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

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Author note

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26

## 27 **1 Background**

28 Autism Spectrum Disorder (ASD)<sup>1</sup> is mainly characterized by socio-emotional  
29 specificities that can be expressed in different ways, including atypical face processing and  
30 difficulties in recognizing emotional facial expressions (Uljarevic & Hamilton, 2013). The latter  
31 might partly arise from perceptual specificities (Deruelle et al., 2008; Mottron et al., 2006), in  
32 line with atypical sensory behaviors, which are also a hallmark of autism (American Psychiatric  
33 Association, 2013). More specifically, a perceptual bias toward local visual information during  
34 the processing of social stimuli such as emotional faces (Deruelle et al., 2008; Jemel et al., 2006;  
35 Kätsyri et al., 2008; but see Corradi-Dell'Acqua et al., 2014; Rondan & Deruelle, 2004), but also  
36 for non-social stimuli (Kéïta et al., 2014; Mottron et al., 2006), has been documented in autism.  
37 This bias could originate from an enhanced processing of local information (Mottron et al.,  
38 2006), and might be related to an earlier and more effective use of High Spatial Frequencies  
39 (HSF – above 6 cycles per degree [cpd] of visual angle - conveying local information) compared  
40 to non-autistic (NA) individuals (Caplette et al., 2016). Alternatively, an impaired processing of  
41 global information has also been suggested (Frith, 1989), and could be related to a less effective  
42 use of Low Spatial Frequencies (LSF - below 2 cpd - conveying coarse information) possibly due  
43 to magnocellular pathway disruption (Greenaway et al., 2013; Milne et al., 2002; Pellicano et al.,  
44 2005; Pellicano & Gibson, 2008). Critically, however, both hypotheses could lead to atypicalities  
45 in predictive processes triggered by LSF.

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<sup>1</sup> 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.

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

56 Moreover, predictions from LSF would be necessary to solve ambiguities in complex  
57 environment and might help inhibiting irrelevant information, favoring an adaptive functioning  
58 (see Bar, 2007; Enns & Lleras, 2008; Yardley et al., 2012; Fan et al., 2020). Relying on this  
59 framework, Beffara et al. (2015) employed an emotional Stroop paradigm with NA individuals,  
60 using spatially filtered primes to investigate whether LSF primes would facilitate, more than HSF  
61 primes, the categorization of unfiltered happy and angry faces presented along with an  
62 incongruent word (in comparison to a congruent word condition). For incongruent stimuli, the  
63 authors observed a reduction of the Inverse Efficiency Score ( $IES = \text{Response Time} / \text{Correct}$   
64  $\text{Response Rate}$ ) after LSF primes, compared to HSF primes, suggesting that top-down predictions  
65 from LSF could have disambiguated the target, in line with the Coarse-to-Fine model.

66 The Coarse-to-Fine model could provide a neurocognitive model of predictive brain  
67 specificities in autism in relation to atypical spatial frequencies processing as autistic individuals  
68 might show reduced top-down predictive processes initiated by LSF (see Caplette et al., 2016).

69 This account is in accordance with the frontal-posterior underconnectivity theory of autism (Just  
70 et al., 2012) suggesting top-down impairments related to a reduced frontal-posterior  
71 communication bandwidth and higher functional connectivity within posterior areas. This model  
72 is supported by MRI studies showing differences in structural integrity of frontal and posterior  
73 brain regions in autism compared to NA (for a meta-analysis, see DeRamus & Kana, 2015), and  
74 by fMRI investigations revealing underconnectivity between the fusiform face area (FFA),  
75 frontal and primary visual cortices (Lynn et al., 2018). The systematic review of O'Reilly et al.  
76 (2017) on MEG/EEG studies also supports long range underconnectivity in autism, particularly  
77 during the processing of angry faces (Mennella et al., 2017). In sum, these studies suggest that  
78 emotional face processing impairments in autism might be partly due to atypical sensory  
79 processing and related to top-down specificities due to atypical spatial frequency processing (see  
80 Caplette et al., 2016; Deruelle et al., 2008; Kovarski et al., 2019) and frontal-posterior  
81 underconnectivity (Just et al., 2012; Mennella et al., 2017).

82 To test this hypothesis, we used an emotional Stroop task with spatially filtered primes (in  
83 HSF and LSF) adapted from Beffara et al. (2015), in which autistic and NA participants were  
84 instructed to categorize emotional faces as happy or angry, while the word “happy” or “angry”  
85 was written on the face in congruence or not with the facial expression. Hypotheses and planned  
86 analyses were pre-registered on OSF (<https://osf.io/345jv>). We expected to find increased Correct  
87 Response Rate (CRR) as well as reduced Response Time (RT) and reduced IES for congruent  
88 compared to incongruent stimuli (accounting for the Stroop effect) and for the NA group  
89 compared to the autistic group. We expected to reproduce the results of Beffara et al. (2015) in  
90 NA, that is, IES for incongruent stimuli should be shortened with LSF primes as they would  
91 favor predictions, but not in autism. Additional analyses were also preregistered to investigate the  
92 effects of emotion and sex. Accordingly, we expected better performances for happy faces than

93 angry faces for both groups (Favre et al., 2015; Uljarevic & Hamilton, 2013). The investigation  
94 of the effect of sex had exploratory purposes. Sex differences in face processing and in its neural  
95 basis have been highlighted (Shaqiri et al., 2018; Vanston & Strother, 2017), also in relation to  
96 spatial frequency processing (Perilla-Rodríguez et al., 2013). In autism, sex and/or gender  
97 differences are increasingly reported, and greater attention should be paid to these variables  
98 (Strang et al., 2020), as enhanced attention to faces in autistic females compared to autistic males  
99 has been suggested (Harrop et al., 2018, 2019).

## 100 **2 Method**

### 101 **2.1 Participants**

102 Assuming an effect size based on a previous study to perform a power analysis required  
103 three conditions detailed by Lakens (2021): (i) the study is sufficiently similar (ii) the study has a  
104 low risk of bias (iii) the study has a large enough sample size for accurate effect size estimation.  
105 None of these conditions were met in the previous similar studies we can refer to (i.e., Beffara et  
106 al., 2015 and Vanmarcke & Wagemans, 2017, investigating spatial frequency priming on  
107 emotional faces in NA and autistic individuals, respectively). ‘Thus, instead of power analysis,  
108 we determined the sample size from an heuristic (Lakens, 2021). More specifically, we planned  
109 to have a sample size at least as large as in the previous studies (29 NA participants in Beffara et  
110 al., 2015; 26 autistic and 26 NA adolescents in Vanmarcke & Wagemans, 2017) and to approach  
111 sample size requirements suggested by Teare et al. (2014). It should be noted that studies with a  
112 clinical population also depend on resources constraints (Lakens, 2021), including the difficulty  
113 to recruit officially diagnosed and autonomous autistic participants during a limited time period.  
114 Hence, 33 autistic (15 females, 16 males, 2 transgender persons female-to-male) and 35 NA  
115 adults (19 females, 15 males, and 1 transgender person female-to-male) were enrolled in the

116 study. Participants were aged from 19 to 47 years ( $Mean = 32.3$  years,  $SD = 7.8$ ) and reported a  
117 normal or corrected to normal vision. Their full-scale intelligence quotient (FSIQ) was above 70,  
118 as estimated using a Wechsler Intelligence Scale (Wechsler Intelligence Scale for Children, 4th  
119 Edition – WISC-IV- or Wechsler Adult Intelligence Scale - 3rd or 4th Edition or Wechsler  
120 Abbreviated Scale of Intelligence – WAIS-III or WAIS-IV-; Wechsler, 1997, 2003, 2008). We  
121 assessed autistic traits in all participants using the Autism-Spectrum Quotient (AQ - Baron-  
122 Cohen et al., 2001).

