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SURVEY GUIDANCE DOCUMENT

Estimating Usual Intakes from Dietary Surveys: Methodologic Challenges, Analysis Approaches, and Recommendations for Low- and Middle-Income Countries

Janet A. Tooze

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Intake is a Center for Dietary Assessment that aims to strengthen policies and programs to improve nutritional status by increasing the availability, quality, comparability, and use of reliable dietary data and metrics in low- and middle-income countries (LMICs). We hope that the availability of valid, concise, effective diet-related metrics, along with *Intake* technical assistance for the planning, design, collection, analysis, and use of dietary data, can play an important role in helping actors in LMICs to develop evidence-based nutrition and agriculture policies and programs to ensure high-quality diets for all.

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Contact Information

Intake – Center for Dietary Assessment
FHI Solutions
1825 Connecticut Avenue NW
Washington, DC 20009-5721

Intake.org

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List of Abbreviations

EPA	Environmental Protection Agency
FFQ	food frequency questionnaire
HEI	Healthy Eating Index
ISU	Iowa State University
LMIC	low- and middle-income country
MSM	Multiple Source Method
NCI	National Cancer Institute
PSEM	portion size estimation method
SPADE	Statistical Program to Assess Dietary Exposure
U.S.	United States

1 Introduction

Collecting quantitative dietary data through a well-designed population-based survey has the potential to provide rich information about the food consumption patterns of that population. To ensure that the analysis of the data collected will be able to meet the defined objectives of the survey, a complex set of methodologic issues must be considered from the outset of the survey planning and design process. The purpose of this technical brief is to provide an overview of the various methodologic issues that are relevant to the collection and analysis of dietary data when a key objective of the survey includes estimating the usual intake of nutrients, food groups, and foods[1] for a population or sub-population, and to provide a set of recommendations for how to approach these data collection and analysis challenges in the context of a dietary survey in a low- or middle-income country.

The brief is organized in three main sections. The brief begins by describing the methodologic and statistical challenges inherent in estimating usual intakes from dietary surveys. This is followed by a description of the different statistical methods that can be used for estimating usual intakes. The brief concludes by translating this information into a set of general recommendations for dietary surveys in low- and middle-income countries (LMICs), where the context for collecting dietary data is likely to be more challenging and resource-constrained than in high-income countries.

[1] For simplicity in language, in this brief we use the term "foods" to refer to both foods and beverages.

2 Challenges in Estimating Usual Intakes from Dietary Surveys

Research has indicated that short-term instruments, such as 24-hour dietary recalls and 4- or 7-day food records, tend to provide less-biased estimates of dietary intake than tools that query usual intake directly, such as food frequency questionnaires (FFQs) (National Cancer Institute, 2015). Therefore, use of a short-term measure is the preferred method for estimating usual, or long-run average, dietary intake.

2.1 Episodically Consumed Foods

Statistical methods have been developed that allow for the estimation of usual intake for a population from these short-term measures; however, their short-term nature can provide some challenges to statistical modeling (Dodd et al., 2006). First, because dietary intake varies from day to day, many foods are consumed episodically,[2,3] as opposed to on a daily basis. Therefore, on any given day, consumption of a single food or even a food group might be missed on a short-term instrument. To overcome this limitation, we can utilize the fact that usual intake can be conceptualized as the probability of consuming the food on a given day, and the amount that is consumed when the food is consumed. For example, if 1 cup of cassava leaves is consumed every other day, the average consumption is 50% times 1 cup, or ½ cup per day. This information can be incorporated into a statistical model by fitting a model that models both the probability that a food is consumed on a given day and the amount consumed on that consumption day (i.e., the consumption-day amount). For most foods, although not all, the probability to consume a food is positively correlated with the amount that is consumed, i.e., those who are more likely to eat a food tend to eat greater amounts of that food. Therefore, some statistical models allow the probability of consumption and the consumption-day amount to be correlated.

2.2 Within-Person Variability

Another challenge that arises when estimating usual intakes from short-term measures is that there is a great degree of variability in intakes from day to day for a single person. Because we are interested in usual consumption, this day-to-day variability represents error around the usual intake, and, because our interest is in usual intake, this within-person variation is considered a nuisance. However, there is another type of variation that is of greater interest to us, namely, the variation between individuals in a population. Obtaining a good estimate of this variation is what allows us to describe the range of intakes in a population and to estimate the proportion of the population that consumes above or below a specific intake of interest. So, we would like to have a method that eliminates the within-person day-to-day variation but provides a good estimate of the person-to-person variation. Fortunately, with repeat short-term measures (e.g., two 24-hour dietary recalls), we are able to separate out how much of the total variation observed in a population is due to differences between individuals and how much is due to within-person day-to-day variation in intakes.

