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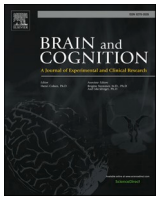

Analyzing the effects of high autistic traits on neural markers of learning and memory: An EEG approach analysis

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A B S T R A C T

Objective: A body of electroencephalographic (EEG) research demonstrates that executive functioning (EF) differences exist in autistic people. Here, we aimed to investigate how and to what extent these EF differences appear in people with high autistic traits in contrast to a low autistic traits comparison.
Methods: The present study used a series of EEG markers (frontal theta power, frontal beta power, the reward positivity ERP component, and the P300 ERP component) to examine potential differences in EF over the course of gambling and oddball tasks. Qualitative research measures to include the perspectives of the autistic people who took part in the study were also used.
Results: While frontal theta and beta power differed between groups, we observed no significant component or correlational differences. However, it was found that high autistic traits participants perceived their task performance as worse than low autistic traits participants despite task performance being equal across groups.
Conclusions: EF differences as measured by frontal theta and beta power were observed across groups. Self-perception of task performance may differ in high autistic traits participants when asked to complete tasks under a time constraint.

1. Introduction

It is well-established that certain executive functioning (EF) differences exist in autistic people in the context of reinforcement learning and working memory (Agam et al., 2014; Hüpen et al., 2016; Van Noordt et al., 2017). These differences include but are not limited to differences in cognition, social communication, and the processing of sensory information. However, what is becoming increasingly apparent is the lack of consensus on how these features of autism might differ as measured by neural activity, and in what contexts. Additionally, there is a lack of input being sought from the autistic community pertaining to their lived experiences, which often leads to biased interpretations of certain study findings.

One approach to measuring cognition is through the examination of electroencephalography (EEG) oscillations (Newson & Thiagarajan, 2019). This technique requires the decomposition of the EEG signal into five specific groups based on characteristic neural oscillations: delta (0.5–4 Hz), theta (4–7 Hz), alpha (7–13 Hz), beta (13–35 Hz), and gamma (>35 Hz) (Klimesch, 1999; Newson & Thiagarajan, 2019; Saby & Marshall, 2012; Wang et al., 2013). In waking EEG, greater theta power is linked with processing of emotional information (Aftanas et al., 2001; Sammler et al., 2007) and with memory-related tasks such as encoding new episodic information (Gevins et al., 1997; Kahana et al., 2001; Klimesch, 1996), as well as retrieval, working memory retention, novelty detection, and recognizing the necessity for top-down control (Jacobs et al., 2006). Of relevance to the present work, frontal theta power is observed during EF and specifically when cognitive control processes are engaged (Cavanagh & Frank, 2014; Huster et al., 2013).

Frontal theta oscillations in autistic individuals differ from those of neurotypical individuals (Coben et al., 2008; Daoust et al., 2004; Murias et al., 2007; Pop-Jordanova et al., 2010; Wang et al., 2013). One factor that may contribute to these differences is the development of the autistic brain compared to the neurotypical brain. Courchesne and colleagues (2007) found that early brain overgrowth is a key feature of autism, resulting in an increased number of neurons in the prefrontal cortex (Courchesne et al., 2011). Researchers also found neural differences in autistic brains using magnetic resonance imaging, with results indicating increased white matter in autistic people (Carper et al., 2002;

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Courchesne et al., 2001). Further, connectivity differences among frontal cortex sub-regions in autistic people have been established (Koshino et al., 2008), which are thought to be related to differences in cognitive function.

Similarly, there are differences in beta EEG power in autistic individuals. Beta spectral activity has been associated with the encoding and retrieval of memories (Hanslmayr et al., 2012; Ketz et al., 2015). In conjunction with alpha power, increases in beta power may depict interference in storing and retrieving a memory trace and a decrease in the ability to process information (Hanslmayr et al., 2012). Additionally, beta oscillatory patterns in cognitive stimulation tasks have been shown to differ between neurotypical and autistic people (Fauzan & Amran, 2015; Hames et al., 2016). In neurotypical individuals, beta power decreases during concentration and analytical thinking assignments (Hames et al., 2016). Conversely, autistic individuals often demonstrate an increase in beta power during EEG concentration tasks or periods of cognitive alertness (Murias et al., 2007; Fauzan & Amran, 2015; Precenzano et al., 2020). Increases in beta power in autistic populations during cognitive stimulatory experiments may indicate hyper-focusing, prevalent anxiety, or task obsession (Fauzan & Amran, 2015).

Another method of studying cognition is through the employment of event-related potentials (ERPs). ERPs are time-locked EEG signals evoked by specific stimuli during a given task (Newman, 2019). For instance, an ERP component known as the reward positivity is characteristically elicited following response feedback, offering insight into the neural activity associated with reward processing (Holroyd & Coles, 2002; Holroyd & Krigolson, 2007). Another ERP component, the P300, is characteristically elicited following stimulus onset and is believed to reflect the updating of working memory related to attentional processes (Polich, 2007). In this sense, ERPs are a viable invaluable tool for measuring underlying neural processes.

