High spatial frequency filtered primes hastens happy faces categorization in autistic adults.

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Abstract

Coarse information of a visual stimulus is conveyed by Low Spatial Frequencies (LSF) and is thought to be rapidly extracted to generate predictions. This may guide fast recognition with the subsequent integration of fine information, conveyed by High Spatial Frequencies (HSF). In autism, emotional face recognition is challenging, and might be related to alterations in LSF predictive processes. We analyzed the data of 27 autistic and 34 non autistic (NA) adults on an emotional Stroop task (i.e., emotional face with congruent or incongruent emotional word) with spatially filtered primes (HSF vs. LSF). We hypothesized that LSF primes would generate predictions leading to faster categorization of the target face compared to HSF primes, in the NA but not in the autism. Surprisingly, HSF primes led to faster categorization than LSF primes in both groups. Moreover, the advantage of HSF vs. LSF primes was stronger for angry than happy faces in NA, but was stronger for happy than angry faces in autistic participants. Drift diffusion modelling confirmed HSF advantage and showed a longer non-decision time (e.g., encoding) in autism. Despite LSF predictive impairments in autism was not corroborated, our analyses suggest low level processing specificities in autism.

Keywords: autism, priming, emotional stroop, visual perception, spatial frequencies, drift diffusion model

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1 Background

Autism Spectrum Disorder (ASD)¹ is mainly characterized by socio-emotional specificities that can be expressed in different ways, including atypical face processing and difficulties in recognizing emotional facial expressions (Uljarevic & Hamilton, 2013). The latter might partly arise from perceptual specificities (Deruelle et al., 2008; Mottron et al., 2006), in line with atypical sensory behaviors, which are also a hallmark of autism (American Psychiatric Association, 2013). More specifically, a perceptual bias toward local visual information during the processing of social stimuli such as emotional faces (Deruelle et al., 2008; Jemel et al., 2006; Kätsyri et al., 2008; but see Corradi-Dell'Acqua et al., 2014; Rondan & Deruelle, 2004), but also for non-social stimuli (Kéïta et al., 2014; Mottron et al., 2006), has been documented in autism. This bias could originate from an enhanced processing of local information (Mottron et al., 2006) and might be related to an earlier and more effective use of High Spatial Frequencies (HSF – above 6 cycles per degree [cpd] of visual angle - conveying local information) compared to non autistic (NA) individuals (Caplette et al., 2016). Alternatively, an impaired processing of global information has also been suggested (Frith, 1989), and could be related to a less effective use of Low Spatial Frequencies (LSF - below 2 cpd - conveying coarse information) possibly due to magnocellular pathway disruption (Greenaway et al., 2013; Milne et al., 2002; Pellicano et al., 2005; Pellicano & Gibson, 2008). Critically however, both hypotheses could lead to atypicalities in predictive processes triggered by LSF.

According to influential models of perception, human visual processing of objects, scenes or faces operates in a Coarse-to-Fine manner (Bar et al., 2006; Goffaux et al., 2011; Kauffmann et al., 2015; Peyrin et al., 2010).). LSF would be quickly extracted by the primary visual cortex and projected onto the orbitofrontal cortex via the dorsal magnocellular pathway (Bullier, 2001). A set of predictions would be made to guide further integration of HSF and recognition by top-down process (Bar et al., 2006). However, spatial frequencies processing of faces would not be systematically Coarse-to-Fine, but rather flexible (Schyns & Oliva, 1999, 1997), depending on various factors (Jeantet et al., 2018) including exposure duration (Goffaux et al., 2011), emotional content (Kumar & Srinivasan, 2011), or task design (Deruelle & Fagot, 2005; Smith & Merlusca, 2014).

Moreover, predictions from LSF would be necessary to solve ambiguities in complex environment and might help inhibiting irrelevant information, favoring an adaptive functioning (see Bar, 2007; Enns & Lleras, 2008; Fan et al., 2020 ; Yardley et al., 2012). Relying on this framework, Beffara et al. (2015) employed an emotional Stroop paradigm with NA individuals,

¹ This term is used in keeping with the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) but we want to mention and acknowledge that “autistic” person/participant is usually preferred by people on the spectrum and less stigmatizing (Gernsbacher, 2017; Kenny et al., 2016). Therefore, we preferentially use the later formulation in this document.

using spatially filtered primes to investigate whether LSF primes would facilitate, more than HSF primes, the categorization of unfiltered happy and angry faces presented along with an incongruent word (in comparison to a congruent word condition). For incongruent stimuli, the authors observed a reduction of the Inverse Efficiency Score ($\text{IES} = \text{Response Time} / \text{Correct Response Rate}$) after LSF primes, compared to HSF primes, suggesting that top-down predictions from LSF could have disambiguated the target, in line with the Coarse-to-Fine model.

The Coarse-to-Fine model could provide a neurocognitive model of predictive brain specificities in autism in relation to atypical spatial frequencies processing as autistic individuals might show reduced top-down predictive processes initiated by LSF (see Caplette et al., 2016). This account is in accordance with the frontal-posterior underconnectivity theory of autism (Just et al., 2012) suggesting top-down impairments related to a reduced frontal-posterior communication bandwidth together and higher functional connectivity within posterior areas (as a result of frontal posterior underconnectivity). This model is supported by MRI studies showing differences in structural integrity of frontal and posterior brain regions in autism compared to NA (for a meta-analysis, see DeRamus & Kana, 2015), and by fMRI investigations revealing underconnectivity between the fusiform face area (FFA), frontal and primary visual cortices (Lynn et al., 2018). The systematic review of O'Reilly et al. (2017) on MEG/EEG studies also supports long range underconnectivity in autism, particularly during the processing of angry faces (Mennella et al., 2017). In sum, these studies suggest that emotional face processing impairments in autism might be partly due to atypical sensory processing and related to top-down specificities due to atypical spatial frequency processing (see Caplette et al., 2016; Deruelle et al., 2008; Kovarski et al., 2019) and frontal-posterior underconnectivity (Just et al., 2012; Mennella et al., 2017).

To test this hypothesis, we used an emotional Stroop task with spatially filtered primes (in HSF and LSF) adapted from Beffara et al. (2015), in which autistic and NA participants were instructed to categorize emotional faces as happy or angry, while the word “happy” or “angry” was written on the face in congruence or not with the facial expression. Hypotheses and planned analyses were pre-registered on OSF (<https://osf.io/345jv>). We expected to find increased Correct Response Rate (CRR) as well as reduced Response Time (RT) and reduced IES for congruent compared to incongruent stimuli (accounting for the Stroop effect) and for the NA group compared to the autistic group. We expected to reproduce the results of Beffara et al. (2015) in NA, that is, IES for incongruent stimuli should be shortened with LSF primes as they would favor predictions, but not in autism. Additional analyses were also preregistered to investigate the effects of emotion and sex. Accordingly, we expected better performances for happy faces than angry faces for both groups (Favre et al., 2015; Uljarevic & Hamilton, 2013). The investigation of the effect of sex had exploratory purposes. Sex differences in face processing and in its neural basis have been highlighted (Shaqiri et al., 2018; Vanston & Strother, 2017), also in relation to spatial frequency processing (Perilla-Rodríguez et al., 2013). In autism, sex and/or

gender differences are increasingly reported, and greater attention should be paid to these variables (Strang et al., 2020), as enhanced attention to faces in autistic females compared to autistic males has been suggested (Harrop et al., 2018, 2019).

