# Using Generalizability Theory and the ERP Reliability Analysis (ERA) Toolbox for Assessing Test-Retest Reliability of ERP Scores Part 1: Algorithms, Framework, and Implementation

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Abstract

The reliability of event-related brain potential (ERP) scores depends on study context and how those scores will be used, and reliability must be routinely evaluated. Many factors can influence ERP score reliability; generalizability (G) theory provides a multifaceted approach to estimating the internal consistency and temporal stability of scores that is well suited for ERPs. G-theory's approach possesses a number of advantages over classical test theory that make it ideal for pinpointing sources of error in scores. The current primer outlines the G-theory approach to estimating internal consistency (coefficients of equivalence) and test-retest reliability (coefficients of stability). This approach is used to evaluate the reliability of ERP measurements. The primer outlines how to estimate reliability coefficients that consider the impact of the number of trials, events, occasions, and groups. The uses of two different G-theory reliability coefficients (i.e., generalizability and dependability) in ERP research are elaborated, and a dataset from the companion manuscript, which examines N2 amplitudes to Go/NoGo stimuli, is used as an example of the application of these coefficients to ERPs. The developed algorithms are implemented in the ERP Reliability Analysis (ERA) Toolbox, which is open-source software designed for estimating score reliability using G theory. The toolbox facilitates the application of G theory in an effort to simplify the study-by-study evaluation of ERP score reliability. The formulas provided in this primer should enable researchers to pinpoint the sources of measurement error in ERP scores from multiple recording sessions and subsequently plan studies that optimize score reliability.

Key Words: generalizability theory, event-related potentials, reliability, ERP Reliability Analysis (ERA) Toolbox, psychometrics

## 1. Introduction

In order for physiological measurements to be viable as endophenotypes or biomarkers, they must demonstrate adequate score reliability, including internal consistency and test-retest reliability (Luck et al., 2011). Psychophysiological research has historically employed classical test theory to evaluate score reliability, but classical test theory does not provide a flexible framework for simultaneously evaluating the contribution of multiple sources of measurement error. Generalizability (G) theory uses a multifaceted approach for estimating score reliability that can account for multiple sources of error, including those sources commonly encountered in psychophysiological research (Baldwin, Larson, & Clayson, 2015; Clayson & Miller, 2017a, 2017b). The current primer builds on previous applications of G theory for estimating internal consistency by providing a tutorial for applying G theory to estimate the temporal stability of event-related brain potentials (ERPs).

One important, but often underappreciated, aspect of score reliability is that it must be evaluated on a study-by-study basis, because score reliability is a property of scores as they are used in a particular population and context, not a universal property of measures (Thompson, 2003; Vacha-Haase, 1998). Hence, researchers have started to advocate for the study-by-study evaluation of ERP score reliability (Clayson, 2020; Clayson, Brush, & Hajcak, 2020; Clayson & Miller, 2017b; Hajcak, Meyer, & Kotov, 2017; Infantolino, Luking, Sauder, Curtin, & Hajcak, 2018; Thigpen, Kappenman, & Keil, 2017), and journals have adopted guidelines for routinely reporting score reliability (e.g., author guidelines for *Psychophysiology* and the *International Journal of Psychophysiology*). To facilitate the study-by-study evaluation of ERP score reliability, Clayson developed the ERP Reliability Analysis (ERA) Toolbox (Clayson & Miller,

2017a), which is open-source MATLAB software that employs algorithms from G theory for estimating internal consistency (https://github.com/peclayson/ERA_Toolbox).

The current primer first describes the conceptual framework of G theory with an emphasis on test-retest reliability. Then, the algorithms for evaluating test-retest reliability are described in detail with examples of their implementation using the ERA Toolbox. The companion manuscript to this primer demonstrates the application of G-theory reliability coefficients for understanding the internal consistency and temporal stability of ERP scores recorded during a Go/NoGo task that used pictures of food as stimuli (Carbine et al., current issue), and N2 scores from that dataset are used below as an example of the application of G theory for understanding the temporal stability of ERP measurements.

## 2. Generalizability Theory

### 2.1. Conceptual Framework

G theory provides a multifaceted approach for estimating score reliability (Brennan, 2001, 2010; Cronbach, Gleser, Nanda, & Rajaratnum, 1972; Shavelson & Webb, 1991; Shavelson, Webb, & Rowley, 1989; Vispoel, Morris, & Kilinc, 2018a, 2018b; Webb, Shavelson, & Haertel, 2006). The application of G theory to psychophysiological research and its advantages over classical test theory for ERP research have been described elsewhere (Baldwin et al., 2015; Clayson et al., 2020; Clayson & Miller, 2017a, 2017b). Some of these advantages include less restrictive assumptions (e.g., classical test theory's strict requirement of parallel forms), the ability to easily handle unbalanced designs, and the treatment of measurement error as a multifaceted entity. These previous studies focused on measurements of internal consistency, and although the strength of G theory for evaluating the temporal stability of ERP scores was previously described, its application was not explicitly formulated or implemented in

the ERA Toolbox. We build on these previous descriptions by elaborating on the application of G theory to additional reliability coefficients, including estimates of test-retest reliability.

When computing reliability coefficients in classical test theory, the emphasis is on estimating the "true" score, which is conceptualized as the score that would be obtained over an infinite number of measurements (allowing for the user to average over random error). However, G theory focuses on estimating the *universe score* (see Table 1 for a definition of italicized terms). The semantic distinction between a "true" score and a "universe" score is important, because the conceptualization of the universe score provides the scaffolding for the reliability algorithms in G theory. The use of the term universe score signifies that any measurement is a generalization from an observed score, and the reliability of observed scores depends on the universe (i.e., context) to which a researcher wants to generalize (Cronbach et al., 1972). This universe is defined by the researcher, and any particular measurement could belong to a variety of universes depending on the application of the research. For example, a researcher could be interested in observed scores generalizing to college undergraduates with anxiety disorders, but those same scores could also generalize to young adults with psychiatric diagnoses. The universe of interest constrains the G-theory algorithms by specifying the potential sources of measurement error.

An advantage of the G-theory framework is the ability to pinpoint multiple sources of measurement error. G-theory refers to these potential sources of error as the *facets* and *conditions* of interest. Facets refer to a set of characteristics that contribute to error (a factor in the analysis of variance [ANOVA] framework), and conditions are the systematic ways that a measurement varies within a facet (a level within a factor in the ANOVA framework). Common examples of facets encountered in ERP studies include the number of trials included in average

ERP waveforms, event type, occasion, experimental paradigm, EEG hardware, or diagnostic group. The levels of an event type facet could include correct and error trials, and the levels of an occasion facet could include measurements from three different time points. It is important to consider all relevant facets and conditions of interest for estimating G-theory reliability coefficients, because failure to do so can result in the overestimation of reliability (Vispoel et al., 2018a).

G theory distinguishes between two types of "studies" that are used for estimating reliability. In a *generalizability (G) "study"*, the variance associated with each facet and condition is estimated, and this requires specifying all conditions and facets of interest (i.e., the *universe of admissible observations*). A *decision (D) "study"* then uses those estimated variance components for a particular purpose, which requires defining the *universe of generalization*. The universe of generalization refers to all of the conditions of the facets that the researcher wants to generalize to, and the universe score refers to this universe of generalization. The D study can include some or all of the facets from the G study and is used to calculate reliability coefficients.

Although G theory refers to the G and D studies as "studies", they also represent two stages of analysis that can be applied to the same dataset. The G study/analysis is the first stage during which variance components of the different facets are estimated (see section 2.3), and the D study/analysis is the second stage during which those variance components are applied to estimate score reliability for a particular purpose (see section 2.4). When only one set of data is available and there is not intent to speculate about score reliability of studies in different contexts, the distinction between a G and D study blurs.

### 2.2. Generalizability and Dependability Coefficients

When conducting reliability analyses, the appropriate coefficient to use depends on the type of inference a researcher would like to draw. G-theory recognizes two types of inferences: relative decisions (norm-referenced) and absolute decisions (criterion- or domain-referenced). If a researcher is interested in the relative position or the ranking of individuals (i.e., the ranking of individuals within each condition of a facet), a *generalizability coefficient* is used. For example, a researcher might be interested in whether healthy controls consistently outperform clinical patients over two measurement occasions. In such instances, the focus is solely on interindividual standings, rather than the absolute values of the scores. Relative decisions are the type of inference rendered by popular classical test-theory reliability coefficients (Brennan, 2003, 2010), such as coefficient $\alpha$ (Cronbach's $\alpha$), a correlation coefficient, and Kuder-Richardson Formula 20 (KR-20).

Absolute decisions are concerned with score consistency or the absolute level of performance, and an *index of dependability* (i.e., *dependability* coefficient) is used to characterize reliability for this type of inference. Dependability coefficients consider both the relative position of individuals and any absolute differences in scores. The dependability coefficient is appropriate for characterizing the number of trials needed to obtain a stable ERP waveform, because the focus is on whether adding trials changes the estimate of the universe score for the ERP. The dependability coefficient is also appropriate when applying a cutoff to observed scores, such as excluding participants who are non-responders in studies assessing skin conductance.

As previously mentioned, whether the researcher uses a generalizability coefficient or a dependability coefficient is based on the desired inference. For the generalizability coefficient, only measurement error associated with the objects of interest impacts reliability. That is,

relative increases among average item or person scores do not reduce reliability. However, the dependability coefficient considers all possible sources of measurement error, and increases in variability associated with any facet reduce reliability. Both reliability coefficients range from 0 to 1, with higher scores reflecting better reliability. The generalizability coefficient is low when interindividual rankings are inconsistent, and the dependability coefficient is low when measurements from the same individuals are inconsistent. The decision boils down to a question of whether a researcher is interested in the relationship between individuals (i.e., are rankings between individuals stable across time?) or whether a researcher is interested in the absolute value of measurements for individuals (i.e., is a person's score at time 1 numerically similar to the same person's score at time 2?).

To summarize, there are two different coefficients: generalizability coefficients, which characterize relative standings of persons, and dependability coefficients, which characterize absolute differences in scores between participants. In the next sections, we illustrate how coefficients of stability are computed using G-theory and emphasize the differences between generalizability and dependability coefficients. The formulas that follow are implemented in the ERA Toolbox (https://github.com/peclayson/ERA_Toolbox) to facilitate their application in ERP studies.

