance evaluations, it is generally as part of a mixed-methods design, whereby both qualitative and quantitative measures are utilized in answering the evaluation questions. Surveys of participants are a common feature of performance evaluations; population-based surveys (those administered among a whole population) are less common. Because population-based surveys can be more resource-intensive than other approaches to collecting quantitative data, commissioners of performance evaluations should only elect to use them when they are appropriate to the evaluation purpose, such as when outcomes need to be measured at the population level or when interventions are administered at the level of a whole community or catchment area, making identification of specific beneficiaries impossible.

The specific circumstances of a given survey, as laid out above, will guide the decisions that follow with respect to sampling, sample size, and the appropriate statistical tests to use, which will also be influenced by the specific evaluation or study questions underlying the report, assessment, or evaluation.

Descriptive and Inferential Statistics

There are two types of statistics: descriptive and inferential. **Descriptive statistics** provide a concise summary of data, numerically or graphically – such as a mean traffic light wait time of four minutes among those surveyed (or a range of three to five minutes). **Inferential statistics** use a random sample of data taken from a population to make inferences or test hypotheses about the whole population. For example, "the median age of Senegal is 18.4 years old (+/- 2.5 %) based on a sample of 5,000 of its citizens", or "Senegalese women who marry after 16 years of age are 6.7 % less likely to experience under-five mortality in their children ($p = 0.038$) than women who marry at 16 or younger."

A study population is needed when using both descriptive and inferential statistics. A **study population** is the group of people of which survey questions are being asked. Descriptive statistics only summarize those from whom data was collected, while inferential statistics require a representative sample of the study population.

Relying on a sample rather than the overall population may lead to bias. A **representative sample** is a sample that reflects the characteristics of a study population and minimizes bias. Random selection does not ensure that a sample is perfectly representative, but it does help to ensure that any differences between the sample and the overall population are random rather than systematic. Differences that are systematic can skew results in a specific direction if the over- or under-represented characteristic is related to an outcome being measured. There are many types of bias. In this document, bias refers to **sampling bias**. Sampling bias results when the traits of the units within the sample frame are different from those in the population that you are trying to study. In Figure 1, the sample frame (blue) is very similar to the black ring (the target population), but not exactly the same. This is because no sampling frame is ever perfect. The key is knowing where the sample frame and target population do not align, and if or how it may result in potential bias. For example, in your study, you may want to draw conclusions about all of the participants in a program, but you select them based on records that only include the participants who regularly came to meetings. This sample might include more of the people who had an easier time engaging with the program or who were more interested in it, and fewer of the people who had a harder time coming to meetings or who were less engaged.

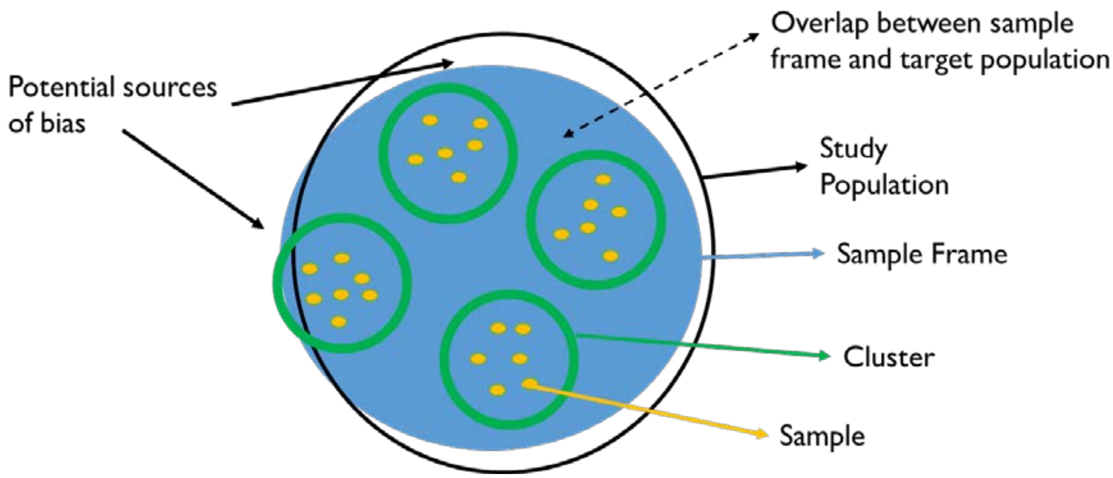

Figure 1: Population, Sample Frame, and Sample

The central role of inferential statistics is that they can be used to test assumptions or hypotheses about a parameter (a parameter is defined as either a numerical characteristic of a population, as estimated by a study variable, or a quantitative variable whose value is chosen for a specific set of circumstance). Hypothesis tests use statistical analysis to compare a hypothesis that there was an effect (or difference, relationship, change, etc.) with the "null hypothesis" or default assumption of no effect (or difference, relationship, change, etc.). In evaluation, the hypotheses being compared are usually that the intervention had an effect versus the null hypothesis that it did not. When the finding is significant, it means that the intervention probably had an effect. A result that is not significant means you cannot reject the null hypothesis that the intervention had no effect.

Study questions often pertain to the relationship between characteristics or aspects of an experience. In evaluations, this is most often of interest to study the relationship between an intervention and an outcome. The outcome is called the "dependent variable" because it responds to (is dependent on) the intervention (e.g., reading skills). In such relationships, the effects of factors other than the intervention that may also affect the outcome of interest are accounted for, in order to isolate the effect of the intervention. The other factors, called control variables, together with exposure to the intervention, are known as "independent variables" (e.g., student age). In addition to establishing relationships, a study may further test these relationships. The kind of test that is most appropriate for a given situation depends on the nature of the variables, for example, whether they are numerical variables like height or nominal variables like marital status.

It is essential to know whether descriptive or inferential statistics are planned for your study because it influences the types of survey data that is needed and the type of statistical tests that can be conducted. To better understand the options for statistical tests, refer to Annex B: Examples of Statistical Tests for Variable Combinations.

Descriptive and Inferential Statistics

Questions to ask yourself:

What is your study population? What population do you want to be able to test hypotheses about, make statements about, and generalize findings to?

Knowing your study population will help the survey team identify a sound sampling frame.

Questions to ask your survey team:

What kinds of statistics are you planning to use? Are you planning to test relationships? Do you intend to make claims about a whole population? Are you only interested in describing the people you have surveyed?

The type of questions you are interested in dictate the statistical tests you may use.

Sampling Basics

Perfect measurement of a characteristic is rarely, if ever, practical, which is why we use sampling to approximate the (unknowable) true value within a certain tolerance for precision.

Statistical error is the unknown difference between an estimated value from a sample and the "true" value based on the whole population. In the most basic sense, it is noise in the data resulting from random chance. A **true value** is a value that would result from ideal measurement.

For example, if you could locate and collect a perfectly precise measure of the height of every single American adult and then calculate sex-disaggregated means, you would have "true" values for the average height of American men and women.

There are many methods of approximating a true value through sampling. The following section provides a foundational overview of approaches.

Probabilistic vs. Non-probabilistic

There are two main types of sampling approaches: probabilistic and non-probabilistic. In a **probabilistic sampling,** every sampling unit (e.g., person or household or school) within the sample frame has some probability of being selected. A **sample frame** is a group of units from which a subset is drawn (e.g., all beneficiaries of a program or all schools covered by an intervention or all schools in a country). The sample frame defines the units eligible to be sampled but does not imply that each unit within the sample frame will be selected for data collection. Recall that the **study population** is the group of people of which survey questions are being asked. More explicitly, the study population are the units that the sample is expected to represent. If random selection is performed by choosing tickets out of a hat, the sample frame is all the tickets in the hat.

Probabilistic methods are used when it is important to ensure that the sampling units selected represent the larger population. A representative sample is achieved through probabilistic sampling approaches. This form of sampling minimizes the potential for sampling bias resulting from the over- or under-representation of people in the final sample relative to the population, because of the way sampling was designed. The objective in developing a good sample frame is to make the probability of being selected as equal as possible among the units of the study population, given the constraints of the sampling approach. However, the probability of being selected for a sample will never be exactly equivalent for all units in the study population. This is because sample frames are imperfect.