2 Method

2.1 Participants

Assuming an effect size based on a previous study to perform a power analysis required three conditions detailed by Lakens (2021): (i) the study is sufficiently similar (ii) the study has a low risk of bias (iii) the study has a large enough sample size for accurate effect size estimation. None of these conditions were met in the previous similar studies we can refer to (i.e., Beffara et al., 2015 and Vanmarcke & Wagemans, 2017, investigating spatial frequency priming on emotional faces in NA and autistic individuals, respectively). Thus, instead of power analysis, we determined the sample size from an heuristic (Lakens, 2021). More specifically, we planned to have a sample size at least as large as in the previous studies (29 NA participants in Beffara et al., 2015; 26 autistic and 26 NA adolescents in Vanmarcke & Wagemans, 2017) and to approach sample size requirments suggested by Teare et al. (2014). It should be noted that studies with a clinical population also depend on ressources constraints (Lakens, 2021), including the difficulty to recruit officially diagnosed and autonomous autistic participants during a limited time period. Hence, 33 autistic (15 females, 16 males, 2 transgender persons female-to-male) and 35 NA adults (19 females, 15 males, and 1 transgender person female-to-male) were enrolled in the study. Participants were aged from 19 to 47 years ($Mean = 32.3$ years, $SD = 7.8$) and reported a normal or corrected to normal vision. Their full-scale intelligence quotient (FSIQ) was above 70, as estimated using a Wechsler Intelligence Scale (Wechsler Intelligence Scale for Children, 4th Edition – WISC-IV- or Wechsler Adult Intelligence Scale - 3rd or 4th Edition or Wechsler Abbreviated Scale of Intelligence – WAIS-III or WAIS-IV-; Wechsler, 1997, 2003, 2008). We assessed autistic traits in all participants using the Autism-Spectrum Quotient (AQ - Baron-Cohen et al., 2001).

Autistic participants were recruited with the help of local Expertise Centers dedicated to autism diagnosis, professionals, or associations for autistic community. We ensured that volunteers previously received a diagnosis by expert clinicians based on the DSM-IV-R (American Psychiatric Association, 2000) or DSM-5 (American Psychiatric Association, 2013) criteria, or on the International Classification of Disease 10th revision (OMS, 1992) by asking them for the written report of their diagnosis. We collected the scores of the Autism Diagnostic Observation Schedule (Lord et al., 1989), the Autism Diagnostic Interview-Revised (Lord et al., 1994) and IQ when they were available. Age at diagnosis was between 10 and 45 years old ($Mean = 28.5$ years, $SD = 10.1$). Some of the autistic participants had one or more comorbidities: Attention Deficit –

Hyperactivity Disorder (ADHD, $N = 3$, one of them was treated with methylphenidate), anxiety disorder ($N = 2$) or history of trauma injury ($N = 2$). Six participants took antidepressants but had no current major depressive episode. Twenty-one autistic participants did not present co-occurring conditions, nor received any treatment. For those who could not provide available IQ data ($N = 8$), estimations of their FSIQ, VIQ, and PIQ were performed using four selected subtests (Vocabulary, Similarities, Block Design and Matrix) of the WAIS-IV (Grégoire & Wierzbicki, 2009; Wechsler, 2008). Ten ASD participants scored below the cut-off of 32 on the AQ (Baron-Cohen et al., 2001). Among them, those who had ADOS scores over the cut-off of 7 (Lord et al., 1989) were included in the analyses as AQ is not a diagnostic tool. However, we excluded participants who had AQ scores < 32 and no ADI or ADOS scores or ADOS < 7 (cutoff for ASD). Detailed information and scores for each participant can be found in the data folder on https://osf.io/dwgj5/?view_only=549ec2f0755142e39056c1a8975cdeef.

NA adults were recruited via advertisements, mailing lists and social networks. They did not have any diagnosis (neurological, psychiatric, or neurodevelopmental), and they all scored below 32 on the AQ.

Groups were matched for sex, age, and education. We excluded transgender individuals ($N = 3$) from the analyses as we planned to study the effect of sex and studies investigating if transgender persons exhibit brain morphology and cognitive abilities more congruent with natal sex or gender identity provided mixed results (for a review, see Nguyen et al., 2019). Written informed consent was obtained from all participants. They all received a monetary compensation for their participation at the end of the study. All procedures performed in this study were in accordance with the Declaration of Helsinki and were approved by the local ethics committee (CER-Grenoble Alps, COMUE University Grenoble Alpes, IRB00010290).

2.2 Material and procedure

Each participant performed the tasks individually in a darkened experimental box of the Psychology and NeuroCognition Laboratory (Univ. Grenoble Alpes). Participants were invited to take a break between tasks. Tasks were presented as follows.

2.2.1 Emotional Stroop Task with priming. This task is a similar version to Beffara et al. (2015). Target stimuli comprised gray scale unfiltered pictures of faces (15 females and 15 males, expressing happiness or anger), 256 x 256 pixels (7.6 x 7.6 degrees for the image; the face width correspond to 4.6 degrees), from the Karolinska Directed Emotional Faces (Calvo & Lundqvist, 2008). A yellow word (in French) was displayed in the forehead of the face: “joie” (i.e., happiness) or “colère” (i.e., anger), in congruence or not with the facial expression. Prime stimuli were the same face identity as the unfiltered target stimuli, with no word, and were either filtered in LSF (less than 8 cycles per image / 1.05 cpd / 4.8 cycles per face) or in HSF (more than 64 cycles per image / 8.42 cpd / 38 cycles per faces), as shown on *Figure 1 A*. Cutoffs were chosen

through the use of a Gaussian filter to maximize the gap between the two types of information and avoiding spatial frequency overlap (Beffara et al., 2015). Note that these cutoffs belong to the range of spatial frequency preferentially used for face processing [from 4.5 to 37 cycle per face; for a review see@jeantet_factors_2018]. These primes stimuli were normalized in contrast and luminance. Spatial frequencies filtering and equalizing procedure were performed with MATLAB (MathWorks, Natick, MA).

Stimuli were displayed centrally on a 23-inch LCD monitor Dell P2319H (refresh rate = 75 Hz, resolution = 800×600 pixels) at a viewing distance of 91 cm. To maintain the distance and central position, participants' head was supported by a chinrest. E-prime version 2.0 (Psychology Software Tools Inc., Pittsburg, PA) was used to display stimuli and collect behavioral data.

