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Accuracy and neural correlates of blinded mediumship compared to controls

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Summary: Anomalous psychological phenomena, in which individuals claim to have access to information not available through conventional means, have been reported since antiquity. Despite tremendous popular interest, few studies have tested these claims rigorously. The current study aimed at filling this gap. We asked volunteers to look at facial photographs of deceased people and guess how the depicted person had died among three choices; we also recorded volunteers' electroencephalogram (EEG) while they were making those choices. The volunteers were of two types: "psychic mediums," who were all professional and make a living of this practice, and controls, who claimed no special ability. The cause of death fell into three possible choices: "heart attack", "death by firearm", or "car accident." The facial photographs were a balanced pool of 201 black and white photographs, where the cause of death was known in each case. The volunteers did not see any of these photographs before the experiment. Data from all participants pooled showed that they were significantly accurate in guessing the cause of death (partial η^2=0.13;p=0.003). Control subjects were primarily responsible for this effect (partial η^2=0.15; p=0.001). In terms of EEG activity, a difference was found between the talented volunteers and the controls in event related potential (ERP) following the presentation of the photographs. The controls had larger amplitude ERP components than the talented volunteers between 80 and 110 ms and between 200 and 350 ms, which could be interpreted as reflecting greater attention and less response inhibition by controls as compared to the talents.

Introduction

Anomalous psychological phenomena, in which individuals claim to have access to information not available through conventional means have been reported since antiquity. A subset of the population called "mediums" are purportedly talented in providing this type of information, especially about deceased individuals. One hypothesis for the perennial popularity of mediums is the understandable wishful thinking that accompanies the emotional need for the bereaved to remain in contact with deceased loved ones. Another hypothesis is that some of the information provided by mediums might be accurate (Beischel and Schwartz 2007; Beischel and Zingrone 2015; Delorme et al. 2013; Rock, Beischel, and Cott 2009), a topic that William James found worthy of scientific investigation (Anon 2019).

The Delorme et al. (2018) experiment had two caveats. First, non-medium controls were not tested, so we could not assess if mediums were more accurate than people who did not claim special skills. Second, information about whether a given individual in the database was alive or deceased could not be absolutely verified for accuracy as we relied on a social media website to collect that information, and it was possible that a number of individuals who we thought were alive were, by the time the experiment was conducted, had actually died. In addition, it was not possible to continue to use the database without having to regularly check if individuals in the database were still alive, making it difficult for other laboratories to reproduce our results.
The current study aimed at removing those limitations. First, we tested control participants in addition to professional mediums. Second, all the facial photographs were photographs of deceased individuals only and we asked participants to indicate the cause of death using three possible choices: "heart attack", "death by firearm", or "car accident." We then tested the following three hypotheses. First, are mediums or controls able to detect the cause of death in photographs of deceased individuals at above-chance levels? Second, are mediums better at this task than controls? Third, is there any brain activity markers that accurately differentiate between correct and incorrect classification?

Methods

Participants
We recruited 24 participants: 12 professional mediums who claimed to be able to connect with deceased individuals based on examination of facial photographs alone, and 12 age-, gender-, and ethnicity- matched controls that claimed to not have that ability (53 +- 9 years; 4 males and 20 females). Mediums were selected from a pool of candidates in the San Francisco Bay Area through word of mouth or from the internet (e.g. https://www.yelp.com/). To be selected, (1) they had to be professionals who regularly provide "readings" for clients, and (2) they had be vetted by at least two individuals/witnesses who claimed that the mediums were able to provide accurate information not readily available to them. For (2), we used Yelp reviews (only mediums with no single bad review were selected) or word of mouth referrals. Control participants were recruited through a Craigslist advertisement. For all participants, the inclusion/exclusion criteria included: Normal or corrected to normal vision; able to sit in front of a computer screen in a dark room; not currently diagnosed with any psychiatric condition or following any psychoactive drug treatment; able to perform the task; and able to commute by their own means to the Institute of Noetic Sciences where the experiment was conducted. Applicants filled out an online survey to apply, and then a research assistant contacted each potential participant by email or by phone to confirm that they met all the inclusion/exclusion criteria. If they did, a recording session was scheduled and they received further instructions to prepare for the session (e.g. directions to the Institute, instructions to wash their hair before the session to increase EEG signal quality, etc.). All participants received a $100 gift card for their participation, and they signed an informed consent. The study was approved with the IONS Institutional Review Board reference DELA_2016_01 amendment 9/1/2017.