Non-probabilistic methods use purposeful selection and judgment factors to choose sampling units. Non-probabilistic methods are used when studying a specific issue, event, or group of people who does not need to be representative (e.g., collecting data from success stories). Non-probabilistic sampling designs limit the kind of statistical analyses that can be done on resulting data. In general, descriptive statistics (which should not be generalized beyond the sample) are best suited to non-probabilistic samples. Inferential statistics are frequently inappropriate for these designs.[1] A **convenience sample** is one example of non-probabilistic sampling when selection is based on convenience of contact. For example, the findings from a convenience sample to determine the median age of women visiting a specific village clinic should not be used to extrapolate the age of women nationally visiting clinics.

An exception to this rule is known as a census, which is when you are able to get information from all or nearly all members of the population to which you want to generalize. This is not considered sampling because you are not selecting a part to represent the whole. Rather, you are trying to capture the whole directly. There is no probability involved (because there is no sampling), but you are able to conduct statistical analyses. If you interview every student enrolled in a given school, you have a census for it, and any claims you make will be accurate for that school (though not for others).

Probability Sampling

As mentioned above, probabilistic or probability sampling is a selection method whereby every sampling unit within the sample frame has a specific *probability* of being selected, and that probability can be estimated. There are five types of probability sampling: simple random, systematic random sampling, stratified, multi-stage, and cluster. This section briefly explains each type. It is possible to have multiple sampling approaches present in one design.

Simple Random Sampling

Simple random sampling is an approach where every unit in the sample frame has *roughly the same probability* of being selected. An example of simple random sampling is randomly selecting beneficiaries from a complete beneficiary list. In this case, the sample frame is the complete beneficiary list. Because all of the sampling units or beneficiaries are known, each has an equal probability of being selected. Simple random sampling is most common in scenarios where the sample frame is small and defined. The larger the sample frame, the more difficult and costly it is to use simple random sampling.

Systematic Random Sampling

In systematic random sampling, sampling units are selected according to a random starting point and a fixed, periodic interval. Selection begins with an ordered or randomized list, and every r-th sampling unit are

[1] In some cases, a specialized parameter might be appropriate (for example, if snowball sampling is used for a social network analysis, specialized statistics can be used that are not dependent on the representativeness of the sample), but this needs to be determined on a case-by-case basis.

selected. In the beneficiary list example, systematic random sampling of beneficiaries in a defined list would be accomplished by either using a spreadsheet or statistical program function to randomize the list and then selecting every fifth beneficiary in the list, for example. The interval is usually selected based on the proportion of the list that will be sampled. If there are 1,000 beneficiaries, and 250 of them are to be sampled, you would randomly order the list and then select every fourth person.

Stratified Sampling

Stratified sampling splits an entire population into homogeneous groups or strata before sampling. The sample is then selected randomly from each stratum. Examples of strata are geographic regions, age groups, grades, or any other classification which: 1) includes the entire population of interest (collectively exhaustive); and 2) defines categories so that each sampling unit is only assigned to one stratum, (mutually exclusive).

Stratified sampling is most commonly used in the following cases: 1) your outcome variable is strongly related to your stratification variable; in these cases, stratification reduces error; 2) to ensure that you can conduct sub-population analyses, either because you guarantee having the minimum sample size allowed through normal stratification or because you have introduced **oversampling** into your stratification scheme; and 3) in cases where your sample frame already stratifies in some way - so stratification is just easier.[2]

Oversampling is a special type of stratified sampling in which disproportional numbers of sampling units are selected from specific strata. This is designed to ensure that there are enough members of a particular group displaying a specific, usually low-prevalence, characteristic to conduct sub-analyses on that group. For example, USAID is often interested in the well-being of marginalized populations, which are usually in the minority of a population. To conduct analyses at this level, more minority individuals need to be included in the overall sample size than the proportion of the population they actually represent, effectively increasing the sub-sample of the marginalized group.[3]

Multistage Sampling

Multi-stage sampling starts with the **primary sampling unit (PSU)**, or the units selected in the first stage of a multi-stage sampling design. It divides the population into smaller and smaller configurations before sampling. The sample is drawn from the smallest unit of analysis. Multi-stage sampling is often preferred for its functionality and cost-effectiveness compared to simple random sampling. Multistage sampling will commonly use multiple approaches to sampling within the various stages.

For example, if you want to randomly select individuals from a household beneficiary list, but you only need one respondent per household, you may start by randomly selecting households from the list (first stage), then ask the members of the household to give you a complete list of household members who meet the

[2] This is potentially problematic and is often used incorrectly in cluster sampling, e.g., "we pre-selected this district purposively and then took 26% of our sample from there because they have 26% of the total population," when actually a PPS approach is what is needed to choose the district.

[3] Note that oversampling is done to facilitate the analysis of specific sub-populations. For analyses of the overall population, any over-sampling that was done will need to be accounted for through weighting to ensure that the minority population is not over-represented in point estimates for the larger population.

inclusion criteria (e.g., women in reproductive age, elderly visiting health clinics, working men), and choose randomly from that list (second stage).

Cluster Sampling

A cluster sample is a special kind of multistage sample.[4] In cluster sampling, you divide the population into clusters, select a subset of those clusters, and then select a sample from within each of the selected clusters. A **cluster** is the smallest area unit selected for a survey. An example of a multistage cluster sample is choosing 20 schools randomly from a list of 300 schools, and then selecting 40 students from each selected school from a total sample of 800 students. An **enumeration area** is a special kind of cluster and the result of having a census. Enumeration areas (EAs) are small geographic units specifically designed for census data collection and often designed to be equal in size.

Clusters may be selected randomly or purposively, and the selection of the sample within the individual cluster is generally probabilistic. When clusters are selected probabilistically, so long as the right weighting is applied at selection and analysis, generalizability is feasible. However, it is important to remember that when choosing clusters purposively, findings should not be extrapolated more broadly than that specific cluster. For example, if an intervention is designed to improve the health status of women in a rural district in the northeast of a country, findings from that sample should not be ascribed to the entire region, only the specific district purposively selected for the cluster. Similarly, when an entire region is probabilistically sampled, the findings from that sample would be representative of the whole region, not only the selected clusters.

The approach to sampling will vary based on the design and the sample frames, but systematic and stratified approaches are both common. In cluster sampling, it is assumed that clusters are naturally defined (e.g., households, schools, clinics, counties) so that the sampling units within are similar in nature (e.g., the individuals within a cluster share many characteristics). Otherwise, sub-populations may be over- or under-represented, depending on which clusters are selected. Later, we will discuss strategies survey designers use to address this challenge.

[4] Not all multistage samples are cluster samples, but all cluster samples are selected in stages.

Sampling Basics

Questions to ask yourself:

What is the primary use of the findings from this study? Have you communicated them with the survey team?	Understanding the intended use of the findings will better equip the survey team to create a strong sampling design.
Are any of your study questions designed to result in quantitative findings about a subpopulation that is 10 percent or less of the total population?	If so, the survey design might need oversampling. Consult with the design team to decide whether oversampling is necessary. **Recall that oversampling is a special type of stratified sampling that intentionally includes more sampling units into the sample size than would be included through a randomized sample. This is designed to ensure that there are enough members of a particular group displaying a specific, usually low-prevalence, characteristic to conduct sub-analyses on that group.[5]

Question to ask your survey team:

Is your survey team planning on making claims about an entire population based on a sample?	If so, confirm that they are also using a probabilistic sampling method. The most common probabilistic design used at USAID is a multi-stage cluster design, in which case confirm that each stage of sampling is clearly defined.

How Do I Choose a Sample Frame?

Sample Frames and Sampling Bias

Recall that a sample frame is a group of units from which a sample is drawn; it will be roughly but not exactly the same as the group of units that the sample is expected to represent, the study population. It defines the units eligible to be sampled. In multi-stage sampling, each stage has a defined sample frame or a selection rule (remember that in multi-stage designs, some stages may be probabilistic while others are not). A sample frame can include households within a political-administrative division, like a county or region, or a list of identifications for people in a specific area, like a local registry or a program participant list. In each case, the sample frame has the potential to introduce sampling bias because the sample frame may differ in small or large ways from the intended study population.

