Combining smart and traditional survey methods: Mode effects and other data integration considerations

# Introduction

Over the past two decade, sensor arrays and machine intelligence have moved from the exclusive domain of technophiles to become so mundane that we often take them for granted. Most people have a smartphone, and more people than ever report that they feel comfortable interacting with them (Couper et al., 2018; Keusch et al., 2022). The sensors contained in a typical smartphone, such as cameras, accelerometers, GPS receivers, ambient light sensors, or gyroscopes, have become embedded in users’ everyday life tasks with the goal of making things easier, faster, and more accurate (Khan et al., First 2013). Users have become accustomed to the ways in which these devices can improve their experience.

In the same two decades, response rates to a broad range of long-running surveys have declined, requiring institutions such as National Statistical Institutes (NSIs) to expend more resources to achieve comparable sample sizes (Luiten et al., 2020; Stedman et al., 2019). The causes behind the falling response rates aren’t clear, although the sheer number of requests for participation and increase in surveyors from the commercial space has been proposed as a factor (Dillman, 2015). In the past, surveys following up with non-responders have suggested issues of salience [“wasn’t relevant”], burden [“no time”], and interest [“too boring”] (Couper et al., 2007; Singer & Couper, 2017; Tait et al., 1995). Unsurprisingly, these same aspects are also well-represented in surveys of what respondents find bothersome in surveys (Husebø et al., 2018; Johnston, 2014; Mayer, 2019). The places where surveys fail to perform, such as in asking repetitive questions, requiring heavy time investment, and precise and accurate measurement of things like time or space, are exactly the places in which sensors and algorithms shine. This fortuitous overlap has not gone unnoticed by survey researchers, and the last decade has been marked by an increase in “smart surveys” seeking to augment existing methodology by using the tools readily at hand within smartphones (Couper et al., 2018; Link et al., 2014; Struminskaya et al., 2020).

Although these smart surveys can be deployed in isolation, researchers whose current surveys might make use of some of the theoretical benefits are interested in integrating results from smart surveys with historical data sources and ongoing, established surveys. This presents an unfortunate conundrum, as the format of data gathered by sensors are often very different from data acquired via survey questions, and can require considerable cleaning and processing before it can even be directly compared (Harding et al., 2021; Kaplan et al., 2020; Keusch et al., 2023; McCool et al., 2021). Incomplete coverage of smartphones, combined with the potential for a differential self-selection bias between smart surveys and traditional surveys complicate the matter further (Stone et al., 2023; Wenz & Keusch, 2023). At the moment, there exists no comprehensive methodology proposing steps for the integration of smart survey data, despite both researcher interest impending necessity.

While the usage of smartphone-acquired sensor data is certainly a new challenge, the field of survey methodology has contended with similar issues in the past. Mixed-mode design, in which a survey is delivered across multiple platforms (e.g. via telephone and face-to-face), has been used for decades to improve low response rates, and adjust for issues of selection and coverage (de Leeuw & Hox, 2008; Klausch, 2014; Schouten et al., 2021b). Lessons learned on mode effect estimation and data integration of other disparate modes can provide a framework for smart surveys.

Finally, The Total Survey Error (TSE) framework offers an attractive entry point for discriminating between different sources of error that may arise between the differing modes of data collection (Biemer & Lyberg, 2003). TSE provides a taxonomy of errors that may be introduced at each step of the survey process, which can then be translated into existing methodology to both estimate and account for systematic differences. Usage of this framework carries with it the additional benefit that researchers have expanded the framework over time to consider various situations that may be good approximations of smart data, including big data (Amaya et al., 2020), found data (Biemer & Amaya, 2020), and web-tracking data (Bosch & Revilla, 2022). Drawing from these varied approaches provides theoretical backing for this new area of research.