In the present work, we aimed to investigate how and to what extent these learning and working memory differences appear in a high autistic traits group in contrast to a low autistic traits comparison. We hypothesized that we would find higher frontal theta and beta activity in a high autistic traits group relative to a low autistic traits group as defined by the Autism Quotient (AQ) across both tasks. Additionally, we expected to find a smaller reward positivity in high autistic traits participants as elicited by a reward gambling task, and consequently a larger P300 as elicited by an oddball task. Furthermore, we expected that participants' AQ scores would be positively correlated with frontal theta and beta activity, negatively correlated with reward positivity amplitudes, and positively correlated with P300 amplitudes. Furthermore, qualitative information on why participants chose particular task strategies to complete the tasks as coded by the research team yielded insights into the underlying processes of reinforcement learning and working memory in high autistic traits participants from their own perspectives.

2. Methods

2.1. Participants

30 individuals (16 female, 10 male, 2 undeclared, 1 non-binary, 1 *trans*-masc.) between the ages of 18 and 27 years old; mean age of 21.47 years old [20.63, 22.31] across two participant groups (11 high autistic traits, 19 low autistic traits) from the University of Victoria and its surrounding community were recruited to participate in this study. Participants included individuals with formal diagnoses of autism and those who self-identified as autistic. Clinically diagnosed autistic participants provided the name of the qualified assessor who completed their diagnosis, along with the date they were diagnosed, to provide researchers with confirmation of a formal autism diagnosis. Participants could not have any self-reported co-occurring neurodevelopmental conditions to participate in this study. Final group placements were determined by participants' scores on a well-standardized measure of autistic traits, the autism Quotient (AQ) (Lugo-Marín et al., 2019), such that not all participants in the high autistic traits group had formal diagnoses of autism. However, all who self-identified as autistic or had a formal clinical diagnosis fell into the high trait group

Participants volunteered either by responding to poster advertisements posted around the University of Victoria campus or via word of mouth and were compensated monetarily depending on the experimental group they identified with; with self-identified neurotypical respondents receiving $10 and self-identified autistic respondents receiving $30. This was to incentivize autistic participants (self-identified or formally diagnosed) to participate in the study, given the increased social, financial, or sensory barriers they might face (Malik-Soni et al., 2022). It was anticipated that self-identified neurotypical participants would fall into the low autistic traits group in this study, with self-identified autistic participants falling into the high autistic traits group. Before beginning the experiment, all participants provided informed consent. The study was approved by the University of Victoria's Human Research Ethics Board (Ethics Protocol Number: 21-0643) in accordance with the Helsinki Declaration.

2.2. Materials

Following informed consent, a laboratory iPad was used to administer subsequent study surveys, which included the AQ, a demographic survey (to determine factors such as age and gender), and an exit survey (see Appendix A). The AQ is a standardized self-report questionnaire that assesses symptoms of autism across social, communication and behavioural domains (Woodbury-Smith et al., 2005). It should be noted that the AQ has a screening cutoff of 26 based on the number of autistic traits reported by the participant, which would indicate that said participant had an increased likelihood of receiving a clinical autism diagnosis (Woodbury-Smith et al., 2005). A 19″ computer monitor running MATLAB was used to display and administer the study tasks (gambling and oddball). A 64-channel ActiCAP EEG system using a 10–20 layout (ActiCAP, Brain Products GmbH, Munich, Germany) was used for data collection alongside the BrainVision Recorder software (Version 1.21, Brain Products GmbH, Munich, Germany) installed on a neighbouring recording computer.

2.3. Procedure

After securing informed consent, the AQ was administered to determine participants' group placement. Participants scoring below the screening cut-off of 26 on the AQ were placed into the low autistic traits group, while participants scoring above 26 were placed in the high autistic traits group (Woodbury-Smith et al., 2005). AQ scores for participants in the low autistic traits group were between 2 and 24 (M = 14.32 [10.93, 18.07]), while AQ scores for participants in the high autistic traits group were between 27 and 47 (M = 33.36 [28.94, 37.79]). Then, participants completed the demographic survey while they were fitted with an EEG cap.

Participants then completed the two experimental tasks on a standard computer keyboard. Experimental tasks were written in MATLAB version R2016a using Psychophysics Toolbox extension version 3.0.12 (Brainard, 1997). During performance of the oddball task, participants saw a series of blue (MATLAB RGB value = [0 0 255]) and green (MATLAB RGB value = [0 255 0]) coloured circles that appeared for 800–1,200 ms in the center of a dark gray screen (MATLAB RGB value = [108 108 108]). Prior to the onset of the first circle and in between the presentation of subsequent circles, a black fixation cross was presented for 300 to 500 ms (MATLAB RGB value = [0 0 0]). The blue circles appeared less frequently (oddball: 25 %) than the green circles (control: 75 %), with the sequence order of presented circles being completely random. Participants were not informed that the frequency of the circles were different and were instructed to mentally count the number of blue circles (oddballs) within each block of trials. Participants completed 4 blocks of 50 trials during performance of the oddball task.

On each trial of the reward-learning (gambling) task, participants viewed a black fixation cross (MATLAB RGB value = [0 0 0]) for 500 ms that was followed by two coloured squares (green and blue with the above-mentioned MATLAB RGB values) for 500 ms followed by the fixation cross turning gray (go cue). Participants were asked on each trial to select one of the two squares (square locations—left, right—were randomized on each trial) once the fixation cross turned gray within a 2000 ms time limit. They were then presented with a black fixation cross for 300 to 500 ms before simple feedback as to their performance ("WIN" for gain, "LOSE" for loss) was displayed for 1000 ms in black font. If the participants responded before the go cue, they were instead delivered "TOO FAST" feedback. If they did not respond before the 2000 ms time limit, it would be considered a loss. Each square had a different probability of eliciting a "WIN," following a 60 % vs. 10 % reward structure. In this task, participants accumulated WINs; however, they were not compensated monetarily based on their task performance. Participants would see the same pair of colours for one block of 20 trials, while the task as a whole consisted of 5 blocks of unique colour pairs.

