Using Generalizability Theory and the ERP Reliability Analysis (ERA) Toolbox for Assessing
Test-Retest Reliability of ERP Scores Part 2: Application to Food-Based Tasks and Stimuli

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Abstract

If an ERP score is to reflect a trait-like characteristic or indicate if an intervention had an effect over time, adequate internal consistency and test-retest reliability of that ERP score across multiple testing sessions must be established. The current paper is a companion paper to Clayson et al. (current issue) that applied generalizability theory formulas and the ERP Reliability Analysis (ERA) Toolbox to assess test-retest and internal consistency in a dataset of event-related brain potentials (ERPs) assessing food-related cognition. Although ERPs in response to food cues have been related to eating behaviors or assessed during a health intervention, the reliability of food-related ERPs generally has not been tested. Within the generalizability theory framework, we assessed the stability (cf., test-retest reliability) and equivalence (cf., internal consistency) of four commonly used food-related ERPs: the late positive potential (LPP), centroparietal P3, N2, and fronto-central P3. 132 participants (92 female) completed two testing sessions held two weeks apart. During the sessions, participants completed a passive food viewing task, a high-calorie go/no-go task, and a low-calorie go/no-go task in a counterbalanced fashion. Coefficients of equivalence for all ERPs were excellent ($> .96$). Coefficients of stability were moderate-to-low, with N2 scores on the low-calorie go/no-go task showing the highest test-retest reliability ($> .65$) and fronto-central P3 scores on the high-calorie go/no-go task showing the lowest (.48). Results suggest the ERPs in the current dataset have high internal consistency and would be reliable in detecting individual differences, but their test-retest reliability is limited. Reliability of these ERPs may be improved with changes in task stimuli, task instructions, and study procedures.

Keywords: internal consistency, test-retest reliability, event-related potentials (ERPs), N2, P3, LPP, food

1. Introduction

Research in psychology, including cognitive and neurophysiology subdisciplines, has come under scrutiny for poor transparency and replicability. To improve rigor and replicability within cognitive psychology and neurophysiology, there has been a call to ensure measures of brain activity, including electroencephalogram (EEG) and event-related brain potential (ERP) measurements, are reliable (Clayson, 2020; Clayson & Miller, 2017a; Hajcak et al., 2017; Thigpen et al., 2017), as reliability is a necessary pre-requisite for validity for any paradigm or brain measurement of interest. As outlined in Clayson et al. (current issue), adequate test-retest reliability is essential to establish if researchers wish to utilize an ERP as a biomarker or endophenotype for psychopathology (e.g., Dang et al., 2020; Light & Makeig, 2015; Meyer et al., 2018; Riesel, 2019) or as a reflection of a trait-like construct (Clayson et al., 2017a). Test-retest reliability is also particularly important to establish if researchers want to make assumptions beyond a single laboratory session or if an intervention has an effect on an ERP (Clayson et al., 2017a; current issue). Once reliability has been established, researchers can then take the necessary steps to confirm their paradigms and ERPs are valid indicators of relevant cognitive processes.

Previous ERP studies have assessed the internal consistency and test-retest reliability of various ERPs primarily using classical test (CT) theory (e.g., Clayson & Larson, 2013; Huffmeijer et al., 2014; Larson et al., 2010; Olvet & Hajcak, 2009; Rentzsch et al., 2008; Weinberg & Hajcak, 2011). However, Clayson et al. (current issue) and Clayson and Miller (2017b) both discuss why generalizability theory (G theory) is better suited for assessing ERP score reliability over CT theory due to the characteristics of ERP data. The goal of the present manuscript was to be a companion paper to the algorithms and implementation presented by

Clayson et al. (current issue), and we direct the reader to our companion article for a primer on G theory and its reliability coefficients, although information on the G-theory constructs is briefly summarized below. In the present manuscript, we focus on the conceptual application of internal consistency and test-retest reliability of ERP scores within a G-theory framework. We used the ERP Reliability Analysis (ERA) Toolbox v.0.5.0 to obtain reliability estimates of several attention and inhibition-related ERPs (https://github.com/peclayson/ERA_Toolbox).

We provide a brief description of the different types of reliability covered in the present manuscript and direct the reader to the companion manuscript for a more detailed description of the G-theory estimates (Clayson et al., current issue). We estimated two types of reliability: coefficients of equivalence and coefficients of stability. Coefficients of equivalence represent estimates of internal consistency, and coefficients of stability characterize test-retest reliability. For each type of reliability, there are two estimated coefficients: a generalizability coefficient and a dependability coefficient (see section 2.2 of Clayson et al., current issue). Generalizability coefficients characterize the relative standing of individuals, which is similar to common CT-theory estimates of reliability such as split-half reliability or coefficient alpha. Dependability coefficients characterize the absolute magnitude of differences in scores. As a result, the dependability coefficient does not ignore the average group-level changes in scores. The choice between whether to use a generalizability or dependability coefficient is dependent on the intended purpose of the measurement and preferences of the individual researcher, and such considerations are covered in detail in the companion manuscript and elsewhere (Brennan, 2001; Yin & Brennan, 2002). We include each coefficient for each type of reliability in the present manuscript to demonstrate their application to ERPs.

2. Conceptual Application

We illustrate the computation of internal consistency and test-retest reliability using ERP scores from a food-related cognition study. Researchers have started to test *via* ERP components which neurophysiological and cognitive factors, such as inhibitory control, reward, and attention, are related to poor and healthy dietary practices and actual food intake (e.g., Carbine et al., 2017; Carbine, Rodeback, et al., 2018; Carbine, Duraccio, et al., 2018; Nijs et al., 2009; 2010). G-theory techniques have previously been used to examine the internal consistency of food-related ERP scores from a single session (e.g., Carbine, Duraccio, et al., 2018; Smith et al., under review). However, ERP studies assessing food-related cognition may also have participants complete multiple laboratory sessions in order to test how possible interventions (e.g., calorie-restrictive diet, financial motivation to lose weight, exercise) affect ERP measures of food-related cognition (e.g., Hanlon et al., 2012; Harris et al., 2013). Such study designs necessitate that ERP measures have high internal consistency and test-retest reliability across the multiple laboratory sessions to ensure that changes in ERP scores over time can be attributed to the intervention or effect of interest and not unreliable measurement. Researchers may also be interested in using an ERP as an indicator of a trait food-related cognitive process, such as levels of inhibitory control (e.g. Carbine et al., 2017; Carbine, Duraccio, et al., 2018), which would require ERP scores to demonstrate acceptable levels of both internal consistency and test-retest reliability.

