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It is well established that neural imaging technology can predict preferences for consumer products. However, the applicability of this method to consumer marketing research remains uncertain, partly because of the expense required. In this article, the authors demonstrate that neural measurements made with a relatively low-cost and widely available measurement method—electroencephalography (EEG)—can predict future choices of consumer products. In the experiment, participants viewed individual consumer products in isolation, without making any actual choices, while their neural activity was measured with EEG. At the end of the experiment, participants were offered choices between pairs of the same products. The authors find that neural activity measured from a midfrontal electrode displays an increase in the N200 component and a weaker theta band power that correlates with a more preferred product. Using recent techniques for relating neural measurements to choice prediction, they demonstrate that these measures predict subsequent choices. Moreover, the accuracy of prediction depends on both the ordinal and cardinal distance of the EEG data; the larger the difference in EEG activity between two products, the better the predictive accuracy.

Keywords: EEG, choice prediction, consumer neuroscience, theta power, N200

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Using EEG to Predict Consumers' Future Choices

In the past 15 years, understanding of the neuroscience underlying decision making has rapidly advanced (for reviews, see Glimcher 2011; Glimcher and Fehr 2013), raising hopes that measurements of neural activity—and a deeper understanding of neural mechanisms—can be applied to marketing research. Two promising avenues for such a contribution have been previously identified (Ariely and Berns 2010). First, insights from neuroscience might improve the marketing message for existing products. Second, neuroscience might provide insights into how products are valued before they even exist in the marketplace, improving product design.

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Both these avenues rely on the proposal that neuroscience can reveal information about consumer preferences that is unobtainable through conventional methods. There is certainly room for improvement. Previous studies have demonstrated that different preference elicitation methods can result in different subject responses (Buchanan and Henderson 1992; Day 1975; Griffin and Hauser 1993; McDaniel, Verille, and Madden 1985). The use of questionnaires for evaluating consumers' preferences, attitudes, and purchase intent can result in a biased or inaccurate result (Fisher 1993; Neeley and Cronley 2004), and even a verbal statement of preferences can also generate conscious or unconscious biases. In some cases, consumers decline to state their actual preferences (for reasons such as discretion or shame), and in other cases, they cannot verbalize a justification for their preferences (Johansson et al. 2006; Nisbett and Wilson 1977).

It can also be difficult (and sometimes impossible) to directly elicit consumers' preferences through choices due to high product cost, ethical considerations, or the hypo-

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thetical nature of a new product under development. This forces the marketer to examine hypothetical choices with hypothetical rewards, resulting in a potential bias in which responses are overstated compared with incentive-compatible choices (Blumenschein et al. 2008; Cummings, Harrison, and Rutstrom 1995; Johannesson, Liljas, and Johansson 1998; List and Gallet 2001; Murphy et al. 2005) or plans (Ariely and Wertenbroch 2002; O'Donoghue and Rabin 2008; Tanner and Carlson 2009). These results are bolstered by neuroscientific evidence that suggests variations in value computations between real and hypothetical choice situations (Kang and Camerer 2013; Kang et al. 2011).

Because marketing messages in many campaigns are intended to influence consumers' preferences, attitudes, and/or actual purchases sometime in the future, all the aforementioned factors confound the task of evaluating consumer preferences and limit the ability to predict choice at the time of the purchase decision. Therefore, finding a cost-effective tool that can predict consumers' future behavior in response to marketing messages, and forecast future preferences for novel products, would be beneficial in consumer marketing applications.

Recent studies have directly addressed the two avenues for incorporating neuroscientific methods into marketing research. Evidence from functional magnetic resonance imaging (fMRI) indicates that the same brain areas that represent values in a choice situation—primarily the medial prefrontal cortex (mPFC) and striatum (for recent meta-studies, see Bartra, McGuire, and Kable 2013; Clithero, Carter, and Huettel 2009; Levy and Glimcher 2012)—also represent values when participants are evaluating individual products in the absence of choice behavior (Falk, Berkman, and Lieberman 2012; Lebreton et al. 2009; Levy et al. 2011; Smith et al. 2014; Tusche, Bode, and Haynes 2010).[1] The magnitude of these signals correlates with the trial-by-trial likelihood that a consumer will choose a particular product, and it can be used to predict subsequent choices with a fully cardinal neural random utility model (NRUM; Webb et al. 2013). The NRUM extends the choice prediction results of the familiar random utility framework (Becker, DeGroot, and Marschak 1964; McFadden 1973) to neural measurements, with the important distinction that there are no unobservable latent variables. In doing so, the model characterizes neural sources of the stochasticity observed in choice behavior (Huettel and Payne 2009; Yoon, Gonzlez, and Bettman 2009), controls for measurement error, and improves choice prediction results.

These results are in line with many studies demonstrating that activity in the mPFC and striatum correlates with various value-related attributes and with known methods for estimating the values participants put on choice objects—ranging from consumable products, to money lotteries, to charitable donations, to durable products, to social preferences, to political preferences (for reviews, see Bartra, McGuire, and Kable 2013; Grabenhorst and Rolls 2011; Kable and Glimcher 2009; Levy and Glimcher 2012; Padoa-Schioppa 2011; Platt and Huettel 2008; Rushworth 2008). Importantly, these same areas are also active for the valuation of novel products that consumers have never before experienced (Barron, Dolan, and Behrens 2013).

However, the applicability of these findings to consumer marketing research remains uncertain, with the current cost of obtaining and operating an fMRI scanner preventing their broad application. Most prominently, an fMRI scanner has a large fixed-cost component; it is expensive to purchase (~$1 million–$2 million), expensive to keep operational ($100,000–$150,000 for insurance, maintenance, and support staff), expensive to locate (requiring a customized room/building), and immobile. Compared with the fixed-cost component, the marginal cost of running an fMRI experiment is relatively low but still on the order of $500 per experiment. These relatively high costs severely limit the use of fMRI in both academic and commercial applications.

There are also technical limitations to fMRI, primarily a relatively low temporal resolution on the order of two seconds (Huettel, Song, and McCarthy 2004). This resolution makes it difficult to examine the rapid dynamics of neural signals that are relevant for the neural mechanisms underlying value representation. A faster sampling rate might convey predictive information for consumers' valuation and choice, information that is blurred by fMRI. For example, consumers can make decisions about consumable products in as little as a third of a second (Milosavljevic, Koch, and Rangel 2011). It may well be the case that a particular, rapid component of the neural signal has more indicative and predictive power for consumers' preferences than the more global signal of fMRI.

To address these concerns, in our study we use an alternative neuroscientific tool called electroencephalography (EEG). From a fixed-cost standpoint, EEG is an order of magnitude cheaper than fMRI (approximately $50,000), requires little support and maintenance, and is widely available in neuroscience laboratories. The marginal cost of running an EEG experiment is only a few dollars, again more than an order of magnitude cheaper than an fMRI experiment. From a technical standpoint, EEG also has a high sampling rate (approximately 1–2 ms; Luck 2005), which enables identification of very fast changes in the neural signal over short time scales (approximately 50 ms; Luck 2005) that may carry strong predictive information about consumer preferences and choice behavior.

In this article, we rigorously examine whether EEG measurements of neural activity—recorded while participants view individual consumer products on a computer screen without making any choices—can be used to predict both rank-ordered preference ratings and actual choices in a subsequent behavioral choice task. We demonstrate that this is indeed the case. We show that specific spatial and temporal components of the EEG signal correlate with participants' future rank-ordered preferences and can be used to predict subsequent choices. To our knowledge, this is the first EEG study to demonstrate a basic principle: we can use

[1]Each of these "nonchoice" studies also find activity in other areas, varying from the dorsomedial prefrontal cortex, the insula, the anterior and posterior cingulate cortex, hippocampus, and parietal cortex. However, the mPFC and striatum are the only regions common across these studies and the only regions identified in the meta-studies referenced previously (which include the nonchoice studies).

measured neural activations to predict choices without the need to ask consumers anything.

LITERATURE REVIEW

Link Between EEG Recordings, Valuation, and Choice

Several studies have linked EEG activity with some aspect of consumer preferences. One of the first, conducted by Ambler et al. (2004), demonstrated a correlation between EEG activity in the parietal cortex and the familiarity rating of a product. Evidence of hemispheric asymmetry in the EEG signal correlating with preference has been demonstrated by Sutton and Davidson (2000). Participants in this study with greater resting activity in the left-frontal electrodes (as reflected by a lower power in the alpha EEG band, 8–13 Hz) selected more pleasant stimuli in a subsequent behavioral task than participants with greater resting activity in the right-frontal electrodes.

A related study also examined the relationship between hemispheric asymmetry in the EEG signal and an aspect of preferences (i.e., risk aversion), but in the absence of choice (Gianotti et al. 2009). In the initial phase of this experiment, participants sat quietly in a room while their baseline or "tonic" neural activity was measured. After the measurements, they engaged in a behavioral task to elicit their preferences for risk. Higher tonic activity in the right prefrontal cortex, measured before the behavioral task, correlated with a higher level of risk aversion (an avoidance-related behavior) as measured in the behavioral task. Importantly, this study demonstrated that EEG activity, measured in the absence of choice behavior, can be used to predict a preference trait.

Several studies have also demonstrated that EEG activity, measured concurrently with choice, is related to choice behavior. For example, in Braeutigam et al.'s (2004) study, both gamma (20–45 Hz) and alpha (8–13 Hz) band oscillations were correlated with participants' choices of consumer products in specific time epochs and brain locations. In a more recent study, Ravaja, Somervuori, and Salminen (2013) demonstrate that relatively greater left-frontal activation (in the alpha band), measured just a few seconds before choice, predicted the affirmative decision to purchase a given consumer product. Greater perceived need for a product and higher perceived product quality (as measured by a questionnaire answered at the end of the decision phase) were also associated with greater relative left-frontal activation (also in the alpha band). However, in both these studies, participants made actual choices during the EEG recording. Therefore, it is still an open question whether EEG data can be used during passive viewing of products to predict choices over some substantial time horizon.