Stimuli
The task involved the presentation of 201 photographs (3 times 67) on a computer screen, one at a time. Each photo was displayed for up to 30 seconds, and disappeared after the participants responded by pressing one of three keys on a keypad to indicate the cause of

death. One third of the photographs involved “car accident” as cause of death, one third “heart attack,” and one third “by firearm.” After selecting a cause of death by pressing a corresponding button on a keypad, the next photo was presented after 3 seconds. Trial-by-trial accuracy feedback was not provided. During the pause between photos, instructions and key button information were presented again to remind participants of the instructions and they were instructed to gaze at a centrally located fixation cross between images. Participants were instructed before the experiment began that images were balanced for a number of features (such as approximate weight) and that they should use their intuition to respond.

The response keys 1, 2, and 3 were fixed for each participant but their correspondence with the cause of death was randomized across participants. Immediately prior to starting the task, each participant had 10 practice trials - using unique face photographs not in the subsequent task - to become familiar with the task. Practice trials were not used in the subsequent data analyses. Image presentation was controlled by the Matlab Psychophysics Toolbox. The size of each image was uniformly presented at 320 x 480 pixels (double the image resolution - see below) at a resolution of 800 x 600 on a CRT monitor (cathode ray tube) screen to ensure proper control by the program of the latency of presentation of each image with millisecond precision. The experiment was conducted inside a solid steel, double-walled, electromagnetically shielded and electrically grounded chamber.

All depicted individuals originated from the “Officer Down Memorial Page” website: https://www.odmp.org/. More than 23,000 police officers died in the exercise of their duty in the United States from 1791 to 2019, and they are cited on that web site, often with photographs. We used 201 images from that database (see image selection process below). All of the work in this study was performed in respect of both the individuals depicted and their family. Participants in the experiment could not leave with copies of any of the photographs they had seen.
If a medium asked if we would communicate with the family about a given individual they had seen, wishing to provide the family with information they had received at no charge, our plan was the following: We would post a message on the ODMP website that a medium had been in contact with the deceased office and that a relative or friends could contact us (at no charge) if they wished to obtain more information. We would have followed up to ensure that the medium was not financially motivated. In general, mediumship has been shown to help in the grieving process (Beischel, Mosher, and Boccuzzi 2015). None of the mediums requested that we contact the family or friends of the deceased individuals that they viewed.

Image selection

The image selection process was designed to minimize the chance of obtaining conventional information that might be relevant to the classification task. For example, overweight individuals might be more likely to suffer from cardiac arrest. Thus, to form a balanced image pool, we first downloaded all of the photographs of all officers with photos, as well as the information associated with them. Many memorial pages indicated the officer’s age when they died, the cause of death, and their photograph. We obtained a total of 2,285 images. The four leading causes of death were by firearm (1357), car crash (380), motorcycle crash (166) and heart attack (113). We decided not to consider motorcycle crashes because that was too similar to car crashes, leaving us with 3 categories of images. Then we manually removed images that were not headshots, where the officer was wearing a hat, or where the photo was of too low quality. We also removed images of individuals who were not obviously caucasian, African American, or