It is possible to obtain estimates of the two types of variation (within- and between-person) with just two 24-hour dietary recalls per person, and, as long as a random sample is obtained, it can also be done with just two 24-hour dietary recalls for a subset of individuals, provided there is a sufficient total sample size with repeat 24-hour dietary recalls. In general, it is beneficial to have at least 50 individuals with at least two 24-hour recalls per survey

[2] Episodically consumed foods are those that are not consumed every day but are consumed periodically, i.e., in "episodes." Practically, a food is considered episodically consumed if it is consumed on fewer than 90%–95% of all days for which dietary data are collected for the sample (or of all days for which dietary data are collected for the sub-sample of interest for analysis). The exact percentage depends on the sample size, i.e., there needs to be a sufficient sample to compare "consumption vs. non-consumption," often using a logistic regression model.

[3] For simplicity in language, in this brief, when we refer to "episodically consumed foods" or "foods consumed episodically," we are also referring to food groups and nutrients that may be episodically consumed.

domain (U.S. Environmental Protection Agency [EPA], 2016; Kirkpatrick et al., 2017). For foods, food groups, and nutrients that are consumed almost every day, ensuring that there are at least 50 individuals per survey domain with at least two 24-hour recalls should be sufficient for applying methods to correct for measurement error. However, for an episodically consumed food, a sufficient number of individuals need to consume the food on at least two days (sometimes referred to as "double hits") in order to have enough people to obtain good estimates of within- and between-person variation. The general rule of thumb of about 50 individuals (or more) with "double hits" applies, but the number of people needed to obtain this approximate number of "double hits" is dependent on the probability of consuming the food on a given day, the number of replicate measures obtained on each person (i.e., the number of repeat 24-hour recalls collected for each person), and the total sample size on which replicates are collected (refer to Box 1) (U.S. EPA, 2016). To obtain a sufficient number of "double hits," it may be more beneficial to obtain more replicates per person than to increase the sample size from which two replicates are obtained. This is because having more than two replicates per individual increases the probability of having at least two recalls per individual on "consumption days" (i.e., days on which the food, food group, or nutrient of interest is reported as "consumed"). Having multiple replicates per person can also be advantageous when fitting some models, such as a model to incorporate never-consumers (Carroll et al., 2012; Kipnis et al., 2009).

When obtaining replicate 24-hour recalls, if they are not collected for the full sample, they should be taken from a random sub-sample of individuals; if certain survey groups are of interest, such as geographic strata, random samples should be taken from within these survey groups. The replicate 24-hour recalls should be collected on non-consecutive days, with the second recall obtained 3–10 days after the first, and with each subsequent recall collected 3–10 days after the previous recall. Some surveys also try to obtain one recall on a weekday and a second on a weekend; although both weekdays and weekends are needed in the sample, it is not strictly necessary to obtain both for each individual.

Importantly, if we do not adjust for the within-person variation in intake, then, although the mean is estimated accurately in the absence of systematic bias, the estimate of variability in the population is inflated by including both within-person and between-person variation. The impact of this is to obtain an estimated distribution that is too wide in the tails, which leads to overestimates of either inadequate or excess intake of nutrients, food groups, and foods in a population. Therefore, it is crucial to separate between-person variation from within-person variation to obtain valid estimates of the distribution of usual intake for a population. The degree of overestimation of specific quantiles of interest (e.g., the 95th percentile) or the percentage above or below a cutoff is dependent on the variability of day-to-day intake of nutrients, food groups, and foods; estimates of nutrients, food groups, and foods with a small degree of day-to-day within-person variation are not affected as much as estimates of nutrients, food groups, and foods with a large degree of day-to-day within-person variation.

2.3 Skewness

Another challenge that arises in estimating usual dietary intakes is that the consumption-day data tend to be skewed to the right, meaning that some individuals have very high intakes of certain foods, food groups, and nutrients. To obtain estimates of usual intake for a population, the normal distribution is appealing, because it is fully described by the mean and the variance. However, when the data are skewed, they cannot be assumed to follow a normal distribution. One solution to this problem is to apply a transformation to the data so that they are approximately normal. Although the data are sometimes so skewed that a log transformation is needed, often a less extreme transformation is required. The Box-Cox transformation method is an appealing way to transform the data, as it reduces right skewness and is at its most extreme equivalent to the log transformation. Often there is interest in obtaining the same mean from the transformed data that one would obtain taking the mean on the original scale. To obtain this mean, a back-transformation is needed that incorporates an additional adjustment to the simple inverse of the original transformation, such as a 9-point approximation (Tooze et al., 2010) or a Taylor series method (Dodd et al., 2006; Tooze et al., 2010).