A **sampling bias** occurs when the traits of the units within the sample frame (e.g., spotty list of program participants or records on the participants who are most interested in the services and come more regularly to meetings) are different from those in the population that you are trying to study (e.g., all program participants). The differences may be slight, based on a trend in behavior, or more extreme, for example, when the choice of sample frame has the effect of entirely excluding a specific sub-group of the population from the sample frame. For example, if all the people who own a cell phone in a specified town are used as a sample frame to randomly select community members for a community-based public health survey, then those without phones would be systematically excluded. This is not to say that using the telephone numbers as a sample frame is wrong. However, excluding those who do not own a phone may introduce bias (Are they older? Less wealthy? Less comfortable with technology?) and should be addressed in the clarification of the study limitations and in the interpretation of its results.

[5] Kish, L.: Survey Sampling. John Wiley & Sons, Inc., New York, London 1965, IX + 643 S., 31 Abb., 56 Tab., Preis 83 s.

Sampling limitations are often addressed in specific sections of both survey design proposals and survey reports. What qualifies as a limitation depends uniquely on each survey design and its associated questions. A **limitation** can be any significant weakness in the design by which the findings could be influenced. In the example given above, a limitation might be that cell phone ownership is correlated with socioeconomic status, and therefore the poorest people in the study population are systematically under-represented.

How Do I Choose a Sample Frame?

Question to ask yourself:

Who are the people your study questions are asking about, and how well does the sample frame matches that study population?	Knowing the primary subject of your study questions will help determine an appropriate sample frame.

Question to ask your survey team:

What is the sample frame for each stage of sampling?	Most population-based surveys at USAID are multi-stage, cluster designs. The survey team should be clear about how selection is approached at each stage.
How is the sample frame being constructed? What are its limitations in generalizing to the study population?	Most sample frames in population surveys are proxies for the total population, and each choice of frame will come with limitations.

Making Generalizations

Sample frames are important. They sometimes limit the extent to which the findings of a study can be generalized. This is a separate issue from the issue of sampling bias; it refers to the ability to make inferences about the overall study population on the basis of a sample. Almost all samples have some degree of bias; but too much bias can impede the ability of researchers to apply findings from within the sample to findings outside the sample. In the same cell phone example, the sample frame is imperfect, but results can be inferred to represent the whole community, albeit with some degree of bias. Findings based on this sample would *not* be appropriate to generalize outside the community from which the cell phone registry was taken, because the sample frame was only selected to represent that one community.

How Do I Review Sample-Size Calculations?

This section gives a basic overview of common parameters and considerations involved in calculating a sample size. **Parameters** are values that need to be set to complete a sample size calculation. It also provides a checklist for reviewing sample size calculations.

Sample Size Formulas: The formula used to calculate sample size depends in part on the nature of the desired statistical test, which, in turn, is partly determined by the nature of the variables being measured.

Annex B of this document provides a quick guide to the most common inferential statistical tests that are used for different combinations of variables.

Common Parameters

Sample size is the number of respondents needed to estimate the statistics of the population of interest with sufficient precision for the inferences you want to make. Different formulas are used to estimate the necessary sample size depending on the sampling methodology and the type of analysis planned. However, all formulas use a common set of parameters. Recall that parameters are values that need to be set to complete a sample size calculation.

This section explains the most common parameters used in sample size calculations: design effect, effect size, statistical power, confidence level, margin of error, significance, non-response, and attrition. For an example of a sample size calculator, refer to USAID's [Feed the Future Sample Size Calculator](#).

Design Effect

For a cluster design or other multi-stage design, it is necessary to factor in a design effect (DEFF) in the sample size calculation. The **design effect** is an additional error that is introduced by the sampling design. Multi-stage designs have less precision and greater potential for error than simple random sampling. DEFF is the difference between the error the survey has because of its design, and the error it would have had under a simple random sample.

The DEFF makes the adjustment needed to find the survey sample size when using sampling methods different from simple random sample. **Effective sample size** is equal to the actual sample size divided by DEFF.

Actual DEFF can only be calculated after data have been collected and analyzed for variance, but design effects can also be estimated before data collection to more accurately estimate the sample size needed in complex designs. For example, to calculate sample size in a cluster design, a survey team needs to know the number of clusters that will be sampled and the size of each cluster. This will ultimately be used to calculate an intraclass correlation coefficient (ICC), which is necessary to calculate DEFF after all data have been collected. The ICC measures the amount of total variation in an outcome that can be attributed to differences between clusters. It uses measures of variation within clusters and variation between clusters. Predicting what this coefficient will be is the most challenging part of estimating DEFF. If there are no existing data (from other surveys in the area, for example), then a range of values should be tested to see how the effective sample size changes in response to different possible DEFFs. The higher the intraclass correlation coefficient, the larger the sample size needed.

DEFFs are always ≥1, where 1 represents simple random sampling, and therefore, there is

Table 1: Sample Size and Design Effect

Examples of sample size calculations for three common Margin of errors: M1 = .05; M2 = .07; M3 = .10.

A. Sample Size Calculation: Design Effect 2.0

	M1	**M2**	**M3**
Estimated Proportion	0.500	0.500	0.500
Alpha	0.050	0.050	0.050
Confidence Level	0.975	0.975	0.975
Margin of Error	**0.050**	**0.070**	**0.100**
Design Effect	**2.0**	**2.0**	**2.0**
Initial Sample Size	769	392	193
Plus 5% Non-response	**807**	**412**	**203**

B. Sample Size Calculation: Design Effect 4.0

	M1	**M2**	**M3**
Estimated Proportion	0.500	0.500	0.500
Alpha	0.050	0.050	0.050
Confidence Level	0.975	0.975	0.975
Margin of Error	**0.050**	**0.070**	**0.100**
Design Effect	**4.0**	**4.0**	**4.0**
Initial Sample Size	1,537	784	385
5% Non-response	**1,614**	**823**	**40**

The two examples above show how the design effect and margin of error influence the sample size needed to be able to accurately estimate the proportion of a variable in a population. The more precision desired, as illustrated by the smaller margin of error, the larger a sample size needed. Similarly, the larger the design effect or possible error introduced by the sampling design, the larger the sample size needed.

no design effect. The higher the design effect, the smaller the effective sample size. A DEFF of 1.5 means that the actual sample needs to be 150 percent higher than what it would be if there was no design effect. Refer to Table 1. Note that with the exact same parameters, only different DEFF's, the first example uses a DEFF of 2 and the second 4- doubling the sample size.

Scenarios that would increase DEFF include when clusters are few and large or when clusters are very different from one another, or the number of PSU's per cluster is high. When existing DEFF data are not possible to find, a common DEFF is 2. A DEFF can be naturally lowered by sampling from a larger number of smaller clusters, rather than only a few larger clusters, to achieve a comparable sample size. The larger or fewer clusters being sampled from, the greater the potential for over-representing the traits of that cluster in the total sample.

Effect Size

The effect size is the strength or magnitude of the difference between the sets of data. Often, the sets of data represent before and after values for a group that received an intervention and for a control or comparison group, to measure the size of the difference in the effect of that intervention relative to the control. The smaller the effect size, the larger the sample required to detect it. Effect sizes are seen in impact evaluations more often than performance evaluations.

The formula used to calculate sample size depends on the specific hypothesis test planned for the data. Sample sizes should be calculated for all outcomes to be measured, and the largest (most conservative) of the sample sizes used. Often, survey teams will measure more than one outcome, and in these cases, they should use the outcome with the smallest estimated effect size for their sample size calculation (which will require the largest sample size to detect). A review of background literature can provide a sense of what the effect sizes might be. It is often wise to calculate sample sizes from a few different effect sizes within a range (e.g., five percent, ten percent, and 20 percent). This is called a sensitivity analysis.

Remember that the effect size you use to calculate sample size is an estimate of the effect size you want to achieve (your target). Use the estimate that is the minimum you wish to be able to detect.

Statistical Power

Statistical power, used for inferential statistics, is the probability that if a real effect exists (for example, the difference between the two groups before and after an intervention), the sample selected will be sufficient to detect it. To calculate a sample size for inferential analysis, the survey team will need to decide on a statistical power. The higher the power, the more likely the study will detect an effect, but it also requires a larger sample. The value for this parameter most often used in social sciences is .80.