### 2.3. Generalizability (G) Study

The ERP data presented and analyzed in the current paper are a subset of the dataset presented in Carbine et al. (current issue; i.e., the companion paper). Details on the rationale for the study, participant characteristics, study design, ERP preprocessing pipeline, and the application and interpretation of reliability analyses are discussed further in the companion paper. Briefly, 132 psychiatrically and neurologically healthy young adults (70% female, $M_{age}$ =

20.65, $SD_{age}$ = 3.16) reported for two laboratory sessions held two weeks apart at the same time of day. At both visits, participants completed a passive food-viewing task, a high-calorie go/no-go task, and a low-calorie go/no-go task. Of the 132 participants, 124 had ERP data from both sessions for the low-calorie go/no-go task that made it through the preprocessing pipeline and were entered into the ERA toolkit. ERP data from the low-calorie go/no-go task are analyzed and presented below only to illustrate the purpose and function of the ERA toolkit in assessing internal consistency and test-retest reliability.

We begin with a G study to identify the universe of admissible observations, which guides the mathematical derivations for estimating score reliability. Potential sources of systematic variability (i.e., facets) in these N2 scores include the number of trials retained for averaging, event type, and measurement occasion, and these are the facets of interest for the G study. The possible conditions of the number-of-trials facet include all possible trials during the low-calorie version Go/NoGo task, during which participants were required to inhibit a response to low-calorie images and make responses to high-calorie images. There were two event types, Go and NoGo trials (high-calorie and low-calorie images, respectively), and two measurement occasions, baseline and a two-week follow-up. Taken together, the universe of admissible observations is any N2 score for any number of correct Go/NoGo trials during the low-calorie Go/NoGo task from participants measured at baseline and at a two-week follow-up.

The next key question is whether these facets should be considered *random* or *fixed*[1]. If the purpose is to generalize beyond the conditions included in a particular G study, the facet should be considered random. A random facet indicates that all observations within the facet are

[1] Whether a facet is considered random or fixed can impact both the estimation of variance components (G study) and the application of those variance components to estimating score reliability (D study). Shavelson and Webb (1991) cover these differences in their primer on generalizability theory. For a more detailed treatment of these differences and their impact on the calculation of reliability, see Brennan (2001).

entirely interchangeable and represent a random sample of the universe of admissible observations. In ERP studies it is common practice to average trials together to improve the signal-to-noise ratio. This practice is expected to lead to more stable estimates of the ERP score, because nonsystematic noise across trials is minimized when many trials are averaged together. The assumption of this practice is that the signal is stable across trials. Hence, for present purposes the number-of trials facet will be considered random, because no special meaning is attributed to any particular trial. Alternatively, if the purpose is to generalize only to those conditions observed, the facet should be considered fixed. A fixed facet indicates that all conditions of interest for generalization of the facet have been sampled, even though there might be other theoretically relevant conditions. The event type facet will be considered fixed, because Go and NoGo trials are the only events of interest. The occasion facet will also be considered fixed, so that test-retest reliability over a two-week period can be estimated. When a facet is fixed, the estimated reliability tends to be higher, but the higher reliability estimate comes at the cost of narrower interpretations.

Another consideration is whether to use a design wherein trials/items[2] (*i*) are crossed with persons (*p*) and occasions (*o*), $p \times i \times o$, or a design wherein trials are nested within occasions, $p \times (i{:}o)$. In the typical ERP study of test-retest reliability, identical stimuli are presented at multiple recording sessions. For example, a study of the error-related negativity (ERN) component of the ERP recorded during a flanker task would present the same flanker stimuli at each recording session. Based on this important design feature, trials are considered crossed with

[2] In intervention research, one group of participants might be assigned to an intervention and another group might be assigned to treatment-as-usual. If participants in each group of participants view different sets of stimuli, stimuli would be nested within treatment condition. If all participants from each group viewed the same set of stimuli, then stimuli would be crossed with intervention. In the former scenario, the effect of stimuli is confounded within intervention, but in the latter scenario variances for each main effect and the interaction between stimuli and intervention could be parsed.

person and occasions, because any trial of a specific event type from time 1 would be entirely interchangeable with any trial of that specific event type from time 2. However, this assumption only holds when identical stimuli are used. For instance, if a study of ERPs to emotionally-salient images used different image sets at each recording session, then a design wherein trials are crossed with persons and occasions would be inappropriate, and in such an instance trials should be nested within occasion. Given that the first scenario appears more common in the ERP literature and was used in the Carbine et al. (current issue) paper, the $p \times i \times$ o design is the focus of the present primer.

We now describe the G-theory algorithms, and this primer represents a compilation of information from Shavelson and Webb (1991), Brennan (2001), Baldwin et al. (2015), Clayson and Miller (2017a), and Vispoel et al. (2018a). This primer focuses on the derivations for estimating internal consistency and test-retest reliability coefficients when considering three facets: number-of-trials, event, and occasion.

An observed ERP score ($X_{piok}$) for a given person ($p$) for a given trial ($i$) for a given event ($k$) for a given occasion ($o$) can be expressed using a linear model, which provides the basis for expressing an observed score in terms of estimable variance components (Brennan, 2001, p. 56; Vispoel et al., 2018a, p. 5). This is considered a crossed design ($p \times i \times o$), because any trial from a given event and occasion is accepted as meaningful, which is an important feature of ERP studies that often include a different number of trials for each event (e.g., fewer target trials relative to standard trials).

$$X_{piok} = \mu_k \quad \text{(event mean)} \quad \text{(Eq. 1)}$$

$$+ \mu_p - \mu_k \quad \text{(person effect)}$$

$$+ \mu_i - \mu_k \quad \text{(trial effect)}$$

$$+ \mu_o - \mu_k \quad \text{(occasion effect)}$$

$$+ \mu_{pi} - \mu_p - \mu_i + \mu_k \quad \text{(person} \times \text{trial effect)}$$

$$+ \mu_{po} - \mu_p - \mu_o + \mu_k \quad \text{(person} \times \text{occasion effect)}$$

$$+ \mu_{io} - \mu_i - \mu_o + \mu_k \quad \text{(trial} \times \text{occasion effect)}$$

$$+ X_{piok} - \mu_{pi} - \mu_{po} - \mu_{io} + \mu_p + \mu_i + \mu_o - \mu_k \quad \text{(residual)}$$

The event mean, $\mu_k$, represents the mean $X_{piok}$ average score across all persons, trials, and occasions for a given event. The universe score, $\mu_p$, reflects a person's expected score over all trials and occasions for an event. $\mu_i$ represents the average score for a particular trial of an event averaged across persons and occasions. $\mu_o$ represents the average score for a particular occasion averaged across persons and trials for a given event. The main effects for person, trial, and occasion are summarized as $\mu_p - \mu_k$, $\mu_i - \mu_k$, and $\mu_o - \mu_k$, respectively. The remaining effects represent the interactions among the measurement facets. For example, the person × occasion effect represents differences in the between-session differences of person means. However, the three-way interaction[3] cannot be separated from the residual, because there is only one observation per cell. Hence, the three-way interaction is part of the residual or error term.

The variability of each effect, aside from the event mean, can be summarized by a variance component. The event mean is not associated with a variance component, because the event facet is fixed and the mean for each event is considered a constant. Similarly, if a group facet were included (e.g., healthy controls vs. people with schizophrenia), it would likely be considered a fixed facet, because only the two groups included in the study are likely to be the

[3] If a three-way interaction is of interest, then another crossed facet needs to be included in the study design in order to have more than one observation for each person for each cell. The highest-order interaction of a fully crossed design will always be confounded with the residual term due to only observing one observation for each cell of the full design.

groups of interest. If the purpose of the study were to generalize to all psychiatric conditions (and included such a sampling of disorders), then a researcher might consider psychiatric diagnosis to be random. The linear model above generalizes to the inclusion of any number of events and groups when they are considered fixed. For simplicity moving forward, $X_{piok}$ is simplified as $X_{pio}$, and interpretations will be about the grand mean, rather than event mean, because the grand mean could represent an event mean, a group mean, or an event mean for a particular group.

The variance of observed scores over all persons, trials, and occasions in the universe is summarized in Equation 2.

$$\sigma^2(X_{pio}) = \sigma_p^2 + \sigma_i^2 + \sigma_o^2 + \sigma_{pi}^2 + \sigma_{po}^2 + \sigma_{io}^2 + \sigma_{pio,e}^2 \qquad \text{(Eq. 2)}$$

This particular G study is associated with seven sources of variance. The between-person variance component, $\sigma_p^2$, represents the universe score variance and reflects how much persons differ from the grand mean. The trial variance component, $\sigma_i^2$, and the occasion variance component, $\sigma_o^2$, are associated with conditions of the trial and occasion facets, respectively. Each second-order interaction is also represented in Equation 2, and they are interpreted similar to a typical interaction effect. These variance components and their interpretation are briefly summarized in Table 2 for ease of reference, and they are described in more detail below using the example dataset. Although G-theory requires computing many variance components for the proper estimation of reliability coefficients, failing to consider each source of measurement variance can result in the overestimation of reliability (Vispoel et al., 2018a). Furthermore, each variance component has a unique interpretation and sheds light on those facets that most affect the variance of observed scores.

### 2.4. Decision (D) Study

In practice, observed scores are averaged together to create a person's score for subsequent statistical analysis. A D study focuses on decisions concerned with averaged scores, rather than single-trial scores, because any particular score ($X_{pio}$) is considered just one possible observation from the universe of admissible observations. The purpose of the present D study example is to estimate the two types of reliability: internal consistency (i.e., *coefficients of equivalence*) and test-retest reliability (i.e., *coefficients of stability*). For each reliability, there are two estimated coefficients: a generalizability coefficient, which characterizes the relative standing of individuals, or dependability coefficient, which characterizes the absolute differences in scores (see section 2.2). The generic formulas for the generalizability coefficient ($E\rho^2$) and dependability coefficients ($\phi$) are shown in Equations 3 and 4, respectively (see Brennan, 2001).

$$E\rho^2 = \frac{\sigma^2(\tau)}{\sigma^2(\tau)+\sigma^2(\delta)} \quad \text{(Eq. 3)}$$

$$\phi = \frac{\sigma^2(\tau)}{\sigma^2(\tau)+\sigma^2(\Delta)} \quad \text{(Eq. 4)}$$

In Equations 3 and 4, estimates of generalizability, $E\rho^2$, and dependability, $\phi$, are generically defined in terms of universe score variance, $\sigma^2(\tau)$, and error variance. The generalizability coefficient uses the relative error variance, $\sigma^2(\delta)$, which ignores sources of variance that do not impact the interindividual standings of persons. The dependability coefficient uses the absolute error variance, $\sigma^2(\Delta)$, and includes all error sources of variance that impact the absolute measurements of scores. Each coefficient represents the ratio of universe score variance to universe score and error variance.

