



Statistical and Operational Challenges for Implementing Adaptive Survey Design

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Overview

- Adaptive Survey Design (ASD) – What and Why
- Survey Examples
 - Achievements
 - Challenges
- Discussions

Adaptive Survey Design

Definition

- Adaptive survey design tailors data collection strategies
 - By giving different treatments to data collection units
 - Treatments are usually defined before the survey starts, but may also be updated via data that are observed during data collection.
 - Allocation of treatments is based on paradata and data that are linked to the survey sample and other data sources

Schouten, B., Calinescu, M., & Luiten, A. (2013). Optimizing quality of response through adaptive survey designs. *Survey Methodology*, 39(1), 29-58.

Overarching Goals

- Collect 'high quality' data on a budget and in a timely manner (optimization with constraints)
 - With high response rate
 - With less than ideal response rates
- Quality measures should be broader than
 - Response rates
 - Nonresponse bias

ASD Adoption

To Overcome Challenges of Low Response Rates and Costly Data Collection

- Widely adopted by U.S. government-sponsored surveys, such as:
 - Survey of Doctorate Recipients
 - National Science Foundation
 - Medicare Current Beneficiary Survey
 - Centers for Medicare and Medicaid Services
 - National Immunization Survey
 - Centers for Disease Control and Prevention
 - National Survey of Early Child Care and Education
 - Administration for Children and Families
 - General Social Survey
 - National Science Foundation

Monitoring Measures in Selected Surveys

- R-indicators
- Response rates and target number of completes for key domains
- Tracking key survey estimates

R-Indicators

Vary, usually focus on survey specific challenging areas

- Focus on representativeness
 - Collect survey data representative for key frame variables (ideally closely related to key survey estimates)
- Identify weak spots of sample representativeness
 - Conduct a quantitative assessment to identify which segments of the sample are over/under producing and causing the achieved sample to be imbalanced in terms of sample representativeness
- Track overall R-Indicators and partial R-indicators based on key demographics and other sampling stratum variables

Data Collection Interventions: Agile response

- To attain target numbers of completes in key analytic domains
- To correct sample imbalances across key domains
- Interventions
 - Redirecting interviewer priorities
 - Stopping work on particular subgroups
 - Inserting additional materials in mailed packets to encourage participation and reiterate importance of the study
 - Applying special calling rules

ASD Progress Toward Objectives

- Partial success in gaining operational efficiency and sample representativeness
- Built a system to monitor R-indicators daily/weekly dashboard for near real-time monitoring
 - Successful real-time visualization of R-Indicators, partial R-indicators, and other production rates by key domains using R Shiny app.
 - Added standard errors of R-Indicators based on bootstrap methods
- Identified appropriate types and timings of interventions based on response rates and other quality measures
 - For example by switching to a different mode or shortening a questionnaire

A Few Notable Achievements

- Successful weekly monitoring of R-Indicators, production rates, and key frame and survey estimates
- Measures of representativeness can improve during data collection after implementing adaptive design
- Target completes for majority of domains were attained
- Implementation of full data processing on flow basis
 - identifying the largest source of error in its estimates