This literature review aims to accomplish the following:

1. Identify, classify, and quantify sources of error that may pose risks for the integration of smart surveys with traditional survey methods
2. Establish patterns of similarity between smart/traditional survey integration and previous research on mixed mode surveys

In Section 2, we describe and outline different examples of smart surveys that provide concrete examples for the sections that follow. In Section 3, we briefly describe and review the literature on Total Survey Error to provide the necessary vocabulary for following sections. In Section 4, we present relevant literature on mixed mode survey methodology and its relationship to the question at hand. In Section 5, we present the literature describing initial findings on mode effects in smart surveys. In Section 6, we present results on estimation methodology and data integration. Finally, in Section 7, we synthesize the findings from the literature, provide recommendations, and suggest experimental methods for closing the gaps in existing literature.

# Smart surveys

## Smartphones and apps

Well before apps gained their current level of prevalence, researchers were investigating the usage of smartphones and other mobile devices independently of their capacity to provide complementary external data to the survey. Couper et. al (2017) offers a comprehensive review of the literature on web surveys completed on mobile devices. Important considerations included differences in coverage, non-response, break-offs, and how best to design web surveys to accommodate the new device (Pearce & Rice, 2013; Peterson et al., 2017; Toepoel & Lugtig, 2015).

The primary difference between completing a web survey on a smartphone and using an app on a smartphone is the length of time a person will need to interact with the device. Aspects such as coverage and differential non-response remain pertinent and to smart surveys. Although smartphone penetration has increased in the United States and Europe, the differences between who has them and who does not have remained.

### Coverage (different section)

The original concern of smartphone coverage was that smartphone coverage may have been limited by key demographics, but it may now be the case that access to the web on non-smartphone devices may be limited by key demographics.

Online surveys are done on many different devices. Mixed-device surveys. Online surveys not yet adapted to small screens. Variability in display of questions. No long matrix questions. Measurement differences can be minimal. (Toepoel & Lugtig, 2015)

## Levels of smartness

The difference between a web survey conducted on a smartphone and a smart survey, while conceptually easy to distinguish, is sometimes fuzzy. In this way, it may be useful to describe different levels of ‘smartness’ that a survey may have. A survey that a user accesses by typing in a website to the browser in their phone, then fills in questions in the same way as they would if they were answering in any other mode, would not be considered a smart survey. On the other hand, the addition of search bar for an input field for, say, the food you last ate could be considered a smart feature as it makes use of a smartphone’s capacity to serve up search results to reduce a user’s total effort in typing out a full phrase. This is a low level of smartness, but if it is compared to an entry blank on a pen and paper survey, it is easy to identify that it is present.

A high level of smartness for a similar question might involve scanning the barcode or taking a picture of the food you ate in order to answer a similar question. Although the gradation is not clear-cut, a high level of smartness tends to involve device sensors as its smart features because these offer an extended set of tools for meeting the goals of smart surveys: reducing burden and measuring concepts that respondents are unlikely to know or cannot measure. Schouten et. al (2021a) list a number of smart features that smart surveys may have: device intelligence, internal sensors, external sensors, access to public online data, access to personal online data, or linkage consent. Often, fully-developed smart surveys will employ combinations of many of these at once.

Following are three examples of smart survey types that are currently in use among NSIs. These surveys share a common history as complicated pen-and-paper diaries that often required interviewer assistance. Their high burden and the presence of questions that are difficult to measure or recall have made them ideal targets for novel methodologies over the years, which allows investigation into the impact of using differing combinations of smart features.

## Mobility

Surveys looking to measure people’s travel behavior identified shortcomings from the beginning (Clarke et al., 1981). The goal of these studies is to reliably measure travel behavior for a sample within a given geographic area, including aspects of the travel such as mode of transportation, precise start and stop times for each trip, and addresses for visited places, which is accomplished by asking respondents to record this information in diaries spanning varied lengths of time depending on the study (Axhausen, 1995). At the Second International Conference for New Survey Methods in Transport, differences in reporting were identified between days incorporating interviewer assistance and not, and between recorded behavior and road sensors (Ampt et al., 1985). Ashley et. al. (2009) discuss trip underreporting across multiple studies that rely on varied modes for comparison against the self-administered travel diary. Although the particulars differ, they share the commonality that the data from self-administered travel diaries consistently shows fewer trips than other sources.

