Data Quality and Reliability Metrics for Event-Related Potentials (ERPs): The Utility of Subject-Level Reliability

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Abstract

Event-related brain potentials (ERPs) represent direct measures of neural activity that are leveraged to understand cognitive, affective, sensory, and motor processes. Every ERP researcher encounters the obstacle of determining whether measurements are precise or psychometrically reliable enough for an intended purpose. In this primer, we review three types of measurements metrics: data quality, group-level internal consistency, and subject-level internal consistency. Data quality estimates characterize the precision of ERP scores but provide no inherent information about whether scores are precise enough for examining individual differences. Group-level internal consistency characterizes the ratio of between-person differences to the precision of those scores, and provides a single reliability estimate for an entire group of participants that risks masking low reliability for some individuals. Subject-level internal consistency considers the precision of an ERP score for a person relative to between-person differences for a group, and an estimate is yielded for each individual. We apply each metric to published error-related negativity (ERN) and reward positivity (RewP) data and demonstrate how failing to consider data quality and internal consistency can undermine statistical inferences. We conclude with general comments on how these estimates may be used to improve measurement quality and methodological transparency. Subject-level internal consistency computation is implemented within the ERP Reliability Analysis (ERA) Toolbox.

Keywords: event-related brain potentials (ERPs); psychometric reliability; data quality; generalizability theory; multilevel modeling; error-related negativity (ERN); reward positivity (RewP)

1. Introduction

Across disciplines, scientific research is facing a replication problem and credibility crisis, in part due to poor methodological transparency and lack of clarity in research practices. A promising avenue forward is to adopt research practices aimed at improving measurement (Baldwin, 2017). In psychophysiology, researchers have placed an emphasis on identifying psychometrically reliable measurements of brain activity to determine whether these measures can be used to make valid statistical inferences in within- and between-subjects investigations (e.g., as biomarkers or endophenotypes of psychopathology; Hajcak, Klawohn, & Meyer, 2019; Hajcak, Meyer, & Kotov, 2017).

Verification of psychometric reliability[1] should be an early step in data analysis, because statistical inferences drawn from unreliable data can lead to mistaken conclusions. This can be accomplished by quantifying the internal consistency of a measure, which is a type of psychometric reliability that characterizes how well measurements can distinguish differences between people. Measurements with high internal consistency are essential for between-subjects investigations examining correlations between neural measurements and individual difference variables (e.g., depression or anxiety symptoms). Measurements with poor internal consistency in correlational analyses increase the likelihood of finding non-replicable results and missing true phenomena (Loken & Gelman, 2017). Problems with drawing valid inferences are exacerbated when combined with other study-related issues, including small sample sizes, which are common

[1] In psychological science and in the present primer, psychometric reliability, or score reliability, typically refers to how clearly average scores distinguish differences between people (i.e., between-person variability) after considering the scores that contribute to those averages (i.e., within-person variability). This definition of reliability is distinct from that used in physics, which considers how consistently an instrument measures a quantity (see Brandmaier et al., 2018). In this primer, reliability only refers to psychometric reliability.

in clinical neuroscience (e.g., Szucs & Ioannidis, 2020)–and even in studies using event-related brain potentials (ERPs; Clayson, Carbine, Baldwin, & Larson, 2019).

Current practices of establishing psychometric reliability in psychophysiological research have been grounded in determining the reliability of measurements from a group of individuals, which results in a single reliability score for the entire group. However, relying on a single group estimate might mask low reliability of scores from some participants. The fields of clinical, social, and cognitive neuroscience would benefit from adopting reliability estimates at the subject-level, which would allow researchers to determine whether subject-level data are of sufficient reliability to make valid statistical inferences. In the current manuscript, we focus on reliability estimates commonly used in ERP research and discuss the implications of using various data quality and reliability estimates at the group- and subject-level to improve and promote the clarity of ERP measurement practices across studies.

ERPs are direct measures of brain activity that assess a multitude of neuropsychological processes (e.g., sensory, cognitive, motor, and emotion-related). ERPs reflect small voltage fluctuations in the continuous electroencephalogram (EEG) that are time-locked to specific events of interest (e.g., presentation of a visual stimulus or execution of a motor response). In terms of measurement, it is important to note that ERPs reflect tiny signals that are embedded in noise. During signal processing, researchers typically average EEG data across many trials from a given paradigm to reduce the contribution of random noise to averaged activity and consequently reveal the ERP signal of interest. However, after this averaging process, an ERP researcher is left with few options to identify the overall data quality or psychometric reliability of a subject's ERP score. Some metrics have been used, including the root mean square (RMS) of the voltage in the pre-stimulus period (Luck, 2014) or signal-to-noise ratio of a given ERP

(e.g., Thigpen, Kappenman, & Keil, 2017), but have not been widely adopted or reported across studies.

Recently, Luck, Stewart, Simmons, and Rhemtulla (2020) proposed a metric referred to as the standardized measurement error (SME) that can capture how noisy a single subject's ERP score is and provide insight into the precision of an ERP score. Unlike conventional classical test theory measures, the SME can be applied at both the subject- and group-level. Researchers can use the SME to determine whether data quality is associated with observed effects and statistical power. For example, when the SME is aggregated across participants in a given experiment, researchers can take the RMS of the SME (i.e., RMS[SME]) and directly compare it to the observed between-subject variability (i.e., sample standard deviation). Inferences regarding whether the observed effects can be attributed to data quality can then be made, which highlights the potential utility of the SME in ERP research. Participants with excessively large SME for a given effect size could be removed from further analysis. Despite these uses, in isolation, the SME provides little inherent information about whether measurement precision is "high enough" for a particular purpose (e.g., comparison of ERP scores across conditions, persons, or groups). However, a bootstrapping procedure can be used to determine whether SME is small compared to a difference between two conditions of interest or group-level internal consistency can be estimated (see Luck et al., 2020). Nonetheless, there remains a need to establish subject-level estimates of internal consistency, to clarify whether the precision of an averaged ERP score is high enough given between-person differences (i.e., individual differences).

Currently, there are no established metrics to determine whether an individual's specific ERP score reflects adequate psychometric reliability for examining individual differences. Instead, efforts in establishing ERP score reliability have primarily focused on the reliability of

ERP measurements at the group level by employing either classical test theory (e.g., Boudewyn, Luck, Farrens, & Kappenman, 2017; Ethridge & Weinberg, 2018; Hajcak et al., 2017; Klawohn, Meyer, Weinberg, & Hajcak, 2020; Larson, Baldwin, Good, & Fair, 2010; Levinson, Speed, Infantolino, & Hajcak, 2017; Meyer, Riesel, & Hajcak, 2013; Olvet & Hajcak, 2009a, 2009b; Sandre et al., 2020) or generalizability theory (Carbine, Clayson, Baldwin, LeCheminant, & Larson, in press; Clayson, Baldwin, & Larson, 2021; Clayson, Carbine, Baldwin, Olsen, & Larson, in press; Clayson et al., 2020; Clayson & Larson, 2019; Clayson & Miller, 2017a, 2017b; Ethridge & Weinberg, 2018; Levinson et al., 2017; Sandre et al., 2020) to determine the consistency of scores across repeated observations (e.g., within-session and/or across testing sessions). Although these approaches offer important insight into ERP score reliability at the group level, they provide no information about subject-level ERP reliability.

There are important implications for determining the psychometric reliability of ERP scores at the subject level. Consistent with traditional signal averaging approaches used in ERP research (e.g., Woodman, 2010), it is often assumed that the meaningful variability in ERP scores primarily occurs between rather than within persons; however, recent research shows that ERP scores may change over the course of experimental paradigms (e.g., Berry, Tanovic, Joormann, & Sanislow, 2019; Brush, Ehmann, Hajcak, Selby, & Alderman, 2018; Volpert-Esmond, Merkle, Levsen, Ito, & Bartholow, 2018), suggesting a need for person-specific psychometric reliability estimates. Extending psychometric reliability to an individual person has the advantage of permitting researchers to examine individual differences in reliability, which has largely been ignored.

When researchers are interested in using ERPs in studies of individual differences or dimensional constructs (i.e., examining correlational relationships between ERPs and other

individual-difference measures), it is important to know whether the reliability of a person's ERP score is compatible with group-level internal consistency estimates. In this case, subject-level internal consistency estimates could be directly compared to the group-level internal consistency estimate to determine how well the group-level internal consistency estimate characterizes each individual (Williams, Martin, DeBolt, Oakes, & Rast, 2020; Williams, Martin, & Rast, 2019; Williams, Mulder, Rouder, & Rast, in press). In instances of mischaracterization, researchers could focus on individual cases of unreliable ERP scores to determine the impact of a host of factors on reliability, including recording characteristics (e.g., electrode impedance), the presence of artifacts, or person characteristics. Researchers could also use subject-level internal consistency estimates as predictor or criterion variables in explanatory models. As predictors, subject-level internal consistency estimates could be used to determine their influence on observed effect sizes and statistical power. As a criterion, researchers could examine whether specific between- or within-subjects variables are associated with different levels of reliability.

Evaluating subject-level data quality and psychometric reliability is also consistent with promoting transparency in research practices (Keil et al., in press; this special issue). In ERP research, the decision to include or exclude a subject's ERP data in statistical analyses is largely left up to the researcher's discretion and is often based on various criteria. For example, this decision could be based on an a priori established threshold (e.g., < 50% of artifact-free trials retained in a subject's ERP score), a minimum number of artifact-free trials retained in their averaged ERP based on group-level internal consistency estimates (e.g., range of 2-15 error trials for ERN; Fischer, Klein, & Ullsperger, 2017; Larson et al., 2010; Meyer et al., 2013; Olvet & Hajcak, 2009b; Pontifex et al., 2010; Steele et al., 2016), or visual inspection. This lack of standardization results in increased researcher degrees of freedom that stands in the way of

promoting transparency and rigor of ERP research. Implementation of subject-level internal consistency estimates may help determine whether data quality is high enough to make valid inferences in both within- and between-subjects questions. In particular, subject-level internal consistency estimates provide objective indicators of whether an individual person's data is of sufficient quality to be included in a study. Adopting subject-level internal consistency estimates would also allow the field to move toward standardization and would ultimately increase the transparency and clarity of measurement by shedding light on the factors that impact internal consistency.

In the current manuscript, we provide an overview of the various estimates that have been typically used to examine data quality and score reliability in ERP studies. We then extend this by discussing the importance of quantifying subject-level internal consistency estimates of ERP scores and have structured the manuscript as follows. First, we describe three different types of data measurement metrics (i.e., data quality, group-level internal consistency, and subject-level internal consistency) and outline situations where one estimate may be preferred over another. Then, we illustrate the application of these estimates by applying them to two published datasets on the reward positivity (RewP; Klawohn, Burani, Bruchnak, Santopetro, & Hajcak, 2020) and error-related negativity (ERN; Klawohn, Santopetro, Meyer, & Hajcak, 2020). In this section, we provide commentary on the coupling between data quality and both group- and subject-level internal consistency estimates, and describe the inherent challenges associated with characterizing the quality of ERP measurements with a single score. We then extend our application to between-subjects investigations and provide an overview of the influence of score reliability on between-subjects effects and how reliability impacts the validity of statistical inferences. Lastly, we summarize the importance of examining and reporting data quality and

reliability estimates. We conclude with general comments on the way in which these estimates may be directly integrated into the broader literature to improve the rigor and clarity of ERP measurements.