The primary aim of this companion paper was to apply the G-theory techniques and formulas discussed in Clayson et al. (current issue) to assessing the internal consistency and test-retest reliability of four ERPs reflecting food-related attention and inhibitory control process: the late positive potential (LPP), the centro-parietal P3, the N2, and the fronto-central P3. These specific ERPs are frequently examined in the ERP and food literature given that attention and

inhibitory control may play an important role in managing food intake and food choice (Carbine, Rodeback, et al., 2018; Guerrieri et al., 2007; Hanlon et al., 2012; Jansen et al., 2009). Briefly, the LPP is a positive-going centro-parietal ERP component that occurs 400+ ms after stimulus onset and is larger when increased attention is allocated towards motivationally or emotionally charged stimuli (Hajcak et al., 2010; Sabatinelli et al., 2007; Schupp et al., 2000). The centro-parietal P3 is a positive-going ERP component occurring between 300 and 500 ms after stimulus onset and is larger when increased attention is allocated towards task-relevant or emotionally-relevant stimuli (Hajcak et al., 2010; Krolak-Salmon et al., 2001; Polich, 2007). The N2 is a negative-going fronto-central ERP component occurring 200 to 300 ms after stimulus onset and larger (i.e., more negative) when withholding a dominant response on a go/no-go task (Folstein & Van Petten, 2008). Finally, the fronto-central P3 is a positive-going ERP component occurring 300 to 600 ms after stimulus onset (Albert et al., 2013; Falkenstein et al., 1999) and is larger in amplitude when withholding a dominant response on a go/no-go task (Gajewski & Falkenstein, 2013; Huster et al., 2013; Kaiser et al., 2003; Wessel & Aron, 2015).

It is important to note that because reliability is context dependent, the observed reliability estimates from this dataset can provide some general guidance, but cannot provide specific generalized information of how reliable these ERPs are in a different dataset that may consist of different participants, different tasks, different stimuli, and a different study design. However, our goal is to use the current dataset to show food-related ERP researchers how to obtain and interpret reliability estimates using G-theory techniques, understand what research questions are appropriate to answer given the estimated reliability, and provide recommendations on how to improve reliability if researchers choose to use similar tasks or study designs. The reported number of trials necessary to obtain reliable ERP scores can also be used as guideposts

for researchers planning to use these ERPs and paradigms. Further, the current manuscript provides the framework and tools for assessing the score reliability of ERPs during separate conditions and trial types and does not assess the reliability of difference scores. Readers interested in an in-depth discussion and tutorial on using the ERA Toolbox to assess the reliability of ERP component difference scores should refer to Clayson et al. (in press).

However, the techniques used in the current manuscript remain beneficial, as many ERP studies, including food-ERP studies, compare separate ERP amplitudes or correlate those amplitudes with external variables as opposed to utilizing difference scores (e.g. Asmaro et al., 2012; Cuthbert et al., 2000; Schupp et al., 2004; Schwab et al., 2017; Versace et al., 2016).

For our particular study, we chose to test the score reliability of the four ERPs when they were elicited during a food passive viewing task (LPP; centro-parietal P3) and food go/no-go tasks (N2; fronto-central P3), which are commonly used in the ERP food-related cognition literature to assess inhibitory control and attentional processes towards food (Carbine, Rodeback, et al., 2018). Given the strong internal consistency of previous food-related ERPs (Carbine, Duraccio, et al., 2018), we hypothesized that the LPP, centro-parietal P3, N2, and fronto-central P3 would show strong internal consistency, as evidenced by high coefficients of equivalence, and test-retest reliability, as evidenced by high coefficients of stability, across two ERP testing sessions.

3. Method

All study materials can be found on the Open Science Framework (OSF) study-specific webpage at <https://osf.io/hpqb7/>. All study procedures were approved by the local Institutional Review Board, and all participants provided written informed consent prior to participation.

3.1. Participants

Initial study enrollment included 152 participants recruited for course credit from undergraduate courses. Exclusion criteria included diagnosed psychological disorders, neurological disorders, and/or head injuries that resulted in a loss of consciousness, which were assessed via self-report. Participants were also excluded if they were taking any psychotropic medication. One participant was subsequently excluded for having a neurological disorder, one for taking antidepressant medication, thirteen for not returning for the second session, and one for having no remaining clean segments after the artifact correction process. Of the remaining 136 participants, three were excluded due to excessive artifact and one for having a technical error. Thus, our final sample consisted of 132 participants (92 [70%] female, $M_{age} = 20.65$, $SD_{age} = 3.16$). Participant demographics can be found in Table 1.

3.2. Procedures

Participants reported for two study sessions held two weeks apart on the same day of the week when possible and at the same time of day. For both sessions, participants were required to get at least 7 hours of sleep the night before and refrain from vigorous physical activity and consuming caffeine 24 hours before in order to control for potential confounds (Carbine et al., 2017; Carbine, Duraccio, et al., 2018). During the first session, participants provided written consent and verbally confirmed they had followed the pre-study requirements. Height and weight were then measured, and participants completed a basic demographics questionnaire (<https://osf.io/v5ms4/>). Participants also recorded the food they had eaten up to that point in the day. This information was given to the participants so that they could eat a similar meal/similar amount of food prior to their second session. Finally, the participants completed a food and sleep visual analog scale (VAS), and then completed three food tasks (passive viewing, high-calorie go/no-go, low-calorie go/no-go) in a counterbalanced fashion while EEG data were recorded. For

the second session, participants confirmed they had met the pre-study requirements upon arrival and that they had consumed a similar amount of food as they had for the first session. They then completed the same food and sleep VAS and the same three food tasks (again, in a counterbalanced fashion) while EEG data were recorded. At the conclusion of the second session, participants were granted course credit, and study participation was concluded.

3.3. Visual Analog Scales

VAS forms were used to assess the sleep quality and hunger levels prior to each EEG session, allowing us to ensure that sleep and hunger levels were equivalent across sessions. The sleep VAS asked participants when they went to bed, when they woke up, and then asked participants to rate the quality of their sleep on a 10-centimeter line anchored from “very low” to “very high” (<https://osf.io/tmpx6/>). Similarly, the food VAS had six questions where participants were asked to report their hunger levels by indicating where they fell on six different 10-centimeter lines (<https://osf.io/z8byp/>; Blundell et al., 2010; Stratton et al., 1998). Food VAS scales have been shown to be reliable and valid in predicting amount of food eaten in a single session and are sensitive to experimental manipulations (Stubbs et al, 2007). Further, internal consistency estimates, as measured by Cronbach’s α , were high for our food VAS measurements (Session 1 Food $\alpha = 0.87$; Session 2 Food $\alpha = 0.91$).