of asian heritage because there were very few of them and it would not be possible to balance them across categories. We then randomly removed a large number of images in the death by firearm category, and a lesser number of images in car crash category, so the histogram of the individuals' ages in those categories matched the ones in the heart attack category (which tended to consist of older individuals). We ended up with a total of 381 photographs: 211 of death by firearm, 102 of death by car crash, and 68 of death by heart attack.
The images were then processed as follows:
- Each photo was cropped by manually indicating the position of the left ear, the right ear, the top of the head and the bottom of the chin (Delorme et al. 2018).
- Each image was then resized to 160 x 240 pixels using linear interpolation while preserving the aspect ratio of the original image. Then the background from each picture was manually removed (set to transparent) using the Gimp software (version 2.10; The GIMP Development Team).
- The image was then converted to gray scale by a custom Matlab script using the luminosity method (i.e. using the weighted sum of 0.21*Red + 0.72*Green + 0.07*Blue).
- Images were normalized by setting the grey level mean for each picture to 122 on a scale of black (or 0) to white (or 255), and setting the standard deviation for the grey level pixels to 55 (on a scale of 0 to 255). Only non-transparent pixels were used to perform this operation. Values below 0 were capped at 0 and values above 255 were capped at 255.
- Using a custom program we developed, each of the 381 photograph was rated independently by three judges on 8 characteristics: gender (M/F), perceived age (20-30, 30-40, 40-50, 50-60, 60-70), direct gaze (yes/no), glasses (yes/no), head position (facing camera, tilted, profile), smile (yes, no), hair color (light, dark), weight (normal weight, overweight, obese), race (caucasian, African American, asian), and picture resolution (acceptable, medium, poor). Prior to making these judgements, the first author (AD) discussed with each judge the meaning of each category, using examples that were not in the database. For example, even a slight smile should be considered a smile and medium hair color should be considered light, not dark. We randomized the order in which the images were rated and raters were blind to how the depicted individual passed. Ratings from the three judges were combined by taking the median rating. For a given image, if one rater judged the individual depicted in the age range 20-30 and the other two judged that the individual was in the range 30-40, then the combined rating was 30-40.
- Three subgroups of photos were then separated with 67 images in each group, consisting of people who died in the three categories aforementioned. These groups were created by a computer program to minimize the differences between the three groups on all 10 characteristics plus two continuous variables of spatial frequencies: low and high spatial frequencies calculated by considering the average spectral amplitude of the pixel closest to origin and further away from the origin in the 2-D FFT decomposition. The Matlab code used to perform this is available from the first author upon request. Then we ran statistical tests (see below) to ensure that the photos in the two subgroups were objectively similar, and we required that the p-value comparing any of the 12 characteristics to be larger than 0.4 for all possible pairings of categories (heart attack and firearm; firearms and auto crash; auto crash and heart attack). Appropriate statistical tests were performed depending on the type of categorical or continuous variables (Fisher test for categorical variables with two values; Chi2 test for categorical variables more two values; paired t-test for spatial-frequency continuous variables). The final pool of photographs used for the experiment was 201 (3 times 67).

Machine learning classification

Before the 201 photographs were used in the experiment, we assessed if an automated algorithm would be able to differentiate between the three categories of images based solely on the 12 characteristics described above. Since the selection procedure above did not remove possible information related to a combination of features (interaction between variables), a machine learning classifier could potentially take advantage of that information.

	Random Forest	Logistic regression	Support vector machine
Auto vs Heart	38.9% - 57.1%	41.5% - 50.9%	41.7% - 56.7%
Auto vs Gun	40.3% - 58.5%	33.3% - 45.6%	33.3% - 50.0%
Heart vs Gun	26.4% - 43.3%	37.5% - 48.3%	34.2% - 49.2%

Table 1. Classifier performance for pairs of categories. Percentage range indicates 95% confidence intervals. Red cells indicate cases where classifier was significantly below chance expectation.

We used 3 types of classifiers: random forest, logistic regression, and support vector machine. To perform these classifications, we used functions from the Matlab statistics toolbox (R2018b). For the random forest classifier, we used the Matlab *treebagger* function with 1,000 learners. Performance was estimated using “Out-of-bag classification error” and the out-of-bag matrix was bootstrapped before computing classification performance to form a 95% confidence interval. For logistic regression, we used the *glmfit* Matlab function (with ‘logit’ link function and binomial distribution) and for support vector machine we used the *fitcsvm* Matlab function with its default parameters. We used a 10x10 cross-validation procedure for both the logistic regression and the support vector machine function. This means that the set of 201 images was randomly divided into 10 sets of about 20 images each. 10 iterations were performed in which 9 of these sets were used to train the classifier and the remaining set was used to test it. For each classifier, we calculated the 95% confidence intervals of the accuracy of classification. We observed that none of the classifier were able to classify images above chance expectations (Table 1).