The mobility survey represents the first of the included surveys to incorporate smart features. Early in the 90s, researchers began to make use of standalone GPS receivers for the purposes of recording all trips (Bricka et al., 2009; Sarasua & Meyer, 1996; Yalamanchili et al., 1999). This worked quite well at capturing user locations, but because it was an external sensor, linkage with data from the respondent was not simple, and methods varied across studies. Although some proponents posed the GPS logger as a complete solution that would eliminate the need for respondent involvement altogether (Wolf et al., 2001), the capacity for accurately determining trip purpose, transportation mode, and the identification of missing data has yet to prove itself as accurate as user input (Bähr et al., 2020; Gong et al., 2014; Nguyen et al., 2020; Sadeghian et al., 2021).

At the same point in time, the increase in Internet penetration and web familiarity led other researchers to experiment with bringing travel diaries online (Adler et al., 2002; Arentze et al., 2001). This allowed for the introduction of different smart features, including machine intelligence that added checks to the data entry stages that prevented impossible or unlikely entries, and linkage to personal data to decrease respondent burden (Hoogendoorn-Lanser et al., 2015). Much like with the GPS loggers, the data collected from the enhanced web-based travel diaries was often quite different.

In the early 2010s, smartphones began to come with embedded GPS technology and other sensors that made it feasible for them to record user locations, and researchers began to develop smart surveys for mobility behavior that made use of these features (Berger & Platzer, 2015; Cottrill et al., 2013; Greaves et al., 2015; Nitsche et al., 2014). Here, too, the specific smart features differed per app: some made use of additional device sensors, fusing the GPS records with accelerometer data (Prelipcean et al., 2018), and some integrated the machine-based check mechanisms with user feedback (Greaves et al., 2015). Soon, recommendations began to emerge for how best to make use of all possible smart features in order to improve data quality and reduce user burden (Harding et al., 2021).

As the travel diary became increasingly smart, it introduced new avenues that could account for previous sources of error, as well as new avenues for error to occur. While GPS coordinates could help to reduce recall error for respondents, the sensor could also fail in a number of ways that pen-and-paper studies were unlikely to fail. Determining the reasons for different outcomes between surveys with and without smart features requires considering each of these levels independently.

## Expenditure

Expenditure data, often gathered in the form of recall or diary studies, is important to researchers and policy-makers alike (Browning et al., 2003). Declining response rates and data that don’t align well with aggregate measures have become a problem for researchers (Crossley & Winter, 2014). There have been multiple efforts to improve the quality of the data generated, but recent work suggests that the intensive burden of having to report all expenditures by writing down amounts and details is a hindrance to both nonresponse and measurement quality (Wenz, 2023). Issues of diary fatigue, where reported expenditure declines over the measurement period, are quite common (Brzozowski et al., 2017).

* Respondents are generally quite good at being aware of when and how they have spent money, and the task is rarely complex. Thus, of the three benefits that smart surveys offer, expenditure research can be said only to benefit from a reduction in burden. This can be done either by offloading laborious tasks onto the available sensors, by taking pictures of the receipts to automatically fill in line items (Jäckle et al., 2019; Wenz, 2023), or by using geolocation to offer reminders when people are in areas where they are likely to make purchases . As with the mobility case, previous efforts to decrease the burden have involved moving the data collection online, incorporating decision rules to attempt to prevent motivated misreporting (Eckman, 2022). (French et al., 2008; Riegler, 2015; Sekula et al., 2005)

Talk about scanning only vs scanning plus diary vs smartphone diary only

## Time use

Short history of time use research and how it has evolved. Discuss app from TSS1. Issues that make it a good fit for smart surveys

