

EEG frequency tagging evidence of intact social interaction recognition in adults with autism

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Lay summary

People with autism are thought to experience the world differently. Here we used brain imaging to investigate spontaneous social interaction recognition in autism as third-party social interaction is a complex but highly relevant stimulus in daily social life. We found that social scenes depicting interaction elicited stronger brain responses than social scenes not depicting interaction in adults with and without autism with no difference between them.

Abstract

To explain the social difficulties in autism, many studies have been conducted on social stimuli processing. However, this research has mostly used basic social stimuli (e.g. eyes, faces, hands, single agent), not resembling the complexity of what we encounter in our daily social lives and what people with autism experience difficulties with. Third-party social interactions are complex stimuli that we come across often and are also highly relevant for social functioning. Interestingly, existing behavioural studies point to altered social interaction processing in autism. However, it is not clear whether this is due to altered recognition or altered interpretation of social interactions. Here, we specifically investigated the *recognition* of social interaction in adults with and without autism. More precisely, we measured neural responses to social scenes depicting either social interaction or not with an electroencephalogram frequency tagging task and compared these responses between adults with and without autism ($N = 61$). The results revealed an enhanced response to social scenes with interaction, replicating previous findings in a neurotypical sample. Crucially, this effect was found in both groups, with no difference between them. This suggests that social interaction recognition is not atypical in adults with autism. Taken together with previous behavioural evidence, our study thus suggests that individuals with autism are able to recognize social interactions, but that they might not extract the same information from those interactions or that they might use the extracted information differently.

Keywords: Electroencephalography, frequency tagging, social cognition, social interaction recognition, autism spectrum disorder

1. Introduction

The social world can be challenging for people with autism spectrum disorder (ASD; henceforth ‘autism’; We acknowledge and respect different preferences for language used to refer to a person with a diagnosis of ASD. Here, we use ‘person with autism’ to respect the preference of the autism sample described in this study, see Supplementary Material for the data), who experience difficulties in social interaction and communication, including non-verbal communicative behaviour (American Psychiatric Association, 2013). In order to explain the social difficulties associated with this neurodevelopmental disorder, much research has been conducted on social stimuli processing. This research has revealed social processing atypicalities in autism (e.g. McPartland et al., 2011; Zilbovicius et al., 2006). Overall, however, findings have been somewhat mixed, with some studies reporting differences in, for example, biological motion processing, face processing, and processing of the eyes between individuals with and without autism (e.g. Annaz et al., 2010; Clark et al., 2008; Holt et al., 2014; Koldewyn et al., 2010; Nackaerts et al., 2012; Price et al., 2012), whereas others found no group differences (e.g. Cusack et al., 2015; Harms et al., 2010; Hubert et al., 2007; Saygin et al., 2010; Song et al., 2012; Wright et al., 2014). Typically, this research on social stimuli processing uses simple stimuli such as a single agent or even isolated body parts like faces, eyes or hands (single agent: e.g. Nijhof et al., 2018; faces: e.g. Kang et al., 2018; eyes: Holt et al., 2014 hands: e.g. Rymaekers et al., 2009, Okamoto et al., 2018), often stripped from any contextual background information (i.e. put against a blank background). Although this has the advantage of increasing experimental control, it does not resemble the complexity of what we encounter in real life, a problem that is especially relevant in autism research, where it has become increasingly clear that anomalies mainly exist for processing more complex social stimuli (Dziobek et al., 2006; Golan et al., 2008; Heavey et al., 2000; Roeyers et al., 2001).

Considering this research, a particularly relevant type of stimuli to understand the social difficulties in autism are third-party social interactions (Quadflieg & Koldewyn, 2017). Indeed, not only does processing social interaction require complex cognitive functioning (Isik et al., 2020), it is also highly relevant for social functioning. For example, research has shown that our impressions of people are strongly shaped by how they interact with others (Costanzo & Archer, 1989; Cowell & Decety, 2015; Mast & Hall, 2004; Sinke et al., 2010), which in turn determines our attitudes towards them (Quadflieg & Penton-Voak, 2017) and guides our own actions (Christ et al., 2014). Social interaction recognition also, quite literally, navigates us through the social world, helping us to not break up interactions when walking through a crowded environment (Efran & Cheyne, 1973; Knowles, 2015). Hence, if the fundamental process of social interaction recognition is atypical in autism, this could have cascading effects on how people with autism process, experience, and take part in the social world, potentially explaining part of why this differs from people without autism.

Existing studies on social interaction processing in autism have used behavioural methods (Liu et al., 2018; van Boxtel et al., 2017; von der Lühе et al., 2016). First, van Boxtel et al. (2017) found that neurotypical adults who score relatively high on autism symptomatology showed a reduced ability to differentiate between interactive and non-interactive actions. Similarly, Liu et al. (2018) showed that motion sequences that depict agents in social interaction tend to be perceived as shorter in duration by neurotypicals, but that this effect was negatively correlated with autism symptomatology. Finally, von der Lühе et al. (2016) found that adults with autism show diminished interpersonal predictive coding. That is, their autism sample made less use of the actions of one agent to predict the actions of another agent. Taken together, these behavioural studies suggest that individuals with autism process social interactions differently than individuals without autism.

Importantly, however, this could have two reasons: 1) it could mean that individuals

with autism have difficulties to recognize social interaction, but 2) could also mean that they are perfectly able to recognize social interactions, but do not extract the same information from those interactions and/or use this information similarly. To clarify the latter, behavioural studies necessarily impose a task. As a result, when performance on that task differs, this does not necessarily mean that participants with autism did not recognize social interaction, but could also mean that they used the information extracted from those interactions differently to perform the task. For example, in the study by van van Boxtel et al. (2017), participants had to indicate the degree of perceived interaction of interacting and non-interacting pairs. However, differences in such a task do not necessarily reflect a perceptual bias but could also reflect a response bias. For example, individuals with autism may have a higher threshold to explicitly label something as interaction. In other words, there is an important distinction between interaction *recognition* and interaction *interpretation*. While behavioural studies show that individuals with autism interpret interactions differently, this does not necessarily mean that they did not recognize them. To test if individuals with autism have difficulties to recognize social interaction, we instead have to measure spontaneous social interaction processing without an explicit task.

