SAGE reference

The SAGE Handbook of Online Research Methods

Web- and Phone-based Data Collection using Planned Missing Designs

Web- and Phone-based Data Collection using Planned Missing Designs

William RevelleDavid M. CondonJoshua WiltJason A. FrenchAshley BrownLorien G. Elleman

The past few years have seen a revolution in the way that we are able to collect data. Using diaries (Bolger *et al.*, 2003; Green *et al.*, 2006) or smartphones (Mehl and Conner, 2012; Wilt *et al.*, 2011b) to measure states within subjects across multiple time periods, or the web to collect measures on thousands of subjects at a time (Gosling *et al.*, 2004; Rentfrow *et al.*, 2008; Revelle *et al.*, 2010; Wilt *et al.*, 2011a) has led to an exciting explosion in the amount of data collected. However, most of these studies ask the same questions of all of their participants.

In this chapter we review an alternative approach where we intentionally give each participant just a small subset of the items of interest but, with the power of basic psychometrics and sampling theory, are able to analyse the data as if far more items were presented. We refer to this procedure as Synthetic Aperture Personality Assessment (SAPA) (Condon and Revelle, 2014; Revelle *et al.*, 2010) to emphasize the use of synthetic covariance matrices. That is, we find the correlations between composite scales, not based upon scoring the raw items, but rather by synthetically finding the covariances between scales based upon basic covariance algebra applied to the pairwise complete item covariances. We think of these techniques as analogous to the techniques used in radio astronomy where the resolving power (aperture) of a set of radio telescopes may be greatly increased by synthesizing the signals collected by each individual telescope. Indeed, by combining the signals of radio telescopes scattered around the world, the effective aperture of these long baseline radio telescopes is the size of the entire earth. Because our covariance matrices are based upon data sets with a great deal of intentionally missing data, we also refer to our data as Massively Missing Completely at Random (MMCAR).

Our approach is not new for it was discussed by Frederic Lord (1955) and then elaborated (Lord, 1977) in the assessment of ability. A variant of the technique that uses Balanced Incomplete Blocks (BIB) or 'spiraling' has been applied in large-scale international surveys such as the Programme for International Student Assessment (PISA) (Anderson *et al.*, 2007). However, with the exception of our own work, we are not aware of the widespread use of this technique in smaller scale studies nor the complete emphasis on randomness that we have used. In this chapter we review the basic technique, discuss how to analyse the data, consider the effective sample size and resulting precision of estimates based upon scales and items, and then we give a few examples of SAPA-based results. We emphasize the application of these procedures to web-based data collection because we have not yet implemented experience sampling or ecological momentary assessments more broadly defined with SAPA technique. However, we believe the techniques are relevant to both within-subject and between-subject means of data collection.

In the spirit of open science, all the software we have developed and all the items we use are in the public domain. We use open-source software for data collection and analysis and public domain items measuring temperament, ability and interests. In addition, we periodically publish the raw data to allow other researchers to use them (e.g. Condon and Revelle, 2015a, 2015b, 2015c, 2016).

Consider the basic problem of trying to determine the relationship between two or more constructs. In the past, psychological scales would be developed for each construct, the relevant items would be given to a relatively small set of subjects and the

covariances/correlations between these constructs would be found by scoring scales based upon the individual item responses. A typical procedure would include administering a number of inventories to a set of freshmen in a group-testing situation at the beginning of a school term. With the normal limitations of such a design, questionnaires could be given to a group of 100–500 students, each of whom would answer all items given, probably at the rate of about 1–6 items per minute, depending on their difficulty. The total testing time would limit the number of items given, and in an hour only several questionnaires, each with 20–40 items, would be given. Another design, taking much longer, would be to recruit a community sample willing to take many questionnaires over the course of several years, e.g. the Eugene–Springfield Community Sample (ESCS) of Goldberg (1999). This procedure has led to a correlation matrix of several thousand items based upon approximately 800 subjects. A third technique, of course, is to use web-based data collection from volunteers, for example in studies such as the German Socio-Economic Panel Study (Wagner *et al.*, 2007); the *http://www.outofservice.com/bigfive* website, which collects data for studies such as Rentfrow and Gosling (2003) and Rentfrow *et al.* (2008); or the site run by John Johnson www.personal.psu.edu/faculty/j/5/j5j/IPIP/ipipneo300.htm, which presents either a 60- or 300-item version of the International Personality Item Pool (IPIP–NEO) (Buchanan *et al.*, 2005; Johnson, 2005). In all these approaches, scales are found by combining scores on the individual items. Unfortunately, volunteers are usually unwilling to answer very many items and thus one is faced with a bandwidth versus fidelity trade-off. One can either ask a few items each for many constructs with the resulting low reliabilities, or many items for each of a few constructs with more reliability but less coverage.

COLLECTING MMCAR DATA USING SAPA

An alternative procedure (SAPA) is to ask a few items for each construct from many subjects, but to randomly sample the items from a much larger pool of items. This allows for identification of the covariances between scales based on the composite covariances of the items rather than the raw item responses. This procedure takes advantage of the fact that people want to know about themselves (perhaps following the Delphic maxim to 'know thyself') and makes up the lack of precision associated with giving few items with the abundance of traffic available on the web. Based upon the participant's responses, the SAPA Project website (sapa-project.org) offers customized and individualized personality feedback and was originally adapted from Buchanan *et al.* (2005) and Johnson (2005) but has since been greatly modified.