123         Autistic participants were recruited with the help of local Expertise Centers dedicated to  
124 autism diagnosis, professionals, or associations for autistic community. We ensured that  
125 volunteers previously received a diagnosis by expert clinicians based on the DSM-IV-R  
126 (American Psychiatric Association, 2000) or DSM-5 (American Psychiatric Association, 2013)  
127 criteria, or on the International Classification of Disease 10th revision (OMS, 1992) by asking  
128 them for the written report of their diagnosis. We collected the scores of the Autism Diagnostic  
129 Observation Schedule (Lord et al., 1989), the Autism Diagnostic Interview-Revised (Lord et al.,  
130 1994) and IQ when they were available. Age at diagnosis was between 10 and 45 years old  
131 ( $Mean = 28.5$  years,  $SD = 10.1$ ). Some of the autistic participants had one or more comorbidities:  
132 Attention Deficit – Hyperactivity Disorder (ADHD,  $N = 3$ , one of them was treated with  
133 methylphenidate), anxiety disorder ( $N = 2$ ) or history of trauma injury ( $N = 2$ ). Six participants  
134 took antidepressants but had no current major depressive episode. Twenty-one autistic  
135 participants did not present co-occurring conditions, nor received any treatment. For those who  
136 could not provide available IQ data ( $N = 8$ ), estimations of their FSIQ, VIQ, and PIQ were  
137 performed using four selected subtests (Vocabulary, Similarities, Block Design and Matrix) of  
138 the WAIS-IV (Grégoire & Wierzbicki, 2009; Wechsler, 2008). Ten ASD participants scored  
139 below the cut-off of 32 on the AQ (Baron-Cohen et al., 2001). Among them, those who had

140 ADOS scores over the cut-off of 7 (Lord et al., 1989) were included in the analyses as AQ is not  
141 a diagnostic tool. However, we excluded participants who had AQ scores < 32 and no ADI or  
142 ADOS scores or ADOS < 7 (cutoff for ASD). Detailed information and scores for each  
143 participant can be found in the data folder on  
144 [https://osf.io/dwgj5/?view\\_only=549ec2f0755142e39056c1a8975cdeef](https://osf.io/dwgj5/?view_only=549ec2f0755142e39056c1a8975cdeef).

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

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

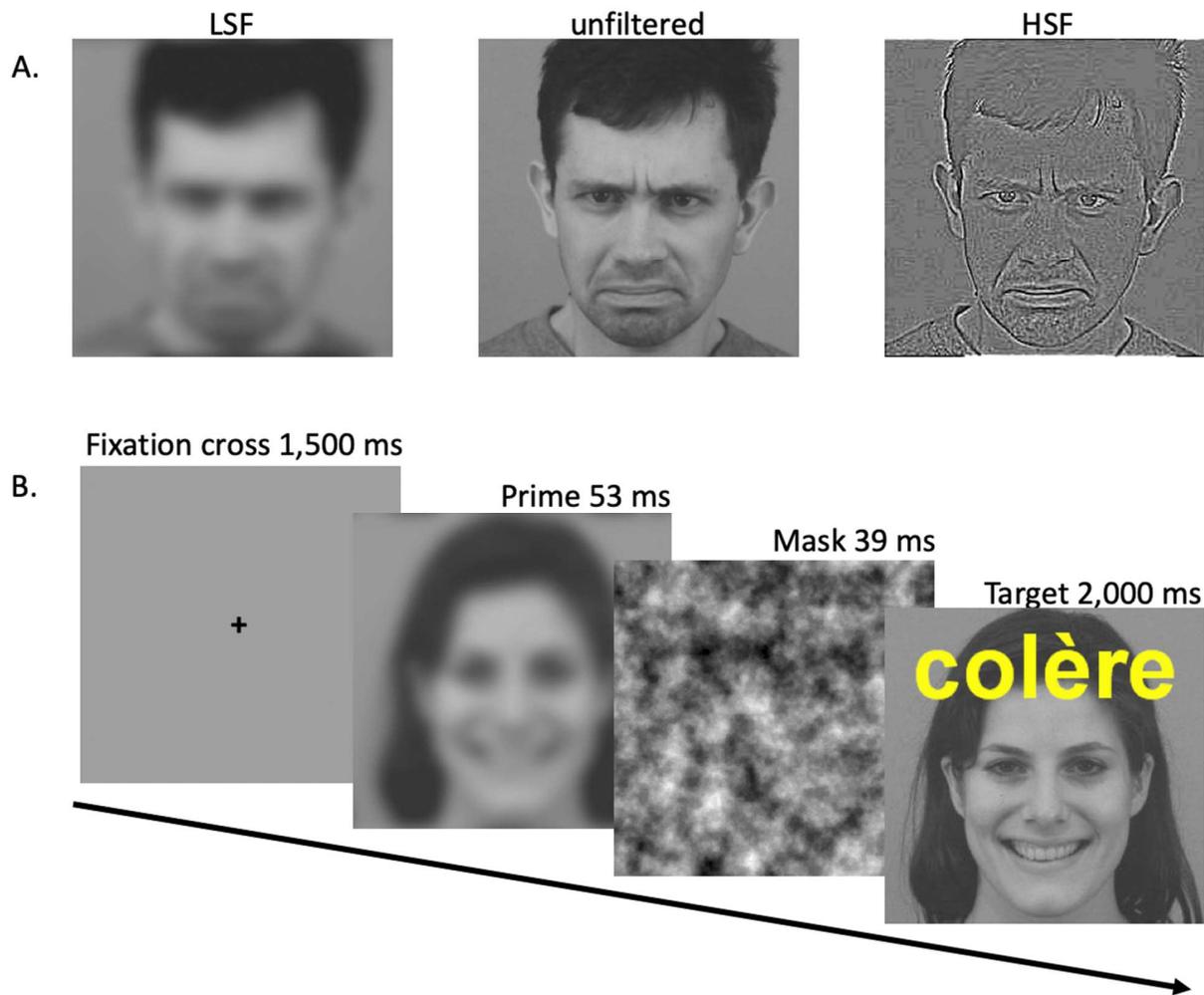
## 156 **2.2 Material and procedure**

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

160 **2.2.1 Emotional Stroop Task with priming.** This task is a similar version to  
161 Beffara et al. (2015). Target stimuli comprised gray scale unfiltered pictures of faces (15 females