Box 1. Formula to Estimate the Probability of Obtaining at Least Two Recalls on Consumption Days

This binomial formula can be used to estimate the probability of at least two recalls with consumption:

$$\Pr(c \geq 2) = \sum_{c=2}^{n} \binom{n}{c} p^c (1-p)^{n-c}$$

where n is the number of recalls per person, c is the number of recalls per person with consumption, and p is the probability of consumption on any recall. To estimate the number of recalls necessary to obtain 50 individuals with at least two recalls on consumption days (i.e., "double hits"), the sample size of 50 needs to be divided by the estimated probability above. For a complex survey, this sample size should then be multiplied by the design effect. For all surveys, the final sample size calculation should also account for non-response.

With two recalls per person and a probability of consumption on any one recall of 40%, the probability of consumption from the formula above is 0.16, and a random sub-sample of 50 ÷ 0.16 = 313 with two recalls would be needed. If each person completed three recalls, the probability from the formula above is 0.3136, and a random sub-sample of 50 ÷ 0.3136 = 159 with three recalls would be needed. If each person completed four recalls, the probability from the formula above is 0.5248, and a random sub-sample of 50 ÷ 0.5248 = 95 with four recalls would be needed. These sub-sample sizes are before adjusting for any design effect and non-response factor. For a complex survey design with an expected design effect of 2 and an expected non-response rate of 20%, these sub-sample sizes would increase to 783, 398, and 238, respectively.

For additional detail on how to use the binomial formula, refer to Appendix 1.

U.S. EPA (2016); Kirkpatrick et al. (2017).

2.4 Sequence, Day, and Seasonal Effects

Another characteristic of dietary intake data is that individuals may report higher intakes on the first administration of a tool than they do on subsequent administrations; this is usually called a sequence effect. There may also be interest in adjusting for weekend vs. weekday consumption on a 24-hour recall so that intake estimates are representative across the 7 days of the week, even if they are not collected proportionately across weekend and weekdays, as typically recommended. Similarly, one may have interest in adjustment for seasonal effects. If a method that is based on a statistical model is used to analyze the data, then these data characteristics (i.e., sequence effects, weekend/weekday effects, and seasonality) may be incorporated as covariates in the statistical model.

By incorporating a covariate into the model, the impact of the effect on intake may be estimated (e.g., higher intakes on weekends), and can then be balanced appropriately across the effect of interest (e.g., multiplying weekdays by 4/7ths and weekends by 3/7ths to obtain estimates that are proportionally representative across all days of the week, including Friday as a weekend day). Furthermore, there is often interest in estimating usual intakes for a sub-population, such as groups defined by age, ethnic groups, or geographic location. It is also possible to use covariates in the statistical model that represent the sub-groups to obtain estimates for each group. This can be a more efficient approach than fitting separate models for sub-groups when it is appropriate to assume common variance parameters across sub-groups, which is often the case and can be tested using standard goodness of fit procedures (Tooze et al., 2010).

3 Analysis Approaches for Estimating Usual Intakes from Dietary Surveys

This section provides an overview of various statistical methods that have been developed to estimate the mean or the distribution of usual intake of foods, food groups, and nutrients. Many of these methods can be applied to dietary components that are consumed nearly every day, as well as to episodically consumed foods. The section consists of four parts:

- A description of a relatively simple analysis method (i.e., "the mean method") that can be used to estimate mean usual intake (but not the distribution of usual intake)
- An overview of general analysis methods for estimating the distribution of usual intakes (i.e., percentiles, but also including the mean usual intake)
- A description of analysis methods for estimating the distribution of usual intakes of episodically consumed foods, food groups, and nutrients, which pose the specific challenges discussed previously
- An overview of possible extensions of the methods described for episodically consumed foods, food groups, and nutrients to address specific data analysis objectives.

3.1 Method to Estimate Mean Usual Intake: The "Mean Method"

The simplest approach to estimate usual intake for a population is to use descriptive statistics (e.g., means and percentiles) from one or more short-term instruments (Dodd et al., 2006), i.e., either calculating these descriptive statistics on 1 day of data for all respondents or calculating them on the within-person mean of multiple days if all respondents have multiple days of data.[4] This method is often referred to as the "mean method." If the interest is in describing only the mean of the population, the mean method is sufficient. However, as described above, because the estimated variance includes both within-person and between-person variation, the standard error of the mean will always be too wide for estimating usual intakes for foods, food groups, and nutrients, consumed daily or episodically. This will result in a biased estimate of the confidence interval.

In addition, for many foods, food groups, and even nutrients, the mean method will produce biased estimates of the distribution of usual intake and of inadequacy or excess, unless a large number of replicate measures (i.e., repeat 24-hour recalls) per person are collected (some authors have estimated that 31–433 days are needed to estimate usual intake for one individual [generally for use in a clinical dietetic setting] and 3–41 repeat recalls per person are needed for estimating distributions of intake for populations [Basiotis et al., 1987] using the mean method). These estimates are for a food, food group, or nutrient, with very little day-to-day within-person variation in intake. For a food, food group, or nutrient with more variation in day-to-day within-person intake, even more repeat recalls per person would be needed. It is not usually feasible to collect the number of replicate measures needed for averaging to estimate the distribution of usual intake using the mean method.