We do not actively advertise the site and have found that some of the traffic comes from people who have posted their feedback from us on their personal webpages, while others find it by searching the web for 'personality tests' or 'personality theory', etc. Recent evidence suggests that such self-selected participants do not differ a great deal from those who are actively recruited to participate in probability-based national panel studies (Hays *et al.*, 2015). Unfortunately, both means of data collection suffer from respondents' willingness to participate and the reasons to opt into a sample are only slightly different from the reasons to opt out (Ansolabehere and Rivers, 2013). However, it is important to realize that not everyone is willing to participate in web-based surveys (Pew Research Center, 2015). As would be expected, given that many of our participants are in college, the daily and monthly rates will vary during the year, but we have been averaging about 45,000 participants a year.

A reasonable question is how valid Internet surveys are in general, and ours in particular. We have compared our item structures and sample characteristics with those reported in the

intensive study of the 800–1,000 people who were individually given many of the items we have used (the ESCS of Goldberg and Saucier, 2016). As we discuss later, in terms of ethnicity, age and education, our sample is much more diverse than the ESCS, but the factor structures are remarkably similar. Additional validity data will come from as yet unanalysed data of peer reports for a subset of our participants. Within the US, the distribution of our sample by state correlates with US Census population values of 0.95. Our sample is certainly more diverse than is normally achieved at a selective research institution, which tends to produce more White, Educated, Industrial, Rich, Developed (WEIRD) subjects (Henrich *et al.*, 2010) than in our sample. However, it is certainly not representative of even the US population because, as we show later, our sample is younger, more educated and has a higher proportion of females than the US population.

The SAPA Logic

Suppose one is interested in measuring facet level data from the 'Big 5' measures of personality (the so-called CANOE or OCEAN of personality: Conscientiousness, Agreeableness, Neuroticism, Openness and Extraversion; Digman, 1990; Goldberg, 1990) and eventually the relationship of these facets to measures of ability (Carroll, 1993; Gottfredson, 1997) and interests (Holland, 1959). Each facet might reflect 5–10 items, with 2–5 facets per broader domain, the measures of ability might include 50–100 items and the measures of interests might involve 100–400 items. That is, the desired item pool is in the order of 400–600 items. But the typical subject is not willing to answer more than 40–75 items. The SAPA solution is to sample items completely at random from the larger pool (or perhaps systematically sample randomly from each of the temperament, ability and interest domains) and then present the items in random sets of 25 at a time. At the end of each set of 25 items, subjects are asked if they want to continue and, if so, another 25 items are presented. They may stop whenever they want and feedback is presented to them based upon the items they have taken. Although the precision of measurement for each construct for each person is low, the precision of the synthetically formed covariances/correlations between scales measuring each construct is quite high.

How does this work? From the larger pool of P items, n items are then selected with probability p_i, where $n = \bar{p_i} P = \sum_{i=1}^{P} P(p_i)$ i.e. the average probability of any item being chosen, p_i, multiplied by the size of the total item pool. Thus, for N subjects filling out the questionnaire, each item has roughly $p_i N$ responses. More importantly, the average number of responses to each pair of items (i, j) is $p_i p_j N$. Consider the case of three months of data with N = 10,000, P = 500 and $p_i = p_j = 0.1$ or n = 50. Every one of the 500 items has been given roughly 1,000 ($p_i N$) times and there are roughly 100 observations per pair of items ($p_i p_j N$). (These numbers are given merely for example purposes. In reality we tend to collect data for longer periods of time and build up about 500–1,000 pair-wise observations.) The subscript on the item probabilities reflects our relative interest in the content of the item. Demographic variables are presented with $p_i = 1$, while more exploratory items might be given with $p_i = 0.05$. When developing new ability items with a concern for their difficulty or when presenting items that are temporally relevant (e.g. attitudes towards an election), item presentation probabilities are increased and they might be presented with $p_i = 0.5$.

Item level statistics (e.g. the mean or variance) are based upon the $p_i N$ observations, while item inter-covariances are based upon $p_i p_j N$ pairwise complete covariances. Structural analyses (e.g. factor analysis or principal components analysis), the internal consistencies of

the individual scales (e.g. coefficients α and ω_h) and also the correlations between individual scales may be found by basic matrix operations on the total inter-item covariance matrix rather than on the raw data matrix. This is not magic, but merely a function of covariance algebra.

In addition to the randomly chosen temperament, ability and interest items, we also collect demographic information from all participants. These data include age, education, marital status, parental education, height, weight, smoking history, country and state of residence, and for those who say they are from the US, their ZIP Code. For these items, $p_i = 1$ and the precision of the resulting statistics are based upon the N participants measured.

Software used to present SAPA items

There are logically three different phases of presenting items and storing the individual responses. All three phases use open-source software with specific code developed for this project. The phases are (1) specifying the item bank, (2) presenting the items and (3) storing the results and giving feedback.

Item Bank

The item bank is stored using MySQL, an open-source relational database management system that is supported by a large user community and also has a commercial version. With the use of extensive help files from the MySQL community, programming is relatively easy. The database is structured with a list of roughly 4,400 temperament, ability and interest items; 2,413 of the temperament items are taken from the open-source International Personality Item Pool (IPIP; Goldberg, 1999).