All VAS items were scored as the number (in centimeters to the nearest tenth) from the lower anchor to where the participant marked on the 10-centimeter line. To score the Food VAS, the second item (i.e., how full do you feel right now) was reversed scored (i.e., the marked number was subtracted from 10) and then the six questions were averaged together to get an overall hunger rating, with higher scores indicating higher hunger levels. Average sleep and food VAS scores are presented in Table 1. Paired samples *t*-test were used to compare VAS scores

between sessions to ensure that sleep quality and hunger levels were similar across the two sessions. Within-subjects Cohen's d_z is presented as a measure of effect size.

3.4. Go/No-Go Tasks

The N2 and fronto-central P3 waveforms associated with the go/no-go task were derived from EEG data collected during two food go/no-go tasks (Carbine et al., 2017; Carbine, Duraccio, et al., 2018). In the high-calorie task, participants were instructed to respond with a right index finger button press whenever they saw a low-calorie food (go trial) and withhold their response whenever they saw a high-calorie food (no-go trial). In the low-calorie go/no-go task, participants were instructed to respond with a right index finger button press whenever they saw a high-calorie food (go trial) and withhold their response whenever they saw a low-calorie food (no-go trial). Each task comprised two blocks of 100 trials, 70% go trials (140 total trials) and 30% no-go trials (60 total trials). This proportion of Go/NoGo trials was used to establish a dominant “go” response (Benikos et al., 2013; Ramos-Loyo et al., 2013). Trials were presented in random order within each block. In each task, food stimuli were presented for 500 ms on a white background with a black fixation cross on a white background presented for 1200 to 1400 ms as the intertrial interval (ITI). Participants had until the next trial to make their response.

3.5. Passive Viewing Task

Data for the centro-parietal P3 and LPP were derived from EEG data collected during a passive viewing food task. Participants completed two blocks where in each block they viewed 60 high-calorie foods, 60 low-calorie foods, and 60 non-food neutral images in random order (180 total trials/block). Images were presented for 2,000 ms on a white background. A black fixation cross on a white background was presented for 500 ms and served as the ITI.

3.6. Task Images

Images for the go/no-go tasks and passive viewing task were taken from the Food-Pics database (Blechert et al., 2014), which contains 568 pictures of standardized food images and 315 pictures of standardized non-food pictures. A complete list of the food and neutral pictures used in these tasks can be found at <https://osf.io/c6qb8/>. The Food-Pics database provides weight and calorie content for each food image. As such, food images for the tasks were classified as high-calorie if their caloric density was more than 3 kcals/g (e.g., chocolate, donuts, cake), resulting in 180 “high-calorie” images. Food images were classified as low-calorie images if their caloric density was less than 1 kcals/g (e.g., apples, celery, carrots), resulting in 200 “low-calorie” images.

In order to ensure that participants accurately categorized food images as either high- or low-calorie foods, a separate sample of 100 undergraduate students rated the selected 380 food pictures as either high- or low-calorie foods. Only images that were accurately identified as high- or low-calorie foods by at least 95% of the students were included in the final tasks. This resulted in 112 high-calorie and 112 low-calorie food images. For each participant during each block of the go/no-go tasks, 30 pictures were randomly selected without replacement for the no-go stimuli and 70 pictures were randomly selected without replacement for the go stimuli. For each participant during each block for the passive task, 60 high-calorie and 60 low-calorie food images were randomly selected without replacement. For the neutral images during the passive task, 112 images from the flowers/leaves, animals, tools, household, kitchen utensils, office, and other objects lists in the Food-Pics database were randomly selected to be used. For each participant for each block, 60 neutral pictures were randomly selected without replacement.

3.7. EEG Measurement and Data Reduction

EEG data were recorded from a 128-channel net with passive Ag/AgCl electrodes using an Electrical Geodesic, Inc. (EGI) NA300 amplifier (20K nominal gain, bandpass = .01 – 100 Hz). Data were referenced online to the central vertex electrode and digitized continuously at 250 Hz. As suggested by the manufacturer, electrode impedances were kept below 50 k Ω . Offline, data from all tasks were first high-pass filtered at 0.1 Hz (0.3 Hz rolloff; passband gain = 99.88%; stopband gain = 1%) and then low-pass filtered at 30 Hz (2 Hz rolloff; passband gain = 99.88%; stopband gain = 1%) in NetStation v.5.3. Data from all tasks were then segmented from 200 ms before the stimulus presentation to 1,000 ms after stimulus presentation. Segmented data was then exported into the ERP PCA Toolkit (Dien, 2010) for ocular artifact correction (blinks and saccades) using independent components analysis (ICA). For ICA, segmented EEG data from all channels were processed through a binary version of EEGLab's *runica* function called *binica* (Delorme & Makeig, 2004). If an ICA component correlated at .9 or higher with either a blink or saccade template made from previous data in the lab or a blink or saccade template provided in the ERP PCA Toolkit, the component was removed from the data. Bad channels were identified if the fast average amplitude exceeded 100 microvolts (μ V) or if the differential average amplitude exceeded 50 μ V, and the nearest neighbor approach using the six surrounding electrodes was used to interpolate channel data. Epochs were rejected if more than 10% of channels were marked as bad for that epoch. Data were then averaged-referenced offline and baseline adjusted using the -200 ms to 0 ms window.

We extracted the N2 as mean amplitude between 200 and 300 ms after stimulus onset (Carbine et al., 2017; Carbine, Duraccio, et al., 2018), since mean amplitude tends to be more reliable than peak or adaptive mean extractions (Clayson et al., 2013). For the fronto-central P3 amplitude on the go/no-go tasks, we extracted the mean amplitude between 400 and 550 ms after

stimulus onset (Carbine, Duraccio, et al., 2018). Both N2 and fronto-central P3 data were averaged over four frontocentral electrodes (6, 7, 106, and 129 [Cz]; see Larson et al., 2011 for electrode montage), which improves signal reliability compared to a single electrode (Clayson & Larson, 2013). Time windows and electrode locations for both the N2 and fronto-central P3 were chosen *a priori* based off previous research from our lab (Carbine et al., 2017, 2018). Average trial numbers by task and session are reported in Table 3.