All electrodes were referenced to electrode AFz during recording, and impedances were maintained below 20 kΩ at all times to ensure data quality. EEG data were recorded at a sampling rate of 500 Hz before being amplified (ActiChamp, Revision 2, Brain Products GmbH, Munich, Germany) and filtered through an antialiasing low-pass filter of 245 Hz.

Exit survey data relating to participants' chosen task strategies and perceived task performance were collected following the completion of the computer task. Task strategy data was hand-coded by the lead researcher using a keyword approach, and patterns across individuals and groups were examined to determine any shared task strategies. Participants self-reported their perceived task performance on a 10-point scale. This data was analyzed to determine how participants in the high versus low autistic traits groups perceived their task performance. These results were then compared to participants actual task performance as measured by task accuracy.

All EEG data were first preprocessed using MATLAB (Version 9.6, Mathworks, Natick, USA) and the EEGLAB open-source toolbox (Delorme & Makeig, 2004) with custom software developed in the Krigolson Laboratory, available here: https://github.com/neuro-tools. To begin, channels were visually inspected for consistently noisy data demonstrating high levels of impedance and removed accordingly (M = 1.73 channels, [0.96, 2.50]). Continuous EEG data were then re-referenced to mastoid channels (TP9, TP10), and a dual-pass Butterworth filter with a band-pass of 0.5 Hz to 30 Hz and a 60 Hz notch filter was applied. To identify and remove ocular artifacts, an independent component analysis (ICA) was conducted on the filtered data to identify components associated with ocular artifacts such as blinks or excessive eye or musculature movements (Delorme & Makeig, 2004). The ICLabel EEGLAB plugin (Pion-Tonachini et al., 2019) was then used to identify ICA components consistent with eyeblinks and remove them. After removing these components, the EEG data were reconstructed from the remaining ICA components. All data were segmented by condition and feedback outcome (win or loss) into shorter epochs spanning from −200 ms to 600 ms post-stimulus onset. These epochs were then baseline-corrected using the 200 ms window pre-feedback onset. Epochs were next examined for artifacts and removed if they contained a gradient larger than 10 μV/ms or an absolute difference of more than 150 μV. The average artifact rejection rate across all participants was 23.20 %. Because of this, n = 1 participant was excluded from the present study due to their overall artifact rejection levels exceeding 40 %. This left us with a sample of n = 29 (11 high autistic traits, 18 low autistic traits) participants.

Following artifact rejection, Fast Fourier transforms for each trial were conducted on a segment of −200 ms to 800 ms from stimulus onset, with a 500 ms Hanning taper at the beginning and end of the segment, and with normalization. Note that this method results in a resolution of 0.67 Hz, thus making the lower frequencies less represented within these analyses than the higher frequencies. The output was then averaged for each condition and participant. Please note that all theta analyses were conducted at electrode site FCz, where the difference in frontal theta (3–7 Hz) between conditions was measured at its maximal in both the gambling and oddball tasks. Similarly, beta analyses were measured at electrode sites F4 and AF8, where the difference in frontal beta (13–35 Hz) between conditions was measured at its maximal in the gambling and oddball tasks, respectively. Inferential statistics (*t*-test and Pearson's correlation) were conducted for beta and theta power. A time frequency approach was not considered here due to its complexity. Group analyses were performed for all difference FFTs for consistency with ERP results in addition to conditional analyses.

ERP analyses were using the same pre-processing steps as described above. Following preprocessing, ERPs were created by averaging the epochs for each of the two experimental groups (high autistic traits, low autistic traits) based on the target cue of a given task; either the presentation of oddball stimuli (oddball or control) or gambling outcome (WIN or LOSE). We examined components locked to feedback onset for the reward positivity and oddball onset for the P300. To reduce bias based on conditional effects, we used overall difference waveforms to identify our respective component timings and calculated their amplitudes based on the channels at which each component could be measured at its maximal. More specifically, the reward positivity was measured at its maximal at electrode, Cz (304 ms post-stimulus onset), and the P300 was measured at its maximal at electrode, Pz (356 ms post-stimulus onset). For the reward positivity, we created difference waveforms by subtracting the average LOSE waveform for a condition from the average WIN waveform for each participant. Then, for the P300, we created difference waveforms by subtracting the average control waveform for a condition from the average oddball waveform for each participant. The reward positivity was quantified for each participant and condition as the mean amplitude ± 25 ms of the grand average peak (308 ms) on the reward difference waveforms, while the P300 was quantified for each participant and condition as the mean amplitude ± 30 ms of the grand average peak (376 ms) on the oddball difference waveforms. Finally, grand average condition and difference ERPs were generated by averaging the respective individual ERP waveforms.