Confidence Level, Margin of Error, and Confidence Interval

Methods to calculate sample size require you to decide on a confidence level and a margin of error. The **confidence level** is one measure of the validity of your results, and the **margin of error** is a measure of their precision. The more precision you want (i.e. the smaller the margin of error), the larger the sample size you will need. Likewise, the higher the level of confidence you want to have in the validity of your results, the larger the sample size you will need.

When calculating a value from data, such as a point estimate or an effect size, statistical techniques are used to determine a range within which the "real" value is likely to fall, with a specified level of confidence. If the confidence level is 95 percent, for example, then if a study could be repeated 100 times, in 95 of them the identified range of values would include the "real" value. The higher the level of confidence you want to have in your result, the larger the sample size needed. Commonly used confidence levels are 90 percent, 95 percent, and 99 percent, but 95 percent is the most common.

The margin of error refers to the amount of error due to random factors you wish to allow in your results; in other words, it determines the amount of precision you will have for your result. Survey teams choose a specific margin of error they want to aim for. Increasing the sample size reduces the amount of error, so reducing the margin of error requires increasing the sample size.

The margin of error is related to the confidence interval; it is half the width of the confidence interval. The confidence interval is the range within which your result falls, at your desired confidence level**.** You might see a confidence interval expressed as: "Mean = 15.6 (CI 14.8; 16.40)" or "Mean = 15.6 ± 0.8."

Significance and Alpha

Significance is a feature of the results of hypothesis tests. A finding is called statistically significant when there is a low probability that it is due to chance alone. When a statistic is significant, it simply means that the survey team is very sure that the finding is real and not due to chance. It doesn't definitively mean the finding is valuable or that it has specific decision-making utility. Significance is related to confidence level and Alpha. At a confidence level of 95 percent, a significant result is one the survey team can be 95 percent sure is due to an actual difference between the samples and not to random chance. On the other hand, **Alpha** is the probability of rejecting the null hypothesis when the null hypothesis is true or the probability of being incorrect. Therefore, if the confidence level is 95 percent, Alpha is 0.05.

Non-Response

When calculating sample size, include a factor of non-response. This means accounting for selected respondents who will choose not to participate or not to answer questions about the outcomes you wish to measure, effectively adding to the needed sample size. The estimated percentage of non-response can be drawn from comparable studies in similar locations. A common non-response rate estimate for sample size calculation is 5-10 percent.

Attrition

Attrition is particularly relevant for longitudinal studies (studies that takes place over a pre-determined time period, using repeated observations of the same subjects). Selected respondents at the beginning of a study may move or decline to participate before it has been completed. In these cases, attrition may also be accounted for but is distinct from non-response.

Attrition and non-response may each introduce bias into your findings, particularly if certain kinds of people are more likely to drop out because of their characteristics. For example, younger and lower-income people are more likely to move and may move away from the study area at higher rates than other people. If the outcome is related to age or wealth, then the loss of these individuals may result in over- or under-estimating the outcome.

Attrition as a limitation should be acknowledged by survey teams, mitigated where possible by weighting the data in the analysis stage to account for missing data, and considered in the interpretation or generalization of findings.

How Do I Review Sample-Size Calculations?

Question to ask yourself:

How much precision do you need around a point estimate? This means, in order for the findings to be useful for the purpose of the intended audience, how close do you need to be to the measurement of interest if it were to be measured perfectly?

Not all measurement purposes require high precision. For example, measuring the average number of children per family for the purpose of describing national demographics might require less precision than knowing how many children in a specific district are undernourished and therefore intended targets of a nutrition intervention. Recall that higher precision requires larger samples sizes. Higher sample sizes require larger budgets. Therefore, it is prudent to understand the degree to which your measurements need to be precise.

Question to ask your survey team:

What parameters are being used to calculate sample size, and how were they selected?

Your survey team should be able to justify the parameters they have selected, including those based upon common practice, and those based on reasonable, data-driven estimates. Review the estimates, especially for parameters relating to your outcomes, to be sure they match your expectations and the degree of precision needed. *See Annex D for Common Sample Size Parameters*

Other Considerations

Population Estimates

Population data are required for sample size calculations for a representative survey, as well as for probability-proportional-to-size selections. In scenarios where quality census data exist, population data can be provided at the enumeration area level. As previously mentioned, **enumeration areas** (EAs) are small geographic units specifically designed for census data collection and often designed to be equal in size, making sampling from them much more straightforward. To be clear, an EA is not a generic term and is only the direct result of having a census.

If there are no quality census data, as in countries with failures of governance or a history of conflict, and widespread population movements, designers of a sampling frame will need to compensate by including an alternative for population estimates that sufficiently representative of the population being studied if they wish for their survey to be representative at the population level. In most cases where EAs are available, they are likely to be preferred for use as clusters, because they have already defined geographic boundaries and associated population data.

Proportional Allocation of the Sample

In cluster designs (and some other cases where people are selected in groups, as when sampling schools or the catchment area of a clinic or service provider), there is a risk of over- or under-representing specific characteristics or traits in the results, because they are more or less prevalent in that cluster or group than in the total population. This can be particularly important when there are differences in characteristics between rural and urban populations.

Consider a situation in which ten towns are eligible for selection, and the population of the towns' ranges from 542 at the low end to 251,724 at the high end, with a total population across the ten of 588,766. If a simple random sample is used to select towns, each with a one-in-ten chance of being selected, then the 542 people in the smallest town will have a one-in-ten chance of selection even while making up <1 percent of the total population. The characteristics of residents of that town will be over-represented relative to the total population. This can be addressed through weighting at analysis (in which analysts "count" some respondents less than others by specific percentages), but another popular approach is to use probability-proportional-to-size (PPS) selection.

In PPS sampling approaches, random selection is still used, but a cluster is assigned a probability of selection that is equal to the proportion of the overall population made up by the residents of that cluster. In our example from above, the smallest town would have 542 chances out of 588,766 of being selected (that is, if tickets were being drawn from a hat to select the town, it would have 542 tickets in the hat, while the largest town would have 251,724 tickets, and so on).

Usually, PPS sampling is achieved using a statistical software program, which requires reasonably reliable population estimates for each cluster. This could be a list of towns within a geographic area, but it may also be a list of EAs or some other geographic unit. In either case, the population estimates used for PPS sampling should be confirmed by survey teams on the ground. This is usually accomplished by conferring with local officials when they arrive in town. The updated population estimates will be used to apply a weight at the analysis stage to correct for any errors in the estimates used and to ensure that the resulting statistics are as representative as possible.[6]

In most countries, relatively current population estimates are readily available, but in some countries where USAID works, particularly those affected by disruptions to governance or on-going conflict, population data may be unavailable or too outdated to use, complicating the use of PPS. In such cases, it is recommended that survey commissioners or implementers consult with implementing partners, other donors, and UN agencies operating in the area, who may have collected population data from towns in which they work. In cases where population estimates are suspected to be of low quality, they may still be used for PPS selection of clusters, but surveyors should confirm population figures for clusters they visit; usually, this information can be obtained from local authorities. If estimates are found to be substantially different from those used for PPS selection, weighting can be applied at analysis to correct for this difference. Such a practice can be beneficial, even when surveyors are reasonably confident in the estimates used for PPS, but is essential when

[6] An alternative to PPS is to define clusters so that they have equal sub-populations, and then the clusters can be selected with a simple, unweighted, random sample. This is the practice behind EAs, which are often determined so as to have a common range of households and equal sub-populations.

data are suspect. See Box 1 for some alternative sources of population data when census data are not available.