Oomen et al. (2022) recently developed and validated an electroencephalogram (EEG) frequency tagging task that can be used to do this. More specifically, in separate blocks, they presented stimuli of social scenes depicting either two interacting agents or non-interacting agents at a fixed frequency. This produced a neural response at exactly that frequency, which revealed an enhanced response over predominantly right lateralized occipitoparietal electrodes, to social scenes with social interaction compared to social scenes without social interaction. By presenting the stimuli at a fixed rate the brain response is restricted to a narrow frequency band, which gives the technique the advantage of being largely resistant to noise and therefore providing a high signal to noise ratio (Norcia et al., 2015a; Retter & Rossion,

2016). Most crucially however, the method applied by Oomen et al. (2022) provides an objective measure of spontaneous social interaction recognition as no explicit task is required. Hence, in the current study, we applied the same task and technique in a sample of adults with and without autism (neurotypical adults) to directly investigate whether third-party social interaction recognition differs between these groups. We expected to replicate the finding of Oomen et al. (2022) and to observe a stronger brain response for interaction than for non-interaction scenes in neurotypical adults. Furthermore, we hypothesized that if the fundamental process of social interaction recognition would be atypical in autism, that this effect would be absent or diminished in individuals with autism.

Open science statement

Our hypotheses, study design, and data-analyses plan were preregistered (https://aspredicted.org/blind.php?x=J6G_DR9). Data and analyses can be found on the Open Science Framework (https://osf.io/qt7z3/?view_only=0da455e567d742ce9dc0b4209238372d)

2. Methods

2.1 Participants

We tested 32 adults with autism and 32 neurotypical adults. Note that the neurotypical control group here was independent to the one reported in Oomen et al. (2022). All 64 participants reported to have normal or corrected-to-normal vision, no neurological condition, and sufficient knowledge of the Dutch language. Participants in the control group reported no known psychiatric condition and had a T-score of 60 or lower on the Social Responsiveness Scale – adult version (SRS-A; Constantino, 2002; Dutch version: Noens et al., 2012). Participants in the autism group had a formal diagnosis of autism and were only included if they had a T-score of 61 or higher on the SRS-A (Constantino, 2002). The SRS-A is a 64-item questionnaire used to measure autism traits with a recommended cut-off of 61. Lastly, participants for both groups were only included if they had an IQ score of 85 or above (i.e. average or above). IQ scores were retrieved from the lab database in case the participant had

previously participated in research of the lab. Alternatively, reports were obtained if an IQ test had been administered elsewhere (e.g. during the diagnostic procedure). If a participant's IQ score was not known yet, or acquired before adulthood, an estimate was obtained after the test session. For this, we administered four subtests of the WAIS-IV-NL (i.e. Block design, Vocabulary, Matrix reasoning, Similarities; Wechsler, 2008), corresponding to the WASI-II short four-subtest form (Wechsler, 2008), in order to obtain WASI-II scores but with Flemish norms. Three participants were excluded overall. One participant was excluded from the autism group due to an SRS score below the cut-off. Two participants were excluded from the control group: one due to an IQ score lower than 85, the other due to bad data quality. In line with our aspired, preregistered sample size, the final sample thus consisted of 31 adults with autism and 30 neurotypical adults. As described in the pre-registration, an a-priori power analysis assuming a large effect size (based on the high SNR of frequency tagging studies and previous behavioral results of the other study on social interaction processing that included an autism sample; von der Lühe et al., 2016) was conducted to determine the sample size (significance-level: 0.05, power: 80%, effect size $d = .80$, sample size per group = 26). We oversampled, and included at least 30 participants per group to account for a possible smaller effect size and for possible exclusion. Note that although we did not preregister to exclude participants based on SRS-A and IQ scores, this is in line with previous research in autism (e.g. Goris et al., 2018; Vettori et al., 2019). Importantly, including the two participants whose exclusion was not based on our preregistered exclusion criteria did not change the results reported here.

Groups were matched on age, gender, and IQ (see Table 1) and as expected differed on the SRS-A as well as on the autism-spectrum quotient (AQ) and Toronto Alexithymia Scale (TAS-20). The AQ is another commonly used questionnaire to measure autism traits through 50 self-report items (Baron-Cohen et al., 2001; Dutch version: Hoekstra et al., 2008). The

TAS-20 is a 20-item self-report to measure alexithymia (Bagby et al., 1994; Dutch version: Trijsburg et al., 1997), which is relatively common in autism (Kinnaird et al., 2019). The AQ and TAS-20 were administered to further describe our sample and, together with the SRS, to conduct exploratory correlational analyses. Note that the AQ and SRS-A scores were comparable to other studies that included adults with and without autism (e.g. Goris et al., 2022; Nijhof et al., 2018). The experimental protocol was approved by the ethics committee of the Faculty of Psychology and Educational Sciences of Ghent University (EC/2020/122), and written informed consent was obtained from participants before the start of the study. Participants were compensated for their time.