162 and 15 males, expressing happiness or anger), 256 x 256 pixels (7.6 x 7.6 degrees for the image;  
163 the face width correspond to 4.6 degrees), from the Karolinska Directed Emotional Faces (Calvo  
164 & Lundqvist, 2008). A yellow word (in French) was displayed in the forehead of the face: “joie”  
165 (i.e., happiness) or “colère” (i.e., anger), in congruence or not with the facial expression. Prime  
166 stimuli were the same face identity as the unfiltered target stimuli, with no word, and were either  
167 filtered in LSF (less than 8 cycles per image /1.05 cpd/ 4.8 cycles per face) or in HSF (more than  
168 64 cycles per image/ 8.42 cpd/ 38 cycles per faces), as shown on *Figure 1 A*. Cutoffs were  
169 chosen through the use of a Gaussian filter to maximize the gap between the two types of  
170 information and avoiding spatial frequency overlap (Beffara et al., 2015). Note that these cutoffs  
171 belong to the range of spatial frequency preferentially used for face processing (from 4.5 to 37  
172 cycle per face; for a review see Jeantet et al., 2018). These primes stimuli were normalized in  
173 contrast and luminance. Spatial frequencies filtering and equalizing procedure were performed  
174 with MATLAB (MathWorks, Natick, MA).

175 Stimuli were displayed centrally on a 23-inch LCD monitor Dell P2319H (refresh rate =  
176 75 Hz, resolution = 800 × 600 pixels) at a viewing distance of 91 cm. To maintain the distance  
177 and central position, participants’ head was supported by a chinrest. E-prime version 2.0  
178 (Psychology Software Tools Inc., Pittsburg, PA) was used to display stimuli and collect  
179 behavioral data.



180

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

184 Instructions were given both orally and on a written form. A training session of 16 trials (2  
 185 faces not included as target stimuli  $\times$  2 Emotions  $\times$  2 Congruency  $\times$  2 Primes) was performed by  
 186 the participant. During the training, participants had a visual feedback mentioning whether the  
 187 response was correct or incorrect. The experimenter also ensured that instructions had been  
 188 correctly understood before leaving the room. The experimental session consisted of 240 trials  
 189 (30 faces  $\times$  2 Emotions  $\times$  2 Congruency  $\times$  2 Primes) with three breaks (every 80 trials). Each trial

190 began with a fixation cross for 1,492 ms, followed by a prime stimulus for 53 ms. Then, to  
191 prevent retinal persistence, a mask appeared for 39 ms. This mask was made of random noise  
192 according to the 1/f decreasing of the amplitude spectra of natural scene images for unfiltered  
193 stimuli. Masks were then filtered with the same LSF or HSF as those used for prime stimuli. The  
194 target stimulus was shown until the participant answered, for a maximum of 2,000 ms.  
195 Participants were asked to answer by pressing with the index of their dominant hand one of the  
196 two corresponding buttons of the Chronos® device (Psychology Software Tools): far-right for  
197 happiness and the next button on the left for anger for right-handed participants, far-left button  
198 for happiness and the next button on the right for anger for left-handed participants. Sides were  
199 not counterbalanced as positive concepts are associated with the right space in right-handed  
200 participants and with the left space in left-handed participants (Casasanto, 2009; Vega et al.,  
201 2013). Participants were instructed to be as fast and accurate as possible. RT from the beginning  
202 of the presentation of the target and CRR were recorded for analysis. The schematic of one trial is  
203 shown on *Figure 1 B*.

### 2.2.2 Color Stroop Task.

204 After the emotional Stroop task, participants  
205 performed the original color Stroop task as a control task to ensure that groups did not differ  
206 neither on their reading abilities nor on their sensitivity to interference (Golden & Freshwater,  
207 1978; Stroop, 1935). Participants were asked to be as fast and as accurate as possible on each of  
208 the three parts of the color Stroop task. First, they were asked to name the color of the item  
209 “XXXX” written on a paper. Then they were asked to read words of colors (“BLUE”, “RED” or  
210 “GREEN”) written in black on a paper. These two parts were used as control situations to  
211 calculate the interference effect for each participant. Finally, during the interference condition,  
212 participants were asked to name the color of a written word by ignoring the word itself (which  
213 was a color word). For each sequence, participants were presented with 5 columns containing 20

214 stimuli each which order was randomized, and they had to perform the task from the top to the  
215 bottom, column by column. Three scores were yielded, one for each of the stimulus sheet, based  
216 on the number of items completed during 45 seconds. The interference score was then calculated  
217 with the procedure of Golden and Freshwater (1978) and all scores were transformed into z-  
218 scores.

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

**2.2.4 Weschler Adult Intelligence Scale.** Verbal Intelligence Quotient (VIQ),  
225 Performance Intelligence Quotient (PIQ) and Full Scale Intelligence Quotient (FSIQ) were  
226 estimated with four selected subtests of the WAIS-IV (Grégoire & Wierzbicki, 2009; Wechsler,  
227 2008): Vocabulary, Similarities, Block Design and Matrix. In case the participant already  
228 performed a Weschler scale, we collected results from the medical record.

## 229 **2.3 Participants and data exclusion**

230 All exclusion criteria were accounted for in the preregistration on <https://osf.io/345jv>. We  
231 excluded participants with a CRR below chance level (50%) at the emotional Stroop task (which  
232 correspond to the exclusion of 1 autistic male and 1 autistic female). We also planned to exclude  
233 participants with several concomitant comorbid conditions which could have influenced the task  
234 (e.g., accumulation of hyperactivity, anxiety and depression) in case they were not excluded  
235 during the recruitment (as sometimes participants do not mention comorbidities before the day of

236 the study). However, the case did not appear. Finally, we also preregistered to exclude  
237 participants who were outliers (CRR or RT below Quartile 1 – 1.5 × Interquartile range or above  
238 Quartile 3 + 1.5 × Interquartile Range) on more than half of the conditions (2 females and 1 male  
239 in the autistic group, and 2 females and 1 male in the NA group). We included these participants  
240 in the final sample, as we also performed the analysis by excluding them, which did not change  
241 our conclusions (see *Supplementary Materials, part 2*).