Box 1: Population Data Sources: Census data is the most straightforward way of estimating population size. However, not every country where USAID works has an up-to-date, quality census. Census data that are old can still be used in many cases, but not if: 1) they are very old (if a census has not been done in several decades, for example), or 2) there have been large-scale population movements due to conflict, natural disaster, or urban migration since the time of the last census. And in some rare cases, there is simply no census at all. Alternative approaches to identifying population data for use in PPS sampling include:

- Tapping into implementing partner (IP) population estimates. IP's usually keep up-to-date population counts for the areas in which they work, or have relationships with local authorities who can provide the data.
- Examining whether there are any USG-supported surveys occurring in the country. The US government supports a wide range of studies in different sectors (for example, the Demographic and Health Surveys and various rounds and regions of the global barometer surveys). If a representative survey is being conducted, you can inquire about the source of the population data they are using.
- Reaching out to UN agencies operating in-country. The United Nations Population Fund (UNFPA) and other UN organizations sometimes conduct population estimation exercises when there is no available census data. If conflict has caused population movements, the International Organization for Migration (IOM) may have data to share.
- Check the availability of estimates derived from satellite imagery, such as LandScan from the Oakridge National Laboratory, which is free to USG. LandScan is developed using best available demographic (Census) and geographic data and remote-sensing imagery analysis techniques to disaggregate and impute census counts to small geographic units within any given administrative boundary.

Other Considerations

Questions to ask yourself:

Did the survey team include a design effect, and if not, do they have a good reason for not including it?

In simple random sampling, which is often possible within beneficiary groups, there is no additional error introduced with design. However, with any multistage cluster design, there should be a listed DEFF within the design document.

Questions to ask your survey team:

How was the DEFF determined?

If a survey design estimates too low a DEFF as a way of keeping sample size and costs low, it risks resulting in an underpowered survey. All multistage surveys should include a design effect that is > 1, and if there is no design effect included in the sample size calculations or the design effect = 1, you should be asking your survey team why.

Sensitivity Analysis

When various sampling designs are being considered, survey teams may conduct a sensitivity analysis to determine reasonable levels for effect size and design effect. Recall that effect size and design effect, as used in a sample size calculation, are (ideally) based on existing, comparable studies or based on knowledge of the field, and the estimates are ultimately chosen by the survey team. The design effect can only be estimated at this stage and is not definitively calculated until the data analysis stage. **Effect size** is an estimation of change to be detected. Therefore, the effect size and design effect used in the sample size calculations are informed estimations for empirical parameters that will be calculated later. To conduct a sensitivity analysis, survey teams first review comparable studies to note the DEFF and effect size. The effect size estimated by other studies can suggest a reasonable effect to assume, given a particular sector or study purpose. Existing studies with similar sampling designs in the location of interest will also provide insight into what one can expect the DEFF to be at the analysis stage. Second, the survey team would use estimated values for the DEFF and effect size, based on these resources, to run sample size calculations at different DEFF and effect size levels, using different sampling designs (e.g., number of clusters). Ultimately, survey teams choose one of the sets of parameters (and the associated sample size) as the one that best meets their (sometimes competing) needs.

By having done sensitivity testing, survey teams can have more confidence in the DEFF and effect size estimations selected as they relate to the purpose of the survey and existing limitations, like time frame and budget.

What Does Sampling Look Like in Practice?

This section gives a basic overview of sampling stages in a cluster design using enumeration areas (EAs) and without EAs. When EAs are available, they should be used. If EAs are not available, aspects of the environment will determine your options, including whether there are independent population estimates available (see Box 1 for sources).

Sampling with EAs

Prior to sampling, survey teams should know the geographic boundaries they wish to focus on. These boundaries will determine the sample frame for the initial stage of sampling. Geographic boundaries are typically at the district, regional, or country level.

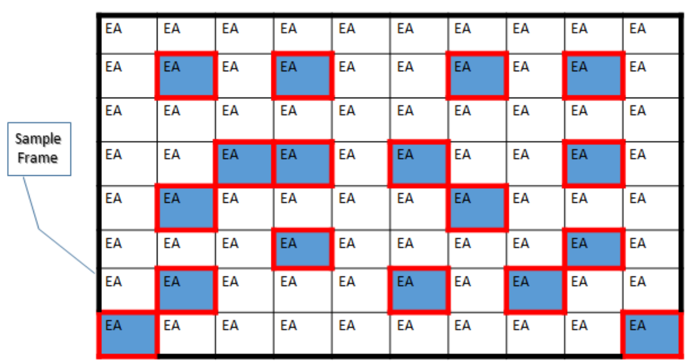

Figure 2: Randomly Selected EAs within the Sample Frame

Stage 1: Selection of EAs (these will be the PSU). Once the sample frame is set, the sample EAs can be selected. Because lists of EAs are sometimes available (often with number IDs, along with population sizes and GPS coordinates), EAs can be selected through either simple or systematic random sampling. They may also be selected using a PPS approach, particularly if they vary considerably in their population size. In either case, data should be weighted at analysis to account for population size. As an illustration, in Figure 2, the cells in red represent the selected EA's from the sample frame. *Note, some EA's are inside the sample frame, but not selected for data collection.*

Stage 2: Selection of HH. If household numbers are available within EAs, then HHs can be selected randomly from an existing list (see Figure 3). If household numbers are not available, a household list can be constructed manually, usually by consulting with local authorities and completing a community map. An alternative approach to household selection is a transect walk. In a **transect walk**, each member of the survey team starts from a specific point within an enumeration area and walks in a randomly selected direction, interviewing every n-th household. If transect walks are used, the rules for selection should be clearly specified and consistent across all EAs in the survey. While not strictly a probabilistic approach to household selection, this kind of approach is commonly used wherever it is impractical for a survey team to list households.

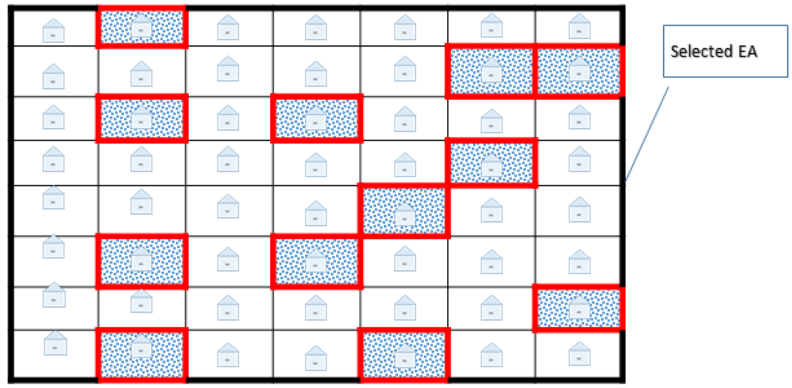

Figure 3: Randomly Selected Households within the Selected EA

Stage 3: Rules for selection of HH members. Once a household is selected, HH members may be selected according to pre-identified selection criteria, or else randomly (the person outlined in red in Figure 4). Some surveys are designed to include all eligible household members in the survey; more commonly, a specific type of respondent is desired (e.g., household heads, women who gave birth in the last six months, or adults between the ages of 18 and 65). If only one respondent is desired per household, and that person has not been pre-identified by role, enumerators should list all eligible household members (if there are more than one), and select randomly among them using a random number chart. Survey designs should be clear and specific about how household members will be selected.

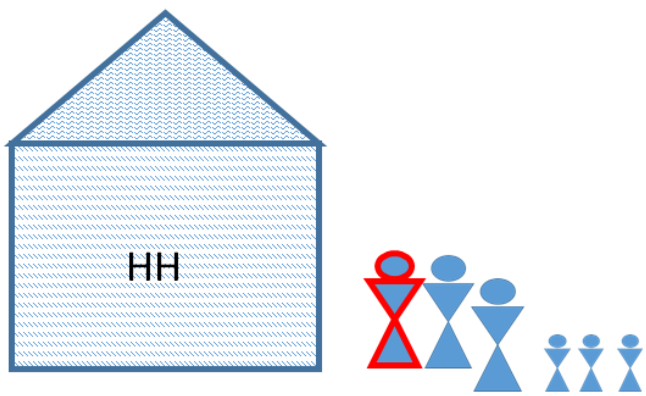

Figure 4: Household Respondent Selection

To summarize, the proceeding sampling steps, the household in Figure 4 was inside the sample frame and geographically located within one of the selected EAs within the sample frame. Among all of the households in the selected EA in which this household live, it was again selected to be part of the data collection. Once the household was selected, a rule was applied whereby only one person, the one highlighted in red in Figure 4, was selected to respond for that household.