Table 1
Participant characteristics

	autism <i>M (SD)</i>	control <i>M (SD)</i>	<i>F (p)</i>
Age	35.00 (7.30)	34.23 (7.70)	
Gender			
Female	11	11	
Male	18	19	
Non-binary	2	0	
Ethnicity			
White	30	28	
Asian	0	1	
Mixed	1	1	
IQ	110.45 (11.12)	106.80 (7.92)	
SRS-A T-score	75.16 (8.32)	48.37 (6.90)	186.80 (< .001)
AQ	35.35 (5.72)	14.40 (7.01)	164.14 (< .001)
TAS-20	58.09 (9.92)	42.00 (8.89)	49.02 (< .001)

Note. Autism group $n = 31$; control group $n = 30$; SRS-A = social responsiveness scale – adults; AQ = autism-spectrum quotient; TAS-20: Toronto Alexithymia Scale – 20 items

2.2 Task and Procedure.

Participants were seated in a Faraday cage circa 80-100 cm from a 24-inch computer screen (refresh rate: 60 Hz). Participants filled in the SRS-A and AQ questionnaires, after which they completed two frequency tagging tasks intermitted by three minutes of resting state EEG. The order of the two tasks was counterbalanced across participants. Only the task that answers our current research question is described here.

The task was identical to the one described by Oomen et al. (2022). The task included four types of images: 36 images that depicted social interaction, 36 images that depicted no social interaction, and to control for potential low-level differences between the two image types, the scrambled versions of both image types. The scrambled images were created by scrambling the images into a 10 x 10 grid. All images included exactly two agents. Other than that, the images within the interaction and non-interaction categories differed greatly from each other in terms agent configuration (e.g. facing or not facing), activity (e.g. talking or playing), and/or contextual background (e.g. supermarket, school), to resemble the complexity of real-life situations. To increase experimental control, the images were black-and-white line drawings, and agents and objects were free from distractors (e.g. shadows, patterns on clothing). Figure 1 shows one example image of each stimulus type. The two types of images were balanced for perceived emotional valance and perceived intensity of the feelings experienced by the agents.

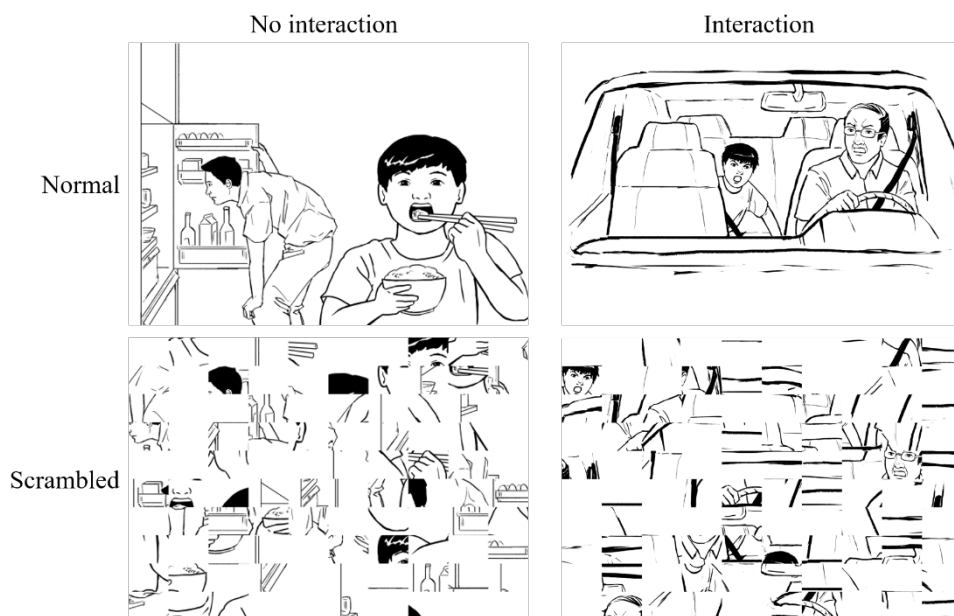


Figure 1. One example image of the four stimulus types (Oomen et al., 2022).

Images were presented at the centre of the screen using sinusoidal contrast modulation at a presentation rate of 1.66 Hz (600 ms). The four types of images were presented block-

wise in blocks of 110 images, with four blocks per category, presented in random order. Images were drawn randomly from their respective categories, never repeating the same image back-to-back. A block started and ended with a 3 s fade in and out (image transparency from 0 to 100% and 100% to 0%). The duration of the task was approximately 18 minutes. The task was programmed in PsychoPy3 (Peirce et al., 2019).

Before the start of the task, participants were told that they would see images of social interaction, images without social interaction, and scrambled images. This information was given together with two example images of the interaction and no-interaction categories that were not included in the actual task. In line with Oomen et al. (2022), we were open about the included stimulus categories to reduce variability regarding the timepoint at which participants recognized them. Participants had two tasks, of which the sole aim was to encourage a constant level of attention. One task was to press the spacebar as fast and accurately as possible whenever the black fixation cross changed to red (400ms), 3 to 6 times per block. Detection was high overall (96% on average). A mixed ANOVA with Interaction Type (no interaction, interaction) and Stimulus Type (scrambled, normal) as within-subject factors and Group (control, autism) as between-subject factor revealed no main or interaction effects on detection rate (all $ps \geq .078$). The second task was a memory task. Participants were instructed to pay attention to the presented images during the task, so that they would be able to indicate which 4 images (out of 8) had appeared during the task. On average, participants recognized 3.49 out of 4 images. A mixed ANOVA with Interaction type (no interaction, interaction) as within-subject factor and Group (control, autism) as between-subject factor revealed no main effects or interaction effect on recognition (all $ps \geq .390$).

2.3 Recording, Pre-processing, and Analyses

EEG was continuously recorded with 64 Ag/AgCl (active) electrodes that were mounted in an elastic cap (ActiCAP, Munich, Germany), using an ActiCHamp amplifier and

BrainVision Recorder software (version 1.21.0402, Brain Products, Gilching, Germany). The sample rate was 1000 Hz. Electrodes were positioned according to the 10%-system, with the exception of two electrodes (TP9 and TP10) that were placed at OI1h and OI2h according to the 5%-system to cover a wider area of posterior-occipital activation. Additional bipolar AG/AgCl sintered ring electrodes were placed above and below the left eye to record vertical electro-oculogram (EOG). FT9 and FT10 electrodes were used to record horizontal EOG. Fz was used as online reference.

