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

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26

27 **1 Background**

28 Autism Spectrum Disorder (ASD)¹ 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.

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.

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 = Response Time/Correct
64 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.

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).

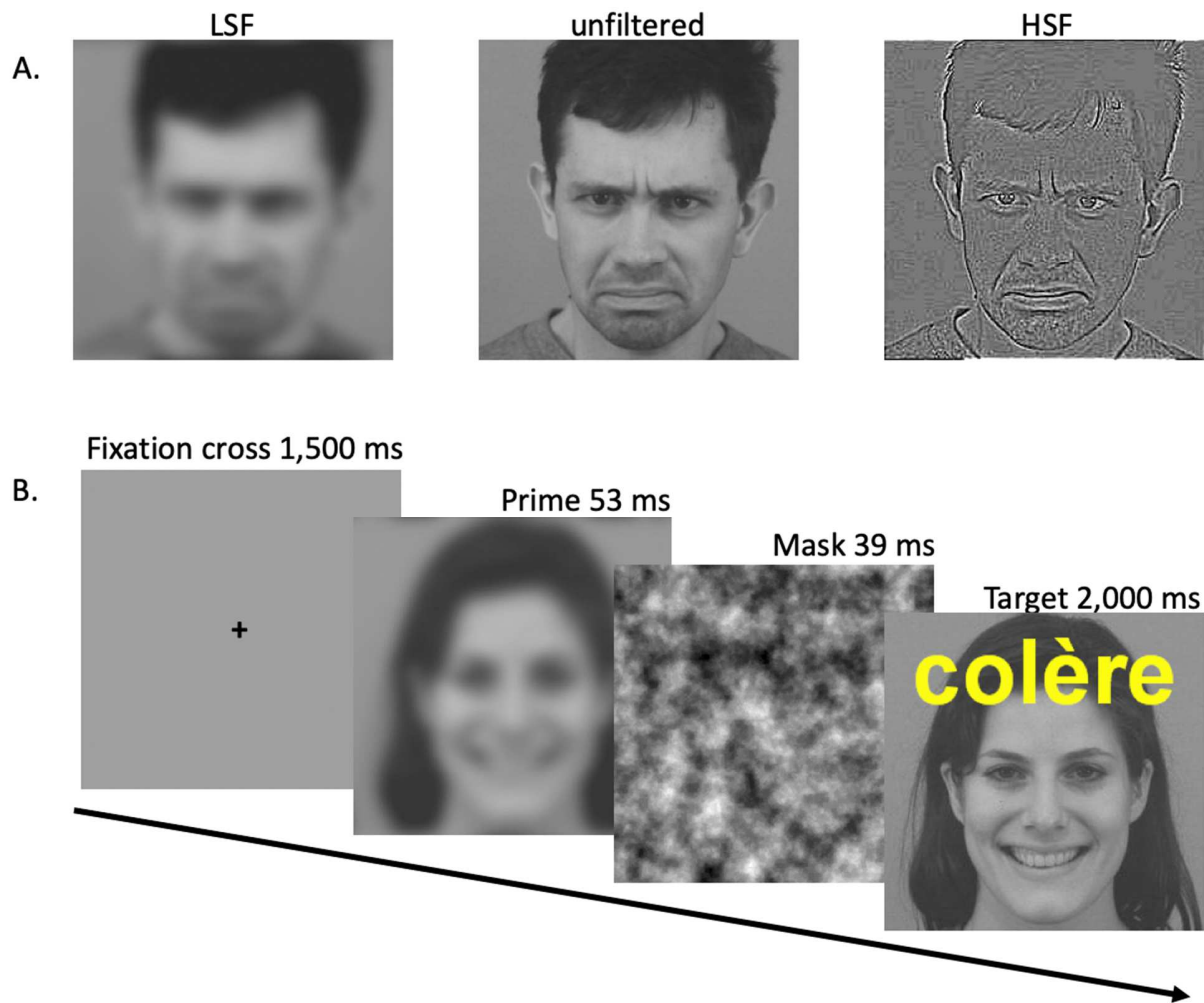
156 **2.2 Material and procedure**

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. 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

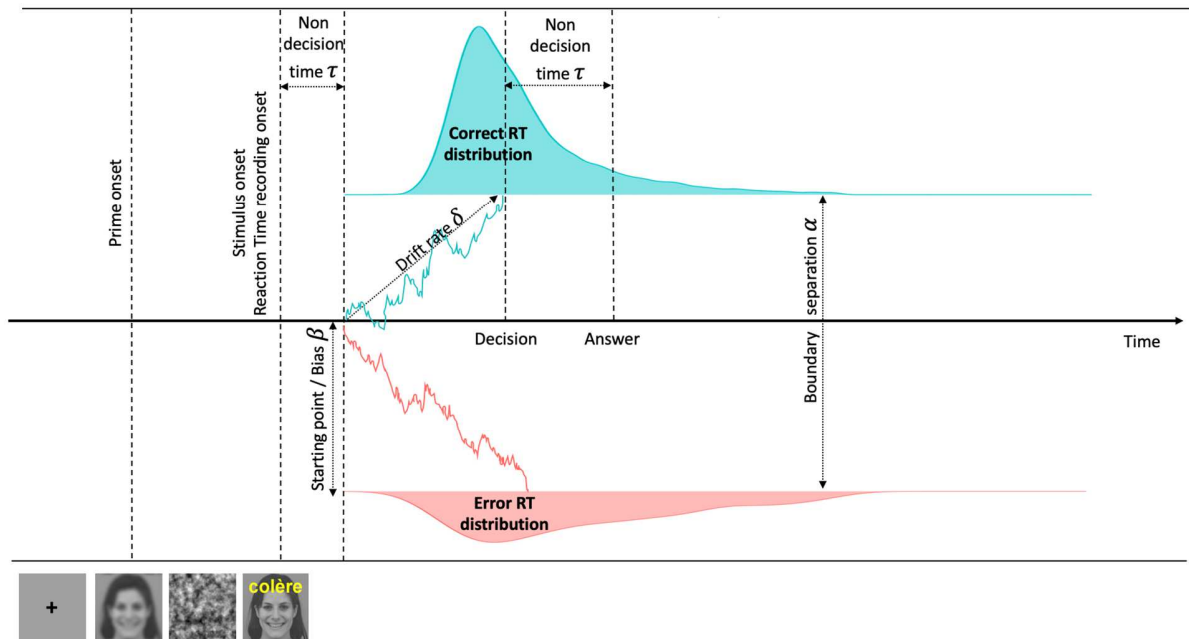
281 difference in the priming effect during the incongruent condition between ASD and NA, we
282 analyzed data using Group (ASD vs. NA) as between-subject predictor as well as Prime (LSF
283 vs. HSF) and Congruency (Incongruent vs. Congruent) as within-subject predictors. As we also
284 planned to study 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 δ (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 α (alpha) is the distance between the two decision bounds, representing the response caution (the
308 larger, the more cautious). The non-decision time β (beta) encapsulates non-decision processes
309 such as encoding and motor response. Finally, the bias τ (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 & 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 ⁻¹⁵
Reading	-0.03 (0.98)	-0.12 (0.59)	3.548
Stroop Effect	0.46 (0.78)	0.53 (0.76)	3.655