**2.4.1. Coefficients of Equivalence.** Coefficients of equivalence are analogous to internal consistency estimates of reliability. For each coefficient of equivalence, the universe score variance, $\sigma^2(\tau)$, includes between-person variance, $\sigma_p^2$, and transient error variance, $\sigma_{po}^2$. The

person × occasion variance is in the numerator of coefficients of equivalence because only generalizing over trials is of interest. The formula for calculating a generalizability coefficient of equivalence is expressed in terms of variance components in Equation 5, and Equation 5 can also be expressed in terms of the number of observations of each effect (see Equation 6).

$$E\rho^2_{CE} = \frac{\sigma^2_p + \sigma^2_{po}}{\sigma^2_p + \sigma^2_{po} + \sigma^2_{pi} + \sigma^2_{pio,e}} \quad \text{(Eq. 5)}$$

$$E\rho^2_{CE} = \frac{\sigma^2_p + \frac{\sigma^2_{po}}{n'_o}}{\sigma^2_p + \frac{\sigma^2_{po}}{n'_o} + \frac{\sigma^2_{pi}}{n'_i} + \frac{\sigma^2_{pio,e}}{n'_i n'_o}} \quad \text{(Eq. 6)}$$

That is, the generalizability coefficient of equivalence represents the ratio of universe score variance ($\sigma^2_p$) and transient error variance ($\sigma^2_{po}$) to universe score variance ($\sigma^2_p$), transient error variance ($\sigma^2_{po}$), specific-factor trial score variance ($\sigma^2_{pi}$), and residual variance ($\sigma^2_{pio,e}$).

The formula for computing a dependability coefficient of equivalence can also be expressed in terms of variance components (Equation 7) and the number of observations of each effect (Equation 8).

$$\phi_{CE} = \frac{\sigma^2_p + \sigma^2_{po}}{\sigma^2_p + \sigma^2_{po} + \sigma^2_{pi} + \sigma^2_{pio,e} + \sigma^2_i + \sigma^2_{io}} \quad \text{(Eq. 7)}$$

$$\phi_{CE} = \frac{\sigma^2_p + \frac{\sigma^2_{po}}{n'_o}}{\sigma^2_p + \frac{\sigma^2_{po}}{n'_o} + \frac{\sigma^2_{pi}}{n'_i} + \frac{\sigma^2_{pio,e}}{n'_i n'_o} + \frac{\sigma^2_i}{n'_i} + \frac{\sigma^2_{io}}{n'_i n'_o}} \quad \text{(Eq. 8)}$$

Coefficients of equivalence calculated from a dataset that includes an occasion facet hold an advantage over internal consistency estimates from a single occasion. The shortcoming of the latter scenario is that the occasion facet is a *hidden facet*[4]. A facet is considered hidden when there is only one sampled condition of a given facet, which prevents variance associated with

[4] Other examples of hidden facets common in ERP research include the type of hardware used to record EEG, data processing pipeline, and experimental paradigm for eliciting ERPs.

that facet from being estimated (Brennan, 2010; Vispoel et al., 2018a). When internal consistency estimates are calculated from a single occasion, reliability estimates can be overestimated due to variance associated with occasion being included in between-person variance. Hence, between-person variance becomes inflated, and residual variance is reduced. The impact of variance associated with occasion is made explicit in the G-theory coefficients of stability, and this is shown in the numerators of Equations 5 through 8.

Considering occasion as a hidden facet in single-session ERP studies illustrates how occasion-specific variance might contribute to some of the variability in estimates of the internal consistency of ERP scores. It is common for internal consistency estimates from a single occasion to be misused because researchers attempt to generalize internal consistency estimates to other measurement occasions (e.g., when previous internal consistency estimates are used to justify the expected internal consistency of another study). However, this approach treats internal consistency estimates as something akin to a test-retest reliability coefficient, because the internal consistency estimates are used as if they generalize to other research. A ready ERP example can be drawn from the error-related negativity (ERN) component. Many ERN studies assume adequate ERN score reliability based on retaining six-to-eight error trials from each participant, and this number is based on psychometric work in undergraduates (Olvet & Hajcak, 2009). However, a recent meta-analysis of ERN score internal consistency from 4,499 participants yielded estimates of coefficient alpha that ranged from .02 to .94 when only using eight error trials (Clayson, 2020). Inferring ERP score reliability based on prior psychometric work is inappropriate. That being said, internal consistency estimates that parse variance associated with measurement occasion should provide more robust estimates of score reliability that are more likely to generalize across a similar test-retest window for similar samples

(Brennan, 2001). Hence, there are distinct advantages to estimating internal consistency of data across multiple occasions.

**2.4.2. Coefficients of Stability.** Coefficients of stability are analogous to test-retest reliability statistics and represent estimates of temporal stability. For each coefficient of stability, the universe score variance, $\sigma^2(\tau)$, includes between-person variance, $\sigma_p^2$, and specific-factor trial score variance, $\sigma_{pi}^2$. The trial × person variance is in the numerator of coefficients of stability because only generalizing over occasions for trials is of interest.

The formula for calculating a generalizability coefficient of stability is shown in Equation 9 and is a generalization from Equation 3. Equation 9 considers variance components that impact the relative standing of persons (see Vispoel et al., 2018a). The relative error variance, $\sigma^2(\delta)$, only considers sources of variance that impact the relative standing of persons. In other words, only those variance components that include an interaction with persons will impact relative error variance, and such variance components include person × trial variance ($\sigma_{pi}^2$), person × occasion variance ($\sigma_{po}^2$), and the residual variance ($\sigma_{pio,e}^2$).

$$E\rho_{CS}^2 = \frac{\sigma_p^2 + \sigma_{pi}^2}{\sigma_p^2 + \sigma_{pi}^2 + \sigma_{po}^2 + \sigma_{pio,e}^2} \quad \text{(Eq. 9)}$$

In words, the generalizability coefficient of stability represents the ratio of universe score variance ($\sigma_p^2$) and specific-factor trial score variance ($\sigma_{pi}^2$) to the combination of universe score variance ($\sigma_p^2$), specific-factor trial score variance ($\sigma_{pi}^2$), specific-factor occasion score variance ($\sigma_{po}^2$), and residual variance ($\sigma_{pio,e}^2$).

In practice, scores are averaged within each facet. For example, all scores of an event are averaged together to compute the score to use for subsequent analysis. Hence, the partitioning of mean scores is of interest when assessing the internal consistency or temporal stability of scores.

A property of the sampling distribution of mean scores is that the larger the sample size the smaller the variance of the distribution (i.e., the variance sum law). Conceptually speaking, recording many ERP trials from a person should result in a better estimate of an average score than recording few trials due to a reduction in trial-by-trial variability from random background noise. Hence, the variance of $\sigma_{pi}^2$ decreases as the number of trials retained for averaging increases. Furthermore, ERP trials are considered a random facet, so any trial score is entirely interchangeable with any other trial score. This notion is reflected in the practice of averaging across all ERP trials to obtain subject average score. Taken together, because the variance of any set of uncorrelated observations is related to the number of observations included in a mean[5], Equation 9 can be expressed in terms of the number of observations of each effect.

$$E\rho_{CS}^2 = \frac{\sigma_p^2 + \frac{\sigma_{pi}^2}{n_i'}}{\sigma_p^2 + \frac{\sigma_{pi}^2}{n_i'} + \frac{\sigma_{po}^2}{n_o'} + \frac{\sigma_{pio,e}^2}{n_i' n_o'}} \qquad \text{(Eq. 10)}$$

The generalizability coefficient of stability can now be computed as a function of each variance component, a given number of trials ($n_i'$), and a given number of occasions ($n_o'$).

The formula for calculating a dependability coefficient of stability is shown in Equation 11 and considers all measured variance components that could impact the absolute magnitude of observed scores. As in the generalizability coefficient, the universe score variance, $\sigma^2(\tau)$, includes between-person variance, $\sigma_p^2$, and specific-factor trial score variance, $\sigma_{pi}^2$. However, the absolute error variance, $\sigma^2(\Delta)$, includes all sources of variance that impact scores. Hence, all sources of variance that contributed to the relative standing of individuals and the sources of

[5] "One well-known property of a distribution of mean scores for a set of uncorrelated observations is that the variance of the distribution is the variance of the individual elements divided by sample size" (Brennan, 2001, p. 31; see also Shavelson & Webb, 1991).

variance associated with occasions and the interactions of occasions with trials are included in the error term.

$$\phi_{CS} = \frac{\sigma_p^2 + \sigma_{pi}^2}{\sigma_p^2 + \sigma_{pi}^2 + \sigma_{po}^2 + \sigma_{pio,e}^2 + \sigma_o^2 + \sigma_{io}^2} \quad \text{(Eq. 11)}$$

Similar to the generalizability coefficient of stability, Equation 11 can be expressed in terms of the number of observations of each effect.

$$\phi_{CS} = \frac{\sigma_p^2 + \frac{\sigma_{pi}^2}{n_i'}}{\sigma_p^2 + \frac{\sigma_{pi}^2}{n_i'} + \frac{\sigma_{po}^2}{n_o'} + \frac{\sigma_{pio,e}^2}{n_i' n_o'} + \frac{\sigma_o^2}{n_o'} + \frac{\sigma_{io}^2}{n_i' n_o'}} \quad \text{(Eq. 12)}$$

The key difference between the dependability coefficient of stability, $\phi_{CS}$, and the generalizability coefficient of stability, $E\rho_{CS}^2$, is that the dependability coefficient accounts for each effect that could impact the absolute magnitude of observed scores. Generally speaking, generalizability coefficients should be higher than dependability coefficients, because absolute error variance tends to be larger than relative error variance. In practice, the difference between absolute and relative error variance can be quite small in the absence of systematic between-occasion or trial × occasion differences. The estimate of the dependability coefficient of stability will approach the estimate of the generalizability coefficient of stability as the variance estimates for occasions and interactions with occasion approach zero.