Vecchiato et al. (2011) provide an important step forward on this question. The authors recorded EEG activity while participants viewed video commercials and then related these measurements to the responses from a questionnaire about the pleasantness of the same commercials (conducted two hours after the EEG session). The theta and alpha band activities were related to the subsequent pleasantness ratings, with activity in the left-frontal cortex related to "pleasant" commercials and activity in the right-frontal cortex associated with "unpleasant" commercials. Although the study demonstrated a link between EEG recordings and a subsequent behavioral response, the use of pleasantness ratings might not be correlated with the actual valuation and subsequent choice of a product, as noted previously. In addition, the authors did not assess predictive power or the precision of predictions. Therefore, in the current study, we aim to overcome these limitations and demonstrate the applicability of using EEG for predicting consumer choices.

Technical Aspects of EEG Measurement

Neurons in the brain communicate through electrical impulses; EEG measures the oscillations of the resulting electrical potentials (voltages) with electrodes located on the human scalp. Each electrode reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. Because voltage fields fall off with the square of distance, activity from deep brain areas is more difficult to detect than activity near the skull. Therefore, most of the measured EEG signals originate from cortical rather than subcortical areas. It is well established that behaviors and mental processes are due to complex interactions among multiple brain areas in various spatial and temporal scales. Only part of this dynamic activity can be measured at the macroscopic level by scalp EEG (Luck 2005; Nunez and Srinivasan 2006).

In this study, we examine the EEG response to consumer products using two common methods, both of which have been shown to represent mental processes that emerge in reaction to various stimuli. The first method is the event-related potential (ERP), which measures the changes in the voltage level in response to a stimulus presented as a function of time. Because the temporal resolution of these measurements is on the order of tens of milliseconds, ERPs can accurately measure when rapid processing activities take place in the human brain and can provide information about a broad range of cognitive and affective processes (Luck 2005; Nunez and Srinivasan 2006). With regard to decision processes, such as categorizing and evaluating a stimulus, two well-known ERP components have been identified: the P300 wave component (i.e., a positive deflection in the scalp potential starting 300 ms after the stimulus presentation; see Polich 2007; Soltani and Knight 2000) and the N200 wave component (i.e., a negative deflection in the scalp potential starting 200 ms after the stimulus presentation; see Folstein and Van Petten 2008).

The second method we employ is event-related spectral perturbations (ERSP). Similar to the ERP technique, ERSP measures the response to a stimulus over time, but it divides the EEG signal into different frequency bands. The ERSP method then examines whether and to what extent there is a change in the power of a given frequency band across time. Importantly, the measured change in power provides both a temporal and a spatial code, which adds valuable information to the ERP data. The frequency spectrum is usually subdivided into frequency bands: delta (1–4 Hz), theta (5–8 Hz), alpha (8–12 Hz), beta (14–30 Hz), and gamma (40 Hz).

Ample data have linked changes in these frequency bands to various cognitive processes, including changes in mental state (Moretti et al. 2004), changes in attention allocated to a task (Klimesch 1999), memory processes (Klimesch 1996), motivation and emotional processes (Knyazev

2007), different sleep stages (Keenan 1999), and consciousness levels (John 2002). For example, the alpha band has been associated with attention focusing (Prime, Tata, and Ward 2003), the theta band with inhibition of elicited responses (Kirmizi-Alsan et al. 2006; Yamanaka and Yamamoto 2010), and the beta band with alertness (Pfurtscheller and Lopes da Silva 1999). However, it is important to emphasize that each frequency band can be associated with many cognitive processes, so whether a particular mental process is active cannot be concluded from simply examining changes in a specific frequency band (Poldrack 2006). It is also important to note that because the spatial resolution of the EEG signal is quite poor, any conclusions about the exact localization of the signal should be taken cautiously and should not be used as evidence that an identified brain area is related to a measured behavior.

METHOD

This study follows the same three-stage experimental procedure used by Levy et al. (2011). In Stage 1, participants received a general description of the study procedure and familiarized themselves with ten consumer products. In Stage 2, neural activity was measured with EEG while participants viewed pictures of the products they encountered in Stage 1. The aim of this stage was to acquire independent measurements of neural activity for each product in isolation. In Stage 3, participants were presented with pairs of the consumer products, made binary choices between all the products they saw during the EEG stage, and then rank-ordered the products according to their preferences. Next, we describe these stages in detail.

Stage 1: Familiarization with the Products

The experimenter briefly described each product and invited the participants to examine them (the products were in their original packages). Participants were not informed of the actual prices of the products. After presenting all the products, we informed participants that at the end of the experiment, they would receive the product they wanted most. We randomly chose the consumer products used in the study from the online website of one of Israel's largest retail stores (Home Center). The products were (1) white digital stereo headphones, (2) a white plastic kettle, (3) a pink bulb desk lamp, (4) a red optical wireless mouse, (5) a red and black 16 GB USB flash drive, (6) a magnetic message board, (7) a rainbow-colored hammock, (8) a white and blue steam iron, (9) a pink yoga mat, and (10) a yellow fry pan. The average price of the products was 80 NIS (Israeli new shekel), ranging from 70 to 90 NIS. This limits the possibility that the value differences we observe are due to differences in purchasing price. Full descriptions of the products, including images, appear in the Web Appendix.

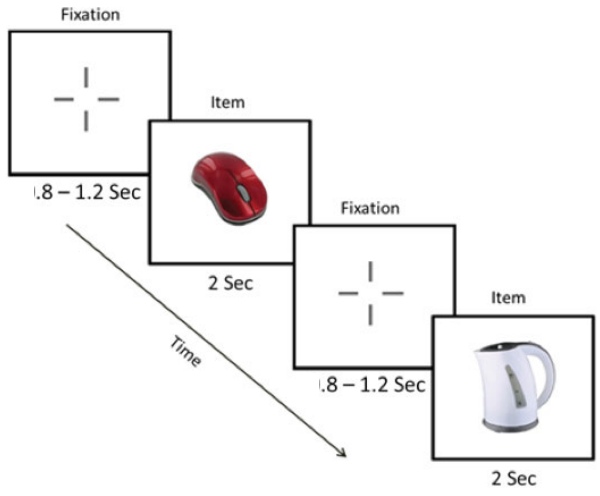
Stage 2: EEG Measurement

After participants examined all the products, Stage 2 of the experiment began. Each participant was seated in a comfortable chair in a dimly lit soundproof room, and an EEG electrode cap was placed on his or her head. Participants were asked to minimize head and body movements as much as possible at the time of the recording. On a standard computer screen, images of all ten products encountered in Stage 1 were sequentially presented. Only one product was presented in each trial, and participants were simply instructed to "think about how much the product was worth to them." Note that during the EEG recordings, participants did not make any actual choices or execute any other motor response.

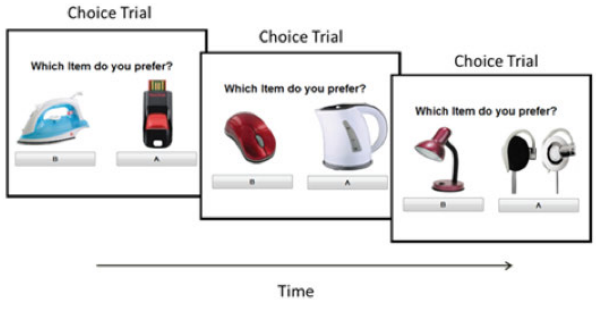
Figure 1, Panel A, depicts the visual presentation of a consumer product. During each trial, a fixation cross was presented at the center of the screen for a randomly varied interval of 800–1200 ms, followed by the presentation of a product for two seconds. The fixation period of the next trial started immediately after the previous trial. To improve the signal-to-noise ratio of our measurement, each product was presented 50 times, in a random order, resulting in 500 total trials. We divided these 500 trials into ten blocks, consisting of 50 trials in each block. Participants were allowed to take short breaks between the blocks. At the end of each block, a message appeared on the screen stating that the participant

Figure 1
EXPERIMENTAL DESIGN

A: Stimuli Design and Timing of Products' Presentation During the EEG Recording Phase



B: Example Trials of the Behavioral Choice Task



could continue the task whenever he or she was ready by pressing the mouse button. The total time of the EEG recording stage was 25 minutes. The Web Appendix provides a full description of the technical details regarding the EEG recording and preprocessing of the signal.

Stage 3: Choice Stage

After completion of the EEG recording, the EEG electrode cap was removed, and participants waited ten minutes before starting the behavioral choice task. Figure 1, Panel B, depicts the visual presentation for this task. On each trial, two products appeared simultaneously on the computer screen, and participants stated which product they preferred (under no time limit). All possible pairwise comparisons of the ten products were presented, totaling 45 pairs, and each pairwise choice was repeated six times, totaling 270 randomly ordered choice trials. The repetition of six choices is important for the measurement error correction we employ in our choice prediction analysis. The location of each product on the screen (left or right) was also randomly altered.

To further validate the results of the behavioral choice task, we conducted two additional measures. First, participants were asked to answer a brief computerized questionnaire, in which they rated how much they liked each product on a seven-point scale, ranging from "dislike a lot" (1) to "like a lot" (7), and also rated how much they wanted each product on a seven-point scale, ranging from "don't want at all" (1) to "want very much" (7). Second, participants rank-ordered the products from 1 ("most preferred") to 10 ("least preferred"). Finally, to control for any possible ownership effects, we asked participants to state, for each product, whether they owned a similar product. The products on all questionnaires were randomly ordered. At the end of the experiment, the participants selected one product.

To ensure that the possession of similar products would not affect the correlation between each of the questionnaires and the scores of the behavioral choice task, we conducted a Pearson partial correlation between the questionnaires and the choice preferences, using the possession of the products as a binary control variable. The analysis revealed that possession of similar products did not have any significant effect on the magnitude or significance of the correlations.

EEG Measurements

To analyze the EEG data, we used two distinct, well-established methods (Nunez and Srinivasan 2006). In the first approach, termed ERP, the general waveform for each electrode (of the 19 electrodes in our setup) is averaged across all repeated presentations of the same product, time-locked to the stimulus presentation. Therefore, we averaged the waveforms of all 50 presentations for each product and for each participant. This enabled us to observe the averaged waveforms across the different products for each participant and to examine whether any systematic differences predicted future choices. The second approach, termed ERSP, evaluates specific frequencies embedded within the general EEG signal. The ERSP analysis reflects changes across time in the power of specific frequency domains as a response to the stimulus presentation. Therefore, for each frequency, average event-locked deviations from the baseline activity (mean power) can be tracked (Makeig et al. 2004). We then examined whether specific frequencies could be used to predict participants' future choices.