The IPIP was developed by Lew Goldberg who adapted a short stem item format developed in the doctoral dissertation of Hendriks (1997) and items from the Five Factor Personality Inventory developed in Groningen (Hendriks *et al.*, 1999). Goldberg (1999) used about 750 items from the English version of the Groningen inventory, and has since supplemented them with many more new items in the same format. The initial development of the IPIP was controversial because some believed that commercial developers could do a better job (Costa and McCrae, 1999). The citation count to the IPIP belies this belief. With at least 2,382 Google Scholar citations to the original publication (Goldberg, 1999) and 1,636 to the subsequent discussion (Goldberg *et al.*, 2006), it is safe to say that open-source personality measurement is a good idea. The IPIP items have been translated into at least 39 languages by at least 65 different research teams, but the SAPA site is currently using just English-based items (taken from ipip.ori.org).

We supplemented the IPIP item bank with 92 interest items taken from the Oregon Vocational Interest Scales (ORVIS; Pozzebon *et al.*, 2010), 60 from the O*Net markers of Holland's RIASEC dimensions of interests (Armstrong *et al.*, 2008; Holland, 1997; Rounds *et al.*, 2010), 60 music preference items (Liebert, 2006), 30 Right Wing Authoritarian items (Altemeyer, 2004), 78 items from the Eysenck Personality Questionnaire (Eysenck *et al.*, 1985), 30 items taken from inventories (e.g. Jackson, 2009; Smederevac *et al.*, 2014) to measure aspects of Reinforcement Sensitivity Theory (Smillie, 2008), 220 items to measure aspects of personality disorders (Krueger *et al.*, 2013), 15 items from the Santa Barbara Sense of Direction scale (Hegarty *et al.*, 2002), as well as 60 ability items developed as part of the International Cognitive Ability Resource project (ICAR; Condon and Revelle, 2014). Additional items that were taken from a number of different scales were given in prior years. The master list of the

4,300 items from the IPIP, ORVIS, O*Net and other sources that we use are available at https://sapa-project.org/MasterItemList/.

Presentation Software

Using the server-side scripting language, PHP: Hypertext Preprocessor, we query the MySQL server for items to present and then display them using HyperText Markup Language 5 (HTML5) on an APACHE-based web server. Participant responses are then pre-processed and stored back to the MySQL server. As would be expected in any software development environment, our PHP scripts have improved over the years to take advantage of changes in MySQ, PHP and to the HTML5. The site was originally hosted at the personality-project.org website and has since been migrated to the sapa-project.org website. (Both of these are hosted at Northwestern University, Evanston, IL).

From the user's perspective, they see a number of screens with 'radio button' response options or a few text box options. These screens or 'pages' include:

- Welcome:

A brief description of the SAPA project, an FAQ about the test, the research behind SAPA, links to literature about current research in individual differences and the benefits that may accrue to the user.

- Consent form:

A brief discussion about how long the test will take, how all responses are anonymous, that participants will receive feedback based upon our norms and a consent button to start the test.

- Demographics:

One question is whether people have taken the survey before, others ask age (in a text box). Pulldown menu options ask about gender, height, weight, marital status, relationship status, frequency of exercise, smoking history, country and state/region where the person grew up, level of education, university major (if relevant), employment status, general field of work and then parental education. More recently, we have started asking about the participants postal or ZIP Code. At this point, the user is assigned (invisibly) a random identification number (RID) that will be used to check for repeated entries in the same web browser session.

- First and subsequent page of questions:

Each page has 25 questions, the first 21 of which are sampled from the temperament and interest item banks, the final four are ability items sampled from our ability item bank. At the end of each of the first three pages, subjects are told that they will have more accurate feedback if they continue. At the end of the fourth page, they are given personality feedback based upon scores calculated from the items they have answered.

- Optional subsequent pages:

Participants are offered the possibility of continuing on and filling out more items

about such things as creative accomplishments, or of sending a message to a friend to rate them on various personality attributes.

Storage and Feedback

As the participant is filling out the survey, results are transmitted to the MySQL server at the end of every page and stored with their RID. Once the participant selects the option saying that they are finished with the entire set of (randomly administered) items to which they chose to respond, they are given scores on various personality scales. These were originally based upon the Big 5 factors but have more recently been replaced with hierarchically organized factors scores with 3, 6 and 12 factors. This scoring is done by applying a key of all possible items for each scale and finding the average response given to the items that were presented. The graphic output gives a location of each of the scores on a line along with a confidence interval for each score.

Data Security

When we first started the site, and for the subsequent eight years, the SAPA project was hosted on an Apple Macintosh desktop computer in the Personality, Motivation and Cognition laboratory at Northwestern University, Evanston, IL. We updated our security settings on APACHE, MySQL and PHP relatively frequently, but not enough to prevent a MySQL injection from taking over the system. After recovering the data (with one week's worth of data lost to the hacker), we moved the site to a more professionally managed server at the main computer cluster on campus. We mention this as a warning of the problems of maintaining web servers.

ANALYZING SAPA/MMCAR DATA

The basic logic of the SAPA procedure follows from some fundamental principles of psychometrics with respect to correlations of items and correlations of item composites. It is well known that the correlation between two scales, A and B with n and m items, respectively, is CovABVAVB. But since the covariance of two item composites is merely the sum of the covariances of the separate items, CovAB=∑j=1n∑k=1m(covaibj) and, similarly, the variance of a composite is the sum of the variances and covariances of the items in that composite VarA=∑j=1n∑k=1n(covaiaj), then

$$r_{AB} = \frac{Cov_{AB}}{\sqrt{V_A V_B}} = \frac{\sum\limits_{j=1}^{n} \sum\limits_{k=1}^{m} (cov_{a_i b_j})}{\sqrt{\sum\limits_{j=1}^{n} \sum\limits_{k=1}^{n} (cov_{a_i a_j}) \sum\limits_{j=1}^{m} \sum\limits_{k=1}^{m} (cov_{b_i b_j})}}.$$