The mean method also does not generally adjust for data characteristics, such as skewness or sequence effects, or incorporate covariates, and therefore cannot rely on normality assumptions, adjust for nuisance effects, or efficiently estimate distributions for sub-populations. Therefore, the method is not recommended unless the interest is only in estimating the mean of the distribution (without reporting a corresponding confidence interval for

[4] It is also possible to use the mean method when only a sub-sample of respondents have repeat 24-hour recall measures. In this case, the within-person mean of multiple days is estimated for the sub-sample of respondents with repeat 24-hour recall measures. This within-person mean is then used along with the 1-day 24-hour recall data for the other respondents to estimate the mean intake for the sample.

the estimate of the mean). The mean method is never recommended for reporting the distribution (i.e., percentiles) of intake.

Although it is common to think of “inadequacy” or “excess” in terms of nutrient intake, such as when comparing to a dietary reference intake value, estimates of distributions of foods and food groups will also be overestimated when using the mean method; for foods and food groups, “excess” and “inadequacy” would generally correspond to servings per day. For example, using this method, the proportion of the population consuming more than 400 grams per day of fruits and vegetables would typically be overestimated, and those consuming less than 2 teaspoons of added sugars would be underestimated.

3.2 Methods for Estimating the Distribution of Usual Intake

Multiple statistical methods have been developed to overcome the problem of having a limited number of repeat measures on a person, as well as the additional challenges discussed above for foods, food groups, and nutrients. These methods, which we term “usual intake methods” follow three basic steps (Dodd et al., 2006). Step 1 applies any data adjustments, which includes transformations to approximate normality or adjustment for sequence, day of week, and/or seasonal effects. Step 2 entails estimating the mean intake on a transformed scale and partitioning the variance into within-person and between-person components. Some methods combine Steps 1 and 2 into a single step. For episodically consumed foods, food groups, and nutrients, Steps 1 and 2 are applied to the consumption-day data for those individuals with two or more consumption days. Step 3 is used to estimate the percentiles of the usual intake distribution from the values generated in Step 2. Because we remove the within-person variation from this estimation, this is sometimes referred to as “shrinking” the distribution. This step includes back-transforming the data to the original scale. If an adjustment factor is used in this step, it will result in a population mean similar to that obtained using the mean method, but with a narrower distribution of usual intake. For episodically consumed foods, food groups, and nutrients, Step 3 also entails an estimate of the probability of consumption. Even though only a subset of respondents will have two or more consumption days, all days of 24-hour dietary recall are used in the statistical modeling process to obtain estimates for the whole sample.

The general approach described in the paragraph above is used to estimate the distribution of usual intake for all foods, food groups, and nutrients. Because it is common for many foods and some food groups to be episodically consumed and because most, but not all, nutrients are consumed each day by most members of a population, some methods were developed specifically for episodically consumed dietary constituents, usually referred to as “foods” methods. All of these methods separate out the probability of consumption from the consumption-day amount.

Some of these methods are model-based approaches, meaning that percentiles of usual intake are based on tabulations of the standard normal distribution, while others are considered model-assisted approaches, in which each individual’s mean intake is rescaled using the estimated variance components and then the distribution of these predicted means (for “pseudo-people” based on individuals in the sample and the model parameters) is used to develop the percentiles of usual intake (Dodd et al., 2006). This is done for all individuals in the sample, using the variance components derived from those with repeat recalls.

3.3 Methods Developed for Analyzing the Distribution of Usual Intake of Episodically Consumed Foods

3.3.1 Iowa State University Foods Method

The first approach developed to estimate the usual intake of episodically consumed foods was the Iowa State University (ISU) foods method (Nusser et al., 1995; Nusser et al., 1996; Dodd et al., 2006). Like the other foods methods, the ISU foods method separates the probability of consumption from the consumption-day amount. The probability of consumption is based on the number of 24-hour recalls with consumption. Next, it applies a two-stage transformation to obtain a distribution of transformed intakes from 24-hour recalls that are almost perfectly normally distributed. (A simplified transformation approach, called the Best-Power method is also available for the

ISU foods method.) The ISU foods method also has the capability of accounting for seasonality, day of week, and/or sequence effects. Provided repeat 24-hour recall data are available for at least a random sub-sample of respondents, the probability of consumption and consumption-day amount are then combined to estimate individual usual intake for all individuals in the sample (including those respondents with only 1 day of 24-hour recall data). This process assumes that the probability of consumption and consumption-day amount are uncorrelated, which is often not the case. When this assumption is violated, it can lead to bias in overestimating the amount consumed by those with a low probability of consumption and underestimating the amount consumed by those with a high probability of consumption, which leads to biased estimates of usual intakes of episodically consumed foods. The current approach of the ISU method uses a model-based approach. Special software (SIDE) has been developed to fit the ISU method (http://www.side.stat.iastate.edu/pc-side.php).