# Total Survey Error

Total Survey Error (TSE) is a paradigm in which the varied ways that error can permeate through a survey can be described, and provides a basis for their joint and independent evaluation for contribution to the overall quality of the survey estimates (Biemer, 2010; Groves & Lyberg, 2010). Total survey error, conceptually, describes the difference between a parameter as it might be measured within a population, and the estimate of the same parameter as it might be measured by a survey (Biemer & Lyberg, 2003, p. 36). If the objective is to compare a smart survey against its non-smart counterpart, we are ultimately interested in the comparison of each of these against the population. While adaptations of the TSE framework have been proposed for big data, found data, and metered data (Amaya et al., 2020; Biemer & Amaya, 2020; Bosch & Revilla, 2022), none have been proposed for smart surveys. This article therefore relates the scheme as presented by Biemer and Lyberg (2003) to the case studies at hand. This version offers sufficient flexibility to categorize and demonstrate the differences in potential error sources between smart surveys and traditional surveys. Figure 1 is a graphical overview of the categorization levels: within total survey error, we distinguish between sampling error, caused by the process by which the sample is drawn from the population, and nonsampling error, of which we distinguish five categories.

For the purposes of this article, briefly describing each of these sources of nonsampling error is sufficient to provide context for the following sections. Specification error arises when there is a mismatch between the parameters of interest for the researchers and the information that the survey will capture. Frame error, also referred to as coverage, results from the failure of the sampling frame to adequately represent the population. Nonresponse error comes from a sampled person’s failure to respond to the survey instrument, either completely, or in part. Measurement error arises when a respondent answers in a way that differs from the truth, whether intentionally or not. Finally, processing error comes from processing, coding, editing, or working with the data.

The categories of nonresponse error benefit from an additional structural layer. Nonresponse can be called unit nonresponse if the sampled person does not respond to any part of the survey, or item nonresponse for when a sampled person has some response, but it is incomplete. Importantly, for diary studies, which are intensive and longitudinal, item nonresponse may be more complex (Lynn & Lugtig, 2017). While traditional item nonresponse is often conceptualized as questions left unanswered, the existence of patterns occurring over time, such as response that decreases over time or ends prematurely suggest the need for a third category of nonresponse or a classification of differential item response patterns.

In addition to the longitudinal aspects of diary survey methods, there are additional considerations specific to smart surveys making use of passive data collection. Bosch and Revilla (2022) note two important deviations for passively-collected data from actively-collected data: it is difficult to distinguish missing data from absence of behavior, and similarly difficult to categorize missing data as either item nonresponse or measurement error. In their adaptation of the TSE framework to Big Data, Amaya et al. (2020) address this by assessing the concept of missing data error in place of nonresponse error, noting that the confounding can be abated when the generation mechanism of the missingness is identifiable.

The following chapter uses the TSE framework as a basis for discussion of the differences that are known to arise within each of these components between different modes of survey administration. Chapter 5 presents what is currently known specifically on the comparison between smart surveys and their non-smart counterparts.

# Mixed-mode surveys and multi-source statistics

A survey may be administered through one or more methods, including face-to-face, paper-based, telephone, or via a smartphone app. The choice of mode by which a survey is administered is known to influence the accuracy of the data collected (DeLeeuw, 2018). When the same survey content is assessed by researchers by differing modes of response, the survey design is considered to be mixed-mode, as distinct from single-mode (de Leeuw et al., 2015a). Each mode of administration in a mixed-mode survey will accumulate error within the non-sampling error components discussed in Chapter 3: specification error, frame error, nonresponse error, measurement error, and processing error. When differences in error exist between different modes, we speak of mode effects.

To some degree, mode effects in fact represent the desirable element of conducting mixed-mode surveys. A telephone-based survey is limited in its coverage by default to persons who possess a telephone and web-based surveys will encounter coverage errors related to Internet access, but the development of a survey design that incorporates both modes will have greater coverage of the total population, assuming that the two modes differ in their coverage error. Most researchers who employ mixed-mode designs make use of this fact in order to improve coverage and response (DeLeeuw, 2018). On the other hand, within the field of mixed-mode design, mode effects not contributing to an increase total survey coverage of these are frequently seen as nuisance elements to be avoided or corrected for against some gold standard measurement (Burton & Jäckle, 2020; Klausch et al., 2013). This view is at least partially at odds with the goals of smart surveys, which often seek to combine the benefits of both active and passive measurements precisely because of the lack of a gold standard.