EEG data acquisition

A 64-channel ActiveTwo EEG system (Biosemi, Inc.) with integrated electrocardiography (ECG) measures was used to collect EEG data at 1,024 Hz sample rate. Electrodes were placed according to the 10-20 nomenclature (standard 64-channel EasyCap). Three sizes of caps were used to accommodate subjects with different head sizes. Electrode SignaGel was applied to each electrode and active electrode offsets were kept below manufacturer guidelines (i.e. ±20 mV). Two auxiliary ECG Biosemi electrodes, positioned under the collar bone (left and right), were used to record the participants’ heart rate. Activity from the left electrode was then subtracted from activity from the right electrode for post-processing. ECG data was extracted from the Biosemi BDF files using EEGLAB. ECG time series were then saved as a csv file in MATLAB, and ECG data was then imported into Kubios HRV Premium v 3.1.0 (University of Kuopio, Kuopio, Finland) to generate R-R intervals, heart rate, SDNN HRV, low (LF), and high (HF) frequency domain measures (LF: 0.04-0.15 Hz; HF: 0.15-0.4 Hz). HRV analysis parameters included a 100 s window width, 50% window overlap; autoregressive spectrum model order = 16 with no factorization, and interpolation rate = 4 Hz. Note that no participants were on medications that could have affected ECG (e.g., beta blockers and calcium channel blockers; Goodnick, Jerry, and Parra 2002; Olgin and Zipes 2007).

Behavioral data (the participant's response to each photo) was saved in two ways. First, keypress data were sent to the EEG amplifier digital input channel using the Biosemi USB interface and saved along with the raw EEG data. One set of markers represented the photo's category of death, and other markers represented the participant's responses. Second, the latency of responses were saved in a separate text file on the computer used to control the presentation and timing of the photos. That computer was different from the computer used to collect the EEG data. After the experiment, the correspondence of the two data streams, both in terms of response type and latency was checked, and it was found to agree within millisecond precision.

Data analysis

Behavioral data analysis

For each photo, responses were encoded as being correct or incorrect. Images which participants failed to respond on time (30 seconds) were ignored. We then ran a general linear model (GLM) with the following variables: response (correct and incorrect), group (medium and control), and type of death. We ran two regression GLMs, one with the percentage response correct on each category above chance expectation as the dependent variable and one with reaction time as the dependent variable. For the percentage of correct responses, we looked at all of the responses on a given category for a given participant and calculated the percentage of correct responses in that category. This allowed to compare performance across categories. To allow assessing if performance on each type of image was above chance expectation (33% of correct responses), we subtracted chance expectation (1/3) from each performance percentage so deviation from chance expectation for each image group would be captured in the intercept of the GLM analysis.

EEG data analysis

EEG data was imported into the EEGLAB software 2019.0 (Delorme and Makeig, 2004) in Matlab R2018b. Raw data were downsampled to 512 Hz, detrended and filtered using an FIR filter at 1 Hz (non-causal zero-phase distortion highpass filter of length 1691 samples with transition band width of 1 Hz, passband edge of 1 Hz and cutoff frequency (-6 dB) of 0.5 Hz) and low pass filtered at 55 Hz (non causal zero-phase distortion 125 points lowpass filter with transition band width 13.75 Hz, passband edge of 55 Hz and cutoff frequency (-6 dB) of 61.875 Hz). Defective EEG channels were identified manually and removed in each participant (2.5±2.0 channels removed on average) and interpolated using spherical splines (Perrin et al. 1989) for group analysis. Bad portions of data, i.e. sections containing obvious artifacts (e.g. body movements, jaw clenching etc.), were also removed by visual inspection of the filtered data (127±134 seconds of data on average, not considering data sections before the experiment started or after the experiment ended). All artifact removal was performed blind with respect to the behavioral responses.

The data were then average-referenced using the EEGLAB function *pop_reref*, temporarily interpolating removed channels for performing average reference then removing them again, and we then used Infomax Independent Component Analysis (ICA) to separate ocular and muscular artifacts (i.e. eye blinks and lateral eye movements). We used the ICLabel v.1.1 EEGLAB plugin (Pion-Tonachini, Kreutz-Delgado, and Makeig 2019) to classify components, and selected those components which were likely to be eye and muscle artifactual component (likelihood superior to 90%). Finally, we computed event related potentials (ERP; with a baseline ranging from -1 s pre-stimulus to 2 s post stimulus onset).