To avoid the issue of multiple comparisons and post hoc hypotheses, we used both previous literature and a basic visual and statistical analysis conducted on the data from our first five participants to determine which electrode to focus on, which ERP and ERSP components to analyze, and the duration of the time window. We continued with our remaining participants—and with the choice prediction exercises that constitute the main hypothesis of the study—only after we decided on these basic aspects of the EEG analysis.

For our first five participants, we compared the average ERP signal in response to a median split of the top five most-preferred products in the sample (across all participants) and the bottom five least-preferred products (for a full report of this analysis, see the "Results" section and Table WA1 in the Web Appendix). We found that the mean amplitude of the N200 component could differentiate between the most- and least-preferred products; however, the P300 component of the ERP signal was not significant. In line with previous studies (Folstein and Van Petten 2008) and the known dynamics of the N200 component (Folstein and Van Petten 2008; Naatanen and Picton 1986; Sutton et al. 1965), we thus focused the remainder of our analysis on a 100 ms time window (200–300 ms after stimulus presentation) that was centered on the N200 peak amplitude (typically observed near 250 ms).

With regard to electrode choice, ample data from EEG studies (Holroyd and Coles 2002; Nieuwenhuis et al. 2004; San Martin et al. 2010; Yeung and Sanfey 2004) and fMRI studies (Bartra, McGuire, and Kable 2013; Grabenhorst and Rolls 2011; Kable and Glimcher 2009; Levy and Glimcher 2012; Padoa-Schioppa 2011; Platt and Huettel 2008; Rushworth 2008) suggest that value representation is located in frontal areas. In accordance with this preliminary hypothesis, we identified that the strongest difference in N200 amplitude (between the top five most-preferred and the bottom five least-preferred products) was in the front of the scalp map, with the strongest effect in electrode Fz—a central electrode located near the front of the brain. Because we focused our analysis on the N200 component and because this component is mainly evident in frontal central electrodes (Folstein and Van Petten 2008; Luck 2005; Nunez and Srinivasan 2006), we centered the rest of our analysis on electrode Fz.

We repeated this strategy for the ERSP analysis. The average ERSP signal in the frequency range 0–40 Hz could differentiate between a median split of the top five most-preferred products and the bottom five least-preferred products (again, see the "Results" section and Table WA1 in the Web Appendix). This guided us to focus on the theta band activity (5–8 Hz) within a time window of 100–400 ms after the stimulus presentation. This observation is in line with previous studies showing a link between theta band activity and valuation (Cohen, Elger, and Ranganath 2007; Gehring et al. 2012). We also hypothesized that alpha waves might be related to participants' subsequent choices; however, we found no evidence to support this hypothesis (see Table WA1 in the Web Appendix).

The accumulation of these results led us to focus our subsequent analyses of the entire sample on the N200 and ERSP theta component in electrode Fz (in the same time windows as previously noted). Importantly, in our subsequent analysis and choice prediction exercise, we did not run any statistical analysis on any other time windows or any other electrodes. To examine the robustness of our findings, at the end of the study we repeated the initial median-split analysis on the remaining ten participants initially held out and repeated our entire analysis on a control electrode, which we describe subsequently. These results matched our initial findings (see Table WA1 in the Web Appendix).

Control Electrode

After conducting all our correlation and choice prediction exercises on the frontal electrode Fz, we examined whether the predictive information of the EEG signal originates in more frontal areas (as would be expected from previous findings) or whether the predictive signal could be detected in other electrodes. Therefore, we engaged in a control exercise by repeating all the analyses in a more posterior but still centrally located electrode—Pz.

RESULTS

Establishing Consistency in Choices and Liking Ratings

The first step in relating neural measurements to choice data is determining the consistency of choices over the six repetitions of each choice pair and gauging the degree of stochasticity in choice behavior. The existence of consistent preferences and/or a clear rank ordering of the consumer products should presumably ensure a suitable range of valuations that can be measured with EEG.

The proportion of choice pairs resulting in an even split between the two products (each product was preferred in half a participant's choices) was markedly low (.02, SE = .01). Furthermore, the proportion of the six repeated pairs in which the participants switched their preference at least once was .25 (SE = .02) (over all participants). This proportion is relatively low considering that this is the probability of observing at least one switch out of six trials from the binomial distribution, with a success probability of .795 on each trial.

To gauge how much of the switching was due to possibly inconsistent preferences, we also examined the proportion of stochastic transitivity violations (Tversky 1969). For each triplet of products {A,B,C}, such violations occur when $P(A|\{A,B\}) \geq .5$, $P(B|\{B,C\}) \geq .5$, and $P(A|\{A,C\}) < .5$. Across all participants, the proportion of violations (of all possible violations) was extremely low (.02, SE = .003), with seven participants exhibiting no violations. Together, these results suggest that participants had relatively clear rank-ordered and consistent preferences for the products, but with an element of stochasticity in choice behavior that is commonly observed.

Behavioral Choice Task Scoring

Following Levy et al. (2011), we assigned a preference score for each product (and each participant) according to the total number of times each participant chose it across all trials (for detailed description of the preference scores, see Table WA2 in the Web Appendix). To assess the validity of these preference scores, we compared them with questionnaire responses and the results of the rank-ordering task. The correlation (across participants) between the average preference score for each product and the average ranking given to each product in the rank-order questionnaire was large and significant ($r = .97$, $p < .001$). There was also a large and significant correlation between the behavioral task preference scores and both the liking of the product ($r = .82$, $p < .001$) and the wanting of the product ($r = .96$, $p < .001$) as measured in the self-report questionnaire.[2] These high correlations corroborate the validity of the behavioral choice task preference scores as measuring participants' rank-ordered preferences.

Finally, because the ability to predict participants' preferences partly depends on the "strength" of their preferences, we computed a min/max range by subtracting the preference score of the lowest product from the score of the highest product (for a full description of these dispersion rates, see Table WA2 in the Web Appendix). Importantly, the average range across participants was large (M = 52, SD = 2) and close to the maximal possible range of 54. Therefore, participants had relatively strong preferences across products, which increases our chances for successfully predicting their future choices from the neural data. Notably, a degree of homogeneity was also present in participants' preferences (i.e., they tended to choose the same products; see Table WA2 in the Web Appendix). This homogeneity will allow for a population-level analysis of the EEG signal, which we explain next. The subject-level analysis follows.

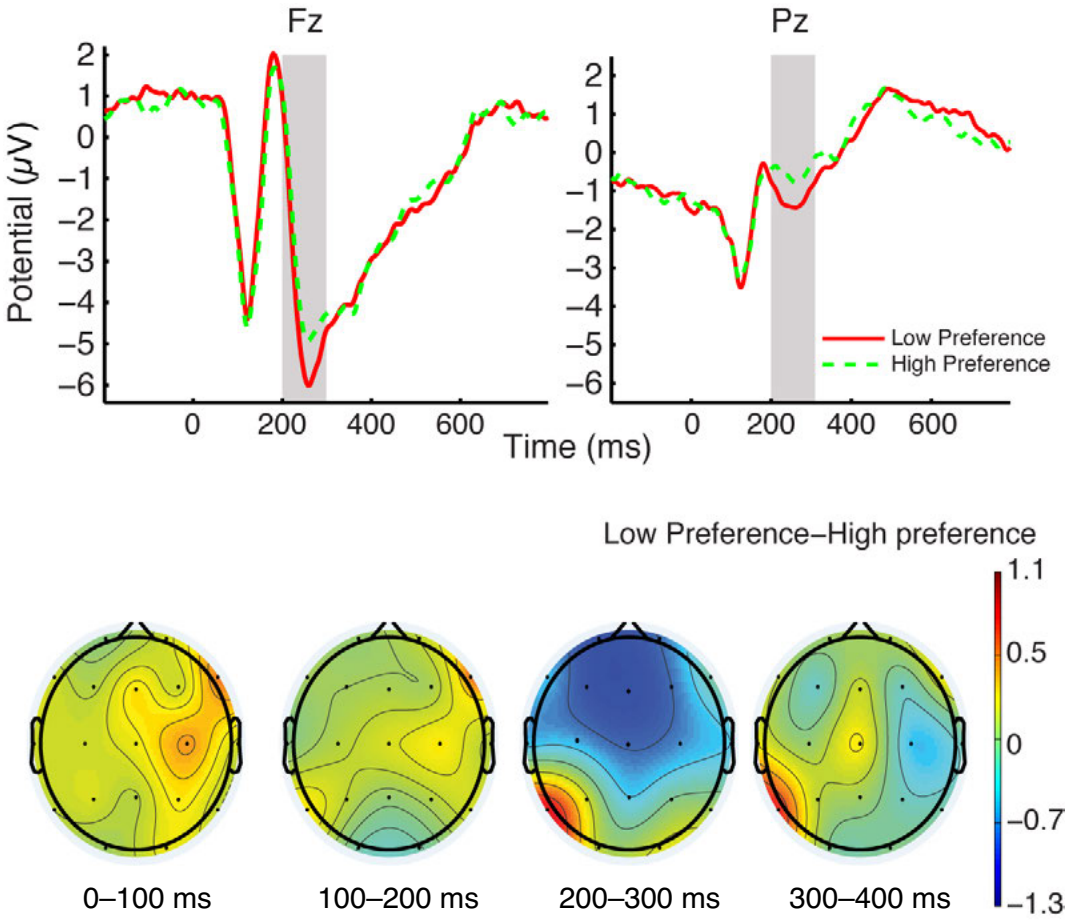
EEG Differentiates Between Most- and Least-Preferred Products Across Population

We begin with a simple population-level analysis designed to identify a difference in the EEG signal in response to a median split of the number of times a product was chosen in the binary choice task (a breakdown of this analysis for the first five participants appears in Table WA2 in the Web Appendix).