More compactly, in matrix algebra, and for the general case of multiple scales, let the raw data be the matrix **X** with N observations on P items converted to deviation scores (with most rows having only n non-missing items). The item variance–covariance matrix is C=XX′N−1 and scale scores, **S** are found by **S = K'X**. **K** is a keying matrix, with K_{ij} = 1 if $item_i$ is to be scored

in the positive direction for scale j; 0 if it is not to be scored and −1 if it is to be scored in the negative direction. In this case, the covariance between scales, $\mathbf{C}_S$, may be found by pre- and post-multiplying the item covariance matrix with a matrix of the keys:

$$\mathbf{C}_s = \mathbf{K}'\mathbf{X}(\mathbf{K}'\mathbf{X})'N^{-1} = \mathbf{K}'\mathbf{X}\mathbf{X}'\mathbf{K}N^{-1} = \mathbf{K}'\mathbf{C}\mathbf{K}.$$

The scale correlations, R_S are found by pre- and post-multiplying the scale covariance matrix $\mathbf{C}_S$ by the inverse of the scale standard deviations, which are merely the square roots of the diagonal of $\mathbf{C}_S$:

$$R_s = (diag(\mathbf{C}_s))^{-.5}\mathbf{C}_s(diag(\mathbf{C}_s))^{-.5}$$

That is, the covariance between any set of scales can be found by multiplying the transposed keying matrix by the inter-item covariance matrix times the keying matrix. The correlations are found by dividing this product by the standard deviations.

Although the correlational structure of the *items* requires the raw data, the correlations of *scales* can be found by keying the item correlation matrix into scale correlations, not the raw data matrix. In the case of a SAPA/MMCAR design, this is very important because although the individual item correlations can be found by 'pairwise complete correlations' or 'available case correlations', it is highly unlikely that any one participant has complete data for any scale. We conduct our structural analyses at the item and scale covariance level, rather than at the raw data level. We believe that the greater resolution of item-level and scale-level covariances made possible by our technique compensates for the lack of complete subject data analysis.

In order to process our SAPA data, we have developed a number of functions included in the *psych* package (Revelle, 2015) in the open-source statistical system R (R Core Team, 2015). These functions are specifically meant to handle the massively missing data structures that we use and are referenced later. In addition, we have developed an additional package, SAPATools (French and Condon, 2015), to facilitate data extraction from the MySQL server and to do some basic data cleaning. Unless explicitly mentioned, the R functions discussed in the following pages are all from the *psych* package.

Data Cleaning

After importing the data from the MySQL server into R, either using functions in the *RMySQL* (Ooms *et al.*, 2015) package, the *SAPA-tools* package, or by just reading the file using a normal HTML browser and copying to the clipboard, the data need some preliminary data checking and cleaning. Some participants will take the questionnaire, receive their feedback and then go back to the beginning of the page to do it again. This is detected by keeping the RID permanent for the web browser session. Thus, the data are first cleaned by removing all duplicate RID numbers. (The data are, however, maintained so that we could, if we desire, go back and find out the characteristics of those who enter more than one set of questions.) Additional data cleaning procedures includes removing subjects who report ages less than 14 or more than 90 and excludes those participants who tell us they have previously participated

in the survey.

Basic Item Information

Descriptive statistics (means, standard deviations, ranges, etc.) are found for all items using the describe function. Demographic information is available for all participants, whereas temperament, ability and interest items are given to just random subsets of participants. Pairwise counts of the frequency of particular item pairs are examined to facilitate further analysis (given the changing nature of items being administered, not all item subsets are administered together – this is particularly the case when doing exploratory studies). Correlations between ability items are found using tetrachoric correlations; correlations between temperament and interest items are found by polychoric correlations. Correlations of continuous variables (e.g. age, height, weight) with dichotomous (ability) or polytomous (temperament and interests) items are found using polyserial correlations. All of these correlations are done using the mixedCor function.

Scale Level Structures

The real power of the SAPA procedure is evident when we examine the correlational structure either at the item or at the scale level. Factor analyses of the item level covariances are done using the fa function and two-parameter item response theory statistics based upon these factor analyses (McDonald, 1999) are done using the irt.fa function. For instance, the tetrachoric correlation matrix of dichotomous ability items may be factored using a minimum residual factor analysis function fa and the resulting loadings, λ_i are transformed to item discriminations by a=$\lambda(1-\lambda 2)$. The difficulty parameter, δ, is found from the τ parameter of the tetrachoric function and the factor loadings of the factor analysis of the tetrachoric matrix: $\delta=\tau(1-\lambda 2)$. Similar analyses may be done with polytomous item responses using polychoric correlations and distinct estimates of item difficulty (location) for each item response.

Similarly, analysis of internal structure of each scale may be done based upon the correlation matrices using functions to find α (alpha, scoreItems), $\omega_{hierarchical}$ and ω_{total} (omega) (Revelle and Zinbarg, 2009) as well as the signal/noise ratio of each scale (scoreItems). The hierarchical cluster structure based upon the item correlations (Revelle, 1979) is found using the iclust function. When examining the correlations of nested scales, that is scales with overlapping items, because they might be subscales of other scales, we use a correction derived from Cureton (1966) and Bashaw and Anderson Jr (1967) (scoreOverlap).