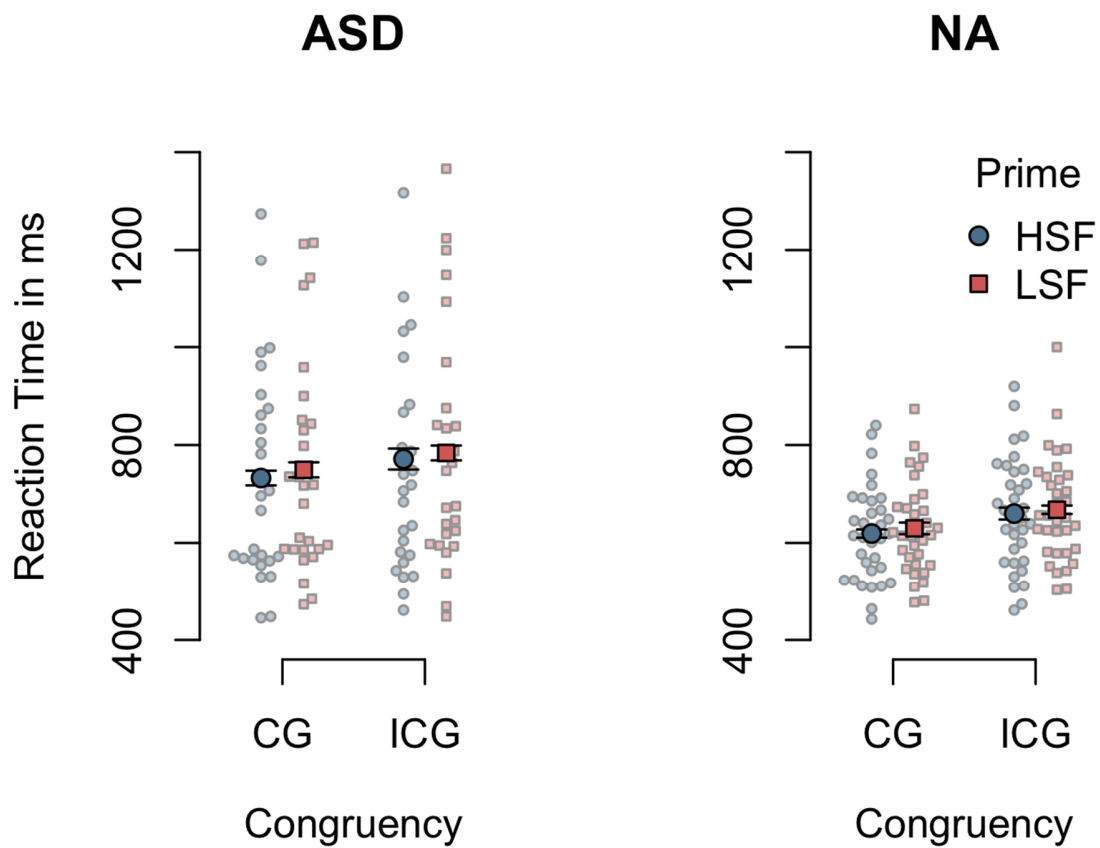
364 *Note.* *FSIQ = Full Scale Intelligence Quotient; VIQ = Verbal Intelligence Quotient; PIQ =
 365 Performance Intelligence Quotient ; AQ = Autism-Spectrum Quotient ; ASD = Autism Spectrum
 366 Disorder ; NA = Non Autistic

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} .