## 3. ERA Toolbox

The ERA Toolbox facilitates the calculation of reliability estimates based on generalizability theory and, as of version 0.5.0, includes the capability to estimate coefficients of equivalence and coefficients of stability using data from multiple recording sessions (i.e., more than one occasion). The N2 amplitude data from the companion paper (i.e., Carbine et al., current issue), which was described above, will be used below to demonstrate how to interpret

the reliability coefficients and outputs from the toolbox. These data are from the low-calorie Go/NoGo task and consist of two event types (Go, NoGo) and two occasions approximately two weeks apart. Both event and occasion are considered fixed facets[6] for these data analyses. For details about the preprocessing pipeline, a discussion of the implications of the present findings, and a statistical analysis of N2, the reader is directed to the companion paper.

A distinct advantage of G theory over classical test theory is that data from all trials are used to estimate variance components, because G-theory estimates of reliability can handle unbalanced observations across participants and events (Baldwin et al., 2015; Clayson et al., 2020; Clayson & Miller, 2017a, 2017b). It is important to use data from all trials, because it reflects how ERP data are typically analyzed. That is, researchers often average all trials of a given event type together. Approaches using classical test theory often calculate internal consistency estimates using coefficient alpha (i.e., Cronbach's alpha), which requires the same number of observations from each participant. To this end, the first X number of trials are commonly selected, and coefficient alpha is estimated for those trials. However, such estimates are prone to trial sampling bias (the first X number of trials might be more salient and uniform than later trials and consequently be systematically biased) and participant sampling bias (participants are often lost from reliability analyses due to not having enough trials to be included in the estimate, which introduces additional uncertainty in reliability estimates in studies of small samples). Split-half reliability estimates have similar issues related to trial and participant sampling bias as coefficient alpha, and the impact of the sampling bias is most problematic when few trials are retained for averaging (Clayson et al., 2020).

[6] The current version of the ERA Toolbox treats event and occasion as fixed facets, and this is likely how most ERP researchers would choose to treat them. The toolbox does not currently have the capability for treating the event or occasion facets as random, but this capability will be implemented in future versions of the toolbox.

In order to take advantage of G theory's consideration of scores from all trials in the estimation of each variance component, the ERA toolbox implements Bayesian multilevel models using Markov Chain Monte Carlo (MCMC) estimation procedures (Baldwin et al., 2015; Clayson & Miller, 2017a; Gelman et al., 2013). The toolbox relies on the open-source packages MatlabStan (Stan Development Team, 2016), CmdStan (Stan Development Team, 2019), and MatlabProcessManager (Lau, 2016) to implement the MCMC estimation procedures in Stan (Carpenter et al., 2017). Convergence of chains[7] is determined by verifying that that the potential scale reduction for the scalar estimands ($\hat{R}$) are below 1.1 and that the effective sample size for each scalar estimand is greater than 10 times the number of chains. The ERA Toolbox primarily acts as a software wrapper around these other packages to estimate the variance components, and then those computed variance components are used to calculate reliability estimates.

We will now demonstrate how to interpret G-theory outputs from the ERA Toolbox using the correct-trial N2 scores from the low-calorie version of the Go/NoGo task. Single-trial amplitude data for each event type and occasion were processed in the ERA Toolbox. Variance components were estimated using MCMC procedures with 3 chains and 10,000 iterations. Convergence of chains was verified by checking $\hat{R}$ and effective sample size. For more information about how to prepare data for processing through the ERA Toolbox, the reader is directed to the documentation for the toolbox (https://github.com/peclayson/ERA_Toolbox). The toolbox outputs will be covered in detail below. This walkthrough mirrors the format of the original G-theory ERP dependability study (Baldwin et al., 2015) and the ERA Toolbox monograph (Clayson & Miller, 2017a) but emphasizes coefficients of stability.

[7] The visual inspection of trace plots can also be helpful for verifying convergence of model chains (Gelman et al., 2013; Lunn, Jackson, Best, Thomas, & Spiegelhalter, 2012). This approach will be implemented in future versions of the toolbox.

### 3.1. G Study Outputs

The purpose of the G study is to estimate the relevant variance components, which include between-person variance, $\sigma_p^2$; between-trial variance, $\sigma_i^2$; between-occasion variance (alternatively, between-session variance), $\sigma_o^2$; person × trial variance, $\sigma_{pi}^2$; person × occasion variance, $\sigma_{po}^2$; trial × occasion variance, $\sigma_{io}^2$; and error variance, $\sigma_{pio,e}^2$. One helpful metric for assessing the relative contribution of each variance component is to examine their standard deviations.

**3.1.1. Standard deviations of variance components.** The point estimates of each standard deviation are shown in Figure 1. It is helpful to compare standard deviations as they provide insight into the relative sizes of the sources of variance (i.e., facets) in the reliability estimates (Baldwin et al., 2015; Clayson & Miller, 2017a; Shavelson & Webb, 1991). The standard deviation is a measure of dispersion and is computed by taking the square root of each variance component. Standard deviations are interpreted as the average distance of a score from the mean of a distribution.

The between-person standard deviation represents an estimate of the universe-score standard deviation over all combinations of trials and occasions. In words, the average distance between a person's average N2 score in the universe of admissible observations and the mean of all persons is 1.98 for Go trials and 1.96 for NoGo trials. The between-person standard deviations for these two event types are quite comparable. If other variance components are equal, it would be expected that these two event types would have comparable reliability estimates.

The between-session (i.e., occasion) standard deviation represents an estimate of the variance for a particular session across all persons and trials, and the between-trial standard

deviation represents an estimate of the variance for a particular trial across all persons and occasions. The between-session standard deviation reflects variance associated with the consistent responding between sessions, but the between-trial variance reflects contributions to scores from trial to trial within a single session, which can be impacted by participant factors (e.g., attention or fatigue) or paradigmatic ones (e.g., variable trial difficulty).

The interaction effects between persons, sessions, and trials are also shown in Figure 1 and indicate differences in a facet associated with the change in level of another facet. For example, the person × session standard deviation reveals the variance in within-person differences in session means from person to person. Because the person × session standard deviation reflects transient error between recording sessions, it is associated with universe score variance for coefficients of equivalence (see equations 5 and 7). Specific-factor trial score variance (i.e., person × trial standard deviation) is associated with universe score variance for coefficients of stability (see equations 9 and 11). Given that the person × session standard deviations are large relative to other sources of variance and that they contribute to the denominator of coefficients of stability, it is likely that coefficients of stability will be lower than coefficients of equivalence.

The within-person standard deviation provides an estimate of variability in single-trial N2 scores and error variance. The within-person standard deviation is a large contribution to score reliability, and when it is large relative to other components, it is likely that many trials will be needed for adequate score reliability.

**3.1.2. Summary.** Based on the findings of the G study, the majority of variance in observed N2 scores is accounted for by between-person variance, person × occasion variance, and within-person/error variance. The variance components across events were also comparable.

Hence, it is likely that similar reliability coefficients will be observed for N2 scores from each event. Given the large person × occasion variance, it is likely that coefficients of stability will be lower than coefficients of equivalence.

### 3.2. D Study Outputs

As mentioned above, the D study uses variance component estimates from the G study to compute reliability estimates in an effort to minimize measurement error. For example, a D study helps a researcher to determine the minimum number of trials necessary to achieve acceptable score reliability. However, what is considered acceptable score reliability is a decision left up to the researcher.

Clayson and Miller (2017b) provided guidelines for what is acceptable ERP score reliability. They recommended using .80 as the minimum threshold for acceptable score reliability for most ERP research. When paradigms are in the early stages of development, they recommended a more relaxed threshold of .70. It is important that the threshold used for determining acceptable score reliability is specified *a priori*, rather than after seeing how much data are lost or whether statistical significance changes with different thresholds. Regardless of the chosen reliability threshold, it is recommended that the observed reliability be reported.

For the present D study, a reliability threshold of .70 was chosen as the cutoff for acceptable reliability because this is the first test-retest reliability analysis using a recently developed version of a Go/NoGo paradigm with food stimuli. The outputs related to coefficients of equivalence are briefly summarized below, and the interested reader is directed to Baldwin et al. (2015) and Clayson and Miller (2017a) for more information about G-theory internal consistency estimates. Consistent with the purpose of this primer, greater emphasis is placed on coefficients of stability than on coefficients of equivalence.

**3.2.1. Coefficients of Equivalence.** The point estimates for dependability coefficients of equivalence as a function of the number of trials included in an average and event are shown in Figure 2. The generalizability coefficients are not shown, because they produced comparable estimates. As expected, the reliability estimates for N2 scores from Go and NoGo trials are very similar. The number of trials needed to obtain adequate reliability was 7 for Go trials and 8 for NoGo trials, and the obtained reliability at these trial cutoffs is shown in Figure 3. The 95% credible intervals for reliability estimates are also shown in Figure 3. The default for the toolbox is to provide the 95% credible intervals for most estimates; credible intervals are the Bayesian analog to confidence intervals (Morey, Hoekstra, Rouder, Lee, & Wagenmakers, 2016).

The output summary for the dependability coefficient of equivalence is shown in Figure 4. The reliability summary characterizes the overall score reliability after applying trial cutoffs to the data. Score reliability is calculated using equation 6 for generalizability and equation 8 for dependability. The overall score reliability uses a central tendency estimate (mean or median) of the retained trials from the sample as $n_i'$, and $n_o'$ is set to 1. Based on the information in Figure 4, it appears that all participants except for two had enough trials to satisfy the trial cutoffs based on the dependability coefficient of equivalence.

**3.2.2. Coefficients of Stability.** Unfortunately, N2 scores failed to achieve an acceptable level of score reliability for generalizability or dependability estimates of stability. For the purposes of this primer, the reliability threshold was relaxed to .60, and there will be a discussion of factors that can contribute to low coefficients of stability below.