Individual and Group Level Scores

When describing the personality characteristics of certain subgroups (e.g. college majors, occupations, ZIP Codes), it is necessary to use scores based upon the raw data. To do this, we use IRT-based estimates from the available items for each subject using irt.fa and score.irt. This procedure, although highly correlated with just adding the item responses, allows slightly more precision in that it takes into account item discriminations and item endorsement frequencies (difficulties).

It is important to realize that the correlations between scales using the synthetic procedures may differ from those based upon the simple sum or IRT-based scores. This is because of the missingness in the data. The individual level scores for a particular measure might be based upon 2–4 items, and the subsequent correlation with another similar scale will be attenuated

by the missingness in the data. However, the structural correlations, based upon the covariance of all of the items in the scale (as many as 20–50) will be much less attenuated.

Because of the sample size, it is also possible to find the correlational structure of the mean scores for groups organized by college major or occupation, for example. These correlations are *between-group* correlations and will not necessarily be the same, and indeed usually are not the same, as the correlations pooled *within-group* or the *overall* correlations. Although some dismiss these correlations of aggregates as showing 'the ecological fallacy' (Robinson, 1950) or the Yule–Simpson 'paradox' (Kievit *et al.*, 2013; Simpson, 1951; Yule, 1903), we find that they tell us meaningful information about how individuals aggregate into groups (Revelle and Condon, 2015).

Precision of SAPA/MMCAR data

The standard error of the correlation between two particular items will be the classical standard error $\sigma_r = \frac{1-r^2}{\sqrt{N-2}}$. For complete data, this is the same formula for the correlation of composite scales. But what about the standard errors of SAPA-based composite scales? What is the appropriate sample size? Is it the number of participants who take any individual pair of items ($p_i p_j N$) or is it somehow closer to N? To answer this question, we rely on simulation. The following is based partly on the work of Brown (2014) who has done a much more thorough simulation than is reported here.

For a population covariance matrix of 0 between two sets of items that correlate 0.3 within and 0 between, we took 1,000 random samples of 10,000 cases for complete data, and for data with a probability of observing a particular item of 0.1, 0.125, 0.25, 0.5 and 1. That is, for the 0.1 condition, the probability of any pair of items having data was 0.01.

In addition, we simulated scales with 1, 2, 4, 8 or 16 items. Each of the 1,000 random samples governed by a particular combination of scale size and proportion of observed items produced a sample correlation calculated in one of two different ways: either as pairwise complete, or using the full information maximum likelihood (FIML) method. Each sample scale correlation was also corrected for alpha reliability, and minres oblimin factor analyses sought a two-factor solution whenever scale size was 16. Four sets of statistics (uncorrected and corrected correlations, factor loadings and intercorrelations) and their standard errors were computed by taking the mean and standard deviation, respectively, of the appropriate set of 1,000 sample statistics.

Results indicated that uncorrected correlations, which were derived using the SAPA method, approach their latent values as scale size increases; that is, as one aggregates over more items. This suggests that analysts who do not correct for reliability would do well to aggregate over items as SAPA does. In addition, both uncorrected and corrected correlations' standard errors decrease as scale size increases; this effect seems to be more pronounced with larger quantities of missing data. In essence, aggregating over items increases effective sample size more than might be expected based solely on the number of cases and the probability of observing a given item (Figure 33.1). Effective sample size, N_e is merely a function of the standard error, σ_r, of the correlation, r, which is $\sigma_r = \frac{1-r^2}{\sqrt{N-2}}$. Thus $N_e = \frac{1-r^2}{\sigma_r^2}+2$. We find the standard error by simulation to estimate the effective sample size. Finally, and as expected, more missing data tends to produce slightly more biased, less precise results among corrected correlations and factor intercorrelations. Factor loadings were less precise when more data were missing, but the effect of missing data on bias was, in this case, relatively

small.