2. Measurement Metrics

We now describe three different types of estimates: data quality, group-level internal consistency, and subject-level internal consistency. These estimates represent scores from individual trials, *i*, recorded from within a person, *j*, within a group, *k*. Internal consistency is an estimate of psychometric reliability and characterizes the homogeneity of test observations (i.e., ERP trials). Internal consistency estimates are often scaled using the between-person variability (e.g., coefficient alpha from classical test theory), and they tend to be high when between-person variability in trials is large compared to within-person variability in trials. Hence, estimates of internal consistency are useful for characterizing whether data are suitable for examining individual differences. If between-person variability in trials is low compared to within-person variability (i.e., low internal consistency), then trials are likely too variable to be of much value for examining individual differences.

2.1 Data Quality

Data quality can be conceptualized as an estimation of true signal relative to measurement error, and estimates of ERP data quality typically characterize the between-trial variability of scores from an individual person. These estimates shed light on the precision of ERP scores and are influenced by factors that contribute to measurement error, which can vary across participants and be impacted by any factor that contributes to background noise, such as participant movement, orientation of neural generators due to individual-specific cortical folding, and nonneural bioelectric signals (Clayson, Kappenman, Gehring, Miller, & Larson, in press;

Luck et al., 2011). In the typical ERP study, many trials are averaged together with the assumption that error is random so that averaging will "cancel out" the error and improve the signal-to-noise ratio of the ERP estimate.

The SME was recently proposed as an estimate of data quality (Luck et al., 2020). The SME is computed for a time-window mean ERP amplitude scoring approach (e.g., average ERP activity between 0 and 100 ms locked to a response) by using the formula for the standard error of the mean; however, as recommended by Luck et al. (2020), this estimate is to be referred to as the SME when quantifying data quality (SME is an umbrella term for the data quality estimates recommended in Luck et al., 2020). We provide the formula for the standard error of the mean below, which is referred to as SME (notation was changed to match the current manuscript's notations; Luck et al., 2020).

$$SME_{ij} = \frac{\sigma_{ij}}{\sqrt{n_{ij}}} \quad \text{(Eq. 1)}$$

The SME_{ij} for trial scores, *i*, from a given person, *j*, is estimated by calculating the standard deviation[2] of the single-trial scores for a given person (σ_{ij}) and dividing by the square root of the number of trials (n_{ij}). As a note, the subscript *k* is intentionally ignored here to emphasize that SME is estimated for data from a single participant, and no information from a group is used in its estimation. Conceptually speaking, SME_{ij} is "the standard error of measurement for an ERP amplitude or latency score, assuming that the score is obtained from a single participant's average ERP waveform" (Luck et al., 2020, p. 5). An advantage of SME is that it provides an

[2] The SME uses the sample standard deviation, not population standard deviation. However, the Greek letter, σ, is used for clear comparison to the generalizability theory formulas that follow.

estimate of data quality specific to the ERP measurement approach used (e.g., the time-window mean amplitude from a specified time window for the scores later used in statistical analysis). The present manuscript focuses solely on the estimation of SME for time-window mean amplitude approaches for the sake of simplicity (for application of SME to other measurement approaches see Luck et al., 2020).

Higher SME scores reflect greater measurement error than lower SME scores. A participant with few trials will have a larger SME than a participant with many trials when between-trial standard deviations (σ_{ij}) for the two participants are identical. This characteristic is consistent with the majority of applied ERP research, which averages all trials for a given event type together.

An alternative approach for estimating data quality for a given participant that is not heavily impacted by the number of trials retained for averaging is to simply estimate a between-trial standard deviation for a person (σ_{ij}). A standard deviation is a measure of dispersion (i.e., spread of the data). In the context of ERPs, between-trial standard deviations represent a trial-independent estimate of data quality. Its relationship to Equation 1 is also straightforward. Data with large between-trial standard deviations will require more trials than data with small between-trial standard deviations to achieve the same SME.

The SME and between-trial standard deviation provide meaningful estimates of data quality for a person's ERP scores. However, a common goal of ERP studies is to describe differences between conditions within a person (e.g., correct vs. error), between individual persons (e.g., correlation between ERP scores and measures of depression symptoms), or between groups of people (e.g., healthy controls vs. people with clinical depression). These data quality estimates provide no information about whether between-trial variance is small compared

to between-condition, -person, or -group variance. Whether between-trial variance is small "enough" is dependent on how data are recorded and the intended comparisons. The same estimate of between-trial variance could be small relative to between-group differences but large relative to between-person differences (e.g., the difference between group average scores could be very large but the difference between average participant scores within a single group could be very small).

2.2 Group-Level Internal Consistency Estimates

Group-level estimates of internal consistency are often used to demonstrate whether differences between person averages are larger than the differences between the trials that comprise those averages. In other words, group-level estimates indicate whether between-person variance (i.e., differences between person average scores) is larger than the average between-trial variance (i.e., differences between trial scores within a person), which justifies subsequent analysis of individual differences (e.g., relationship with other correlates). A common approach to estimating the internal consistency of ERP scores is to compute the split-half parallel estimate (r_{xx}), which is derived from classical test theory (Cho, 2016; Nunnally & Bernstein, 1994). Split-half internal consistency involves splitting data into two parallel halves and computing the correlation between the halves. Given that the data are reduced by half, the observed correlation is then adjusted using the Spearman-Brown prophecy formula to predict the internal consistency of the full length of the test (Brown, 1910; Spearman, 1910).

In ERP research, split-half internal consistency is typically estimated by scoring the ERP on odd- and even-numbered trials, separately; the correlation between scores on odd and even trials indicates the amount of reliable variance within subjects – the tendency for a person's scores to be similar across subsets of trials. An advantage of computing split-half internal

consistency over coefficient alpha (i.e., Cronbach's alpha) is that all available ERP scores are used in its estimation, while the estimation of coefficient alpha requires each participant to have the same number of trials. Coefficient alpha is conceptually akin to the average of all possible split halves (Cronbach, 1951). However, ERP trials are typically unbalanced across participants due to artifact rejection parameters or participant behavioral responses (e.g., correct vs. error trials). A disadvantage of split-half internal consistency is that internal consistency is estimated based on one of many possible ways to split the data. Any single split-half estimate might not accurately represent the internal consistency of all ERP trials. Furthermore, when few trials contribute to an average ERP score, the derived average scores from each half can be unstable for different ways of splitting the data (see Figure 1).

Estimates from generalizability theory can overcome this disadvantage by using ERP scores from all trials in the estimation of internal consistency, which removes the sampling error endemic to selecting an approach to split the data (Baldwin, Larson, & Clayson, 2015; Carbine et al., in press; Clayson, Carbine, et al., in press; Clayson & Miller, 2017a, 2017b). Within classical test theory, an observed score represents the summation of the "true" score and a unitary measurement error. Generalizability theory uses a multifaceted framework for estimating score reliability and can consider multiple sources of variance, such as the number of trials retained for averaging, measurement occasion, diagnostic group, or event type, in addition to unaccounted for measurement error. Generalizability theory can also handle unbalanced designs, does not require the use of parallel forms, and can pinpoint different sources of variance that contribute to average scores. The dependability coefficient (ϕ) from generalizability theory represents an estimate of internal consistency that is analogous to coefficient alpha from classical test theory (Shavelson & Webb, 1991). The dependability coefficient differs from coefficient alpha in that it accounts for

the consistency of absolute differences in scores and the relative standings of individuals (coefficient alpha only considers the latter). The formula for calculating dependability is provided below, and its full derivation for use in ERP research can be found elsewhere (Baldwin et al., 2015; Clayson & Miller, 2017a).

$$\phi_k = \frac{\sigma_p^2}{\sigma_p^2 + {\sigma_{ik}^2}\Big/{n'_{ik}}} \quad \text{(Eq. 2)}$$

Group-level dependability (ϕ_k) is estimated as function of between-person variance (σ_p^2), between-trial variance (σ_{ik}^2), and a given number of trials (n'_{ik}). The subscript for a person, *j*, is intentionally ignored in the between-trial variance notation, σ_{ik}^2, to emphasize that this estimate conceptually represents an average estimate of between-trial variance across all persons. The number of trials used for n'_{ik} is a central tendency estimate (e.g., mean or median) for the number of included trials for a group of participants.

A disadvantage of these group-level internal consistency estimates is that they consider between-trial variance (i.e., residual/error variance) to be constant across participants. The assumption of constant between-trial variance might not be reasonable in all cases. For example, it is conceivable that some participants might have lower intraindividual variability in ERP scores (i.e., low between-trial variance) and others might have higher intraindividual variability in ERP scores (i.e., high between-trial variance) than the average group member. As a result, a group-level internal consistency estimate would likely mischaracterize the "true" internal consistency of ERP scores for either person.

2.3 Subject-Level Internal Consistency Estimates

Subject-level estimates of internal consistency represent a hybrid between group-level internal consistency and person-specific data quality. These estimates relax the assumption of constant (i.e., homogenous) between-trial variance across participants, which allows for a comparison of different person-specific between-trial variances. The formula for estimating subject-level internal consistency is an extension of the dependability formula from Equation 2.

$$\phi_{jk} = \frac{\sigma_p^2}{\sigma_p^2 + {\sigma_{ijk}^2}/{n_{ijk}}} \quad \text{(Eq. 3)}$$

Subject-level dependability for a given person, *j*, from a group, *k*, (ϕ_{jk}) is computed as function of between-person variance (σ_p^2), person-specific between-trial variance (σ_{ijk}^2), and the person-specific number of included trials (n_{ijk}). Conceptually speaking, the ϕ_{jk} is a ratio representing the size of between-person differences in average scores from a group compared to the variability of single-trial scores that contribute to an individual person's average. A key characteristic of subject-level internal consistency is that it uses person-specific estimates of between-trial variance that can vary across participants. A second characteristic is that each person-specific between-trial variance estimate is coupled with their own number of trials. Unlike group-level estimates, an internal consistency estimate is provided for each person, and internal consistency estimates for individual persons within a group can be compared. These estimates can also be compared against the group to determine whether the group-level estimate adequately characterizes individuals (see Williams et al., 2020; Williams et al., 2019; Williams et al., in press).

The interpretation of subject-level internal consistency is similar to that of group-level estimates, because Eq. 3 uses the same generic formulation (between-person variance/total variance, and total variance is the summation of between-person and within-person variances). Therefore, an estimate of internal consistency characterizes the size of between-person variance relative to total variance. Subject-level internal consistency ranges between 0 and 1, with estimates closer to 1 indicating higher internal consistency (i.e., dependability). When within-person variance is *high* relative to total variance, subject-level internal consistency will be closer to 0 (i.e., between-person variance is likely too low, given within-person variance, for examining individual differences). When within-person variance is *low* relative to total variance, subject-level internal consistency will be closer to 1. Scores with high internal consistency (e.g., > .80) are well suited to examining individual differences between participants, such as in correlational analyses (see Clayson & Miller, 2017b). The impact of between-trial variance, σ^2_{ijk}, on subject-level internal consistency can be reduced by increasing the number of trials retained for averaging for a given person, n_{ijk}. Different subject-level internal consistency can be observed for people with the same number of trials, n_{ijk}, but different between-trial variances, σ^2_{ijk}. This illustrates that a person with low data quality (i.e., high between-trial variance) would need more trials to obtain the same estimate of subject-level internal consistency as a person with high data quality.