Welch's two-sample t-tests were conducted to examine the potential group differences (high autistic traits vs low autistic traits) for frontal theta and beta during both the gambling and oddball tasks. Additionally, Pearson's r correlations were conducted between participants' scores on the AQ and theta power in each task to establish whether a higher degree of autistic traits as measured by the AQ might hold some relation to theta power. Pearson's r correlations were repeated for beta power using AQ scores and beta power in each task. For our ERP analyses, a test of existence was conducted on each of our components (namely the P300 and reward positivity) using a one-sample *t*-test. Then, after confirming the existence of our components of interest, Welch's two-sample t-tests were conducted to examine the potential group differences (high autistic traits vs low autistic traits) for each component. Finally, Pearson's r correlations were conducted between participants' scores on the AQ and component amplitudes to establish whether or not a higher degree of autistic traits as measured by the AQ might hold some relation to these components.

Behavioural data measuring participants' task performance were analyzed using custom code written in MATLAB to provide further context for the qualitative data collected in the exit survey described above. This code was used to compute the mean reaction time and win rate for each participant. Welch's two-sample t-tests were then conducted in R to further examine the potential group differences in mean reaction time and/or win rate (used here to account for task performance) between our high and low-autistic traits groups.

3. Results

Welch's two-sample t-tests were performed to determine whether significant group differences between the high and low autistic groups

could be established as measured by frontal theta frequency during both the gambling and oddball tasks (shown in Table 1). Frontal theta was similar between groups in the gambling task, t(27) = 1.038, p = 0.309, *d* = 0.397 (Fig. 3). The 2 (feedback condition; Win, Loss) x 2 (group, high AT, low AT) ANOVA on theta power revealed no interaction effect, *F*(54, 1) = 0.145, p = 0.705, η_2 = 0.002, an effect of group, *F*(54, 1) = 6.754, p = 0.012, η_2 = 0.105, but no effect of condition, *F*(54, 1) = 3.581, p = 0.064, η_2 = 0.056. Additionally, frontal theta was similar between groups in the oddball task, t(27) = -0.071, p = 0.944, *d* = -0.027. The 2 (oddball condition; Oddball, Control) x 2 (group, high AT, low AT) ANOVA on theta power revealed no interaction effect, *F*(54, 1) = 0.056, p = 0.814, η_2 = 0.000, an effect of group, *F*(54, 1) = 4.895, p = 0.031, η_2 = 0.074, and an effect of condition, *F*(54, 1) = 6.534, p = 0.013, η_2 = 0.099. Pearson's correlation tests between participants' AQ scores and frontal theta were not statistically significant.

Welch's two-sample t-tests were performed to determine whether significant group differences between the high and low autistic groups could be established as measured by frontal beta frequency during both the gambling and oddball tasks (shown in Table 2). Frontal beta was similar between groups in the gambling task, t(27) = 0.400, p = 0.692, *d* = 0.153 (Fig. 4). The 2 (feedback condition; Win, Loss) x 2 (group, high AT, low AT) ANOVA on Beta power revealed no interaction effect, *F*(54, 1) = 0.471, p = 0.495, η_2 = 0.008, no effect of group, *F*(54, 1) = 0.002, p = 0.966, η_2 = 0.00, and no effect of condition, *F*(54, 1) = 0.793, p = 0.377, η_2 = 0.014. Additionally, frontal beta was similar between groups in the oddball task, t(27) = 0.830, p = 0.830, *d* = 0.318. The 2 (oddball condition; Oddball, Control) x 2 (group, high AT, low AT) ANOVA on beta power revealed no interaction effect, *F*(54, 1) = 0.024, p = 0.878, η_2 = 0.000, no effect of group, *F*(54, 1) = 1.145, p = 0.289, η_2 = 0.021, and no effect of condition, *F*(54, 1) = 0.045, p = 0.833, η_2 = 0.000. Pearson's correlation tests between participants' AQ scores and frontal beta were not statistically significant.

One-way t-tests were performed to confirm the existence of both the reward positivity (t(28) = 8.02, p < 0.001, *d* = 0.327; Fig. 5) and P300 (t(28) = 11.16, p < 0.001, *d* = 0.327; Fig. 6). Following these tests of existence, Welch's two-sample t-tests were performed to determine whether significant group differences between the high autistic traits and low autistic traits groups could be established as measured by the amplitudes of both the reward positivity and P300 (shown in Table 3). For the reward positivity, no significant difference was found, t(27) = 0.665, p = 0.512, *d* = 0.254; Fig. 7). The 2 (feedback condition; Win, Loss) x 2 (group, high AT, low AT) ANOVA on reward positivity amplitude revealed no interaction effect, *F*(54, 1) = 1.513, p = 0.772, η_2 = 0.001, nor an effect of group, *F*(54, 1) = 2.083, p = 0.155, η_2 = 0.031, but an effect of condition, *F*(54, 1) = 10.945, p = 0.002, η_2 = 0.160. For the P300, no significant difference was found, t(27) = 1.336, p = 0.193, *d* = 0.511; Fig. 8). No significant correlations were found between participants' scores on the AQ and reward positivity or feedback P300 amplitudes. The 2 (oddball condition; Oddball, Control) x 2 (group, high AT, low AT) ANOVA on P300 amplitude revealed no interaction effect, *F*(54, 1) = 0.052, p = 0.820, η_2 = 0.000, nor an effect of group, *F*(54, 1) = 0.295, p = 0.589, η_2 = 0.003, but an effect of condition, *F*(54, 1) = 45.749, p < 0.001, η_2 = 0.448.