Results

Behavioral results

When considering all participants, we observed a main effect of response accuracy (F(1,66)=9.71; partial η^2=0.13;p=0.003) as well as a main effect of group (F(1,66)=11.7; partial η^2=0.15; p=0.001). Accuracy was on average 1.9% higher than chance expectations, although controls were more accurate than mediums as a group (accuracy of 4.0% above chance expectations for controls compared to -0.2% for mediums). No difference was found in accuracy for cause of death (F(2,66)=0.18; p=0.84).

For reaction time, again we observed a group effect (F(1,66)=221; η^2=0.04;p<1e-10) with mediums taking on average 4911 ms (+- 87 ms) to answer compared to 3177 ms (+- 61 ms) for controls. We also observed an interaction between response type (correct versus incorrect) x subject group (F(1,66)=4.31; η^2=0.001; p=0.04), with mediums being slower on images for which their responses were incorrect vs. correct (5023 ms vs 4686 ms), while controls showed the opposite trend with 3,132 ms for incorrect vs 3,251 ms for correct responses. There was also an interaction between group, response type, and image type, with a small effect size (F(1,xx)=3.64; η^2=0.002; p=0.03). No other effects or interactions were observed.

EEG results

We first assessed the time periods of interest to study across the whole scalp. This helps reduce the number of statistical tests performed. To do this, we plotted the RMS (Root Mean Square) of all of the electrodes across time (Figure 1). We then visually selected peaks of interest, a peak between 80 and 110 ms (P80-110) and a peak between 200 and 350 ms (P200-350). Note that this procedure is performed blindly with respect to experimental conditions because all conditions and subject groups are pooled.

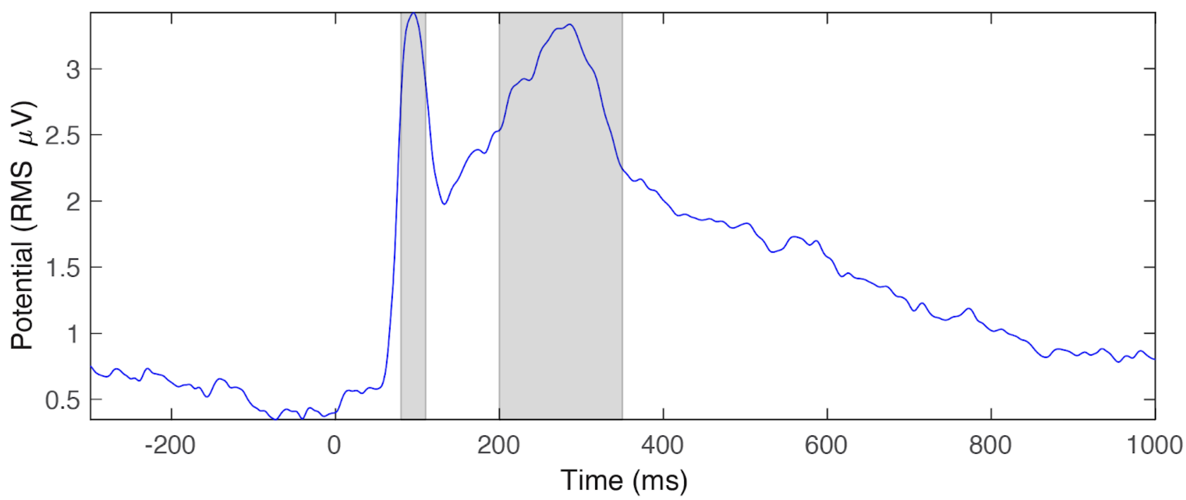

Figure 1. Regions of interest selected in the RMS ERP. We manually selected two regions, between 80 and 110 ms (P80-110) and between 200 and 350 ms (P200-350).