The point estimates for dependability coefficients of stability as a function of the number of trials included in an average and event are shown in Figure 5. The generalizability coefficients are not shown due to being very comparable to the dependability coefficients for these N2

scores. Figure 5 shows the number of trials needed from each session to obtain a given dependability coefficient of stability. The advantage of estimating the temporal stability of ERPs as a function of the number of trials included in an average is that this approach is more consistent with how data from multiple sessions are used. It is possible that more trials are needed to ensure adequate temporal stability than are needed to ensure single-session internal consistency (see Larson, Baldwin, Good, & Fair, 2010). The present N2 scores needed more trials to obtain acceptable coefficients of stability than were needed to obtain acceptable coefficients of equivalence.

The number of trials from each session needed to obtain a .60 dependability coefficient of stability was 18 for Go trials and 19 for NoGo trials (see top of Figure 6). A closer look at the variance components from the G study and the formulas for computing the dependability sheds light on why more trials are needed for adequate temporal stability. The primary reason has to do with how the person × occasion variance, $\sigma_{po}^2$, contributes to the reliability of each type of coefficient. The person × occasion variance is comparable to between-person variance, $\sigma_p^2$, for both event types. The coefficient of equivalence includes person × occasion variance in the numerator (see Equation 8), but the coefficient of stability does not (see Equation 12). The numerator of the coefficient of stability includes the person × trial variance, $\sigma_{pi}^2$, which was quite small. Furthermore, as the number of trials ($n_i'$) included increases, there will be no impact on the numerator of the coefficient of equivalence ($\sigma_p^2 + \frac{\sigma_{po}^2}{n_o'}$), because increasing $n_i'$ has no impact on the numerator. However, increasing $n_i'$ will reduce the numerator of the coefficient of stability ($\sigma_p^2 + \frac{\sigma_{pi}^2}{n_i'}$). Because both equations have the same terms in the denominator (see Equations 8 and 12), the denominator will decrease at the same rate as trials are added. Hence, for these N2

scores the numerator of the coefficient of equivalence will always be larger than the numerator of the coefficient of stability, which will lead to a larger coefficient of equivalence.

There is an important distinction between the factors that impact the occasion variance component and the factors that impact the person × occasion variance component. The variance associated with changes in scores across all persons from session 1 to session 2 is reflected in the occasion variance component, $\sigma_o^2$. This variance component reflects changes that impact all persons equally (e.g., if all person average scores from session 1 to session 2 dropped 1 μV, it would be reflected in $\sigma_o^2$). Examples of factors that could impact such variance include practice or carryover effects, time between assessments (e.g., developmental changes), or the impact of an intervention[8]. The person × occasion variance is interpreted as how much differences in person means between sessions vary from person to person (e.g., one person's average score might be the same for each session, but another person's score might be much larger for session 1 than for session 2).

There are a number of factors that might contribute to why differences in session scores might vary from person to person. The extent to which scores differ could be due to differences in state factors (e.g., persons could be inconsistently tested at different times of day; a person could be alert during a morning recording session at time 1 but drowsy during an evening recording session at time 2), changes in physical or mental health status, changes related to EEG recording (e.g., bad channels, different impedance levels), or changes in the experimental environment (e.g., physiological or environmental interference). The size of the person ×

[8] In intervention research, score reliability from participants in an intervention group is likely of less concern than score reliability in a control group. If an intervention is effective and impacts scores across time, then occasion and person × occasion variances will be higher than if there is no impact. The higher variance components would lead to worse score reliability. In the control group, scores would ideally be more stable and yield lower occasion and person × occasion variances.

occasion variance component highlights the importance of controlling for these various factors when conducting experiments to maximize observed reliability by minimizing potential sources of error. These considerations that impact test-retest reliability highlight the context dependent nature of score reliability (see Time as Another Context section in Clayson & Miller, 2017b).

The large person × occasion variance component is also the primary reason for the low coefficient of stability compared to the coefficient of equivalence. To estimate the test-retest reliability using the coefficient of stability, the number of occasions, $n_o'$, is fixed to 1 (Vispoel et al., 2018a). In the denominator of Equation 12, the between-person, between-occasion, and person × occasion variance components are the only terms that cannot be minimized by adding more trials, $n_i'$. Given how large the person × occasion variance component is, it essentially placed a ceiling on the maximum reliability that could be achieved and caused the relationship between reliability and the number of trials to asymptote just below .70.

The overall reliabilities after applying trial cutoffs for the coefficients of stability are shown in Figure 7. These reliability estimates are the observed test-retest reliability coefficients for these N2 scores. Four participants did not have enough trials to satisfy the cutoffs shown in Figure 6. In order to compute the overall score reliability for the coefficients of stability, an estimate of $n_i'$ is needed. The overall score reliability uses an estimate of the central tendency (mean or median) for the trials from those participants that satisfied the trial cutoff as $n_i'$. The number of occasions, $n_o'$, is set to 1 to estimate stability of scores from session 1 to session 2 (Vispoel et al., 2018a).

The dependability and generalizability coefficients of stability were very similar (see Figures 6 and 7). This was due to the between-occasion and trial × occasion variance components being small compared to other sources of variances. Anything that increases the

magnitude of these variance components would increase the difference between the generalizability and dependability coefficients. For example, in the context of an intervention study, a researcher would likely expect the intervention to change the ERP scores from a baseline assessment to a follow-up assessment. If these changes are similar across individuals, much of this change would be captured by between-occasion variance. In the context of an intervention study, it is likely that a researcher would use generalizability coefficients to demonstrate score reliability, because changes in mean person scores would be expected.

**3.2.3. Summary.** This D study demonstrated the impact of the number of trials on coefficients of equivalence and coefficients of stability. The coefficients of stability required more trials than the coefficients of equivalence to obtain acceptable score reliability. Findings of the D study were consistent with expectations set up by the G study that yielded large person × occasion variance components, which led to decreased coefficients of stability.

## 4. The Balance Between Internal Consistency and Test-Retest Reliability

Internal consistency and test-retest reliability should be considered together when making judgments about the usefulness of ERP scores, and there may be instances when excellent reliability in both domains is not desired. It is possible that scores can still be useful when failing to meet adequate reliability standards of either internal consistency or test-retest reliability (but not both). We next briefly consider the utility and practical implications of excellent internal consistency and poor test-retest reliability and then poor internal consistency and excellent test-retest reliability.

ERP measurements that have excellent internal consistency and poor test-retest reliability can be useful, particularly when they relate to individual difference measures (i.e., characterize between-person differences). ERP scores must demonstrate adequate internal consistency when

the purpose is to relate ERP scores to an external correlate, because internal consistency reflects how well scores differentiate participants. If scores fail to differentiate participants, they cannot meaningfully relate to other individual difference measures. Consider an example of ERP amplitudes that demonstrate adequate internal consistency and correlate modestly with clinical symptom status. It might be expected that clinical symptom status would wax and wane over time or change in response to an intervention. If amplitudes correlate with clinical symptom status over multiple timepoints, ERP amplitudes might show poor test-retest reliability, because they move with clinical symptom status rather than remain stable over multiple recording sessions.

Alternatively, measurements might show excellent test-retest reliability but poor internal consistency. Such measurements might be useful for measuring trait-like characteristics (e.g., cognitive functioning) or for studying within-person differences (e.g., error vs. correct) or group differences (e.g., controls vs. patients). Studying group differences in this fashion is consistent with the categorical approach to studying psychiatric disorders, and there is utility in this approach when trying to establish the selectivity of ERP effects for certain diagnostic categories. Insofar as the purpose of the measurements is to differentiate between groups, rather than differentiate between participants, measurements with excellent test-retest reliability and poor internal consistency have utility. However, such measures would be poor candidates for studies of individual differences.

Many ERP studies only collect recordings during one measurement occasion, and do not have information about test-retest reliability. When ERP measurements from a single occasion yield low internal consistency, they are of little use for studies of individual differences, but they might still show adequate measurement precision (i.e., low between-trial variance) for a

comparison of conditions or groups (Clayson et al., 2020). To support such investigations, the standardized measurement error (SME) could be used to show that SME is low compared to the comparison of interest (see Luck, Stewart, Simmons, & Rhemtulla, 2020 for a detailed description). The SME provides an estimate of measurement precision or data quality, and it could be used to show that individual-subject measurement precision is adequate enough for a given comparison. Although SME and score reliability are often fairly related, these estimates can diverge when few trials are retained for averaging and the variability in numbers of retained trials is high (Clayson et al., 2020).

We have a few recommendations that follow the spirit of G theory. In any given study, the type of reliability that needs to be demonstrated depends on the application of the ERP measurements. First, we echo many others and recommend demonstrating the internal consistency of ERP scores as a prerequisite to examining their relationships with external correlates (see also, author guidelines for *Psychophysiology* and *International Journal of Psychophysiology*, as well as Clayson & Miller, 2017b; Hajcak et al., 2017; Infantolino et al., 2018; Thigpen et al., 2017). Failing to demonstrate that ERP scores can reliably distinguish between participants undermines their utility as individual difference measures.

Second, when the purpose of using ERP measurements is to study stable, trait-like characteristics or to examine the stability of group differences, the test-retest reliability of scores must first be demonstrated. When G-theory estimates of test-retest reliability are reported, the generalizability or dependability coefficient should be reported to show the consistency of the rankings of participants and the consistency of scores of participants, respectively. Additionally, it would be helpful to report the variance components, so all necessary information is provided for computing reliability estimates with different numbers of trials and occasions. Such

information would help other researchers in the planning stages of follow-up studies. To achieve adequate test-retest reliability it might be necessary to exclude participants with too few trials to obtain a reliable single-session measurement, and the G-theory formulas developed in this primer can be used to this end. Failing to adhere to such psychometric rigor jeopardizes the promise of ERP scores as biomarkers and endophenotypes by reducing the quality and likelihood of replicability of ERP research.

## 5. Conclusion

A substantial strength of G theory is its multifaceted approach toward understanding score reliability, which allows for identifying sources of measurement error. The current primer outlined the approach to using G theory to calculate coefficients of stability (i.e., test-retest reliability) for ERP studies and outlined how to interpret variance components to determine sources of error. We also provided a walkthrough of how to conduct these analyses using the ERA Toolbox. The ERA Toolbox can be used to calculate coefficients of equivalence and coefficients of stability for scores from any number of trials, events, occasion, and groups. We hope that this primer and the open-source ERA toolbox facilitate the evaluation of ERP scores on a study-by-study basis.