An estimate of subject-level internal consistency can also be calculated that is independent of the number of trials retained for averaging. Equation 3 is an extension of Equation 4 below, which is a generalization of the intraclass correlation coefficient (ICC). The derivation of the subject-level ICC (i.e., individually-varying ICC) is provided in detail elsewhere (Williams et al., 2019; Williams et al., in press).

$$ICC_{jk} = \frac{\sigma_p^2}{\sigma_p^2 + \sigma_{ijk}^2} \quad \text{(Eq. 4)}$$

The person-specific ICC_{jk} is a function of between-person variance, σ_p^2, and between-trial variance, σ_{ijk}^2. Unlike the subject-level dependability estimate (ϕ_{jk}), this ICC provides an estimate of internal consistency that is independent from the number of retained trials for a given person. If there is little difference in between-trial variance estimates for persons within a group, then ICCs will be similar across individuals. If, however, between-trial variance is not stable across participants, then ICCs will also vary across people.

3. Application of Internal Consistency and Data Quality Estimates

We now apply data quality and internal consistency estimates covered above to two published datasets on the reward positivity (RewP) and error-related negativity (ERN). We also generally compare the different metrics to demonstrate how to interpret them. The RewP (Klawohn, Burani, et al., 2020) and ERN data (Klawohn, Santopetro, et al., 2020) are from the same 83 participants with major depressive disorder (MDD) and 45 healthy controls, and the reader is directed to the published articles for a discussion of the RewP and ERN findings as they relate to depression. The focus of this primer is on the data quality and internal consistency. Data from both groups are summarized in Tables 1 and 2.

For all relevant characteristics of data recording and reduction, see the published articles (for the doors task, see Klawohn, Burani, et al., 2020; for the flanker task, see Klawohn, Santopetro, et al., 2020). Briefly, for the doors task, single-trial ERP scores were extracted from feedback-locked epochs and quantified as the average activity from 250 to 350 ms at electrode FCz following the presentation of feedback that indicated a gain (i.e., reward) or a loss. For the flanker task, single-trial ERP scores were extracted from response-locked epochs and quantified as the average activity from 0 to 100 ms at electrode FCz following a correct or error response.

The advantage of comparing RewP and ERN data within the same participants is that it allows for an examination of fairly balanced data from a modest number of fixed trials (RewP, see Table 1) and very unbalanced data from a wide range of trials (ERN, see Table 2). The data from these two different ERPs and tasks will help shed light on the impact of numbers of trials on data quality and internal consistency.

Mixed-effects models were used in the estimation of group-level dependability, subject-level dependability, and subject-level ICCs. A standard mixed-effects model is used to estimate variance components for group-level dependability (Baldwin et al., 2015; Clayson & Miller, 2017a). In this standard model separate intercepts are fit for each participant (i.e., random intercepts), and the residual variance (i.e., between-trial variance) across participants is fixed. An extension of the standard mixed-effects model is the mixed-effects location scale model, which relaxes the assumption of fixed residual variance across participants (Williams et al., 2019; Williams et al., in press). Mixed-effects location scale models are used to model individual-subject between-trial variances that can subsequently be used to estimate subject-level dependability and ICCs. A defining characteristic of both types of mixed-effects models is that information is partially pooled across parameters to improve their estimation.

The use of partial pooling is a key distinction between the estimation of between-trial standard deviations for subject-level internal consistency in Eq. 3 and SME_{ij} in Eq. 1. Partial pooling in mixed-effects models combines information across participants (i.e., between-person variance) and across trials from each individual subject (i.e., between-trial variance), which results in more efficient parameter estimates than the arithmetic solution (e.g., Gelman, 2006; Gelman et al., 2012). When information is partially pooled across participants, extreme observations are pulled toward or “shrunk” closer to the group mean, because participants from

the same population are expected to be similar to each other. Partial pooling is useful in ERP psychometric reliability estimation, because shrinkage most strongly impacts participants with few trials to improve parameter estimation.

To estimate variance components for each mixed-effects model, Bayesian models that use Markov Chain Monte Carlo (MCMC) estimation procedures were used (Gelman et al., 2013). Specifically, MCMC estimation procedures used 4 chains of 10,000 iterations each within the R (R Development Core Team, 2020) package *brms* (Bürkner, 2017, 2018) to estimate the variance components. Convergence of chains was confirmed by verifying that the potential scale reduction for the scalar estimands ($\hat{R}$) were below 1.1, by verifying the effective sample size for each scalar estimand was greater than 40 (10 times the number of chains), and by visual inspection of trace plots (Gelman et al., 2013; Lunn, Jackson, Best, Thomas, & Spiegelhalter, 2012). Variance components can also be estimated using two freely available open-source packages: the *vICC* package[3] in *R* (https://github.com/donaldRwilliams/vICC; Williams, 2020) or using the ERP Reliability Analysis (ERA) Toolbox in MATLAB (https://github.com/peclayson/ERA_Toolbox; Clayson, Carbine, et al., in press; Clayson & Miller, 2017a). The ERA Toolbox is open-source software that uses generalizability theory to characterize the internal consistency and test-retest reliability of ERP scores and implements the generalizability theory formulas from the present manuscript.

3.1 Data Quality

The two data quality estimates of interest, SME (SME_{ij}) and between-trial standard deviations (σ_{ij}), are summarized in Tables 1 and 2 for both groups and shown in Figure 2 for

[3] Another useful *R* package is *ICCier* (Williams et al., 2020). The package uses mixed effects location scale models to estimate variance components for use in applications of classical test theory reliability.

participants with MDD (see Supplemental Figure 1 for healthy controls)[4]. The most visually striking aspect of the plots in Figure 2 is the strong linear relationship between SME and between-trial standard deviations. When the number of trials included in an estimate is very similar across persons, as is the case for RewP to gain and loss trials (*SD*s ~ 1), there should be a near perfect relationship between the two estimates. SME is simply the between-trial standard deviation, σ_{ij}, divided by the square root of the number of trials (see Equation 1), and when the number of trials is nearly identical for each participant, SME basically amounts to dividing all participant's between-trial standard deviations by a constant.

Conversely, when the number of recorded trials is dissimilar across participants, there is a weaker relationship between SME and between-trial standard deviations. For ERN data there is high variability in the number of trials (*M* = 30.1, *SD* = 14.7 for participants with MDD; *M* = 27.4, *SD* = 12.3 for healthy controls) with as few as six trials retained for averaging (see Table 1). These aspects of ERN data lead to a weaker relationship between SME and between-trial standard deviations. If fairly similar between-trial variances are assumed, SME should be smaller on average for those participants with many error trials than those for with only a few. However, a strong relationship is observed when many trials are recorded, as is the case for CRN (*M* = 299.1, *SD* = 20.9 for participants with MDD; *M* = 301.6, *SD* = 17.8 for healthy controls). If between-trial standard deviations were held constant and the number of trials increased from 1 to 300, a nonlinear relationship would be observed between SME and between-trial standard

[4] Figures are included to show the relationship between measurement metrics in general, rather than the relationship of the metrics in any particular group of participants. As such, only figures for participants with MDD are shown in the manuscript, and the remaining figures for controls are shown in the supplemental material.

deviations (see Equation 1). A more rapid decrease in SME would be expected across an increasing number of trials in low trial-count data than in high-trial count data.

As acknowledged by Luck et al. (2020), it is difficult to know what constitutes a "small enough" SME score (and between-trial standard deviation, for our purposes). Comparing SME estimates among participants can shed light on which participants might have poor data quality relative to other participants within a group. For example, in the top left panel of Figure 2 there is a participant that appears to have poor data quality (high SME and between-trial standard deviation) relative to other participants in the group. However, what SME value constitutes poor data quality really depends on the intended purpose of the measurement, and it likely has no universal meaning across ERPs. A heuristic recommended by Luck et al. (2020) is to consider SME scores in the context of psychometric reliability.

3.2 Group-Level Internal Consistency

The two relevant group-level estimates of internal consistency, split-half internal consistency (r_{xx}) and group-level dependability (ϕ_k), are summarized in Tables 1 and 2. For ERN and RewP data, split-half internal consistency and group-level dependability are fairly similar, and the 95% credible intervals for dependability include each split-half internal consistency estimate, except for the ERN estimates in healthy controls. The question of which internal consistency estimate is "better" is a theoretical one.

Split-half internal consistency and group-level dependability estimates are more likely to diverge when there are few trials than when there are many trials due to sampling error endemic in split-half internal consistency. When there are few trials, sampling error can have a large impact on the stability of split-half internal consistency estimates due to the variability in estimating a mean score from only half of the data (see Figure 1). For example, a split-half

estimate will be more limited by sampling variability when halving six trials than when halving 300 trials. This is likely why the numerical difference is larger between split-half internal consistency and group-level dependability for ERN than it is for CRN. In healthy controls, the estimated credible interval for ERN score dependability does not contain the split-half internal consistency, and it is possible that the split-half internal consistency is underestimating the internal consistency due to sampling error. It is also possible for split-half internal consistency to overestimate the internal consistency due to the same sampling error. Hence, generalizability theory coefficients of internal consistency likely provide more robust estimates of ERP score internal consistency when few trials are available. On the other hand, both the split-half internal consistency and group-level dependability estimates are nearly identical for CRN scores due to the many trials retained for averaging, which mitigates the impact of sampling variability on split-half internal consistency estimates. If a researcher wishes to operate within the classical test theory framework, the average of randomly resampled[5] split-half internal consistency coefficients could be estimated to characterize ERP score internal consistency (see Clayson et al., 2021).

3.3 A Comparison of Data Quality and Group-Level Internal Consistency

Group-level internal consistency provides some context for data quality estimates and helps to clarify whether data quality estimates are "small enough" for an intended purpose. Estimates of internal consistency provide an estimate of the size of between-person variance to total variance (total variance = between-person variance plus between-trial variance). If between-

[5] The use of split-half internal consistency is also covered in detail in the Appendix of Clayson et al. (2021). Different split-half estimates that rely classical test theory, such as a Pearson correlation coefficient of two-part coefficient alpha, can also be randomly resampled within widely available software, such as the Microsoft Excel-based package REL$_{EX}$ (Steinke & Kopp, 2020) or in the *R* package *splithalf* (Parsons, 2020).

person variance is held constant, small between-trial variance will yield higher internal consistency than large between-trial variance. Hence, the precision of ERP score measurements can have a substantial impact on internal consistency. Estimates of internal consistency simply clarify whether ERP data quality is high enough to examine individual differences between persons by quantifying the proportion of between-person variance to total-score variance.

Between-person variance also has a large impact on internal consistency. If between-trial variance is held constant, small between-person variance will lead to lower internal consistency than large between-person variance. Hence, data from the same person can be psychometrically reliable in one context, but not another, depending on the between-person variance of the group. Group heterogeneity in average scores is important to achieve adequate internal consistency for studying individual differences between people. This aspect of psychometric reliability sheds light on why measurements that show large between-condition or between-group differences can yield poor reliability (Fröhner, Teckentrup, Smolka, & Kroemer, 2019; Hedge, Powell, & Sumner, 2017; Infantolino, Luking, Sauder, Curtin, & Hajcak, 2018). Furthermore, any factor that might impact between-person or between-trial variance can impact psychometric reliability within and between studies (Clayson, 2020).