In their book Mixed-Mode Official Surveys, Schouten et al. devote a chapter to the discussion of smart devices as an emerging new mode, noting that the new types of data “challenge the comparability of response with and without” the data (2021a, p. 223). The task of combining data generated by smart and non-smart surveys may ultimately bear greater resemblance to combining data from different sources if the variables arising from traditional surveys and smart surveys differ in their level of aggregation or frequency, corresponding to situations 7 or 8 respectively as discussed by Waal, Delden, and Scholtus (2020). We can therefore contrast the mixed-mode paradigm with the multi-source paradigm in which the existence of differential error between data sources can provide a method by which to compensate for the disadvantages of each (De Broe et al., 2021). Although the perspectives between mixed-mode and multi-source statistics differ, the methodology for the estimation of differences between the two is very similar, and so this paper condenses literature out of both disciplines. We will assess the relevant literature on mode/source differences at each level of nonsampling error within the TSE framework.

## Specification error

There has been relatively little attention paid explicitly to the concept of specification error as it relates to mixed-mode survey design, although the importance of proper concept specification as the “backbone” of survey quality has been repeatedly emphasized (de Leeuw et al., 2015b; Salant & Dillman, 2008). Specification is the process by which the concepts of interest are translated into a variable that can be measured by the survey instrument, and specification error the mismatch between the two. Careful alignment of theory and questions by involving everyone in the process, along with a pretesting stage, can identify specification error (de Leeuw et al., 2015b). Regardless of whether the operationalization has been sound, survey modes that don’t differ in their presentation of the question are unlikely to elicit differences here -- except perhaps longitudinally (Lynn & Lugtig, 2017). In this way, the unified mode approach, in which all modes have questions phrased as similarly as possible, limits the introduction of mode specification effects (Dillman & Edwards, 2016; Dillman et al., 2014). The line between mode specification effect and mode measurement effect is not always clear in the data. In their chapter on Mixed-Mode Research, Hox et al. (2017) note the potential for instruments to “reflect different constructs across modes,” in the worst case scenario of mode measurement effects.

Unlike in the mixed-mode domain, the difficulties arising from mode specification effect come up regularly in multi-source literature, both because the data sources under consideration may be created independently of each other, and because the collecting instrument may limit the ways that the concept can be operationalized (Zhang, 2012). Here, too, there is confounding with measurement effect, but often the presence of clear differences in the operationalization of a concept lend itself to seeing differences at the level of specification rather than measurement.

## Frame Error

* Maybe change to selection error and combine?
* I think here it’s relevant because the frames are potentially quite different because smartphone
* Web resp are somewhat higher educated and more affluent -> transfer to app? (Groves, 2006; Groves et al., 2006)
* Registers (Groves, 2006; Groves et al., 2006)

## Nonresponse error

* Auxiliary information for controlling for the confounding of selection and measurement error (also here registers?)
* Re-interview design (Biemer & Lyberg, 2003; Elliott et al., 2000)

### Unit nonresponse

* Systematic selection error of the estimator of the sample mean – depends on difference in means of resp and non resp individuals as well as the selection rate(Bethlehem et al., 2011)

### Item nonresponse

* More impactful differences because of patterns of missingness that are more likely to be present with apps than traditional

## Measurement Error

Measurement error – can differ both in the amount of random error and systematic effect