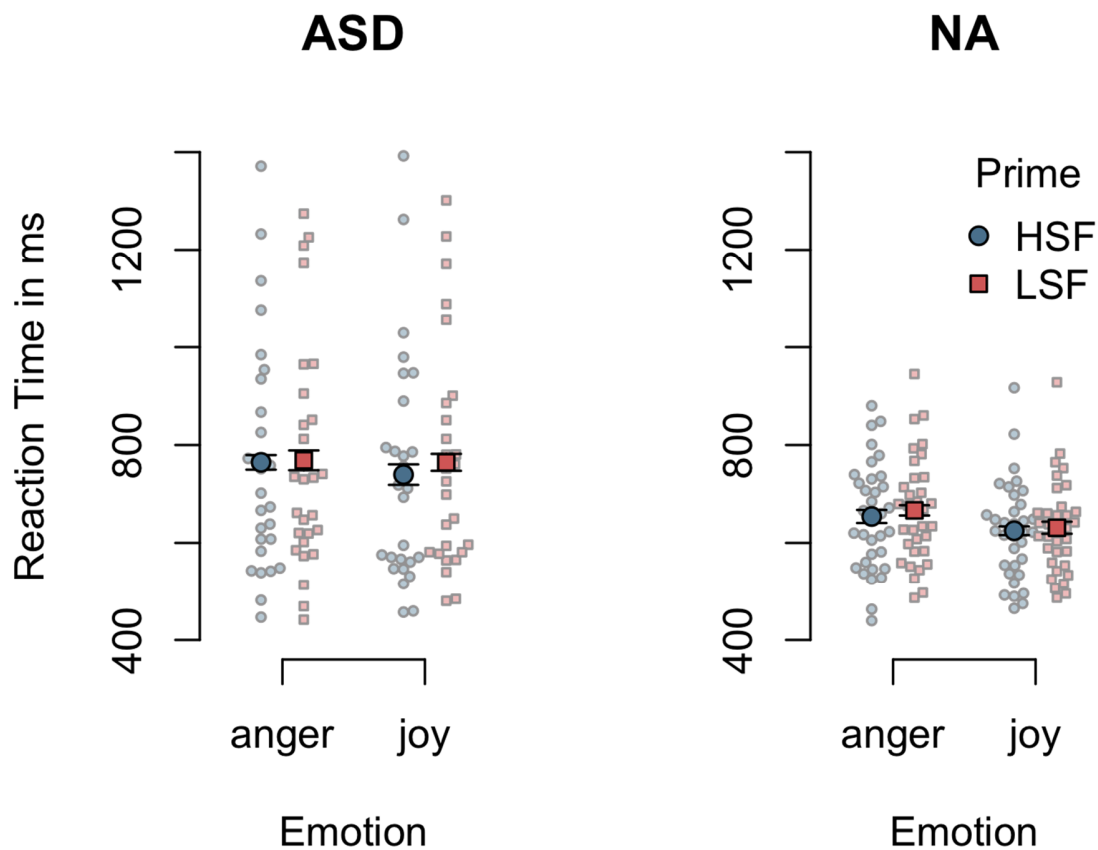


382

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 ($BF_{01} = 1.618 \cdot 10^{-17}$).

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

676 (Lanillos et al., 2020) could also help to better understand and reduce heterogeneity issues in
677 autism.

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

685 **5 Conclusion**

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

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. 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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738 **7 References**

- 739 Agustí, A. I., Satorres, E., Pitarque, A., & Meléndez, J. C. (2017). An emotional stroop task with
740 faces and words. A comparison of young and older adults. *Consciousness and Cognition*,
741 53, 99–104. <https://doi.org/10.1016/j.concog.2017.06.010>
- 742 American Psychiatric Association. (2000). Diagnostic and statistical manual of mental disorders,
743 –text revision (DSM-IV-TR). American psychiatric association. *Washington, DC*.
- 744 American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders*
745 *(DSM-5®)*. American Psychiatric Pub.
- 746 Arvidsson, O., Gillberg, C., Lichtenstein, P., & Lundström, S. (2018). Secular changes in the
747 symptom level of clinically diagnosed autism. *Journal of Child Psychology and*
748 *Psychiatry, and Allied Disciplines*, 59(7), 744–751. <https://doi.org/10.1111/jcpp.12864>
- 749 Ashwin, C., Chapman, E., Colle, L., & Baron-Cohen, S. (2006). Impaired recognition of negative
750 basic emotions in autism: A test of the amygdala theory. *Social Neuroscience*, 1(3), 349–
751 363. <https://doi.org/10.1080/17470910601040772>
- 752 Austin, P. C., & Brunner, L. J. (2003). Type i error inflation in the presence of a ceiling effect.
753 *The American Statistician*, 57(2), 97–104. <https://doi.org/10.1198/0003130031450>
- 754 Bacon-Macé, N., Macé, M. J. M., Fabre-Thorpe, M., & Thorpe, S. J. (2005). The time course of
755 visual processing: Backward masking and natural scene categorisation. *Vision Research*,
756 45(11), 1459–1469. <https://doi.org/10.1016/j.visres.2005.01.004>

- 757 Baldwin, S. A., & Larson, M. J. (2017). An introduction to using bayesian linear regression with
758 clinical data. *Behaviour Research and Therapy*, 98, 58–75.
759 <https://doi.org/10.1016/j.brat.2016.12.016>
- 760 Bar, M. (2007). The proactive brain: Using analogies and associations to generate predictions.
761 *Trends in Cognitive Sciences*, 11(7), 280–289. <https://doi.org/10.1016/j.tics.2007.05.005>
- 762 Bar, M., Kassam, K. S., Ghuman, A. S., Boshyan, J., Schmid, A. M., Dale, A. M., Hämäläinen,
763 M. S., Marinkovic, K., Schacter, D. L., Rosen, B. R., & Halgren, E. (2006). Top-down
764 facilitation of visual recognition. *Proceedings of the National Academy of Sciences*,
765 103(2), 449–454. <https://doi.org/10.1073/pnas.0507062103>
- 766 Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-
767 spectrum quotient (AQ): Evidence from asperger syndrome/high-functioning autism,
768 males and females, scientists and mathematicians. *Journal of Autism and Developmental*
769 *Disorders*, 31(1), 5–17. <https://doi.org/10.1023/A:1005653411471>
- 770 Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for
771 confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language*,
772 68(3), 255–278. <https://doi.org/10.1016/j.jml.2012.11.001>
- 773 Beffara, B., Wicker, B., Vermeulen, N., Ouellet, M., Bret, A., Molina, M. J. F., & Mermillod, M.
774 (2015). Reduction of interference effect by low spatial frequency information priming in
775 an emotional stroop task. *Journal of Vision*, 15(6), 16. <https://doi.org/10.1167/15.6.16>
- 776 Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal
777 decision making: A formal analysis of models of performance in two-alternative forced-