Figure 1. A. Example of a stimulus filtered in Low Spatial Frequencies (LSF), unfiltered, and filtered in High Spatial Frequencies (HSF). B. Example of a trial with LSF filtered prime and incongruent word stimuli.

Instructions were given both orally and on a written form. A training session of 16 trials (2

faces not included as target stimuli $\times$ 2 Emotions $\times$ 2 Congruency $\times$ 2 Primes) was performed by the participant. During the training, participants had a visual feedback mentioning whether the response was correct or incorrect. The experimenter also ensured that instructions had been correctly understood before leaving the room. The experimental session consisted of 240 trials (30 faces $\times$ 2 Emotions $\times$ 2 Congruency $\times$ 2 Primes) with three breaks (every 80 trials). Each trial began with a fixation cross for 1,492 ms, followed by a prime stimulus for 53 ms. Then, to prevent retinal persistence, a mask appeared for 39 ms. This mask was made of random noise according to the 1/f decreasing of the amplitude spectra of natural scene images for unfiltered stimuli. Masks were then filtered with the same LSF or HSF as those used for prime stimuli. The target stimulus was shown until the participant answered, for a maximum of 2,000 ms. Participants were asked to answer by pressing with the index of their dominant hand, one of the two corresponding buttons of the Chronos® device (Psychology Software Tools): far-right for happiness and the next button on the left for anger for right-handed participants, far-left button for happiness and the next button on the right for anger for left-handed participants. Sides were not counterbalanced as positive concepts are associated with the right space in right-handed participants and with the left space in left-handed participants (Casasanto, 2009; Vega et al., 2013). Participants were instructed to be as fast and accurate as possible. RT from the beginning of the presentation of the target and CRR were recorded for analysis. The schematic of one trial is shown on *Figure 1 B*.

2.2.2 Color Stroop Task. After the emotional Stroop task, participants performed the original color Stroop task as a control task to ensure that groups did not differ neither on their reading abilities nor on their sensitivity to interference (Golden & Freshwater, 1978; Stroop, 1935). Participants were asked to be as fast and as accurate as possible on each of the three parts of the color Stroop task. First, they were asked to name the color of the item “XXXX” written on a paper. Then they were asked to read words of colors (“BLUE”, “RED” or “GREEN”) written in black on a paper. These two parts were used as control situations to calculate the interference effect for each participant. Finally, during the interference condition, participants were asked to name the color of a written word by ignoring the word itself (which was a color word). For each sequence, participants were presented with 5 columns containing 20 stimuli each which order was randomized, and they had to perform the task from the top to the bottom, column by column. Three scores were yielded, one for each of the stimulus sheet, based on the number of items completed during 45 seconds. The interference score was then calculated with the procedure of Golden and Freshwater (1978) and all scores were transformed into z-scores.

2.2.3 Autism Spectrum Quotient. The AQ (Baron-Cohen et al., 2001) is a 50 items self-reported questionnaire aimed to evaluate the presence of traits associated with the autism-spectrum. Participants were asked to rate their agreement or disagreement with statements on a 4-point Likert scale. Each item scored 1 or 0, a score of 32 and above being usually associated with high autistic traits.

2.2.4 Weschler Adult Intelligence Scale. Verbal Intelligence Quotient (VIQ), Performance Intelligence Quotient (PIQ) and Full Scale Intelligence Quotient (FSIQ) were estimated with four selected subtests of the WAIS-IV (Grégoire & Wierzbicki, 2009; Wechsler, 2008): Vocabulary, Similarities, Block Design and Matrix. In case the participant already performed a Weschler scale, we collected results from the medical record.

2.3 Participants and data exclusion

All exclusion criteria were accounted for in the preregistration on <https://osf.io/345jv>. We excluded participants with a CRR below chance level (50%) at the emotional Stroop task (which correspond to the exclusion of 1 autistic male and 1 autistic female). We also planned to exclude participants with several concomitant comorbid conditions which could have influenced the task (e.g., accumulation of hyperactivity, anxiety and depression) in case they were not excluded during the recruitment (as sometimes participants do not mention comorbidities before the day of the study). However, the case did not appear. Finally, we also preregistered to exclude participants who were outliers (CRR or RT below Quartile 1 – $1.5 \times$ Interquartile range or above Quartile 3 + $1.5 \times$ Interquartile Range) on more than half of the conditions (2 females and 1 male in the autistic group, and 2 females and 1 male in the NA group). We included these participants in the final sample, as we also performed the analysis by excluding them, which did not change our conclusions (see *Supplementary Materials, part 2*).

Aberrant trials with RT < 300 ms were excluded, corresponding to 1.43% of the trials.

2.4 Main analytical strategy

2.4.1 Pre-registered analysis. For the main analysis on the Emotional Stroop task, RT on correct trials was the dependent variable. In the preregistration (<https://osf.io/345jv>), we also planned to analyze CRR and Inverse Efficiency Scores (IES = RT / CRR in a given condition; Bruyer & Brysbaert, 2011; Townsend & Ashby, 1978). Eventually, we did not analyze CRR because the mean CRR for each group was above 96 % and ceiling effect would have inflated Type 1 error (Austin & Brunner, 2003). Regarding the IES, Bruyer and Brysbaert (2011) recommend its use only if CRR is high (> 90 %) and if there is a positive correlation between RT and error rate (i.e., negative correlation between RT and CRR). In our experiment, despite high CRR for each group, we observed lower CRR for 12 participants in some conditions thus increasing the variability of the data and decreasing the power of the analysis with the IES (Bruyer & Brysbaert, 2011). Moreover, CRR and RT were not always significantly correlated. Hence, as analysis on IES should be interpreted with caution, and not independently from RT analysis, we reported IES results in *Supplementary Materials* only (*part 3*). Nevertheless, conclusions drawn from IES analysis are similar to those with RT analysis.

Multilevel models appeared to be the most appropriate for our analysis as they can account for dependencies between repeated observations and also for variation at more than one level (e.g., groups and individuals), thus giving information about the generalizability of the findings (Barr et al., 2013; Nalborczyk et al., 2019) and maximizing robustness. We used Bayesian linear multilevel modeling (BLMM) as it allowed us to keep the maximal random-effect structure justified by the experimental design (Nalborczyk et al., 2019), which is recommended to avoid spurious effect (Barr et al., 2013). In contrast, frequentist multilevel models could not converge when fitting the maximal model. As RT (and IES) distribution were skewed, we used an Ex-Gaussian distribution for the outcome (which is a combination of Gaussian and decaying exponential process) instead of applying a non-linear transformation on the data which could have potentially conducted to misleading results by distorting the scale ratio (Lo & Andrews, 2015).