Both the LPP and centro-parietal P3 data were averaged over six electrodes (62 [Pz], 67, 71, 72, 76, and 77), chosen *a priori* based off previous research conducted in our lab (Hanlon et al., 2012). As the LPP often begins between 300 and 400 ms after stimulus onset and lasts up to or beyond 700 ms (Moran et al., 2013), we chose *a priori* to use a collapsed localizer approach focused on the six *a priori* chosen electrodes to extract the LPP scores (Luck & Gaspelin, 2017). Specifically, we collapsed across both sessions and all stimuli. Doing so ensured we were not biased to picking a time window that showed a maximal difference between variables of interest and increasing Type I error (Luck & Gaspelin, 2017). Based on the collapsed localizers, we chose to extract the LPP as mean amplitude between 300 and 600 ms after stimulus onset (similar to Hanlon et al., 2012). Similarly, we chose *a priori* to use a collapsed localizer approach (over session and stimuli) to extract the centro-parietal P3 ERP component. The centro-parietal P3 was measured as the mean amplitude from 150 to 250 ms after stimulus onset. Average trial numbers by session are reported in Table 3.

3.8. Reliability Analyses

Reliability was assessed using the ERA Toolkit v.0.5.0. Please refer to Clayson et al. (current issue) for details on the equations used to calculate reliability using G theory. For the passive task, we assessed the reliability for four different trial types: only high-calorie stimuli,

only low-calorie stimuli, neutral stimuli, and all food stimuli (includes both the high- and low-calorie stimuli). High- and low-calorie stimuli were analyzed both separately and collapsed together since some ERP food studies do not distinguish by food type. Single-trial data for each of the four trial types and session (one, two) were processed over the time windows and electrodes outlined previously for the LPP and centro-parietal P3. For both the high-calorie and low-calorie go/no-go tasks, single-trial data for each trial type (correct go, correct no-go) and session (one, two) were processed over the time windows and electrodes outlined previously for the N2 and fronto-central P3. Of the 132 final participants, 124 participants had data from the high- and low-calorie go/no-go tasks for both sessions that made it from preprocessing into the reliability analyses and 125 participants had data from the passive viewing task for both sessions that made it from preprocessing into the reliability analyses.

Coefficients of equivalence (i.e., internal consistency) and coefficients of stability (i.e., test-retest reliability) were estimated for each set of ERP scores. Dependability and generalizability estimates were then computed for coefficients of equivalence and coefficients of stability (for an extended discussion on coefficient types, see Clayson et al., current issue). Each reliability analysis on each ERP produced a point estimate for the dependability/generalizability coefficient, a 95% credible interval for the coefficient, and the number of trials necessary to meet the acceptable minimum dependability/generalizability threshold set by the researchers. The reader is directed to Clayson and Miller (2017a) for a discussion on acceptable minimum reliability thresholds for ERP paradigms. Given the novelty of assessing the test-retest reliability of passive food viewing and food go/no-go tasks, it was decided *a priori* to set our reliability threshold to .70 as the cutoff for acceptable reliability.

For the analyses, we used three Markov Chain Monte Carlo chains (10,000 draws each) to estimate variance components. Number of trials was considered a random facet, trial type and session were considered fixed facets, and trials were crossed with subjects and sessions (see the companion paper for a discussion on making choices about random/fixed facets and crossed/nested trials). In order to quantify and understand the amount of variance contributed by each facet to the reliability estimates, standard deviation components (produced by the output) are reported for between-person variance, between-trial variance, between-session variance, person $\times$ trial variance, person $\times$ session variance, trial $\times$ session variance, and within person (or error) variance for each task. Variance outputs are posted to OSF (<https://osf.io/sa6ph/>).

4. Results

4.1. Visual Analog Scales

Two participants were excluded from sleep VAS analyses and two participants were excluded from Food VAS analyses for incomplete data. Paired samples *t*-tests showed that sleep quality ($t[129] = 1.39$; $p = .17$; $d_z = 0.12$) and hunger ($t[129] = 0.10$; $p = .92$; $d_z = 0.01$) did not significantly differ between the two sessions.

4.2. Coefficients of Equivalence

4.2.1. Passive Viewing Task. Waveforms for the LPP and centro-parietal P3 for the 125 participants in the passive task reliability analyses are presented in Figure 1A for the first session and Figure 1B for the second session¹. Dependability and generalizability coefficients for

¹To confirm that the LPP and centro-parietal P3 demonstrated the expected differences by trial type, we conducted a 2-Session (one, two) $\times$ 3-Trial (high-calorie, low-calorie, neutral) repeated measures ANOVA. LPP results showed a main effect of trial, $F(2, 248) = 16.22$, $\eta_p^2 = 0.12$, $p < .001$. Follow-up pairwise comparisons with Bonferroni adjustments revealed a larger LPP to high-calorie than to low-calorie stimuli and to high-calorie than to neutral stimuli ($ps < .001$), as expected. Centro-parietal P3 results also showed a main effect of trial, $F(2, 248) = 28.02$, $\eta_p^2 = 0.18$, $p < .001$. Follow-up pairwise comparisons with Bonferroni adjustments revealed a larger P3 to high-calorie than to low-calorie stimuli, to high-calorie than to neutral stimuli, and to low-calorie than to neutral stimuli ($ps < .001$), as expected.

estimates of equivalence at the .70 reliability threshold for LPP and centro-parietal P3 scores by trial type are presented in Table 3. Both dependability and generalizability coefficients for LPP scores ranged from .97 - .99; for centro-parietal P3 scores, both dependability and generalizability coefficients ranged from .96 - .98, also suggesting high internal consistency on the passive food viewing task for both LPP and P3 measurements. Trial cutoffs for meeting the .70 reliability threshold for both the dependability and generalizability coefficients are presented in Table 4. In sum, participants needed 14 to 15 trials for the LPP and 11 to 12 trials for the centro-parietal P3 to meet the reliability threshold cutoff for both dependability and generalizability. With these cutoffs, three participants for the LPP and two participants for the centro-parietal P3 did not have sufficient trials to meet the .70 reliability threshold (see Table 4).

As it is recommended that a .80 reliability threshold be used for studies that are not preliminary in nature (Clayson & Miller, 2017a), we also provide the number of trials necessary to meet the .80 reliability threshold in order to help guide future research (see Table 4). Generally, 24 to 26 trials were needed for the LPP and 18 to 20 trials were needed for the centro-parietal P3 to meet the reliability threshold cutoff for both dependability and generalizability. With these cutoffs, four participants for the LPP and three participants for the centro-parietal P3 did not have enough trials to meet the .80 reliability threshold.