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

## 243 **2.4 Main analytical strategy**

### 244 **2.4.1 Pre-registered analysis.**

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

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

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

279 All parameters included in the finite set of models that we considered are justified by our  
280 pre-registered hypotheses and theoretical questions. Thus, to test our main hypothesis of a

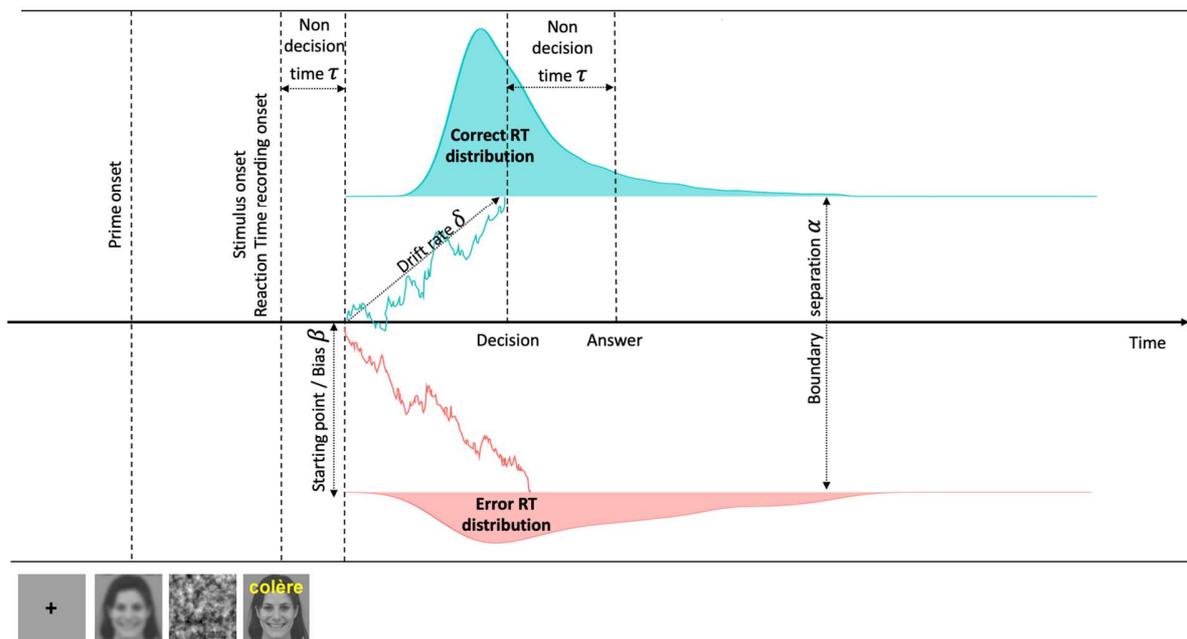
281 difference in the priming effect during the incongruent condition between ASD and NA, we  
282 analyzed data using Group (ASD vs. NA) as between-subject predictor as well as Prime (LSF  
283 vs. HSF) and Congruency (Incongruent vs. Congruent) as within-subject predictors. As we also  
284 planned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

#### 2.4.2 Exploratory analysis.

Given the caveats previously mentioned to analyze  
298 CRR (i.e., ceiling effect) and IES (i.e., variability in CRR and non-significant correlation between  
299 CRR and RT) with planned analysis, we performed an additional exploratory analysis using Drift  
300 Diffusion Models (DDMs), which allows analyzing data from two alternative force choice tasks  
301 when accuracy and RT are recorded together. The DDM assumes that in each trial of a task,  
302 evidence is accumulated in a noisy process until the accumulator hits one of the two decision  
303 bounds (Ratcliff & McKoon, 2008), which in our case, is a correct or incorrect response. The  
304 DDM decomposes the data into four latent cognitive processes (Wagenmakers, 2009) represented

305 in *Figure 2*. The drift rate  $\delta$  (delta) is the average slope of the accumulation process toward the  
306 boundaries, representing the ease of processing (the larger, the easier). The boundary separation  
307  $\alpha$  (alpha) is the distance between the two decision bounds, representing the response caution (the  
308 larger, the more cautious). The non-decision time  $\beta$  (beta) encapsulates non-decision processes  
309 such as encoding and motor response. Finally, the bias  $\tau$  (tau) represents the bias toward one of  
310 the two responses. Having a bias toward one response means that the preferred response is  
311 initiated quickly and often (Voss et al., 2004). Whereas the bias can be fixed at 0.5 (representing  
312 a neutral bias / an unbiased model - Voss et al., 2004), in the present study it was interesting to  
313 estimate it according to the Group and the Prime as RT was recorded from the stimulus onset,  
314 that is after the processing of the prime. Thus, the prime might influence the bias. The total RT  
315 corresponds to the sum of the decision and non-decision components. More details on these  
316 models and the analytic strategy adopted can be found in the *Supplementary Materials, parts 4, 5,*  
317 *and 6*. We chose the best model using the WAIC (Watanabe – Akaike information criterion - Yao  
318 et al., 2018).

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



327

328 *Figure 2.* Graphical illustration of the Wiener diffusion model applied to the emotional Stroop

329 task. RT = Reaction Time

330

### 3 Results

331 All figures and analyses were done using R version 3.6.1 (R Core Team, 2020) and R

332 Studio version 1.2.5019 (RStudio Team, 2020).

#### 3.1 Group Comparison

334 Groups comparison on Age, Education, FSIQ, PIQ, VIQ, AQ as well as reading and

335 interference effect (on the color Stroop task) were performed with Bayesian independent t-tests

336 using the BayesFactor package (Morey &amp; Rouder, 2018) with default priors (the scale of the

337 Cauchy prior was fixed to  $\sqrt{2}/2$ ). We reported the Bayes factor in favor of the null hypothesis338 ( $BF_{01}$ ), which allows quantifying the relative evidence in favor of the null hypothesis compared339 to the alternative hypothesis (Wagenmakers et al., 2018). For instance, “ $BF_{01}= 2$ ” means that the

340 data are two times more likely under the null hypothesis than under the alternative hypothesis.  
341 Thus, the BF is interpreted in a continuous manner. However, for a more categorical  
342 interpretation, we referred to common guidelines (Jarosz & Wiley, 2014; Jeffreys, 1961; Lee &  
343 Wagenmakers, 2013), with  $BF_{01}$  below one indicating evidence in favor of the alternative  
344 hypothesis. More specifically, a  $BF_{01}$  from 1/10 to 1/3 indicates moderate evidence in favor of the  
345 alternative hypothesis; a  $BF_{01}$  from 1/30 to 1/10 indicates strong evidence and a  $BF_{01}$  less than  
346 1/30 indicates very strong evidence in favor of the alternative hypothesis. Symmetrically, a  $BF_{01}$   
347 from 3 to 10 indicates moderate evidence in favor of the null hypothesis; a  $BF_{01}$  from 10 to 30  
348 indicates strong evidence and a  $BF_{01}$  over than 30 indicates very strong evidence in favor of the  
349 null hypothesis. A  $BF_{01}$  from 1/3 to 3 indicates no remarkable evidence (i.e., anecdotal or  
350 inconclusive evidence).