Behavioural data derived from the tasks' event markers (shown in Table 4) indicated that those in the high autistic traits group performed no differently than the low autistic traits group regarding mean reaction time (t(20.73) = 0.82, p = 0.42) and task performance as measured by task accuracy (t(17.71) = 0.27, p = 0.79). Exit survey data collected from participants indicated that those belonging to the high autistic traits group perceived their performance on the reward gambling task to be lower (M = 4.36) than those in the low autistic traits group (M = 6.00) on a 10-point scale, t(15.19) = 2.154, p = 0.047 even though there was no actual difference in performance.

Task strategies derived from qualitative survey data between groups as hand coded by the research team using a key word approach did not appear to differ upon inspection, with participants in the high autistic traits group reporting task strategies coded by probability (n = 8), colour preference (n = 2), and guessing (n = 1). Participants in the low autistic traits group, however, reported tasks strategies coded by probability (n = 16), colour preference (n = 1), guessing (n = 1), and no response (n = 1). Note that in this case probability refers to how likely participants believed a given square would elicit a "WIN" given the probability values they were presented with at the beginning of the task.

Table 1
Correlation matrix of Autism Quotient scores and frontal theta.

	AQ Scores	Gambling frontal theta	Oddball frontal theta
AQ scores	1.000	0.255	0.244
Gambling frontal theta	0.255	1.000	
Oddball frontal theta	0.244		1.00

Note. p < 0.05*.

4. Discussion

The current study aimed to investigate how and to what extent EF differences as captured by learning and working memory measures may appear in a high autistic trait population in contrast to a low autistic traits comparison. More specifically, we hypothesized that we would find enhanced frontal theta and beta activity, a smaller reward positivity, and a larger P300 in those with high autistic traits. Furthermore, we expected that participants' AQ scores (i.e., self-reported autistic traits) would be positively correlated with frontal theta activity, negatively correlated with reward positivity amplitudes, and positively correlated with P300 amplitudes.

Though all *t*-test results in this study were null, conditional theta results in the oddball task suggest a group difference in processing oddballs and controls, but not in the difference between them. This may be indicative of an overall difference in attentional processing between high and low autistic groups. Furthermore, no significant correlations were found between participants' AQ scores and frontal theta activity, frontal beta activity, reward positivity amplitudes, or P300 amplitudes. As the AQ is a measure of self-reported behavioural traits, a higher score does not necessarily indicate that an individual has higher or lower support needs as described by the different diagnostic levels noted in the *Diagnostic and Statistical Manual of Mental Disorders*. For instance, variation in AQ scores based on these self-reported behavioural traits are found within neurotypical populations as well, with males typically scoring higher than females, and students studying 'hard' sciences (i.e., physics, engineering) typically scoring higher than non-science and biological science students (Austin, 2005).

Lastly, in examining the qualitative survey data obtained from participants during the exit survey, it was found that while no apparent differences in actual reward gambling task strategy were found between groups, there was a significant difference in participants' perceived task performance. While both groups described task strategies that aligned with the well-established explore/exploit dilemma suggesting the existence of a universal task strategy (Hassall et al., 2019), high autistic traits participants perceived their task performance to be markedly worse than their low autistic traits counterparts.

We believe that the reason we found a lack of significant ERP differences between groups in the present work is because no differences between high and low autistic traits populations exist in the context of reinforcement learning and working memory as measured by the reward positivity and P300 *when a time constraint is present*. It has been well-documented that autistic people are more likely to engage in slow, deliberate thinking in contrast to their neurotypical counterparts who may engage in faster decision-making (Vella et al., 2018; Haigh et al., 2018), which is an important factor to consider during task design. To elaborate, task designs that force autistic people to engage in a faster

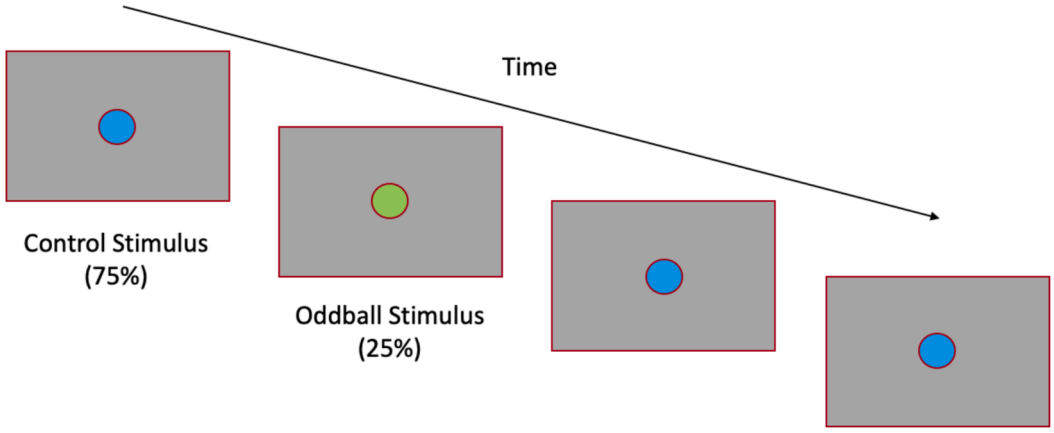

Fig. 1. Visual depiction of oddball task.