- 778 choice tasks. *Psychological Review*, *113*(4), 700–765. <https://doi.org/10.1037/0033->
779 295X.113.4.700
- 780 Bruyer, R., & Brysbaert, M. (2011). Combining speed and accuracy in cognitive psychology: Is
781 the inverse efficiency score (IES) a better dependent variable than the mean reaction time
782 (RT) and the percentage of errors (PE)? *PSYCHOLOGICA BELGICA*, *51*(1), 5–13.
783 <http://hdl.handle.net/1854/LU-2001824>
- 784 Buc Calderon, C., Verguts, T., & Gevers, W. (2015). Losing the boundary: Cognition biases
785 action well after action selection. *Journal of Experimental Psychology: General*, *144*(4),
786 737.
- 787 Bullier, J. (2001). Integrated model of visual processing. *Brain Research Reviews*, *36*(2), 96–107.
788 [https://doi.org/10.1016/S0165-0173\(01\)00085-6](https://doi.org/10.1016/S0165-0173(01)00085-6)
- 789 Bürkner, P.-C. (2017). Brms: An r package for bayesian multilevel models using stan. *Journal of*
790 *Statistical Software*, *080*(i01). <https://ideas.repec.org/a/jss/jstsof/v080i01.html>
- 791 Calvo, M. G., & Lundqvist, D. (2008). Facial expressions of emotion (KDEF): Identification
792 under different display-duration conditions. *Behavior Research Methods*, *40*(1), 109–115.
793 <https://doi.org/10.3758/BRM.40.1.109>
- 794 Calvo, M. G., & Nummenmaa, L. (2016). Perceptual and affective mechanisms in facial
795 expression recognition: An integrative review. *Cognition and Emotion*, *30*(6), 1081–1106.
796 <https://doi.org/10.1080/02699931.2015.1049124>
- 797 Caplette, L., Wicker, B., & Gosselin, F. (2016). Atypical time course of object recognition in
798 autism spectrum disorder. *Scientific Reports*, *6*, 35494. <https://doi.org/10.1038/srep35494>

- 799 Casasanto, D. (2009). Embodiment of abstract concepts: Good and bad in right- and left-handers.
800 *Journal of Experimental Psychology. General*, 138(3), 351–367.
801 <https://doi.org/10.1037/a0015854>
- 802 Chung, S., & Son, J.-W. (2020). Visual perception in autism spectrum disorder: A review of
803 neuroimaging studies. *Journal of the Korean Academy of Child and Adolescent*
804 *Psychiatry*, 31(3), 105.
- 805 Corradi-Dell'Acqua, C., Schwartz, S., Meaux, E., Hubert, B., Vuilleumier, P., & Deruelle, C.
806 (2014). Neural responses to emotional expression information in high- and low-spatial
807 frequency in autism: Evidence for a cortical dysfunction. *Frontiers in Human*
808 *Neuroscience*, 8. <https://doi.org/10.3389/fnhum.2014.00189>
- 809 De Gardelle, V., & Kouider, S. (2010). How spatial frequencies and visual awareness interact
810 during face processing. *Psychological Science*, 21(1), 58–66.
811 <https://doi.org/10.1177/0956797609354064>
- 812 DeRamus, T. P., & Kana, R. K. (2015). Anatomical likelihood estimation meta-analysis of grey
813 and white matter anomalies in autism spectrum disorders. *NeuroImage: Clinical*, 7, 525–
814 536. <https://doi.org/10.1016/j.nicl.2014.11.004>
- 815 Deruelle, C., & Fagot, J. (2005). Categorizing facial identities, emotions, and genders: Attention
816 to high- and low-spatial frequencies by children and adults. *Journal of Experimental Child*
817 *Psychology*, 90(2), 172–184. <https://doi.org/10.1016/j.jecp.2004.09.001>
- 818 Deruelle, C., Rondan, C., Salle-Collemiche, X., Bastard-Rosset, D., & Da Fonséca, D. (2008).
819 Attention to low- and high-spatial frequencies in categorizing facial identities, emotions

- 820 and gender in children with autism. *Brain and Cognition*, 66(2), 115–123.
821 <https://doi.org/10.1016/j.bandc.2007.06.001>
- 822 Diener, E., & Diener, C. (1996). Most people are happy. *Psychological Science*, 7(3), 181–185.
823 <https://doi.org/10.1111/j.1467-9280.1996.tb00354.x>
- 824 Enns, J. T., & Lleras, A. (2008). What's next? New evidence for prediction in human vision.
825 *Trends in Cognitive Sciences*, 12(9), 327–333. <https://doi.org/10.1016/j.tics.2008.06.001>
- 826 Favre, P., Polosan, M., Pichat, C., Bougerol, T., & Baciú, M. (2015). Cerebral correlates of
827 abnormal emotion conflict processing in euthymic bipolar patients: A functional MRI
828 study. *PLOS ONE*, 10(8), e0134961. <https://doi.org/10.1371/journal.pone.0134961>
- 829 Feczko, E., Miranda-Dominguez, O., Marr, M., Graham, A. M., Nigg, J. T., & Fair, D. A. (2019).
830 The heterogeneity problem: Approaches to identify psychiatric subtypes. *Trends in*
831 *Cognitive Sciences*, 23(7), 584–601. <https://doi.org/10.1016/j.tics.2019.03.009>
- 832 Frith, U. (1989). *Autism: Explaining the enigma* (2 edition). Wiley-Blackwell.
- 833 Gabry, J., Simpson, D., Vehtari, A., Betancourt, M., & Gelman, A. (2019). Visualization in
834 bayesian workflow. *Journal of the Royal Statistical Society: Series A (Statistics in*
835 *Society)*, 182(2), 389–402. <https://doi.org/https://doi.org/10.1111/rssa.12378>
- 836 Gernsbacher, M. A. (2017). Editorial perspective: The use of person-first language in scholarly
837 writing may accentuate stigma. *Journal of Child Psychology and Psychiatry*, 58(7), 859–
838 861. <https://doi.org/10.1111/jcpp.12706>

- 839 Goffaux, V., Peters, J., Haubrechts, J., Schiltz, C., Jansma, B., & Goebel, R. (2011). From coarse
840 to fine? Spatial and temporal dynamics of cortical face processing. *Cerebral Cortex*,
841 21(2), 467–476. <https://doi.org/10.1093/cercor/bhq112>
- 842 Golden, C. J., & Freshwater, S. M. (1978). *Stroop color and word test*.
- 843 Greenaway, R., Davis, G., & Plaisted-Grant, K. (2013). Marked selective impairment in autism
844 on an index of magnocellular function. *Neuropsychologia*, 51(4), 592–600.
845 <https://doi.org/10.1016/j.neuropsychologia.2013.01.005>
- 846 Grégoire, J., & Wierzbicki, C. (2009). Comparaison de quatre formes abrégées de l'échelle
847 d'intelligence de wechsler pour adultes – troisième édition (WAIS-III). *Revue Européenne*
848 *de Psychologie Appliquée/European Review of Applied Psychology*, 59(1), 17–24.
849 <https://doi.org/10.1016/j.erap.2007.08.003>
- 850 Grossman, J. B., Klin, A., Carter, A. S., & Volkmar, F. R. (2000). Verbal bias in recognition of
851 facial emotions in children with asperger syndrome. *Journal of Child Psychology and*
852 *Psychiatry*, 41(3), 369–379. <https://doi.org/10.1111/1469-7610.00621>
- 853 Halit, H., Haan, M. de, Schyns, P. G., & Johnson, M. H. (2006). Is high-spatial frequency
854 information used in the early stages of face detection? *Brain Research*, 1117(1), 154–161.
855 <https://doi.org/10.1016/j.brainres.2006.07.059>
- 856 Harms, M. B., Martin, A., & Wallace, G. L. (2010). Facial emotion recognition in autism
857 spectrum disorders: A review of behavioral and neuroimaging studies. *Neuropsychology*
858 *Review*, 20(3), 290–322. <https://doi.org/10.1007/s11065-010-9138-6>