Sampling without EAs

Sampling without EAs is different than sampling with EAs - but only in the first stage of sampling. When EAs are not available for an area, survey teams will usually use a locally relevant administrative unit instead – like a county or village. It is essential that the unit be locally relevant because survey teams will likely depend on local authorities for confirmation of population estimates. The choice of administrative units will depend on a number of factors, including availability of population estimates, logistical constraints, and the number of clusters to be visited.

What Does Sampling Look Like in Practice?

Question to ask your survey team:	
Does your country have EAs? If so, what year was the census? Have there been large population movements since the census was conducted?	When quality EAs are available, they are the best option. However, if large population movements took place after the census or data quality is questionable, the data may not be usable as a reference for population data. Recall that EAs are small geographic units specifically designed for census data collection and often designed to be equal in size, making sampling from them much more straightforward. To be clear, an EA is not a generic term and is only the direct result of having a census.
Questions to ask your survey team:	
If using PPS, what approach does the survey team intend to take to confirm estimates used in PPS allocation in the field?	The population estimates used to calculate the sample size should be confirmed in the field. The data is then weighted based on the confirmed population numbers, not the estimated numbers used to calculate sample size. Weighting means counting a respondent's value as slightly more or less than one, based on the portion of the population their cluster represents. This is done because the population numbers gathered during data collection will always be the most recent compared to other available data.

Why is My Input in These Decisions Important?

Survey design teams will make dozens of decisions over the course of a survey design. In most cases, these decisions do not necessarily have a right or wrong answer but *do* entail a set of trade-offs with respect to your study questions and how you will be able to interpret findings. The intended utilization of the data will inform which trade-offs are tolerable and which are not. Without your input, survey teams may find themselves making judgment calls based on their assumptions about how you will use the data; even experienced survey designers may make the wrong choice if they do not know your priorities.

Reasons you want to be involved in survey design: Decisions made during design will impose permanent, irreversible constraints on how data can be used.

- You may be tempted to think that even if you cannot get the sample size you need for the analyses you desire; a small survey will be better than nothing. **This is not true**. There is likely to be a better use for your resources, because an underpowered survey will not give you the information you want.

- If your survey is underpowered, you probably won't be able to answer the questions you want to answer about your data, but you also won't know *why* your findings are weak. You won't be able to tell if they're weak because there's no finding to detect, or if they're weak because your survey was simply too underpowered to detect it.
- The sample size you need depends on the statistics you plan to use. Survey teams need a very clear idea of your data needs and the intended use of the findings to know what statistical analyses are likely to be needed. Discuss the kind of statistics that meet your use needs with the survey team before they finalize the sampling design.
- Sampling determines who is represented by the data; if you want all voices represented in your survey, you have to be confident in your sampling design and your ability to generalize. Discuss the issue of generalizability directly with your survey team, and know the selection rules at each stage of sampling.

About the Authors

The authors are staff from MECap*.

Julie Uwimana has been with MECap since 2016, previously serving as an M&E Fellow with the Bureau for Policy, Planning and Learning (PPL), and the Monitoring, Evaluation, and Learning team in the Bureau for Food Security (BFS). While at BFS, she supported the Feed the Future Zone of Influence representative surveys in Mali and Ethiopia. Before joining USAID, she spent seven years working on monitoring, evaluation, and learning with USAID implementing partners, as well as the Department of State. She holds a Master’s Degree in International Development from the Graduate School of Public and International Affairs at the University of Pittsburgh.

Jennifer Kuzara has been with MECap since 2015, serving as an M&E Fellow with USAID Somalia and the Middle East Bureau before joining MECap's core team as a Senior M&E Specialist. Prior to joining USAID, she worked with CARE in Atlanta for seven years, where she led and supported population-based surveys and contributed to the development and piloting of a socio-psychological tool to measure women's empowerment. She also held a fellowship at the Centers for Disease Control and Prevention (CDC), where she supported the Community Guide for Preventive Services in conducting systematic reviews and meta-analyses of public health program evaluations. She holds a Ph.D. in Anthropology and a Masters of Public Health in Epidemiology from the Rollins School of Public Health, both earned at Emory University. In addition, she holds a certificate in Global Mental Health from the Harvard Program for Refugee Trauma and has received supplemental training in Formal Demographic Methods from Stanford University, in transcultural psychiatry from McGill University, with a focus on the development and validation of conflict-sensitive, culturally-aware psychometric tools, and in research design and field methods from the National Science Foundation.

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Annex A: Sampling Design Review Checklist

Sampling Review Checklist

☐	A population-based survey is needed	Population-based surveys should not be chosen lightly. They are more complicated than some other kinds of surveys because they typically require multistage sampling, which can be more expensive and time-consuming than other approaches. They should only be used when it is essential to characterize the whole population of an entire geographic area. In many cases, study questions focused on project beneficiaries can be answered using simpler sampling approaches that are representative of the beneficiary group (but not necessarily the larger population).
☐	Use of the findings are clear	How does the information gathered align with the project for activity theories of change? What are the programmatic implications of the findings? Use should be at the forefront of decision-making when determining the variables for the analysis. What are the 'need to know' and 'good to know' characteristics to be collected? The more variables and characteristics being collected in the survey, the more costly it will be. Using a shorter survey may allow for a larger sample within the same budget. What sub-populations might be of interest in the analysis? If a sub-analysis is planned on a minority group, over-sampling may be needed to attain adequate representation.
☐	An intentional sampling design exists	If a design document mentions sampling, it should also explain how the sampling will be conducted. The design should include step-by-step processes for sampling unit selection. For example, is it simple random sampling from a beneficiary list or multistage-stage cluster sampling? If the latter, have they explained sampling at each stage, including how clusters will be selected? This information should be clear.
☐	Randomness is clearly identified	Confirm that each stage of sampling for which generalizability is desired has an element of randomness. What is important is that each stage of sampling should be clearly explained with respect to why and how randomization is being introduced or not. If selection is purposive - particularly in the first stage of sampling - it affects generalizability.
☐	Appropriate sample frame	Compare the sample frame identified in the design to the subject of the study question being investigated. In an effort to cut time and cost, a survey team may propose a sample frame smaller than what is needed for the desired generalizability. This is problematic. The data from a representative study can only be generalized to the population included in the sample frame. For example, if your frame includes only adults aged 25-60, you cannot generalize to those outside this age range.
☐	Limitations are clearly addressed	Sample frames are imperfect. Limitations that exist with the selection of a sample frame should be recorded in detail.

Sampling Review Checklist

☐	Design effect is justified	If your survey includes a cluster design, then the sample size calculation includes a design effect estimate. Design effects can be naturally lowered without increasing the sample size by visiting and sampling fewer respondents, each from a larger number of clusters. However, a sampling design that includes a large number of clusters is more expensive than a sampling design that uses fewer because of the increased need for travel, logistics planning, and time. Although lowering a design effect estimate is tempting because it lowers the sample size calculated, the design effect itself will be based on the actual nature of your data; underestimating it will result in an underpowered survey, which is wasteful of the resources invested in conducting the survey. **An underpowered survey is not "better than nothing"** -- if the budget is not sufficient for an adequate sample size using the most accurate available estimates, the survey commissioners should consider narrowing the scope of the survey or using an alternative to a population-based survey.
☐	Effect size is justified	The smaller effect size, the larger the sample size needed to detect it. However, misjudging or unjustifiably increasing an effect size estimate in your sample size calculation in order to decrease sample size can lead to an underpowered survey. Ensure that the estimated effect size is justified based on comparable research and anticipated results.
☐	Use of standard parameters	Power, confidence level, and margin of error are parameters with a range of common standard values. When reviewing a sampling design, ensure that the values for these parameters fall within those standards.
☐	Non-response is applied	In all voluntary data collection efforts, some respondents will choose not to participate or to refuse to answer some questions. The higher the estimated non-response rate, the larger the sample size will need to be. In longitudinal or panel surveys, there should also be a separate correction applied for attrition.

Source: This survey checklist was compiled by the authors to assist commissioners in ensuring that their sampling design is complete and technically sufficient to meet their aims.