Figure 2 reports the average mean amplitude of the N200 component across participants (in electrodes Fz and Pz) for the five most-preferred products and the five least-preferred products. We find evidence of an association between neural activity and behavior in the downward (negative) deflection of the N200 signal starting 200 ms after the stimulus presentation. The average deflection of the N200 is larger in magnitude for the five least-preferred products than the five most-preferred products, and this difference was significant in both Fz (paired t-test; $t(14) = -2.72$, $p < .05$) and Pz ($t(14) = -3.18$, $p < .01$) electrodes. However, note that the overall deflection of the N200 component across all products is much larger in electrode

[2]We computed for each questionnaire how well it was able to predict the choices participants made in the behavioral task. For the ranking questionnaire, the proportion of correct predictions of actual choices using the ranking given to each product was .88 (SD = .07) and significantly different from chance level ($t(14) = 22$, $p < .001$). Liking the product was also a significant predictor (M = .67, SD = .11; $t(14) = 5.98$, $p < .001$). The same was evident for wanting the product in question (M = .69, SD = .09; $t(14) = 8.17$, $p < .001$).

Figure 2
GRAND-AVERAGE ERP WAVEFORMS RECORDED AT ELECTRODE SITE Fz (TOP LEFT) AND AT Pz (TOP RIGHT) DURING THE EEG RECORDING PHASE



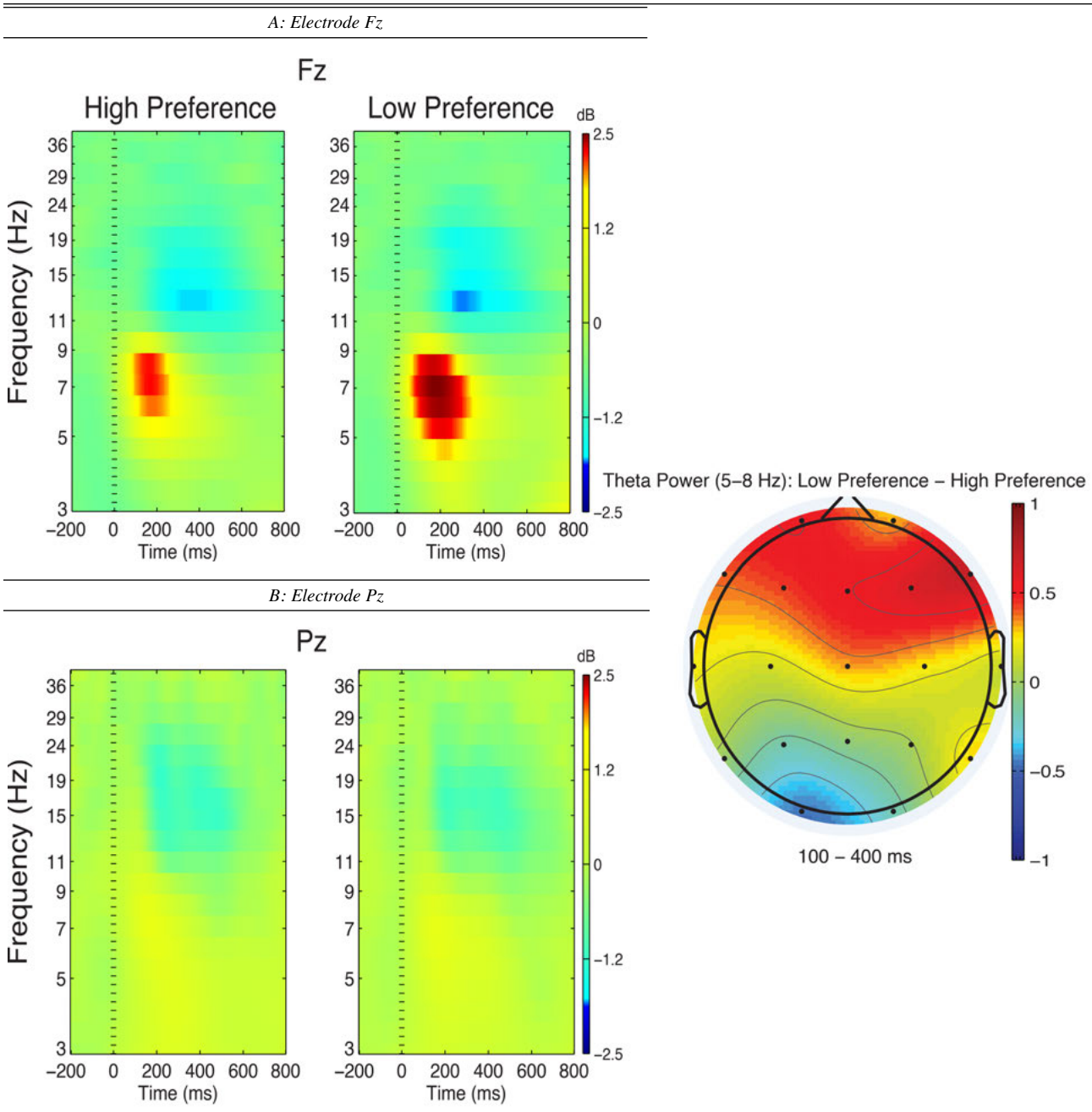
Notes: The red line shows the average ERP response to the five least-preferred products, and the green dashed line corresponds to the five most-preferred products. There is a significant N200 effect ($p < .05$) with larger (negative) deflection to least-preferred products in both electrodes. The scalp maps show the distribution of voltage from 0–500 ms after the products presentation divided into time intervals of 100 ms for least-preferred minus most-preferred products. According to the map, the effect is prominent during the 200–300 ms time window and focused on the frontal parts of the scalp.

Fz (M = –4.925 μV, SD = 5.55) than in electrode Pz (M = –1.09 μV, SD = 3.96), suggesting that the origin of the signal is more frontal. As the scalp map in Figure 2 illustrates, the largest difference in the average voltage distribution for the least-preferred minus the most-preferred products (within the N200 time frame) is evident in the frontal parts of the scalp.

In addition to the population-level correlation found in the N200 component, we conducted an ERSP analysis to examine whether a specific frequency domain within the EEG signal carries predictive power. Figure 3 compares the mean theta band activity in response to the five most-preferred products with that of the five least-preferred products. The average theta power following the presentation of the least-preferred products (M = 1.72 dB, SD = 1.36) was significantly stronger than that following presentation of the most-preferred products (M = 1.28 dB, SD = 1.07) in electrode Fz ($t(14) = –3.75, p < .01$). However, this difference was not apparent in electrode Pz ($t(14) = –.58, p < .57$).

Because previous studies have demonstrated a correlation between the slow alpha waves (8–10 Hz) and valuation (albeit using a hemispheric asymmetry analysis; Vecchiato et al. 2011), we also computed the difference between the most-preferred and least-preferred products in terms of slow alpha waves activity. We identified slow alpha waves from the same ERSP analysis, but now focused on the 8–10 Hz frequency band. There was no significant difference

Figure 3
ERSP FOR MOST-PREFERRED (LEFT) AND LEAST-PREFERRED PRODUCTS (RIGHT)



Notes: Logarithmic scale of EEG frequency (3–40 Hz) is indicated on the y-axis. Hot colors indicate higher power, as shown on the scale on the right. The power in the theta frequency band (5–8 Hz) for least-preferred products was stronger than that for most-preferred products ($p < .01$) only at electrode Fz. The scalp map shows the distribution of theta power from 100–400 ms after the products presentation for least-preferred minus most-preferred products. According to the map, the effect is primarily located at the frontal parts of the scalp.

between the groups ($M_{most\text{-}preferred}$ = .86, SD = 1.22 vs. $M_{least\text{-}preferred}$ = 1.05, SD = 1.5; t(14) = –1.18, p = .25), suggesting that, at least in our experiment, the predictive information of the frequency domain is relatively narrow; predictive information is not a general trait of many frequencies, but it is rather focused on the theta frequency band.

Correlation of EEG Activity and Preference for Products Across Population

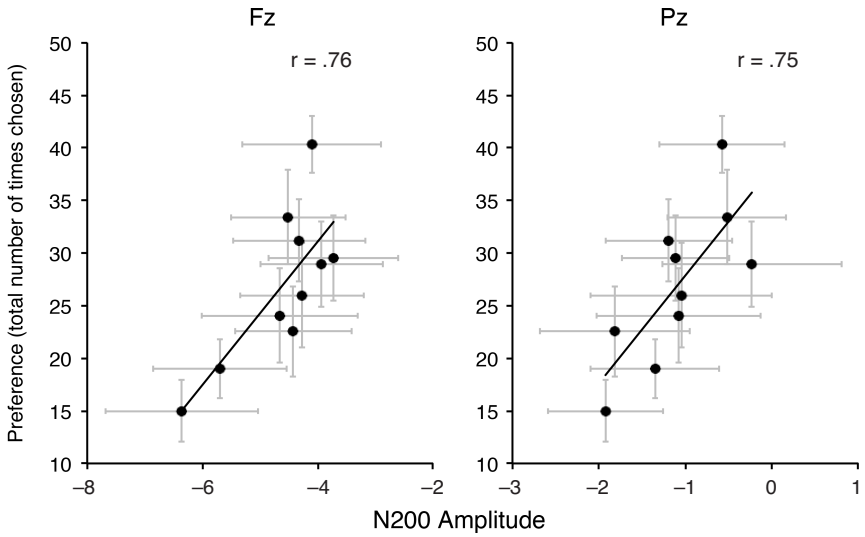
Having established an average, population-level difference in the N200 component for most- and least-preferred products, we now examine whether the EEG activity measured for a particular product is correlated with the ranking

of that product, across all participants. For each product, we observed the magnitude of the N200 amplitude (averaged over 50 repetitions and over all participants) and the preference scores for each product (the number of times all participants chose each product).