Figure 33.1The effective sample size is a function of the observed standard error of the correlation and is Ne = (1−r2)/σ2r + 2. For this particular simulation, the average within scale correlation was set to .3 and the average between set correlation to 0. Means shown are from 1,000 replications. What is important to observe is when using the MMCAR composite scales, that effective sample size increases dramatically as the number of items per scale is increased
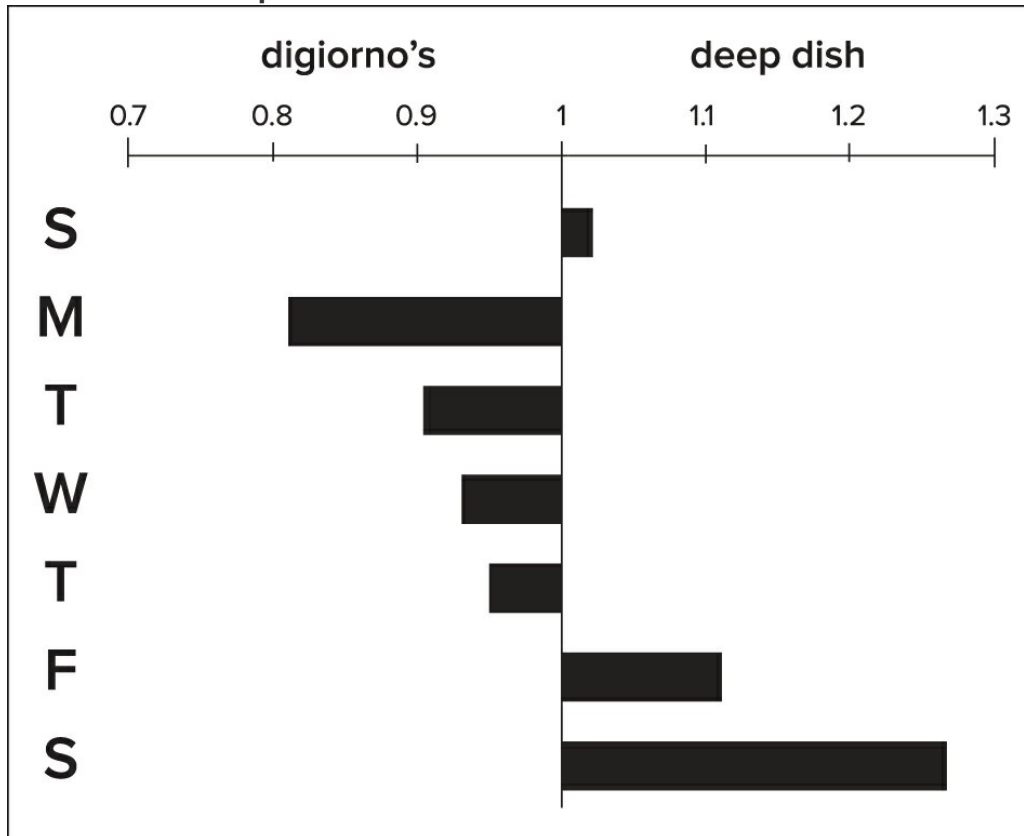
Also of interest here is the fact that the FIML method did not greatly improve upon the quality of the relevant statistics. Both statistical bias and data patterns, as described earlier, were the same regardless of analytic method. FIML produced slightly more precise solutions than the standard SAPA method, but it is much more computationally intense and time-consuming and, more-over, it is better suited to the analysis of data that possesses only a few distinct patterns of missingness, as in the commonly used balanced incomplete block design. Based upon our simulations (Brown, 2014), we propose that our method represents a simple and economical way for survey researchers with sample sizes of at least 200 to increase breadth of coverage without sacrificing statistical rigor. Obviously, for smaller sample sizes, the sampling probability for each item needs to be larger than we are using for our larger samples.

EXAMPLES OF SAPA RESULTS

The following are short summaries of some of the major projects conducted using SAPA. These include analysis of the correlates of items differing in their saturation of affective, behavioural, cognitive and desire content (Wilt, 2014), and examinations of alternative structures of items administered in several different personality inventories (Condon, 2014).

We have already reported the development of an open-source ability test used in the SAPA project (Condon and Revelle, 2014) and are now using SAPA procedures to validate other item types. In addition, one of the powers of the technique is that side studies can be conducted by introducing items with relatively low probabilities of being included and then just waiting a long time, or alternatively give some items with a high probability of being administered and then run them for just a few weeks.

Demographics of the SAPA Participants

The demographics in this section are based on a sample of 207,002 participants, whose self-report data were collected between August 2010 and December 2015. Participants from this sample are 63 per cent female. Participants grew up in 215 countries, with the US accounting for 73 per cent of the sample. Twenty-two countries besides the US have 500 or more participants, with the top three being Canada (8,895), the UK (5,577) and Australia (4,024). Participants from the US identify as 67 per cent white, 10 per cent African American, 9 per cent Hispanic, 5 per cent Asian American, 1 per cent Native Alaskan/Hawaiian/American, 6 per cent multiracial and 1 per cent 'other'. The mean age of participants is 26 (*sd* = 11; *median* = 22). The age distribution is highly skewed for both males and females (Figure 33.2). The modal participant is between 19 and 22 and is currently in college or university (Table 33.1). This distribution is roughly the same for males and females (Figure 33.3).

These results highlight both a strength and weakness of voluntary web-based data collection. In terms of age and gender it is clearly the case that our data are not representative of the population. However, it is also the case that our data represent much greater diversity of subject characteristics than found in the typical university-based sample or even community-based samples such as the ESS.

Figure 33.2Although there are roughly twice as many females as males, the age distributions are roughly the same
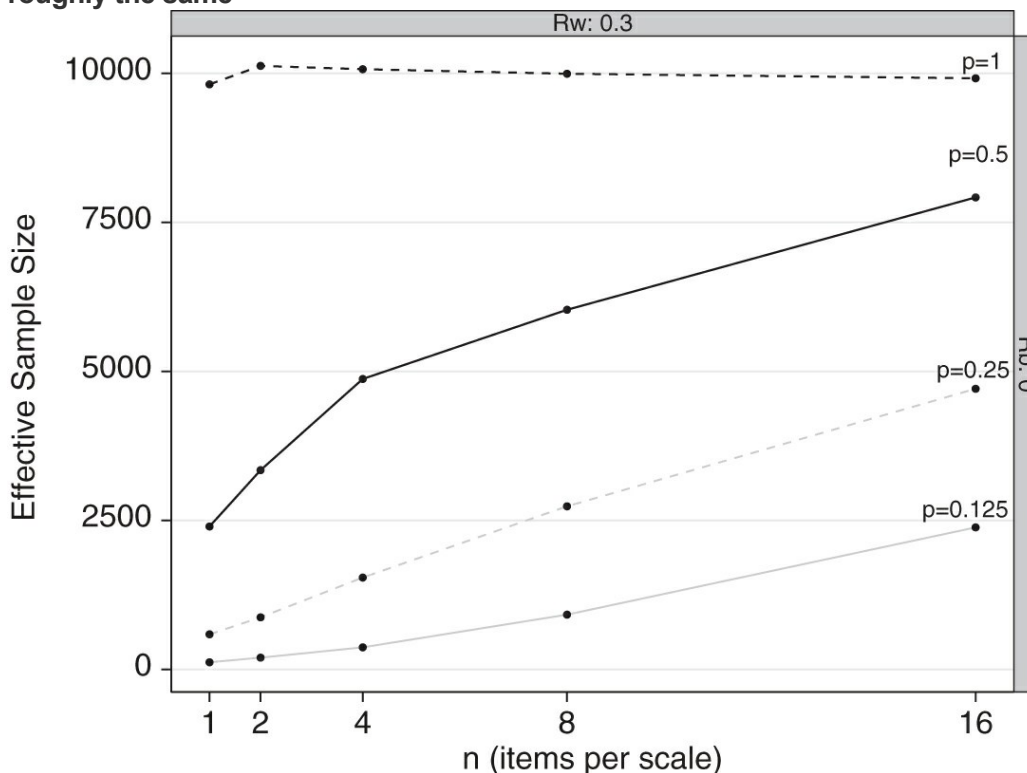
Table 33.1Highest education attained, by age