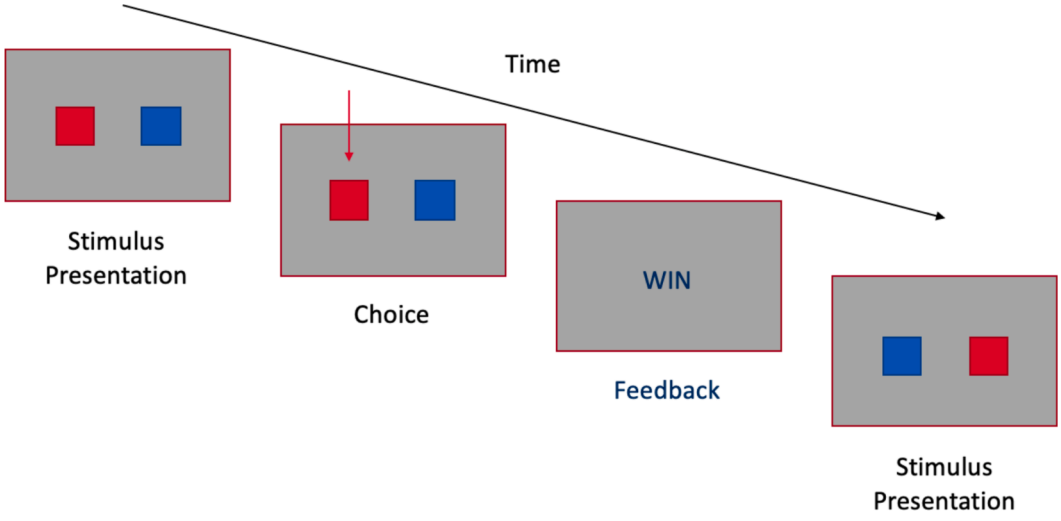

Fig. 2. Visual depiction of reward gambling task.

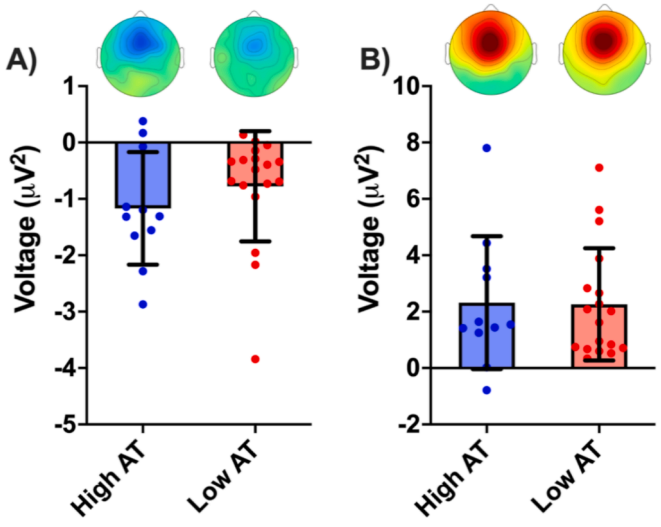

Fig. 3. Theta power for high (Hight AT) and low (Low AT) autistic trait groups in the a) gambling and b) oddball tasks and respective topo plots. Error bars represent 95% Confidence Intervals.

Table 2
Correlation matrix of Autism Quotient scores and frontal beta.

	AQ Scores	Gambling frontal beta	Oddball frontal beta
AQ scores	1.00	0.305	0.381
Gambling frontal beta	0.305	1.00	
Oddball frontal beta	0.381		1.00

Note. $p < 0.05$*.

decision-making style due either to task instruction or time limits set within tasks (in this case a 2000 ms response window) may impact how autistic people perform and thus have an impact on their ERP components. More specifically, studies that allow larger response windows during similar reinforcement learning tasks may allow autistic participants to demonstrate their previously described superior task performance (Vella et al., 2018), while studies with shorter response windows may not.

This proposed account for the lack of ERP differences observed in the present work is supported by the Dual Process Theory of autism, which asserts that while autistic people may take longer to reach a decision on a reinforcement learning task, they may outperform their neurotypical counterparts (Vella et al., 2018). While high autistic traits participants performed the tasks employed in the present study as well as their low autistic traits peers, certain time accommodations might need to be

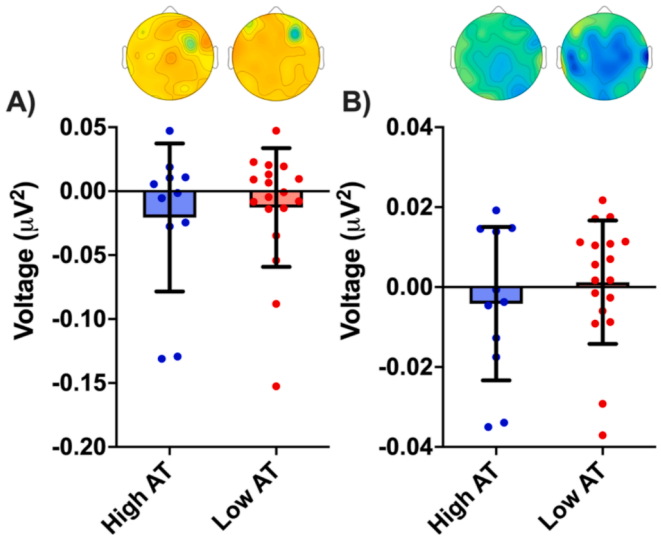

Fig. 4. Beta power for high (Hight AT) and low (Low AT) autistic trait groups in the a) gambling and b) oddball tasks and respective topo plots. Error bars represent 95% Confidence Intervals.

made so that we can see these participants perform optimally. This is opposed to having participants perform under a confounding stress condition with increased task demand not experienced by their neurotypical or low autistic traits counterparts.