Although data quality estimates provide little useful information to justify comparing individual differences with external correlates, they can help to justify the data quality is high enough to compare between-condition and between-group differences. For example, if the difference between two conditions were 5 μV and the RMS[6] of SME for each condition were

[6] The root mean square is used, instead of the arithmetic mean, because standard deviations cannot be directly summated. To summate standard deviations, they must first be squared. After summation, the square root of the added squared standard deviations (i.e., variances) is calculated to convert the scores back to the units of measurement.

below 2 μV, then data quality would likely be high enough to justify the comparison of the two conditions (see Luck et al., 2020). In such an instance, it could still be reasonable to compare scores between the two conditions in the presence of little-to-no between-person variance for each separate condition (i.e., poor ERP score reliability for each separate condition). Taken together, data quality estimates become interpretable once the comparison of interest is known and then a decision can be made about whether precision is high enough for the comparison.

3.4 Subject-Level Internal Consistency

Estimates of subject-level internal consistency circumvent the assumption of constant between-trial variances across participants. Individual subject-level dependability and ICCs are plotted in Figures 3 and 4 for people with MDD (see Supplemental Figures 2 and 3 for healthy controls), respectively, in ascending order of smallest to largest point estimates. Summary statistics for these estimates are also summarized in Tables 1 and 2. Data for a person with 95% credible intervals (i.e., the Bayesian analog to confidence intervals) that do not include the group-level estimate using the standard mixed-effects models[7] are highlighted in blue. These plots provide a simple visualization of how well group-level internal consistency characterizes individual participant data, and those readers interested in formally testing whether group-level internal consistency estimates reasonably apply to person-specific data are directed to Williams et al. (2019).

Group-level dependability estimates (which are impacted by the number of recorded trials) and group-level ICCs (which are not impacted by the number of recorded trials)

[7] A population residual variance is estimated during the fitting of the mixed-effects location scale models. This population residual variance could be used to estimate group-level internal consistency. However, for comparison's sake the group level-reliability estimate for the standard mixed-effects models is used.

mischaracterized data for 20-36% and 7-33% of participants, respectively (see Figures 3 and 4). The differences between persons is striking when the range of estimates is considered (see Tables 1 and 2). In participants with MDD, the range of subject-level ICCs for ERP scores for gain trials was .02 to .58, which represents a 29-fold increase from the least to most reliable score. These findings indicate that the large between-person differences in between-trial variance (i.e., intraindividual variability) limits how well group-level internal consistency characterizes data for individual persons.

The relationship between dependability coefficients and ICCs begins to weaken in the context of few trials retained for averaging and highly variable numbers of trials, such as in the case of ERN. This is due to the same considerations that impacted the relationship between SME and between-trial standard deviations above: if a participant has a large between-trial variance, its impact can be minimized if many trials are recorded (see Equation 3).

3.5 Comparison of Data Quality and Subject-Level Internal Consistency

Subject-level internal consistency clarifies whether person-specific data quality is high enough for an examination of individual differences. The added benefit of subject-level internal consistency is that person-specific data quality estimates are used in their estimation. Hence, the trial-dependent and trial-independent estimates of data quality and subject-level internal consistency should be fairly related when between-person variance is high (see Figures 6 and 7 for participants with MDD; see supplemental Figures 5 and 6 for healthy controls). Furthermore, in the context of moderate or high between-person variance, the trial-dependent and trial-independent estimates of subject-level internal consistency should closely mirror the companion data quality estimates (SME, between-trial standard deviations) because between-person variance is constant.

There are circumstances when the relationship between data quality and subject-level internal consistency would be expected to weaken. When between-person variance is moderately low and between-trial variance is fairly high, it can be difficult to obtain adequate score internal consistency. The impact of data quality on internal consistency can be minimized by recording many trials. For example, in ERP studies of auditory brainstem responses between-trial variance is large compared to between-person variance, but adequate internal consistency can still be obtained by recording several thousand trials over the course of 15 minutes (Clayson et al., 2020). However, recording thousands of trials is not feasible for many ERPs. For example, when more trials are recorded in the pursuit of higher internal consistency, it is possible that nuisance factors (e.g., changes in cognitive or affective state) might impact the signal of interest and alter the validity of the measurement, even if higher internal consistency is observed. The extent to which this is problematic is dependent on the ERP of interest and is a question for the data in hand.

Another instance when it may be nearly impossible to obtain adequate internal consistency is when there is little-to-no between-person variance. Although somewhat counterintuitive, it is conceivable of an instance that ERP scores for a given group of participants are nearly identical, which would result in very low between-person variance. In such instances it is very unlikely that ERP scores would yield adequate internal consistency, because all ERP recordings are impacted by nuisance factors that impact background noise, which will lead to some between-trial variance. Theoretically, if there is no between-person variance (all person averages are identical), then psychometric internal consistency would be zero (even with high data quality). ERP scores that mimic this scenario would be very poorly suited to examining

individual differences with external correlates, despite potentially being useful for between-condition or between-group comparisons.

The relationship between SME_{ij} and ϕ_{jk} is clear from their formulas shown in Equations 1 and 3. ϕ_{jk} essentially uses an approximation of ${SME_{ij}}^2$ (σ^2_{ijk}/n_{ijk}), and scales it using the between-person variance to communicate the size of individual differences in average scores compared to the single-trial data that contribute to those scores. Therefore, a person's data could have high internal consistency in one group but low internal consistency in another group, despite that SME_{ij} would be identical. ϕ_{jk} is conceptually an estimate of data quality for an intended purpose (i.e., is data quality high enough to examine individual differences in this sample of participants?). An important distinction between the σ^2_{ijk} used in ϕ_{jk} and the SME_{ij} is that σ^2_{ijk} is estimated using multilevel models, which takes advantage of partial pooling to improve parameter estimation (see section 3). The ICC_{jk} from Eq. 4 also uses σ^2_{ijk}, which is the square of the numerator from Eq. 1, and ICC_{jk} also is estimated using multilevel models.

4. Impact of Internal Consistency on Between-Group Effects

Numerical group differences were observed for many of the estimates of internal consistency, but it is unclear how much impact ERP score internal consistency has on the magnitude of between-group ERP differences. The literature suggests that psychometrically unreliable data can dramatically impact not only between-person effects (i.e., relationships with external correlates) but also between-group effect sizes (Hajcak et al., 2017). For example, unreliable scores can lead to magnitude or sign errors in between-group relationships (Flegal, Kit, & Graubard, 2017; Gelman & Carlin, 2014) and reduced statistical power (Boudewyn et al., 2017; Clayson & Miller, 2017b; Fischer et al., 2017; Kolossa & Kopp, 2018; Luck & Gaspelin,

2017). To demonstrate how internal consistency impacts between-group differences in ERPs, we systematically evaluated whether a range of subject-level dependability coefficients impacted the magnitude of group differences between healthy controls and people with major depressive disorder. For this demonstration, subject-level dependability estimates were chosen over data quality estimates due to their ease of interpretation. Furthermore, when between-person and within-person variance estimates are constant, changes in the numbers of trials included in a subject average will only impact the precision of the estimate (see Eq. 3).

We examined group differences for CRN amplitude, because all participants had many CRN trials, which allowed for an examination of a wide range of dependability coefficients, from .10 to .90 in increments of .01. Furthermore, all participants were able to be used in all analyses, which circumvents issues related to statistical jitter in the between-group effect size due to variability from removing participants at higher levels of internal consistency (due to a participant having an insufficient number of trials to obtain a given level). To simulate data at each dependability coefficient, trials were randomly sampled without replacement from each participant based on the person-specific estimate of the number of trials needed to obtain a given subject-level dependability coefficient[8]. This random sampling procedure was used to avoid sampling error associated with any one draw of the data and used 10,000 iterations for each subject at each dependability level. Cohen's *d* was used as a measure of between-group effect size (Cohen, 1988). To avoid the biasing effects of heterogeneity of error variances, equal

[8] In other words, the specific number of trials that a participant needed to obtain a subject-level dependability coefficient was used, so a different number of trials could be used from each participant. When the number of trials estimated to achieve a given dependability coefficient was not an integer, the number of trials used in the random sampling procedure was always rounded up to the next integer.

variances were not assumed, and pooled standard deviations were used in the calculation of effect sizes (Bonett, 2008).

Figure 8 shows the relationship between subject-level dependability estimates[9] and Cohen's *d*. The solid line represents the average of the point estimates of Cohen's *d* for a given dependability estimate shown on the *x* axis, and the dashed line shows a Cohen's *d* of 0.58, which is the observed effect size for the between-group comparison when including all trials for each individual in analysis. The dark shaded regions correspond to the 95% confidence interval for the observed point estimates, and the light shaded regions represent the minimum to maximum for the point estimates. The mean of the point estimates increased as the dependability threshold increased (from 0.28 to 0.55; see Figure 8). The variability in Cohen's *d* for each threshold also decreased as dependability increased. Point estimates were between -0.34 and 0.99 (range = 1.33) for a dependability cutoff of .10 and between 0.28 to 0.87 (range = 0.59) for a dependability cutoff of .90. For the sake of simplicity, we assumed that between-person and within-person variances were constant across the sampling procedures. It is important for future work to assess the stability of variance estimates and their impact on subject-level internal consistency of ERP scores when the number included trials varies.

It is clear that increases in internal consistency were related to increased effect sizes for between-group comparisons of CRN. For example, increasing internal consistency changed the qualitative effect size interpretations of between-group point estimates of Cohen's *d* from small (0.28) to medium (0.55; Cohen, 1988). The positive relationship between internal consistency

[9] It should be noted that resampling trials will change the person and group averages, which also moves the effect size. Nonetheless, this exercise provides a useful illustration of the impact of subject-level internal consistency on between-group differences.

and effect sizes are consistent with between-group (Hajcak et al., 2017) and within-person ERN analyses (Clayson & Miller, 2017a). Between-group ERN effect sizes also increased with increases in internal consistency in people with generalized anxiety disorders (Hajcak et al., 2017), and within-person CRN vs. ERN comparisons similarly increased with increases in internal consistency (Clayson & Miller, 2017a).

Furthermore, the variability of between-group effect sizes for low internal consistency levels was considerable, and this variability generally decreased as internal consistency increased. These findings demonstrate that such high measurement error in instances of low internal consistency can greatly *attenuate* or *exaggerate* effect sizes (i.e., magnitude error) and cause the effect to move in the opposite direction (i.e., sign error) from what would be observed in the population (Gelman & Carlin, 2014; Loken & Gelman, 2017; Schönbrodt & Perugini, 2013). For example, at low levels of internal consistency some sampling iterations showed that participants with MDD had larger rather than smaller CRN than healthy controls. Although it is commonly assumed that measurement error weakens relationships, this assumption only holds true when sample sizes are very large, because when measurement error is random, such random variation can strengthen or weaken an effect size simply due to chance (Loken & Gelman, 2017). These issues are relevant to both between-group differences and within-group correlates with external variables and are especially problematic in studies with small samples (Baldwin, 2017; Brand & Bradley, 2016; Loken & Gelman, 2017; Schönbrodt & Perugini, 2013). Thus, using ERP data with poor score internal consistency can lead to imprecise statistical inferences.