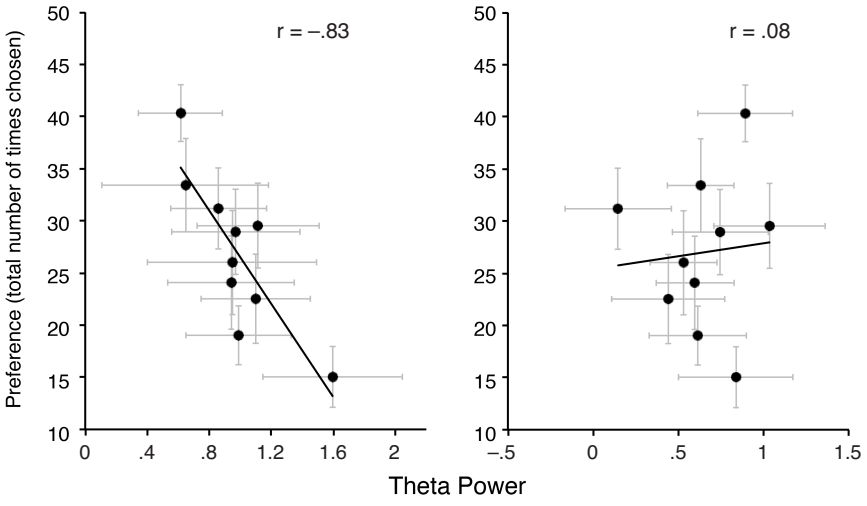
As Figure 4, Panel A, illustrates, the correlation between the average N200 amplitude for a product and the preference score for each product across all participants was high, positive, and significant (Fz: r = .76, $p < .01$; Pz: r = .75, $p < .05$). That is, the lower the measurement of (negative) N200 amplitude, the higher the preference ranking of that product in the subsequent behavioral choice task across the population of participants. Note that the correlation remained significant even when we analyzed the data using Spearman

Figure 4
POPULATION-LEVEL ANALYSIS

A: N200 ERP Component



B: Theta Band (5–8 Hz) Power



Notes: The graph shows a scatterplot of the correlation across products between the average EEG activity in response to viewing the products and the preference scores of the products as measured by the total number of times all participants chose each product during the subsequent behavioral task for electrodes Fz (left) and Pz (right). The horizontal error bars denote the standard error of the EEG activity for each product across participants. The vertical error bars represent the standard error of the means of the preference ratings for each product across participants. As Panel A shows, the smaller deflection (less negative) N200 amplitude was strongly associated with higher preference scores ($p < .01$) in both electrodes, while stronger theta power (Panel B) was negatively correlated with higher preference scores ($p < .01$) only at electrode Fz.

correlation, which is less sensitive to extreme values (Spearman's r = .64, $p < .05$).

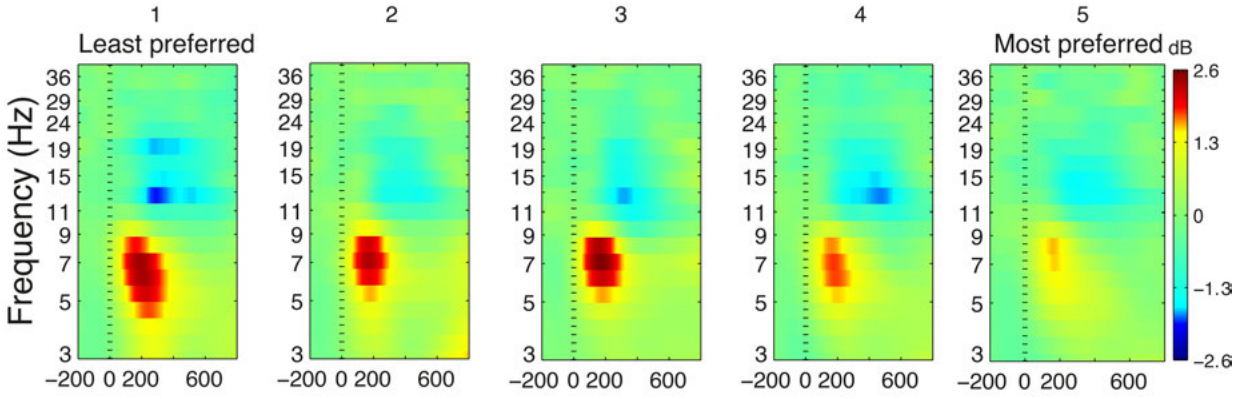
Similarly, for each participant, we correlated the average theta activity response to passively viewing each product (averaged over 50 repetitions) with the preference scores for all products. As Figure 4, Panel B, illustrates, the correlation between the average theta activity and the average total number of times that product was chosen across all participants was high, negative, and significant in electrode Fz (Pearson r = –.83, $p < .001$; Spearman r = .76, $p < .05$ [left panel]) but not in electrode Pz (Pearson r = –.08, $p = .82$ [right panel]). That is, the lower the theta activity measured in electrode Fz during passive viewing of a product, the higher the preference ranking of that product in the subsequent choice task. The existence of a significant effect only in electrode Fz suggests that the predictive information of the theta power originates in more frontal areas.

For illustrative purposes, we divided the rank-ordered products (across the population) into two element bins and plotted the ERSP levels as a function of product presentation. Figure 5, Panel A, describes this relationship in electrode Fz for an example participant (participant 3), and Panel B depicts the group average. As both panels show, the power in the theta frequency band is decreasing as a function of preference score. Therefore, the weaker the theta activity, the higher the preference score.

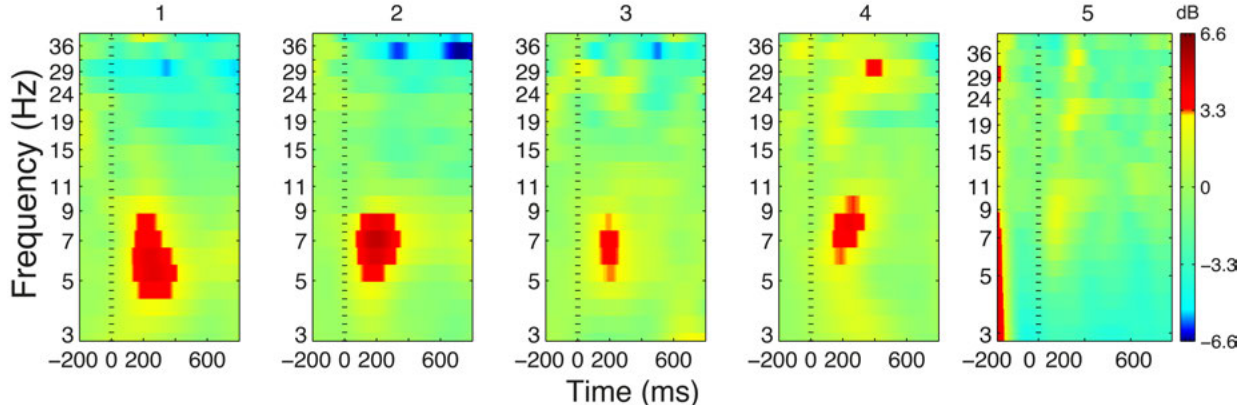
The correlation we found between EEG activity and preference for the products across participants is noteworthy. This correlation indicates that it is possible to use the EEG to identify products that are ranked highly by a population of participants. Of course, this is only possible because such a population-level ranking exists (i.e., participants have a relatively similar preference ranking of the products). Table WA2 in the Web Appendix reports the total number of times

Figure 5
ERSP RESPONSE FROM Fz ELECTRODE TO RANK-ORDERED PRODUCTS

A: The ERSP Activity by Preference Score for a Single Participant (Participant 3)



B: The Average ERSP Activity by Preference Score Across All Participants



Notes: ERSP activity in response to viewing the ten products (each plot represents the average of two products) ordered by participants' preference scores as measured in the subsequent behavioral choice task (1 represents the two products that were least preferred, and 5 represents the two products that were most preferred). Logarithmic scale of EEG frequency (3–40 Hz) is represented on the y-axis. Hot colors (red) indicate higher power (in dB), as shown on the scale on the right. The black dotted line (zero on the x-axis) represents stimulus presentation onset.

each participant chose a product (of the 54 possible trials), as well as the total across the population (810 possible trials). For example, participants chose the USB flash drive in 75% of the choice trials in which it was presented, in contrast with the magnetic message board, which was chosen in only 27% of trials. For these two products, such a stark ordering will yield a correlation with our neural measure when the corresponding EEG measurements of these two products are very different. For example, the average N200 value for the flash drive across participants was –5.23 μV, significantly larger than that for the magnetic message board, at –8.95 μV ($p < .0001$).

To examine the full sample, we computed the intersubject correlations of the preference rankings between every pair of participants. Table WA3 in the Web Appendix shows that there was a range of intersubject correlation values, with 6 (of 105) correlation coefficients significantly different from zero ($p < .05$) and another 5 with marginally significant coefficients ($p < .1$). The average correlation coefficient was $r_{average} = .12$, which was not significantly different from zero due to the high range of coefficient values (from –.50 to .83 with a Cronbach's alpha reliability index of $\alpha = .67$). Therefore, the correlation we found between EEG activity and preference for the products across participants is partly due to the intersubject correlation, which induces a sizable population-level ranking.

Correlation of EEG Activity and Preference Within Subject

Having established an average population-level effect of the N200 component and the number of times a consumer product was chosen in the population, we next examined whether this component was correlated with the ranking of a product at the subject level. For each participant, we observed the preference scores for each of the ten products (the number of times the participant chose each product). Thereafter, for each participant, we ranked the products from one to ten and observed the corresponding amplitude of the N200 component (averaged over 50 repetitions of each product). We then averaged each of these ranked scores and each of the corresponding N200 amplitudes across all participants.

As Figure 6, Panel A, illustrates, the correlation between the average N200 amplitude and the average preference score for the ranked products was high, positive, and significant ($r = .7$, $p = .023$) in electrode Fz but not in electrode Pz ($r = .34$, $p = .33$). That is, the smaller the N200 deflection (less negative magnitude), the higher the preference score of that product in the subsequent choice task. The correlation was stronger and remained significant when we used the Spearman correlation (Fz: $r = .77$, $p = .013$; Pz: $r = .35$, $p = .31$).

We analyzed the theta power band of EEG signal in a similar manner. As Figure 6, Panel B, illustrates, the correlation between the average theta power and the preference score across all participants was high, positive, and significant (Pearson $r = –.77$, $p < .01$; Spearman $r = –.60$, $p = .07$ [left panel]) in electrode Fz but not in electrode Pz (Pearson $r = .05$, $p = .88$; Spearman $r = .04$, $p = .91$ [right panel]). That is, the lower the theta activity measured in electrode Fz during viewing of a product, the higher was the preference ranking of that product in a subsequent behavioral choice task conducted ten minutes later. Again, the existence of a correlation only in electrode Fz suggests that the predictive information of both the N200 and the theta power originates in more frontal areas.

CHOICE PREDICTION USING EEG MEASUREMENTS

Having established that the average EEG activity within products and within subjects correlates with choice preference, we next address the main hypothesis of our study: Can EEG data be used to derive a measurement of the value people place on a consumer product, and can this measurement be used to predict their trial-by-trial choices? To answer this question, we conducted analyses on both the N200 and the theta power activity using two methods recently introduced in the neuroeconomic literature.