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

360

361

362 Table 1:

363 *Subject demographics – Means (M), standard deviations (SD) and BF01.*

	ASD (N=27)	NA (N=34)	BF01
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 x 10 <sup>-15</sup>
Reading	-0.03 (0.98)	-0.12 (0.59)	3.548
Stroop Effect	0.46 (0.78)	0.53 (0.76)	3.655

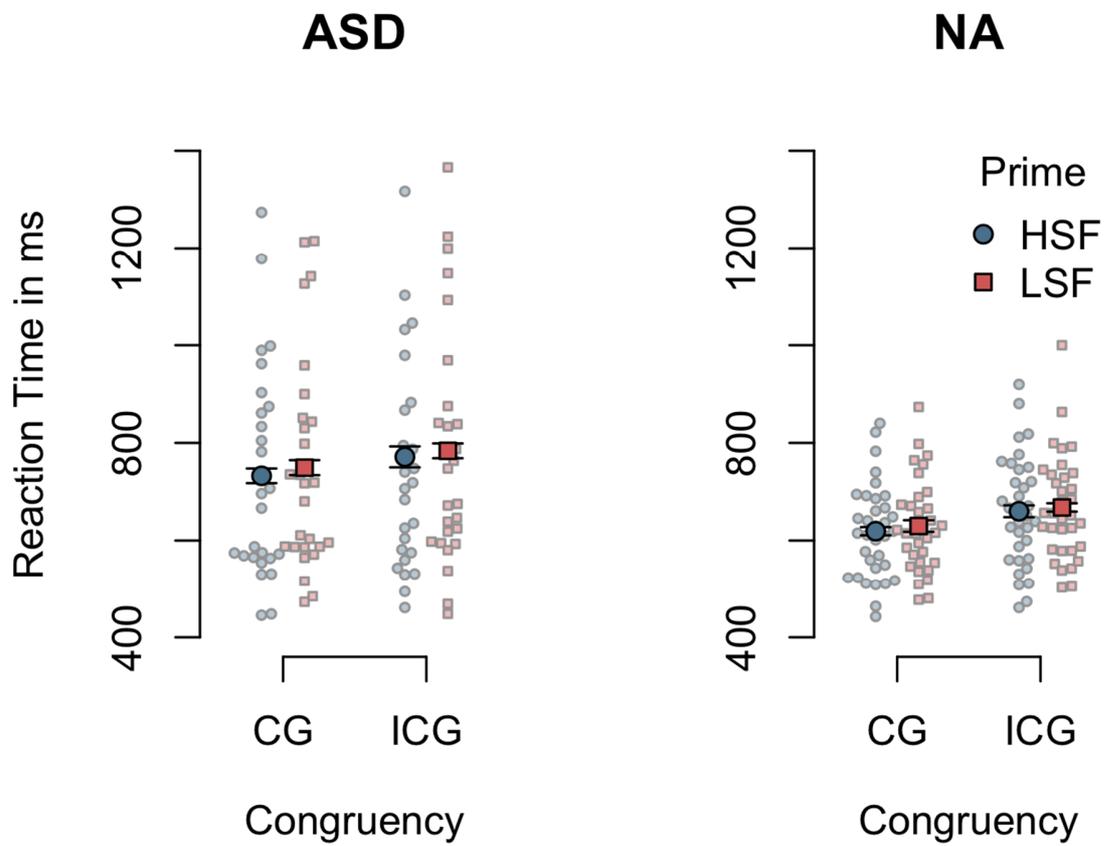
364 *Note.* \*FSIQ = Full Scale Intelligence Quotient; VIQ = Verbal Intelligence Quotient; PIQ =  
 365 Performance Intelligence Quotient ; AQ = Autism-Spectrum Quotient ; ASD = Autism Spectrum  
 366 Disorder ; NA = Non Autistic

367

### 368 **3.2 Preregistered analysis (response time analysis)**

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

375 For all analyses, posterior convergence was assessed using trace plots and the Gelman-  
376 Rubin diagnostic  $\hat{R}$  (Rhat). We summarized fixed effect estimates via their posterior mean and  
377 95% credible interval (CrI), which contains the 95% most probable values of a parameter given  
378 the model, the data and the prior (Baldwin & Larson, 2017). Bayesian CrIs provide an intuitive  
379 interpretation of the parameter (Baldwin & Larson, 2017; Nalborczyk et al., 2019) and are also  
380 useful to summarize uncertainty (i.e. the wider the interval, the most uncertain is the parameter  
381 estimate). We also reported the  $BF_{01}$ .

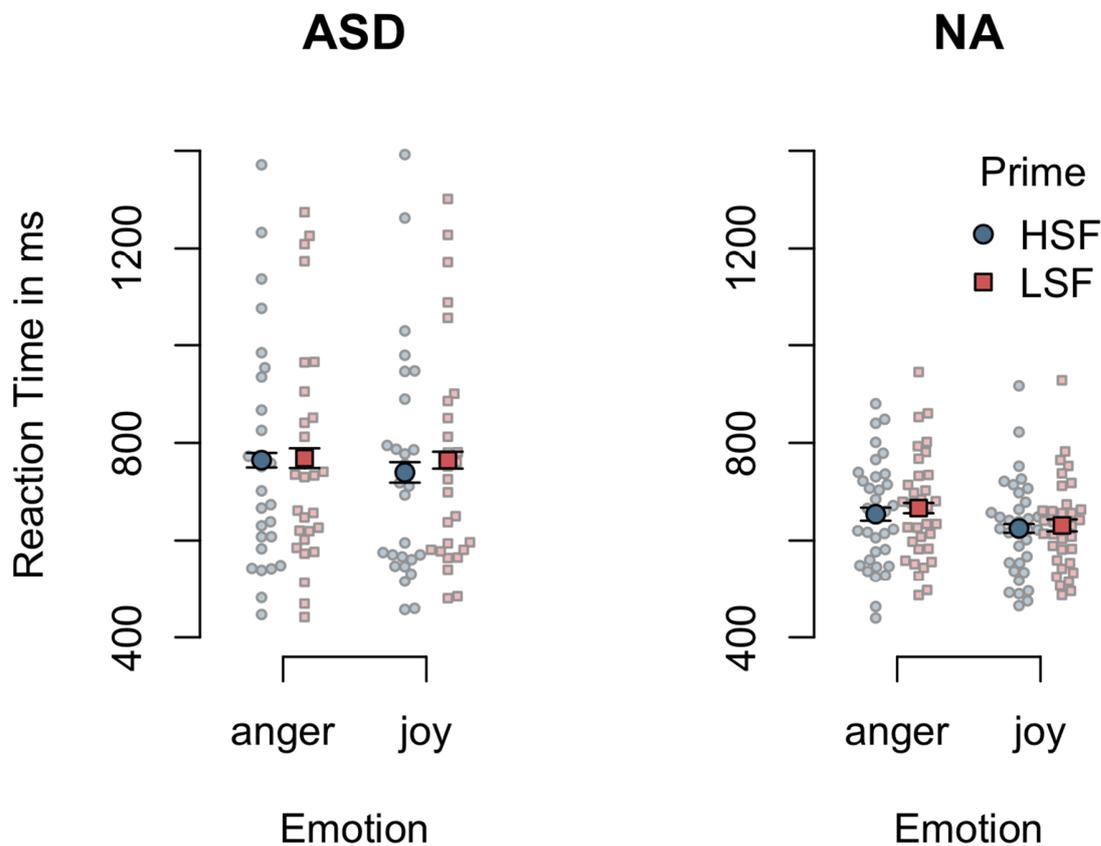


382

383 *Figure 3.* Distribution of RT (ms) according to group, prime and congruency. Small points

384 represent mean RT by participant, large points represent condition mean RT and error bars

385 represent within-subjects 95 % confidence interval. CG = congruent; ICG = incongruent.