5. Discussion

The current primer provides a conceptual overview of various estimates of data quality, group-level internal consistency and subject-level internal consistency. Most estimates of data

quality and group-level internal consistency have been covered in other work, but to our knowledge this primer presents the first application of subject-level internal consistency to ERP scores. The findings from the subject-level internal consistency analyses indicated that group-level internal consistency mischaracterized approximately one-third of participants in most cases for RewP and CRN/ERN for participants with MDD. The subject-level internal consistency of CRN and ERN scores was mischaracterized in approximately one-fourth of healthy participants, and the internal consistency of RewP scores was mischaracterized for only a few healthy participants. Consistent with behavioral research (Williams et al., 2019), we believe that the current findings demonstrate the need to consider subject-level internal consistency in ERP research that focuses on individual differences.

Historically, there has been a great deal of interest in examining relationships between RewP/ERN and various external correlates (e.g., depression scores, response times). However, the factors that impact within-person variance (i.e., between-trial variance) have unfortunately received much less attention (Clayson, Baldwin, & Larson, 2013; Clayson, Kappenman, et al., in press; Clayson & Miller, 2017b), and the present findings highlight that there is considerable variability in between-trial (i.e., within-person) variance. The typical ERP study averages all trials together for a given event type based on the assumption that the true ERP signal is constant over the course of the entire task, and consistent with this practice the current primer considered all within-person variance to simply reflect measurement error. However, changes in cognitive or affective state over the course of a task can impact ERP signals, and such within-person changes might be of interest. Some recent RewP and ERN studies used mixed-effects models to explain changes in trial-to-trial scores (e.g., Berry et al., 2019; Brush et al., 2018; Clayson & Larson, 2019; Volpert-Esmond et al., 2018), and such mixed-effects models have the statistical capability

to separate within-person variance into true-score variance and measurement error (e.g., within-person changes in ERP amplitudes across the course of a task). These models can examine factors that impact between-trial variance within and across participants, and their application to ERPs is described in a recently published primer (Volpert-Esmond, Page-Gould, & Bartholow, in press; this special issue).

Recent work has started to examine internal consistency as an outcome to determine how to improve ERP score internal consistency. Different methodological choices for analyzing ERN scores have been shown to impact internal consistency, with split-half internal consistency estimates ranging from .70 to .88 and from .68 to .91 in two different samples in the same study (Klawohn, Meyer, et al., 2020) and from .67 to .84 in another study (Sandre et al., 2020, this special issue). These ranges are actually quite wide, considering that the relationship between internal consistency and the number of trials is nonlinear, and more and more trials are needed to improve internal consistency as estimates approach 1, assuming constant between-trial variance (Clayson & Miller, 2017a). However, interpretations were based on visual inspection of estimates, not statistical comparisons. To draw stronger conclusions about the factors that impact ERN score internal consistency, a recent meta-analysis of 4,499 participants from 68 samples nested within 43 studies examined internal consistency estimates of ERN scores (Clayson, 2020). Estimated coefficient alphas for eight ERN trials ranged from .02 to .94, and coefficient alphas were partially moderated by the type of paradigm, clinical status of the sample, approach for correction of ocular artifact, measurement sensors, and approach to calculating alpha. However, in light of the fact that many ERP studies do not follow recommended guidelines for the reporting of data processing pipelines (Clayson et al., 2019), the meta-analysis could not examine all steps of the data processing pipeline.

The current primer provides an avenue for directly examining the impact of methodological choices and other person characteristics on the internal consistency of ERP scores. Future work can use estimates of subject-level internal consistency or person-specific data quality as outcome variables to determine the unique impact of different factors on internal consistency and data quality. This approach can be used to examine the impact of between-person variables (e.g., depression scores, cognitive functioning, clinical status) and within-person variables (e.g., data processing pipelines, time on task). Such efforts would be helpful for refining an optimal processing pipeline for different ERPs (Keil et al., in press; this special issue).

An advantage of using generalizability theory to estimate subject-level internal consistency is this theory's flexible framework. The subject-level internal consistency formulas in Eqs. 3 and 4 can be extended to incorporate other sources of measurement error. For example, the formulas could be extended to estimate the subject-level internal consistency of difference scores (Clayson et al., 2021), subject-level test-retest reliability (Clayson, Carbine, et al., in press), or any other factor(s) of interest. It is important to emphasize that these approaches to estimating psychometric reliability and their implementation within the ERA Toolbox are most appropriate for time-window mean amplitude scores. When the peak amplitude or latency is of interest, the peak amplitude or latency of the "true" ERP peak of interest is uncertain, because the average of single-trial scores would not be the same as the score extracted from the subject average (for a detailed discussion, see section 3 of Luck et al., 2020). Future work might consider how to appropriately analyze such metrics using subject-level internal consistency estimates.

Subject-level internal consistency can be used to exclude participants with internal consistency that is too low for an intended purpose. A general recommendation is to specify data inclusion/exclusion rules *a priori* and to report the number of participants excluded using this approach, and guidance about reliability thresholds for data inclusion are provided elsewhere (see Clayson & Miller, 2017b). However, the consequences of excluding participants using psychometric reliability on statistical inferences in healthy or clinical samples is virtually unknown, and such a practice runs the risk of reducing the generalizability of findings (Clayson, 2020). This is particularly the case for ERPs that depend on participant behavior, such as making an error. Some high-performing participants make relatively few errors, and these participants might be excluded from analyses for having too few error trials to achieve presumably adequate internal consistency. However, the use of subject-level internal consistency uses a participant's own error estimate. Therefore, adequate internal consistency can still be achieved with few trials when error variance is small. Furthermore, excluding participants based on any criterion potentially limits the generalizability of findings, and this issue is not specific to the use of subject-level internal consistency for doing so.

Measurement metrics were presented as trial-"independent" (e.g., ICCs) and trial-"dependent" estimates (e.g., dependability), and each type of estimate has its advantages. Trial-independent estimates provide general information about variance and give a sense of how many trials will be needed to approach an adequate trial-dependent estimate, such as internal consistency. For example, an ICC that is close to one suggests few ERP trials will be needed to obtain a psychometrically reliable estimate, whereas an ICC close to zero suggests many trials will be needed (Clayson & Miller, 2017a). On the one hand, only one scenario can lead to a high ICC, and this occurs when between-subject variability is very high compared to within-person

between-trial variability. It makes intuitive sense that only a handful of ERP trials would be needed to demonstrate that internal consistency is adequate when an ICC is high. On the other hand, ICCs can be low due to small between-person variability *or* large between-trial variability. However, the number of recorded trials can mitigate the impact of high between-trial variability on the ICC, which is the type of information provided by the trial-dependent estimates.

Each of the metrics described in this primer is context dependent, insofar as these metrics only provide information about observed ERP scores for an intended comparison. A demonstration of high data quality or internal consistency speaks only to the ERP scores in hand, and studies cannot assume adequate data quality or psychometric reliability based on prior work. Many diverse factors can impact the between-person and within-person variation of ERP scores, which limit the generalizability of data quality and psychometric reliability metrics across ERPs, samples, and studies (Clayson, Kappenman, et al., in press; Clayson & Miller, 2017b). The studies of ERN already discussed provide ready examples that illustrate these challenges. Intuition about SME provides another: whether SME is small enough is based on observed data and the intended comparison. If the difference between a control group and one psychiatric group were 10 μV and the SMEs for each group were 5 μV, then the SME would be considered small enough for such a comparison. However, the same SMEs would be considered too large if a 4 μV difference were observed between the same control group and a different psychiatric group. Although a demonstration of high data quality and internal consistency of ERP scores does not generalize beyond the data in hand, the usefulness of these metrics do. The same guiding principles about whether ERP scores show adequate psychometric reliability in one context generalize to other contexts, and even generalize beyond ERP research. These metrics can be routinely used to demonstrate adequate psychometrics in every ERP study, and

application of these metrics to different datasets will serve to flesh out their similarities and differences.

Moving forward, we have a few recommendations. Estimates of psychometric reliability and data quality characterize the data in hand, and the estimates from the present dataset cannot be used to infer the internal consistency or data quality of other ERN or RewP research. We hope that the current primer helps to remove barriers to the estimation of internal consistency and data quality of ERP scores in future research. When the examination of individual differences is of primary interest, we continue to recommend the study-by-study evaluation of the internal consistency of ERP scores (Clayson, 2020; Clayson, Carbine, et al., in press; Clayson & Miller, 2017a, 2017b; Hajcak et al., 2017; Infantolino et al., 2018; Thigpen et al., 2017), which is consistent with the author guidelines of the *International Journal of Psychophysiology* and *Psychophysiology*. Reporting estimates of psychometric reliability and data quality is also consistent with the spirit of data transparency, which is a guiding principle of open science practices (Keil et al., in press; this special issue). Estimates of internal consistency clarify whether between-person differences are large enough relative to error variance and provide a context for interpreting statistical inferences (LeBel & Paunonen, 2011; Thompson, 2003; Wilkinson & The APA Task Force on Statistical Inference, 1999). When the comparison of between-condition and between-group differences are of primary interest, we recommend including estimates of data quality, such as SME, and possibly internal consistency (see Figure 8) to justify such comparisons (Luck et al., 2020).

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Table 1

Summary Statistics for ERP to Gain and Loss Trials

Participants with MDD				
Measurement	Gain		Loss	
	M (*SD*)	Range	*M* (*SD*)	Range
Number of Trials	29.7 (1.2)	23 to 30	29.7 (1.0)	23 to 30
Data Quality				
SME_{ij}	1.98 (1.16)	0.95 to 11.19	1.82 (0.53)	0.96 to 3.92
σ_{ij}	10.74 (6.18)	5.21 to 60.26	9.90 (2.85)	5.24 to 21.45
Group-Level Internal Consistency	Estimate	95% CI	Estimate	95% CI
r_{xx}	.89	--	.94	--
ϕ_k	.90	(.87, .93)	.92	(.89, .94)
Subject-Level Internal Consistency	*M* (*SD*)	Range	*M* (*SD*)	Range
ϕ_{jk}	.92 (.07)	.37 to .97	.92 (.03)	.78 to .97
ICC_{jk}	.33 (.10)	.02 to .58	.31 (.08)	.11 to .50
Healthy Controls				
Measurement	Gain		Loss	
	M (*SD*)	Range	*M* (*SD*)	Range
Number of Trials	28.8 (2.1)	23 to 30	29.3 (1.4)	25 to 30
Data Quality				
SME_{ij}	1.93 (0.59)	1.07 to 3.21	1.80 (0.46)	1.05 to 3.34
σ_{ij}	10.35 (3.12)	5.56 to 17.08	9.75 (2.41)	5.74 to 16.72
Group-Level Internal Consistency	Estimate	95% CI	Estimate	95% CI
r_{xx}	.95	--	.90	--
ϕ_k	.94	(.91, .96)	.92	(.88, .95)
Subject-Level Internal Consistency	*M* (*SD*)	Range	*M* (*SD*)	Range
ϕ_{jk}	.94 (.03)	.86 to .97	.92 (.03)	.82 to .96
ICC_{jk}	.38 (.11)	.19 to .58	.30 (.07)	.17 to .45