We fitted our models with the *brms* package (Bürkner, 2017), using weakly informative priors. The intercept estimates the overall effect and was given the default student prior. The slopes of the parameters were given a normal prior with a mean of 0 and a standard deviation of 50. The standard deviation of the random intercepts was given an exponential prior with a scale of 0.1. Finally, the beta and sigma parameters of the exgaussian distribution were given respectively the default gamma prior with a shape of 1 and a scale of 0.1, and an exponential prior with a scale of 0.1. We ran 4 Markov Chain Monte-Carlo (MCMC) for each model to generate samples from the posterior distribution. Each MCMC included 5,000 iterations and a warmup of 2,000 iterations, resulting in 12,000 posterior samples.

All parameters included in the finite set of models that we considered are justified by our pre-registered hypotheses and theoretical questions. Thus, to test our main hypothesis of a difference in the priming effect during the incongruent condition between ASD and NA, we analyzed data using Group (ASD vs. NA) as between-subject predictor as well as Prime (LSF vs. HSF) and Congruency (Incongruent vs. Congruent) as within-subject predictors. As we also planned to study the impact of Emotion (Happy vs. Angry) and participants Sex (Male vs. Female) in our analysis, we also ran more complex models including first Emotion as a within-subject predictor and then Sex as a between-subject predictor. Two of the models included Sex as a predictor: a full model and a more parsimonious model. Each predictor was coded using deviation coding (i.e., -0.5; 0.5). Finally, we ran five other models including standardized FSIQ or PIQ and AQ scores as covariates (as our two groups differed on these measures – see the Results section), either independently or additionally. We chose the best model using the LOOIC (Leave one out cross validation information criterion - Vehtari et al., 2017; Yao et al., 2018), which is aimed to evaluate the predictive accuracy of a model and is particularly suitable for model comparison (for more details regarding model selection, see the *Supplementary Materials, part 1*). We estimated the fixed effects for the intercept and for each predictor as well as their interaction. We also estimated the related random intercepts and slopes as well as their interactions for participants and stimuli.

2.4.2 Exploratory analysis. Given the caveats previously mentioned to analyze CRR (i.e., ceiling effect) and IES (i.e., variability in CRR and non-significant correlation between CRR and RT) with planned analysis, we performed an additional exploratory analysis using Drift Diffusion Models (DDMs), which allows analyzing data from two alternative force choice tasks when accuracy and RT are recorded together. The DDM assumes that in each trial of a task, evidence is accumulated in a noisy process until the accumulator hits one of the two decision bounds (Ratcliff & McKoon, 2008), which in our case, is a correct or incorrect response. The DDM decomposes the data into four latent cognitive processes (Wagenmakers, 2009) represented in *Figure 2*. The drift rate δ (delta) is the average slope of the accumulation process toward the boundaries, representing the ease of processing (the larger, the easier). The boundary separation α (alpha) is the distance between the two decision bounds, representing the response caution (the larger, the more cautious). The non-decision time β (beta) encapsulates non-decision processes such as encoding and motor response. Finally, the bias τ (tau) represents the bias toward one of the two responses. Having a bias toward one response means that the preferred response is initiated quickly and often (Voss et al., 2004). Whereas the bias can be fixed at 0.5 (representing a neutral bias / an unbiased model - Voss et al., 2004), in the present study it was interesting to estimate it according to the Group and the Prime as RT was recorded from the stimulus onset, that is after the processing of the prime. Thus, the prime might influence the bias. The total RT corresponds to the sum of the decision and non-decision components. More details on these models and the analytic strategy adopted can be found in the *Supplementary Materials, parts 4, 5 and 6*. We chose the best model using the WAIC (Watanabe – Akaike information criterion - Yao et al., 2018).

It is worth noting that the use of DDM for conflict task is challenging on both theoretical and methodological grounds (Servant et al., 2014). Particularly, DDM requires the use of optimal decision-making strategies (Bogacz et al., 2006), whereas conflicting tasks imply suboptimal decision-making strategies due to interference (Servant et al., 2014). Specific diffusion models for these types of tasks have been proposed (Servant et al., 2014), but the computational availability of these options is limited. Moreover, Lin et al. (2020) recently demonstrated that they exhibit similar results as DDM on a Stroop task, explaining our choice of fitting DDM on our data.

Figure 2. Graphical illustration of the Wiener diffusion model applied to the emotionnal Stroop task. RT = Reaction Time

3 Results

All figures and analyses were done using R version 3.6.1 (R Core Team, 2020) and R Studio version 1.2.5019 (RStudio Team, 2020).

3.1 Group Comparison

Groups comparison on Age, Education, FSIQ, PIQ, VIQ, AQ as well as reading and interference effect (on the color Stroop task) were performed with Bayesian independent t-tests using the BayesFactor package (Morey & Rouder, 2018) with default priors (the scale of the Cauchy prior was fixed to $\sqrt{2}/2$). We reported the Bayes factor in favor of the null hypothesis (BF_{01}), which allows quantifying the relative evidence in favor of the null hypothesis compared to the alternative hypothesis (Wagenmakers et al., 2018). For instance, “ $BF_{01} = 2$ ” means that the data are two times more likely under the null hypothesis than under the alternative hypothesis. Thus, the BF is interpreted in a continuous manner. However, for a more categorical interpretation, we referred to common guidelines (Jarosz & Wiley, 2014; Jeffreys, 1961; Lee & Wagenmakers, 2013), with BF_{01} below one indicating evidence in favor of the alternative hypothesis. More specifically, a BF_{01} from 1/10 to 1/3 indicates moderate evidence in favor of the alternative hypothesis; a BF_{01} from 1/30 to 1/10 indicates strong evidence and a BF_{01} less than 1/30 indicates very strong evidence in favor of the alternative hypothesis. Symmetrically, a BF_{01}

from 3 to 10 indicates moderate evidence in favor of the null hypothesis; a BF_{01} from 10 to 30 indicates strong evidence and a BF_{01} over than 30 indicates very strong evidence in favor of the null hypothesis. A BF_{01} from 1/3 to 3 indicates no remarkable evidence (i.e., anecdotal or inconclusive evidence).

Results suggested moderate evidence that there was no difference between groups on age ($BF_{01} = 3.769$), reading ($BF_{01} = 3.548$) and Stroop effect (i.e., interference score - $BF_{01} = 3.655$) on the color Stroop task. Differences between groups on VIQ ($BF_{01} = 1.688$) and on Education ($BF_{01} = 0.738$) were inconclusive. This analysis also revealed group differences on FSIQ with moderate evidence ($BF_{01} = 0.29$) and on PIQ with very strong evidence ($BF_{01} = 0.028$). Autistic participants had higher scores on FSIQ and PIQ, but lower education level. With no surprise, there was also extremely strong evidence of group differences on AQ ($BF_{01} = 2.987 \times 10^{-15}$), with higher AQ scores for autistic participants. All relevant statistics regarding groups description are set out in *Table 1*.