Off-line pre-processing of the raw data was done using Letswave 6). First, a fourth-order Butterworth band-pass filter was applied to the data with a low and high cut-off of 0.1 Hz and 100 Hz. The data was then segmented according to the four block types. To remove eye blinks, we computed an ICA matrix for each participant on the merged segmented data sets using the Runica algorithm and a square matrix. ICs of each participant were inspected and the IC-related to eye blinks were manually removed. Next, noisy electrodes were interpolated using three (or two in case of OI1/2h electrodes) neighbouring electrodes. After interpolation, the data was re-referenced to an average reference and Fz was included as a regular electrode. The fade in and out were then cropped from the signal, resulting in 60 s epochs that started at 3 s and ended at 63 s after the onset of a block. Next, epochs within each block type were averaged and a Fast Fourier Transform was applied to transform the data of each electrode to normalized (divided by $N/2$) amplitudes (μV) in the frequency domain. Finally, for the statistical analyses, we computed and exported the signal to noise-subtracted amplitudes (SNS) at each frequency bin by subtracting the average voltage amplitude of the 20 neighbouring bins (10 on each side, excluding the immediately adjacent bin), from the amplitude of the frequencies of interests. For visualization we computed the signal-to-noise ratio (SNR). The SNR computation was identical to the SNS computation, except that division was used instead of subtraction.

Statistical analyses on the SNS data were conducted in R (R Core Team, 2017). Frequency tagged brain responses are often not only evident at the frequency of stimulation (F) but also across its higher harmonics ($2F$, $3F$, etc.). Therefore, to accurately capture the evoked brain response, the relevant harmonics should be summed (Retter et al., 2021; Retter & Rossion, 2016). Based on the previous study (Oomen et al., 2022), which was in turn based on visual inspection of pilot data, we included the first 8 harmonics (1.66 Hz, 3.33 Hz, 5.00 Hz, 6.66 Hz, 8.33 Hz, 10.00 Hz, 11.66 Hz, 13.33 Hz).

To ensure an unbiased selection of electrodes, independent of condition effects or hypotheses, regions of interests were chosen based on visual inspection of the scalp topography across groups and conditions (collapsed localizer approach; Luck & Gaspelin, 2017; see Supplementary Material Figure s1 for the collapsed scalp topography). Following Oomen et al. (2022), we plotted the collapsed topography with a scale from 0 to the maximum amplitude across electrodes (i.e. 4.14 μ V). As the obtained topography matched that of the previous study (Oomen et al., 2022), namely lateral posterior activity, we used the same clusters and electrodes: a right posterior cluster including PO8, PO4, and O2, and a left posterior cluster including the corresponding electrodes on the left hemisphere, namely PO7, PO3, and O1. Additionally, we explored whether there were other, non-occipitoparietal sites that showed activity at weaker levels. This revealed an additional frontocentral cluster of activity. Analysis of this cluster showed comparable results to that of the lateral posterior clusters (see Supplementary Material for the results of this analysis).

On the SNS data, we conducted a mixed ANOVA with Interaction Type (no interaction, interaction), Stimulus Type (scrambled, normal), and Laterality (left, right) as within-subject factors, and Group (control, autism) as between-subject factor. As pre-registered, we also explored the relationship between the Interaction Type x Stimulus Type interaction effect ([normal interaction - scrambled interaction] - [normal no interaction -

scrambled no interaction]) and participants' scores on the SRS-A, AQ, and TAS-20. For this we performed a Spearman rho correlation. For the correlation, *t*-tests, and *F*-tests, we accompanied the *p*-values with Bayes Factors (BFs). BFs were calculated with a noninformative Jeffreys prior, a Cauchy prior on the standardized effect size, and a default prior (Rouder et al., 2012).

3. Results

The repeated measures ANOVA revealed a significant main effect of Interaction Type, Stimulus Type and Laterality (See Table 2 for all statistics and Supplementary Table s1 for all means and standard deviations). The main effect of Interaction type, $F(1, 59) = 14.18, p < .001, \eta_p^2 = .19, BF_{10} = 6.36E+$, revealed a stronger response for the interaction stimuli than for the no-interaction stimuli. The main effect of Stimulus Type, $F(1, 59) = 16.32, p < .001, \eta_p^2 = .22, BF_{10} = 6.67E+3$, revealed a stronger response for the normal stimuli than for the scrambled stimuli. The main effect of Laterality, $F(1, 59) = 7.63, p = .008, \eta_p^2 = .11, BF_{10} = 39.77$, revealed a stronger response in the right cluster than in the left cluster. There was no main effect of Group, $F(1, 59) = 0.08, p = .777, \eta_p^2 = .00, BF_{10} = 0.27$.

The repeated measures ANOVA further revealed an Interaction Type x Stimulus Type interaction, $F(1, 59) = 48.18, p < .001, \eta_p^2 = .45, BF_{10} = 3.23E+10$, and an Interaction Type x Laterality interaction, $F(1, 59) = 4.83, p = .032, \eta_p^2 = .08, BF_{10} = 69.13$, which were further qualified by an Interaction Type x Stimulus Type x Laterality three-way interaction, $F(1, 59) = 12.73, p = .001, \eta_p^2 = .18, BF_{10} = 136.99$. To follow up on this three-way interaction, we looked at the Interaction Type x Stimulus Type effect separately for the left and right cluster. This revealed that there was an Interaction Type x Stimulus Type