Note: The 95% credible interval (95% CI) is shown for group-level dependability and based on Bayesian mixed-effects model. MDD = major depressive disorder; SME_{ij}= standardized measurement error; σ_{ij} = between-trial standard deviation; r_{xx} = split-half reliability with Spearman-Brown Prophecy adjustment; ϕ_k = group-level dependability based on standard mixed-effects model; ϕ_{jk} = subject-level dependability based on mixed-effects location scale model; ICC_{jk} = subject-level intraclass correlation coefficient based on mixed-effects location scale model

Table 2

Summary Statistics for Correct-Related Negativity (CRN) and Error-Related Negativity (ERN)

	Participants with MDD			
Measurement	CRN		ERN	
	M (*SD*)	Range	*M* (*SD*)	Range
Number of Trials	299.1 (20.9)	228 to 330	30.1 (14.7)	7 to 78
Data Quality				
SME_{ij}	0.68 (0.16)	0.42 to 1.41	2.34 (0.98)	0.91 to 7.28
σ_{ij}	11.66 (2.62)	7.47 to 24.37	11.70 (3.63)	6.14 to 32.56
Group-Level Internal Consistency	Estimate	95% CI	Estimate	95% CI
r_{xx}	.98	--	.81	--
ϕ_k	.98	(.97, .98)	.86	(.80, .90)
Subject-Level Internal Consistency	*M* (*SD*)	Range	*M* (*SD*)	Range
ϕ_{jk}	.98 (.01)	.92 to .99	.84 (.09)	.51 to .97
ICC_{jk}	.15 (.05)	.04 to .27	.20 (.06)	.05 to .35

	Healthy Controls			
Measurement	CRN		ERN	
	M (*SD*)	Range	*M* (*SD*)	Range
Number of Trials	301.6 (17.8)	235 to 329	27.4 (12.3)	6 to 50
Data Quality				
SME_{ij}	0.67 (0.25)	0.42 to 2.07	2.33 (1.08)	1.25 to 7.05
σ_{ij}	11.59 (3.91)	7.48 to 31.72	11.08 (2.94)	5.30 to 17.57
Group-Level Internal Consistency	Estimate	95% CI	Estimate	95% CI
r_{xx}	.99	--	.73	--
ϕ_k	.99	(.99, .995)	.83	(.75, .90)
Subject-Level Internal Consistency	*M* (*SD*)	Range	*M* (*SD*)	Range
ϕ_{jk}	.99 (.01)	.94 to .997	.81 (.10)	.46 to .91
ICC_{jk}	.35 (.10)	.06 to .52	.18 (.04)	.10 to .28

Note: The 95% credible interval (95% CI) is shown for group-level dependability and based on Bayesian mixed-effects model. MDD = major depressive disorder; SME_{ij}= standardized measurement error; σ_{ij} = between-trial standard deviation; r_{xx} = split-half reliability with

Spearman-Brown Prophecy adjustment; ϕ_k = group-level dependability based on standard mixed-effects model; ϕ_{jk} = subject-level dependability based on mixed-effects location scale model; ICC_{jk} = subject-level intraclass correlation coefficient based on mixed-effects location scale model

Figure Captions

Figure 1. Single-trial error-related negativity scores from six participants with major depressive disorder. The scores are separately colored to illustrate the data that would contribute to an odd/even split-half reliability coefficient. Box and whiskers plots separately summarize the following data for each split half for each participant. The middle line in the box plots represents the median, the two hinges represent the 25th and 75th percentiles, respectively, and the two whiskers extend from the hinge to the largest value or no farther than 1.5 times the interquartile range. Colored diamonds represent the average score for single trials from each split half for each participant. Labels for each participant's data show the number of trials retained for averaging, between-trial standard deviations (σ_{ij}), standardized measurement error (SME_{ij}), and subject-level dependability coefficients (ϕ_{jk}).

Figure 2. The relationship between between-trial standard deviations (σ_{ij}) and standardized measurement error (SME_{ij}) for reward positivity (RewP) to gain and loss trials, correct-related negativity (CRN), and error-related negativity (ERN). Note different limits on x- and y-axes.

Figure 3. Subject-level dependability estimates (ϕ_{jk}) for each person with their respective 95% credible intervals. When the credible intervals do not include the group-level dependability estimate, the credible intervals are highlighted in blue. Data are ordered from the smallest to largest point estimate. Note different limits on y-axes.

Figure 4. Subject-level intraclass correlation coefficients (ICC_{jk}) for each person with their respective 95% credible intervals. When the credible intervals do not include the group-level ICC, the credible intervals are highlighted in blue. Data are ordered from the smallest to largest point estimate.

Figure 5. The relationship between subject-level dependability estimates (ϕ_{jk}) and subject-level intraclass correlation coefficients (ICC_{jk}) for reward positivity (RewP) to gain and loss trials, correct-related negativity (CRN), and error-related negativity (ERN).

Figure 6. The relationship between subject-level dependability estimates (ϕ_{jk}) and standardized measurement error (SME_{ij}) for reward positivity (RewP) to gain and loss trials, correct-related negativity (CRN), and error-related negativity (ERN).

Figure 7. The relationship between subject-level intraclass correlation coefficients (ICC_{jk}) and between-trial standard deviations (σ_{ij}) for reward positivity (RewP) to gain and loss trials, correct-related negativity (CRN), and error-related negativity (ERN). Note different limits on x-axes.

Figure 8. Representation of the variability of effect sizes when drawing 10,000 random samples of trials without replacement from each participant at each subject-level dependability (ϕ_{jk}). The effect sizes for the comparison of correct-related negativity (CRN) scores between healthy controls and people with major depressive disorder. The solid line represents the average of the point estimates of Cohen's *d*, and the dashed line shows a Cohen's *d* of 0.58, which is the observed effect size for the between-group comparison when including all trials from each participant. The dark shaded regions correspond to the 95% confidence interval for the observed point estimates, and the light shaded regions represent the minimum to maximum for the point estimates.

Figure 1

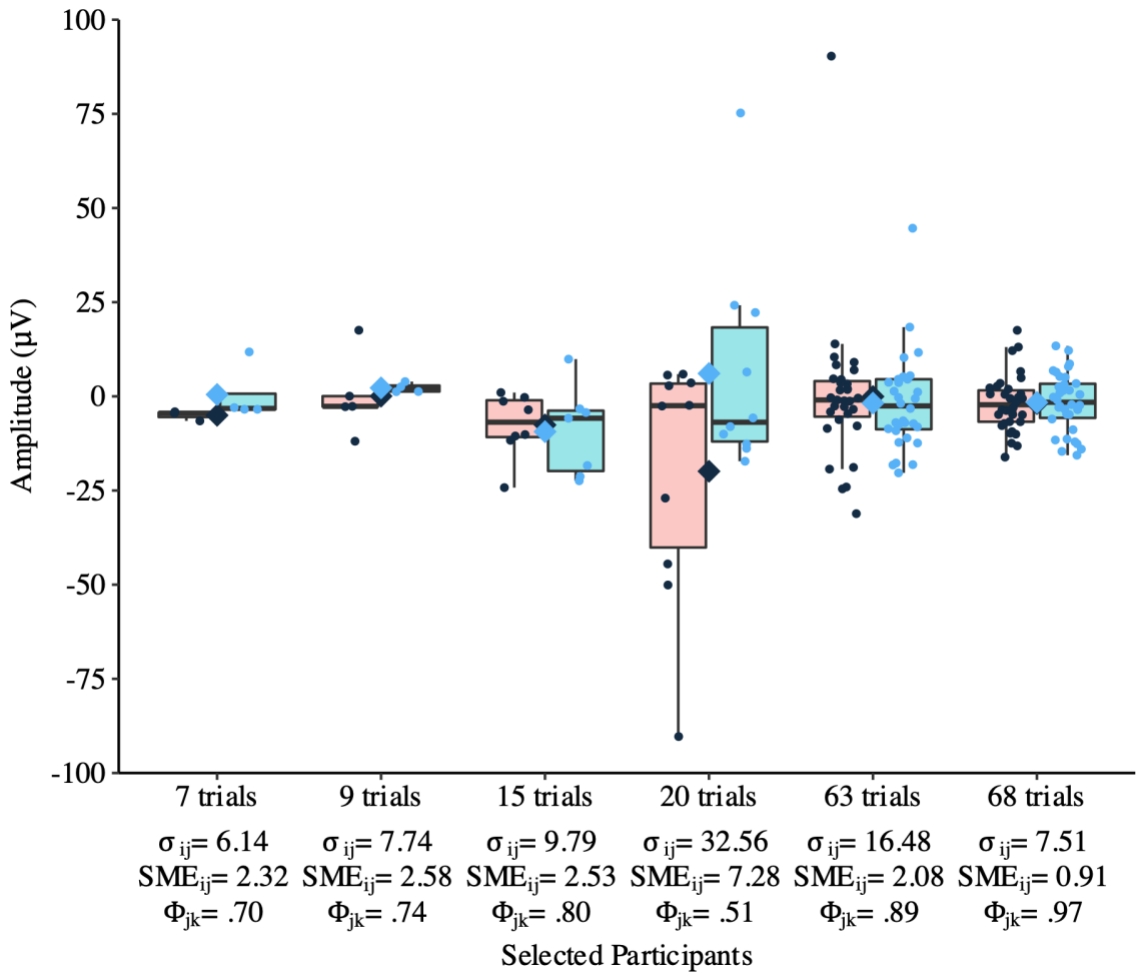

100
75
50
25
0
-25
-50
-75
-100
Amplitude (μV)
7 trials
9 trials
15 trials
20 trials
63 trials
68 trials
σ ij= 6.14
SMEij= 2.32
Φjk= .70
σ ij= 7.74
SMEij= 2.58
Φjk= .74
σ ij= 9.79
SMEij= 2.53
Φjk= .80
σ ij= 32.56
SMEij= 7.28
Φjk= .51
σ ij= 16.48
SMEij= 2.08
Φjk= .89
σ ij= 7.51
SMEij= 0.91
Φjk= .97
Selected Participants