- 859 Harrop, C., Jones, D., Zheng, S., Nowell, S., Schultz, R., & Parish-Morris, J. (2019). Visual
860 attention to faces in children with autism spectrum disorder: Are there sex differences?
861 *Molecular Autism*, 10(1), 28. <https://doi.org/10.1186/s13229-019-0276-2>
- 862 Harrop, C., Jones, D., Zheng, S., Nowell, S. W., Boyd, B. A., & Sasson, N. (2018). Sex
863 differences in social attention in autism spectrum disorder. *Autism Research*, 0(0).
864 <https://doi.org/10.1002/aur.1997>
- 865 Holmes, A., Winston, J. S., & Eimer, M. (2005). The role of spatial frequency information for erp
866 components sensitive to faces and emotional facial expression. *Cognitive Brain Research*,
867 25(2), 508–520.
- 868 Jahshan, C., Wolf, M., Karbi, Y., Shamir, E., & Rassovsky, Y. (2017). Probing the magnocellular
869 and parvocellular visual pathways in facial emotion perception in schizophrenia.
870 *Psychiatry Research*, 253, 38–42. <https://doi.org/10.1016/j.psychres.2017.03.031>
- 871 Jarosz, A., & Wiley, J. (2014). What are the odds? A practical guide to computing and reporting
872 bayes factors. *The Journal of Problem Solving*, 7(1). [https://doi.org/10.7771/1932-](https://doi.org/10.7771/1932-6246.1167)
873 [6246.1167](https://doi.org/10.7771/1932-6246.1167)
- 874 Jeantet, C., Caharel, S., Schwan, R., Lighezzolo-Alnot, J., & Laprevote, V. (2018). Factors
875 influencing spatial frequency extraction in faces: A review. *Neuroscience &*
876 *Biobehavioral Reviews*, 93, 123–138. <https://doi.org/10.1016/j.neubiorev.2018.03.006>
- 877 Jeffreys, H. (1961). *Theory of probability, clarendon.*

- 878 Jemel, B., Mottron, L., & Dawson, M. (2006). Impaired face processing in autism: Fact or
879 artifact? *Journal of Autism and Developmental Disorders*, *36*(1), 91–106.
880 <https://doi.org/10.1007/s10803-005-0050-5>
- 881 Jeste, S., & Geschwind, D. (2014). Disentangling the heterogeneity of autism spectrum disorder
882 through genetic findings. *Nature Reviews. Neurology*, *10*.
883 <https://doi.org/10.1038/nrneurol.2013.278>
- 884 Just, M. A., Keller, T. A., Malave, V. L., Kana, R. K., & Varma, S. (2012). Autism as a neural
885 systems disorder: A theory of frontal-posterior underconnectivity. *Neuroscience &*
886 *Biobehavioral Reviews*, *36*(4), 1292–1313.
887 <https://doi.org/10.1016/j.neubiorev.2012.02.007>
- 888 Kauffmann, L., Ramanoël, S., Guyader, N., Chauvin, A., & Peyrin, C. (2015). Spatial frequency
889 processing in scene-selective cortical regions. *NeuroImage*, *112*, 86–95.
890 <https://doi.org/10.1016/j.neuroimage.2015.02.058>
- 891 Kätsyri, J., Saalasti, S., Tiippana, K., Wendt, L. von, & Sams, M. (2008). Impaired recognition of
892 facial emotions from low-spatial frequencies in asperger syndrome. *Neuropsychologia*,
893 *46*(7), 1888–1897. <https://doi.org/10.1016/j.neuropsychologia.2008.01.005>
- 894 Kenny, L., Hattersley, C., Molins, B., Buckley, C., Povey, C., & Pellicano, E. (2016). Which
895 terms should be used to describe autism? Perspectives from the UK autism community.
896 *Autism*, *20*(4), 442–462. <https://doi.org/10.1177/1362361315588200>

- 897 Kéïta, L., Guy, J., Berthiaume, C., Mottron, L., & Bertone, A. (2014). An early origin for detailed
898 perception in autism spectrum disorder: Biased sensitivity for high-spatial frequency
899 information. *Scientific Reports*, *4*, 5475. <https://doi.org/10.1038/srep05475>
- 900 Khalid, S., Ansorge, U., & Finkbeiner, M. (2015). Supraliminal but no subliminal priming by
901 high-spatial frequency faces in a face-sex discrimination task. *Psychology*, *6*(12), 720–
902 726. <https://doi.org/10.4236/psych.2015.612146>
- 903 Kouider, S., Eger, E., Dolan, R., & Henson, R. N. (2009). Activity in face-responsive brain
904 regions is modulated by invisible, attended faces: Evidence from masked priming.
905 *Cerebral Cortex*, *19*(1), 13–23. <https://doi.org/10.1093/cercor/bhn048>
- 906 Kovarski, K., Caetta, F., Mermillod, M., Peyrin, C., Perez, C., Granjon, L., Delorme, R.,
907 Cartigny, A., Zalla, T., & Chokron, S. (2019). Emotional face recognition in autism and in
908 cerebral visual impairments: In search for specificity. *Journal of Neuropsychology*,
909 *n/a*(*n/a*). <https://doi.org/https://doi.org/10.1111/jnp.12221>
- 910 Kumar, D., & Srinivasan, N. (2011). Emotion perception is mediated by spatial frequency
911 content. *Emotion*, *11*(5), 1144–1151. <https://doi.org/10.1037/a0025453>
- 912 Lai, M.-C. (2020). Editorial: Meaningfully stratifying the autism spectra. *Journal of the American*
913 *Academy of Child & Adolescent Psychiatry*. <https://doi.org/10.1016/j.jaac.2020.08.002>
- 914 Lakens, D. (2021). *Sample size justification*.
- 915 Lanillos, P., Oliva, D., Philippsen, A., Yamashita, Y., Nagai, Y., & Cheng, G. (2020). A review
916 on neural network models of schizophrenia and autism spectrum disorder. *Neural*
917 *Networks*, *122*, 338–363. <https://doi.org/10.1016/j.neunet.2019.10.014>