3.3.2 National Cancer Institute Method

The National Cancer Institute (NCI) method uses a Box-Cox transformation to transform consumption-day amount data to approximate normality, and then uses a statistical model to estimate the mean usual intake on the transformed scale, with adjustment for sequence, day of week, and/or seasonal effects through the use of a statistical model with covariates (Tooze et al., 2006; Tooze et al., 2010). The transformation may be performed prior to statistical modeling or incorporated into the modeling procedure. Although the latter has the advantage of selecting the transformation with covariate adjustment, practically there is little difference whether the transformation is estimated as part of the model or prior to modeling. The advantage of the NCI method over the ISU foods method is that the NCI method simultaneously models the probability of consumption and the consumption-day amount, allowing the two parts of the model to be correlated. It is also possible to incorporate covariates identifying sub-groups into the modeling procedure to produce estimates for sub-populations.

The NCI method is a hybrid of a model-based and model-assisted approach. To estimate usual intake, the between-person variance components are assumed to have a bivariate normal distribution for the two-part model, but the distribution is estimated using a Monte Carlo procedure in which draws from the distribution are added to individual mean predicted values for "pseudo-people" to represent the distribution of interest. Provided repeat 24-hour recall data are available for at least a random sub-sample of respondents, the model may be used to predict usual intake for all respondents in the sample (including those respondents with only 1 day of 24-hour recall data). SAS macros have been developed to fit the NCI method (https://epi.grants.cancer.gov/diet/usualintakes/macros.html).

3.3.3 Multiple Source Method

Like the NCI method, the Multiple Source Method (MSM) from the European Food Consumption Validation Project (Haubrock et al., 2011) uses the Box-Cox transformation and allows for the incorporation of covariates. However, as opposed to the NCI method, the MSM is based on a shrinkage technique applied to residuals of two regression models, one for the probability of consumption and one for the consumption-day amount. The MSM allows for correlation between the probability of consumption and the amount consumed. It uses a model-assisted approach to estimate distributions. Like the ISU foods and the NCI method, provided that at least a random sub-sample of respondents have data for multiple 24-hour recalls, usual intake can be predicted with the MSM for all respondents in the sample (including those respondents with only 1 day of 24-hour recall data). A program has been developed for the MSM (https://msm.dife.de/). However, the website expresses caution when using the program with models containing covariates.

3.3.4 Statistical Program to Assess Dietary Exposure Method

The Statistical Program to Assess Dietary Exposure (SPADE) was developed for the Dutch National Food Consumption Survey 2007–10. It also uses a Box-Cox transformation and uses a model-based approach to estimate distributions (Dekkers et al., 2014). The SPADE method does not take into account correlation between probability of consumption and consumption-day amount, and currently requires 24-hour recalls on at least two days for all respondents in the sample. Software is available in R (http://rivm.nl/en/Topics/S/SPADE/Access_to_SPADE).

3.3.5 Comparison of Methods for Analysis of Episodically Consumed Foods

Although all methods developed for estimating the distribution of usual intake of episodically consumed foods, food groups, and nutrients partition within-person from between-person variation to provide percentiles that are adjusted for within-person variation in food, food group, and nutrient intake, the ISU foods method and the SPADE method do not allow for correlation between the probability of consumption and the consumption-day amount, and therefore are not recommended for general use with episodically consumed foods, food groups, or nutrients. The NCI method and the MSM have been shown to perform similarly for estimating the distribution of usual intake in a population (Goedhard et al., 2012; Laureano et al., 2016; Souverein et al., 2011). For foods, food groups, and nutrients that are not episodically consumed, or for which the probability of consumption and the consumption-day amount are not correlated, the ISU foods method and the SPADE method will also perform similarly to the other methods to estimate distributions of usual intake in a population. The NCI method, the MSM, and the ISU foods method all allow for a random sub-sample to have repeat 24-hour dietary recalls in order to predict usual intake for the full sample of respondents; the SPADE method, in contrast, currently requires all individuals in the sample to have at least two 24-hour dietary recalls.