386

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

390 The results of the BMLM are summarized in *Supplementary Materials, Table 3*. The  
 391 analysis revealed a main effect of Congruency, with very strong evidence for faster RT for  
 392 congruent trials ( $Mdn = 602$  ms,  $IQR = 501 - 765$ ) than for incongruent trials ( $Mdn = 631$  ms,  
 393  $IQR = 516 - 818$ ;  $\beta = -14.78$ , 95% CrI [-20.64, -9.17],  $BF_{01} = 1.481 \times 10^{-4}$ ), accounting for the  
 394 efficiency of the emotional Stroop effect in our experiment.  $BF_{01}$  indicated strong evidence for  
 395 the effect of Group, with longer RTs in the ASD group ( $Mdn = 664$  ms,  $IQR = 531 - 883$ )

396 compared to NA ( $Mdn = 586$  ms,  $IQR = 492 - 725$ ), with a large uncertainty on the mean estimate  
397 as expressed by the width of the credible interval ( $\beta = 66.78$ , 95% CrI [16.93, 113.38],  $BF_{01} =$   
398 0.069). There was moderate evidence for an effect of Emotion ( $\beta = 18.9$ , 95% CrI [5.59, 31.99],  
399  $BF_{01} = 0.194$ ), with slower RT for anger ( $Mdn = 627$  ms,  $IQR = 517 - 803$ ) than for happiness  
400 ( $Mdn = 605$  ms,  $IQR = 498 - 771$ ). Regarding the main effect of Prime, there was very strong  
401 evidence for faster RT after HSF primes ( $Mdn = 609$  ms,  $IQR = 501 - 783$ ) than after LSF primes  
402 ( $Mdn = 623$  ms,  $IQR = 512.5 - 795.5$ ;  $\beta = -12.91$ , 95% CrI [-18.7, -6.93],  $BF_{01} = 1.277 \times 10^{-4}$ ).  
403 Critically, we did not observe the expected three-way interaction between Group x Prime x  
404 Congruency, graphically represented on *Figure 3* ( $\beta = 2.28$ , 95% CrI [-14.63, 19.04],  $BF_{01} =$   
405 5.494). However, there was anecdotal evidence for a positive interaction between Group x Prime  
406 x Emotion ( $\beta = 21.19$ , 95% CrI [3.08, 39.21],  $BF_{01} = 0.403$ ), as depicted in *Figure 4*. Post-hoc  
407 analysis revealed that HSF primes led to reliably shorter RTs than LSF primes for happiness ( $\beta =$   
408 20.74, 95% CrI [ 9.71, 31.49]) in the ASD group, but the effect was three times smaller and more  
409 uncertain for anger ( $\beta = 6.48$ , 95% CrI [ -4.22, 17.72]). In the NA group, the opposite was  
410 observed: reliably shorter RTs for HSF primes than LSF primes for anger ( $\beta = 15.73$ , 95% CrI [  
411 6.10, 25.19]) but a less reliable effect and two times smaller for happiness ( $\beta = 8.82$ , 95% CrI [  
412 0.78, 18.61]).

### 413 3.3 Exploratory analysis (Drift Diffusion Modeling)

414 This exploratory analysis did not include Sex or Emotion. Model comparison revealed that  
415 the best model (i.e., the model with the lowest WAIC) was the model including Congruency,  
416 Prime, Group (and their interactions) as predictors on the drift rate, as well as Group as predictor  
417 on the boundary separation, the non-decision time and the bias, and random intercepts by  
418 participant for each parameter. We also added the effect of Prime and Group x Prime interaction

419 on the bias, as each trial began at the stimulus presentation, after the prime. Posterior predictive  
420 checking (represented in *Supplementary Materials, Figure 16*) shows that the model was efficient  
421 at simulating data that looks like the observed data. The detailed results of the DDM can be found  
422 in the *Supplementary Materials, Table 10*.

423 The analysis revealed extremely strong evidence that Congruency increased the drift rate  
424 ( $\beta = 0.32$ , 95% CrI [0.27, 0.38],  $BF_{01} \approx 0$ ). In other words, congruent stimuli were easier to  
425 process than incongruent stimuli. Additionally, there was anecdotal evidence that Prime  
426 decreased the drift rate ( $\beta = -0.11$ , 95% CrI [-0.2, -0.03],  $BF_{01} = 0.516$ ), indicating that stimuli  
427 with HSF prime were easier to process than those with LSF prime. There was also moderate  
428 evidence that the Group has no influence on the drift rate ( $\beta = -0.01$ , 95% CrI [-0.42, 0.38],  $BF_{01}$   
429 = 4.872).

430 Because both the boundary separation and the non-decision time parameters need to be  
431 larger than 0, we used a log link function for these two parameters. Therefore, we have to apply  
432 the inverse link function (i.e.,  $\exp(\beta_i)$ ) to interpret them. For the boundary separation (i.e.,  
433 response caution),  $\exp(\beta_1) \approx 1.08$  which means that going from NA to ASD led to an increase of  
434 approximately 8 % of the boundary-separation parameter value. However, this effect was more  
435 likely to appear under the null hypothesis ( $BF_{01} = 6.715$ ). For the non-decision time,  $\exp(\beta_1) \approx$   
436 1.20 which means that going from NA to ASD led to an increase of approximately 20 % of the  
437 non-decision time parameter value. In other words, non-decisional processes took longer in the  
438 ASD group than in the NA group with very strong evidence ( $BF_{01} = 0.011$ ). The linear model for  
439 the bias parameter is on the logit (log-odds). For the bias parameter,  $\exp(\beta_1) \approx 1.17$  meaning that  
440 going from LSF to HSF increased of approximately 17 % the bias parameter odd-ratio. HSF

441 (vs. LSF) primes were associated with a “bias” towards accurate responses with extreme  
442 evidence ( $BF_{01} = 1.618 \times 10^{-17}$ ).

## 443 **4 Discussion**

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

### 457 **4.1 Decreased RT with congruent stimuli and with happy faces**

458 The present results revealed the expected emotional Stroop effect, with incongruent  
459 stimuli increasing RT, accounting for the interference of the written emotion during the  
460 processing of the target (emotional face). This result replicates previous findings (Agustí et al.,  
461 2017; Beffara et al., 2015; Favre et al., 2015; Ovaysikia et al., 2011; Shankland et al., 2021)  
462 regardless of some methodological differences (e.g. location of the word), and extended them to

463 autism. Results from the complementary analysis using DDM are in line with BLMM analysis on  
464 RT, showing that incongruent stimuli decrease the ease of processing, in accordance with a recent  
465 study using DDM on a Stroop paradigm in NA (Lin et al., 2020). We also found a main effect of  
466 Emotion, with happy faces decreasing RT in both groups. This happy faces advantage was  
467 observed in a previous study employing an emotional Stroop paradigm in bipolar individuals and  
468 controls (Favre et al., 2015), and is also in line with positive facial expressions being recognized  
469 faster than negative ones (Calvo & Nummenmaa, 2016; Leppänen & Hietanen, 2003, 2004).  
470 Faster processing of happy faces can be explained by the highly distinctive perceptual features of  
471 these stimuli, such as open mouth with visible teeth (for a review, see Calvo & Nummenmaa,  
472 2016), or could be related to the tendency to have positive bias about individuals in relation to a  
473 normatively positive mood (Diener & Diener, 1996; Leppänen & Hietanen, 2003, 2004).