Figure 2

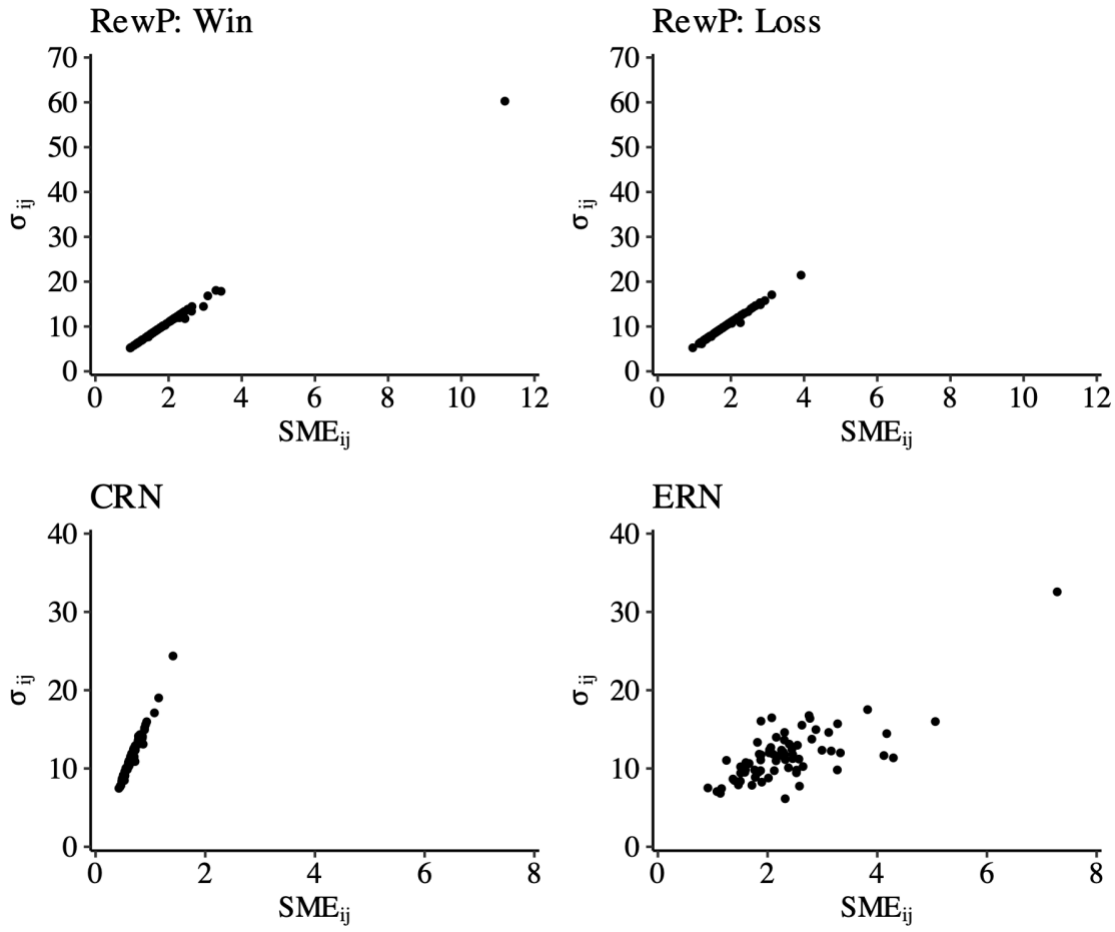


Figure 3

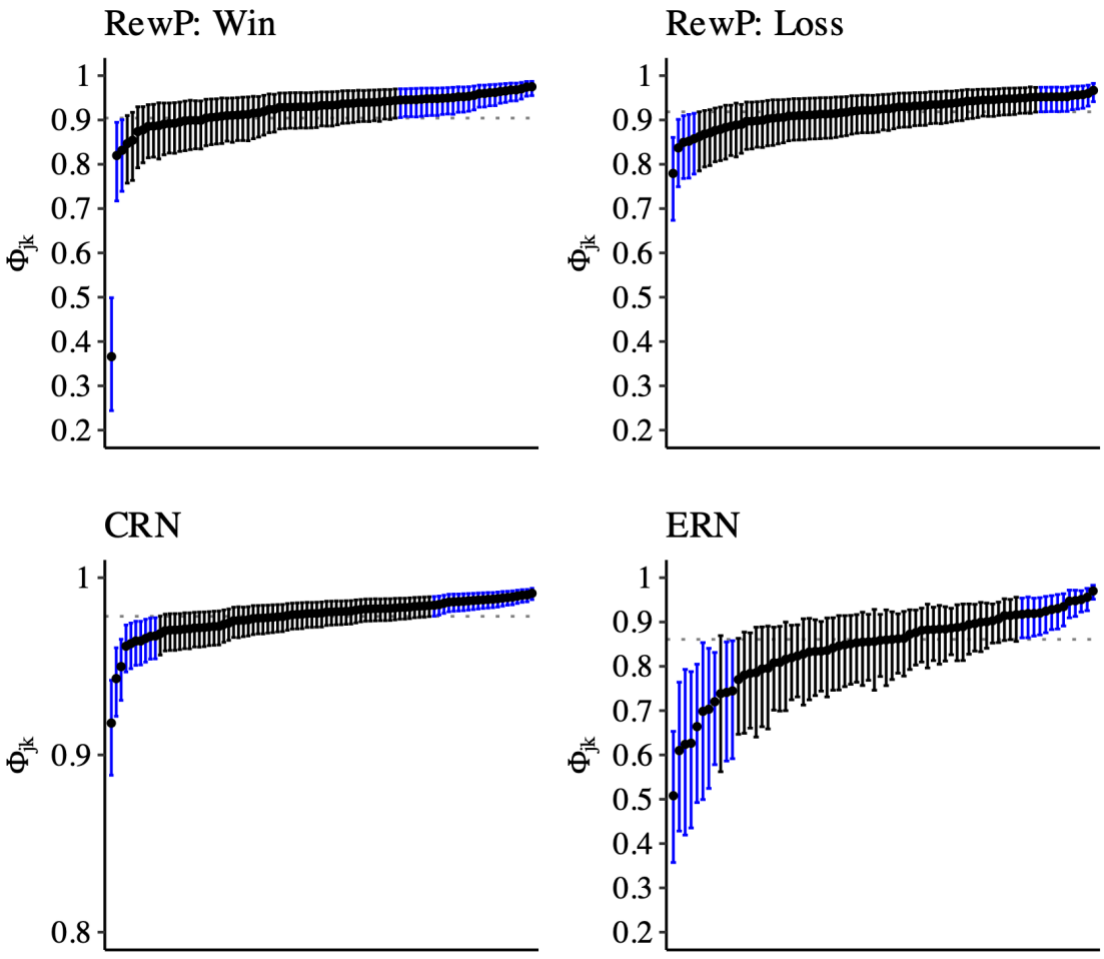


Figure 4

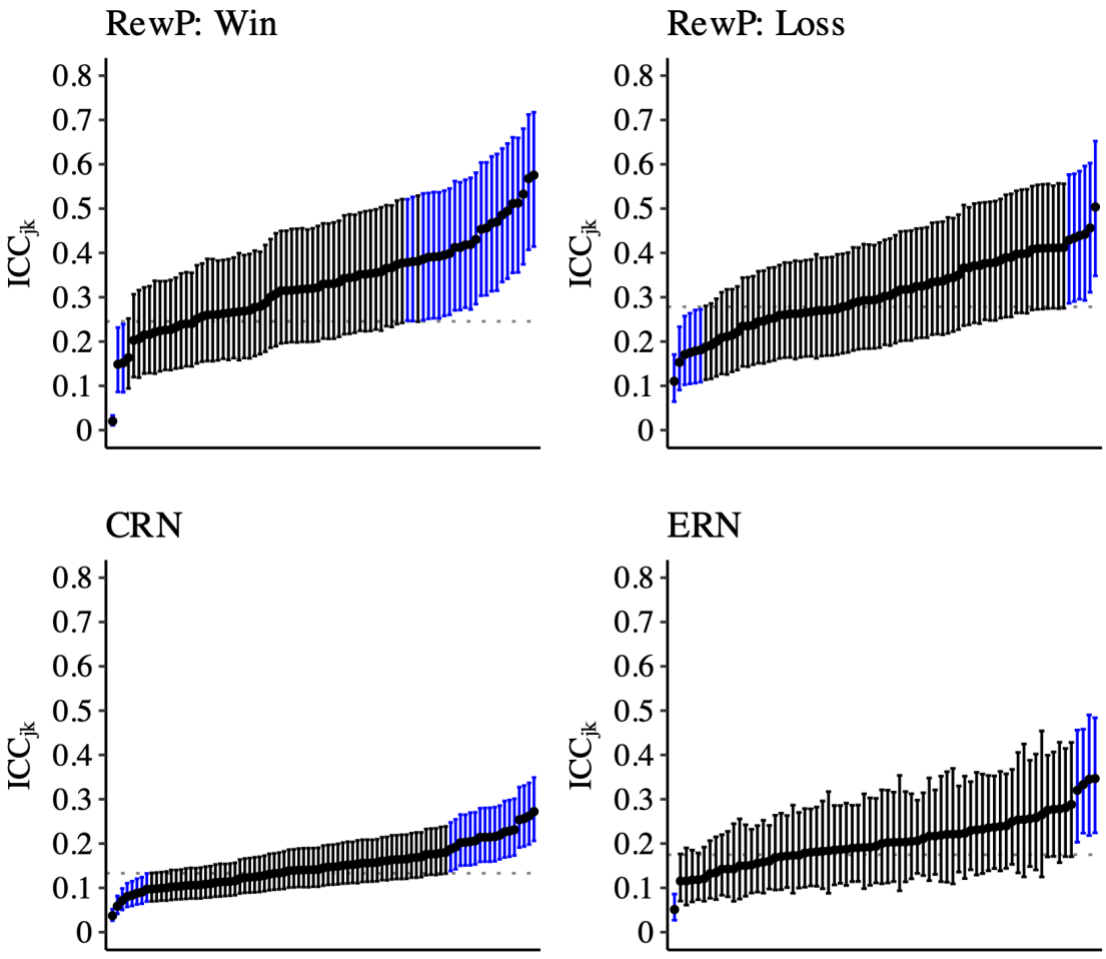


Figure 5

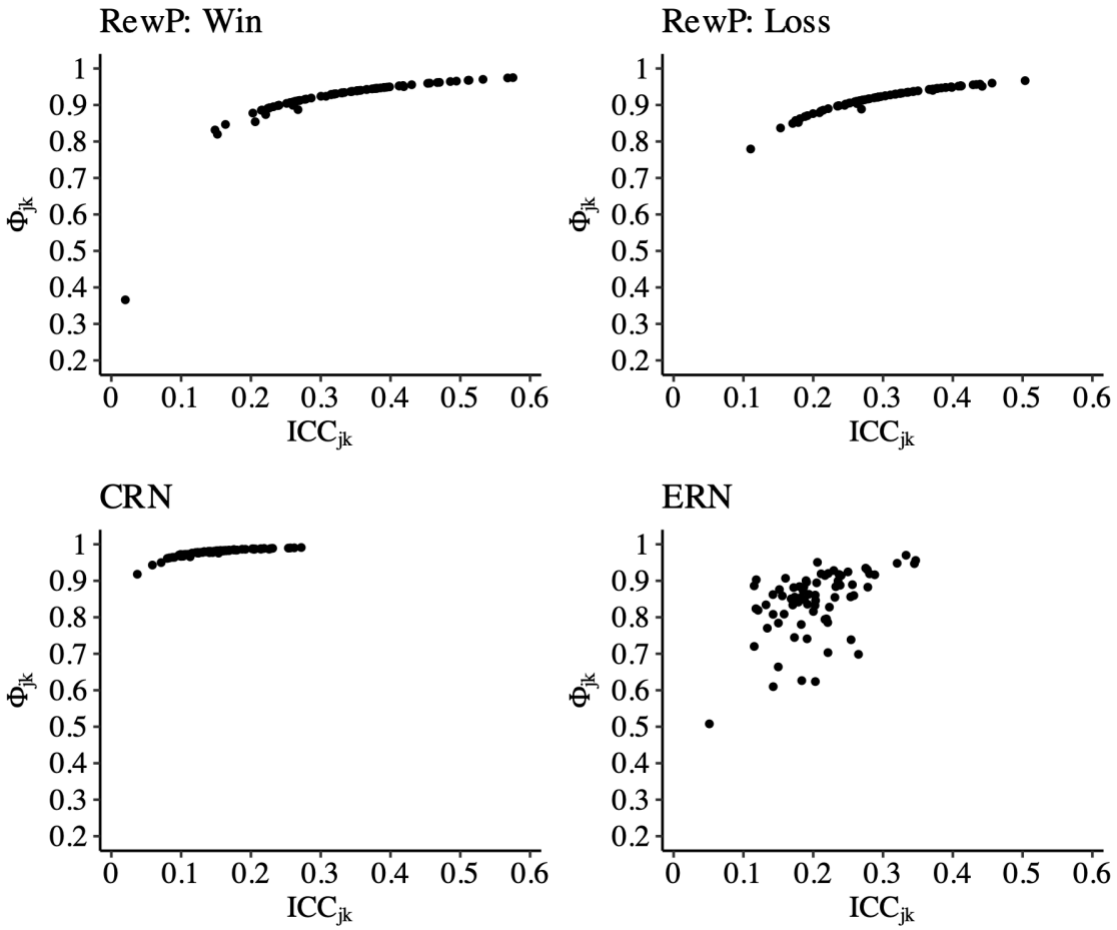

RewP: Win
RewP: Loss
CRN
ERN
Φ_{jk}
ICC_{jk}
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
0.1
0.2
0.3
0.4
0.5
0.6