Table 33.1   Highest education attained, by age

Education level	Age					
	14–18	*19–22*	*23–29*	*30–39*	*40–49*	*50–90*
< 12 years	25,319	463	325	236		165
High school graduate	7,363	2,477	1,715	1,152	715	624
Currently in university	13,263	44,210	16,747	9,016	4,279	1,870
Some college	164	2,166	3,202	2,547	1,538	1,205
College degree	152	3,086	9,810	6,599	3,683	2,571
In graduate or professional school	164	1,089	4,860	2,031	887	386
Graduate or professional degree	42	271	3,570	5,019	3,322	3,009

Figure 33.3The female-to-male ratio of participants is highest for college students
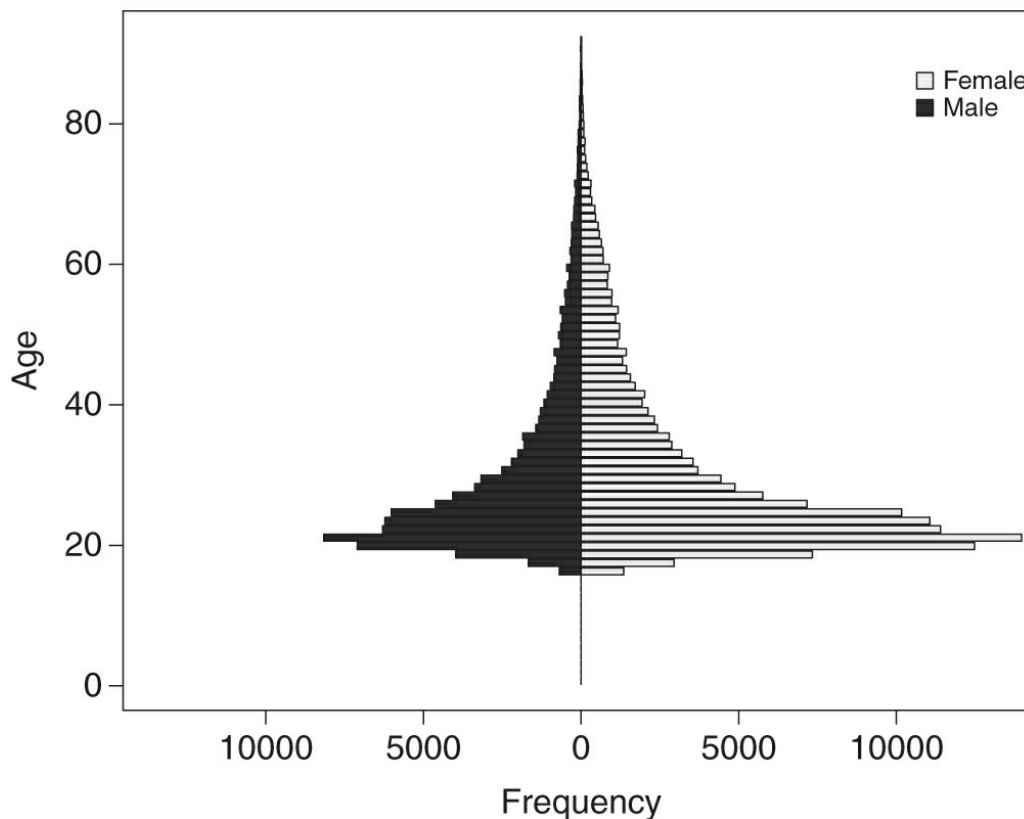
Personality Questionnaires and the ABCDs

Personality traits have been conceptualized as individual differences in patterns of affect (A), behaviour (B), cognition (C) and desire (D) over time and space (Allport, 1937; Johnson, 1997; Revelle, 2008; Winter *et al.*, 1998), and yet the most common assessments of the Big 5 traits (Costa and McCrae, 1992b; Goldberg, 1992) do not explicitly refer to these ABCD components (Pytlik Zillig *et al.*, 2002). We therefore conducted a content analysis in order to identify items for each Big 5 trait that reflected primarily one A, B, C or D content (Wilt, 2014; Wilt and Revelle, 2015). We identified items from each ABCD domain for each trait and created facet scales from these items: for example, the ABCD facet scales of agreeableness were labelled as sympathetic *affect*, considerate *behaviour*, trusting *cognition* and *desire*. Using the *psych* package (Revelle, 2015) in R (R Core Team, 2015), we employed the SAPA

technique to generate a synthetic correlation matrix containing the ABCD items assessing the Big 5. From this correlation matrix, we determined that (1) a Big 5 structure emerged from factor analysis of the items; (2) even when correcting for item overlap, using the scoreOverlap function, Big 5 trait domain scales correlated highly with their respective ABCD facet scales, (3) ABCD scales within each trait were positively correlated with each other and (4) items had strong correlations with their respective ABCD facet scale.