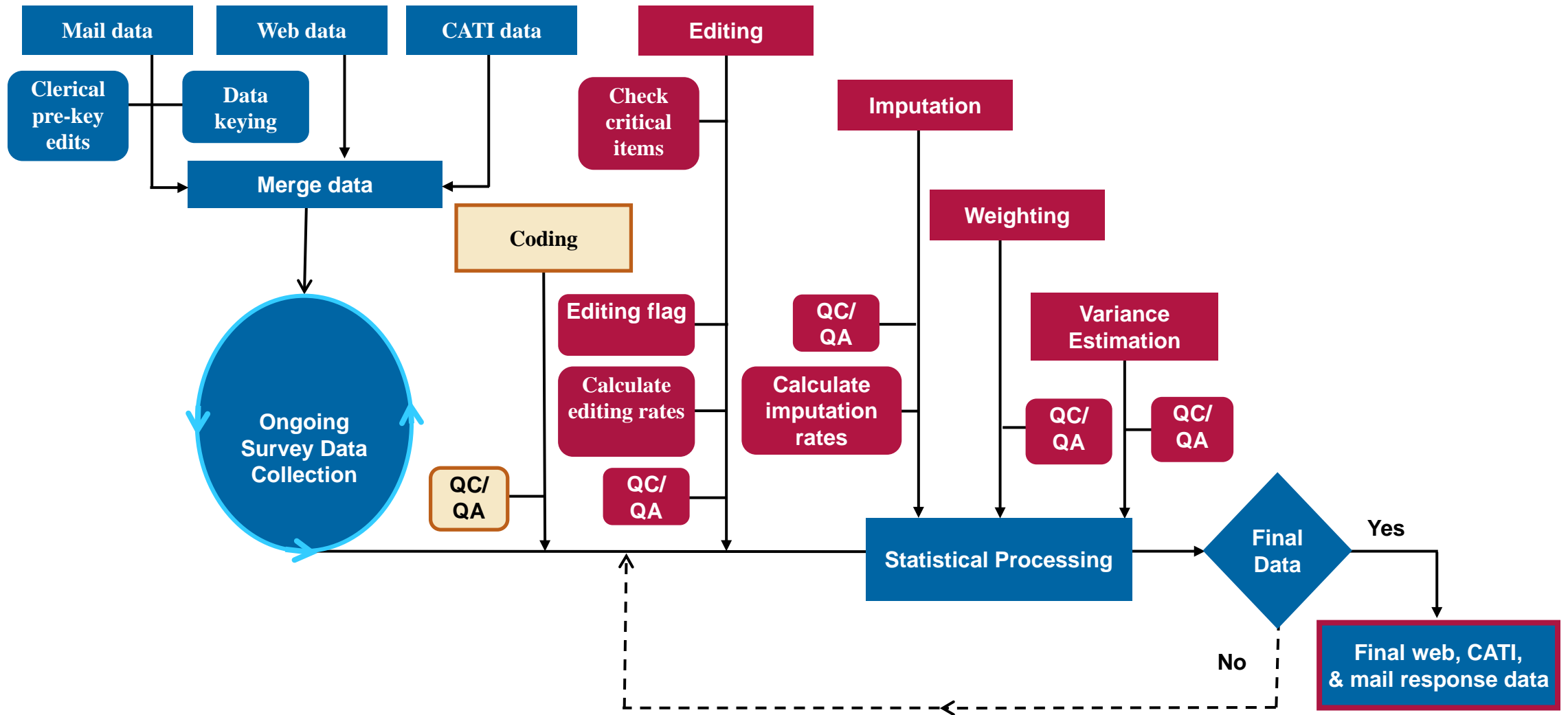
But Is It Really?

- Lack of comprehensive look at data quality
- Minimize error: $E(\hat{\theta} - \theta)^2 = V(\hat{\theta}) + B^2(\hat{\theta})$
- Aim to closely align ASD monitoring measures with MSE, given the constraints with time and budget
- Flow processing may help identify major error components
 - Could lead to allocate resources to best reduce total survey error, instead of simply focusing on raising the response rate.

Flow Data Processing

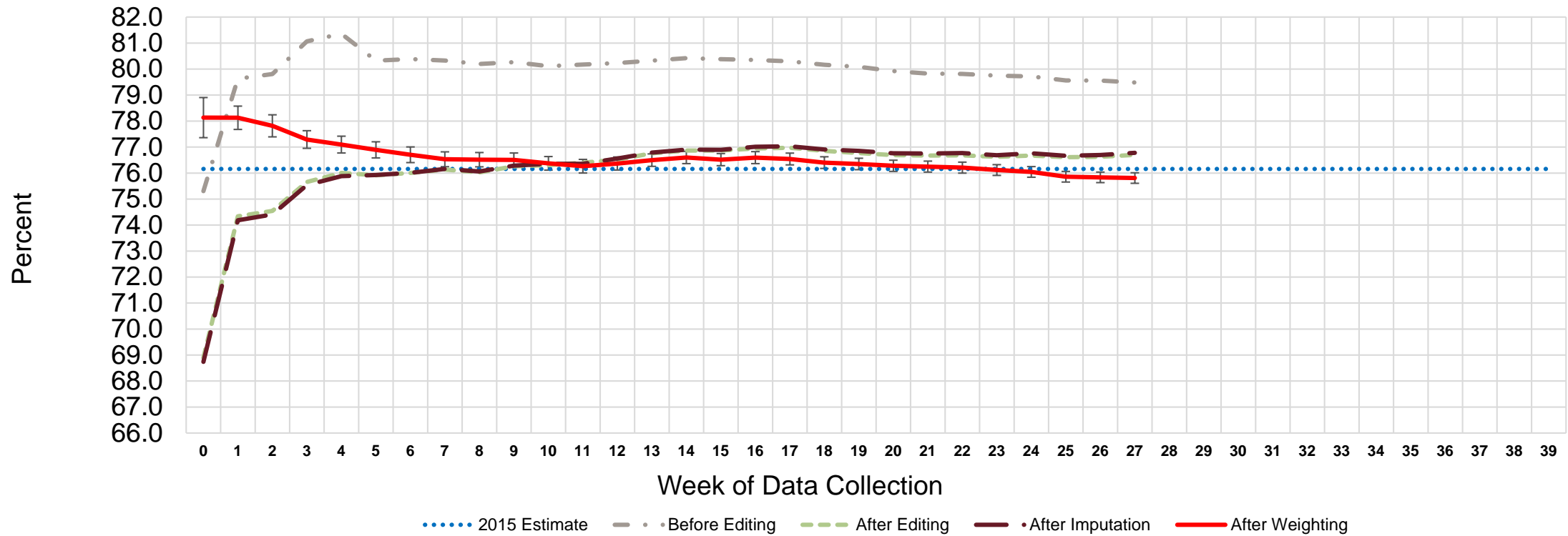
- Operate coding, editing, imputation and weighting procedures iteratively on a regular basis as respondent data come in
- Run rigorous quality check of all data processing systems and programs through iterative runs
- Monitor key survey estimates at each data processing step during data collection—may disclose
 - Any systematic errors associated with data processing
 - Source of errors
- Disseminate final data with high quality in a timely manner