Table 2. *Statistics*

Test	Direction	Statistics
Main effects		
Interaction type	int > no int	$F(1, 59) = 14.18, p < .001, \eta_p^2 = .19, BF_{10} = 6.36E+$
Stimulus type	norm > scram	$F(1, 59) = 16.32, p < .001, \eta_p^2 = .22, BF_{10} = 6.67E+3$
Laterality	right > left	$F(1, 59) = 7.63, p = .008, \eta_p^2 = .11, BF_{10} = 39.77$
Group	control = autism	$F(1, 59) = 0.08, p = .777, \eta_p^2 = .00, BF_{10} = 0.27$
Interaction effects		
Interaction Type x Stimulus Type		$F(1, 59) = 48.18, p < .001, \eta_p^2 = .45, BF_{10} = 3.23E+1$
Interaction Type x Laterality		$F(1, 59) = 4.83, p = .032, \eta_p^2 = .08, BF_{10} = 69.13$
Interaction Type x Stimulus Type x Laterality		$F(1, 59) = 12.73, p = .001, \eta_p^2 = .18, BF_{10} = 136.99$
Group x Interaction Type x Stimulus Type effect		$F(1, 59) = 0.33, p = .565, \eta_p^2 = .01, BF_{10} = 0.30$
Follow-up: Interaction Type x Stimulus Type x Laterality		
Left cluster		$F(1, 60) = 33.37, p < .001, \eta_p^2 = .36, BF_{10} = 5.04E+4$
Right cluster		$F(1, 60) = 93.11, p < .001, \eta_p^2 = .61, BF_{10} = 9.35E+10$
Left cluster, normal	int > no int	$t(60) = 6.13, p < .001, d_z = 0.78, BF_{10} = 1.81E+5$
Right cluster, normal	int > no int	$t(60) = 9.31, p < .001, d_z = 1.19, BF_{10} = 2.69E+10$
Left cluster, scrambled	int < no int	$t(60) = -2.03, p = .046, d_z = 0.26, BF_{10} = 0.95$
Right cluster, scrambled	int < no int	$t(60) = -3.81, p < .001, d_z = 0.49, BF_{10} = 72.89$
Follow-up: Group x Interaction Type x Stimulus Type		
Control group		$F(1, 29) = 45.68, p < .001, \eta_p^2 = .61, BF_{10} = 7.74E+4$
Autism group		$F(1, 30) = 41.00, p < .001, \eta_p^2 = .58, BF_{10} = 3.65E+4$

Note. int = interaction; no int = no interaction; norm = normal; scram = scrambled

interaction for both clusters, but this effect was stronger in the right cluster, $F(1, 60) = 93.11$, $p < .001$, $\eta_p^2 = .61$, $BF_{10} = 9.35E+10$, than in the left cluster, $F(1, 60) = 33.37$, $p < .001$, $\eta_p^2 = .36$, $BF_{10} = 5.04E+4$. In both clusters, the Interaction Type x Stimulus Type effect indicated that responses were stronger for interacting than for non-interacting stimuli when they were presented normal (Left: $t(60) = 6.13$, $p < .001$, $d_z = 0.78$, $BF_{10} = 1.81E+5$; Right: $t(60) = 9.31$, $p < .001$, $d_z = 1.19$, $BF_{10} = 2.69E+10$), but not when they were presented scrambled. Instead, for the scrambled images, a weaker effect in the opposite direction emerged, with stronger responses for non-interacting than for interacting stimuli (Left: $t(60) = -2.03$, $p = .046$, $d_z = 0.26$, $BF_{10} = 0.95$; Right: $t(60) = -3.81$, $p < .001$, $d_z = 0.49$, $BF_{10} = 72.89$).

In contrast with our hypothesis, we did *not* find a Group x Interaction Type x Stimulus Type effect, $F(1, 59) = 0.33$, $p = .565$, $\eta_p^2 = .01$. Supporting this non-significant Group x Interaction type x Stimulus Type effect, a Bayesian test of the 3-way interaction showed moderate evidence for H0 ($BF_{10} = 0.30$). Similarly, separate tests of the Interaction Type x Stimulus Type effect in the two groups revealed a significant interaction for both the control group, $F(1, 29) = 45.68$, $p < .001$, $\eta_p^2 = .61$, $BF_{10} = 7.74E+4$, and the autism group, $F(1, 30) = 41.00$, $p < .001$, $\eta_p^2 = .58$, $BF_{10} = 3.65E+4$. None of the other effects not reported here reached significance, all $ps \geq .125$. See Figure 2 for a visualization of the SNS data of all stimuli conditions separately for region and group, Figure 3 for a SNR plot over electrodes of interest per condition per group, and Figure 4 for the topographies per condition per group.

In addition to the confirmatory analyses reported above, we also ran explorative (but preregistered) correlation analyses investigating whether social interaction processing correlated with autism symptomatology (SRS-A and AQ) and alexithymia (TAS-20). These correlations were not significant with Bayesian analyses revealing moderate evidence against a correlation between social interaction processing and autism symptomatology (SRS-A: $r_s = -$

0.03, $p = .842$, $BF_{10} = 0.29$; AQ: $r_s = 0.04$, $p = .823$, $BF_{10} = 0.29$) or alexithymia (TAS-20: $r_s = -0.09$, $p = .474$, $BF_{10} = 0.31$).