Table 1
Subject demographics – Means (M), standard deviations (SD) and BF_{01} .

	ASD (N=27)	NA (N=34)	BF_{01}
Age	32.56 (8.23)	32.21 (7.51)	3.769
Education	14.56 (2.85)	15.97 (2.68)	0.738
FSIQ	124.00 (16.10)	114.09 (14.67)	0.29
VIQ	126.67 (14.96)	121.38 (14.43)	1.688
PIQ	116.67 (13.80)	103.71 (14.66)	0.028
AQ	36.26 (7.30)	15.21 (6.20)	2.987×10^{-15}
Reading	-0.03 (0.98)	-0.12 (0.59)	3.548
Stroop Effect	0.46 (0.78)	0.53 (0.76)	3.655

Note. *FSIQ = Full Scale Intelligence Quotient; VIQ = Verbal Intelligence Quotient; PIQ = Performance Intelligence Quotient ; AQ = Autism-Spectrum Quotient.

3.2 Preregistered analysis (response time analysis)

Model comparison revealed that the best model (i.e., the model with lowest LOOIC) was the model including Congruency, Prime, Group, and Emotion as well as their interactions as predictors and no covariate (see *Supplementary Materials, Table 1 and Table 2*). We checked the quality of this model with posterior predictive checking (Gabry et al., 2019), which showed that our model was good to generate data similar to those observed (see *Supplementary Materials, Figure 1*).

For all analyses, posterior convergence was assessed using trace plots and the

367 Gelman-Rubin diagnostic $\hat{R}$ (Rhat). We summarized fixed effect estimates via their posterior mean
 368 and 95% credible interval (CrI), which contains the 95% most probable values of a parameter
 369 given the model, the data and the prior (Baldwin & Larson, 2017). Bayesian CrIs provide an
 370 intuitive interpretation of the parameter (Baldwin & Larson, 2017; Nalborczyk et al., 2019) and
 371 are also useful to summarize uncertainty (i.e. the wider the interval, the most uncertain is the
 372 parameter estimate). We also reported the BF_{01} .

Figure 3. Distribution of RT according to group, prime and congruency. Small points represent mean RT by participant, large points represent condition mean RT and error bars represent within-subjects 95 % confidence interval. CG = congruent ; ICG = incongruent.

Figure 4. Distribution of RT according to group, prime and emotion. Small points represent mean RT by participant, large points represent condition mean RT and error bars represent within-subjects 95 % confidence interval.

The results of the BMLM are summarized in *Supplementary Materials, Table 3*. The analysis revealed a main effect of Congruency, with very strong evidence for faster RT for congruent trials ($Mdn = 602$ ms, $IQR = 501 - 765$) than for incongruent trials ($Mdn = 631$ ms, $IQR = 516 - 818$; $\beta = -14.78$, 95% CrI $[-20.64, -9.17]$, $BF_{01} = 1.481 \times 10^{-4}$), accounting for the efficiency of the emotional Stroop effect in our experiment. BF_{01} indicated strong evidence for the effect of Group, with longer RTs in the ASD group ($Mdn = 664$ ms, $IQR = 531 - 883$) compared to NA ($Mdn = 586$ ms, $IQR = 492 - 725$), with a large uncertainty on the mean estimate as expressed by the width of the credible interval ($\beta = 66.78$, 95% CrI $[16.93, 113.38]$, $BF_{01} = 0.069$). There was moderate evidence for an effect of Emotion ($\beta = 18.9$, 95% CrI $[5.59, 31.99]$, $BF_{01} = 0.194$), with slower RT for anger ($Mdn = 627$ ms, $IQR = 517 - 803$) than for happiness ($Mdn = 605$ ms, $IQR = 498 - 771$). Regarding the main effect of Prime, there was very strong evidence for faster RT after HSF primes ($Mdn = 609$ ms, $IQR = 501 - 783$) than after LSF primes ($Mdn = 623$ ms, $IQR = 512.5 - 795.5$; $\beta = -12.91$, 95% CrI $[-18.7, -6.93]$, $BF_{01} = 1.277 \times 10^{-4}$). Critically, we did not observe the expected three-way interaction between Group $\times$ Prime $\times$ Congruency, graphically represented on *Figure 4* ($\beta = 2.28$, 95% CrI $[-14.63, 19.04]$, $BF_{01} = 5.494$). However, there was anecdotal evidence for a positive interaction between Group $\times$ Prime $\times$ Emotion ($\beta = 21.19$, 95% CrI $[3.08, 39.21]$, $BF_{01} = 0.403$), as depicted in *Figure 4*. Post-hoc analysis revealed

that HSF primes led to reliably shorter RTs than LSF primes for happiness ($\beta = 20.74$, 95% CrI [9.71, 31.49]) in the ASD group, but the effect was three times smaller and more uncertain for anger ($\beta = 6.48$, 95% CrI [-4.22, 17.72]). In the NA group, the opposite was observed: reliably shorter RTs for HSF primes than LSF primes for anger ($\beta = 15.73$, 95% CrI [6.1, 25.19]) but a less reliable effect and two times smaller for happiness ($\beta = 8.82$, 95% CrI [-0.78, 18.61]).

3.3 Exploratory analysis (Drift Diffusion Modeling)

This exploratory analysis did not include Sex or Emotion. Model comparison revealed that the best model (i.e., the model with the lowest WAIC) was the model including Congruency, Prime, Group (and their interactions) as predictors on the drift rate, as well as Group as predictor on the boundary separation, the non-decision time and the bias, and random intercepts by participant for each parameter. We also added the effect of Prime and Group x Prime interaction on the bias, as each trial began at the stimulus presentation, after the prime. Posterior predictive checking (represented in *Supplementary Materials, Figure 16*) shows that the model was efficient at simulating data that looks like the observed data. The detailed results of the DDM can be found in the *Supplementary Materials, Table 10*.

The analysis revealed extremely strong evidence that Congruency increased the drift rate ($\beta = 0.32$, 95% CrI [0.27, 0.38], $BF_{01} \approx 0$). In other words, congruent stimuli were easier to process than incongruent stimuli. Additionally, there was anecdotal evidence that Prime decreased the drift rate ($\beta = -0.11$, 95% CrI [-0.2, -0.03], $BF_{01} = 0.516$), indicating that stimuli with HSF prime were easier to process than those with LSF prime. There was also moderate evidence that the Group has no influence on the drift rate ($\beta = -0.01$, 95% CrI [-0.42, 0.38], $BF_{01} = 4.872$).