For each subject, we then ran a General Linear Model (GLM) with weighted least square optimization (LIMO version 2.0 extension of EEGLAB; Pernet et al. 2011). As factors, we used the type of response (correct and incorrect) and the cause of death in an interaction design. We thus obtained 6 beta parameters (correct-heart, correct-auto, correct-gun, incorrect-heart, incorrect-auto, incorrect-gun). These beta parameters were then averaged over the time range of interest (80-110 ms and 200-350 ms as defined above), exported as a text file and fed into a second level GLM to assess random effects across subjects using the Statistica software package 13.0 (TIBCO Software Inc.). This type of hierarchical analysis is standard in brain imaging analysis (Stephan et al. 2006). Uncorrected parametric statistics were corrected with false discovery rate (FDR; Benjamini and Yekutieli 2001). Electrodes significant at 0.01 after FDR are shown as large black disks in Figure 2. We found robust differences between controls and mediums mostly in the occipital regions for both P80-110 and P200-350 (Figure 2). No other differences and interactions were found. We also performed similar analyses under LIMO 2nd level and found comparable results (supplementary figure 1). Standard EEGLAB analyses comparing only subject group (mediums vs non-mediums) and ignoring other independent variables also led to a similar difference (supplementary figure 2).

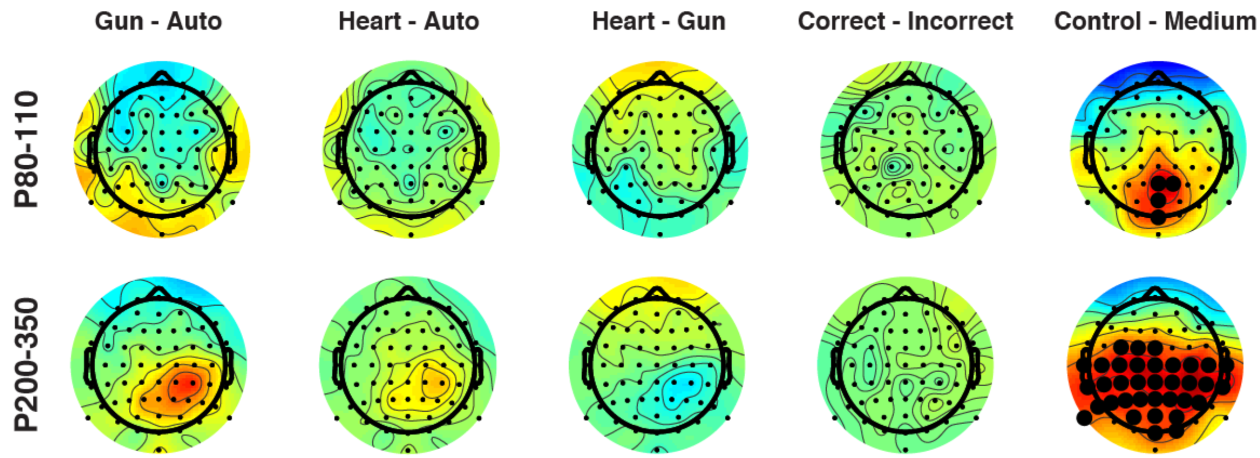

Figure 2. Partial correlation coefficients and significance for each categorical variable in the GLM model. Interactions between variables are not shown but none indicated significant effects. The top row represents the positivity between 80 and 110 ms and the bottom row represents the positivity between 200 and 350 ms. The black dots show significant electrodes at 0.01 threshold after correction for multiple comparisons using FDR.

ECG - Mean heart rate was significantly higher (t=2.39; df=22; p=0.03) for mediums (76 bpm) than controls (67 bpm). Other heart rate variability measures failed to reach significance: SDNN (t=0.92; df=22; p=0.37), LF HRV (t=0.89; df=22; p=0.38) and HF HRV (t=0.75; df=22; p=0.45).

Discussion

Because the set of 201 images contained the same number of individuals who died of different causes, our null hypothesis was that there would not be any difference in terms of correct responses across the different categories. We found that when all participants were considered together, they were nevertheless able to accurately detect the cause of death in photographs of deceased individuals at above-chance expectation, an effect surprisingly driven by the control subjects and not by the mediums. Regarding brain activity, we observed positive differences in the 80-110 ms and the 200-250 ms time range for controls as compared to mediums.