3.4 Extensions to Methods for Analysis of Episodically Consumed Foods

3.4.1 Extensions to "Never-Consumers"

The models for episodically consumed foods described above fit a two-part model, where one part models the probability of consumption and the second part models the amount consumed on a consumption day. When predictions are made from the first part of the model, everyone is given a non-zero probability of consumption, even though it may be very small, essentially implying that everyone will eventually consume the food. For certain broad food groups, like fruit, this is probably a reasonable assumption. Even though, for example, more than 10% of the population may not consume fruit on a given day, it is reasonable to assume that most people consume some type of fruit over the time period for which we would like to characterize usual intake, e.g., 1 or 2 years. For other food groups, like alcohol or nuts, in which there are groups of people who never consume the food or beverage, this assumption is less tenable. Therefore, in addition to daily consumers and episodic consumers, there can be "never-consumers" in a population. Some researchers have proposed an extension of the NCI method to a three-part model (Kipnis et al., 2009). This model adds the probability of being a never-consumer to the model using a logistic regression model with a predictor of being a never-consumer, such as reporting "never" on a FFQ (with a long reference period, e.g., the past year). Kipnis et al. (2009) fit the three-part model in simulated 24-hour recall datasets with 2, 4, or 6 days of recall per person. With only two 24-hour recalls, only 74% of the three-part models could be fit; however, with 4 or 6 days of recall per individual in the sample, the model was stable; Keogh and White (2011) also had some difficulties with model fitting with only 2 days of recall per individual in the sample.

Although the two-part model assigns some probability of consumption, and therefore at least a small amount of usual intake to all individuals in the sample, it is not expected to have a large impact on the mean intake estimated for the population for food, food groups, and nutrients. However, some slight overestimation in the mean would occur if there were a high proportion of never-consumers in the sample (as they would be assumed to consume a small amount of the food, food group, or nutrient). In an analysis comparing the estimation of alcohol intake by the NCI method to alcohol intake as estimated by an alcohol intake questionnaire that identified 58.7% of respondents as alcohol consumers, the mean intakes estimated were very similar, and both estimates showed predictive relationships with liver enzymes. However, the distributions varied, with the NCI method estimating a higher 10th and 25th percentile than the estimates provided by the alcohol intake questionnaire (Agarwal et al., 2015). In simulation studies with 50% never-consumers, Goedhart et al. (2012) determined that including never-consumers in modeling did not affect the upper percentiles of the distribution, indicating that the NCI method is sufficient to estimate the upper percentiles of the distribution compared to a three-part model. Keogh and White (2011) compared the never-consumers model to a two-part model for modeling diet-health relationships and found that the estimated parameters associating diet to health were almost identical when all individuals had at least two 24-hour dietary recalls, but that the never-consumers model was slightly better when only a subset of the sample had at least two 24-hour dietary recalls; there was attenuation of the estimated odds ratio, but differences were small. This finding suggests that with a two-part model it is possible to estimate diet-health relationships without a large degree of bias, even when the diet component of the analysis includes foods, food groups, or nutrients with a high proportion of never-consumers.

3.4.2 Extensions to Multivariate Modeling

Although some two-part models for episodically consumed foods accommodate the correlation that often exists between the probability of consumption and the consumption-day amount, none of the models described above allow for correlation among different foods, food groups, or nutrients. To evaluate dietary patterns that encompass multiple food groups and nutrients, Zhang et al. (2011) proposed an extension of the NCI method that simultaneously models all food groups and nutrients of interest, allowing for correlation among intakes of all dietary components. Due to the complexity of this multi-part model (i.e., modeling the Healthy Eating Index-2015 [HEI-2015]), which requires simultaneous examination of 21 latent variables (2 each for the 6 episodically consumed constituents, 1 each for the 8 daily consumed dietary constituents, plus energy), a different statistical method is needed to fit the multi-part models. Specifically, a method called Markov Chain Monte Carlo is used. This method works by simulating many realizations of the constituents to estimate the distributions ("Monte Carlo"), while using an algorithm to ensure the correct distribution is estimated ("Markov Chain"). Like most of the other usual intake methods, this method requires at least two 24-hour recalls for at least a random sub-sample of respondents. Software for fitting this model for the HEI-2015 using a SAS macro is available online (https://epi.grants.cancer.gov/hei/sas-code.html). While this model has been specifically developed for estimating dietary indices such as the HEI, it can also be adapted to be used when there is general interest in joint modeling of multiple dietary components, which can be a mix of episodically and non-episodically consumed foods, food groups, and nutrients.

3.4.3 Supplementing the 24-Hour Recall Data with Data from a Food Frequency Questionnaire

Some researchers have proposed including information from a FFQ as a covariate in both parts of the statistical model when using the two-part model approaches; most commonly, information on frequency of consumption is incorporated, but when portion size information is available, estimated usual intakes from a FFQ could also be used as a covariate. When estimating distributions of usual intake of foods, food groups, or nutrients, including FFQ information does not appear to have a large impact on estimated values (Tooze et al., 2010; Goedhart et al., 2012). Therefore, it is expected that use of 24-hour recalls alone should be sufficient to estimate usual intakes for estimating distributions of food, food group, and nutrient intake to assess a population's intake or inform food fortification policies. However, when estimating diet-health relationships, utilizing a FFQ as a covariate can be beneficial if a food, food group, or nutrient is highly episodically consumed. This can help improve the precision with which an individual's intake can be predicted (Kipnis et al., 2009; Carroll et al., 2012). When a FFQ is used with 24-hour recalls, FFQ information is used to supplement the recalls, rather than to replace the estimates of usual intakes from the 24-hour recalls with the estimates from the FFQ. Most commonly, the FFQ data are included as a covariate in a statistical model and, therefore, while beneficial to improve precision, are not required to obtain an unbiased estimate of the diet-health relationship. Implementation of a FFQ necessitates validation in the population of interest prior to utilizing it in a dietary survey.