4.2.2. Go/No-Go Tasks. Waveforms for the N2 and fronto-central P3 by high-calorie and low-calorie task for the 124 participants in the go/no-go task reliability analyses are presented in Figure 2A for the first session and Figure 2B for the second session². Dependability and

²To confirm that the N2 and fronto-central P3 demonstrated the expected go/no-go effects, we conducted a 2-Session (one, two) x 2-Task (high-calorie, low-calorie) x 2-Trial (go, no-go) repeated measures ANOVA. N2 results showed a main effect of trial, $F(1, 123) = 50.74$, $\eta_p^2 = 0.29$, $p < .001$. N2 amplitude was larger toward no-go than go trials, as expected. Fronto-central P3 results also showed a main effect of trial, $F(1, 123) = 121.14$, $\eta_p^2 = 0.50$, $p < .001$. P3 amplitude was larger toward no-go than go trials, as expected.

generalizability coefficients for estimates of equivalence at the .70 reliability threshold for the N2 and fronto-central P3 for all trial types by task are presented in Table 5. For N2 scores on both the high-calorie and low-calorie go/no-go tasks, dependability and generalizability coefficients ranged from .97 - .99; or fronto-central P3 scores on the high-calorie and low-calorie go/no-go tasks, dependability and generalizability coefficients ranged from .96 - .98, suggesting very high internal consistency on the food go/no-go tasks for both N2 and P3 measurements. Trial cutoffs for meeting the .70 reliability threshold for both the dependability and generalizability coefficients are presented in Table 6. In sum, participants needed 7-8 go trials and 7-8 no-go trials for the N2 and 10-12 go trials and 10 no-go trials for the fronto-central P3 to meet the reliability threshold cutoff for both dependability and generalizability. With these cutoffs, two participants for the N2 and two participants for the fronto-central P3 did not have enough trials to meet the .70 reliability threshold (see Table 6).

To further help guide future research, trial cutoffs for the recommended .80 reliability threshold are also presented in Table 6. As a summary, 12-13 go trials and 13 no-go trials for the N2 and 17-20 go trials and 17-18 no-go trials for the fronto-central P3 were needed to meet the reliability threshold cutoff for both dependability and generalizability. With these cutoffs, three participants for the N2 and four participants for the fronto-central P3 did not have enough trials to meet the .80 reliability threshold (see Table 6).

4.3. Coefficients of Stability

4.3.1. Passive Viewing Task. Dependability and generalizability coefficients for estimates of stability for LPP and centro-parietal P3 measurements are presented in Table 7. No dependability or generalizability coefficients for estimates of stability met the .70 reliability threshold cutoff. In other words, participants did not have enough trials for reliability to reach at

least a .70 level. In order to quantify the dependability and generalizability for all trial types, the reliability threshold for data inclusion was relaxed to .50. Relaxing the threshold was simply done in order to characterize how reliability could be improved to meet acceptable standards in future research.

Both dependability and generalizability coefficients for LPP scores ranged from .58 - .64, suggesting moderate test-retest reliability on the passive food viewing task. For centro-parietal P3 scores, both dependability and generalizability coefficients ranged from .57 - .63, also suggesting moderate test-retest reliability. Trial cutoffs for meeting the .50 reliability threshold for both the dependability and generalizability coefficients are presented in Table 8. In sum, participants needed 17-26 trials for the LPP and 14-24 trials for the centro-parietal P3 to meet the .50 reliability threshold cutoff for both dependability and generalizability. With these cutoffs, four participants for the LPP and three to four participants for the centro-parietal P3 did not have enough trials to meet the .50 reliability threshold (see Table 8).

Given the lower reliability threshold, we attempted to extrapolate with our given dataset the number of trials that would be necessary (even if they were beyond the length of our present task) to achieve higher levels of reliability in order to help inform future research. Unfortunately, with the current dataset, score reliability estimates asymptote below the .70 reliability threshold, which is likely due to the person $\times$ session variance being relatively large (see supplemental material on OSF and Clayson et al., current issue, for formulas). Therefore, trial numbers to meet a .60 reliability threshold are presented in Table 8. In sum, between 48 and 188 trials for the LPP and between 44 and 109 trials for the centro-parietal P3 were needed to meet the .60 reliability threshold cutoff for both dependability and generalizability. With these cutoffs, 19 to 23 participants for the LPP and 52 to 86 participants for the centro-parietal P3 did not have enough

trials to meet the .60 reliability threshold (see Table 8). As a note, the estimates of dependability and generalizability asymptote below .60 for the centro-parietal P3 for low-calorie trials.

4.3.2. Go/No-Go Tasks. Dependability and generalizability coefficients for estimates of stability for the N2 and fronto-central P3 by task are presented in Table 9. As a note, dependability or generalizability coefficients for estimates of stability failed to meet the .70 reliability threshold cutoff. As such, the threshold reliability was relaxed to .40 in order for all trial types to meet the reliability threshold and for us to obtain estimates of current reliability levels. For N2 scores on both the high-calorie and low-calorie go/no-go tasks, dependability and generalizability coefficients ranged from .48 - .68, suggesting overall moderate test-retest reliability on the food go/no-go tasks. Then, for fronto-central P3 scores on the high-calorie and low-calorie go/no-go tasks, dependability and generalizability coefficients ranged from .48 - .61, also suggesting overall moderate test-retest reliability on the food go/no-go tasks. Trial cutoffs for meeting the .40 reliability thresholds for both the dependability and generalizability coefficients are presented in Table 10. In sum, participants needed 4-7 go trials and 5-13 no-go trials for the N2 and 6-14 go trials and 8-20 no-go trials for the fronto-central P3 to meet the reliability threshold cutoff for both dependability and generalizability. With these cutoffs, two participants for the N2 and two participants for the fronto-central P3 did not have enough trials to meet the .40 reliability threshold (see Table 10).

Given the lower reliability threshold, we again attempted to extrapolate beyond the current task length to estimate the number of trials needed to achieve higher levels of reliability. Unfortunately, with the current dataset, it was score reliability asymptote below the .70 reliability threshold. It was only possible to calculate the number of trials necessary to meet a .60 reliability for the low-calorie task- N2 generalizability/dependability go: 18; N2

generalizability/dependability no-go: 19; P3 dependability go: 209; P3 dependability no-go: 41; P3 generalizability go: 163; P3 generalizability no-go: 40. With these trial cutoffs, four participants (ignoring the extrapolation for P3 go trials) did not have enough trials to meet the .60 reliability threshold.

Trial numbers to meet a .50 reliability threshold are also presented in Table 10. In sum, 8-16 go trials and 8 no-go trials for the N2 and 18-8,584 go trials and 13-97 no-go trials for the P3 were needed to meet the reliability threshold cutoff for both dependability and generalizability. Ignoring the P3 trial extrapolation, two participants for the N2 did not have enough trials to meet the .50 reliability threshold (see Table 10). As a note, for a .50 reliability threshold cutoff, the dependability estimate asymptote below .50 for go P3 scores during the high-calorie task and both the dependability and generalizability estimates asymptote below .50 for no-go N2 scores during the high-calorie task.