- 918 Lee, M., & Wagenmakers, E.-J. (2013). *Bayesian data analysis for cognitive science: A practical*
919 *course*.
- 920 Leppänen, J. M., & Hietanen, J. K. (2003). Affect and face perception: Odors modulate the
921 recognition advantage of happy faces. *Emotion, 3*(4), 315–326.
922 <https://doi.org/10.1037/1528-3542.3.4.315>
- 923 Leppänen, J. M., & Hietanen, J. K. (2004). Positive facial expressions are recognized faster than
924 negative facial expressions, but why? *Psychological Research, 69*(1), 22–29.
925 <https://doi.org/10.1007/s00426-003-0157-2>
- 926 Lin, H., Saunders, B., Friese, M., Evans, N. J., & Inzlicht, M. (2020). Strong effort manipulations
927 reduce response caution: A preregistered reinvention of the ego-depletion paradigm.
928 *Psychological Science, 0956797620904990*. <https://doi.org/10.1177/0956797620904990>
- 929 Lix, L., Keselman, J. C., & Keselman, H. (1996). *Consequences of assumption violations*
930 *revisited: A quantitative review of alternatives to the one-way analysis of variance f test*.
931 <https://doi.org/10.2307/1170654>
- 932 Lo, S., & Andrews, S. (2015). To transform or not to transform: Using generalized linear mixed
933 models to analyse reaction time data. *Frontiers in Psychology, 6*.
934 <https://doi.org/10.3389/fpsyg.2015.01171>
- 935 Lord, C., Rutter, M., & Couteur, A. L. (1994). Autism diagnostic interview-revised: A revised
936 version of a diagnostic interview for caregivers of individuals with possible pervasive
937 developmental disorders. *Journal of Autism and Developmental Disorders, 24*(5), 659–
938 685. <https://doi.org/10.1007/BF02172145>

- 939 Lord, C., Rutter, M., Goode, S., Heemsbergen, J., Jordan, H., Mawhood, L., & Schopler, E.
940 (1989). Autism diagnostic observation schedule: A standardized observation of
941 communicative and social behavior. *Journal of Autism and Developmental Disorders*,
942 *19*(2), 185–212. <https://doi.org/10.1007/BF02211841>
- 943 Lynn, A. C., Padmanabhan, A., Simmonds, D., Foran, W., Hallquist, M. N., Luna, B., &
944 O’Hearn, K. (2018). Functional connectivity differences in autism during face and car
945 recognition: Underconnectivity and atypical age-related changes. *Developmental Science*,
946 *21*(1), e12508. <https://doi.org/10.1111/desc.12508>
- 947 Mennella, R., Leung, R. C., Taylor, M. J., & Dunkley, B. T. (2017). Disconnection from others in
948 autism is more than just a feeling: Whole-brain neural synchrony in adults during implicit
949 processing of emotional faces. *Molecular Autism*, *8*(1), 7. [https://doi.org/10.1186/s13229-](https://doi.org/10.1186/s13229-017-0123-2)
950 [017-0123-2](https://doi.org/10.1186/s13229-017-0123-2)
- 951 Milne, E., Swettenham, J., Hansen, P., Campbell, R., Jeffries, H., & Plaisted, K. (2002). High
952 motion coherence thresholds in children with autism. *Journal of Child Psychology and*
953 *Psychiatry*, *43*(2), 255–263. <https://doi.org/https://doi.org/10.1111/1469-7610.00018>
- 954 Mottron, L., Dawson, M., Soulières, I., Hubert, B., & Burack, J. (2006). Enhanced perceptual
955 functioning in autism: An update, and eight principles of autistic perception. *Journal of*
956 *Autism and Developmental Disorders*, *36*(1), 27–43. [https://doi.org/10.1007/s10803-005-](https://doi.org/10.1007/s10803-005-0040-7)
957 [0040-7](https://doi.org/10.1007/s10803-005-0040-7)
- 958 Nalborczyk, L., Batailler, C., Løevenbruck, H., Vilain, A., & Bürkner, P.-C. (2019). An
959 introduction to bayesian multilevel models using brms: A case study of gender effects on

- 960 vowel variability in standard Indonesian. *Journal of Speech, Language, and Hearing*
961 *Research*, 62(5), 1225–1242. https://doi.org/10.1044/2018_JSLHR-S-18-0006
- 962 Nguyen, H. B., Loughhead, J., Lipner, E., Hantsoo, L., Kornfield, S. L., & Epperson, C. N. (2019).
963 What has sex got to do with it? The role of hormones in the transgender brain.
964 *Neuropsychopharmacology*, 44(1), 22–37. <https://doi.org/10.1038/s41386-018-0140-7>
- 965 OMS. (1992). *CIM-10/ICD-10 : Descriptions cliniques et directives pour le diagnostic*. Editions
966 Masson.
- 967 O'Reilly, C., Lewis, J. D., & Elsabbagh, M. (2017). Is functional brain connectivity atypical in
968 autism? A systematic review of EEG and MEG studies. *PLOS ONE*, 12(5), e0175870.
969 <https://doi.org/10.1371/journal.pone.0175870>
- 970 Ovaysikia, S., Chan, J. L., Tahir, K., & DeSouza, J. F. X. (2011). Word wins over face:
971 Emotional Stroop effect activates the frontal cortical network. *Frontiers in Human*
972 *Neuroscience*, 4. <https://doi.org/10.3389/fnhum.2010.00234>
- 973 Pellicano, E., Gibson, L., Maybery, M., Durkin, K., & Badcock, D. R. (2005). Abnormal global
974 processing along the dorsal visual pathway in autism: A possible mechanism for weak
975 visuospatial coherence? *Neuropsychologia*, 43(7), 1044–1053.
976 <https://doi.org/10.1016/j.neuropsychologia.2004.10.003>
- 977 Pellicano, E., & Gibson, L. Y. (2008). Investigating the functional integrity of the dorsal visual
978 pathway in autism and dyslexia. *Neuropsychologia*, 46(10), 2593–2596.
979 <https://doi.org/10.1016/j.neuropsychologia.2008.04.008>