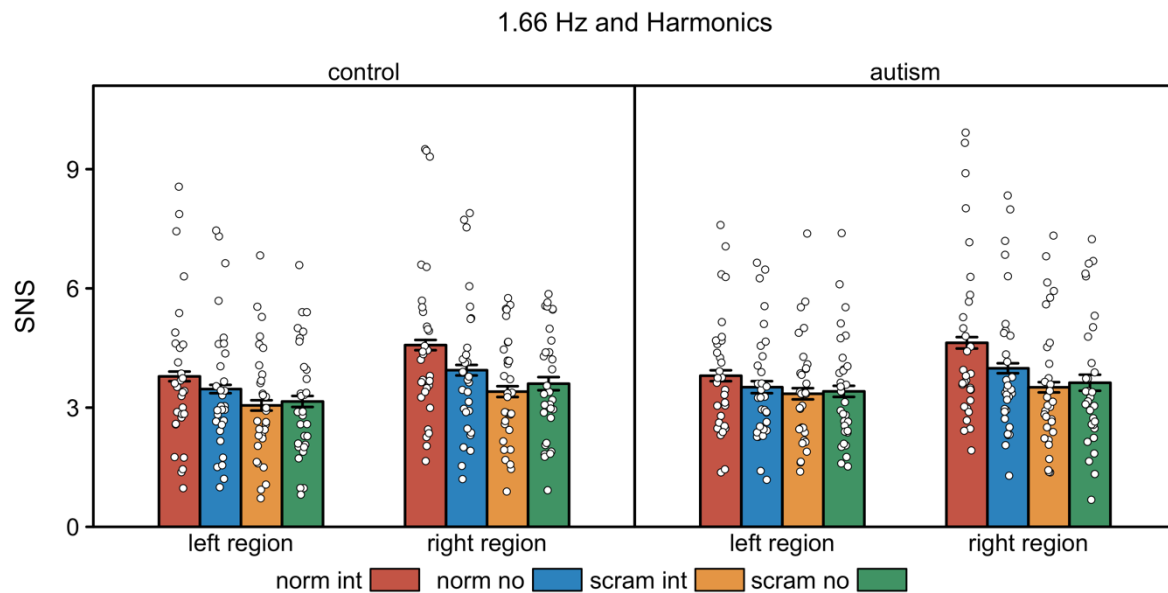


Figure 2. Signal to noise-subtracted amplitudes (SNS) per condition and region and for the two groups separately. Error bars represent errors of the mean (SEMs) corrected for within-subject designs (Morey, 2008).

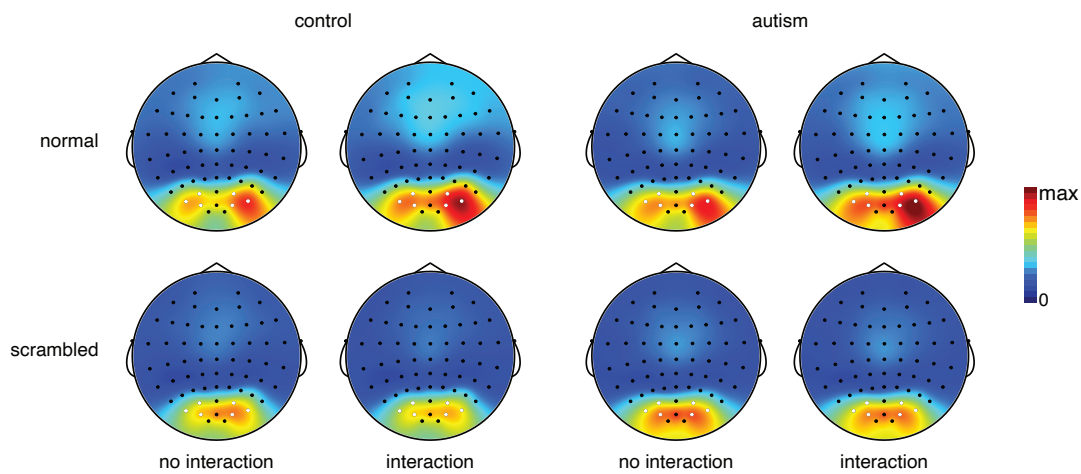


Figure 4. Topographies per group, per condition. Topographies are scaled from 0 to the maximum amplitude of the four conditions and two groups (i.e. 5.19 μV). Included electrodes are indicated in white.