This idea is further supported by participants' behavioural data. While there were no differences in participants' mean reaction times or task performance, high autistic traits participants perceived their task performance to be worse than those in the low autistic traits group. This could be attributed to the increased processing time needed by high autistic traits participants (Vella et al., 2018; Haigh et al., 2018). Despite feedback being given to participants at the end of each trial (indicating whether their choice had resulted in a "WIN" or "LOSE"), the fact that high autistic traits participants may not have been given adequate time to feel sure of their decisions or weigh them to their satisfaction could have had an impact on their perceived task performance.

5. Conclusions

To summarize, we found a statistical difference in conditional frontal theta activity for the oddball task between high and low autistic traits groups. However, there were no significant differences in frontal beta activity, nor any correlations between participants' AQ scores and frontal theta or frontal beta activity. Furthermore, we found no marked differences in reward positivity or P300 amplitudes between our high and low autistic traits groups, nor any correlations between participants' AQ scores and either component's amplitude. No differences in participants' mean reaction time, task performance, or reward gambling task strategy by group were found. However, participants in the high autistic traits group perceived their task performance to be worse than those in the low autistic traits group.

Table 3
Correlation matrix of Autism Quotient scores and ERP component amplitudes.

	AQ Scores	Feedback P300	RewP
AQ Scores	1.000	0.001	−0.039
Feedback P300	0.001	1.000	
RewP	−0.039		1.00

Note. $p < 0.05$*.

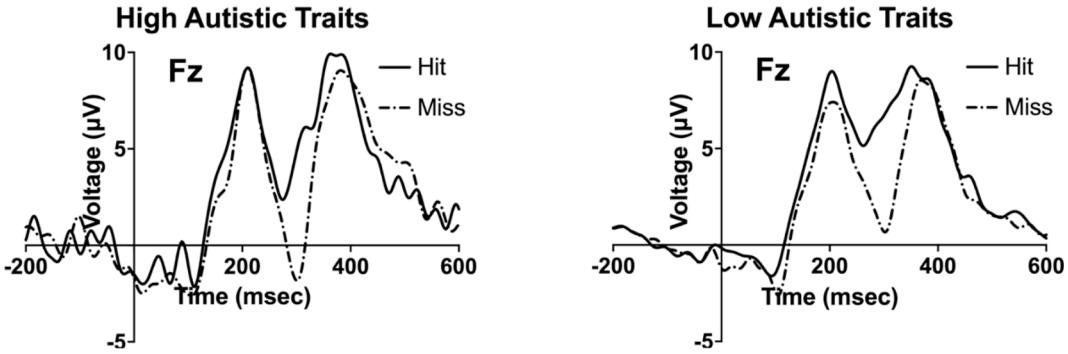

Fig. 5. Conditional waveforms for high and low autistic traits groups in reward gambling task.

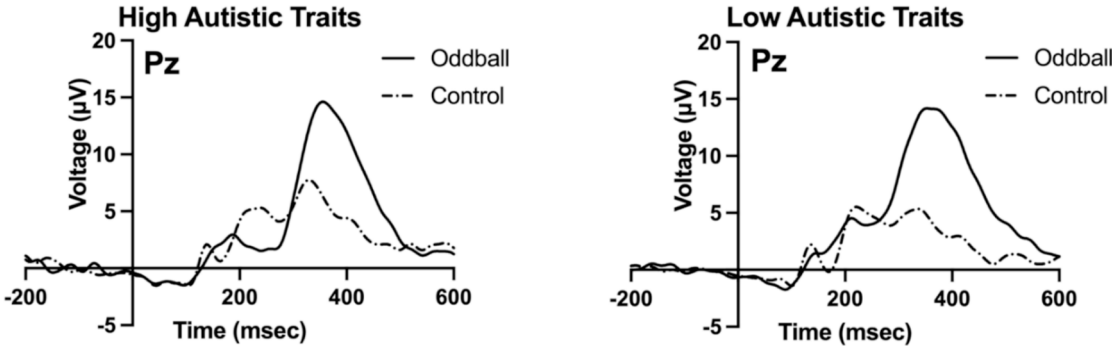

Fig. 6. Conditional waveforms for high and low autistic traits groups in oddball task.

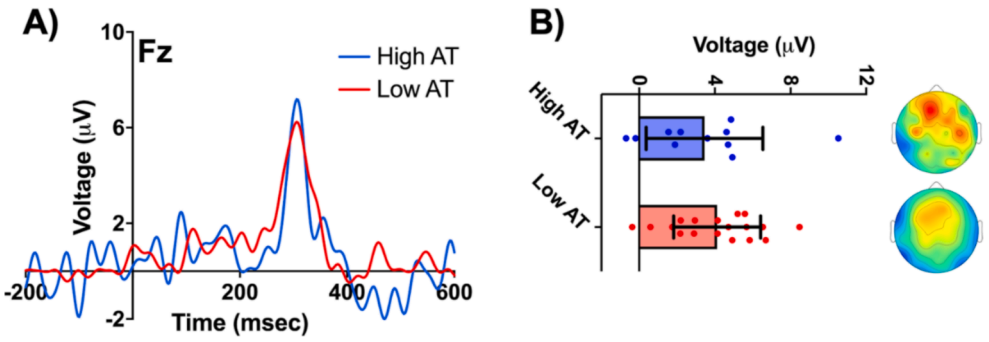

Fig. 7. Topographic map showing theta band activity in the oddball task for low AT participants.