5. Discussion

Our goal was to assess the internal consistency and test-retest reliability using G-theory techniques of commonly used ERP scores in the food-related cognition literature. Specifically, we assessed the LPP and centro-parietal P3 during a passive food viewing task and the N2 and fronto-central P3 during food go/no-go tasks in sessions separated by two weeks. All ERP scores had excellent internal consistency ($> .96$; see coefficients of equivalence) and met the .70 reliability threshold in relatively few trials (7-15). In contrast, ERP measurements demonstrated modest test-retest reliability (.48 - .68; see coefficients of stability), suggesting ERPs were only modestly consistent across time points in terms of individual absolute scores (i.e., dependability) and interindividual rankings (i.e., generalizability).

Examining each source of variance in ERP scores helps explain why we observed acceptable internal consistency, but lower test-retest reliability estimates in our dataset. One of the largest sources of variance was the person $\times$ session variance, which indicates that the within-person differences in ERP amplitudes between the two sessions were relatively large from person to person (Clayson et al., current issue). For example, one individual may have had very similar LPP amplitudes to low-calorie foods during both session one and session two, but another individual had very different LPP amplitudes to low-calorie foods between the two sessions. Such variations by session had a larger impact on test-retest reliability than on internal consistency. In our study design, we tried to keep factors that might have influenced individual differences between sessions consistent (e.g., sleep levels, amount of food eaten, or time of testing session). However, it is possible that other factors varying between participants, whether at the participant level (e.g., stress levels) or data recording level (e.g., different impedance levels during EEG recordings) could have differentially affected the between session variability for different participants.

It is also important to note that the largest source of variance in our dataset was within-person variance. One way to decrease the contribution of within-person variance to reliability estimates is to record more trials (Clayson et al., current issue; Clayson et al., 2020). In fact, test-retest reliability tends to require more trials than internal consistency to achieve acceptable levels (Clayson et al., current issue; Larson et al., 2010), which may in part account for why our dataset demonstrated acceptable internal consistency but lower test-retest reliability (i.e., we had enough trials to meet the reliability threshold cutoff for equivalence but not stability). However, increasing trial numbers in our dataset would only marginally improve stability coefficients, since the relatively large person $\times$ session variance would still significantly limit our overall test-

retest reliability. The observation that 8,584 trials would be needed for P3 high-calorie go trials to meet a .50 generalizability threshold further demonstrates the limitations of increasing trials in the current dataset and how increasing trials is not always a feasible solution. In sum, simply recording more trials is not a panacea for low test-retest reliability but should be beneficial for datasets that have more reasonable levels of person $\times$ session variance. In datasets with low test-retest reliability and large within-person variance, other efforts made to reduce contributions to within-person variance, such as reducing measurement error, may better help improve reliability coefficients.

Another reason for the more modest levels of test-retest reliability may have been due to the current tasks used to elicit the ERPs, particularly in terms of stimuli and task instructions. LPP scores elicited in response to emotionally-charged stimuli (i.e., happy and disgusted faces) on a task where participants were required to make responses (i.e., modified flanker task) have demonstrated acceptable test-retest reliability (average ICC = .85; Huffmeijer et al., 2014). Simple food images on a white background (as are used in the current tasks) may not be emotionally-charged enough to elicit a reliable response. Tasks using food images that are more emotionally or motivationally engaging (such as images of fast foods or images an individual has rated as being extremely appetizing, appealing, or their favorite) may improve stability coefficients. Studies that assess how individuals respond to highly unappetizing foods (e.g., rotten foods, unsanitary foods, foods an individual doesn't like) might also elicit a greater emotional response and result in higher test-retest reliability. Specifically, for the passive food viewing task, the current task did not have participants make a response to stimuli or indicate that they were paying attention to the stimuli, which could increase mind-wandering and therefore increase noise (i.e., within-person variance) in ERP measurements. Future tasks aimed

at assessing food-related attention may benefit from having individuals make some type of response to stimuli instead of simply viewing images, which would improve test-retest reliability by helping participants consistently pay attention to the task and presented stimuli. In sum, if researchers want to increase the test-retest reliability of similar food-related tasks, potential changes to task stimuli and instructions may help improve reliability. We encourage researchers requiring adequate test-retest reliability for their research questions to consider some of the suggested changes and assess if the test-retest reliability of the desired ERPs improve.

ERPs that demonstrate higher internal consistency with lower test-retest reliability are still acceptable for detecting relationships between individual difference measures, or in other words, are able to reliably differentiate between people (Clayson, 2020; Clayson et al., 2020; Clayson & Miller, 2017a; Dang et al., 2020). This is particularly true for more state-like than trait-like characteristics. State-like characteristics are expected to fluctuate or change depending on the situation, and as such will not demonstrate as high of test-retest reliability compared to trait-like characteristics, which would need to be stable over long periods of time. Therefore, it is typically more important to have high internal consistency compared to high test-retest reliability for more state-like characteristics. For example, if our goal were to better understand how an ERP, such as the LPP, related to a state-like eating behavior, such as intensity of food cravings assessed *via* questionnaires, the ERP scores from the current dataset would be well suited because these ERP scores could be used to discriminate between persons. Given our modest test-retest reliability for a period of two weeks, we would be limited in making inferences about the relationship between the LPP and eating behaviors over time or eating characteristics that are more trait-like.

Our more modest test-retest reliability of the ERPs in the current dataset also limits in other ways what research questions our data would be best suited to answer. We would want to interpret our data with caution if we were to test how these ERPs changed across time due to some type of diet or exercise intervention, as changes in ERP amplitude could be due to the effect/intervention of interest, lower reliability, or unmeasured nuisance variables. Both test-retest reliability and internal consistency also need to be established in order to endorse an ERP as a reflection of some trait-characteristic that differentiates participants from each other. In the current dataset, for example, it would not be best to use the N2 and fronto-central P3 as indicators of trait food-related inhibitory control, as they are not as stable across one session to the other. Overall, our ERPs would be best suited to examine external characteristics correlated with other individual difference measures and would likely not be useful for examining trait characteristics or changes in response to an intervention. Our results further highlight the importance of assessing both coefficients of internal consistency (i.e., equivalence) and test-retest reliability (i.e., stability) so that researchers can be confident in what types of questions their dataset is capable of reliably answering.