Figure 6

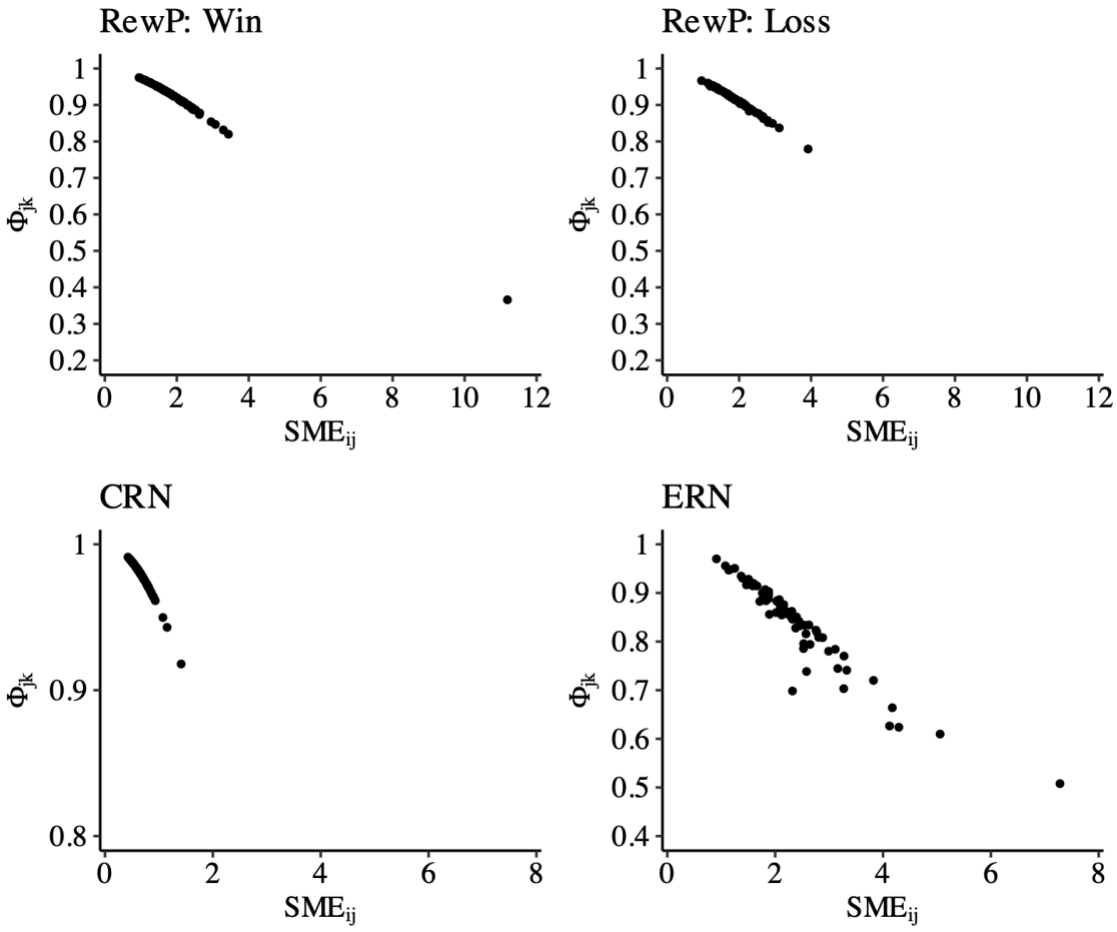


Figure 7

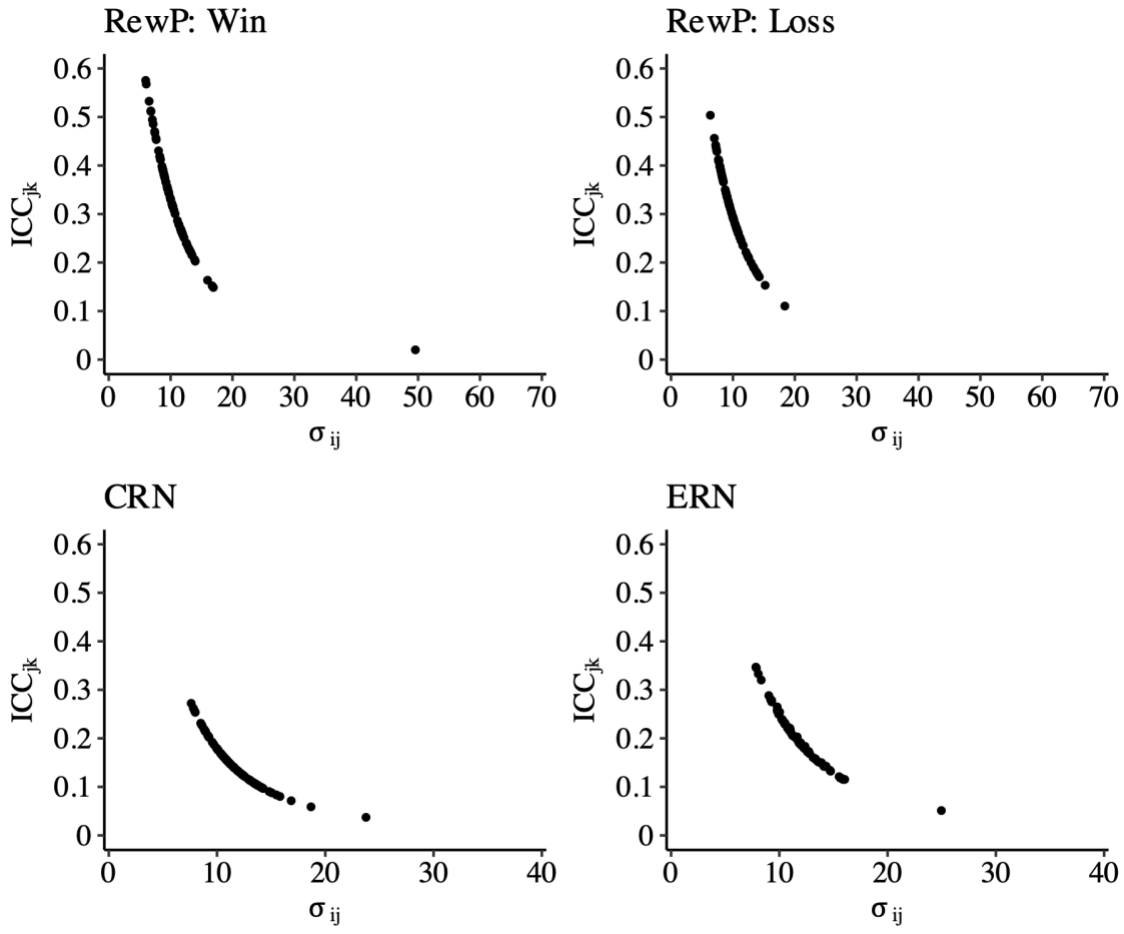
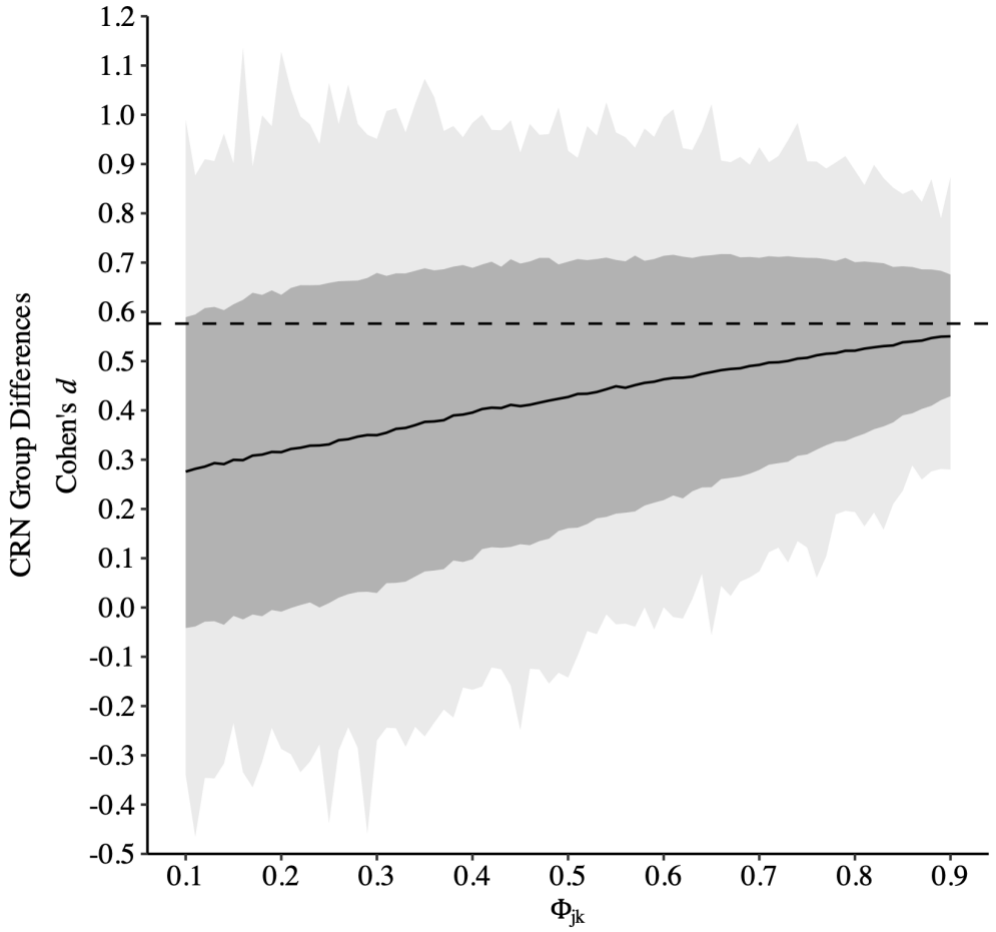

RewP: Win
RewP: Loss
CRN
ERN
ICCjk
σij
0
0.1
0.2
0.3
0.4
0.5
0.6
0
10
20
30
40
50
60
70

Figure 8


CRN Group Differences
Cohen's d
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Φjk