Annex B: Examples of Statistical Tests for Variable Combinations

This table is intended to be illustrative of the most common test for each scenario; for each test, however, there may be variations or exceptions. Examine all the options for the particular case under review before deciding on a test or tests. In order to match a significance test to the data being studied, it is critical to also understand the assumptions included within each inference test.

<table>
<tr><th>What kind of variable is your outcome?
(This is your dependent variable)</th><th>What kinds of variables are likely to affect your outcome? (This is your independent variable)</th><th>Example questions</th><th>Applicable statistical test</th></tr>
<tr><td colspan="4">In this table, you will find information on which statistical tests can be used, depending on the nature of your dependent (or outcome) variable, and which and how many independent variables you are considering. These tests generally test whether the relationship between two variables is significant or they model the probability of an outcome given a set of conditions.

The information is designed to help you determine whether the tests suggested by your survey team to inform sample size calculations are the appropriate ones for your needs. The list of suggested tests is not exhaustive; and in some cases, additional information (such as the distribution of a variable or whether it meets certain assumptions) will influence the choice of test.

For each type of dependent variable, we provide examples of tests of the relationship between that variable and a single independent variable, as well as what tests to consider when there are multiple independent variables. Please note that in most cases, multivariate tests will use regression; there are many specific types of regression modeling, depending on the types of variable as well as on the behavior of the data in a given study. This table does not attempt to provide guidance at that level. Please consult a statistician or established statistical resource for more information on the specific tests and when and how to apply them.</td></tr>
<tr><td rowspan="5">Nominal (Binary)

Nominal variables are those whose values are named but have no ordered meaning or numerical significance. Binary variables are nominal variables with only two possible values. This includes all variables with a yes/no outcome and those measuring the presence or absence of a condition.</td><td>Nominal (Binary)</td><td>Are women more likely than men to be unemployed?</td><td>Chi-square or Fisher's Exact</td></tr>
<tr><td>Nominal (Categorical)</td><td>Do people in rural, peri-urban, or urban areas have different rates of COPD?</td><td>Chi-square</td></tr>
<tr><td>Ordinal</td><td>Was grade level associated with the intention to attend college?</td><td>Chi-square trend test or Wilcoxon-Mann-Whitney or Wilcoxon Signed Rank</td></tr>
<tr><td>Ratio or interval</td><td>Did household income affect the likelihood of attending college?</td><td>Logistic regression (or probit)</td></tr>
<tr><td>Multiple independent variables</td><td>Did household income affect the likelihood of attending college, after controlling for college attendance in other family members?</td><td>Logistic regression (or probit)</td></tr>
</table>

What kind of variable is your outcome? (This is your *dependent* variable)	**What kinds of variables are likely to affect your outcome?** (This is your *independent* variable)	**Example questions**	**Applicable statistical test**
Nominal (Categorical) Categorical variables are nominal variables with multiple possible answer choices (so long as the answer choices are not ordered). Examples include: race or ethnicity, marital status, political party affiliation.	Nominal (Binary)	Is there a difference between women and men in whether they have no diabetes, Type 1 diabetes, or Type 2 diabetes?	Chi-square
	Nominal (Categorical)	Are there differences by race in political party registration?	Chi-square
	Ordinal	Was the level of educational attainment associated with the make of car purchased?	There is no good test for this combination of variables; consider transformation of the ordinal variable to a binary one
Nominal (Categorical) ***continued***	Ratio or interval	Did the average daily temperature during the week of the election have an effect on voting outcomes (multiparty)?	There is no good test for this combination of variables; consider transformation of the categorical variable, or use a Poisson test only after ensuring assumptions are met
	Multiple independent variables	Did the average daily temperature during the week of the election have an effect on voting outcomes (multiparty) after controlling for precipitation and age?	Multiple logistic regression
Ordinal Ordinal variables are those whose values are named and ordered but not inherently numeric. Examples include: Likert-scale data, socio-economic status, course grades, age (when divided into categories).	Nominal (Binary)	Did girls or boys have higher average grades?	Chi-square-trend test or Mann-Whitney test
	Nominal (Categorical)	Did people living in different administrative districts have different levels of satisfaction with government services?	Kruskal-Wallis
	Ordinal	Was the level of socioeconomic status associated with satisfaction with the performance of a local politician?	Spearman Rank-Order Correlation
	Ratio or interval	Was average body weight associated with satisfaction (on a four-point Likert scale) with care received during medical appointments?	There is no good test for this combination of variables; consider transformation of the ordinal variable or use ordered logistic regression only after ensuring assumptions are met

What kind of variable is your outcome? (This is your *dependent* variable)	**What kinds of variables are likely to affect your outcome?** (This is your *independent* variable)	**Example questions**	**Applicable statistical test**
	Multiple independent variables	Was average body weight associated with satisfaction (on a four-point Likert scale) with care received during medical appointments, after controlling for sex and age?	Ordered logistic regression if assumptions are met
Ratio or interval Ratio variables are continuous numerical variables in which zero has a unique, meaningful value, and no negative values are possible. Examples include height, weight, or cost.	Nominal (Binary)	Is the mean daily temperature higher across Michigan weather stations than it was on the same date 20 years ago?	Student's T-test
	Nominal (Categorical)	Are there significant differences by region of the United States in the amount of television watched?	ANOVA
Ratio or interval *continued* Interval variables are continuous numerical variables for which there is an equal interval between each pair of neighboring values and in which negative values are possible. Examples: Temperature measured in F or C; time measured against calendar years. *The same kinds of tests are generally used for ratio and interval variables; but ratio variables can be multiplied by one another to create composite variables, while interval variables cannot.*	Ordinal	Was satisfaction with government services (on a four-point Likert scale) associated with media consumption (in hours)?	Spearman Rank-Order Correlation
	Ratio or interval	Was household income in childhood associated with earnings 20 years later?	Pearson Correlation or linear regression
	Multiple independent variables	Was household income in childhood associated with earnings 20 years later, controlling for sex and year of birth?	ANCOVA or multiple logistic regression

Annex C: Sampling Approaches

This section provides an overview of the strengths and limitations of common types of probability and non-probability sampling.

Types of Sampling Approaches			
Sampling Type	**Prob. / Non-Prob.**	**Best used when…**	**Limitations**
Simple Random	Probability	…lists of unique identifiers (names, addresses, and phone numbers) are available from which to sample. This design has the lowest potential for sampling error.	Expensive and usually infeasible for population-based surveys (e.g., those that represent an entire geographic region).
Systematic Random Sampling	Probability	…the population is defined, exhaustive, and in list form (e.g., beneficiary list).	Not possible when population is undefined.
Stratified	Probability	…population characteristics (e.g., age range, school grade) are an important consideration in an analysis because it allows for representative sub-analysis between strata.	You need access to information about the stratification variable at the time of sampling in order to use this approach.
Cluster	Probability	…sampling of smaller-scale geographic units is desirable, for programmatic reasons (e.g., interventions were conducted at the community level) or logistical reasons (e.g., communities are far apart, remote, or difficult to get to, or the budget does not allow for enumerators to cover a large geographic area).	Increases potential for sampling error, and requires statistical corrections and a larger sampling size for the same survey power.
Multi-Stage	Probability	…along with cluster sampling, or any time dividing the population into progressively smaller units, is helpful (e.g., sampling a town, then a household, then a respondent within the household).	Increases potential for sampling error, and requires statistical corrections and a larger sample size for the same survey power.
Convenience	Non-Probability	…you are interested in interactions with a particular space, facility, or resource (e.g., experiences of health clinic visitors in the afternoon vs. morning hours).	Not appropriate for representative samples or generalizing to a population larger than those sampled.
Purposive	Non-Probability	…when you are interested in learning more about a specific group of people (e.g., members of the PTA, auto-mechanics, fruit vendors).	Not suitable for use when you need to generalize findings beyond the group being studied.
Snowball	Non-Probability	…you need to understand a specific network or group (e.g., when conducting social network analysis), particularly of hard-to-find people or people with a specific or rare interest (e.g., IV drug-users, revolutionary war reenactors).	The initial sample may introduce bias into the overall sample because you will be accessing an existing social network, in which traits may be shared. Not suitable for use when you need to generalize findings beyond the group being studied.