Although reliability is context dependent, our ERP reliability results are similar to other test-retest reliability and internal consistency estimates of various ERPs. In terms of test-retest reliability, conflict N2 scores measured by Clayson and Larson (2013) demonstrated similar modest levels of test-retest reliability over a period of two weeks (average ICC = .52). Error-related negativity (ERN) scores over a period of two weeks have shown slightly higher, although still moderate, estimates of test-retest reliability (average ICC = .66 - .70; Larson et al., 2010; Olvet & Hajcak, 2009) and continue to show similar moderate levels of test-retest reliability over a test-retest period of 1.5 to 2.5 years (ICC = .62; Weinberg & Hajcak, 2011). Finally, error

positivity (Pe) scores in some samples have demonstrated more acceptable levels of test-retest reliability over a two week period ($ICC = .75$; Olvet & Hajcak, 2009); however, other samples have demonstrated a lower level of test-retest reliability for Pe scores ($ICC = .48$; Larson et al., 2010), which is similar to the test-retest reliability we observed during our high-calorie go/no-go task.

For internal consistency, conflict N2, ERN, and Pe scores have all demonstrated a similar pattern as the current dataset in that internal consistency estimates tend to be higher than test-retest reliability estimates (average $ICC = .93$; average ERN $ICC = .74$; average Pe $ICC = .78$; Clayson & Larson, 2013; Olvet & Hajcak, 2009). Interestingly, the ERN and Pe internal consistency estimates seem to be considerably lower than the conflict N2 and current estimates of internal consistency for the LPP, centro-parietal P3, N2, and front-central P3. Our current higher internal consistency estimates compared to previous estimates of the ERN and Pe may in part be due to the current ERPs being stimulus-locked as opposed to response-locked (like the ERN and Pe) and that the current tasks used elicited a higher number of trials (average trials $45.09 - 202.87$; see Table 2) compared to typical tasks used to elicit error trials for the ERN and Pe (average 27.38 error trials; Olvet & Hajcak, 2009). Overall, ERP scores seem to demonstrate moderate test-retest reliability and higher levels of internal consistency. Reliability of ERP scores, however, should be assessed in each study before conducting statistical analyses, given different ERP characteristics, analyses, and tasks can influence reliability levels.

As with any study, the current study had limitations and strengths. The greatest limitation was that the current dataset consisted of predominantly young-adult, healthy-weight, Caucasian women, although our sample size was moderate to large for an ERP study (Clayson et al., 2019). Therefore, the presented reliability coefficients may differ in a more diverse sample, and the

recommendations on how to improve reliability may not hold or be as effective in different populations of interest (such as individuals with overweight, obesity, or eating disorders). In terms of strengths, study sessions were as identical as possible (same time of day/day of the week, same pre-study requirements, identical tasks, similar sleep levels, similar food intake and hunger levels, etc.), which allowed us to ensure that reliability coefficients were not influenced by some potential confounding variables that would differentially affect ERPs from one session to the next. The use of G theory was also a significant strength, as G theory handles unbalanced study designs and multiple variance components in a way that is better suited for ERP research than CT theory (Clayson & Miller, 2017b).

In conclusion, coefficients of equivalence (i.e., internal consistency) of LPP, parieto-central P3, N2, and fronto-central P3 scores in the current dataset were extremely high, making these ERPs ideal for studies of individual differences. Coefficients of stability (i.e., test-retest reliability) were moderate, suggesting a potential difficulty in using similar stimuli or components in treatment studies or longitudinal paradigms. Potential changes in task stimuli, task instructions, and study procedures may improve reliability. Making such alterations and assessing any changes in reliability would also help food-related ERP researchers better understand what task and study factors influence the variance components (e.g., within person, person $\times$ session) of food-related ERP scores. It is important to note that reliability is context dependent, and as such the reliability results obtained from our sample may not necessarily generalize to other ERPs that were collected using different tasks, in individuals with different demographics, and analyzed using a different data processing pipeline. However, we hope our results will help guide researchers examining food-related ERPs in how they design their tasks

(i.e., providing estimates of how many trials are necessary for acceptable dependability/generalizability levels) and how they interpret their reliability results.

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Table 1

Participant Demographics

	Value
Age (years): Mean (SD)	20.65 (3.16)
Height (inches): Mean (SD)	67.51 (14.85)
Weight (pounds): Mean (SD)	146.10 (25.44)
BMI (kg/m ²): Mean (SD)	23.53 (7.10)
Education (years): Mean (SD)	13.52 (1.68)
Sex: Number of females (%)	92 (70%)
Ethnicity: Number of Caucasian (%)	117 (87%)
Ethnicity: Number of Hispanic (%)	3 (2%)
Ethnicity: Number of Asian (%)	6 (5%)
Ethnicity: Number of other (%)	6 (5%)
Handedness: Number of right-handed (%)	118 (89%)
Sleep VAS Visit 1 (cm): Mean (SD)	6.97 (1.76)
Sleep VAS Visit 2 (cm): Mean (SD)	6.79 (1.61)
Food VAS Visit 1 (cm): Mean (SD)	3.61 (1.59)
Food VAS Visit 2 (cm): Mean (SD)	3.62 (1.69)

Note. SD = standard deviation. BMI = body mass index. % = percent. High school education = 12. cm = centimeters.

Table 2

Trial Numbers by Task, Session, and Trial

Task	Event	Session 1		Session 2	
		Mean (SD)	Range	Mean (SD)	Range
Passive viewing	Food	200.70 (44.36)	4 - 240	202.87 (39.95)	12 - 240
	High-calorie	100.39 (22.00)	1 - 120	101.35 (19.99)	5 - 120
	Low-calorie	100.26 (22.68)	3 - 120	101.41 (20.04)	9 - 120
	Neutral	100.55 (22.04)	4 - 120	101.85 (19.42)	3 - 120
High-calorie go/no-go	Go	118.48 (22.14)	14 - 139	119.14 (22.95)	17 - 140
	No-go	46.84 (8.84)	12 - 59	46.40 (9.76)	9 - 58
Low-calorie go/no-go	Go	114.74 (21.83)	38 - 138	117.92 (24.03)	27 - 140
	No-go	44.54 (10.19)	6 - 58	45.09 (10.65)	4 - 60

Note. SD = standard deviation.

Table 3

Passive Task: Coefficients of Equivalence

Reliability	Event	P3	LPP
		Mean (95% CI)	Mean (95% CI)
Dependability	Food	0.98 (0.97, 0.98)	0.99 (0.98, 0.99)
	High-calorie	0.96 (0.95, 0.97)	0.97 (0.96, 0.98)
	Low-calorie	0.96 (0.95, 0.97)	0.97 (0.96, 0.98)
	Neutral	0.96 (0.95, 0.96)	0.97 (0.97, 0.98)
Generalizability	Food	0.98 (0.97, 0.98)	0.99 (0.98, 0.99)
	High-calorie	0.96 (0.95, 0.97)	0.97 (0.96, 0.98)
	Low-calorie	0.96 (0.95, 0.97)	0.97 (0.96, 0.98)
	Neutral	0.96 (0.95, 0.96)	0.97 (0.97, 0.98)

Note. LPP = late positive potential. CI = credible interval.