Ordinal Analysis

A requirement for relating neural measurement to choice prediction is establishing that the ordering of the neural measurements corresponds to the choices observed in the behavioral task. To verify this, we rank-ordered each product according to its EEG measurement of neural activity. We report the number of correct predictions of pairwise choices in our choice task, assuming that a product with larger magnitude is chosen. For the ERSP theta power measurement, the product with the strongest theta power was ranked last, and the product with the weakest theta power was ranked first. For the ERP measurement, we ranked each product according to the mean (negative) deflection of the N200 response. The product associated with the largest N200 deflection was ranked last, and the product with the smallest N200 deflection was ranked first.

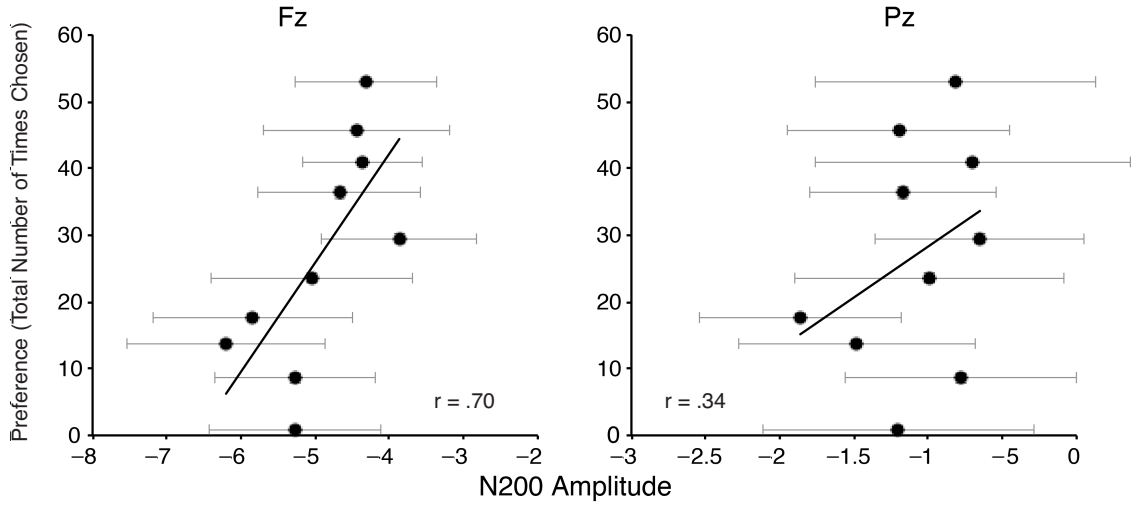
Both the ERSP and ERP measurements in electrode Fz predicted choice behavior. With the theta power of electrode Fz, the proportion of correct predictions of pairwise choices was .59 (SD = .12), ranging from .42 to .73 across participants, and was significantly different from chance ($t(14) = 2.83$, $p < .05$). The results of the N200 amplitude were similar, with a prediction rate of .57 (SD = .15) and marginal significance ($t(14) = 1.84$, $p = .09$). Importantly, this predictive power was not evident in electrode Pz for either the theta power (M = .48, SD = .11; $t(14) = –.84$, $p = .41$) or the N200 (M = .50, SD = .16; $t(14) = –.12$, $p = .90$). These results demonstrate the specificity of the predictive power of the EEG signal to more frontal electrodes.

Similarly, the proportion of correct predictions improved as a function of the ordinal distance of the ranked products for electrode Fz, but not for Pz (Figure 7). For example, in the 54 trials in which the pairwise choice involved products with adjacent neural ranking (ordinal distance of 1), the proportion of correct predictions was not different from chance (M = .53, ±.02). At an ordinal distance of 9, involving the six pairwise choices between the highest- and lowest-ranked products, the proportion of correct predictions was .79 (±.1). The results for the N200 amplitudes were similar, with a proportion of correct predictions of .53 (±.02) for products with adjacent neural measurements and a prediction rate of .70 (±.10) for products with an ordinal distance of 9.

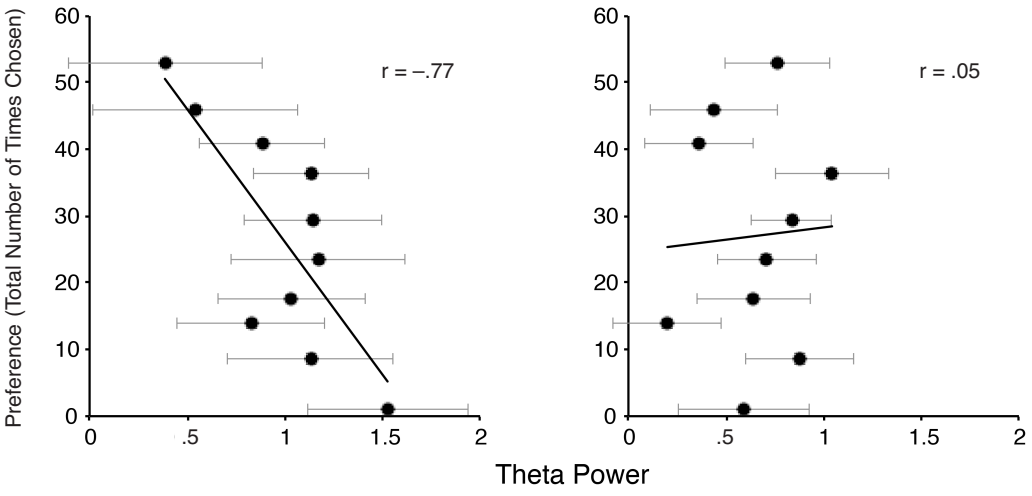
To capture this trend statistically, we conducted a linear regression analysis between the ordinal distance of the theta

Figure 6
PARTICIPANT-LEVEL ANALYSIS

A: N200 ERP component



B: Theta Band (5–8 Hz) Power



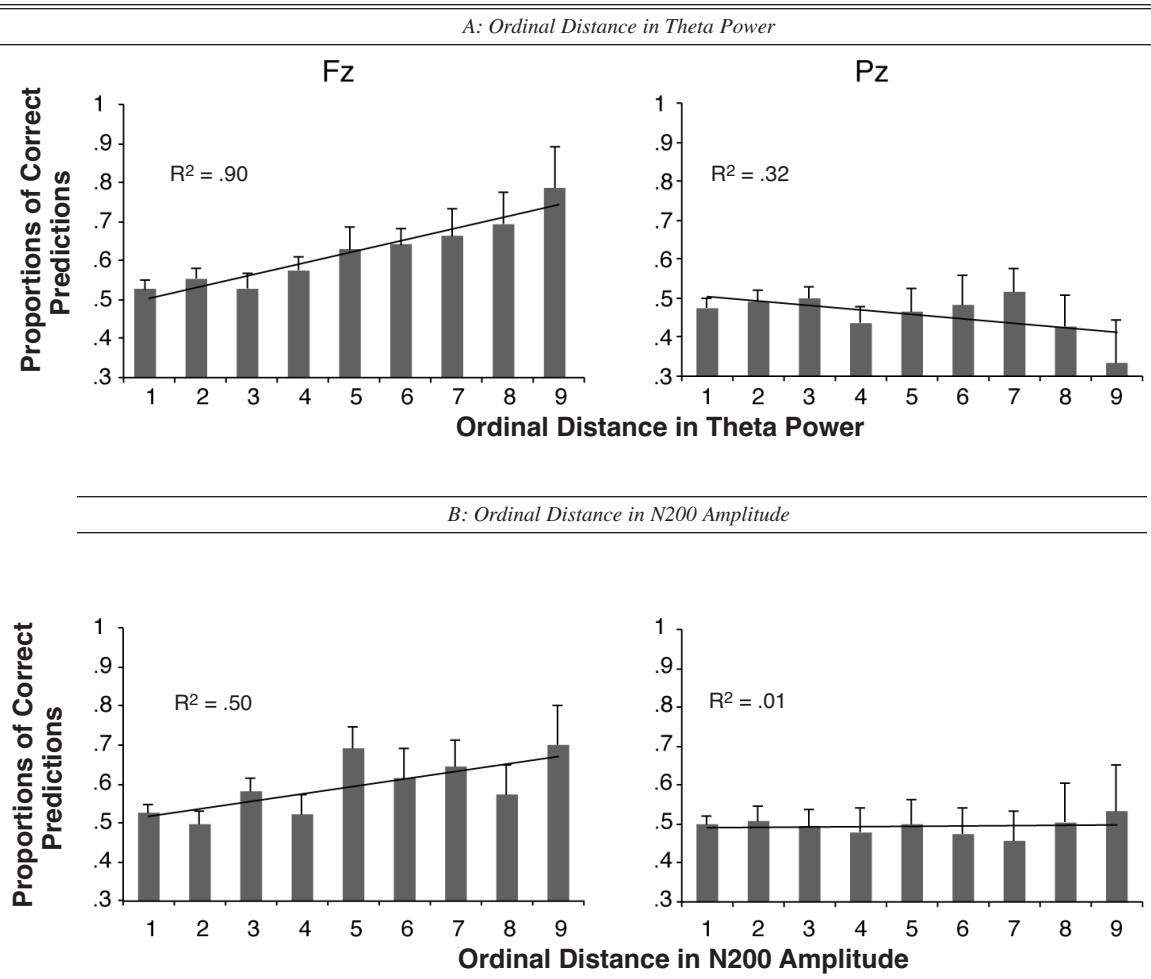
Notes: The graph shows a scatter plot of the correlation across participants between the preference score of each product for each participant (as measured by the total number of times each participant chose each product during the subsequent behavioral task) with the corresponding average EEG activity for each product for electrodes Fz (left) and Pz (right). The horizontal error bars denote the standard error of the EEG activity for each product across participants. The vertical error bars represent the standard error of the means of the preference ratings for each product across participants (the vertical error bars are not evident because they are smaller than the black circle). As Panel A shows, the smaller deflection (less negative) N200 amplitude was strongly associated with higher preference scores ($p < .01$) only at electrode Fz, while stronger theta power (Panel B) was negatively correlated with higher preference scores ($p < .01$) also only at electrode Fz.

band and the proportion of correct predictions. The relationship is strong and significant in electrode Fz ($R^2 = .91, p < .001$) but not electrode Pz ($R^2 = .32, p > .05$). The results are similar for the N200 (Fz: $R^2 = .50, p < .05$; Pz: $R^2 = .01, p > .05$). This again strengthens the notion that the predictive information is specific to frontal areas.