#### 474 **4.2 No evidence of top-down predictions from LSF**

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

484 Firstly, while filtering is frequently carried out to disentangle global from local  
485 processing, there are some limits to this approach. Contrary to local information, which is only

486 conveyed by HSF, global information can be extracted by both LSF and HSF (see Corradi-  
487 Dell'Acqua et al., 2014). Indeed, even with HSF only, a global parsing can be realized by  
488 integrating details together, assuming that there is more available information in HSF primes  
489 compared to LSF primes. Additionally, the use of a Gaussian filter shape (commonly used for  
490 spatial frequency filtering) has the advantage to reduce artifacts on HSF images but does not  
491 entirely exclude the unwanted part of the spectrum (Perfetto et al., 2020). Hence, Perfetto et al.  
492 (2020) recently showed that the direction of the differences in accuracy can switch according to  
493 the type of filter used. Critically, the authors highlighted that the use of Gaussian filters lead to  
494 HSF advantage over LSF in scene categorization (with a stimulus presented during 53 ms  
495 followed by a 500 ms mask). Given these, the Coarse-to-Fine processing might be not observable  
496 in our experiment, but could be revealed with other stimuli where local and global information  
497 could be orthogonalized.

498         Secondly, beyond the filter characteristics mentioned above, studies' findings are also  
499 determined by other differences in spatial frequency filtering choices (Perfetto et al., 2020). One  
500 important point is contrast normalization, which is critical to assess the role of spatial frequency  
501 without being influenced by the difference in contrast energy contained in LSF and HSF (Perfetto  
502 et al., 2020). Absence of contrast normalization disadvantages HSF processing (Perfetto et al.,  
503 2020) and could thus induce a LSF bias. However, most studies on emotional face perception use  
504 stimuli normalized in contrast. A second important point is the cutoffs used for spatial filtering,  
505 which differ from one study to another. Despite the LSF cutoff used in our study (8 cycles per  
506 image/4.83 cycles per face/1.05 cpd) belonging to the range of spatial frequency preferentially  
507 used for face processing (from 4.5 to 37 cycle per face; for a review see Jeantet et al., 2018) and  
508 is similar or superior to some studies (e.g., Vuilleumier et al., 2003 has a cutoff of 6 cycles per  
509 image), it is slightly lower than cutoffs applied in other studies (Goffaux et al., 2011; Khalid et

510 al., 2015; Schyns & Oliva, 1999). It is possible that the use of a higher cutoff (e.g., 2 cpd) could  
511 affect the results. Thus, to better compare results across studies and to draw consistent  
512 conclusions, future studies would benefit (i) from using more standardized procedure regarding  
513 spatial frequency filtering, as suggested by Perfetto et al. (2020), who provided recommendation  
514 and code for filtering procedure, and (ii) from testing different band pass filters.

515 Thirdly, the time course of the task could affect spatial frequency processing and HSF  
516 advantage. Indeed, LSF advantage has been found for short exposure duration (i.e., 30 ms, 75  
517 ms), whereas longer exposure duration would favor HSF (Goffaux et al., 2011; Schyns & Oliva,  
518 1997). In the current experiment, the exposure time of the prime stimulus was indeed short (53  
519 ms) but followed by a mask (39 ms) and by the target stimulus (2,000ms). The backward  
520 masking appearing 53 ms after the prime onset might prevent retinal persistence but not the  
521 extraction and accumulation of visual information necessary for achieving the task (see Bacon-  
522 Macé et al., 2005), which is moreover reinforced by information in the target stimulus, that have  
523 a long presentation. This hypothesis is also supported by brain activity recorded in face-  
524 responsive regions (i.e. FFA, occipital face area, and superior temporal sulcus) during a fame-  
525 judgment task with masked primes (Kouider et al., 2009). Interestingly, supplementary analysis  
526 using DDM reinforces this idea. In our design, RT were considered from the beginning of the  
527 target and results showed enhanced bias toward good answers after presentation of HSF prime.  
528 However, we also found evidence that HSF primes enhanced the ease of processing, although  
529 anecdotal, which could be in line with the processing of the prime still ongoing. The design of the  
530 task could favor HSF for decision-making and not completely exclude Coarse-to-Fine processing  
531 in the former stages, which can be further investigated with neurophysiological exploration in  
532 addition to behavioral responses (Bar et al., 2006; Goffaux et al., 2011; Kauffmann et al., 2015;  
533 van Ravenzwaaij et al., 2016).

534 Finally, some studies suggested that HSF, and not LSF only, could play an important role  
535 in the early stages of face processing (De Gardelle & Kouider, 2010; Halit et al., 2006).  
536 Importantly, De Gardelle and Kouider (2010) reported subliminal priming effect for both HSF  
537 and LSF primes during an identification task of famous faces, showing that both frequency bands  
538 can be unconsciously perceived and that the parallel extraction of HSF and LSF information  
539 could limit the generalization of the Coarse-to-Fine model. The authors related their findings to  
540 the diagnostic model developed by Schyns and Oliva (1999). According to this model, the use of  
541 spatial frequency scale would be flexible and modulated by the task (Schyns & Oliva, 1999;  
542 Smith & Merlusca, 2014). Hence, the diagnostic information (i.e., information required for  
543 achieving the task) could vary according to the emotions used in the task, with happy face  
544 (Kumar & Srinivasan, 2011; Schyns & Oliva, 1999) and fearful face (Holmes et al., 2005;  
545 Vuilleumier et al., 2003; Winston et al., 2003) recognition relying more on LSF, while sadness  
546 relying more on HSF (Kumar & Srinivasan, 2011). However, it can also vary according to the  
547 type of task. For instance, happy face recognition could rely more on HSF when an explicit  
548 judgment is required, such as the degree of happiness. This could be explained by HSF  
549 conveying fined details about wrinkles that are necessary for the task (Jeantet et al., 2018). It is  
550 possible that diagnostic information in our task relies more on HSF than LSF as well. Indeed,  
551 global processing (relying on LSF) could interfere with the inhibition of the word written on the  
552 forehead of the target stimulus. On the contrary, using a local processing (i.e., HSF) by focusing  
553 on local features such as the mouth region, could facilitate the inhibition of the word.  
554 Interestingly, this strategy was reported by several autistic and NA participants at the end of the  
555 experiment.