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## Acknowledgments

Michael Larson is the Editor-in-Chief of the *International Journal of Psychophysiology* and one of the Editors of this special issue. Editing of the manuscript was handled by an Action Editor of the journal, and Dr. Larson was blinded from viewing the reviews or comments. We have no additional conflicts of interest.

Table 1

*Definitions of Terms Used in Generalizability (G) Theory*

| G Theory Term | Conceptual Definition |
|---|---|
| Condition | Systematic ways that a condition of measurement can vary (analogous to a level of a factor in an ANOVA; e.g., controls vs. patients or baseline vs. follow-up) |
| Coefficient of Equivalence | An estimate of internal consistency and can be a dependability or a generalizability coefficient |
| Coefficient of Stability | An estimate of temporal stability and can be a dependability or a generalizability coefficient, commonly referred to as coefficient of stability |
| Decision (D) Study | Approach to designing a measurement procedure for a particular purpose; a D study is used to estimate reliability coefficients (e.g., identifying the number of trials needed for adequate internal consistency of ERP scores) |
| Dependability Coefficient ($\phi$) | A reliability coefficient that assesses score consistency or the absolute level of performance |
| Facet | A set of possible conditions of measurement or a characteristic of the measurement situation (analogous to a factor in an ANOVA; e.g., participant group or assessment occasion) |
| Fixed Facet | A facet is fixed when all possible conditions of the universe of generalization are exhausted, which is often the case for ERP event type (e.g., correct and error trials) |
| Generalizability Coefficient ($E\rho^2$) | A reliability coefficient that assesses stability in the relative position or rankings of persons (similar to coefficient alpha or split-half reliability estimates from classical test theory) |
| Generalizability Study | Procedure use to isolate and estimate sources of variance in observed scores, and these variance estimates are used in the D study |
| Random Facet | A facet is random when the observations are considered interchangeable and are a random sample of the universe (e.g., trial 1 vs. trial 10 vs. trial 200) |
| Universe of Admissible Observations | The entire range of possible conditions of facets and how those facets are defined and combined |

| | |
|---|---|
| Universe of Generalization | All possible conditions of a facet to which a researcher wants to generalize |
| Universe Score | A person's observed score over all observations in the universe of generalization (analogous to "true score" in classical test theory) |

Note: ANOVA = analysis of variance

Table 2

*Mathematical Representations and Interpretations of Variance Components Related to the Temporal Stability of Event-Related Potentials*

| Symbol | Label | Interpretation |
|---|---|---|
| $\sigma_p^2$ | between-person variance | Universe score variance; differences in person scores from the grand mean |
| $\sigma_i^2$ | between-trial variance | Differences in person scores across all trials and persons; impacted by stimuli differences such as difficulty |
| $\sigma_o^2$ | between-occasion variance | Differences in person scores related to changes from session 1 to session 2 across all persons; impacted by practice effects and development changes |
| $\sigma_{pi}^2$ | person × trial variance | Differences in person mean differences across trials; impacted by within person differences across trials (e.g., how quickly a person becomes fatigued) |
| $\sigma_{po}^2$ | person × occasion variance | Differences in person mean differences between sessions; impacted by between-session differences in physical or mental health status or a response to a treatment intervention |
| $\sigma_{io}^2$ | trial × occasion variance | Differences in trial mean differences between-sessions; impacted by differences in sets of stimuli (e.g., parallel forms) |
| $\sigma_{pio,e}^2$ | error variance | Variances in scores not accounted for by between-person variance or the variance of other measured facets |

*Note*. Some characteristics that impact each variance component are described in the Interpretation column. This is not an exhaustive list of examples, and more examples can be found in the body of the manuscript.

## Figure Captions

Figure 1. Point estimates for each component used to calculate reliability estimates. Components include between-person, between-trial, between-session (alternatively, between-occasion), person × trial interaction, person × occasion variance, trial × occasion interaction, and within-person variance (i.e., error variance).

Figure 2. Dependability coefficients of equivalence of N2 scores as a function of event type and the number of trials included. The dotted line represents the user-specified reliability threshold, which was 0.70 in this instance.

Figure 3. The number of trials needed to obtain an acceptable dependability coefficient of equivalence for Go and NoGo trials. What is considered an acceptable threshold is user defined and was 0.70 in this instance. The point estimate and 95% credible interval of the dependability coefficients of equivalence for the given number of trials are also shown.

Figure 4. Summary characteristics of N2 scores stratified by condition (Go, NoGo). The “n Included” column indicates the number of participants that were included after applying the trial cutoffs for each event (see Figure 3). The “n Excluded” column indicates the number of participants that were excluded after applying the trial cutoffs. The dependability point estimates and 95% credible intervals characterize the overall score dependability for those participants that had enough trials to meet the trial cutoffs. The trial summary reflects the mean, median, standard deviation, minimum, and maximum number of trials retained after applying the trial cutoffs from each event.

Figure 5. Dependability coefficients of stability of N2 scores as a function of event type and the number of trials included. This plot shows the relationship between the number of trials and test-retest score reliability. The dotted line represents the user-specified reliability threshold, which was 0.60 in this instance.

Figure 6. The number of trials needed to obtain acceptable dependability (top) and generalizability (bottom) coefficients of equivalence for Go and NoGo trials. What is considered an acceptable threshold is user defined and was 0.60 in this instance. The point estimate and 95% credible interval of the coefficients of equivalence for the given number of trials are also shown.

Figure 7. Summary characteristics of N2 scores stratified by condition (Go, NoGo) and coefficient type (dependability, top; generalizability, bottom). The “n Included” column indicates the number of participants that were included after applying the trial cutoffs for each event (see Figure 3). The “n Excluded” column indicates the number of participants that were excluded after applying the trial cutoffs. The reliability point estimates and 95% credible intervals characterize the overall score reliability for those participants that had enough trials to meet the trial cutoffs. The trial summary reflects the mean, median, standard deviation, minimum, and maximum number of trials retained after applying the trial cutoffs from each event.

Figure 1

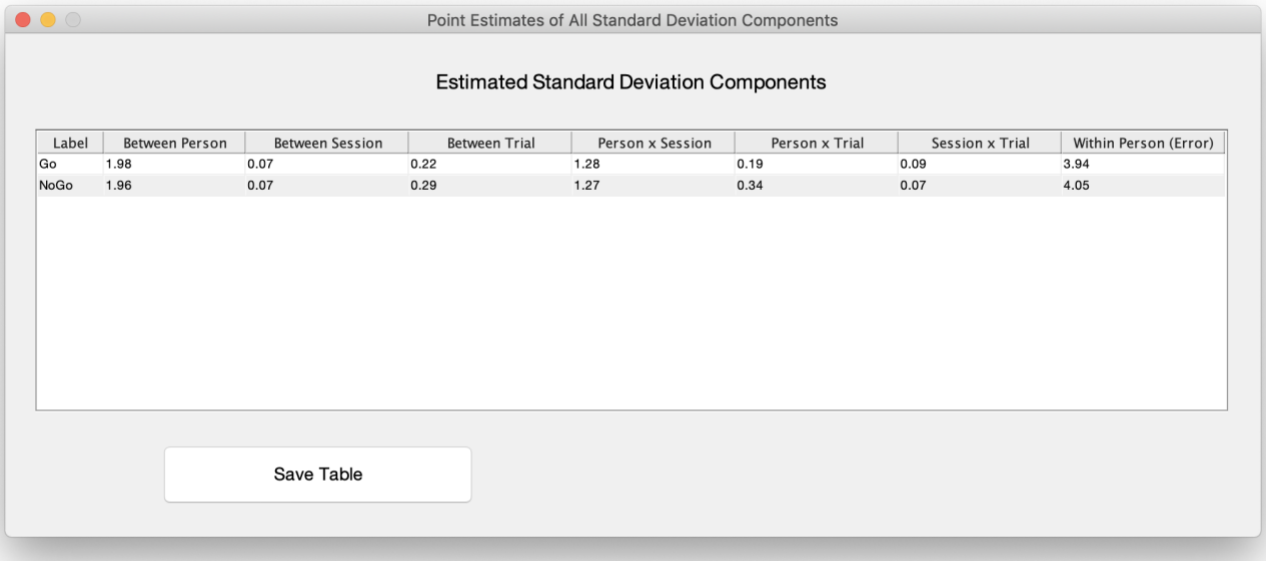

Point Estimates of All Standard Deviation Components
Estimated Standard Deviation Components
Label | Between Person | Between Session | Between Trial | Person x Session | Person x Trial | Session x Trial | Within Person (Error)
Go | 1.98 | 0.07 | 0.22 | 1.28 | 0.19 | 0.09 | 3.94
NoGo | 1.96 | 0.07 | 0.29 | 1.27 | 0.34 | 0.07 | 4.05
Save Table

Figure 2

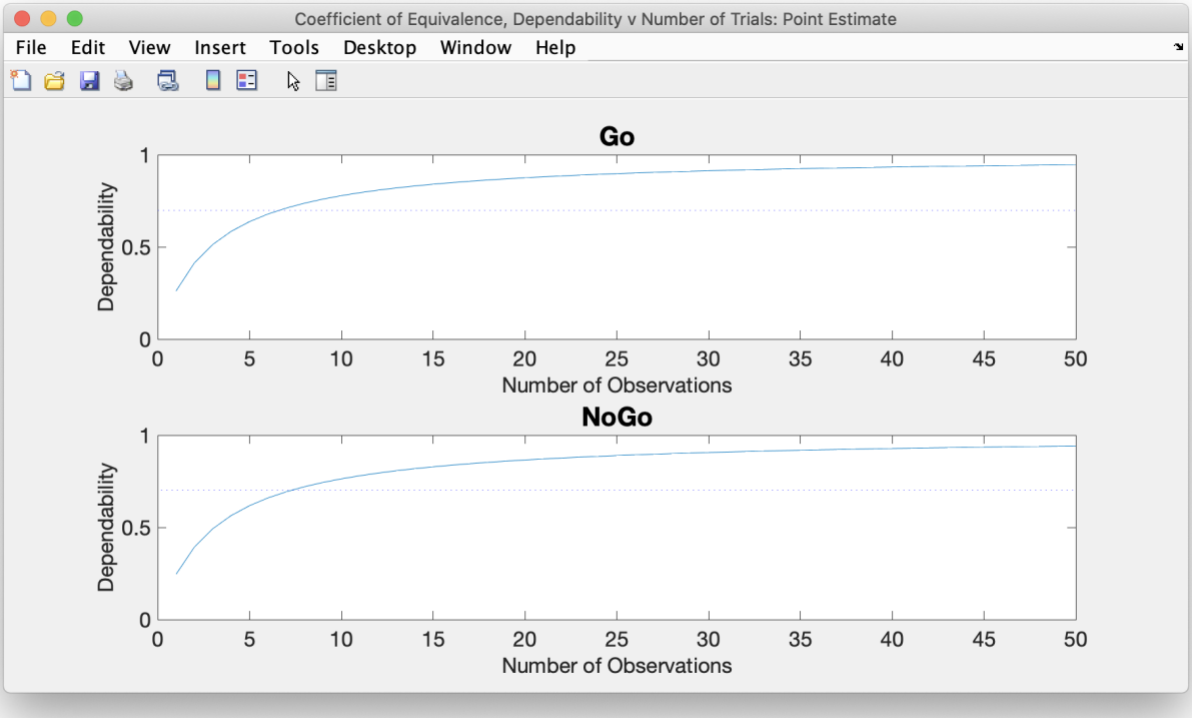

Coefficient of Equivalence, Dependability v Number of Trials: Point Estimate
File Edit View Insert Tools Desktop Window Help
Go
Dependability
Number of Observations
NoGo
Dependability
Number of Observations