Because both the boundary separation and the non-decision time parameters need to be larger than 0, we used a log link function for these two parameters. Therefore, we have to apply the inverse link function (i.e., $\exp(\beta_i)$) to interpret them. For the boundary separation (i.e., response caution), $\exp(\beta_1) \approx 1.08$ which means that going from NA to ASD led to an increase of approximately 8 % of the boundary-separation parameter value. However, this effect was more likely to appear under the null hypothesis ($BF_{01} = 6.715$). For the non-decision time, $\exp(\beta_1) \approx 1.20$ which means that going from NA to ASD led to an increase of approximately 20 % of the non-decision time parameter value. In other words, non-decisional processes took longer in the ASD group than in the NA group with very strong evidence ($BF_{01} = 0.011$). The linear model for the bias parameter is on the logit (log-odds). For the bias parameter, $\exp(\beta_1) \approx 1.17$ meaning that going from LSF to HSF increased of approximately 17 % the bias parameter odd-ratio. HSF (vs. LSF) primes were associated with a “bias” towards accurate responses with extreme evidence ($BF_{01} = 1.618 \cdot 10^{-17}$).

4 Discussion

The current study investigated impairments in top-down predictions initiated by LSF processing (Bar et al., 2006), during the visual categorization of emotional faces in autistic compared to NA participants. An emotional face Stroop task with spatially filtered primes (LSF and HSF) was designed and two analyses were performed. The first analysis (preregistered) was completed with BLMM on RT. We observed slower RTs for incongruent stimuli compared to congruent stimuli (Stroop effect), for happy faces compared to angry faces, and faster RT for HSF primes compared to LSF primes, irrespective of the Group. As LSF primes did not reduce RT, there was no behavioral evidence for top-down predictions initiated by LSF in our task, neither for the autistic group, nor for the NA group. A second analysis with DDM allowed to account for accuracy together with RT and to obtain complementary results. HSF primes eased the processing and facilitated correct responses. Importantly, autistic adults seemed to process stimuli as easily as NA (similar drift rate), but differed from NA on the non-decision processing, which might reveal specificities in stimulus encoding or motor processes.

4.1 Decreased RT with congruent stimuli and with happy faces

The present results revealed the expected emotional Stroop effect, with incongruent stimuli increasing RT, accounting for the interference of the written emotion during the processing of the target (emotional face). This result replicates previous findings (Agustí et al., 2017; Beffara et al., 2015; Favre et al., 2015; Ovaysikia et al., 2011; Shankland et al., 2021) regardless of some methodological differences (e.g. location of the word), and extended them to autism. Results from the complementary analysis using DDM are in line with BLMM analysis on RT, showing that incongruent stimuli decrease the ease of processing, in accordance with a recent study using DDM on a Stroop paradigm in NA (Lin et al., 2020).

We also found a main effect of Emotion, with happy faces decreasing RT in both groups. This happy faces advantage was observed in a previous study employing an emotional Stroop paradigm in bipolar individuals and controls (Favre et al., 2015), and is also in line with positive facial expressions being recognized faster than negative ones (Calvo & Nummenmaa, 2016; Leppänen & Hietanen, 2003, 2004). Faster processing of happy faces can be explained by the highly distinctive perceptual features of these stimuli, such as open mouth with visible teeth (for a review, see Calvo & Nummenmaa, 2016) or could be related to the tendency to have positive bias about individuals in relation to a normatively positive mood (Diener & Diener, 1996; Leppänen & Hietanen, 2003, 2004).

4.2 No evidence of top-down predictions from LSF

In the present study, HSF primes decreased RT of target stimuli compared to LSF primes, irrespective of the Group and the Congruency. This result contradicts our initial hypothesis based on Beffara et al. (2015), predicting enhanced performances after LSF primes in the incongruent condition in the NA group. Our results are at odds with the Coarse-to-Fine model of visual perception (Bar et al., 2006) and with its extension to faces (Goffaux et al., 2011; Khalid et al., 2015). Nevertheless, other studies found an HSF advantage during emotional faces categorization (Deruelle & Fagot, 2005; Jahshan et al., 2017; Kovarski et al., 2019; Shankland et al., 2021) or no behavioral advantage for either filtering during emotional faces categorization (Vanmarcke & Wagemans, 2017). Several hypotheses could explain our results.

Firstly, while filtering is frequently carried out to disentangle global from local processing, there are some limits to this approach. Contrary to local information, which is only conveyed by HSF, global information can be extracted by both LSF and HSF (see Corradi-Dell’Acqua et al., 2014). Indeed, even with HSF only, a global parsing can be realized by integrating details together, assuming that there is more available information in HSF primes compared to LSF primes. Additionally, the use of a Gaussian filter shape (commonly used for spatial frequency filtering) has the advantage to reduce artifacts on HSF images but does not entirely exclude the unwanted part of the spectrum (Perfetto et al., 2020). Hence, Perfetto et al. (2020) recently showed that the direction of the differences in accuracy can switch according to the type of filter used. Critically, the authors highlighted that the use of Gaussian filters lead to HSF advantage over LSF in scene categorization (with a stimulus presented during 53 ms followed by a 500 ms mask). Given these, the Coarse-to-Fine processing might be not observable in our experiment, but could be revealed with other stimuli where local and global information could be orthogonalized.

Secondly, beyond the filter characteristics mentioned above, studies’ findings are also determined by other differences in spatial frequency filtering choices (Perfetto et al., 2020). One important point is contrast normalization, which is critical to assess the role of spatial frequency without being influenced by the difference in contrast energy contained in LSF and HSF (Perfetto et al., 2020). Absence of contrast normalization disadvantages HSF processing (Perfetto et al., 2020) and could thus induce a LSF bias. However, most studies on emotional face perception use stimuli normalized in contrast. A second important point is the cutoffs used for spatial filtering, which differ from one study to another. Despite the LSF cutoff used in our study (8 cycles per image/4.83 cycles per face/1.05 cpd) belonging to the range of spatial frequency preferentially used for face processing (from 4.5 to 37 cycle per face; for a review see Jeantet et al., 2018) and is similar or superior to some studies (e.g., Vuilleumier et al., 2003 has a cutoff of 6 cycles per image), it is slightly lower than cutoffs applied in other studies (Goffaux et al., 2011; Khalid et al., 2015; Schyns & Oliva, 1999). It is possible that the use of a higher cutoff (e.g., 2 cpd) could affect the results. Thus, to better compare results across studies and to draw consistent

conclusions, futures studies would benefit (i) from using more standardized procedure regarding spatial frequency filtering, as suggested by Perfetto et al. (2020), who provided recommendation and code for filtering procedure, and (ii) from testing different band pass filters.