Cardinal Analysis: NRUM

It is noteworthy that the magnitude difference in the ranking of the EEG measurements for each product carries predictive power. This observation is consistent with a possible cardinal scale underlying the measure of value on which the ordinal ranking is based. This is because knowing "how

Figure 7
ORDINAL PREDICTION AS A FUNCTION OF NEURAL DISTANCE



Notes: Data represent the proportion of correct choice predictions as a function of theta power and N200 distance at electrode Fz and at Pz. The products were ranked according to the theta power or N200 they generated, and proportions of correct predictions were calculated separately for each ordinal distance. Error bars represent one standard error of the mean of the proportion of correct predictions across participants.

much" a person values a consumer product (relative to another product) can yield improved prediction rates.

To examine this possibility, we use the NRUM and choice prediction procedure described in Webb et al. (2013). The NRUM estimates the likelihood that a participant will choose one product over another on the basis of the difference in neural activity recorded for those two products. An additional advantage of this model is that it applies standard econometric techniques (e.g., a random-effect Probit model) to partially account for the large amount of measurement error present in neural variables. Repetitions of choice trials per choice pair (six repetitions in this experiment) are used to estimate the variance of the measurement error through a random effect. This partially corrects for the downward bias introduced by measurement error and yields improved choice prediction results when using neural data.

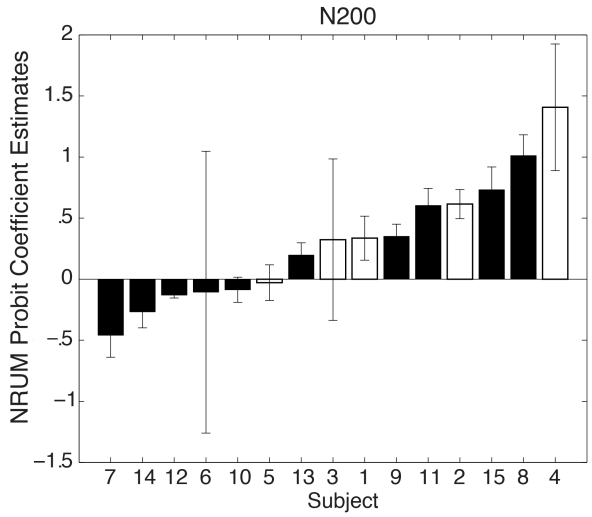
In Panel A of Figure 8, we report the estimated probit coefficient from the NRUM for the N200 signal for each participant. An increase in the difference of our neural measurement led to a significant increase in the likelihood of choosing the higher alternative for 8 of the 15 participants. For 4 participants, there was no significant result, and the parameter estimate went in the opposite direction for the remaining 3 participants, a result consistent with the high degree of measurement error observed in our neural signal.[3] We should note that by chance, we would only expect ~1 participant to have a positive and significant result, and the magnitudes of these results are similar to those reported in Webb et al. (2013).

To examine the magnitude of the choice prediction results from the model, we took the fitted choice probabilities in each trial and simulated 1,000 choices for each trial. We

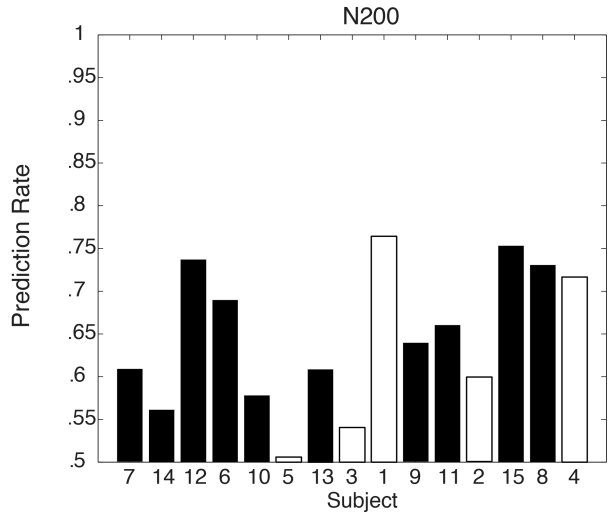
[3]For an in-depth discussion of measurement error and its impact on relating neural measurement to choice prediction, see Webb et al. (2013), in particular section IV.C and footnotes 19 and 20.

Figure 8
CARDINAL ANALYSIS

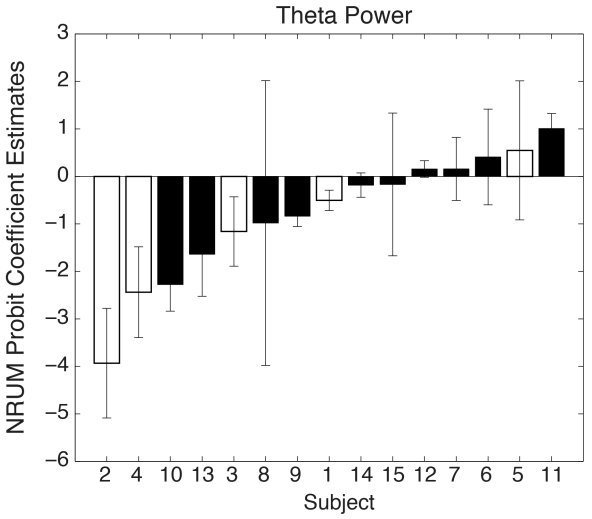
A: The Estimated Probit Coefficient from the NRUM for Each Participant for the N200 Signal at Electrode Fz



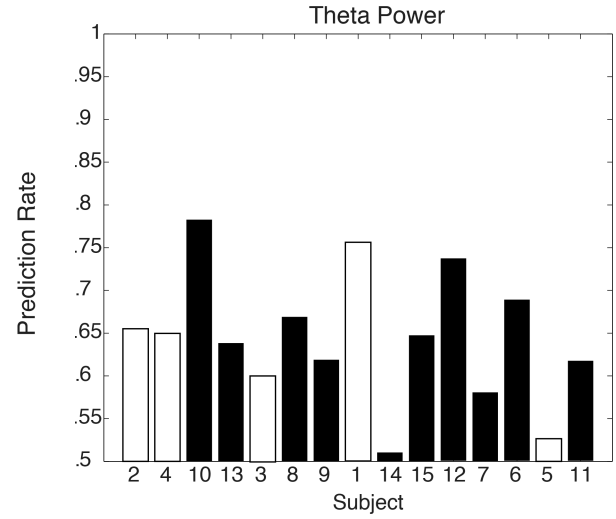
B: The Fraction of Simulated Trials on Which the Simulated Choices Match the Actual Choices from the Behavioral Data



C: The Same as A but for Theta Power



D: The Same as B but for Theta Power



Notes: Error bars represent the 95% confidence intervals. The first five participants are depicted in white.

report the fraction of simulated trials in which the simulated choices match the actual choices from the behavioral data in Panel B of Figure 8. Prediction rates lie significantly above chance for all but one of our participants and range up to .76. Across the entire sample, the average prediction rate is .64 ($p < .01$) and remains at .65 if we drop the three participants with negative parameter estimates. To verify that our prediction rates hold up out-of-sample, for each participant we also estimated the NRUM on only half the choice pairs and repeated our prediction exercise for the remaining choice pairs. This exercise uses half the data (for each participant) to predict the remaining choices of that participant. Prediction rates remained significantly above chance for 13 of the 15 participants, and the average out-of-sample prediction rate across the subject pool was .59 ($p < .01$).

We report similar results for the ERSP theta band in Panels C and D of Figure 8, though for this measurement, an increase in the differenced theta band activity significantly

increases the likelihood of choosing the lower valued alternative. Choice prediction rates reported in Panel D range up to .78, with an average prediction rate of .65 (before and after we dropped the one participant with a positive estimate). The average out-of-sample prediction rate was .60 and significantly different from chance ($p < .01$).

DISCUSSION

We demonstrate that EEG measurements of neural activity, taken while a person visually evaluates a consumer product, can predict preferences in a subsequent binary choice task over the same products. Importantly, the accuracy of our predictions depends on both the ordinal and cardinal distance of the neural measurement. The larger the magnitude differences in our EEG measures, the better the predictive accuracy. A smaller (negative) deflection in the N200 amplitude and a weaker theta band power correlate with a more-preferred product at the subject level, and notably, these same measurements, averaged over the entire sample, correlate with the frequency that a particular product was preferred in our subject population.

Our findings have clear implications for marketing research and application. First, this study demonstrates that consumer preferences can be predicted using EEG methods. Compared with other measurement techniques in neuroscience, EEG is less expensive, widely available, and even portable enough to be used in the field. Our results focus on consumer products, but the general nature of evidence for value measurements in the prefrontal cortex using fMRI methods (e.g., Bartra, McGuire, and Kable 2013; Levy and Glimcher 2012) implies that, in principle, EEG can also be used for predicting the outcome of marketing-related strategies or campaigns, not simply preferences for consumer products. This notion may even extend to the valuation of novel products with which the consumer has had no experience (Barron, Dolan, and Behrens 2013) or products that are currently under development.

Second, we obtained the EEG measurements used to predict choices while participants were not making actual decisions (or any motor response whatsoever) but simply viewing each product in isolation. This procedure is relevant to situations in which the marketer cannot directly ask consumers for their preferences (in questionnaires or actual choice tasks) or in situations in which consumers passively view advertising messages on various content-delivery media. By eliminating the need to elicit any response from the consumer directly, our methods avoid many elicitation biases and may lead to less interference in the valuation process.