4 Recommendations for Dietary Surveys in Low- and Middle-Income Countries

Dietary surveys that are carried out in LMIC settings may have specific challenges to implementation that need to be considered in the planning and design of the survey. For example, countries that are collecting data for a dietary survey for the first time may need to devote considerable time and resources to develop the necessary dietary databases (e.g., food, recipe and ingredient listing, food composition database for the survey, standard recipe database, portion size estimation method (PSEM) measurement list, and PSEM conversion factor database) to support the survey data collection and analysis effort. The resources required for these dietary pre-survey activities need to be accounted for in the planning of the overall timeline and budget for the survey. The different methods discussed in this paper for addressing the general challenges associated with using short-term instruments to capture usual intake, and the specific challenges associated with estimating usual intake for episodically consumed foods, food groups, and nutrients, also have important resource implications. Therefore, when designing a dietary survey for use in a low- or middle-income country, the advantages and drawbacks of each method must be weighed carefully against the specific objectives of the survey, the timeline and resources available for carrying out the survey work, and the amount of pre-survey work required to develop the requisite dietary databases for the survey. To help survey designers in LMICs weigh these considerations, this technical brief concludes by providing a summary of general recommendations for addressing the challenges associated with estimating usual dietary intake.

When the objective of a dietary survey is to estimate usual dietary intake, the interactive, multiple-pass 24-hour recall method (Gibson and Ferguson, 2008), with repeat recalls collected on a random subset of the sample, is the most appropriate method to use to collect the dietary data. When resources allow, a minimum sample size of 200 respondents per survey domain is recommended. Assuming a moderately skewed distribution, this sample size recommendation allows for estimating a true percentage of 50% with a precision of approximately 9 percentage points and allows for estimating quantiles with a relative margin of error of approximately 5% if the percentile is near the middle of the distribution and with a relative margin of error of approximately 8%–12% if the percentile is in the tail of the distribution (for example, the 10th or 90th percentile) (Carriquiry 2020). This recommended minimum sample size of 200 respondents per survey domain is for a simple random sample design unadjusted for non-response. Typically, this sample size would need to be inflated to account for a design effect and expected non-response. For example, in the case where a design effect of 2 and a non-response factor of 20% is assumed, this simple random sample of 200 would be adjusted upward to a sample size of 500 respondents per survey domain.

To be able to account for the within-person variation in the dietary data and to allow for statistical models to be applied that remove this excess variability from the usual intake estimates, a second day of 24-hour recall should be collected for a random sub-sample of a minimum sample size of 50 respondents per survey domain before adjusting for a design effect and non-response factor. When there are episodically consumed foods, food groups, or nutrients of interest, these minimum numbers should be increased. In this case, the binomial formula in Box 1 should be used to calculate the appropriate sub-sample size on which to collect a repeat day of recall and how many days of recall should be collected, according to the expected probability of consumption associated with the respective nutrients, food groups, and foods of interest. As described in Box 1, the number calculated from this formula would then need to be adjusted upward to account for the anticipated design effect and expected non-response rate for the survey.

Based on the studies discussed in this brief, the use of a FFQ as a supplement to a quantitative 24-hour recall dietary survey instrument appears to have the most added value when it is of interest to estimate diet-health relationships. But even when the estimation of diet-health relationships is among the key stated objectives of a survey, the decision to use a FFQ should be carefully considered in the context of a LMIC. The development of a FFQ should ideally be informed by dietary data collected in the context where the survey will be implemented. In many LMICs, there may not have been earlier dietary surveys carried out, which means there is a lack of information on which to base the design of the FFQ. And even in survey contexts where dietary data do exist on which to base the design and development of a FFQ, it is essential to recognize that the design and validation of a FFQ requires considerable time and resources. In the context of dietary surveys carried out in LMICs, there may be advantages to increasing the sample size for which repeat recalls are collected and/or to increasing the number of repeat recalls collected per respondent, instead of developing, validating, and collecting dietary data using a FFQ in addition to the interactive, multiple-pass 24-hour recall method.

To analyze dietary data to obtain estimates of usual intake, a method that removes the within-person variation from the data and allows for correlation between the probability of consumption and the consumption-day amount should be used. Otherwise, the intake estimates for nutrients, foods, and food groups that are episodically consumed will be biased. If repeat recalls are not collected for all respondents, but only for a random subset of respondents, then a method of analysis tailored to address this type of design will need to be used. As discussed earlier, the NCI method and the MSM both meet these criteria; however, if covariates will be included in the model, then the NCI method should be used for analysis.