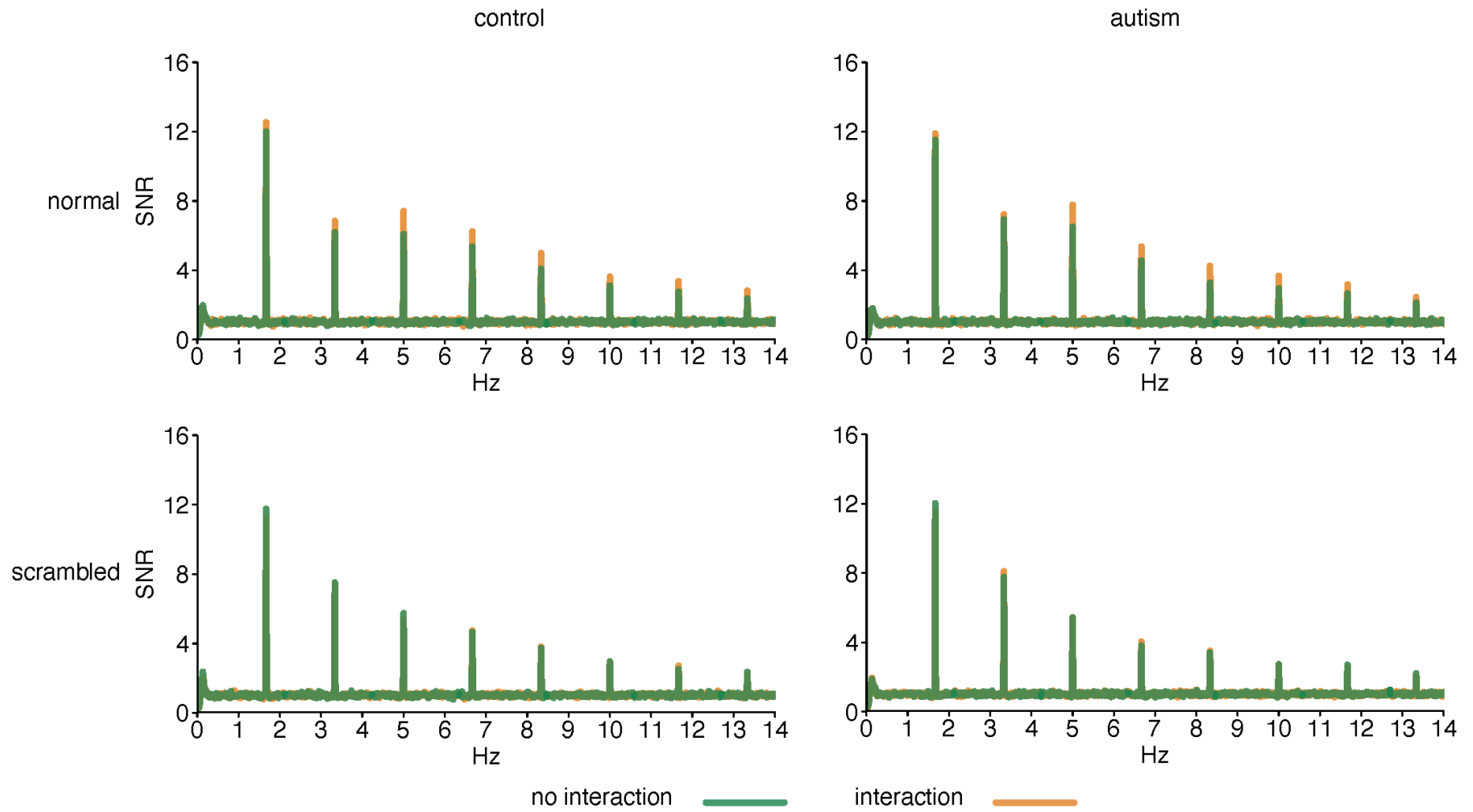


Figure 3. Signal-to-noise (SNR) over electrodes of interest per condition per group.

4. Discussion

To explain the social difficulties in autism, a large body of research has studied social stimuli processing (e.g. a single agent: Nijhof et al., 2018; or mere body parts: Kang et al., 2018). This research has revealed social processing atypicalities in autism in, for example, biological motion processing, face processing and processing of the eyes (e.g. Annaz et al., 2010; Clark et al., 2008; Holt et al., 2014; Koldewyn et al., 2010; Nackaerts et al., 2012; Price et al., 2012; although there are also studies that found no atypicalities e.g. Cusack et al., 2015; Harms et al., 2010; Hubert et al., 2007; Saygin et al., 2010; Song et al., 2012; Wright et al., 2014). In contrast, there are, to the best of our knowledge, just a few studies that have investigated social interaction processing (Liu et al., 2018; van Boxtel et al., 2017; von der Lühse et al., 2016). Existing behavioural studies point to altered social interaction processing in autism, however it is not clear whether this can be attributed to the fundamental process of social interaction recognition, which we tested in the current study. If the fundamental process of recognizing social interaction is atypical in autism, this could have a cascading effect on how people with autism extract information from, and in turn adapt their behaviour to, third-party social interactions. We therefore applied an EEG frequency tagging task that was previously validated by Oomen et al. (2022) to study social interaction recognition. More precisely, we investigated the process of inferring social interaction from context by measuring neural responses to social scenes depicting either social interaction or not in adults with and without autism. As hypothesized, we replicated the findings by Oomen et al. (2022), that is, we found stronger responses over predominantly right-lateralized occipitoparietal electrodes to social scenes depicting two interacting agents than to social scenes depicting two non-interacting agents. However, contrary to our expectations, we found this effect in both groups with no difference between them.

By replicating the findings of Oomen et al. (2022), the current study increases

confidence in the reliability of the EEG frequency task used to measure social interaction recognition objectively. Not only is this important for the current study, but also, more broadly, for possible future studies into social interaction recognition that aim to answer more fundamental questions (e.g. how valence modulates social interaction recognition) or questions related to other clinical conditions that are associated with social difficulties (e.g. Williams syndrome, Schizophrenia, Social anxiety, or Personality Disorders; Kennedy & Adolphs, 2012). Besides replicating the previously found social interaction recognition effect (Oomen et al., 2022) in our control group, we also found the same effect in the autism group, with no difference between the groups. This lack of group difference was supported by a Bayesian test, and by a correlational analysis that showed no relationship between social interaction processing and autism symptomatology. Thus, our results show that social interaction recognition is not atypical in autism.

Our findings may seem at odds with previous behavioural studies that suggest aberrant processing of social interactions in autism (e.g. Liu et al., 2018; van Boxtel et al., 2017; von der Lühе et al., 2016). However, as aforementioned, these behavioural results can be explained in two ways: 1) Individuals with autism have difficulties to recognize social interaction or 2) individuals with autism are perfectly able to recognize social interactions, but do not extract the same information from those interactions and/or use this information similarly. The current study measured social interaction processing objectively, that is, without an explicit task, and found no differences between groups. As such, it dismisses the first explanation and helps interpret the findings of previous behavioural research on social interaction processing and autism. For example, Liu et al. (2018) showed that motion sequences that depict agents in social interaction tend to be perceived as shorter in duration by neurotypicals, but that this effect was negatively correlated with autism symptomatology. Following the above reasoning, the results of the current study suggest that this negative

correlation may not be due to atypical social interaction recognition per se, but due to something else that affects a more cognitive process of perception of time (e.g. enjoyability: Agarwal & Karahanna (2000); arousal: Gil & Droit-Volet, 2011).