Subtle cues in images. Being able to differentiate individuals who died of diseases as compared to accidental death (such as accident and homicide) may be an indication that participants use subtle facial cues to perform the classification. E.g., facial features have been shown to indicate signs of cardiovascular diseases (Christoffersen Mette et al. 2014) and cigarette smoking (Okada et al. 2013). Adolescents' faces may also help predict adult health and mortality (Reither, Hauser, and Swallen 2009). While we cannot rule out the use of such features in our task, the fact that our machine learning classifier was not able to perform classification above chance levels when considering 12 features per photograph suggests that health cues based on facial features would have to be very subtle. Note that performance on the heart attack category was not higher than performance on death by firearm or death by accident.

Mediums versus controls. Controls performed much better at the task than mediums. This is opposite to our original hypothesis. Differences in motivation probably cannot explain such results, as we would expect mediums to be more motivated than controls. On the other hand, performance anxiety might be a potential factor. Mediums might have felt under pressure to perform, but this would not be the case for controls. Assuming that the baseline heart rate was similar in both subject groups (which we could not verify because it would require 24 hour recordings), greater stress was potentially reflected by significantly elevated heart rate in mediums compared to controls (Ulrich-Lai and Herman 2009). This may provide a clue why mediums did not perform well. That is, intuition may rely on emotions and perceptions that arise before thoughts are formulated, and that analytical judgment may impair intuition (Volz and von Cramon 2006). For example, high scores on the Cognitive Reflexion Test (which underlies analytical thinking) is correlated with lower scores on *divergent thinking* (Corgnet, Espín, and Hernán-González 2016). This suggests that thinking too much may hinder important dimensions of creative thinking. In addition, some mediums reported to us that it was difficult for them to differentiate between the type of death, as they reported feeling the pain of the deceased individual. They might interpret such pain as a heart attack, but the pain may have also occurred by being shot in the chest, or by chest trauma associated with a car accident. Additionally, mediums reported that the time pressure did not allow them to really connect with the deceased beings like they normally do, and were trying unusual strategies to respond as fast as possible. With respect to speed of response, it is interesting to mention that performance above chance expectation at this type of task has been observed for fast responses, which is consistent with the fact that controls had higher performance and did not think as long before they answered (Cardeña 2018).

EEG analysis

Our approach to ERP analysis consisted first in identifying the time period of the largest deflection compared to baseline, then analyzing those regions. This approach might ignore changes in activity in a reduced subset of channels. However, due to volume conduction, any change in brain activity tends to recruit a large set of scalp channels, so we believe we captured the most important portions of the grand average ERP. The portion between 80 and 110 ms likely correspond to the visual P100. This early ERP activity, at about 100 ms, is influenced by both visual detail information (Hopf and Mangun 2000; Taylor et al. 1999) and facial configuration (Halit, de Haan, and Johnson 2000). We did find differences in this early visual peak associated with accurate mediumship performance (Delorme et al. 2018) albeit in the opposite direction (with higher potential amplitude associated with decreased performance). Interestingly, this potential is also influenced by attention (Mangun and Hillyard 1991). Because it is unlikely that differences between mediums and controls would be due to low level face information, we can hypothesize that the difference reflected different types of allocation of attention.

The later peak at 200 to 350 ms would reflect higher sensory processing. It most likely corresponds to the N200, that is a negative-going wave that peaks 200-350 ms post-stimulus and is found primarily over anterior scalp sites (Folstein and Van Petten 2008). The N200 is known to increase in conflicting situations like the Eriksen flanker task (Heil et al. 2000) and go/no-go paradigm (Pfefferbaum et al. 1985) and is thought to reflect response inhibition. Given the ERP amplitude is larger for controls compared to mediums, we can infer that the N200 amplitude would be higher in mediums reflecting higher conflict on each image, and that this could potentially explain their delayed behavioral responses. This is consistent with performance anxiety some mediums were reporting, and with their increased heart rate. Assuming the global effect we observed on image type detection was robust, this could potentially explain their poor behavioral performance.

To conclude, we found differences in EEG in how mediums and controls processed face photographs, and we also found that as a whole, participants were capable of categorizing the type of death above chance expectation. We recommend that others try to investigate these effects in other pools of participants. The images and presentation scripts used in our study are available upon request. To help minimize performance anxiety, we also recommend that future studies investigate mediums under conditions that more closely match what they do as part of their professional work.

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