Extending the model to account for never-consumers is not necessary in most contexts, and would require supplementing the 24-hour recall data with a FFQ that uses a longer reference period (e.g., 1 year) to identify the never-consumers. In addition, based on the studies carried out to explore the fitting of a three-part model, at least 2 days of recall would be recommended to be collected on all respondents, and ideally more days of recall on all respondents should be collected to increase the likelihood of achieving the “fit” of a three-part model. The additional resources required to supplement data collection in this way are likely both infeasible and impractical for large-scale dietary surveys in LMICs. Therefore, when weighing the competing priorities for resource allocation for the design and implementation of a dietary survey, the data requirements to use a three-part model for analysis should probably not be a priority for most dietary surveys carried out in LMICs.

Extensions to multivariate modeling could be considered for a dietary survey carried out in a low- or middle-income country, if it is of interest to model adherence to a defined dietary pattern. But unless analyzing adherence to the dietary pattern reflected by the U.S. HEI is of interest, some work would be required to adapt the existing multivariate modeling code for the desired analysis. A multi-part model, such as that proposed by Zhang et al. (2011) to analyze adherence to the U.S. HEI is computationally more time consuming and more difficult to assess model fit than the two-part foods methods described earlier. It is also possible that such a multi-part model would have higher demands than the NCI method or the MSM in terms of sample size for the model to be able to be fit efficiently. If assessing adherence to a dietary pattern, while allowing for simultaneous correlation between multiple dietary components, is a research question of interest to a survey to be carried out in a LMIC, then it may be possible to apply this method in supplementary analyses of the data (i.e., as post-hoc analyses), but due to the sophistication and computational complexity of the model, it may not be advisable to design a first dietary survey in a LMIC for the specific purpose of applying such a model to the data collected.

In summary, in LMICs, when methodological choices have to be made for carrying out a dietary survey, it is recommended to: i) prioritize the sample size and the number of repeat 24-hour recalls collected to provide the most robust estimates of the distribution of usual intakes and; ii) analyze the data collected with a model that allows for correlation between the probability of consumption and the consumption-day amount. Additional tools or analytic methods, such as the development and use of a FFQ or extensions to modeling, may be relevant to consider, depending on the specific objectives of the survey; but when the survey is the first dietary survey to be carried out in a particular country or context, the resources required for developing, adapting, and/or applying such tools are likely to be overly burdensome given the extent of work and resources required for carrying out a first dietary survey in any given context.

Appendix 1. Detailed Example of the Use of the Binomial Formula Provided in Box 1

As described in Box 1, the binomial formula below can be used to estimate the probability of at least two recalls with consumption, where *n* is the number of recalls per person, *c* is the number of recalls per person with consumption, and *p* is the probability of consumption on any recall.

$$\Pr(c \geq 2) = \sum_{c=2}^{n} \binom{n}{c} p^c (1-p)^{n-c}$$

Here, we show how the formula works in practice by carrying out the calculations reported in Box 1 in a step-wise manner.

Assume the probability of consuming the dietary component on any one recall is 40% and 50 "double hits" are desired:

- If each person completes two recalls,

  $\Pr(h = 2) = \binom{2}{2} 0.40^2 0.60^0 = (1)(0.16)(1) = 0.16$, and the sample size needed is $\frac{50}{0.16} = 313.$

- If each person completes three recalls,

$$\begin{aligned}\Pr(h \geq 2) &= \binom{3}{2} 0.40^2 0.60^1 + \binom{3}{3} 0.40^3 0.60^1 \\ &= \frac{3!}{2!\,1!}(0.16)(0.60) + \frac{3!}{3!\,0!}(0.0256)(1) \\ &= 0.2880 + 0.0256 \\ &= 0.3136, \text{ and the sample size needed is } \frac{50}{0.3136} = 159.\end{aligned}$$

- If each person completes four recalls,

$$\begin{aligned}\Pr(h \geq 2) &= \binom{4}{2} 0.40^2 0.60^2 + \binom{4}{3} 0.40^3 0.60^1 + \binom{4}{4} 0.40^4 0.60^0 \\ &= \frac{4!}{2!\,2!}(0.16)(0.36) + \frac{4!}{3!\,1!}(0.064)(0.60) + \frac{4!}{4!\,0!}(0.0256)(1) \\ &= 0.3456 + 0.1536 + 0.0256 \\ &= 0.5248, \text{ and the sample size needed is } \frac{50}{0.5248} = 95.\end{aligned}$$

As mentioned in Box 1, these sub-sample sizes are before adjusting for any design effect and non-response factor. For a complex survey design with an expected design effect of 2 and an expected non-response rate of 20%, these sub-sample sizes would increase to 783, 398, and 238, respectively.

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