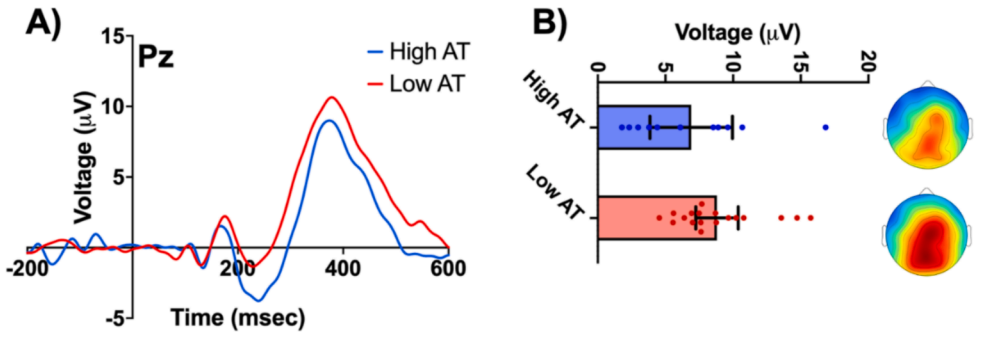

Fig. 8. A) Difference waveforms for the oddball task (Fz), and B) the resulting topo plots and P300 amplitudes.

Table 4
Mean behavioural data by group.

	RT (ms)	Wins	Losses	Win Rate
High autistic traits	344.103	44.546	51.727	0.462
Low autistic traits	369.947	45.778	51.444	0.470

5.1. Limitations

As with others aiming to investigate a clinical or sub-clinical population, we were limited in sample size due to our specific eligibility criteria. Additionally, many of the high autistic traits participants in this study had not received a clinical autism diagnosis. However, having participants use a self-report measure was done deliberately so as not to exclude those adults who have not been afforded the privilege of receiving a clinical diagnosis. We were also limited by our task design in the present work. These tasks would be worth adapting for future studies to allow autistic or high autistic traits participants to perform optimally without the confound of increased task demand. Finally, our interpretations of what frontal theta and beta oscillations represented within each task were limited as we examined theta and beta oscillations throughout the time course of each task. Though this tells us important information about overall neural activation, it provides no insight into neural oscillations associated with specific stimuli during a task.

5.2. *Implications for future research*

The findings of this study highlight the potential of including sub-clinical, self-diagnosed autistic participants in future research. More specifically, a comparison between clinically diagnosed autistic participants and high autistic traits participants on a larger scale could yield further insights into the validity of self-diagnosis in addition to potential frequency band differences that may exist across groups not identified in the present work. Additionally, this study calls attention to the need to use standardized tasks that better accommodate autistic people when conducting research of this style, with particular consideration being given to the additional processing time needed by autistic participants (Vella et al., 2018; Haigh et al., 2018). We hope that this work will draw attention to the need to take the perspectives of the autistic community into account, and that the autistic community will see themselves represented in this text and know their voices are an invaluable contribution to the work that we do.

CRediT authorship contribution statement

Ellis M. Parsons: Writing – original draft, Investigation, Formal analysis, Conceptualization. **Mathew R. Hammerstrom:** Writing – review & editing, Visualization. **Anya Nazaroff:** Writing – original draft, Formal analysis, Data curation. **Mckinley Kemp:** Writing – original draft, Formal analysis, Data curation. **Patrick Montgomery:** Resources, Conceptualization. **Sarah Macoun:** Supervision, Resources. **Olave E. Krigolson:** Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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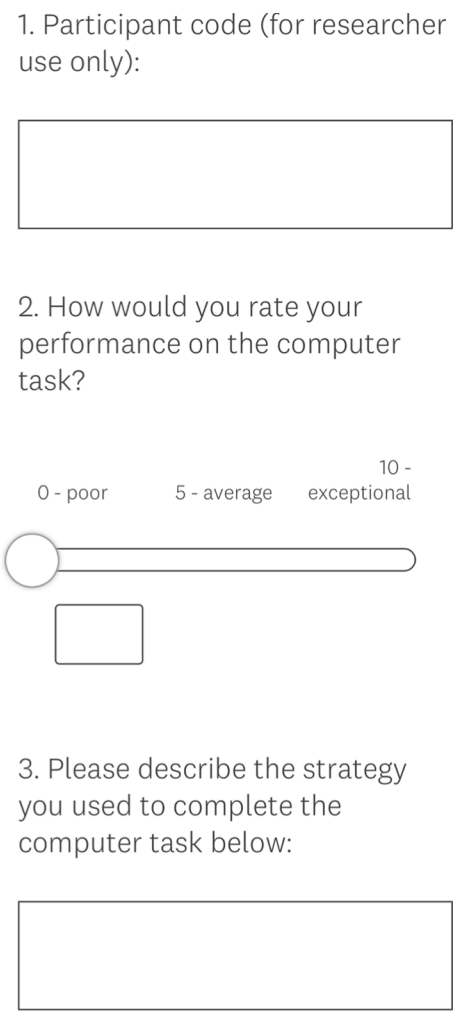
Appendix A

Exit Survey Questions



Data availability

The authors are unable or have chosen not to specify which data has been used.

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