Evaluate measurement equivalence

* Dillman et al, 2014 resp in interview may interpret question differently from web survey
* Two types – mode effects that shift the response distribution (differences in estimates between modes, but not between correlations), vs change in question-answer process which can produce answers not equivalent between modes (Hox et al., 2017)
* Type IV/V designs like switching modes of administration
* effect of systematic measurement error differing estimates of means and otals, random measurement error variance and reduce correlations (biemer & lyberg 2003 vs alwin 2007)?
* Klausch thesis introduction – if you combine modes where one is assumed to be a benchmark, like survey vs smart survey, means the overall measurement error bias of mixed mode design is increased
* For e.g. mobility, where someone goes may be like sensitive questions. For sensitive questions, measurement effect between web and nonweb (Burkill et al., 2016)

## Processing error

* More important than in traditional mixed-mode settings
* May pull from differences between processing less aggregated sources? GPS trackers -> travel diary -> recall; processing of diary studies versus other
* Part of the processing may not be visible

Notes:

* Variants
  + Mode choice bias vs real measurement differences (2012
  + Sequential vs concurrent
  + Single vs multiple per resp.
* Mode effects are evaluated relative to some benchmark mode
* Diary vs recall (“on a typical day…”) as comparison?
  + If so: time use diary sleep vs recall sleep (Kaplan et al., 2020)
* Confounding (Vannieuwenhuyze & Loosveldt, 2013)
  + Mode-specific response distributions are impacted by selection *and* measurement
  + Just looking at a difference between estimates from two surveys with different modes provides a combined estimate of the total source of mode effect
* Role of auxiliary variables in estimation -- exogeneity / not affected by measurement effects within the multiple modes. Often what’s available is weakly related to response mechanisms (source?)
* MEPS experiment

<Small paragraph on coverage, but probably this is the other WP2 deliverable>

# Mode effects in smart surveys

TSS1 – WP2 deliverable 2.1 consumption interview vs none

* Diary vs app comparisons
  + Combined mode effect
    - (Wenz, 2023): Compares data from scanned receipts, scanned receipts plus direct entry with national budget survey, uses inverse probability weighting to match the sample composition of the app to the diary (could be considered reducing mode selection effect)
      * Distribution from SR+DE aligns with LCF for median total expenditure, but receipts alone underestimate expenditure (101.30 vs 122.80 vs 70.10)
      * Percentage zero expenditures is higher in the two-week period from scanned-only
      * SR for food and groceries is not significantly different from the benchmark, but SR + DE overestimates
  + Mode measurement effect
  + Mode selection effects
    - Coverage and participation bias in budget app (Jäckle et al., 2019)

# Estimation Methodology

## Experimental

* Probability samples with experiments for relative differences (probability sample, assigned a data collection mode, test hypotheses about differences)
  + Design- based analysis of factorial designs embedded in probability samples (van den Brakel, Jan A., 2013)
  + Design-based Analysis of Embedded Experiments with Applications in the Dutch Labour Force Survey (van den Brakel, 2008)
  + Analysis of Experiments Embedded in Complex Sampling Designs (van den Brakel & Renssen, 2005)
* Split sample – random assignment to a mode, then follow-up repeated measurement with one mode
  + Disentangling mode-specific selection and measurement bias in social surveys (Schouten et al., 2013)
  + Selection error in single- and mixed mode surveys of the Dutch general population (Klausch et al., 2015) -> imputation for unit nonresponse after the followup
* Longitudinal random allocation in a panel – quasi simplex model
  + The impact of mixing modes on reliability in longitudinal studies. (Cernat, 2015)
  + Estimation of mode effects in the health and retirement study using measurement models. (Cernat et al., 2016)

## Non-experimental

* Comparing mixed-mode to single mode to separate selection and measurement bias (observed variables insensitive to survey mode)
  + A method for evaluating mode effects in mixed mode surveys (Vannieuwenhuyze et al., 2010)
  + Evaluating Relative Mode Effects in Mixed-Mode Surveys: Three Methods to disentangle Selection and Measurement Effects (Vannieuwenhuyze & Loosveldt, 2013)
* Estimate classification error rates Measurement error categorical variables with overlapping datasets - Latent class analysis
  + Estimating classification errors under edit restrictions in composite survey-register data using multiple imputation latent class modelling (MILC) (Boeschoten & Oberski, 2017)
  + Measuring temporary employment. Do survey or register data tell the truth? (Pavlopoulos & Vermunt, 2015)
  + Estimating error rates in an administrative register and survey questions using a latent class model (Oberski, 2017)
* MTMM
  + The Validity and Reliability of Survey Questions: A Meta-Analysis of MTMM Studies. (Scherpenzeel & Saris, 1997)
* Prediction of a “true” values of numeric variables of interest, given multiple data sources covering only subsets of the population – latent variable
  + Estimation from contaminated multi-source data based on latent class models. (Guarnera & Varriale, 2016)