Link to Feedback-Related Negativity

From a technical standpoint, our observed correlations of preferences with both frontocentral N200 amplitude and theta power are in line with previous studies. Previous work suggests that feedback-related negativity (FRN), a frontocentral negative potential, shares the same scalp distribution, time course, morphologies, and functional dependencies as the N200 component (Holroyd, Pakzad-Vaezi, and Krigolson 2008) and is strongly linked to people's choices (for a review, see Walsh and Anderson 2012). Importantly, the FRN component is mainly identified in response to feedback (Simons 2010). For example, the FRN appears 200–300 ms after the display of unfavorable versus favorable outcomes and indexes how "good" or "bad" an outcome is within a given context (Goyer, Woldorff, and Huettel 2008; Hajcak et al. 2006; Kreussel et al. 2012; Masaki et al. 2006; Nieuwenhuis et al. 2004). Research has also found that for unfavorable outcomes, the more negative they are perceived to be, the stronger is the FRN response they elicit, and the FRN also emerges in response to passively viewing outcomes (Yeung, Holroyd, and Cohen 2005).

Importantly, there is also a link between FRN activity related to choice values and theta power. Studies focusing on the frequency characteristics of the FRN have found that strong frontal theta power activity is linked to FRN activity and emerges in response to the presentation of unfavorable outcomes (Cohen, Elger, and Ranganath 2007). In addition, Gehring et al. (2012) extracted theta oscillations using the Morlet wavelet transform and found a frontally focused theta (4–7 Hz) activity for monetary losses compared with monetary gains.

The FRN component appears not only in experiments involving active choice, but also in experiments in which outcomes are received without choice behavior. For example, Yeung, Holroyd, and Cohen (2005) show that the FRN can be elicited for unfavorable outcomes when choices are not actively made but only passively viewed by participants. However, in our experimental design, participants did not receive products (i.e., feedback) following choice. Thus, this raises the possibility that the unfavorable outcome-related negativity (as identified by both the N200 and the FRN) emerges not only in response to actual feedback but also in valuation without active choice or feedback. This suggests that it is a more general valuation response to unfavorable stimuli and strengthens the notion that—even at the level of EEG activity—the neural representations of values share similar properties and are located within the same brain structures when people make actual choices and when they only evaluate options without actively choosing.

Thus, in accordance with other scholars (e.g., Holroyd, Pakzad-Vaezi, and Krigolson 2008), we suggest that both the FRN (which involves an actual feedback) and the N200 originate from the same value-related cognitive mechanism. We further suggest that the N200 value-related signal is similar to the FRN value-related signal, but only in situations in which no choices are involved. Our study strongly implies that EEG signals can be used without feedback or active choice to measure how valuable an option is.

Response Inhibition as a Possible Mechanism for N200 Amplitude

It is also possible that the increased N200 and theta power after the presentation of an unwanted product is a manifestation of response inhibition, though without the need to inhibit actual motor responses. Studies using a go/no-go task, which requires a participant to perform an action given certain stimuli (e.g., press a button [go]) and to inhibit that action under a different set of stimuli (e.g., do not press the same button [no-go]), have demonstrated that the frontocentral N200 generates a larger (more negative) deflection after the presentation of a no-go signal than the presentation of a go signal (Enriquez-Geppert et al. 2010;

Falkenstein, Hoormann, and Hohnsbein 1999; Van Veen and Carter 2002). The go/no-go task also elicits frontal theta power activity that is greater in response to a no-go signal than a go signal (Kirmizi-Alsan et al. 2006; Yamanaka and Yamamoto 2010). However, most of the studies investigating event-related brain activity using the go/no-go task focused on situations in which participants needed to actively inhibit an immediate motor response (Yeung, Botvinick, and Cohen 2004).

Importantly, in our study participants did not engage in actual decisions while we measured their EEG activity. Therefore, the N200 component we identify might have a larger deflection in response to more unwanted products because these products elicited a stronger response inhibition, which can occur even without active choice. Our findings regarding the theta power activity agree with this notion as well. The stronger theta power we observed for least-preferred products might be due to the stronger response inhibition these products elicited compared with the most-preferred products. This possibility again strengthens the notion that similar neural value representations are in operation when we evaluate options for active choice and when we evaluate options without any active choice or any motor action.

Classification of N200 Signal

Previous studies have characterized several distinct N200 potentials. The N2a, also termed the "mismatch negativity potential," is mainly localized in the frontocentral areas of the scalp and is typically elicited in response to an unpredictable, low-probability, auditory stimulus in a sequence of stimuli (Naatanen et al. 2007). Conversely, the N2b component, which is not restricted to auditory tasks, is observed only during conscious attention to various stimuli and is mainly associated with response selection, inhibition, and error monitoring with maximal effect at electrode Fz (Patel and Azzam 2005). A third type, the N2c, is mainly associated with categorization of stimuli in classification tasks and is larger for infrequent than for frequent stimuli. The N2c is typically localized in posterior scalp sites and is usually accompanied by a larger P300 component (Luck 2005), which we did not observe in our data. Therefore, we suspect that the N200 found in our study could be classified as an N2b potential. First, it is localized in the frontocentral areas of the scalp. Second, because our study is focused only on the visual aspects of the products and does not involve any auditory stimuli, it is likely not the N2a component. Third, the N2b is related to response inhibition, and inhibition is possibly one of the mechanisms underlying the N200 effect found in our study.

Relationship Among EEG, fMRI, and Choice Prediction

Previous EEG studies have demonstrated a link between hemispheric asymmetry in the theta band (though using a different type of measurement than that in the current study) and some aspects of valuation of consumer products, such as pleasantness and liking ratings (Lee et al. 2013; Vecchiato et al. 2011). Our data extend these findings in several ways. First, we found a correlation between the theta band power and participants' rank-ordered preferences without requiring any hemispheric asymmetry in our analysis. Second, to our knowledge, this is the first study to correlate a component of the general EEG waveform (N200), identified in an event-related potential, with subsequent choice behavior. Third, we demonstrate that the predictive power depends on the magnitude of the theta power band, suggesting a cardinal scale for our measurement. Finally, we demonstrate that the signal likely originates from frontal areas. We now briefly discuss each of these contributions.

In our study, the most predictive information representing participants' preferences originated from a more frontal electrode (Fz) than a more posterior electrode (Pz). This suggests that the most informative neural activity originated from more frontal areas. Note, however, that with sufficient power, volume conduction can cause any EEG effect to be detected in any electrode. Therefore, the localization of EEG waveforms is inaccurate and not specific to an area of the frontal cortex. In addition, it is very difficult to use EEG to source signals that originate from deep brain areas, such as the ventromedial prefrontal cortex, dorsomedial prefrontal cortex, insula, or anterior cingulate cortex, which previous fMRI studies have used to predict participants' subsequent choices (e.g., Falk, Berkman, and Lieberman 2012; Smith et al. 2014). Thus, it is important to emphasize that this study finds stronger predictive power originated from a frontal electrode (not the more posterior Pz electrode) rather than from a specific localization of the source.

Our finding that the predictive accuracy depended on ordinal and cardinal distance in EEG measurements is in line with previous fMRI results (Levy et al. 2011; Webb et al. 2013). These studies used a measure of neural activations in the mPFC and striatum (brain areas known to represent expected and perceived subjective values for various reward types; Bartra, McGuire, and Kable 2013; Levy and Glimcher 2012) while participants passively viewed different products inside the scanner. The authors then used these measured neural activations to construct an ordinal neural ranking of the products, and this ranking predicted choice outcomes with accuracy of up to 82%–83% for products with the greatest neural ranking distance. Perhaps surprisingly, given the nature of EEG technology, we achieved 79% accuracy for products with the greatest neural ranking distance. In a similar fMRI experimental setup, Smith et al. (2014) report within-subject correlations of a similar magnitude, as well as a 77% prediction rate for preference ratings for specific products across the population. This result, together with our observed correlation between EEG activity and the frequency with which a product was chosen in the population, suggests that neural activity measured with either fMRI or EEG can have significant predictive power, both within and across subjects for each product. Both measurement techniques convey important information about current valuations and subsequent choices.

Although our prediction rates were significant when averaged over all the products, we emphasize that the observed predictive power depended on both the neural distance and the preference distance found in behavior. An accuracy rate of almost 80% was only possible when participants had stark preferences between the products considered. When the products were close in preference—and in the magnitude of the neural measure—the prediction was not above chance. The magnitude of these results, and the effect of measurement error in choice prediction, is in line

with previous studies (Webb et al. 2013), and our prediction rates using EEG are similar to prediction rates reported in previous fMRI studies (e.g., Falk, Berkman, and Lieberman 2012; Lebreton et al. 2009; Levy et al. 2011; Smith et al. 2014; Tusche, Bode, and Haynes 2010).

Table 1 reports the prediction rates from the studies noted previously alongside our results. There are several points to note from this exercise. First, our study is the first to use EEG methods to significantly predict choices. Second, although our prediction rates are not exceptionally high, they are in line with the current state of fMRI studies (perhaps surprisingly so, given the low signal-to-noise ratio typically associated with EEG methods). Third, because the prediction rates vary across all these studies, prediction rates are likely sensitive to the choice set chosen in a given experiment and the analysis methods employed. We contend that EEG can be a practical tool for marketing research.

The ability to predict consumer choices without eliciting any response from the consumer is a valuable research tool, and EEG has several important advantages over fMRI. The purchase and operational costs of an EEG system are relatively low, it is portable and less restrictive for participants, and the data-sampling rate is high. However, we emphasize that additional studies are necessary to understand the generality of our findings before this technique can be reliably used for commercial purposes.

Table 1
AVERAGE PREDICTION RATES

Study	*Average Prediction Rate*	*Analysis Method*	*Imaging Tool*
Tusche, Bode, and Haynes (2010)	70%–82%	Within subject (SVM)	fMRI
Levy et al. (2011)	56%	Within subject (ordinal analysis)	fMRI
Webb et al. (2013)[a]	56%	Cardinal NRUM	fMRI
Webb et al. (2013)[a]	69%	Cardinal NRUM + other observables	fMRI
Smith et al. (2014)	61%	Within subject (ordinal analysis)	fMRI
Smith et al. (2014)	77%	Within group (cardinal analysis)	fMRI
Smith et al. (2014)	61%	Across groups (cardinal analysis)	fMRI
The current study	59%	Within subject (cardinal analysis)	EEG
The current study	65%	Cardinal NRUM	EEG

[a]The prediction rates that Webb et al. (2013) report are for multiple choice trials. The single-trial probabilities are reported here for easy comparison with other studies.

Notes: The average prediction rates for future choices in different studies in which participants did not make actual choices while their brain activity was measured. Analysis method refers to the prediction methods used in the study. Note that all prediction rates are significantly above the chance level of 50%. SVM = support vector machine.

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