Thirdly, the time course of the task could affect spatial frequency processing and HSF advantage. Indeed, LSF advantage has been found for short exposure duration (i.e., 30 ms, 75 ms), whereas longer exposure duration would favor HSF (Goffaux et al., 2011; Schyns & Oliva, 1997). In the current experiment, the exposure time of the prime stimulus was indeed short (53 ms) but followed by a mask (39 ms) and by the target stimulus (2,000ms). The backward masking appearing 53 ms after the prime onset might prevent retinal persistence but not the extraction and accumulation of visual information necessary for achieving the task (see Bacon-Macé et al., 2005), which is moreover reinforced by information in the target stimulus, that have a long presentation. This hypothesis is also supported by brain activity recorded in face-responsive regions (i.e. FFA, occipital face area, and superior temporal sulcus) during a fame-judgment task with masked primes (Kouider et al., 2009). Interestingly, supplementary analysis using DDM reinforces this idea. In our design, RT were considered from the beginning of the target and results showed enhanced bias toward good answers after presentation of HSF prime. However, we also found evidence that HSF primes enhanced the ease of processing, although anecdotal, which could be in line with the processing of the prime still ongoing. The design of the task could favor HSF for decision-making and not completely exclude Coarse-to-Fine processing in the former stages, which can be further investigated with neurophysiological exploration in addition to behavioral responses (Bar et al., 2006; Goffaux et al., 2011; Kauffmann et al., 2015; Ravenzwaaij et al., 2017).

Finally, some studies suggested that HSF, and not LSF only, could play an important role in the early stages of face processing (De Gardelle & Kouider, 2010; Halit et al., 2006). Importantly, De Gardelle and Kouider (2010) reported subliminal priming effect for both HSF and LSF primes during an identification task of famous faces, showing that both frequency bands can be unconsciously perceived and that the parallel extraction of HSF and LSF information could limit the generalization of the Coarse-to-Fine model. The authors related their findings to the diagnostic model developed by Schyns and Oliva (1999). According to this model, the use of spatial frequency scale would be flexible and modulated by the task (Schyns & Oliva, 1999; Smith & Merlusca, 2014). Hence, the diagnostic information (i.e., information required for achieving the task) could vary according to the emotions used in the task, with happy face (Kumar & Srinivasan, 2011; Schyns & Oliva, 1999) and fearful face (Holmes et al., 2005; Vuilleumier et al., 2003; Winston et al., 2003) recognition relying more on LSF, while sadness relying more on HSF (Kumar & Srinivasan, 2011). However, it can also vary according to the type of task. For instance, happy face recognition could rely more on HSF when an explicit judgment is required, such as the degree of happiness. This could be explained by HSF conveying fine details about wrinkles that are necessary for the task (Jeantet et al., 2018). It is possible that diagnostic

information (i.e. information required for achieving the task) in our task relies more on HSF than LSF. Indeed, global processing (relying on LSF) could interfere with the inhibition of the word written on the forehead of the target stimulus. On the contrary, using a local processing (i.e., HSF) by focusing on local features such as the mouth region, could facilitate the inhibition of the word. Interestingly, this strategy was reported by several autistic and NA participants at the end of the experiment.

Nevertheless, these hypotheses do not fully explain the differences between our results and those reported by Beffara et al. (2015) on NA participants (as the stimuli were the same), who showed an advantage of LSF primes over HSF primes on the IES in the incongruent condition. In our experiment, results on IES were similar to those on RT (See *Supplementary Materials, part 3*). The use of a different analytic strategy might explain inconsistencies with previous results: here, instead of running ANOVA, we fitted multilevel models using ExGaussian distribution. RT (and IES) distributions are generally not normal, thus, even when an ANOVA is robust to violation of normality (Lix et al., 1996), the ExGaussian distribution should better fit the data-generating process and hence, it is more appropriate to answer the research question (Lo & Andrews, 2015). Additionally, we also used multilevel models which avoid using data aggregation, as this can mislead conclusions (Speelman & McGann, 2013). The prime effect in this experiment might not be reliable, however, another recent study using the same paradigm in NA participants and frequentist multilevel models also showed faster RT for HSF primes compared to LSF primes suggesting that the effect found was reproducible (Shankland et al., 2021).

4.3 Different visual processing style in autism

We found a main effect of Group, with autistic participants being slower than NA participants. This effect is in line with our expectations and with other studies on face processing in autism (e.g., Grossman et al., 2000; Harms et al., 2010; Kovarski et al., 2019). The exploratory analysis shows that while there is no group difference on the drift rate, meaning that evidence accumulation is similar in both groups, a difference between groups exists on the non-decision time, which is longer in autistic participants. This pattern could simply reflect that the task itself is not more difficult for autistic participants compared to NA participants, but groups might differ on other aspects, such as encoding or motor response (Pirrone et al., 2017). The non-decision time encompasses the non-decision processes from the stimulus encoding to the motor response. Unfortunately, these processes cannot be disentangled here. Additionally, whereas DDM is a well-established approach, it should be noted that exactly which cognitive processes are reflected in RT is still a matter of debate (see Weindel et al., 2020). Thus, even if it could be surprising that a much longer RT observed in some autistic participants is only due to perceptual and motor processes, we cannot rule out that some other decisional and non-decisional processes are also involved, despite not yet determined with these models. Additionally, it should

be noted that motor time (included in non-decisional processes) can vary according to several experimental factors, including cognitive processes (Buc Calderon et al., 2015; Weindel et al., 2020). For these reasons, further studies joining DDM and EEG recording could help to assess if inferences from the model are compatible with electrophysiological activity (Weindel et al., 2020), and to determine whether visual encoding differs between autistic and NA participants. For instance, it could be done by investigating the N200 peak latencies similarly to Nunez et al. (2019). Indeed, N200 is suspected to be related to pre-attentive phase before evidence accumulation and is suggested to track visual encoding (Nunez et al., 2019). Combining behavioral data, mathematical models, and neurophysiology is as promising as it is challenging, particularly because a linking proposition between the processes has yet to be established (Schall, 2019; Weindel et al., 2020). However, new approaches are being developed in that direction (Ravenzwaaij et al., 2017; Turner et al., 2016; Weindel et al., 2020).

Surprisingly, few studies have investigated differences between autism and NA using DDM. Pirrone et al. (2017) used DDM on a perceptual judgment task (i.e., orientation discrimination) and found similar drift rate, wider boundary separation parameter, and increased non-decision time in autistic adults compared to NA. On the contrary, Powell et al. (2019) found smaller drift rate, smaller boundary separation and comparable non-decision time in autistic compared to NA adolescents during a face identification task. The differences in the results could be explained by the use of different tasks (e.g., orientation discrimination, face identification, or emotion recognition with inhibition and priming) and/or by age differences (adults vs adolescents). Additionally, there is a great heterogeneity in our ASD group, which might implicate the existence of ASD subgroups and could also explain that, contrary to Powell et al. (2019) we did not find group differences on the drift rate. Similarly to Powell et al. (2019), we suggest that DDM refined our understanding of group differences between autism and typical development, as analyses on RT, CRR, or IES only, could mask differences in specific cognitive processes. Future studies should be considered for the investigation of specific hypotheses on parameters.