Annex D: Common Sample Size Parameters

Common Sample Size Parameters			
Parameters	Description	Symbolic Notation	Method of Selection
Power	The probability that, if there is an effect or relationship, in reality, you will be able to detect it with the design you have chosen. It is based on your sample size, effect size, and significance level. It is standard to use 80 or 90 percent.	β	Choose from among agreed standards
Effect Size	The strength of a relationship between two variables.	d	Data-driven estimation
Alpha	Alpha is the probability that you will find something significant even though it is not there. (Type I error or false positive.) Remember that the level you set for alpha determines the significance level and confidence level in your analysis	α	*Choose from among agreed standards*
Confidence Level	The probability that the value of a parameter falls within a specified range of values.	$1-\alpha$	Choose from among agreed standards
Margin of Error	The amount of random error you wish to allow in your results.	E	Agreed Standard
Design Effect	The ratio of the actual variance in a sample due to aspects of the design to an estimate of what the variance would have been in a simple random sample of the population.	D_{eff}	Data-driven estimation

Annex E: Timeframe

The length of time required to complete your survey will depend on a variety of factors, including the scope, sample size, purpose, the amount of development required for survey tools (i.e., are you using pre-validated tools or developing and validating new tools?), and the amount of stakeholder engagement and feedback required. It is reasonable to estimate at least a one-year total lifespan for studies with a representative survey component, for example. This timeline has been adapted from the Feed the Future Zone of Influence Survey Toolkit, Gantt Chart Timeline.

Illustrative Timeframe			
Phase	**Illustrative Tasks**	**Approximate Time**	**Notes**
Preparation	• Prepare study design and implementation plan • Prepare sample design • Survey instrument design • Complete translations • Submit for Internal Review Board (IRB) approval • Develop pretest and pilot protocols • Prepare data structure and codebook • Prepare data cleaning plan • Develop data monitoring plan	3-6 months	At the preparation stage, the IRB process should be made clear by the implementer. Often IRB approval can take time and, if not adequately planned for delay data collection.
Develop Training Materials, if needed	• Develop training schedules • Develop training content • Develop testing materials	1-2 months	Both the enumerators and enumerator supervisors will need to be trained in the survey content, purpose, and protocols. In some cases, training materials will only need to be adapted and not created.
Household Identification and Selection	• Acquire or compile a list of each household in the sampled clusters/EAs • Confirm population estimates • Prepare data weighting protocol	1 month	This step will depend on the desired approach to household selection. No matter the approach, households within each of the selected clusters will need to be identified and documented, and the cluster populations confirmed.

Illustrative Timeframe			
Phase	Illustrative Tasks	Approximate Time	Notes
Conduct Trainings	• Training of trainers • Train enumerators • Train supervisors, etc.	1 month or less	Time needs to be allocated to the actual trainings after the training materials are developed or appropriately adapted. Too much time between training and field work should be avoided because enumerators forget some of the information.
Conduct Data Collection	• Deploy enumerators to assigned clusters • Complete questionnaires with selected households	2-3 months	Depending on the design, households might be interviewed at the time of selection. If the design lists the households first and then randomizes the selection based on the list, interviewing might encompass separate steps as it is here.
Clean Data	• Review data for inconsistencies, enumerator errors, etc. • Compile data into preferred format for the data set	1-2 months	Implement the data cleaning plan developed in the preparation stage.
Analyze Data	• Run predetermined statistical tests • Review findings	2-4 months	Often survey managers can ask for key findings or key data tables to be submitted around this time before the report is complete and approved.
Write Report	• Draft report content • Coordinate with relevant stakeholders to review and edit draft • Finalize report	1-2 months	
	Total Timeframe	12 -18 months	

Annex F: Terms

Alpha	The probability of rejecting the null hypothesis when the null hypothesis is true or the probability of being incorrect.
Cluster	The sampling cluster, or simply cluster, is the smallest area unit selected for a survey.
Cluster Sample	A cluster sample is a special kind of multistage sample. In cluster sampling, you divide the population into clusters, select a subset of those clusters, and then select a sample from within each of the selected clusters.
Confidence Level	A measure of the validity of your results.
Convenience Sample	Non-probabilistic sampling where selection is based on convenience of contact.
Descriptive Statistics	Provides a concise summary of data, numerically or graphically.
Design Effect (DEF)	An additional error that is introduced by the sampling design.
Effect Size	An estimation of change to be detected.
Effective Sample Size	Equal to the actual sample size divided by the design effect.
Enumeration Areas	Small geographic units specifically designed for census data collection and often designed to be equal in size, making sampling from them much more straightforward.
Inferential Statistics	Use a random sample of data taken from a population to make inferences or test hypotheses about a population.
Intraclass Correlation Coefficient	A measure of the similarity among units in a cluster relative to the similarity among units across multiple clusters.
Limitation	Any significant weakness in the survey design by which the findings could be influenced.
Margin of Error	A measure of the precision of your results.
Multi-Stage Sample	Multi-stage sampling starts with the primary sampling unit (PSU) and divides the population into smaller and smaller configurations before sampling.
Non-probabilistic Sampling	Uses purposeful selection and judgement factors to choose sampling units.
Oversampling	A special type of stratified sampling in which disproportional numbers of sampling units are selected from specific strata.
Parameters	Values that need to be set so that a sample size calculation can be completed.

Terms Continued

Primary Sampling Unit	The unit selected in the first stage of sampling of a multi-stage sampling design.
Probabilistic Sampling	Every sampling unit (e.g., person or household or school) within the sample frame has some probability of being selected.
Purposive Sample	A non-probabilistic sampling method that chooses the sample based on specific characteristics.
Representative Sample	A sample that accurately reflects the characteristics of a study population and minimizes bias.
Sample Frame	A group of units from which a subset is drawn.
Sample Size	Sample size is the number of respondents needed to estimate the statistics of the population of interest with sufficient precision for the inferences you want to make.
Sampling Bias	Bias that results when the traits of the units within the sample frame are different from those in the population that you are trying to study.
Simple Random Sample	Simple random sampling is an approach where every unit in the sample frame has roughly the same probability of being selected.
Snowball Sample	A non-probabilistic sampling method whereby study subjects refer other study subjects to the researcher.
Statistical Error	The unknown difference between an estimated value from a sample and the "true" value based on the whole population.
Stratified Sample	Stratified sampling splits an entire population into homogeneous groups or strata before sampling. The sample is then selected randomly from each stratum.
Study Population	The group of people study questions are being asked about. More explicitly, the study population are the units that the sample is expected to represent.
Systematic Random Sample	In systematic random sampling, sampling units are selected according to a random starting point and a fixed, periodic interval. Selection begins with an ordered or randomized list, and every r-th sampling unit are selected.
True Value	A value that would result from ideal measurement.

Resources

During the creation of this guide, the authors used the following resources to validate the content and definitions presented. These resources might also be useful to you as they provide detailed information on sampling and statistics.

- The USAID Feed the Future ZOI Survey toolkit provides in depth technical guidance for survey implementers. The guidance is specific to the Feed the Future initiative but also a great reference for more advanced technical information - in particular, the Listing Manual, Sampling Guide, and the Gantt Chart Timeline.

- Health Knowledge page on Statistical Methods and University of Minnesota, CYFAR pages explain in detail the different types of statistical tests available based on variable types and usage.

- The Sample Size and Power Calculations chapter from Dr. Andrew Gelman at Columbia University and this article from the International Journal of Epidemiology describe the statistical concepts behind sample size calculations.

- This Minitab Blog entry offers a very clear breakdown on the meaning and interconnectivity between confidence level, confidence intervals, margin of error, and significance.

- *Survey Sampling* by Leslie Kish is a seminal text informing the practice of survey sampling; it provides additional explanations for several of the methods and rules of thumb explained here and is the source of the eponymous Kish grid used frequently for household surveys. (1965. John Wiley & Sons, Inc. New York).

- USAID's Technical Note on Impact Evaluation provides an overview of experimental and quasi-experimental designs for evaluations.

- The World Bank Group and the International Development Bank produced the Impact Evaluation in Practice handbook, now in its second edition. Readers who want to explore experimental and quasi-experimental designs in greater depth can refer to this resource, which also includes a chapter with guidance for practitioners on sampling approaches.