Flow Data Processing—Ongoing Data Collection/Processing Overview



Tracking Survey Estimates Through Flow Processing: Example

Estimated % of Full-Time Employed by Week of Data Collection and Stage of Data Processing



Operational Challenges

- Managing a complex set of interventions occurring simultaneously, including locating and gaining cooperation interventions can be tricky
 - But necessary for highly mobile population.
- Devoting excessive effort to hard-to-locate or uncooperative cases needs to be avoided
 - Need to pursue adaptive design goals that are not at the detriment of overall response.
- For RDD surveys (like the NIS) very little prior information is available for both respondents and nonrespondents
 - Until they are screened for survey eligibility, nonrespondents are unknown (i.e., households with young children that do not respond)
 - The vast, vast majority of NIS nonresponse happens prior to screening.
 - Modifying the data collection approach can be difficult to adjust for sample imbalances
 - We only know respondent demographics, not of the entire sample.

Statistical Considerations

- Making use of prior round information and outcomes to inform current round modeling, targeting of cases.
- Strategies to pursue multiple adaptive design goals, appropriate weighting the importance of different goals.
- Helpful to have locating-specific R-indicator reflecting variation in locating outcomes. But it's not obvious how to measure this/how useful it is when cases are returning to locating.
- Choice of models (alternative to logistic regression) to estimate response propensities and avoid errors in maximum likelihood methods.

Statistical Challenges (Cont'd)

- For some surveys (like RDD surveys) a population-based R indicator that compares the responding sample to some external information about the target population is more useful
 - Compute the distance between responding sample distributions and external target population distributions
- Measures all over
 - Quality measures: R-indicators, production rates, editing and imputation rates, estimate changes at each stage of data collection, empirical MSEs
 - Optimal point to inform intervention decision

Discussion – Survey Project Teams

- Effective and timely communications across survey project teams must include survey operation managers, survey directors, statisticians, and survey methodologies to:
 - Understand the survey's overarching goal for data collection and its priorities for high quality data
 - Implement adaptive survey design (or more broadly survey design and implementation) under the overarching goal
 - Determine data collection interventions that are optimized for data quality
 - Collect and store paradata (including data collection processes) for appropriate post-data collection process

Discussion – Issues to consider

- Auxiliary variables inform adaptive survey designs
 - Are they enough for the weighting adjustments?
 - Do response propensities get distorted?
- Estimation – still based on underlying sample design
- Bayesian approach was attempted for prediction of response propensities.
 - How is it being used for estimation?

Discussion

- Best practices for implementing ASD still emerging
 - Multiple intervention types, sometimes concurrent (ex: locating and data collection)
 - Multiple ASD objectives
- Further research and evaluation needed to guide surveys

Thoughts on the Future Direction of ASD

Bring adaptive survey design approach into an evolving data lifecycle

- No longer single source: Multiple data sources – sampling frame, survey production data (or paradata), survey response data, data with benchmark values, other alternative data
- Real-time data/record linkage
- Measures other than R-indicators
- In order to know data quality, data processing/curation need to be iterated in near real-time during data collection
- Big Data computing framework needed as data processing, linkage of data (not statics), coding, editing, imputation, weighting
- Adaptive survey design seamlessly embedded in the entire data lifecycle
- Quality measures fully linked to total survey (data) framework