556 Nevertheless, these hypotheses do not fully explain the differences between our results  
557 and those reported by Beffara et al. (2015) on NA participants (as the stimuli were the same),

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

### 571 **4.3 Different visual processing style in autism**

572 We found a main effect of Group, with autistic participants being slower than NA  
573 participants. This effect is in line with our expectations and with other studies on face processing  
574 in autism (e.g., Grossman et al., 2000; Harms et al., 2010; Kovarski et al., 2019). The exploratory  
575 analysis shows that while there is no group difference on the drift rate, meaning that evidence  
576 accumulation is similar in both groups, a difference between groups exists on the non-decision  
577 time, which is longer in autistic participants. This pattern could simply reflect that the task in  
578 itself is not more difficult for autistic participants compared to NA participants, but groups might  
579 differ on other aspects, such as encoding or motor response (Pirrone et al., 2017). The non-  
580 decision time encompasses the non-decision processes from the stimulus encoding to the motor

581 response. Unfortunately, these processes cannot be disentangled here. Additionally, whereas  
582 DDM is a well-established approach, it should be noted that exactly which cognitive processes  
583 are reflected in RT is still a matter of debate (see Weindel et al., 2020). Thus, even if it could be  
584 surprising that a much longer RT observed in some autistic participants is only due to perceptual  
585 and motor processes, we cannot rule out that some other decisional and non-decisional processes  
586 are also involved, despite not yet determined with these models. Additionally, it should be noted  
587 that motor time (included in non-decisional processes) can vary according to several  
588 experimental factors, including cognitive processes (Buc Calderon et al., 2015; Weindel et al.,  
589 2020). For these reasons, further studies joining DDM and EEG recording could help to assess if  
590 inferences from the model are compatible with electrophysiological activity (Weindel et al.,  
591 2020), and to determine whether visual encoding differs between autistic and NA participants.  
592 For instance, it could be done by investigating the N200 peak latencies similarly to Nunez et al.  
593 (2019). Indeed, N200 is suspected to be related to pre-attentive phase before evidence  
594 accumulation and is suggested to track visual encoding (Nunez et al., 2019). Combining  
595 behavioral data, mathematical models, and neurophysiology is as promising as it is challenging,  
596 particularly because a “linking functions” between the processes has yet to be defines (Schall,  
597 2019; Weindel et al., 2020). However, new approaches are being developed in that direction  
598 (Turner et al., 2016; van Ravenzwaaij et al., 2016; Weindel et al., 2020).

599 Surprisingly, few studies have investigated differences between autism and NA using  
600 DDM. Pirrone et al. (2017) used DDM on a perceptual judgment task (i.e., orientation  
601 discrimination) and found similar drift rate, wilder boundary separation parameter, and increased  
602 non-decision time in autistic adults compared to NA. On the contrary, Powell et al. (2019) found  
603 smaller drift rate, smaller boundary separation and comparable non-decision time in autistic  
604 compared to NA adolescents during a face identification task. The differences in the results could

605 be explained by the use of different tasks (e.g., orientation discrimination, face identification, or  
606 emotion recognition with inhibition and priming) and/or by age differences (adults vs  
607 adolescents). Additionally, there is a great heterogeneity in our ASD group, which might  
608 implicate the existence of ASD subgroups and could also explain that, contrary to Powell et  
609 al. (2019) we did not find group differences on the drift rate. Similarly to Powell et al. (2019), we  
610 suggest that DDM refined our understanding of group differences between autism and typical  
611 development, as analyses on RT, CRR, or IES only, could mask differences in specific cognitive  
612 processes. Futures studies should be considered for the investigation of specific hypotheses on  
613 parameters.

614         Critically, the expected three-way interaction between Group, Prime, and Congruency was  
615 not observed. Thus, we could not confirm our main hypothesis inferring impairments in top-down  
616 processing initiated by LSF primes in autism. However, the results reveal a different pattern of  
617 spatial frequencies processing according to the emotion in autism compared to NA. While autistic  
618 participants answered reliably faster after HSF primes for happy faces, the effect was reduced for  
619 angry faces. In NA, happiness is recognized faster and more accurately compared to other  
620 emotions in paradigms using forced-choice response (for a review, see Calvo & Nummenmaa,  
621 2016). Despite the existence of inconsistencies across studies, accuracy in autistic individuals  
622 usually differs little from NA in happiness recognition when the emotion is well characterized,  
623 but differs for other emotions, particularly for negative ones (Ashwin et al., 2006) such as anger  
624 or fear, but also surprise (for a review, see Uljarevic & Hamilton, 2013). Thus, the findings of the  
625 present study suggest that efficient emotion recognition in autism might rely on HSF. This  
626 hypothesis is supported by the local bias reported in autism while processing non-social (Kéïta et  
627 al., 2014; Mottron et al., 2006) and social stimuli (Deruelle et al., 2008; Jemel et al., 2006). On  
628 the contrary, NA answered reliably faster after HSF primes for anger, and the effect was smaller

629 and less reliable for happiness. This might be explained by the availability of spatial frequency  
630 information for correctly performing the task (De Gardelle & Kouider, 2010). In NA individuals,  
631 faster happiness recognition is usually driven by LSF information (see Jeantet et al., 2018). Thus,  
632 happy faces might be processed more globally than angry faces, suggesting that LSF primes  
633 would be more useful for happy faces than for angry faces. As a consequence, the difference in  
634 RT after HSF primes and LSF primes would be smaller for happy faces than for angry faces.

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

#### 653 **4.4 Sex differences**

654 Differences between non autistic males and females have been found in various aspects of  
655 vision according to a study including 800 participants (Shaqiri et al., 2018). Additionally, males  
656 and females differ in emotional face processing and in the neural network of face processing (for  
657 a review see, Vanston & Strother, 2017). Some dissimilarities are also observed in autism with  
658 autistic females exhibiting better social attention (Harrop et al., 2019), as well as better  
659 camouflaging abilities compared to autistic males (Schuck et al., 2019). Despite the increasing  
660 interest in sex effects in both typical and atypical populations, their relation to perceptual  
661 processes have been rarely studied in autism. While sex was present in the initial analysis,  
662 accordingly to preregistration, the best model did not include this variable. Thus, further research  
663 should be carried out while including autistic females and considering sex in analyses with larger  
664 samples.

#### 665 **4.5 Limitations**

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



698 help to disentangle which type of non-decision processes differ between autism and NA during  
699 visual processing of emotional faces.

## 700 **6 Declaration**

### 701 **6.1 Ethics approval and consent to participate**

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

### 707 **6.2 Availability of data and materials**

708 The datasets generated and/or analyzed during the current study are available in the Open  
709 Science Framework repository,  
710 [https://osf.io/dwgj5/?view\\_only=549ec2f0755142e39056c1a8975cdeef](https://osf.io/dwgj5/?view_only=549ec2f0755142e39056c1a8975cdeef). Any other materials are  
711 available from the corresponding author on reasonable request.

### 712 **6.3 Competing interests**

713 The authors declare that they have no competing interests.

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## 718 **6.5 Author's contribution**

719 **Adeline Lacroix**: Conceptualization; Data curation; Formal analysis; Funding acquisition;  
720 Investigation; Methodology; Project administration; Resources; Software; Supervision;  
721 Validation; Visualization; Writing - original draft, review and editing **Ladislav Nalborczyk**: Data  
722 curation; Formal analysis; Methodology; Roles/Writing - original draft; Writing - review &  
723 editing **Frederic Dutheil**: Writing - review & editing **Klara Kovarski**: Writing - review &  
724 editing **Sylvie Chokron**: Writing - review & editing **Marta Garrido**: Writing - review & editing  
725 **Marie Gomot**: Data curation; Writing Review & Editing **Martial Mermillod**:  
726 Conceptualization; Funding acquisition; Supervision; Methodology; Data curation; Writing -  
727 review & editing

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