Table 4

Passive Task: Coefficients of Equivalence Trial Cutoffs

Reliability	Event	.70 Threshold		.80 Threshold	
		P3	LPP	P3	LPP
Dependability	Food	11	15	19	25
	High-calorie	11	14	19	24
	Low-calorie	11	15	18	26
	Neutral	12	14	20	24
	Number of participants lost	2	3	3	4
Generalizability	Food	11	15	19	25
	High-calorie	11	14	19	24
	Low-calorie	11	15	18	26
	Neutral	12	14	20	24
	Number of participants lost	2	3	3	4

Note. LPP = late positive potential.

Table 5

Go/No-Go Tasks: Coefficients of Equivalence

Reliability	Event	N2	P3
		Mean (95% CI)	Mean (95% CI)
Dependability	High-calorie task: Go	0.99 (0.98, 0.99)	0.98 (0.98, 0.98)
	High-calorie task: No-go	0.97 (0.96, 0.97)	0.96 (0.95, 0.96)
	Low-calorie task: Go	0.99 (0.99, 0.99)	0.98 (0.98, 0.99)
	Low-calorie task: No-go	0.97 (0.96, 0.97)	0.96 (0.95, 0.97)
Generalizability	High-calorie task: Go	0.99 (0.98, 0.99)	0.98 (0.98, 0.98)
	High-calorie task: No-go	0.97 (0.96, 0.97)	0.96 (0.95, 0.96)
	Low-calorie task: Go	0.99 (0.99, 0.99)	0.98 (0.98, 0.99)
	Low-calorie task: No-go	0.97 (0.96, 0.97)	0.96 (0.95, 0.97)

Note. CI = credible interval.

Table 6

Go/No-Go Tasks: Coefficients of Equivalence Trial Cutoffs

Reliability	Event	.70 Threshold		.80 Threshold	
		N2	P3	N2	P3
Dependability	High-calorie task: Go	8	12	13	20
	High-calorie task: No-go	8	10	13	18
	Low-calorie task: Go	7	10	12	17
	Low-calorie task: No-go	8	10	13	17
	Number of participants lost	2	2	3	4
Generalizability	High-calorie task: Go	8	12	13	20
	High-calorie task: No-go	7	10	13	18
	Low-calorie task: Go	7	10	12	17
	Low-calorie task: No-go	8	10	13	17
	Number of participants lost	2	2	3	4

Table 7

Passive Task: Coefficients of Stability for .50 Threshold

Reliability	Event	P3	LPP
		Mean (95% CI)	Mean (95% CI)
Dependability	Food	0.61 (0.49, 0.71)	0.62 (0.50, 0.72)
	High-calorie	0.63 (0.51, 0.73)	0.61 (0.48, 0.72)
	Low-calorie	0.57 (0.43, 0.68)	0.58 (0.46, 0.69)
	Neutral	0.60 (0.47, 0.71)	0.63 (0.51, 0.73)
Generalizability	Food	0.61 (0.50, 0.72)	0.62 (0.50, 0.72)
	High-calorie	0.63 (0.52, 0.73)	0.61 (0.49, 0.72)
	Low-calorie	0.57 (0.44, 0.68)	0.59 (0.46, 0.70)
	Neutral	0.60 (0.48, 0.71)	0.64 (0.52, 0.74)

Note. LPP = late positive potential. CI = credible interval.

Table 8

Passive Task: Coefficients of Stability Trial Cutoffs

Reliability	Event	.50 Threshold		.60 Threshold	
		P3	LPP	P3	LPP
Dependability	Food	18	23	105	100
	High-calorie	15	20	46	78
	Low-calorie	24	26	*	188
	Neutral	19	17	109	49
	Number of participants lost	4	4	86	23
Generalizability	Food	18	22	98	93
	High-calorie	14	20	44	71
	Low-calorie	23	26	*	170
	Neutral	19	17	97	48
	Number of participants lost	3	4	52	19

Note. LPP = late positive potential. * = estimates asymptote below threshold.

Table 9

Go/No-Go Tasks: Coefficients of Stability for .40 Threshold

Reliability	Event	N2	P3
		Mean (95% CI)	Mean (95% CI)
Dependability	High-calorie task: Go	0.58 (0.45, 0.69)	0.48 (0.34, 0.61)
	High-calorie task: No-go	0.48 (0.31, 0.59)	0.48 (0.33, 0.61)
	Low-calorie task: Go	0.68 (0.57, 0.77)	0.59 (0.46, 0.70)
	Low-calorie task: No-go	0.65 (0.54, 0.75)	0.60 (0.48, 0.71)
Generalizability	High-calorie task: Go	0.58 (0.45, 0.69)	0.48 (0.34, 0.61)
	High-calorie task: No-go	0.48 (0.31, 0.59)	0.48 (0.33, 0.61)
	Low-calorie task: Go	0.68 (0.58, 0.77)	0.59 (0.47, 0.70)
	Low-calorie task: No-go	0.65 (0.54, 0.75)	0.61 (0.48, 0.71)

Note. CI = credible interval.

Table 10

Go/No-Go Tasks: Coefficients of Stability Trial Cutoffs

Reliability	Event	.40 Threshold		.50 Threshold	
		N2	P3	N2	P3
Dependability	High-calorie task: Go	7	20	16	*
	High-calorie task: No-go	13	14	*	97
	Low-calorie task: Go	4	8	8	18
	Low-calorie task: No-go	5	7	8	13
	Number of subjects lost	2	2	2	3
Generalizability	High-calorie task: Go	7	19	16	8,584
	High-calorie task: No-go	13	14	*	89
	Low-calorie task: Go	4	8	8	18
	Low-calorie task: No-go	5	6	8	13
	Number of subjects lost	2	2	2	3

Note. * = estimates asymptote below threshold.

Figure Captions

Figure 1. A) First session and B) second session LPP (mean amplitude 300-600 ms after stimulus) and centro-parietal P3 (mean amplitude 150-250 ms after stimulus) ERP waveforms averaged over electrodes 62 [Pz], 67, 71, 72, 76, and 77.

Figure 2. A) First session and B) second session N2 (mean amplitude 200-300 ms after stimulus) and fronto-central P3 (mean amplitude 400-550 ms after stimulus) ERP waveforms averaged over electrodes 6, 7, 107, and 129 [Cz].

Figure 1

A)

B)

Figure 2

A)

B)