Critically, the expected three-way interaction between Group, Prime, and Congruency was not observed. Thus, we could not confirm our main hypothesis inferring impairments in top-down processing initiated by LSF primes in autism. However, the results reveal different pattern of spatial frequencies processing according to the emotion in autism compared to NA. While autistic participants answered reliably faster after HSF primes for happy faces, the effect was reduced for angry faces. In NA, happiness is recognized faster and more accurately compared to other emotions in paradigms using forced-choice response (for a review, see Calvo & Nummenmaa, 2016). Despite the existence of inconsistencies across studies, accuracy in autistic individuals usually differs little from NA in happiness recognition when the emotion is well characterized, but differs for other emotions, particularly for negative ones (Ashwin et al., 2006) such as anger or fear, but also surprise (for a review, see Uljarevic & Hamilton, 2013). Thus, the findings of the present study suggest that efficient emotion recognition in autism might rely on HSF. This

hypothesis is supported by the local bias reported in autism while processing non-social (Kéïta et al., 2014; Mottron et al., 2006) and social stimuli (Deruelle et al., 2008; Jemel et al., 2006). On the contrary, NA answered reliably faster after HSF primes for anger, and the effect was smaller and less reliable for happiness. This might be explained by the availability of spatial frequency information for correctly performing the task (De Gardelle & Kouider, 2010). In NA individuals, faster happiness recognition is usually driven by LSF information (see Jeantet et al., 2018). Thus, happy faces might be processed more globally than angry faces, suggesting that LSF primes would be more useful for happy faces than for angry faces. As a consequence, the difference in RT after HSF primes and LSF primes would be smaller for happy faces than for angry faces.

In sum, even if results do not corroborate our initial hypotheses, they suggest specificities in emotional face processing in autistic individuals, related to low-level vision. Autism is characterized by social symptoms and by difficulties in processing social information (American Psychiatric Association, 2013). However, social information is complex and needs both low-level and higher-level cognitive functions (e.g. Theory of mind) to be processed. Spatial frequency filtering is one way to study emotional face processing. Although investigating static and grey-scale images with prototypical emotion offers a reduced ecological validity, it seems crucial to separate social from non-social information to better understand the different challenges experienced by autistic individuals when they process these complex stimuli. Indeed, specificities in visual perception such as spatial frequency processing as well as motion perception might contribute to the difficulties experienced by autistic individuals with the social world that can lead to social isolation (Chung & Son, 2020). In line with this hypothesis, the autistic participants in our study often expressed distress either when we explained the task, after the training session, or at the end of the task, because they know that they struggle to recognize facial expressions. Subjective experience has been informally discussed with the participants, but not included in the analyses nor in the discussion. Future studies should include a formal assessment of autistic experience in the methodology in order to improve our understanding of specificities in autistic perception.

4.4 Sex differences

Differences between males and females have been found in various aspects of vision according to a study including 800 participants (Shaqiri et al., 2018). Additionally, males and females differ in emotional face processing and in the neural network of face processing (for a review see, Vanston & Strother, 2017). Some dissimilarities are also observed in autism with autistic females exhibiting better social attention (Harrop et al., 2019), as well as better camouflaging abilities compared to autistic males (Schuck et al., 2019). Despite the increasing interest in sex effects in both typical and atypical populations, their relation to perceptual processes have been rarely studied in autism. While sex was present in the initial analysis,

accordingly to preregistration, the best model did not include this variable. Thus, further research should be carried out while including autistic females and considering sex in analyses with larger samples.

4.5 Limitations

The experiment was performed with autistic adults, with no intellectual disability. Hence, our findings cannot generalize to the whole autism spectrum. Moreover, as often reported in autism research, there was a wild variability in the autistic group. Heterogeneity might reflect changes in diagnostic practices (e.g., spectrum notion), more inclusive of individuals with less obvious symptoms (Arvidsson et al., 2018; Rødgaard et al., 2019). Variability might mask potential differences and underline the need to have genetics (Jeste & Geschwind, 2014) and behavioral specifiers to stratify autistic individuals in more homogenous subgroups or on different dimensions (Lai, 2020; Rosen et al., 2021; Rødgaard et al., 2019) to better understand and support autistic individuals on the whole spectrum according to their specific needs (Feczko et al., 2019). Machine learning techniques (Stevens et al., 2019) and computational modeling (Lanillos et al., 2020) could also help to better understand and reduce heterogeneity issues in autism.

The current paradigm did not show evidence in favor of the Coarse-to-Fine model, thus, we suggest that future tasks could use shorter presentation time of the target stimulus (Goffaux et al., 2011; Schyns & Oliva, 1997) and/or different bandpass. Additionally, a task involving implicit emotion processing might favor LSF information compared to explicit tasks as used here (see Deruelle & Fagot, 2005 ; Vuilleumier et al., 2003). Finally, neuroimaging might provide crucial understanding for Coarse-to-Fine processing in the brain in addition to behavioral mechanisms (Bar et al., 2006; Goffaux et al., 2011; Kauffmann et al., 2015).

5 Conclusion

Contrary to our expectations, we were not able to infer top-down impairments during visual processing in autism. The expected stronger priming effect of LSF compared to HSF was not found. On the contrary, HSF primes led to faster RT and easier visual processing than LSF primes in both groups. Nevertheless, our findings suggest a different processing of spatial frequencies in autism compared to NA, depending on the emotional content, pointing to the possibility of emotion recognition in autism relying more on HSF than LSF. Indeed, happy faces, which are recognized faster, benefit more than angry faces from HSF primes than LSF primes in autism, but this is not observed in NA. Additionally, supplementary analysis with DDM suggests slower non-decision-related processes, such as stimulus encoding in autistic participants. Surprisingly, few studies used DDM for the comparison between autistic and NA participants so far. This could be an interesting tool to analyze the data more deeply and better understand

differences in the underlying cognitive processes. Further studies, coupling DDM and EEG could help to disentangle which type of non-decision processes differ between autism and NA during visual processing of emotional faces.

6 Declaration

6.1 Ethics approval and consent to participate

Written informed consent was obtained from all individual participants included in the study. All procedures performed in this study involving human participants were in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki) and approved by the local ethics committee (CER-Grenoble Alps, COMUE University Grenoble Alpes, IRB00010290).

6.2 Availability of data and materials

The datasets generated and/or analyzed during the current study are available in the Open Science Framework repository, https://osf.io/dwgj5/?view_only=549ec2f0755142e39056c1a8975cdeef. Any other materials are available from the corresponding author on reasonable request.

6.3 Competing interests

The authors declare that they have no competing interests.

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6.5 Author's contribution

Adeline Lacroix: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing - original draft **Ladislav Nalborczyk:** Data curation; Formal analysis; Methodology; Roles/Writing - original draft; Writing - review & editing **Frederic Dutheil:** Writing - review & editing **Klara Kovarski:** Writing - review & editing **Sylvie Chokron:** Writing - review & editing **Marta Garrido:** Writing - review & editing **Marie Gomot:** Data

curation; Writing Review & Editing **Martial Mermillod**: Conceptualization; Funding
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