- 980 Perfetto, S., Wilder, J., & Walther, D. B. (2020). Effects of spatial frequency filtering choices on
981 the perception of filtered images. *Vision, 4*(2), 29.
- 982 Perilla-Rodríguez, L., Moraes, R. de, & Fukusima, S. (2013). Lateral visual hemifield asymmetry
983 and sex differences in recognizing low and high spatial frequency filtered faces.
984 *Psychology & Neuroscience, 6*(3), 253–260. <https://doi.org/10.3922/j.psns.2013.3.03>
- 985 Peyrin, C., Michel, C. M., Schwartz, S., Thut, G., Seghier, M., Landis, T., Marendaz, C., &
986 Vuilleumier, P. (2010). The neural substrates and timing of top-down processes during
987 coarse-to-fine categorization of visual scenes: A combined fMRI and ERP study. *Journal*
988 *of Cognitive Neuroscience, 22*(12), 2768–2780. <https://doi.org/10.1162/jocn.2010.21424>
- 989 Pirrone, A., Dickinson, A., Gomez, R., Stafford, T., & Milne, E. (2017). Understanding
990 perceptual judgment in autism spectrum disorder using the drift diffusion model.
991 *Neuropsychology, 31*(2), 173–180. <https://doi.org/10.1037/neu0000320>
- 992 Powell, G., Jones, C. R. G., Hedge, C., Charman, T., Happé, F., Simonoff, E., & Sumner, P.
993 (2019). Face processing in autism spectrum disorder re-evaluated through diffusion
994 models. *Neuropsychology, 33*(4), 445–461. <https://doi.org/10.1037/neu0000524>
- 995 Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-
996 choice decision tasks. *Neural Computation, 20*(4), 873–922.
997 <https://doi.org/10.1162/neco.2008.12-06-420>
- 998 Ravenzwaaij, D. van, Provost, A., & Brown, S. D. (2017). A confirmatory approach for
999 integrating neural and behavioral data into a single model. *Journal of Mathematical*
1000 *Psychology, 76*, 131–141.

- 1001 R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation
1002 for Statistical Computing. <https://www.R-project.org/>
- 1003 Rondan, C., & Deruelle, C. (2004). Face processing in high functioning autistic adults: A look
1004 into spatial frequencies and the inversion effect. *Journal of Cognitive and Behavioral*
1005 *Psychotherapies*, 4(2), 149–163.
- 1006 Rosen, N. E., Lord, C., & Volkmar, F. R. (2021). The diagnosis of autism: From kanner to DSM-
1007 III to DSM-5 and beyond. *Journal of Autism and Developmental Disorders*.
1008 <https://doi.org/10.1007/s10803-021-04904-1>
- 1009 RStudio Team. (2020). *RStudio: Integrated development environment for r*. RStudio, PBC.
1010 <http://www.rstudio.com/>
- 1011 Rødgaard, E.-M., Jensen, K., & Mottron, L. (2019). An opposite pattern of cognitive performance
1012 in autistic individuals with and without alexithymia. *Journal of Abnormal Psychology*,
1013 128(7), 735–737. <https://doi.org/10.1037/abn0000408>
- 1014 Schall, J. D. (2019). Accumulators, neurons, and response time. *Trends in Neurosciences*, 42(12),
1015 848–860.
- 1016 Schuck, R. K., Flores, R. E., & Fung, L. K. (2019). Brief report: Sex/gender differences in
1017 symptomology and camouflaging in adults with autism spectrum disorder. *Journal of*
1018 *Autism and Developmental Disorders*, 49(6), 2597–2604. [https://doi.org/10.1007/s10803-](https://doi.org/10.1007/s10803-019-03998-y)
1019 [019-03998-y](https://doi.org/10.1007/s10803-019-03998-y)

- 1020 Schyns, P. G., & Oliva, A. (1999). Dr. Angry and Mr. Smile: When categorization flexibly
1021 modifies the perception of faces in rapid visual presentations. *Cognition*, *69*(3), 243–265.
1022 [https://doi.org/10.1016/S0010-0277\(98\)00069-9](https://doi.org/10.1016/S0010-0277(98)00069-9)
- 1023 Schyns, P. G., & Oliva, A. (1997). Flexible, diagnosticity-driven, rather than fixed, perceptually
1024 determined scale selection in scene and face recognition. *Perception*, *26*(8), 1027–1038.
1025 <https://doi.org/10.1068/p261027>
- 1026 Servant, M., Montagnini, A., & Burle, B. (2014). Conflict tasks and the diffusion framework:
1027 Insight in model constraints based on psychological laws. *Cognitive Psychology*, *72*, 162–
1028 195. <https://doi.org/10.1016/j.cogpsych.2014.03.002>
- 1029 Shankland, R., Favre, P., Kotsou, I., & Mermillod, M. (2021). Mindfulness and de-
1030 automatization: Effect of mindfulness-based interventions on emotional facial expressions
1031 processing. *Mindfulness*, *12*(1), 226–239. <https://doi.org/10.1007/s12671-020-01515-2>
- 1032 Shaqiri, A., Roinishvili, M., Grzeczowski, L., Chkonia, E., Pilz, K., Mohr, C., Brand, A.,
1033 Kunchulia, M., & Herzog, M. H. (2018). Sex-related differences in vision are
1034 heterogeneous. *Scientific Reports*, *8*(1), 7521. <https://doi.org/10.1038/s41598-018-25298-8>
- 1035 Smith, M. L., & Merlusca, C. (2014). How task shapes the use of information during facial
1036 expression categorizations. *Emotion*, *14*(3), 478–487. <https://doi.org/10.1037/a0035588>
- 1037 Speelman, C., & McGann, M. (2013). How mean is the mean? *Frontiers in Psychology*, *4*.
1038 <https://doi.org/10.3389/fpsyg.2013.00451>
- 1039 Stevens, E., Dixon, D. R., Novack, M. N., Granpeesheh, D., Smith, T., & Linstead, E. (2019).
1040 Identification and analysis of behavioral phenotypes in autism spectrum disorder via