### Specification effects

* Measurement error assuming “Overlapping Numerical Variables with a Benchmark”
  + Combining official and Google Trends data to forecast the Italian youth unemployment rate (Naccarato et al., 2018)
* Reconciling high frequency and low frequency data – quadratic minimization
  + Solving large-data consistency problems at Statistics Netherlands using macro-integration techniques (Mushkudiani et al., 2018)
  + Macro-Integration for Solving Large Data Reconciliation Problems (Mushkudiani et al., 2014)
* Administrative sources and surveys using HMM Overlapping numerical variables without a benchmark
  + Overlapping numerical variables without a benchmark: Integration of adminis-trative sources and survey data through Hidden Markov Models for the production of labour statistics (Filipponi & Guarnera, n.d.)

### Measurement effects

* Propensity score matching resp. using covariates, difference in survey estimates is measurement effect, assuming covs. explain selection
  + Estimating nonresponse bias and mode effects in a mixed-mode survey (Lugtig et al., 2011)
  + Estimation of unobservable selection effects in on-line surveys through propensity score matching: An application to public acceptance of healthy eating policies (Capacci et al., 2018)
* Estimate measurement error Overlapping units and variables – SEM
  + Estimating the Validity of Administrative Variables (Bakker, 2012)
  + Modelling Measurement Error to Estimate Bias in Administrative and Survey Variables (Scholtus et al., 2015)
  + Latent Class Multiple Imputation for multiply observed variables in a combined dataset (Boeschoten et al., 2016)
* Classification error (generic, maybe other error types) with audit data
  + (van Delden et al., 2016) Accuracy of Mixed-Source Statistics as Affected by Classification Errors.
* Linking two data sources at individual level – estimating quality of probabilistic linkage
  + Using the bootstrap to account for linkage errors when analysing probabilistically linked categorical data (Chipperfield & Chambers, 2015)
  + Inference based on estimating equations and probability-linked data. (Chambers et al., 2009)
* Variance estimation in Combining several sources of aggregate data - Macro-integration by inequality restriction/balancing
  + On New Variance Approximations for Linear Models with Inequality Constraints (Knottnerus, 2016)
  + A Balanced System of Industry Accounts for the U.S. and Structural Distribution of Statistical Discrepancy (Chen, 2012)

### Distinguishing selection and measurement mode effect

* Interview/re-interview to disentangle selection and measurement bias
  + Nonresponse bias and measurement bias in a comparison of face to face and telephone interviewing (Biemer, 2001)
* Using aux. vars “unconfoundedness assumption” from causal inference theory
  + Propensity score weighting
  + Matching
    - ???(Morgan & Harding, 2006; Rosenbaum, 2021; Stuart, 2010)
  + Imputation
    - ???(Kang & Schafer, 2007; Schafer & Kang, 2008)
  + Regression estimation
    - ???(Imbens, 2004)
* ???(Vannieuwenhuyze & Loosveldt, 2013)

### Selection effects

* Weighting/regression-based inference for generic selection effects in non-experimental settings
  + Assessing the effect of data collection mode on measurement (Jäckle et al., 2010)
* Mode preference as covariate for explaining selection effects
  + Assessing the use of mode preference as a covariate for the estimation of measurement effects between modes: a sequential mixed mode experiment. (Vandenplas et al., 2016)