The Factor Structure of Personality Inventories

A primary goal of the SAPA-project for the past several years has been to examine the structural properties of a number of personality inventories that share overlapping items in the IPIP. Although there are 1,034 items contained in eight different inventories: 100 in the Big 5 marker scales (Goldberg, 1999), 100 in the Big 5 aspect scales (DeYoung *et al.*, 2007), 240 in the IPIP–HEXACO (Ashton *et al.*, 2007), 300 in the IPIP–NEO (Goldberg, 1999), 127 in the IPIP–Multidimensional Personality Questionnaire (Tellegen and Waller, 2008), 48 items in the Questionnaire Big 6 scales (Thalmayer *et al.*, 2011), and 79 in the Eysenck Personality Questionnaire (Eysenck *et al.*, 1985); there are only 696 unique items. For instance, some of the 100 items in the Big 5 factor markers (Goldberg, 1999) are the same as the ones used in the Big 5 Aspects Scales (DeYoung *et al.*, 2007). This set of 696 items includes all the items from at least 255 of the personality scales listed at the IPIP website, including IPIP items designed to match these inventories as well as the Hogan Personality Inventory, for example (Hogan and Hogan, 1995).

Based upon the correlation matrix of nearly 24,000 participants, we tested for the number of factors that would best represent the structure. Unfortunately, the exploratory factor structure of these 696 items did not yield any clean solution for the number of factors, but the most interpretable solutions represented 3, 5 or 15 factors (Condon, 2014). Most importantly, these solutions were not nested in the standard hierarchical representation reported by many, but were best described as forming a heterarchy. With careful item analysis, a set of 150 items was found to represent all levels of this heterarchy quite well, with scales that could reliably distinguish these 3, 4 or 15 dimensions. The data for the 23,681 participants and the 696 items are available for others to use through *DataVerse*, an open-source data repository (Condon and Revelle, 2015b, 2015c).

Work is underway to examine how these dimensions relate to differences in interests and desires across college majors and across occupational groups as these appetites are reflected in the interest dimensions known as the Realistic, Investigative, Analytic, Social, Enterprising, Conventional (RIASEC) (Holland, 1997).

The International Cognitive Ability Resource

Cognitive ability assessment differs from many other measures of individual differences because it requires tools that evaluate maximal performance levels rather than levels of typical behaviour. In other words, cognitive ability items are objectively scored as correct or incorrect. This important difference makes it more challenging to measure cognitive ability than other constructs; more test security is required to maintain fairness and validity. Still, researchers and clinicians are strongly motivated to employ cognitive ability measures that can provide quick, reliable and cost-efficient assessment by virtue of the fact that the many aspects of cognitive ability are highly predictive of a wide range of outcomes (Deary, 2009).

Several brief electronic measures of cognitive ability are available, but few (if any) are both widely validated and available for use in non-proctored environments (i.e. over the Internet). None exist in the public domain. The International Cognitive Ability Resource (ICAR; Condon and Revelle, 2014) was developed in order to fill this absence. Following the initial creation of four item types that were validated using the SAPA-Project, an international collaboration of German, British and American universities has since been formed to encourage the development of a range of cognitive ability measures (see icar-project.com for more information).

A prior report of the preliminary results was based upon the first 65,000 subjects (Revelle *et al.*, 2010) and a subsequent report discussed the validation of the expanded inventory with another 24,000 participants (Condon and Revelle, 2014). The data from this latter article are available in an open-source repository (Condon and Revelle, 2015a, 2016). Sample data from this project are also available as the ability data set in the *psych* package.

EXAMPLES OF SCALE DEVELOPMENT AND VALIDATION ACROSS BROAD DOMAINS

The breadth of constructs that can be simultaneously assessed using the the SAPA methodology allows for evaluation of the relative contribution of factors across broad domains of individual differences. By domains, we allude to the affective, cognitive and conative domains which have long been recognized in the social sciences (McDougall, 1923; Condon, 2014; Holland, 1959, 1997; Carroll, 1993; McGrew, 2009; Costa and McCrae, 1992a; Digman, 1990; Goldberg, 1990). If not for the use of the SAPA technique, cross-sectional evaluation of the contribution of these broad domains of individual differences to achievement would be impractical because thorough evaluation of cognitive abilities, vocational interests and temperament in addition to achievement outcomes would require several hours of participants' time and attention. We have previously reported SAPA studies on music preferences (Liebert, 2006; Revelle *et al.*, 2010) and trust (Evans and Revelle, 2008) and have since extended these to studies of psychopathy (Wright, 2014) and creative achievements.

Summary and conclusions

Telemetric methods have revolutionized the ways in which we can collect data. However, there is a natural tendency to continue our traditional reluctance to have missing observations even as we collect orders of magnitude more data. We believe that this is a mistake and have outlined the power of using a Massively Missing Completely At Random (MMCAR) item administration technique. We have shown the power of introducing such missingness into our designs. We have also emphasized the methodology and results from our web-based project (SAPA), but believe that similar techniques would be useful with modern smart phone apps.

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