Figure 3

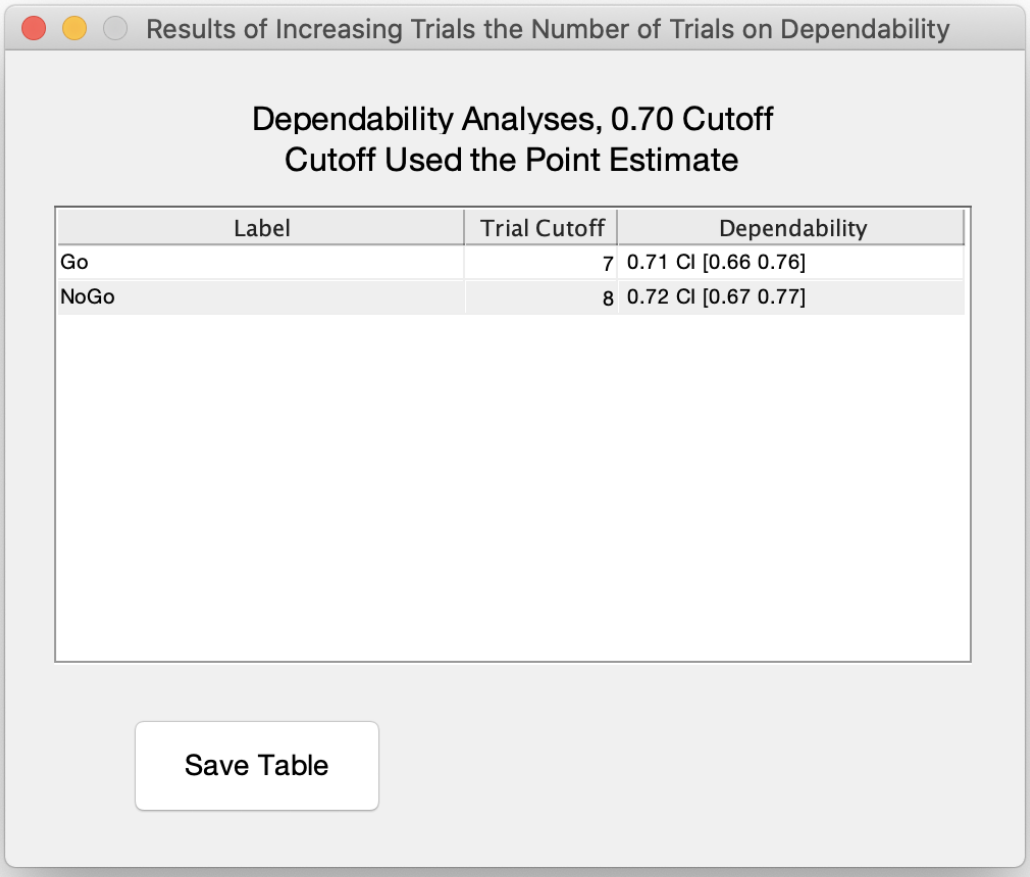

Results of Increasing Trials the Number of Trials on Dependability
Dependability Analyses, 0.70 Cutoff
Cutoff Used the Point Estimate
Label
Trial Cutoff
Dependability
Go
7
0.71 CI [0.66 0.76]
NoGo
8
0.72 CI [0.67 0.77]
Save Table

Figure 4

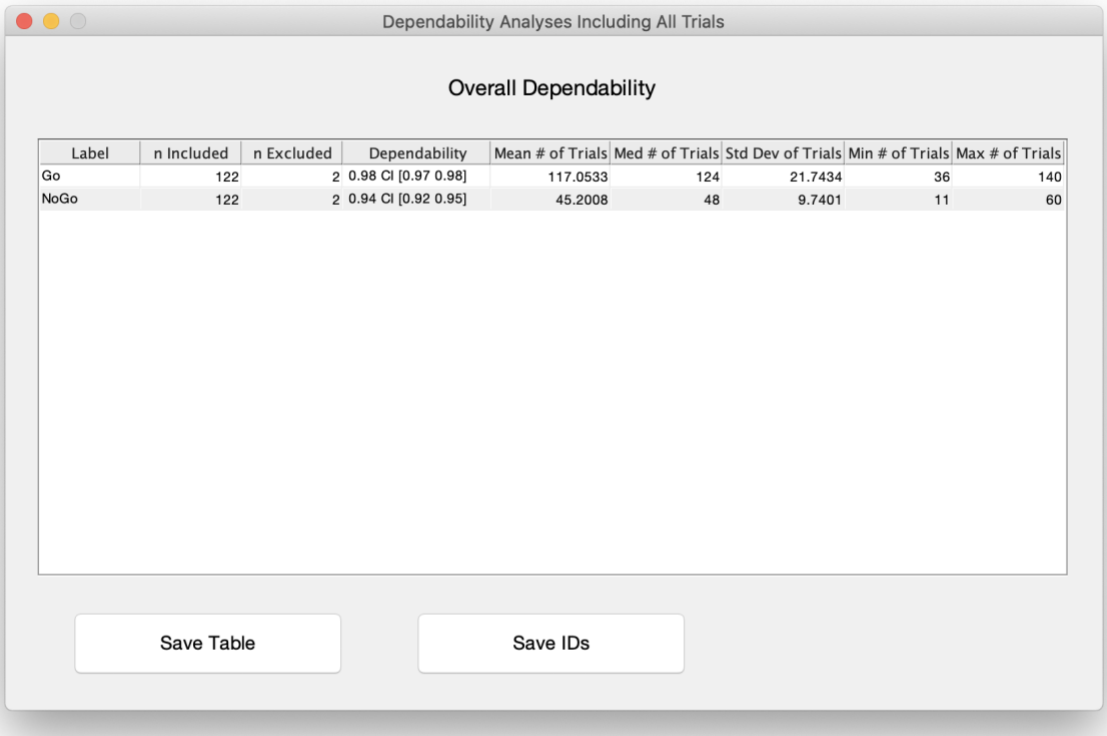

Dependability Analyses Including All Trials
Overall Dependability
Label | n Included | n Excluded | Dependability | Mean # of Trials | Med # of Trials | Std Dev of Trials | Min # of Trials | Max # of Trials
Go | 122 | 2 | 0.98 CI [0.97 0.98] | 117.0533 | 124 | 21.7434 | 36 | 140
NoGo | 122 | 2 | 0.94 CI [0.92 0.95] | 45.2008 | 48 | 9.7401 | 11 | 60
Save Table
Save IDs

Figure 5

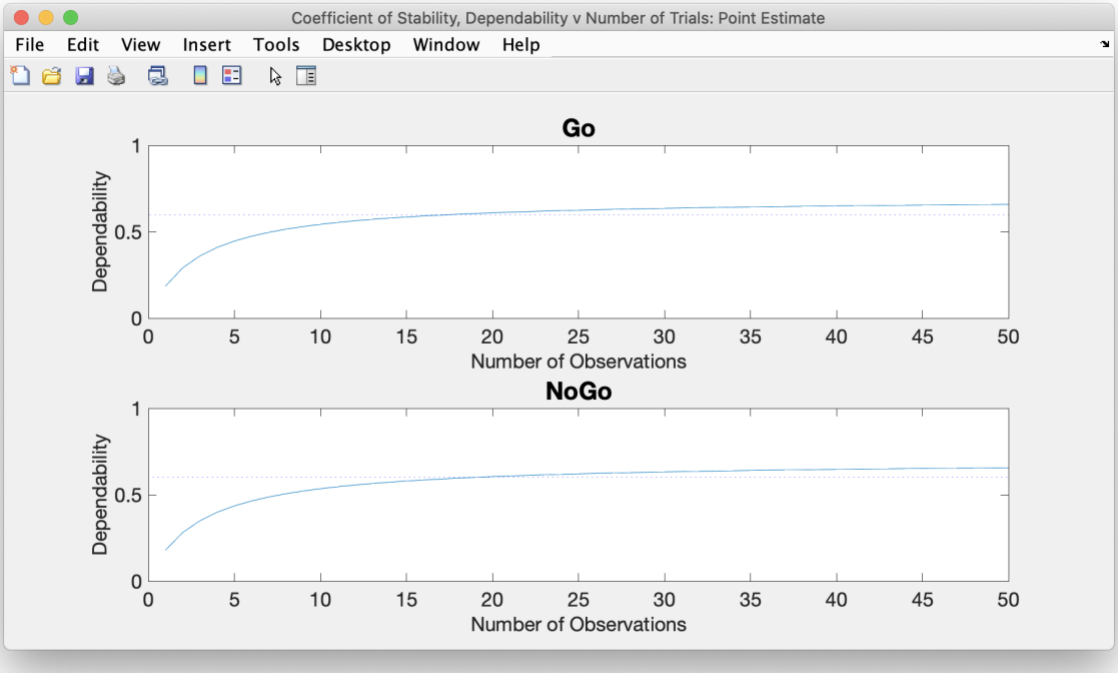
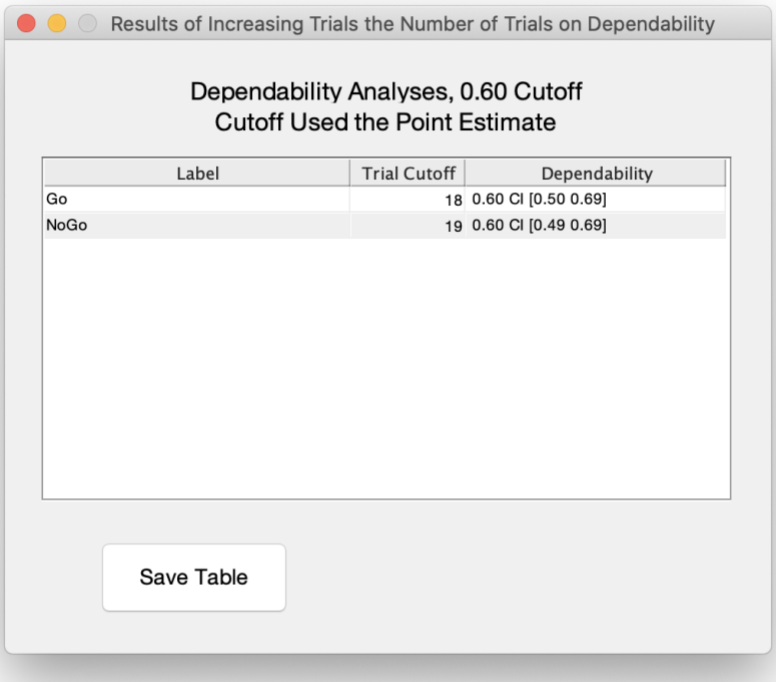