# data integration

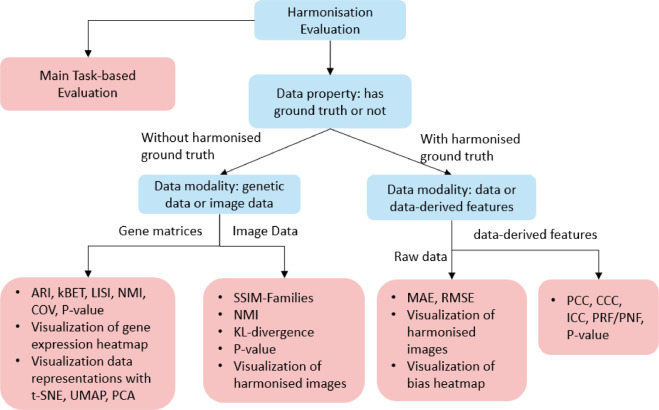
* \*\*Mixed-mode measurements as treatments in causal modelling framework counterfactual.. potential outcomes through regression, then overall estimates are combos of real answers and predicted answers
  + Suzer-Gurtekin, Z. T., Heeringa, S., & Vaillant, R. (2012). Investigating the Bias of Alternative Statistical Inference Methods in Sequential Mixed-Mode Surveys. Proceedings of the JSM, Section on Survey Research Methods, 4711-2.
* \*\*Multiple imputation of non-observed answers
  + Kolenikov, S., & Kennedy, C. (2014). Evaluating three approaches to statistically adjust for mode effects. Journal of survey statistics and methodology, 2(2), 126-158.
  + Park, S., Kim, J. K., & Park, S. (2016). An imputation approach for handling mixed-mode surveys. The Annals of Applied Statistics, 10(2), 1063-1085.
* \*\*Reweighting of survey response – calibration correction of survey response to fixed-mode distributions
  + Buelens, B., & van den Brakel, J. A. (2015). Measurement error calibration in mixed-mode sample surveys. Sociological Methods & Research, 44(3), 391-426.
  + Buelens, B., and J. van den Brakel (2017). “Comparing two inferential approaches to handling measurement error in mixed-mode surveys,” Journal of Official Statistics, 33(2), 513-531.
* \*\* Covariate adjustments to correct for measurement effects
  + Vannieuwenhuyze, J.T., Loosveldt, G., Molenberghs, G. (2014) Evaluating mode effects in mixed-mode survey data using covariate adjustment models. J. Off. Stat. 30(1), 1–21
* \*\*IRT-based Bayesian hierarchical model/latent traits
  + Mariano, L. T., & Elliott, M. N. (2017). An Item Response Theory Approach to Estimating Survey Mode Effects: Analysis of Data from a Randomized Mode Experiment. Journal of Survey Statistics and Methodology, 5(2), 233-253.
* \*\*Re-interview after observational study and adjustment to benchmark mode
  + Klausch, T., Schouten, B., Buelens, B., & Van Den Brakel, J. (2017). Adjusting measurement bias in sequential mixed-mode surveys using re-interview data. Journal of Survey Statistics and Methodology, 5(4), 409-432.
* \*\* Combine eDiary and sensor measurements using visual analytics approach (mixed-methods approach, quantitative and qualitative)
  + (Resch et al., 2020)
* Reducing variance estimates with small area estimation, which can be used not only for geographic areas, but distinct small categories that are related
  + Small Area Estimation. (Boonstra et al., 2008)
  + Towards small area estimation at Statistics Netherlands (H. J. Boonstra et al., 2008)
* Variance estimation in Combining several sources of aggregate data - Macro-integration by inequality restriction/balancing
  + Macro-Integration with Inequality Constraints: An Application to the Integration of Transport and Trade Statistics (H. J. H. Boonstra et al., 2011)

Bootstrap inference using estimating equations and data that are linked with complex probabilistic algorithms (Chipperfield, 2020)

# Synthesis

Tie in with the French TUS experiment from TSS2: households complete both paper and app-based diaries, split on order of completion.

Ideas:



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