Similarly, von der Lühne et al. (2016) found that adults with autism show diminished interpersonal predictive coding. Here again, following our above reasoning, this findings by von der Lühne et al. (2016) might indicate that, although individuals with autism spontaneously recognize social interactions, they take less advantage of the acquired social information to anticipate other's actions (i.e. the interactive actions of one agent to predict the response of the interaction partner). Lastly, in a neurotypical sample, van Boxtel et al. (2017) found that adults who score relatively high on autism symptomatology showed a reduced ability to differentiate between interactive and non-interactive actions. Furthermore, they found a negative correlation between autism symptomatology and interactivity ratings for the interactive actions. However, these results are acquired by an explicit task in which participants had to judge the degree of interaction. As a result, it might be that autism is not associated with a reduced ability to recognize social interactions, but that individuals who score relatively high on autism happen to judge the degree of social interaction differently. That is, one can judge a social interaction as more or less engaging, while still detecting that there is in fact social interaction. Put more generally, taken together with previous behavioural evidence, our results suggest that it is not social interaction recognition per se that is atypical in autism, but rather how individuals with autism interpret and act upon the information they extract from such interactions, which highlights the importance of a recognition/interpretation distinction when studying social interaction processing. An exciting avenue for future research will be to further explore this hypothesis and specifically to investigate the degree to which anomalies in extracting information from and responding to social interactions can explain social difficulties in autism. For this, behavioural studies can be used but also

different neuroscience techniques that measure not only early recognition processes but also later interpretative processes.

Besides an enhanced neural response to interactive (vs. non-interactive) normal stimuli for both the autism and the control group, we also found a difference between interactive and non-interactive scrambled stimuli, but in the opposite direction. More specifically, we found an enhanced response for the scrambled stimuli without social interaction compared to the scrambled stimuli with social interaction. Although this reversed pattern can be observed in the original study as well (Oomen et al., 2022), the difference was not significant there, possibly due to the smaller sample ($N = 28$ versus 61 in the current study). Differences in the neural response elicited by scrambled stimuli suggest the presence of low-level differences (e.g. luminance) influencing the brain response. Crucially, however, these low-level influences acted in the opposite direction as the influence of social interaction. Therefore, they cannot explain the observed enhancement of neural responses for interaction (vs. non-interactive) normal stimuli. If anything, the opposite effect for scrambled stimuli indicates that the strength of the effect in the normal stimuli may have been slightly underestimated and further highlights the importance of comparing the experimental effects to a baseline condition capturing low-level differences.

This study has four limitations that can be addressed by future research. First, our results are limited to an autism population that matches our sample characteristics (e.g. adults with an IQ above 85). We therefore cannot generalize our findings to other individuals on the autism spectrum, such as children or those with a lower IQ. Future studies are warranted to test the degree to which our findings generalize to such populations, as well as the developmental trajectory of social interaction recognition. In fact, the task used here lends itself well for such research, as it does not require verbal task instructions and can measure brain responses with high precision, both of which are important advantages for research in

younger populations (infants, and young kids), who have limited verbal capabilities and often have difficulties to sit still (Azhari et al., 2020; Maguire et al., 2014; Raschle et al., 2012).

A second limitation is that participants were aware of the stimulus categories. In line with the original study (Oomen et al., 2022), we were open about the included stimulus categories during the introduction of the task. Because block designs allow participants to become aware of the categories regardless, providing the participants with this information beforehand reduces variability regarding the timepoint at which participants recognize the stimulus categories. It is important to note however, that awareness of the stimuli categories is by no means unique to our study design. Previous autism (ERP or frequency tagging) studies were often either open about the stimulus categories (own vs close-other name or face, e.g. Cygan et al., 2014; Nijhof et al., 2018; Nowicka et al., 2016) or the stimulus categories were easily identifiable (face vs. object: Sysoeva et al. (2018); face vs. house: Vettori et al., 2020). Furthermore, although we were open about the stimulus categories to the participants, the tasks they had to perform were not connected to the stimulus categories, and participants were not aware of the research question. Nevertheless, it would be interesting for future research to investigate the role of prior awareness of the stimulus categories on brain responses.

Third, the EEG frequency tagging task with which we measured social interaction recognition was only recently created and validated (Oomen et al., 2022). To ensure that the findings retrieved from the task are reflective of social interaction recognition, we used a wide variety of social stimuli that were balanced for valence and intensity and differed greatly from each other in terms of irrelevant features such as agent configuration, agent activity, and contextual background. (See Oomen et al., 2022). As such, the only systematic difference between the interaction and no-interaction stimuli was the absence or presence of interaction. Nevertheless, it remains possible that there are differences between interaction and non-interaction images that were not yet tested (e.g. complexity, cognitive load). Hence, future

studies are warranted that use different stimuli sets, either extracted from the database by Oomen et al. (2022) or created new (e.g. photographs of real people), to confirm our results.

Lastly, our study was powered to detect a medium to large effect size. More precisely, a post-hoc sensitivity analyses indicates that with our sample size only effects sizes larger than $d = 0.5$ would have been significant. Such an effect would be appropriate to assume based on the high SNR of frequency tagging studies and on the study by von der Lühе et al. (2016), the other study on social interaction processing that included an autism sample, which found a large effect. Additionally, a Bayesian analysis indicated evidence for the null hypothesis, with the data being three times more likely under the null than under the alternative hypothesis. Nonetheless, it remains possible that there are small differences in interaction recognition between individuals with and without autism that we were unable to detect. Hence, future research may consider repeating this study with even larger sample sizes to rule out this possibility. That said, if such studies would conclude that small differences do exist, an important question will be whether these differences are not just statistically but also practically significant, as small effect sizes are unlikely to have a large impact on autism phenomenology.

To conclude, we found an enhanced response to social scenes with social interaction compared to social scenes without social interaction over predominantly right-lateralized occipitoparietal electrodes, replicating previous findings in a neurotypical population (Oomen et al., 2022). However, we found this effect in the control group as well as the autism group with no difference between them. The results suggest that social interaction recognition, as assessed with EEG frequency tagging, is not atypical in adults with autism.

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