- 1041 unsupervised machine learning. *International Journal of Medical Informatics*, *129*, 29–36.
1042 <https://doi.org/10.1016/j.ijmedinf.2019.05.006>
- 1043 Strang, J. F., Miesen, A. I. van der, Caplan, R., Hughes, C., daVanport, S., & Lai, M.-C. (2020).
1044 Both sex- and gender-related factors should be considered in autism research and clinical
1045 practice. *Autism*, *24*(3), 539–543. <https://doi.org/10.1177/1362361320913192>
- 1046 Stroop, J. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental*
1047 *Psychology*, *18*(6), 643–662. <http://psycnet.apa.org/journals/xge/18/6/643/>
- 1048 Teare, M. D., Dimairo, M., Shephard, N., Hayman, A., Whitehead, A., & Walters, S. J. (2014).
1049 Sample size requirements to estimate key design parameters from external pilot
1050 randomised controlled trials: A simulation study. *Trials*, *15*(1), 1–13.
- 1051 Townsend, J., & Ashby, F. (1978). *Methods of modeling capacity in simple processing systems*.
1052 *Cognitive theory*, eds castellan j, restle f.
- 1053 Turner, B. M., Rodriguez, C. A., Norcia, T. M., McClure, S. M., & Steyvers, M. (2016). Why
1054 more is better: Simultaneous modeling of eeg, fMRI, and behavioral data. *NeuroImage*,
1055 *128*, 96–115.
- 1056 Uljarevic, M., & Hamilton, A. (2013). Recognition of emotions in autism: A formal meta-
1057 analysis. *Journal of Autism and Developmental Disorders*, *43*(7), 1517–1526.
1058 <https://doi.org/10.1007/s10803-012-1695-5>
- 1059 Vanmarcke, S., & Wagemans, J. (2017). Priming facial gender and emotional valence: The
1060 influence of spatial frequency on face perception in ASD. *Journal of Autism and*
1061 *Developmental Disorders*, *47*(4), 927–946. <https://doi.org/10.1007/s10803-016-3017-9>

- 1062 Vanston, J. E., & Strother, L. (2017). Sex differences in the human visual system. *Journal of*
1063 *Neuroscience Research*, 95(1), 617–625. [https://doi.org/https://doi.org/10.1002/jnr.23895](https://doi.org/10.1002/jnr.23895)
- 1064 Vega, I. de la, Dudschig, C., De Filippis, M., Lachmair, M., & Kaup, B. (2013). Keep your hands
1065 crossed: The valence-by-left/right interaction is related to hand, not side, in an incongruent
1066 hand-response key assignment. *Acta Psychologica*, 142(2), 273–277.
1067 <https://doi.org/10.1016/j.actpsy.2012.12.011>
- 1068 Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical bayesian model evaluation using leave-
1069 one-out cross-validation and WAIC. *Statistics and Computing*, 27(5), 1413–1432.
1070 <https://doi.org/10.1007/s11222-016-9696-4>
- 1071 Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model:
1072 An empirical validation. *Memory & Cognition*, 32(7), 1206–1220.
1073 <https://doi.org/10.3758/BF03196893>
- 1074 Vuilleumier, P., Armony, J. L., Driver, J., & Dolan, R. J. (2003). Distinct spatial frequency
1075 sensitivities for processing faces and emotional expressions. *Nature Neuroscience*, 6(6),
1076 624–631. <https://doi.org/10.1038/nn1057>
- 1077 Wagenmakers, E.-J. (2009). Methodological and empirical developments for the ratcliff diffusion
1078 model of response times and accuracy. *European Journal of Cognitive Psychology*, 21(5),
1079 641–671. <https://doi.org/10.1080/09541440802205067>
- 1080 Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau,
1081 Q. F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018).
1082 Bayesian inference for psychology. Part i: Theoretical advantages and practical

- 1083 ramifications. *Psychonomic Bulletin & Review*, 25(1), 35–57.
1084 <https://doi.org/10.3758/s13423-017-1343-3>
- 1085 Wechsler, D. (1997). *WAIS-III, wechsler adult intelligence scale: Administration and scoring*
1086 *manual*. Psychological Corporation.
- 1087 Wechsler, D. (2003). *Wechsler intelligence scale for children-WISC-IV*. Psychological
1088 Corporation.
- 1089 Wechsler, D. (2008). *Wechsler adult intelligence scale—fourth edition (WAIS-IV)*. San Antonio,
1090 TX: The Psychological Corporation.
- 1091 Weindel, G., Anders, R., Alario, F.-X., & Boris, B. (2020). *Assessing model-based inferences in*
1092 *decision making with single-trial response time decomposition*.
1093 <https://doi.org/10.31234/osf.io/kc26f>
- 1094 Winston, J. S., Vuilleumier, P., & Dolan, R. J. (2003). Effects of low-spatial frequency
1095 components of fearful faces on fusiform cortex activity. *Current Biology*, 13(20), 1824–
1096 1829.
- 1097 Yao, Y., Vehtari, A., Simpson, D., & Gelman, A. (2018). Using stacking to average bayesian
1098 predictive distributions (with discussion). *Bayesian Analysis*, 13(3), 917–1007.
1099 <https://doi.org/10.1214/17-BA1091>
- 1100 Yardley, H., Perlovsky, L., & Bar, M. (2012). Predictions and incongruity in object
1101 recognition: A cognitive neuroscience perspective. In D. Weinshall, J. Anemüller, & L.
1102 van Gool (Eds.), *Detection and identification of rare audiovisual cues* (pp. 139–153).
1103 Springer. https://doi.org/10.1007/978-3-642-24034-8_12