Coefficient of Stability, Dependability v Number of Trials: Point Estimate
File Edit View Insert Tools Desktop Window Help
Go
Dependability
1
0.5
0
0 5 10 15 20 25 30 35 40 45 50
Number of Observations
NoGo
Dependability
1
0.5
0
0 5 10 15 20 25 30 35 40 45 50
Number of Observations

Figure 6


Results of Increasing Trials the Number of Trials on Dependability
Dependability Analyses, 0.60 Cutoff
Cutoff Used the Point Estimate
Label
Trial Cutoff
Dependability
Go
18
0.60 CI [0.50 0.69]
NoGo
19
0.60 CI [0.49 0.69]
Save Table

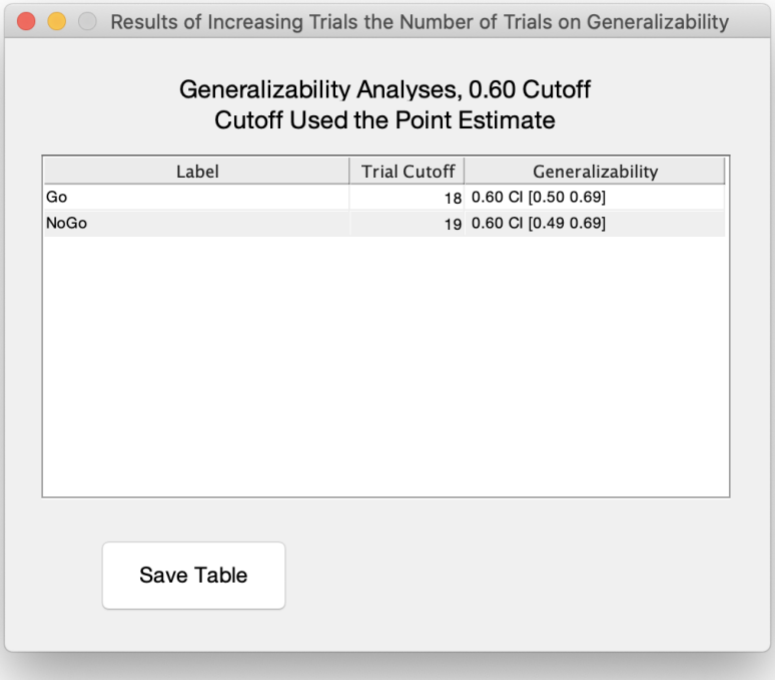
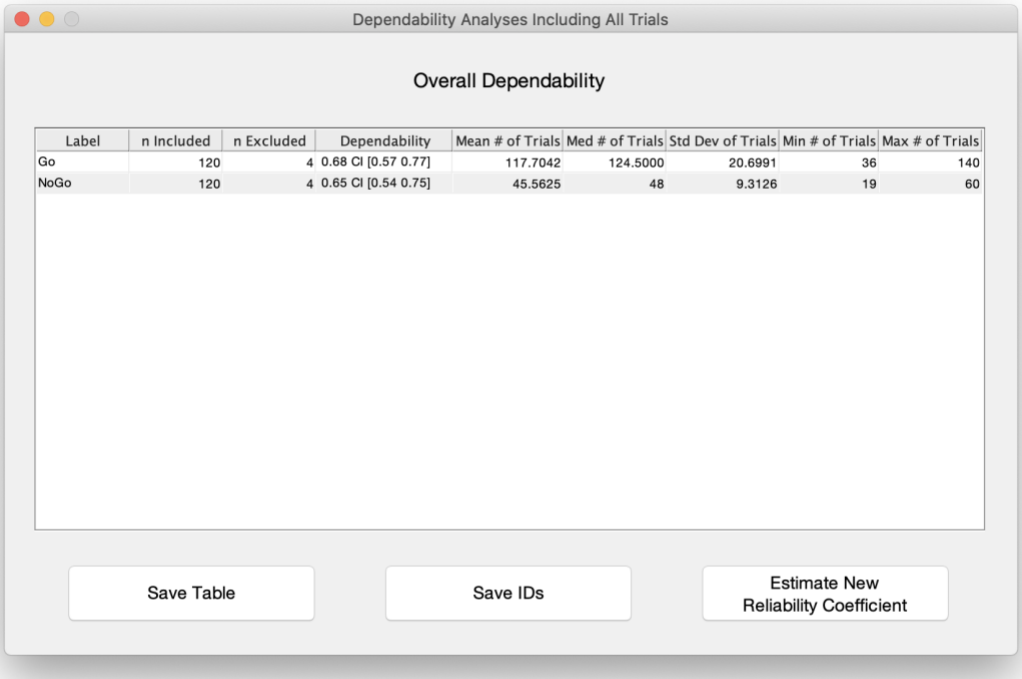
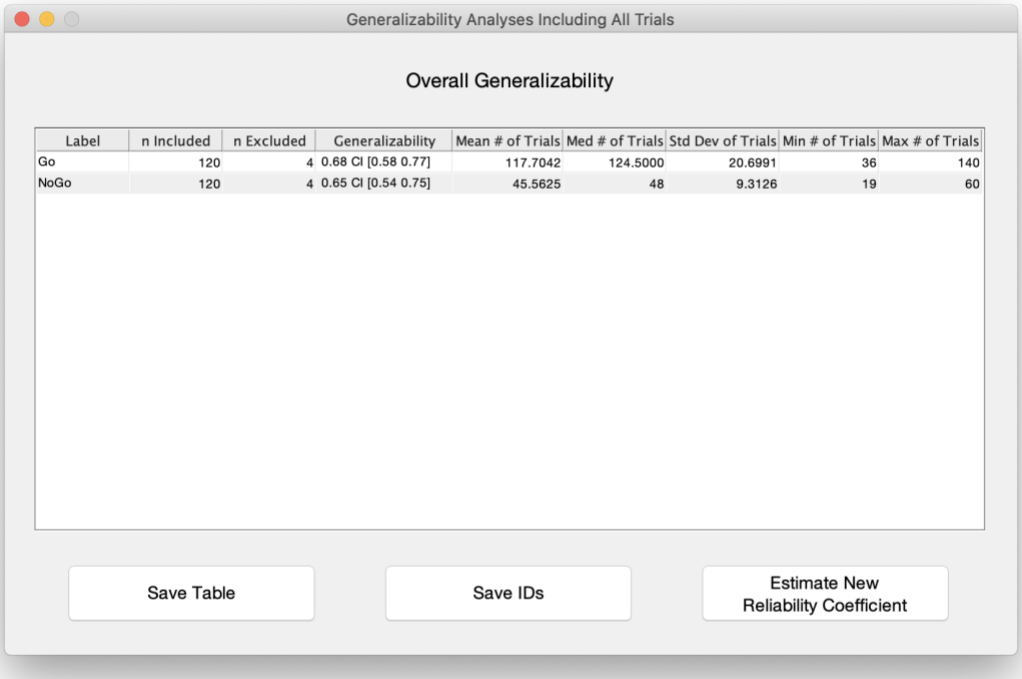

Results of Increasing Trials the Number of Trials on Generalizability
Generalizability Analyses, 0.60 Cutoff
Cutoff Used the Point Estimate
Label
Trial Cutoff
Generalizability
Go
18
0.60 CI [0.50 0.69]
NoGo
19
0.60 CI [0.49 0.69]
Save Table

Figure 7


Dependability Analyses Including All Trials
Overall Dependability
Label | n Included | n Excluded | Dependability | Mean # of Trials | Med # of Trials | Std Dev of Trials | Min # of Trials | Max # of Trials
Go | 120 | 4 | 0.68 CI [0.57 0.77] | 117.7042 | 124.5000 | 20.6991 | 36 | 140
NoGo | 120 | 4 | 0.65 CI [0.54 0.75] | 45.5625 | 48 | 9.3126 | 19 | 60
Save Table
Save IDs
Estimate New Reliability Coefficient


Generalizability Analyses Including All Trials
Overall Generalizability
Label | n Included | n Excluded | Generalizability | Mean # of Trials | Med # of Trials | Std Dev of Trials | Min # of Trials | Max # of Trials
Go | 120 | 4 | 0.68 CI [0.58 0.77] | 117.7042 | 124.5000 | 20.6991 | 36 | 140
NoGo | 120 | 4 | 0.65 CI [0.54 0.75] | 45.5625 | 48 | 9.3126 | 19 | 60
Save Table
Save IDs
Estimate New Reliability Coefficient